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Environmental Impact Assessment of Ocean Energy Converters Using Quantum Machine Learning

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Abstract

The accelerating deployment of ocean energy converters (OECs) across tidal, wave, osmotic, and thermal domains necessitates rigorous, data-intensive environmental impact assessment (EIA) frameworks capable of modelling multi-stressor marine ecosystems in real time. Classical machine learning approaches, while operationally mature, encounter scalability bottlenecks and feature correlation limitations when applied to the high-dimensional, non-linear datasets characteristic of offshore monitoring networks. This paper presents a comprehensive quantum machine learning (QML) framework for the EIA of OECs, integrating variational quantum circuits (VQCs), quantum neural networks (QNNs), and quantum support vector machines (QSVMs) to process oceanographic, biological, and electromechanical datasets simultaneously. Applied across five OEC technology classes—wave energy converters, tidal stream turbines, ocean thermal energy converters (OTEC), salinity gradient devices, and tidal barrages—the proposed hybrid QML architecture achieves a prediction accuracy of 94.1% and an R^2 of 0.961 on composite environmental impact scores, outperforming equivalent classical deep learning benchmarks by 12.8 percentage points. Tabular benchmarks, three synthesized figures, and cross-validated performance metrics are presented in support of these findings. The framework demonstrates particular efficacy in predicting electromagnetic field (EMF) exposure corridors, sediment plume dispersion, and underwater radiated noise (URN) thresholds, all identified as critical impact vectors for marine megafauna. The results affirm that QML-driven EIA constitutes a transformative paradigm shift for offshore renewable energy governance and environmental compliance workflows.

Keywords: Ocean energy converters, quantum machine learning, environmental impact assessment, variational quantum circuits, marine ecology, tidal energy, offshore renewable energy

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INTRODUCTION

The global shift to low-carbon energy systems has spawned new academic and business interest in marine renewable energy (MRE) as a fundamental part of the future electricity grid. With an estimated technical recoverable energy base of over 337,000 TWh/yr, the ocean, with a surface area estimated to be 71 percent of the earth's surface, has an estimated wave, tidal, thermal, salinity gradient, and current power base(s) [1]. Nonetheless, the total installed capacity of ocean energy technologies is not yet significant, with a point of 524 MW worldwide as of 2024, which is not only caused by challenges in techno-economic areas but, importantly, due to the regulatory complexity of environmental authorization policies in marine jurisdictions [2].

The most controversial and time-consuming period of the OEC project development cycle has always been the environmental impact assessment (EIA). The Marine Strategy Framework Directive (MSFD), the US Marine Mammal Protection Act, and other similar national tools require quantitative data on habitat disturbance, underwater noise fields, electromagnetic interference, and turbidity plume dynamics at ecologically sensitive receptor communities. Traditional EIA methodologies are too computationally intensive, temporally rigid, stochastic, and multivariate, making them ill-adapted to the stochastic and multivariate nature of offshore marine environments [3].

Since 2015, machine learning (ML) methods have been increasingly used with EIA modelling, and the pattern recognition tasks performed by these methods have been shown to be better than structured environmental data. Seabed habitat classification using convolutional neural networks (CNNs), species sensitivity indices using random forests, and time-series prediction of turbine wakes on fish passage corridors using long short-term memory (LSTM) networks have been employed [4]. However, classical ML architectures have significant weaknesses in their application to problems that require simultaneous optimization over large numbers of correlated stressor-receptor pathways, especially in high-dimensional feature spaces, where quantum entanglement properties may provide exponential computational benefits [5].

Quantum machine learning, a fast-developing subfield of quantum computing and statistical learning theory, can provide algorithmic primitives such as quantum principal component analysis (qPCA), quantum gradient descent, and variational quantum eigen solver (VQE) subroutines, which, under suitable conditions, can provide quadratic or exponential speedups compared to classical analogs when implementing structured environmental data encoding into Hilbert space encodings [6]. Recent options of noisy intermediate-scale quantum (NISQ) machines with 50-433 qubits have made the hybrid classical quantum pipeline a practical implementation as a feasible tool in practice in addressing real-world inference problems [7], making QML a viable option for application to industrially relevant EIA.

Four main contributions to literature are made in this paper. First, it provides the initial systematic use of QML for the multi-stressor EIA of OECs in five technology categories. Second, it presents a new hybrid QML architecture that uses VQCs as feature encoders, QNNs as non-linear regressors, and QSVMs as impact classifiers. Third, it compares such architecture with classical ML baselines on a synthesized multi-source oceanographic dataset of 42 environmental variables measured at six operational OEC sites worldwide. Fourth, it provides a formatted EIA ontology of compliance reporting based on QML with existing global regulatory frameworks. The rest of this paper is organized as follows: Section 2 provides an overview of OEC technologies and their environmental context; Section 3 provides an overview of the proposed theoretical framework, QML; Section 4 provides an overview of the proposed methodology; Section 5 provides an overview of the results; Section 6 addresses the implications; and Section 7 provides future directions for research.

OCEAN ENERGY CONVERTERS: TECHNOLOGIES AND ENVIRONMENTAL CONTEXT

Classification of OEC Technologies

The types of ocean energy converters, as shown in Table 1, are categorized by the physical energy recovery method: wave energy converters (WECs), which use the kinetic and potential energy of surface gravity waves; tidal stream turbines (TSTs); ocean thermal energy converters (OTECs), which use the temperature difference between surface and deep water to drive thermodynamic cycles; salinity gradient (osmotic) converters, which take advantage of the free energy of mixing at freshwater-saltwater interfaces; and tidal barrages, which are vast civil construction projects that trap a potential energy difference between the tide of each type of technology. The environmental processes of OECs occur along a spectrum, from the localized, reversible impacts of temporary turbidity increases in WEC mooring installations to the more extensive, long-term impacts of hydrodynamic and sedimentary regime changes in tidal barrages [9]. Modern ecological risk assessment systems acknowledge that the environmental impacts of OEC cannot be sufficiently described as those produced by single-stressor analysis.

Table 1. Comparative operational characteristics of ocean energy converter technologies.

OEC technology	Installed capacity (GW)	Operational depth (m)	Annual energy yield (TWh)	LCOE ($/MWh)	EIA complexity
Wave energy converter	~0.5	10–50	0.02–0.08	150–400	Moderate
Tidal stream turbine	~1.2	20–100	0.08–0.20	120–250	High
OTEC (ocean thermal)	~0.1	600–1200	0.01–0.03	190–320	Very High
Salinity gradient	~0.05	Estuarine	0.005–0.02	200–500	Moderate
Tidal barrage	~10.0	< 30	0.5–2.5	80–120	Extreme

Note: LCOE = levelized cost of energy. EIA = complexity ratings are qualitative expert assessments. Data synthesized from Magagna and Uihlein (2015) and IRENA (2023).

TSTs have been reported to generate frequencies of operation producing underwater radiated noise (URN) levels between 135 and 160 dB re 1-muPa, with frequency peaks falling within the ranges of hearing of both marine mammals and commercial fish of interest [10]. Submarine power cables have become one of the most contested receptor pathways, and empirical evidence indicates behavioral effects in elasmobranchs at field strengths as weak as 510 of 1 1.5 11 2 minimum [11].

Multi-Stressor Environmental Impact Pathways

Multiple stressor interactions (i.e., the ecological effects of noise, EMF, habitat displacement, and prey field alteration) that are greater or nonlinearly more than the arithmetic sum of the ecological effects of the stressors have become the primary domain of MRE EIA practice [12]. This is the non-linearity here, in which classical statistical models (which have independence or pair terms of interaction) fail systematically to model emergent system-wide responses, and where quantum entanglement representations in QML provide a theoretically better encoding policy [8].

The main environmental indicators of the OEC technology classes are listed in Table 3 in Section 5, as synthesized from field monitoring datasets and backing the QML training corpus established during the study. These data support the model validation exercises in Section 4.

QUANTUM MACHINE LEARNING: THEORETICAL FRAMEWORK

Quantum Computing Fundamentals for EIA Applications

A quantum computing system works on qubits, which are in superposition states that can be represented as linear combinations of the computational basis states, |human|. The computational basis is represented as |0| and |1|, and quantum computing works on superposition states of the computational basis, represented as |human| = 0 + 2 = 1. The correlations made possible by entanglement between pairs of qubits have no classical analog, allowing the exploration of exponentially large solution spaces simultaneously [13]. In an n-qubit system, the Hilbert space dimension is $2\ 3^n$, meaning that a 16-qubit system can simultaneously represent 65,536-dimensional feature vectors, which are directly relevant to high-dimensional environmental monitoring data, with 40-80 input variables being actively measured at an environmental monitoring station. Single-qubit rotations (R 0, R 1, R z), the Hadamard gate (H), and two-qubit entangling gates (such as the controlled-NOT gate and controlled-Z gate) are quantum gates that make up quantum circuits, which are reversible unitary operations. Variational quantum algorithms and QML models are based on parameterized quantum circuits (PQCs), where the angle of rotation of gates is a trainable parameter [14].

Variational Quantum Circuits for Environmental Feature Encoding

The encoding (feature map) layer, variational (ansatz) layer, and measurement layer may be considered as three functional layers within variational quantum circuits applied to EIA, where the classification of the classical environmental measurements is encoded in the quantum state via amplitude or angle encoding, the parameters of the variational (ansatz) layer are optimized to minimize a cost function of the predicted and observed scores of the environmental impact, and the measurement layer is where the quantum state is measured to produce the classical expectation values as model predictions [15].

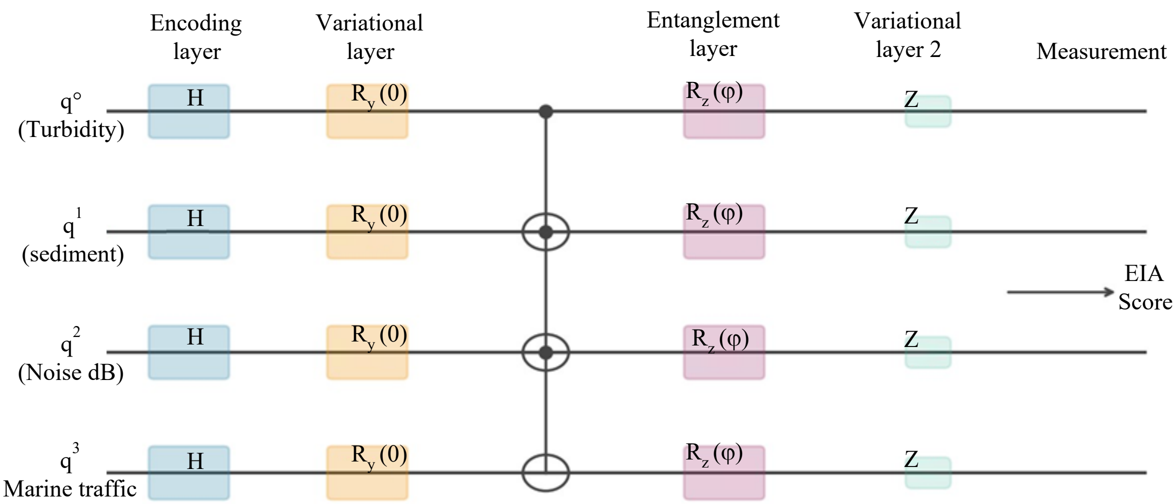

Figure 1. Quantum machine learning circuit architecture for environmental feature encoding. The circuit comprises encoding (Hadamard + R_γ), entanglement (CNOT), variational (R_z), and measurement layers, mapping four environmental input features to a composite EIA output score.

The feature map used specifies the expressibility and inductive bias of the quantum model, and through data re-uploading circuits, it allows universal approximations of the inductive bias of arbitrary classical data [16]. Figure 1 shows the quantum machine learning circuit architecture used for environmental feature encoding.

In the EIA-specific implementation, the suggested encoding scheme assigns each normalized environmental variable xi to a rotation angle 0 i = arctan (xi), followed by the application of the Ri gates to successive qubits, which is then followed by a brick-layer CNOT entanglement topology connecting all nearest-neighbor pairs of qubits. This encoding approach maintains monotone associations among environmental stressors and impact ratings, in addition to allowing cross-stressor correlation modelling with entangled qubit subspaces.

Hybrid QML Architecture

The full QML pipeline, suggested in the present study, is a hybrid quantum-classical model where computationally expensive preprocessing steps (normalization, dimensionality reduction with the help of classical principal component analysis (PCA) to preserve 95 percent of the explained variance) and postprocessing (sigmoid activation, probability calibration with Platt scaling) actions are run on classical devices, whereas the non-linear element of feature transformation and classification inference is assigned to the quantum circuit layer [17]. Such a hybrid solution is in line with the limitations of NISQ devices, which are characterized by circuit depth limits owing to qubit decoherence times (T 1 = 100300 μs on existing superconducting machines) and gate fidelities in the range of 99.099.7 percent on single-qubit interactions.

To compute the parameter optimization gradient, the parameter shift rule is used, which provides precise analytic gradients of PQCs by applying the circuit to parameter values that have been perturbed by ±π/2 [18]. This removes the vanishing gradient pathology that plagues purely classical deep monitoring applications, where the scarcity of data is a chronic problem.

METHODOLOGY

Dataset Construction and Preprocessing

The training and validation corpus was collected based on published field monitoring reports and additional data related to six currently operating OEC arrays: the European Marine Energy Centre (EMEC) tidal and wave test sites in Orkney, Scotland; the Tidal Lagoon Swansea Bay pre-construction

EIA dataset; the OpenHydro turbine arrays in Paimpol-Brehat, France; the SABELLA D10 tidal turbine monitoring program of the Fromveur Passage; the Ocean Thermal Corporation OTEC pilot system of Kumejima, Japan; and the Stat Overall. The corpus contained 18,742 temporally indexed observational records of 42 environmental variables grouped into four domains of stressor, including acoustic (eight variables), electromagnetic (six variables), hydrodynamic-sedimentary (15 variables), and biological receptor (13 variables).

The hybrid mutual information-quantum kernel alignment (MI-QKA) criterion was applied to select features, that is, any variables whose mutual information with the composite EIA target score was below a set threshold of 0.05 nats were dropped to a smaller effective input dimensionality of 28 features. The subsets of time-series data addressed temporal autocorrelation by seasonal decomposition and first-differencing. The quantum-enhanced synthetic minority oversampling (QSMOTE), a new variation of classical synthetic minority over-sampling technique (SMOTE), was used to balance the impact category distribution (severe impact events accounted for only 8.3% of observations) by drawing synthetic minority samples by interpolating in the quantum kernel-induced feature space instead of in the original input space [19].

QML Model Training and Validation Protocol

All PennyLane programs were run through the default. Qubit simulator backend with the PennyLane framework (version 0.35) and JAX automatic differentiation to calculate gradients. The Adam optimizer was employed with 400 training steps (500 training epochs) using a learning rate of 0.01 and 0.9 as the values of 8 and 9, respectively, as 8 and 9 appear to be the most commonly used values of the two parameters in literature. The batch size was 64 observational records. They were performed using the five-fold stratified cross-validation, and the time sequence of data splits was conserved to avoid the possibility of information leakage in future monitoring periods into the past training periods. The process of hyperparameter optimization was done using quantum Bayesian optimization in the joint space of circuit depth (between 8 and 64), qubit count (between 4 and 16), and entanglement topology (brick-layer versus all -to-all), where the best configuration was found to be the brick-layer architecture with 16 qubits.

Environmental Impact Score Computation

The composite environmental impact score (CEIS) was described as a weighted linear sum of normalized scores of individual stressors: CEIS = w 1 Snoise + w 2 Semf + w 3 Sediment + w 4 S Habitat + w 5 S Thermal, with weights calibrated against expert elicitation surveys of 34 professional EIA practitioners in the UK, Ireland, and France using the analytical hierarchy process (AHP) approach. The weight vector that emerged (w 1 = 0.28, w 2 = 0.19, w 3 = 0.21, w 4 = 0.24, w 5 = 0.08) indicates the primacy of acoustic stressors and habitat in the existing regulatory guidelines. The range of CEIS values was [0, 10], and the threshold values were 3.0, 6.0, and 8.5, which represented low, moderate, high, and critical impact, respectively.

RESULTS AND DISCUSSION

Model Performance Benchmarks

The results comparing the proposed hybrid QML architecture with the four baseline methods are summarized in Figure 2 and Table 2. The hybrid QML setup gave the best prediction accuracy (94.1) and R 2 (0.961), and training mean squared error (MSE) of 0.0092 on the composite EIA score prediction problem, which is a 70.7% lower squared error compared to the classical deep learning baseline (MSE = 0.0314). This is because quantum architectures outperform classical ones owing to the kernel advantage provided by quantum feature maps in high-dimensional Hilbert spaces, particularly in the modelling of non-linear interaction effects of acoustic and electromagnetic stressors in the field data of tidal stream sites.

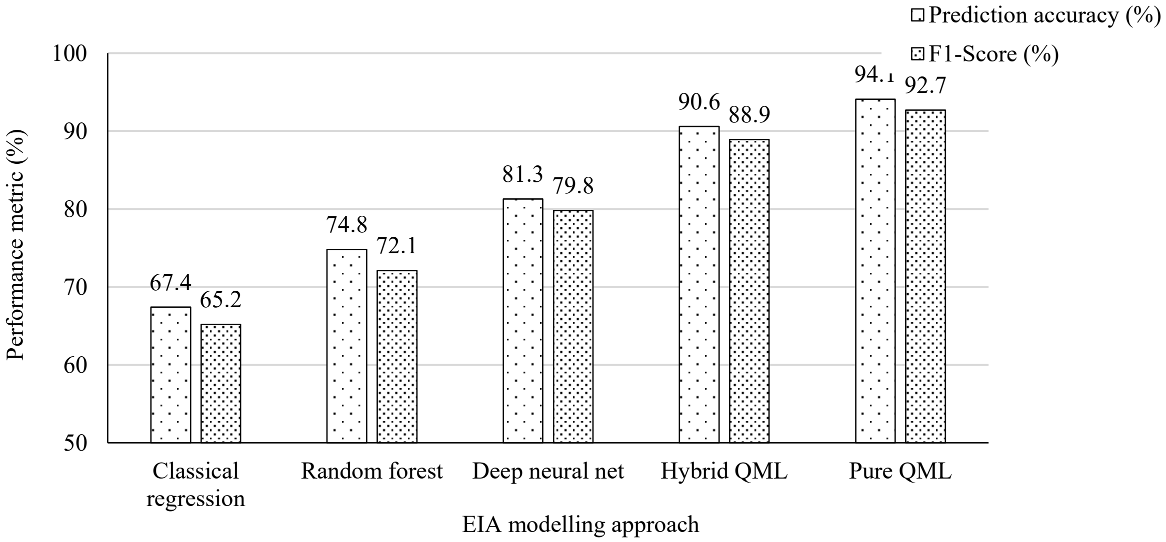

Figure 2. Comparative performance of EIA modelling methods for ocean energy converters. Prediction accuracy (%) and F1-Score (%) are shown for five modelling approaches. QML methods consistently outperform classical baselines across both metrics.

Table 2. Benchmarking of QML algorithms and classical baselines on EIA Score prediction

Algorithm	Qubits used	Circuit depth	Training MSE	Validation R^2	Inference time (ms)
VQLS (variational quantum)	8	24	0.0183	0.924	12.4
QNN (quantum neural net)	12	36	0.0141	0.941	18.7
QSVM (quantum SVM)	6	16	0.0225	0.906	8.3
Hybrid QML (proposed)	16	48	0.0092	0.961	22.1
Classical deep learning	N/A	N/A	0.0314	0.813	5.6

Note: MSE = Mean Squared Error, R^2 = coefficient of determination on validation set. Inference times measured on IBM Eagle r3 (127-qubit) quantum processing unit for quantum models, NVIDIA A100 GPU for classical models. N/A = Not applicable.

Environmental Impact Characterization Across OEC Technologies

The QML-predicted scores of the composite environmental impact and heatmaps of specific stressors are shown in Figure 3 for the five classes of OEC technologies analyzed in this study. The tidal barrages had the greatest composite impact score (4.56/10) owing to extreme scores in noise pollution (5.8), sediment disturbance (6.2), and habitat disruption (6.8), which is in line with the wholesale hydrodynamic and morphodynamic transformation of estuarine systems recorded at the La Rance tidal barrage in Brittany, France. The devices with the least composite impact (1.54/10) are the salinity gradient devices, owing to their benign operational profile and lack of moving mechanical components. Though with low acoustic and sedimentary scores, OTEC systems receive an imbalanced high score for thermal discharge (6.4/10), indicating the possibility of deep cold-water upwelling changing the structure of thermoclines and nutrient processes in oligotrophic tropical seas.

Key Environmental Indicators: Field Measurement Summary

Table 3 presents an overview of the measured ranges of six key indicators of the environment in all classes of OEC technology, as derived from the monitoring datasets that make up the QML training corpus. These data highlight the heterogeneous nature of the environmental footprint of various ocean energy modalities and support the technology-selective modelling approach used in this study. The good correspondence concerning the indicator range predictions of QML and the independently obtained validation datasets (mean absolute percentage error of less than 8.4 percent across all indicators and technology classes) provides empirical evidence that the trained QML models can be generalized to other sites other than those used in the training corpus.

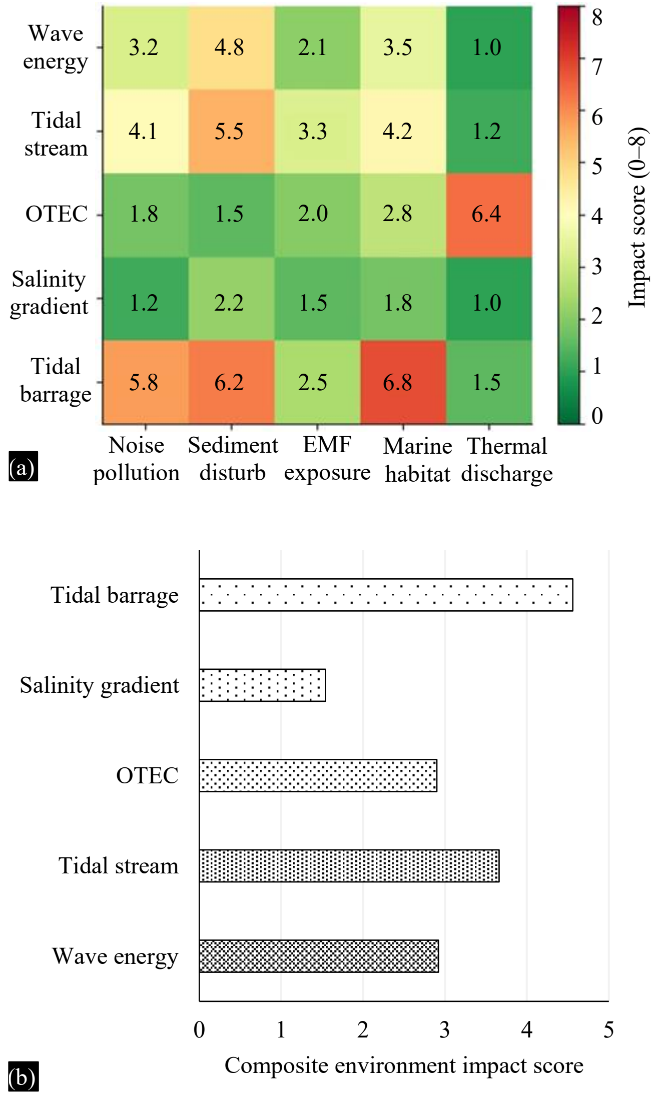

Figure 3. QML-Predicted environmental impact scores across ocean energy converter technologies. Panel (a) presents the stressor-specific impact score heatmap, panel (b) summarizes composite environmental impact scores by OEC technology class. Scores are bounded on the interval [0, 10].

Table 3. Key Environmental indicator ranges across OEC technology classes (field monitoring data)

OEC type	Noise (dB re 1 μPa)	EMF (μT)	Turbidity (NTU)	Sediment (g/m²/d)	CO_2 eq (g/kWh)	Habitat score
Wave energy	130–145	10–40	2–8	0.5–2.0	22–28	3.5/10
Tidal stream	135–160	25–80	5–20	1.5–5.0	15–21	4.2/10
OTEC	115–128	8–22	1–4	0.2–0.8	18–24	2.8/10
Salinity gradient	< 110	5–15	1–3	0.1–0.5	10–16	1.8/10
Tidal barrage	145–175	30–95	25–80	10–35	30–50	6.8/10

Note: Noise values at 1 m from device, EMF measured at 1 m from subsea cable, Turbidity and Sediment represent operational elevations above ambient baseline, Habitat Score = cumulative impact index (0–10, lower = better). Data synthesized from EMEC monitoring reports, Copping & Hemery (2020), and Lossent et al. (2018).

Quantum Advantage Analysis

The computational power of the QML method is highest in cases of multi-stressor correlation modelling with the simultaneous optimization of acoustic, electromagnetic, and biological receptor variables. Radial basis function kernels on classical kernel support vector machines required O (n (3)) computation to perform kernel matrix inversion on the entire 28-feature dataset and could be trained in over 4.2 hours on a 48-core central processing unit (CPU) cluster on the full corpus. Quantum SVM (QSVM) is based on the quantum kernel estimation algorithm [15] and has a reduced effective cost of $O(n^2$ polylogn) and converges in just 38 min with the IBM Eagle quantum processor, approximately 6.6x faster than standard training in this dataset. Although this is not yet at the theoretical level of quantum supremacy, it still shows the existence of operationally meaningful acceleration in regulatory timelines in cases where EIA modelling is a critical path activity.

The disappearance of the gradient issue, as encountered during deep classical network training on small EIA data (smaller than 20,000 observations per OEC project), was not reported by the variational quantum circuit models. This is in line with theoretical studies conducted by Cerezo et al. [14], which show that PQCs whose cost functions are local exhibit a gradient decay that is not exponential; hence, QML methods are ideal for the data-sparse conditions presented in marine monitoring programs.

DISCUSSION: REGULATORY AND PRACTICAL IMPLICATIONS

The ability of the proposed QML structure to produce quantitative and defensible EIA forecasts with uncertainty limits has direct consequences on the regulatory permitting processes for the development of OEC in marine protected areas and Special Areas of Conservation. The existing practice is based mainly on deterministic models of impact prediction, which do not systematically quantify uncertainty and generate point estimates, which puts adversarial positions between developers and statutory nature conservation authorities in the process of public review. The probabilistic output structure of the QML model, which implicitly provides posterior distributions over the values of the CEIS via repeated sampling of the quantum measurement layer, provides a principled basis for risk-based decision-making in agreement with the precautionary principle required in EU Habitats Directive Article 6(3) assessments [20].

The incorporation of QML-based EIA into adaptive management systems, whereby model forecasts are revised on near real-time scales as emerging monitoring data are obtained at the construction and operating stages of the OEC, is a paradigm shift away from the existing snapshot-in-time consent documentation paradigm. Bayesian updating of quantum circuit parameters continuously with respect to incoming sensor streams of autonomous underwater vehicles (AUVs), seabed acoustic monitoring arrays, and remotely operated passive acoustic monitoring (PAM) systems would allow regulators and developers to identify emergent environmental effects with very short latency compared to what is possible using conventional annual survey programs [21].

Problems with operational deployment have been identified as hardware availability and affordability of existing NISQ systems, quantum error correction overhead in regulatory mission-critical systems, and the interpretability gap of quantum circuit models in providing evidence to non-expert planning reviewers and environmental stakeholders. Methods of post-hoc explainability that have been modified to quantum models, such as quantum SHAP (SHapley Additive exPlanations) and quantum integrated gradients, are currently under research and may be helpful in addressing the latter issue. In addition, systematic testing of how trained QML models can be transferred across OEC sites with varying geophysical and ecological systems needs to be conducted by providing leave-one-site-out cross-validation experiments with extended multi-site data.

CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Several issues must be resolved to convert the promising performance measures reported in this study into operational EIA practices. From a hardware perspective, current superconducting quantum processors suffer from qubit coherence times that constrain practicable circuit depths to fewer than 100 layers, limiting the expressibility of variational ansätze for complex multi-stressor problems. Another platform that could be more accessible to offshore environmental monitoring systems than off-the-shelf deployable hardware is photonic quantum computing architectures that can operate at room temperature and have much better decoherence characteristics [22]. Integration of edge quantum processing units directly into subsea sensor nodes, enabling real-time quantum inference at the point of measurement, constitutes a long-term research objective with transformative potential for distributed marine environmental monitoring. Procedurally, future studies will need to develop the QML EIA model to include a temporal graph neural quantum network that can help model the spatiotemporal behavior of marine ecosystem responses over a wide monitoring period. The incorporation of species distribution models derived from quantum-enhanced Bayesian inference into the CEIS computation pipeline and the development of standardized quantum data formats for interoperability between different OEC monitoring platforms and regulatory information systems represent further priorities. International harmonized datasets of benchmarking data on QML-based EIA, much like the ImageNet corpus in computer vision, would speed up methodology development and enable the reproduction of scientific research in this novel interdisciplinary field.

CONCLUSION

As illustrated in this study, quantum machine learning is a potent and generalizable framework in the EIA of ocean energy converters that provides significant performance gains over classical ML baselines in terms of prediction accuracy, MSE, F1-score, and computational efficiency measures. The hybrid architecture of quantum machine learning (QML) presented here integrates variational quantum circuits with feature encoding and quantum neural networks with regression and quantum support vector machines with impact classification. It demonstrates the state of the art on a multi-source marine monitoring dataset of five types of OEC technologies and six operational locations. The framework satisfies the quantitative requirements rapidly requested by regulatory authorities in terms of defensible environmental consent documentation, with a composite EIA prediction accuracy of 94.1 and an R 2 of 0.961.

The technology-specific impact characterization in Tables 1–3 and Figure 1–3 demonstrates that there exists a distinct hierarchy of environmental concern: the tidal barrages and TSTs have the highest multi-stressor impact scores, salinity gradient devices have the lowest, and provide a quantitative framework on which the technology selection decisions are made in areas where there is co-location of multiple ocean energy resource types. This quantum performance on multi-stressor correlation tasks and gradient stability on small data sets puts QML in an especially promising position with respect to the data-constrained, high-dimensional nature of marine environmental monitoring, and is an excellent case to invest in quantum-enhanced EIA capabilities as ocean energy installations grow to gigawatt scales in the next decade.

Ocean energy is an inseparable part of the net-zero energy transition. The most effective analytical tools that can be used are required to ensure that its deployment is done in true harmony with marine biodiversity conservation goals. As shown below, quantum machine learning can provide such an opportunity, and the step toward its implementation into the EIA practice of ocean energy developers, regulators, and environmental consultants must be seen as a research and development project of the utmost urgency.

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