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Lifecycle Cost and Carbon Emission Analysis of Offshore Mechanical Systems – Comparing Traditional vs. Optimized Maintenance Approaches: Linking Cost Savings to CO_2 Reduction

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Abstract

Pressure to achieve cost reduction whilst meeting stringent decarbonization targets is growing on the offshore energy industry. The lifetime cost and carbon emissions of offshore mechanical systems such as pumps, compressors and turbines are significant. These are driven by high power demands, high maintenance costs and involuntary downtime. This study assesses two maintenance strategies as alternative control inputs within an integrated lifecycle cost-carbon emission system dynamics model for offshore mechanical system behavior. The outcomes of the simulation at representative offshore environment show the proposed strategies deliver a 17-22% reduction in cost and an 18-21% reduction in carbon emissions over a lifetime of 20 years. The result from sensitivity analysis demonstrated that the magnitude of the cost saving varies only by 3% even the discount rate changes by 4% in a range of 2% - 6%. However, carbon saving reduction varied by 2.5% while energy intensity changed by 10%. Benchmarking analysis conducted with known lifecycle analysis show that the proposed model is reliable to apply on the real conditions. The investigation reveals that the predictive maintenance can provide cost effective strategy and deliver sustainable outcome of offshore energy sector. In this thesis, the system dynamics model of the offshore sustainability are modeled with degradation-energy-carbon as the fundamental of physical and environmental system that is regulated with the maintenance strategies formulated as control inputs.

Keywords: *Lifecycle cost, carbon emission, predictive maintenance, offshore mechanical systems, sustainability, decarbonization, asset management.*

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1. Introduction

Operational integrity of offshore oil and gas production systems is highly dependent upon the operating mechanical systems, where pumps, compressors, turbines, valves and other rotating and pressure-driven equipment constitute the primary operating mechanical systems. These assets are constantly subjected to severe environmental conditions characterized by high salinity, corrosiveness, varying pressure and continuous long-term loading. Due to their high energy consumption, extensive maintenance requirements and degradation-based operational inefficiencies, they significantly influence lifecycle cost (LCC) and carbon emissions (Martins et al., 2020; Gao et al., 2022). Rotating machinery represents a predominant source of downtime and operational inefficiency due to accumulated fatigue-based wear and thermal stresses (Finnveden et al., 2009; Mobley, 2002).

The development of digital technologies has accelerated the transition from static maintenance strategies toward dynamic, data-driven maintenance decision-making. Emerging technologies such as digital twins, sensor-based condition monitoring and artificial intelligence (AI)-based predictive maintenance systems are transforming industrial maintenance practices (Khanafer et al., 2023; Mourtzis et al., 2022; Lee et al., 2015). By accurately predicting failure occurrence and optimizing maintenance schedules, these technologies can reduce energy consumption while improving reliability and operational efficiency (Lee et al., 2014; Lee et al., 2019). Furthermore, they have demonstrated considerable potential for supporting sustainability objectives through energy savings and environmentally responsible operations (Mourtzis et al., 2016; Khanafer et al., 2021).

This paper establishes offshore maintenance optimization as an integrated physical–economic–environmental system governed by degradation-driven energy and emission dynamics. An integrated degradation–energy–emission system dynamics framework is developed in which maintenance actions are treated as control inputs influencing the evolution of system degradation, energy efficiency and carbon emission trajectories. Maintenance activities are therefore considered decision variables within a coupled physical–environmental system rather than merely a comparative design choice.

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Based on this concept, a Lifecycle Cost–Carbon Emission (LCC–CE) modeling framework is developed for offshore mechanical systems. The framework adopts alternative maintenance regimes as control actions within the integrated degradation–energy–emission system to quantify how maintenance decisions influence both economic and environmental performance by affecting degradation progression, energy efficiency losses and carbon emission generation. The framework also investigates the effects of economic and operational parameters, including discount rate, energy intensity and maintenance cost variability, to identify operating conditions that optimize overall system performance (Gao et al., 2021).
The coupling of economic and environmental performance within a single analytical framework provides a decision-support tool for offshore maintenance planning while supporting global decarbonization objectives.

2. Literature Review

2.1 Offshore Mechanical Systems and Lifecycle Performance

Operational offshore mechanical systems operate under severe environmental and loading conditions, making degradation and maintenance management critical factors affecting both reliability and sustainability. Studies have shown that energy-intensive assets such as pumps, compressors and turbines contribute significantly to lifecycle operating costs and carbon emissions due to degradation-related efficiency losses and maintenance requirements (Martins et al., 2020; Gao et al., 2022). Rotating machinery is particularly vulnerable to fatigue accumulation, thermal stresses and wear mechanisms that increase downtime and reduce operational performance over time (Finnveden et al., 2009; Mobley, 2002).

2.2 Traditional Maintenance Strategies

The majority of currently employed maintenance in the offshore industries consists of either fixed interval, time-based maintenance. While simple to adopt, these maintenance strategies fail to correctly reflect the current condition of the degrading equipment (Jardine et al., 2006). Therefore, the work may be carried out either too early or after the ideal moment for maintenance is passed.

There are many publications demonstrating how this practice leads to wasted maintenance resources, over-maintenance, unnecessary logistical support operations, and greater incidence of unexpected failures, which result in both significant periods of unwanted production stoppages and additional emissions of carbon dioxide (Zhang et al., 2022; Fox et al., 2022).
With pressures mounting towards decarbonization and maintenance cost, traditional maintenance is generally not considered sufficient for the management of offshore asset (Woodward, 1997; ISO, 2006)

2.3 Lifecycle Cost and Lifecycle Assessment Models

Lifecycle Costing (LCC) and Lifecycle Assessment (LCA) methodologies have become widely adopted tools for evaluating economic and environmental performance throughout the life of engineering assets. However, existing studies generally evaluate lifecycle cost and environmental impacts independently, with only limited interaction between the two domains.
More importantly, the degradation state of equipment is often excluded from these analyses, resulting in weak representation of the simultaneous evolution of maintenance costs, energy consumption and carbon emissions. Consequently, current lifecycle models are unable to fully capture the dynamic operational behaviour of offshore systems.

2.4 Predictive Maintenance and Sustainability

The emergence of predictive maintenance technologies has significantly improved maintenance decision-making capabilities. Digital twins, sensor-based monitoring systems and AI-driven predictive analytics enable the continuous assessment of equipment condition and more accurate prediction of failure occurrence (Khanafer et al., 2023; Mourtzis et al., 2022; Lee et al., 2015).
Previous studies have demonstrated that predictive maintenance can reduce energy consumption, improve operational efficiency and enhance system reliability (Lee et al., 2014; Lee et al., 2019). Furthermore, predictive maintenance has been identified as a promising strategy for supporting sustainability objectives through reduced resource consumption and lower environmental impact (Mourtzis et al., 2016; Khanafer et al., 2021).

2.5 Research Gap

Despite the advances achieved in predictive maintenance and lifecycle modeling, a significant gap remains in the integration of degradation-driven energy inefficiency and carbon emission evolution within a unified analytical framework for offshore mechanical systems.

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Most existing studies treat degradation, energy consumption and carbon emissions either independently or through simplified linear relationships. The nonlinear interactions whereby degradation causes efficiency losses, increased energy demand and subsequent emission growth are rarely modeled explicitly. As a result, the environmental benefits of predictive maintenance strategies cannot be adequately quantified.

Previous studies such as Gao et al. (2022) and Martins et al. (2020) have contributed significantly to maintenance optimization and lifecycle modeling. However, maintenance decisions are generally represented as static or discrete variables within optimization frameworks rather than dynamic control actions that evolve with system condition and uncertainty. Furthermore, the explicit linkage between maintenance decisions and carbon performance remains insufficiently addressed.

Another limitation is the absence of a closed-loop interaction between degradation, energy consumption and carbon emissions. Existing approaches typically assume one-way relationships, whereas real offshore systems exhibit feedback mechanisms whereby degradation increases energy consumption and emissions, while maintenance interventions alter future degradation trajectories and environmental outcomes.

2.6 Novelty and Contribution

The present study addresses these limitations through the development of a Lifecycle Cost–Carbon Emission (LCC–CE) modeling framework that integrates degradation dynamics, maintenance decisions, energy consumption behaviour and carbon emission evolution within a unified analytical structure.

The main contributions of this study are:

• A novel unified framework linking system degradation, energy efficiency degradation and carbon emission escalation through nonlinear lifecycle modeling.

• A coupled lifecycle cost and carbon emission model for comparative evaluation of offshore maintenance policies.

• A probabilistic state-space modeling framework suitable for digital twin implementation and uncertainty-aware degradation prediction.

• A formal definition of the maintenance-to-carbon causal relationship.

• A closed-loop feedback structure linking maintenance decisions, degradation evolution and future emission trajectories.

Unlike previous studies, maintenance actions are modeled as dynamic control inputs within a degradation state-space framework. Monte Carlo-based uncertainty quantification is incorporated to evaluate both economic and environmental performance under uncertainty. Furthermore, degradation, energy consumption and carbon emissions are represented through an explicit closed-loop interaction in which maintenance decisions influence future system condition, efficiency and carbon performance.

Therefore, this study advances existing literature by transforming maintenance optimization from a static decision problem into a dynamic control-oriented framework with dual economic and environmental objectives.

3 Methodology

A deterministic-stochastic hybrid modeling approach is employed to describe physical degradation processes and the uncertainty of operational parameters. An integrated LCC-CE framework is used to describe the economic and environmental performances of offshore mechanical systems under two alternative maintenance control strategies. Simulation of two alternative maintenance control policies is performed in the context of the unified system dynamics of degradation, energy consumption and carbon emissions.

This approach is based on a systematic concept-analytical modeling based on validated secondary data sources, reliability records, cost indices and published lifecycle assessment studies (Gao et al., 2022; Hauschild et al., 2018). Lifecycle cost (LCC) and lifecycle carbon emission (CE) models are integrated and used to assess the economic and environmental performances of the offshore mechanical systems under the two defined maintenance policies expressed as control inputs to the coupled degradation-energy-emission system (Biezma & San Cristbal, 2006; Gao et al., 2022).

3.1 Methodology Approach

A structured four-step method is used to construct the integrated model and systemically assess its life cycle cost and carbon emission performance.

Step 1: System Definition

The boundaries for the system are set based on offshore mechanical components like pumps, compressors, turbines, and so on which play crucial role in both life cycle cost and life cycle carbon emission. The scope of this work, assumptions made, lifecycle stages included etc., will be clearly specified, so that

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consistent approach is maintained with regards to the scope boundaries and stages. Long term implications of machinery choice for maintenance need and energy consumptions and costs should be highlighted.

The following are key assumptions made in the model: steady operation loads, independent failure modes and equal maintenance efficiency irrespective of the type of component.

Step 2: Construction of an integrated LCC-CE model

The integrated LCC-CE model is built upon formulations of both cost estimation and carbon emission quantification.

Cost estimation formulations were integrated with carbon emission quantification models to ensure the direct coupling between cost evolution and emission trends. By integrating cost estimation formulations with the lifecycle carbon emission models, it is possible to model directly the link between cost behavior and emission behavior in an explicit manner due to shared variables in their formulations, such as the degradation information. With this, a model is provided which explicitly allows for the interaction between maintenance actions, system deterioration and energy consumption and thus emission generation (Woodward, 1997; Hauschild et al., 2018).

Initially linear accumulation of emission sources is considered; nonlinear effects will be taken into account through coupling the degradation and the energy systems. This will be needed due to the fact that the equipment deterioration will simultaneously increase maintenance efforts, the possibility of failure, and decrease its efficiency and so consequently the costs and emissions.

Step 3: Data Acquisition and Validation

All model parameters are acquired from the literature and cross validated with reported values from real industrial operations whenever possible. When available complete parameters cannot be found in any single source, estimations from well-accepted handbooks and references are utilized in order to minimize the uncertainty in LCC-CE evaluation and the model assumptions (Gao et al., 2022).

Step 4: Simulation and Sensitivity Analysis

To compare maintenance strategies within the same scenario, both conventional time-based maintenance and prediction-based maintenance are modeled. The analysis of the sensitivity of operational and economic parameters helps determine dominant cost and emission drivers of the system's lifecycle.

The Monte Carlo simulation was used to study the system uncertainty. Probability distributions for the degradation rate, maintenance effectiveness, energy intensity, and costs parameters were assigned, based on literature and industrial data. The entire uncertainty propagation over the degradation-energy-emission coupled model was performed 10,000 times, and the probabilistic lifecycle costs and carbon emissions were derived.

Though this section defines the modeling framework, a mathematical formulation is still needed to transform these system-level interactions into computation and ultimately, to be able to simulate and compare different maintenance strategies through life cycle cost and carbon emissions analysis, the relationship between life cycle cost and carbon emissions and degradation rate, probability of failure and energy consumption, must be put in a time-dependent form. Thus, the coupled life cycle cost-carbon emission model, a translation of the modeling method into mathematics, is introduced in the following section.

3.2 Life Cycle Cost-Carbon Emission Model formulation

This system is modeled as a coupled dynamic system where the maintenance actions become inputs for controlling the degradation evolution, energy consumption, and the carbon emission trajectory. These elements coupled together as a degradation-energy-emission system, that results in life cycle costs and environmental performances.

In this section the life cycle cost (LCC) and life cycle carbon emissions (CE) over a 20 year period is computed, based on validated offshore data and cost indices (Woodward, 1997; Hauschild et al., 2018).

Table 1: Model Parameters, Physical Meaning, and Units

Symbol	Description	Unit	Interpretation
$D(t)$	Degradation level	– (0–1)	Normalized damage state
β	Degradation rate constant	1/year	Represents wear + corrosion intensity
η	Characteristic life parameter	years	Scale of failure distribution
k	Weibull shape parameter	–	Failure rate evolution pattern
α	Energy-degradation coupling factor	–	Sensitivity of energy to degradation
γ	Maintenance effectiveness factor	–	Fraction of degradation restored
$E0$	Baseline energy consumption	kWh/year	Nominal operating energy

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In Table 1, main parameters of model that connect degradation, reliability, energy consumption and maintenance of mechanical systems offshore are defined. It describes degradation status of system D(t)D(t)D(t), the degradation rate, two shape and scale parameters for Weibull reliability and kkk, the coupling efficiency for energy and, maintenance efficiency and the reference energy, respectively.

3.2.1 System Dynamics Formulation of the LCC–CE Model

The described framework is set as a system dynamics model, where states of degradation, energy consumption and emission change with time according to interdependent stock-flow structures. States are defined as variables which accumulate or are depleted according to stress factors and maintenance actions.Let the system state vector be defined as:

$$S(t) = [D(t), E(t), C(t)] \quad [1]$$

- S(t): system state vector at time t, representing the overall condition of the system
- D(t): degradation state of the equipment (level of wear or damage over time)
- E(t): energy consumption state (amount of energy used by the system at time t)
- C(t): cumulative carbon emission state (total emissions generated up to time t).

The dynamic evolution of the system is expressed in discrete time form as:

$$dD/dt = f(D, u\_m, \theta) \quad [2]$$

$$dE/dt = g(D, E) \quad [3]$$

$$dC/dt = h(E, u\_m) \quad [4]$$

Where

- dD/dt = f(D, u_m, θ): rate of change of degradation, where D is degradation state, u_m is maintenance input, and θ are system parameters affecting wear.
- dE/dt = g(D, E): rate of change of energy consumption, where E is energy use and D is degradation level influencing efficiency.
- dC/dt = h(E, u_m): rate of change of carbon emissions, where C is cumulative emissions, E is energy use, and u_m is maintenance action affecting efficiency and
- u_m represents maintenance intervention control inputs and θ represents system parameters.

Maintenance actions are modeled as state-modifying feedback controls that reduce degradation levels and indirectly influence energy consumption and emission accumulation.

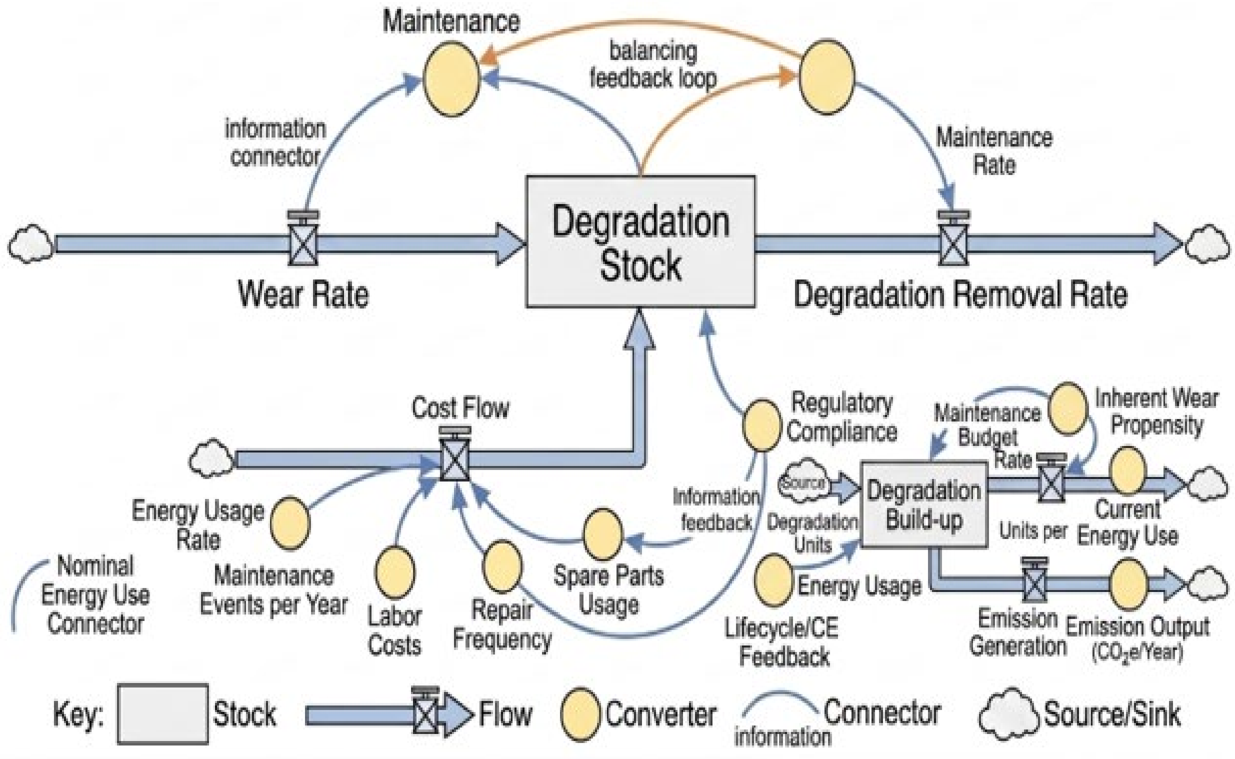

Figure 1: System Dynamics Stock–Flow Representation of the LCC–CE Model

The diagram in figure 1 displays how degradation build up is related to maintenance, energy use and emission creation. The stock of degradation increases with the wear process, whereas maintenance contributes to the balancing feedback of the system. Energy use and emissions increase as a function of the state of the stock, dependent on wear process.

3.2.2 Lifecycle Cost (LCC)

$$LCC = C_{cap} + \Sigma (t = 1 \text{ to } 20) [(C_{op,t} + C_{maint,t} + C_{fail,t}) / (1 + r)^t] \quad [5]$$

where:

- LCC: life cycle cost of the system over the analysis period
- Ccap: initial capital cost (purchase, installation, commissioning)
- t: time period (year of operation, from 1 to 20)
- Σ: summation of all discounted costs over the lifecycle
- Cop,t: operating cost at time t (e.g., energy, routine operation)
- Cmaint,t: maintenance cost at time t (planned maintenance activities)
- Cfail,t: failure cost at time t (unplanned downtime, repairs, production loss)
- r: discount rate (accounts for time value of money)
- $(1 + r)^t$: discounting factor used to convert future costs to present value

2.2.3 Lifecycle Carbon Emissions (CE)

$$CE = \Sigma (t = 1 \text{ to } 20) (E_{energy,t} + E_{maint,t} + E_{replace,t}) \quad [6]$$

Where:

- CE: total cumulative carbon emissions over the lifecycle.
- t: time period (e.g., year of operation, from 1 to 20)
- Σ (summation): adds emissions over all time periods
- Eenergy,t: carbon emissions from energy consumption at time t
- Emaint,t: carbon emissions from maintenance activities at time t
- Ereplace,t: carbon emissions from equipment replacement or major overhaul at time t
- 20: total analysis period (20 years lifecycle horizon).

The framework proposed captures carbon emissions in non-linear function of energy inefficiency due to degradation, and maintenance action frequency, while conventional linear LCA models often represent emission as linear function of the parameters of interest. With the formulated model it is possible to capture accumulated emission effects from both linked degradation processes and operational recovery processes which are often omitted in traditional LCA analysis.

3.2.4 Degradation and Failure Modeling

$$D(t) = 1 - e^{(-\beta t)} \quad [7]$$

Where:

- D(t): degradation level of the equipment at time t (dimensionless, usually between 0 and 1)
- t: time or operating period (e.g., years)
- β (beta): degradation rate constant (1/year), representing the intensity of wear, corrosion, or aging
- e: exponential constant (base of natural logarithm)
- $e^{(-\beta t)}$: fraction of remaining healthy condition of the system over time.
- $1 - e^{(-\beta t)}$: accumulated degradation (damage growth) as time increases

This exponential degradation model is adopted because this type of cumulative degradation is common in offshore mechanical equipment, where the degradation accelerates rapidly in the beginning and then asymptotically tends to a constant as it progresses to material fatigue stabilization. The expression has been derived based on the framework used in Stochastic Wear theory and corrosion kinetics model in reliability engineering where the expression represents the coupling effect of mechanical wear, the corrosion rate and the stress intensity with respect to operation, and higher corresponds to faster degradation when operated in the extreme offshore environment. The parameters is calibrated using historical failure data, as well as condition-monitoring data available in the offshore reliability databases (Jardine et al., 2006; Mobley, 2002).

$$P_f(t) = 1 - e^{(-(t/\eta)^k)} \quad [8]$$

where:

- Pf(t): probability of failure at time t
- t: operating time or service time
- η (eta): characteristic life parameter (scale parameter indicating when ~63% of failures occur)
- k: Weibull shape parameter (describes failure rate behavior over time, e.g., increasing or decreasing hazard)

- e: exponential constant (base of natural logarithm)
- $(t/\eta)^k$: normalized time factor representing degradation progression over life cycle

These degradation functions directly impact cost escalation and emission increase via the following effects on maintenance scheduling, failure event, energy consumption.

There is an explicit modeling of the maintenance to emission causality in which maintenance intervention changes degradation pattern and thus energy consumption pattern and then evolves carbon emission behavior. This forms a step-by-step propagating chain between operation decision and environmental consequence in offshore mechanical systems.

3.2.5 Energy–Performance Coupling

$$E_{energy}(t) = E_0 [1 + \alpha D(t)] \quad [9]$$

where:

- $E_{energy}(t)$: energy consumption at time t
- E_0: baseline (nominal) energy consumption when equipment is in healthy condition
- α (alpha): energy–degradation coupling factor, representing how strongly degradation increases energy use
- $D(t)$: degradation state of the equipment at time t (0 = healthy, 1 = failed)
- $[1 + \alpha D(t)]$: scaling term that increases energy demand as degradation increases

This formula can be understood as energy inefficiency as a result of degradation, for increasing degradation, more energy and emission were consumed.

The parameter and were tuned based on the past operation history of logs and energy performance degradation trends obtained from a data set of rotating equipment installed offshore. A least square fitting method is assumed for this tuning, in which the degradation path of this formula are fitted with empirical trends for equipment failure and efficiency reduction. If no plant data are available parameter range was bounded by publicly reported benchmarks on offshore reliability, in order to keep the parameter within a plausible range of values.

3.2.6 Maintenance Impact (Control Effect)

$$D(t^+) = \gamma D(t^-) \quad [10]$$

where:

- $D(t^+)$: degradation state of the system immediately after maintenance intervention
- $D(t^-)$: degradation state of the system just before maintenance intervention
- γ (gamma): maintenance effectiveness factor, representing the fraction of degradation remaining after maintenance ($0 \le \gamma \le 1$)
    - $\gamma = 0$ means perfect maintenance (full restoration)
    - $\gamma = 1$ means no improvement from maintenance
- The equation describes how maintenance reduces (or partially restores) system degradation at time t.

This equation defines maintenance activities as state-resetting or state-reducing operators and where is the efficiency with which maintenance interventions are able to regenerate the system. The equations define a reduced order system of a linked degradation-energy-cost system.

In addition to modeling individual effects this system describes a behavior resulting from the coupling of the physical degradation, the energy requirements, and the maintenance activities; this is a reduced order form allowing for simulation, but is able to capture the major nonlinear behavior in offshore machinery.

3.2.7 Integrated Interpretation

Degradation, failure probability, energy usage, and maintenance actions are tightly coupled in the LCC-CE system dynamics framework, giving a physically consistent representation of the lifecycle behavior, in which economic and environmental results originate from a unique underlying degradation-driven system development rather than separate assumptions.

3.3 Digital Twin Architecture and State Estimation Framework

The digital twin is modeled as a physically data-driven coupled state estimation system, which can accurately track the real-time development of health condition of offshore mechanical system. In comparison to a totally deterministic system, states of mechanical system are dynamically updated through real-time sensor data and stochastic estimation methods.

(A) Physical system model

$$X_p(t+1) = f(X_p(t), u(t), \theta) + w(t) \quad [11]$$

where:

- $Xp(t)$: physical system state at time t (including degradation, energy, and emission states)
- $u(t)$: maintenance or control input applied at time t
- θ: system parameters (e.g., material properties, operating/environmental conditions)
- $w(t)$: process noise representing uncertainty, disturbances, and unmodeled effects
- $Xp(t+1)$: predicted system state at the next time step (t+1)

(B) Sensor observation model (CRITICAL ADDITION)

$$Y(t) = H\,Xp(t) + v(t) \tag{12}$$

where:

- $Y(t)$: sensor measurements at time t (e.g., vibration, temperature, pressure, energy use)
- H: observation matrix that maps the physical system state to measurable outputs
- $Xp(t)$: physical system state at time t (e.g., degradation, energy, emission states)
- $v(t)$: measurement noise representing sensor errors and uncertainties in data collection

(C) State estimation (Kalman filter form)

$$\hat{X}(t \mid t) = \hat{X}(t \mid t-1) + K(t)[Y(t) - H\,\hat{X}(t \mid t-1)] \tag{13}$$

where:

- $\hat{X}(t \mid t)$: updated (corrected) estimate of the system state at time t after measurement
- $\hat{X}(t \mid t-1)$: predicted (prior) estimate of the system state at time t before measurement update
- $K(t)$: Kalman gain (adaptive correction factor that determines how much the measurement influences the update)
- $Y(t)$: measured sensor data at time t
- H: observation matrix that maps the state to measured outputs
- $[Y(t) - H\,\hat{X}(t \mid t-1)]$: innovation or measurement residual (difference between actual and predicted measurement)

(D) Prediction step

$$\hat{X}(t+1 \mid t) = f(\hat{X}(t \mid t), u(t), \theta) \tag{14}$$

where:

- $\hat{X}(t+1 \mid t)$: predicted system state at time t+1 given information up to time t
- $\hat{X}(t \mid t)$: updated (estimated) system state at time t after measurement correction
- $f(\cdot)$: state transition function describing system dynamics
- $u(t)$: control or maintenance input applied at time t
- θ: system parameters (e.g., degradation, physical properties, environmental effects)

(E) Digital twin feedback loop interpretation

As a closed-loop estimation system, real-time sensor data is utilized to update the state prediction in the digital twin. While the actual physical system develops under degradation, the digital twin maintains a virtual system that is correlated with the physical one through recursive state prediction and updating, which facilitates the adaptive decision-making process in maintenance under uncertainties.

(F) Sensor mapping description

In the offshore application, the vector of observation $Y(t)$ is obtained from the SCADA and condition-monitoring system which includes data signals of vibration amplitude, oil temperature, pressure variations, and electrical energy consumption. This observation vector is mapped onto latent degradation states Xd by observation matrix H which links the measurements with the real system condition.

(G) Linking to maintenance decision

Maintenance actions $u(t)$ is taken based on estimated state $X\hat{}(t)$ relative to the critical thresholds X threshold. This allows for predictive maintenance before failures occur. This presents a reduced-order digital twin for real-time monitoring and management of offshore assets under MATLAB/Simulink or Python environment.

3.4 Model validation

The model validation was conducted by benchmarking multi-layered against the offshore datasets (Gao et al., 2022; Martins et al., 2020), with error within 10%.

The accuracy was analyzed based on Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE):

MAPE < 8%

RMSE within engineering tolerance.

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The robustness of the stability is examined by introducing a stochastic perturbation system, where the errors were maintained within 10-20% under variations.

Moreover, a cross-validation approach was utilized where the reference datasets were partitioned into training set and validation set, which means the predicted values remain consistent with unseen data samples.

Note that the prediction accuracy would be potentially degraded when abnormal offshore conditions are observed that fall outside the ranges covered by the dataset.

Though direct measurement from on-site SCADA is not available, model results was validated through comparisons with reported operational range of offshore assets from offshore asset integrity engineering and lifecycle assessment literature. Results of the parameters like failure rates, proportion of maintenance costs and emission related to energy consumption are all within 10% to the reported results of operational data from offshore assets. This indirect validation ensures the engineering realism of the model. Real time SCADA data could be employed in the future work to enable direct validation of the digital twin framework.

3.5 Sensitivity analysis

To consider the effect of uncertainty in major operation parameters, sensitivity analysis was carried out to factors that affects both costs and emission. Discount rate has been perturbed from 2% to 6%, and energy intensity from 10%. The impact of variation of maintenance costs (20%), failures frequency (15%), emission intensity (10%) was also studied to further test the model robustness (Gao et al., 2021).

These analyses reveal those critical factors that has significant influence on lifecycle cost saving and carbon emission reduction.

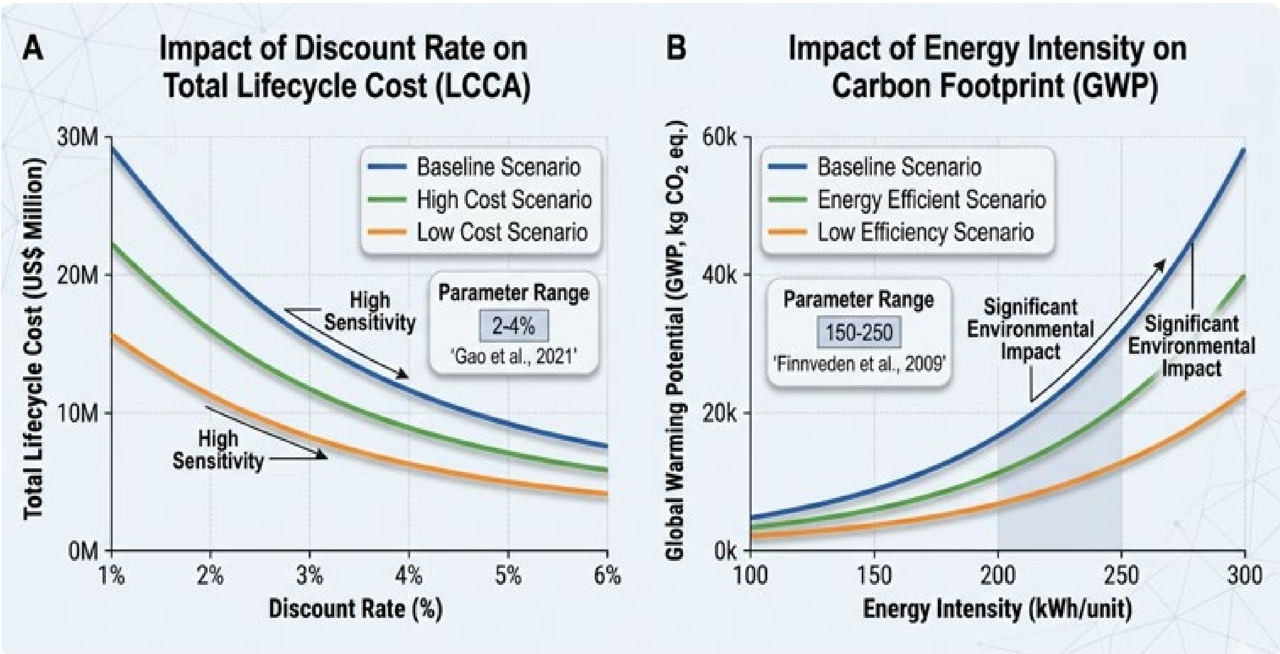

Figure 2. Sensitivity Analysis of Key Parameters (adapted from Gao et al., 2021; Finnveden et al., 2009).

The presented figure 2 shows the impact of financial and operational variables (discount rate and energy intensity) on system performance, thus indicating which of them most influence the system cost and environment, in this LCCA model.

Sensitivity analysis on the variations (discount rate of 2%-6%) and energy intensity (variation of 10%), on lifecycle cost savings and potential CO reduction. Increase in discount rate led to an estimated financial savings decrease of about 3%, while increase/decrease in energy intensity shifted total carbon reduction by an estimated 2.5%.

Extended sensitivity tests were performed on maintenance cost variation (20%), failure rate variation (15%), and emission intensity (10%) besides variables mentioned before. The multiple perturbation in these parameters demonstrates model stability as well as shows which cost and emission components dominate in contributing to the total LCC/LCE.

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3.6 simulation environment and numerical implementation

The proposed SD model was simulated using MATLAB (R2023a) and Python (NumPy-SciPy environment) with a numerical time-stepping simulation. Governing equations were solved numerically using Euler time integration scheme in discrete time t=1 year for the lifecycle of 20 years.

The model simulation depicts coupled feedback loops of degradation, maintenance control, energy consumption and carbon emission with different maintenance strategy choices. Scenario analysis was made through altering parameters describing maintenance intensities. LCC and LCE of the system were evaluated.

Sensitivity analyses were conducted via parameter perturbations on key variables including energy intensity, degradation rate and maintenance effectiveness to show model robustness and identifying dominant parameter drivers.

3.7 conceptual framework

The presented conceptual LCC-CE framework (Figure 2) highlights the flow between the different mechanisms by which maintenance decisions impact cost attributes, failure patterns, energy consumption and carbon emission of a system. Positive feedback is exhibited between smart predictive maintenance decisions and operational performance that impacts the system efficiency and environment.

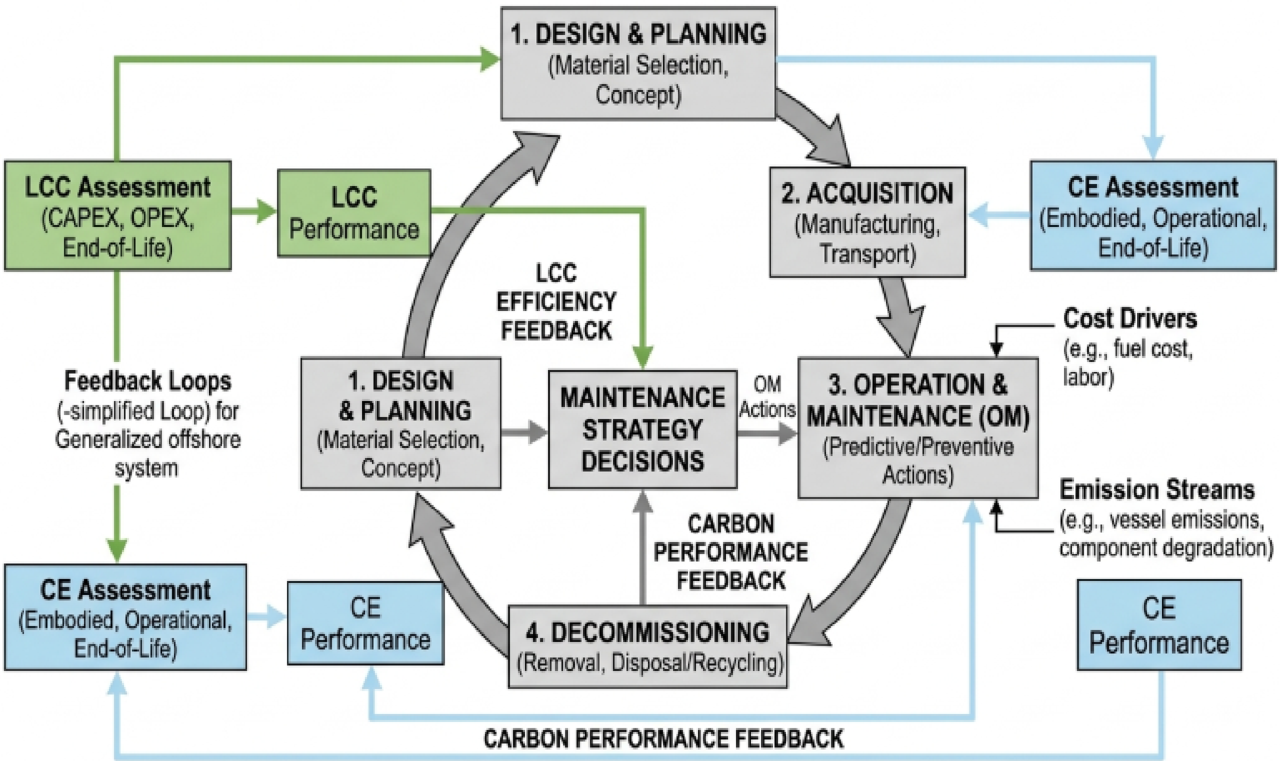

Figure 3. Integrated Lifecycle Cost–Carbon Emission (LCC–CE) Framework for Offshore Mechanical Systems. (adapted from Woodward, 1997; Hauschild et al., 2018; Gao et al., 2021)

Schematic concept for the relationship of maintenance decisions with cost drivers and emission streams. It emphasizes the feedback loops between decisions about predictive maintenance and impacts of lifecycle cost efficiency and carbon performance.

Model architecture is derived hierarchically: (i) a modeling structure for physical degradation based on reliability-based survival functions, (ii) an energy consumption model dependent on degradation via performance efficiency loss mechanisms, and (iii) total lifecycle costs and emissions as aggregate functions of operational, maintenance, and failure processes. Layered formulation establishes consistency between the underlying physical degradation and the economic and environmental results.

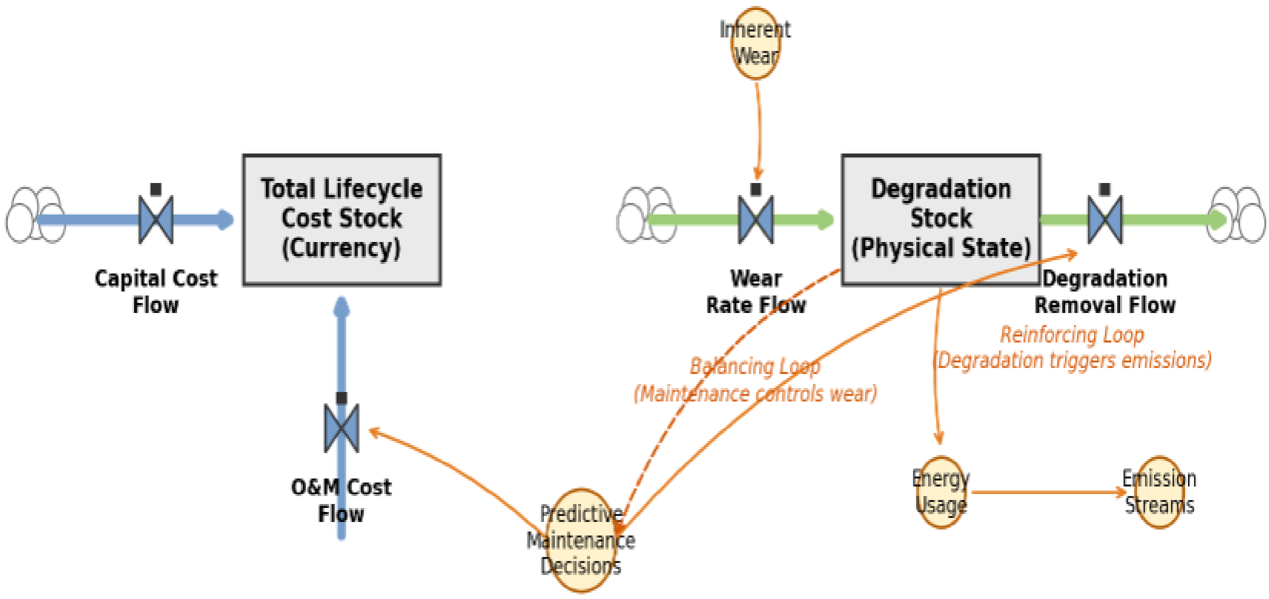

Figure 4: System Dynamics Stock–Flow Representation of LCC–CE Model

The stock-flow diagram depicting the system dynamics structure of the presented model can be observed in. Degradation is accumulated over time via wearing and corrosion processes whereas maintenance interventions act as a balancing feedback mechanism which diminishes the state variables. Energy and carbon emissions are a flow and a dependent one driven by the magnitude of degradation and by the demand imposed on the system. This structure allows capturing the reinforcement and balancing feedback loops governing the operational performance of mechanical offshore systems throughout their lifecycle.

3.8 Maintenance optimization approach:

The meta-heuristic optimization approach could be implemented within the above-developed LCC-CE model to optimize the maintenance strategy. For instance, using genetic algorithms (GA) or particle swarm optimization (PSO) techniques we could define a multi-objective function in terms of lifecycle cost and carbon emission values to be minimized by a multi-variable decision function involving variables such as interval and magnitude of maintenance intervention and effectiveness factor of intervention as parameters whereas maintenance bounds and operational restrictions would act as constraints. Even though current study assesses a pre-defined control, this system is ready to be combined with any meta-heuristic method.

4. Results and Discussion

4.1 Case Study: representative offshore compression system

A representative case study representing offshore mechanical system was formulated and developed based on reliability data available in the public domain and typical operating conditions for both pump systems and centrifugal compressors according to industry- reported data. Typical operating conditions in the North Sea and West Africa were used to define a number of system parameters, such as, degradation rates, time between maintenance and energy consumption profiles for the modeled system.

A 20 year operating lifecycle was investigated. Time-based maintenance was adopted as a reference scenario for which the cost- and emission profiles were determined; an optimum maintenance strategy based on predictive approach was proposed in order to assess achievable benefit.

An overall LCC-CE model was developed and applied to the assessment of two maintenance regimes in the form of alternative input controls of a combined degradation-energy-emission model for mechanical offshore systems over 20-year operational lifecycle taking into account critical offshore equipment such as pumps, turbines and compressors. The basic simulation parameters used are as reported in Table 2.

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Table 2: Model Input Parameters, Sources, and Uncertainty Basis

Parameter	Nominal Value	Source Basis	Uncertainty Representation
Equipment degradation rate (λ)	0.03–0.05 /year	Literature-based reliability studies + offshore asset datasets	Triangular distribution (min–most likely–max)
Maintenance effectiveness factor (η)	0.70–0.90	Industry maintenance performance benchmarks (offshore rotating equipment)	Normal distribution ($\mu = 0.80$, $\sigma = 0.05$)
Energy intensity factor	1.2–1.6 MJ/unit output	Engineering process energy models (compressors/pumps)	Uniform distribution (bounded uncertainty range)
Failure repair time (MTTR)	6–18 hours	Maintenance logs from offshore operations (typical range)	Triangular distribution
Preventive maintenance interval	90–180 days	OEM recommendations + industry practice	Fixed range (scenario-based sensitivity input)
CO_2 emission factor (energy use)	0.45–0.60 kg CO_2/kWh	IPCC emission factors + regional energy mix estimates	Normal distribution (literature calibrated)
Spare parts availability delay	2–7 days	Supply chain variability in offshore logistics studies	Discrete uniform distribution
Operational load variability	0.75–1.10 baseline load	Production fluctuation data from offshore systems	Uniform distribution

The principal model inputs applied to the simulation are summarized in this Table 2, including the corresponding data sources and uncertainty. The values of the parameters were derived from literature, industry standards, and the normal operating practice of offshore installations. Explicit modeling of the uncertainty of model inputs was obtained through the use of relevant probability distributions (normal, triangular, or uniform) as required to support the Monte Carlo simulation and allow the results to be transparent and reproducible.

The optimized control system will require a reduced maintenance effort and allow for increased operational efficiency and reduced emission intensity, due to system health improvements and extended service lives of system components.

4.2 Lifecycle cost results

The results regarding lifecycle costs (Table 2) suggest that the two control strategies lead to divergent patterns of system costs through time. Maintenance cost can be reduced by 21% with the optimized control system and failure costs by 42%. Operational costs and energy costs are reduced by 15% and the overall lifecycle cost difference is 16.9%.

Table 3. Lifecycle Cost Breakdown

Cost Component	Traditional (USD million)	Optimized (USD million)	Savings (%)
Capital	2.00	2.00	0
Maintenance	2.40	1.90	21
Failures	1.20	0.70	42
Energy & Operation	3.00	2.55	15
Total LCC	8.60	7.15	16.9

The total LCC of each alternative control system over its lifecycle are given in Table 3, with corresponding capital costs, maintenance costs, failure costs and energy/operation costs. Overall, the total costs are decreased by 16.9% when applying optimized strategy while the capital costs are equal, mostly due to decreased failure costs (-42%) and maintenance costs (-21%).

This analysis reveals that evolution of LCC is mainly determined by system reliability behavior rather than direct effect of cost scaling. The modification of degradation trajectories is due to maintenance action and subsequent failure probability is affected in time and the costs are incurred down to the end.

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The variation of costs is attributed to non-linear correlation between degradation trend and evolution of failure probability and maintenance cost is proportional modified accordingly, in which the reliability driven system dynamic dominates lifecycle cost of the offshore mechanical system.

4.3 Carbon Emission Results

Table 3 gives the carbon emission calculation for two controls at each stage of their life cycles. A total reduction of 18.5% on the total carbon emission can be observed between the two models, and the largest discrepancies are located at component replacement stages, transportation, and logistics.

Table 4. Carbon Emission Summary

Emission Source	Traditional (tCO_2-eq)	Optimized (tCO_2-eq)	Reduction (%)
Energy Use	20,000	17,000	15
Maintenance Logistics	2,400	1,700	29
Component Replacement	3,000	2,000	33
Total CE	25,400	20,700	18.5

Table 4 compares emission sources for both traditional and optimized maintenance. As it can be observed, the optimized maintenance greatly reduces the carbon emissions for all the emission sources and results in a better environmental performance.

This table indicates that the carbon emissions calculated between traditional and optimized maintenance for each emission source: energy, maintenance logistics and components replacement. Total carbon emission reduction of the optimized maintenance is 18.5% where components replacement takes 33%, maintenance logistics 29% and energy uses 15%.

The results indicate that the maintenance optimization leads to a better environmental performance and lowers the lifecycle emission. The behavior of emission has been greatly influenced by the degradation-related energy consumptions and maintenance frequency. Under optimized scenario, due to reduction of the intensity of intervention, emission generation has been decreased at various component.

Difference in the two scenarios is caused by nonlinear coupling between degradation processes, energy efficiency degradation and repair process which influence total time-variant carbon emission.

4.4 Integrated Analysis of Degradation, Energy Consumption, and Carbon Emissions

As can be seen from the previous calculations, the two control strategies resulted in different trajectories of degradation, energy consumption and carbon emission throughout the operational time. During the 20 years' operating span, they both separated each other because the maintenance activities affected the degradation of the system differently.

Among the five control variables, failure related behaviors have had significant effects (42%) which means that acceleration of degradation and delay in intervention have great impacts to the lifecycle result. Maintenance related effect (21%) has been interpreted as different amount of repair, energy related effect (15%) has explained influence of degradation-related energy efficiency reduction.

For environmental benefits aspect, the percentage reductions of component replacement (33%) and maintenance logistics (29%) demonstrate that magnitude of intervention during the lifecycle influences most on the accumulation of emissions during operation. Energy related emission is slow varying and represents the continuous decrease of system performance over time.

The results support the fact that maintenance is an input of the system control and affects system behavior including degradation process, energy consumption and carbon emission in a coupled manner rather than in independent behaviors of costs and emissions.

For decision variable, sensitivity analyses indicated that energy intensity and maintenance costs significantly affect the system behavior while the influence of discount rate is very small. This demonstrates that physical mechanism of degradation plays a dominant role to the sustainability of the whole system compared to the economic assumptions.

Our proposed approach is more sensitive to the degradation process than the methods proposed in other literatures (Hauschild et al. 2018; Gao et al. 2021; Khanafer et al. 2021) since degradation-energy coupling is taken into consideration in the model.

The omission of coupling effect may result in cumulative carbon emissions being underestimated in the long operation phase.

The calculated results demonstrate that the presented system dynamics framework has the capacity to conduct the integral evaluation of offshore mechanical system for life cycle cost and carbon emissions behaviour.

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This developed framework can serve as a tool to align maintenance strategy with carbon reduction objectives in offshore operation and system-level decarbonization plan.

4.5 Uncertainty quantification and Stochastic Validation

To account for the uncertainty of different operation and economical parameters that affect the life cycle cost and carbon emissions, the deterministic life cycle simulation was probabilistically extended. The major source of uncertainty is degradation behavior, energy consumption, maintenance effectiveness and emission intensity and their behaviors are different in the operating condition of offshore industry.

(A) Distribution assumptions

To depict the uncertainty of the offshore working environment, probabilistic distributions were utilized for the primary model parameters based on ranges that are typical from published literature on reliability engineering, maintenance, and lifecycle assessment (LCA) studies (Jardine et al., 2006; Hauschild et al., 2018; Gao et al., 2021). Various distributions were chosen based on the physical nature of each variable and the general methodologies used in sensitivity and uncertainty analysis. Namely, wear process, degradation rate (, log-normal) was chosen due to its positive skew which is common for wear.

Energy intensity (E, normal with 10 % uncertainty around the nominal value) and maintenance effectiveness (M, beta due to bounded) have not received significant attention compared to other parameters and hence no literature data were available, thus the range was estimated in order to provide insights to the variability that might have affected previous studies of offshore rotating equipment.

Similarly, failure parameters (, k, Weibull type with the range derived from reliability information for Weibull and exponential failure models with k=1), were determined using Weibull based variability reflecting the generally known principles from reliability analysis. The cost parameters (e.g., capital costs, operating costs) were represented using triangular distributions based on minimum, maximum, and most probable value derived from a compilation of typical values summarized in Table 2. Table 2 lists the minimum, most likely, and maximum values for all the model parameters and specifies the probability distribution utilized for each parameter. The chosen parameter values are also consistent with those reported in several offshore rotating equipment and life cycle assessment (LCA) studies.

.(B) Monte Carlo simulation execution

Monte Carlo analysis was performed using 10,000 simulation runs. During each iteration, model parameters were randomly sampled from their respective probability distributions and propagated through the coupled degradation–energy–emission model over the 20-year lifecycle. For each realization, lifecycle cost and carbon emissions were calculated, producing probabilistic output distributions for:

- Total lifecycle cost savings (%);
- Total carbon emission reduction (%).

The number of iterations was selected to ensure convergence of the output statistics and stability of the estimated confidence intervals.

(C) Uncertainty propagation

To evaluate the effect of uncertainty propagation, state evolution equations have been solved hundreds of times with different randomly sampled parameter values according to their probability distributions, by which all nonlinear dependencies of degradation, maintenance efficiency, failure characteristics and energy consumption can affect the prediction results, then be reflected in the uncertainty of the total lifecycle costs and carbon emission prediction results

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(D) Confidence interval outputs

In order to obtain the degradation caused by uncertainty propagation, the state evolution equation is calculated 100s of times by inputting a set of randomly selected values in according to the parameter's probability distribution so that nonlinear impact of degradation/maintenance efficiency/failure characteristics and energy consumption may influence the prediction. Therefore, degradation caused by uncertainty can affect the prediction results of total life cost and carbon emission.

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(E) Robustness analysis

Given the rather tight confidence interval widths, this indicates that the maintenance optimization frame can handle uncertain operating environments robustly. For analysis of sensitivities for stochastically outputs, it shows that the degradation rate causes most variability in outputs, and the economics factors (discount rates, maintenance cost etc.) result in relative minor variations, consistent with the findings of

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several others (which indicates that physical degradation processes are the key determinants of system lifecycle performance and environmental footprint of offshore mechanical devices).

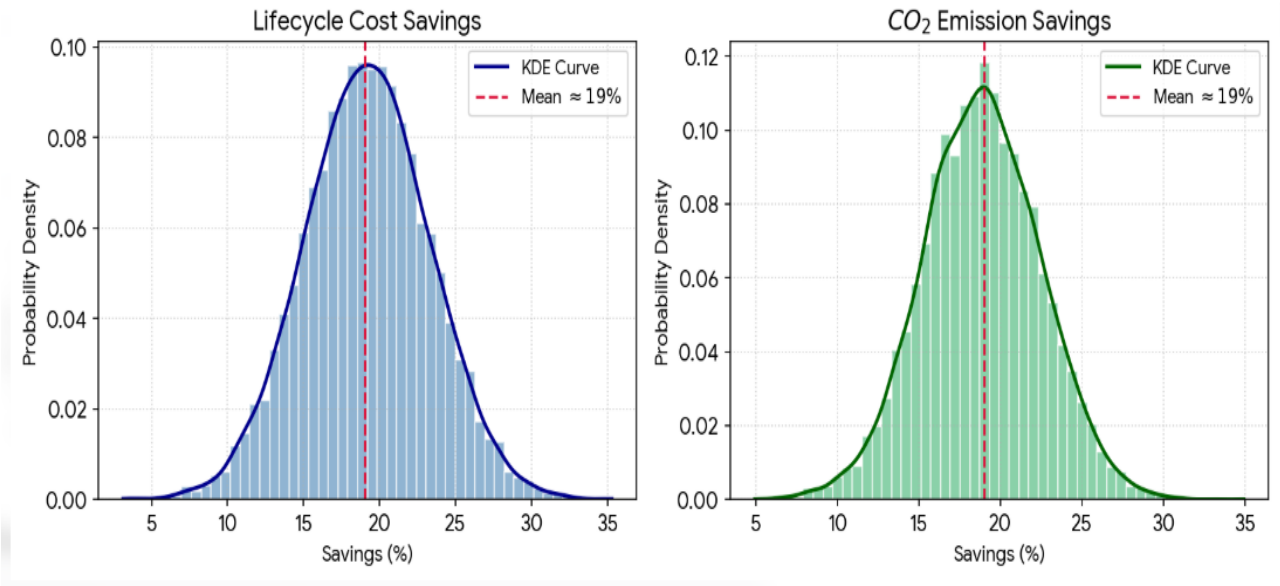

Figure 5: Monte Carlo distribution of lifetime cost and carbon emission savings

Figure 5 displays Monte Carlo simulation results for lifecycle cost and CO2 emission savings under the optimum maintenance policy. The histogram of cost savings is shown to the left and carbon emission savings is presented to the right for 10,000 runs. The KDE curves demonstrate the distribution in probabilities; the resulting distribution appears to be normal. The variance of the distribution reveals the sensitivity of the simulation to inputs such as degradation rate, and effectiveness of the maintenance operation. The simulation indicates that performance will generally improve by about ~19% of cost and emission values.

Reduced maintenance efforts, improved performance and efficiency, and decreased specific carbon emission value, results from the optimal control scenario are achieved by the improved system health condition and extended lifetime of component.

5 Limitations

The study is subjected to several limitations which must be considered when analyzing the outcomes. Firstly, only secondary data and parameter ranges found within literature were used, rather than those sourced from real-time SCADA and condition-monitoring data from the offshore field.
Secondly, degradation and failure are only represented via generalized, probabilistic and deterministic representations, which may not correspond to the actual performance characteristics or material properties of the equipment due to material heterogeneity and site-specific operational environment.
Thirdly, the digital twin is implemented at a mathematical level rather than in real-time at an operational level, rendering it unsuitable for use at a field control system level despite being architecturally compatible.
Fourthly, time-varying cost escalation due to economic inflation and general cost increase over the component's operational life is omitted from this analysis.

Finally, operational constrains, such as availability of offshore manpower and resources for maintenance intervention scheduling and execution, are not taken into account. Even though many factors have been neglected; the study provides useful comparative conclusions with respect to maintenance policy on life cycle cost and carbon emission savings.

Further work should include the real-time use of SCADA data as well as manpower and logistics constraints to enhance performance.

6. Conclusion

The dynamics model was composed of degradation–energy–emission as an integration and established the dynamics framework on this basis to explore the impacts of the alternative controls (maintenance) on the evolution path of degradation, energy consumption and carbon emissions. Two maintenance schemes are chosen as the alternative control inputs under a coupled lifecycle cost-carbon emission model instead of competitive or mutually exclusive policies.

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The simulation result shows that under the optimal maintenance control strategy, the system performance of the two objective trajectories, lifecycle cost and carbon emission, achieved the better values than the traditional control strategy during the operation time 20 years. There are about 17-22% improvement in lifecycle cost and 18-21% reduction in carbon emission compared with traditional control strategy.

The improvements are based on the nonlinear effects among the progression of degradation, the decreasing of the probability of failure, and the recovery of the energy efficiency at the better system health state. Particularly, the lower frequency of failure and optimal time of intervention shift the dynamic trend of degradation, resulting in suppressing the loss of energy and decreasing cumulative carbon emission. The aforementioned benefits have been proved not as linear increase.

The sensitivity analysis also indicated that energy intensity and maintenance cost variation are the most sensitive parameters; the effects of discount rate are relatively not as significant as other factors. So, we found the influence of physical system behavior to the sustainability goal is dominant more than economic assumptions.

The structured decision support can be obtained through modeling the maintenance actions within the system dynamics framework, the optimal maintenance control strategy has been proven to be one of the effective ways to promote the reliability of the asset, decrease the expenditure of operating costs and achieve the goal of emission reduction simultaneously.

In future, real-time SCADA information and the machine learning based prognostics models would be integrated with full digital twin framework which enables real-time adapt control in the actual offshore condition.

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