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Reinforcement Learning–Based Multi-Objective Optimization and Adaptive Control of Grid-Connected Tidal Energy Systems for Sustainable Coastal Power Generation under Stochastic Marine Conditions

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Abstract: *As a sustainable and reliable renewable energy source, tidal-wave energy has become an increasing subject of interest for generation in coastal areas to meet the growing demand for this type of predictable and environmentally friendly power. Nevertheless, highly dynamic and stochastic marine conditions such as variations of tidal velocity, turbulence intensity, hydrodynamic loading represent challenges for maintaining stable operation of grid-connected tidal energy systems. Such uncertainties can greatly hamper power extraction efficiency, structural safety and the stability of the grid. This paper presents a new reinforcement learning–based multi-objective optimization and adaptive control framework for grid-connected tidal energy conversion systems to maximize the energy capture while guaranteeing the system reliability and robustness against uncertainties of operation environments. The proposed framework combines deep reinforcement learning (RL) - agent with a multi-objective optimization mechanism to facilitate smart, real-time decision-making. The RL agent learns the optimal control policies and keeps interacting with tidal system and grid environment by adjusting operating parameters of turbine such as blade pitch angle, generator torque and power converter settings. The objective function consists of a weighted linear combination of several objectives such as maximizing power, minimizing loads and fatigue on structures, mechanical stress minimization, and grid integration stability requirements. An evolutionary multi-objective optimization layer is then built on top, to drive control parameters dynamically by resolving Pareto-optimal trade-offs among conflicting objectives. A grid-connected tidal energy system with high fidelity, is modeled including hydrodynamic turbine models, drivetrain dynamics, power electronic converters and the grid interface components. Realistic tidal flow profiles with added turbulence, random perturbations and environmental variability are used to obtain representations of stochastic marine conditions. The method is tested under various operating scenario, such as different tidal speed, impulsive flow variation and grid disturbances. Simulation results confirm the effectiveness of the presented RL-based multi-objective control framework compared to traditional control approaches, including fixed-pitch control and model predictive control (MPC). The system has higher power capture efficiency, less load fluctuation, and greater structural durability. In particular, the power extraction increases by up to 20%, while structural load changes are reduced by more than 30%, which prolongs system life. In addition, the suggested controller is capable of keeping stable operation of the grid with enhanced power quality and smaller variations in stochastic states. The findings demonstrate the success of combining reinforcement learning with multi-objective optimization in advanced control approaches for tidal energy. This tool provides a scalable and adaptive framework for next-generation tidal energy systems to support reliable, efficient coastal power generation. This work furthers intelligent renewable energy systems at sea and assists the transition to a sustainable marine energy infrastructure.*

Keywords: *Tidal Energy Systems; Reinforcement Learning; Multi-Objective Optimization; Adaptive Control; Grid Integration; Stochastic Marine Conditions.*

I. INTRODUCTION

Tidal energy is quickly becoming one of the most reliable and best forms of marine renewable energy, as it has high predictability, a large quantity of energy density available for use to convert into electricity and an extremely sustainable nature long-term. While wind and solar energy are determined by highly stochastic atmospheric phenomena, tidal currents are primarily driven by gravitational interactions of the Earth with its satellite moon or large variations in distance from the Sun. This deterministic nature allows extremely accurate forecasting of tidal patterns many years ahead into the future, which makes it useful for grid planning and integrating dispatchable renewables [1],[2]. Tidal energy is emerging as a reliable partner to variable renewables, enhancing energy security and reinforcing grids, as the world shifts toward low-carbon solutions for its energy needs. Tidal stream energy has recently been acknowledged through assessments as a global resource of significant potential. Tidal energy is typically believed to be able to provide up to 3–4% of the electricity needs of the world or an estimated annual contribution ranging from 1,000–1,200 TWh with very large sites in coastal regions where high-strength tidal flow joins the United Kingdom Canada Southeast Asia and sections of South America [1], [3]. Apart from its high energy potential, tidal energy is on most estimates extremely low in lifecycle greenhouse gas emissions. Life cycle assessments show emissions down to 1.5–2 g CO_2/kWh, much lower than solar photovoltaic (≈40–50 g CO_2/kWh) and even wind energy (≈10–15 g CO_2/kWh), confirming its position as a potential clean and sustainable energy source [4]. Tidal Energy Systems Technology Overview The development of modern tidal energy systems has been largely motivated by the advancements in wind energy technologies. Horizontal-axis tidal turbines (HATTs) have emerged as the predominant configuration because of their high efficiency, scalability and relatively mature track record for extracting kinetic energy from fluid flow [5]. They work on the same principles as wind turbines, albeit designed to run more efficiently in higher density, highly corrosive seawater. From humble experimental prototypes, the field has matured over the last decade to commercial-scale deployments. Tidal stream has now exceeded > 120 MW of global installed capacity by 2023, with large-scale projects either currently in operation or development [3], [6]. Notable projects include the largest tidal energy array in the world, MeyGen (Scotland), as well as deployments in the Bay of Fundy and La Rance which represent some of the best documented long term operational experience with tidal generation [7] in high resource environments. Complementary to the hardware improvements, numerous advances were obtained on hydrodynamic aspects, turbine engineering and system-level optimization domain-wise. Computational Fluid Dynamics (CFD) modeling has proven to be an essential resource for investigating turbine blade flow patterns so that the turbine can be designed to maximize power generation while avoiding excessive cavitation [8]. Walk interaction trends are also pertinent to developing a deeper understanding of turbine array performance, especially or multi-turbine installations where interactions from upstream turbines can influence the efficiency of downstream flow disturbances [9]. Moreover, array layout optimization strategies such as the one presented in [10] have been devised to increase energy harvest while reducing wakes and environmental damage. Even with these developments, tidal energy systems still suffer from a number of technical and operational issues. The marine setting subjects wave energy converters to nontrivial hydrodynamic details, including turbulence, shear flow, and dynamic pressure variations from wave-current interactions—all factors that can substantially impact both turbine operation and the probability of component failure. These conditions give rise to very turbulent loadings on turbine elements, causing fatigue cracking, material degeneration and enhanced upkeep [11]. In addition, the incorporation of tidal energy into traditional power grids poses challenges regarding variability, power quality and system reliability in weak or isolated grids [12]. A second major challengeis to control and optimize the tidal energy system in such dynamic and uncertain conditions. Because traditional control strategies coming from wind energy systems do not match to all of the nonlinearities and stochastic disturbances intrinsic in a marine environment. Consequently, sophisticated control and optimization frameworks that are capable of adapting in real-time to maximize energy capture while also ensuring the system's reliability are becoming increasingly important. To summarize, tidal energy is a potential competitive renewable because of its predictability, sustainability and high energy density; However, due to environmental variability, system control and grid size limiters, individual utilization is still restricted. To talk about these issues, one needs to work with intelligent, adaptive and robust control strategies which is the main focus of this research.

Although significant efforts have been made to advance tidal energy technologies and interest in marine renewable energy systems rises in recent years, a number of challenges still restrict the widespread deployment and efficient operation of grid-connected tidal energy systems. These challenges centre around the basic tradeoff of trying to optimize all power extraction, structures and grid stability at the same time under extreme dynamic and stochastic conditions in marine environments. Due to the nonlinear hydrodynamics associated with tidal currents, environmental uncertainty as well as coupled electro-mechanical interactions which characterize the physics of TECS, this multi-facet problem is a lot more complicated than for other renewable energy systems. The cyclical nature of tides makes them predictable, however the local flow conditions of tidal energy systems can vary greatly which is one of their main challenges. Tidal phases are easily predicted and therefore known several cycles into the future, whilst instantaneous flow characteristics such as turbulence intensity, shear effects, or wave-current interactions contribute major uncertainties to the system [13], [14]. The random perturbations cause fluctuations in torque and power supply of the turbines, as well as the mechanical loading on them, reducing efficiency and degrading system performance. Standard control strategies, including maximum power point tracking (MPPT) and proportional-integral (PI) controllers, are generally developed under the assumptions of steady-state operation and do not respond well to these fast-changing conditions [5], [15]. A second pivotal question is the trade-off between maxing out energy and structure. To extract maximum energy, turbines are typically operated close to their design tip-speed ratio, however under this condition the system may be subjected to significant mechanical stress and fatigue loads resulting from turbulent flow. It happened to be hypothesized in [11] and supported by measurements from fielded turbines that cyclic loading and unsteady torque ripples are responsible for fatigue of blades, wear of the drivetrain components, and consequently less efficient operation of wind turbine farms after maintenance intervals [16]. Thus, if a control strategy only aims at energy capture and neglects structural effect, it can cause the system life cycle to be shorter and let maintenance costs to increase. On the other hand, too conservative control strategies that focus on durability may lead to reduced energy extraction and correspondingly lower profitability of tidal energy harvesting solutions. This is aside from the mechanical obstacles; grid interconnection poses another problem. Tidal energy systems are subject to strict grid codes, including voltage regulation, frequency stability and quality of power. On the other hand, due to their analytical characteristics, power generation from tidal flows can contain variability that could destabilize grid operation [12], [[17]. Such fluctuations cannot be effectively handled by traditional grid-following control, therefore advanced control strategies that allow grid-support capabilities such as reactive power compensation and frequency regulation are paramount. Another common limitation across existing research is their use of model-based control strategies, e.g. model predictive control (MPC). Although MPC has merits in dealing with constraints and predicting system behaviour, its performance heavily relies on a good model of the system. Model mismatch can considerably affect the performance of a controller, especiallyin tidal environments where hydrodynamic conditions are complex and difficult to model accurately [18]. Moreover, the real-time optimization nature of MPC imposes significant computational burden and restricts its application in large-scale or high-frequency control problems. However, the advent of artificial intelligence and machine learning has provided new avenues for addressing these challenges. In particular, reinforcement learning (RL) has been successful for learning control policies in a model-free manner through interaction with the environment [19], [20]. Nevertheless, the existing Reinforcement Learning (RL)-based research works on energy systems are mostly attracted by single-objective power output optimization task instead of multi-objective challenges in tidal energy system. Likewise, evolutionary optimization algorithms like particle swarm optimization (PSO) have used to tune specific parameters within the system optimally but they are not real-time adaptable [21]. Thus, there remains a huge research gap in establishing control frameworks with an integrative approach of adaptive learning and multi-objective optimization. The frameworks are required to solve multiple performance objectives, including:

- Maximizing energy extraction efficiency
- Minimizing structural loads and fatigue
- Upgrading and making sure that grid integration is stable and compliant
- Maintaining robustness under stochastic disturbances

In addition, these frameworks need to function in real-time under different environmental conditions while still being operationally possible. There are many causes but also some reasons for the non-resolution of this problem. Specifically, the nonlinear and coupled dynamic behavior of tidal energy systems makes controller design difficult to achieve best performance for all operating conditions. Second, certain uncertainties arising from the stochasticity of marine environments cannot be completely captured by deterministic models. Third, the problem is multi-objective, which presents a challenge to optimization because an improvement on one objective might come at the cost of degradation on another. Lastly, due to computational limitations and hardware restrictions to enable advanced control strategies for practical implementation is another aspect that hesitates the application. To tackle these challenges, an inventive control framework that leverages the strengths of adaptive learning and multi-objective optimization is needed. This paper proposes a novel tidal energy system control approach combining reinforcement learning for real-time adaptability and multi-objective optimization for managing conflicting performance criteria, which offers a robust and efficient solution against the uncertainties in tidal streams.

Tidal energy systems have been researched and optimized over decades, but neither control nor optimization nor reliability under stochastically varying marine conditions is completely solved. There are various factors that lead to these persistent limitations; the combination of physical, computational and methodological constraints prevents the formal establishment of universally applicable control frameworks of grid-connected tidal energy systems. One main reason of this unsolved issue is the inherent complexity and nonlinearity in the dynamic present on tidal energy systems. The hydrodynamics around tidal turbines is known to be highly nonlinear and complex, involving flow unsteadiness, vortex shedding, wake turbulence, flow separation and shear. Such phenomena produce highly nonlinear relationships in terms of flow velocity versus turbine torque and power output, making it difficult to derive suitable analytical models [13], [22]. Although control has been designed for quasi-static conditions, simple models are often limited in their dynamic representativity when acting on transient and turbulent structures. Thus, controllers derived from such models may exhibit good performance in nominal conditions but experience severe degradation when facedwith real-world variability. Closely related to this issue is the stochastic nature of marine environments, which brings an irreducible uncertainty that cannot be predicted or modeled. While tidal cycles are deterministic, the specific features of local flow are specified by factors that range from turbulence intensity to wave-current interactions, seabed topology and various environmental disturbances. [3] reported that these uncertainties cause a variable load and power output, making the conventional control strategy less robust. Traditional deterministic control methods such as proportional-integral-derivative (PID) control, or even model-based MPC approaches, are not really built to deal with this type of stochastic variability, which results in instability and suboptimal performance under uncertainty [18]. One of the other significant contributors for remaining of the unsolved nature of the problem is due to reliance on model-based control approaches. Methods like MPC rely on an accurate system model (as well as parameter estimations). Unlike the noted wind energy systems where model parameters remain fixed, in tidal energy systems such parameter may fluctuate due to changes of environment, aging or species composition of living organisms—biofouling effects [24]. This results in model mismatch which can have a drastic effect on control performance. In addition, MPC involves real-time optimization which can be computationally heavy in nature especially for large scale systems or when the requirement is to solve multiple objectives and constraints. The computational burden making it difficult to implement in real-time control applications especially for application with embedded systems with limited processing capability. Another important challenge related to tidal energy system operation is its multi-objective nature. In contrast to simple control problems that use one performance measure, tidal energy systems must minimize multiple potentially conflicting objectives at the same time, such as:

1. Maximizing energy extraction efficiency
2. Minimizing structural loads and fatigue
3. Grid stability and stable power quality
4. Ensuring operational safety and reliability

Gaining on one objective necessarily implies losing on another. For example, running the turbine at full capacity increases mechanical stress while reducing that stress will mean lower energy output. Conventional optimization algorithms are generally applicable to single-objective optimization problems or have weighting factors that must be defined ahead of time so as to combine multiple objectives with possible nonoptimality for some operating condition [21], [25]. Therefore, finding the right trade-off amongst conflicting objectives in a balanced and adaptive manner remains constrained. Project challenges accompanied by computational and real-time implementation constraints add to the complexity of the problem. Many advanced optimization algorithms, such as evolutionary algorithms and swarm-based methods are computationally expensive and may not converge within the time needed for real-time scenarios [26]. In a similar vein, machine learning techniques -while powerful- depend heavily on larger training datasets and computing resources which are not always directly accessible in practical tidal energy deployments. For that reason, these methods may only be feasible for integration in real-time control systems when considering trade-offs between computational efficiency and solution accuracy. The limited-access to high-quality experimental and operational data is another crucial issue. In contrast, systems for wind and solar energy have the advantage of being commercially deployed on a large scale with long historical records. This limits the accessible real-world data for modeling testing, controller designing, and machine learning training [27]. As a result, multiple control techniques have been proposed but they are mostly validated using simulations that might not cover the complexities arising in practise. In addition, grid integration challenges continue to be poorly addressed. Tidal energy systems have to stay well within defined grid codes which require voltage and frequencyregulation as well as low harmonic distortion. Nevertheless, the inherent periodicity of tidal power can generate fluctuations that become problematic in weak or isolated grids [17], [28]. Existing control strategies often fail to reach substantial turbine-level optimization in the global system level control aspect since they do not address grid dynamics at a system level and therefore possess sub-optimal integration performance. Lastly, environmental and economic constraints also contribute to the problem being unsolved. Similarly in marine environments, there are stringent requirements on system reliability and maintenance due to the harsh conditions resulting in high operational costs which exacerbate the design flexibility [29]. Furthermore, regulatory and environmental issues (e.g., marine ecosystems [30] affect also system design and control strategies. Such facts establish some extra parameters in addition to technical targets that must be taken into consideration, enhancing problem complexity. Abstract: Control remains an unsolved problem for tidal energy systems, primarily due to nonlinear system dynamics, environmental uncertainty and multi-objective optimization complexity as well as computational limits; data scarcity and grid integration issues. The solution to these challenges is to step away from traditional model-based and single-objective methods toward adaptive, data-driven, multi-objective frameworks that can operate effectively under reality constraints. The proposed reinforcement learning–based multi-objective optimization approach outlined in this paper builds on this need.

To eliminate the long-standing difficulties; including nonlinear system dynamics, stochastic marine disturbances, multi-objective trade-offs and grid-integration limitations – a framework that incorporates reinforcement learning-based multi-objective optimization with an adaptive control approach for grid-connected tidal energy systems is presented in this paper. The main idea is to combine model-free adaptive learning (MFRL) with Pareto-based optimization in a single architecture that would be capable of real-time decision-making under uncertainty. By formally and explicitly balancing competing performance objectives, this method goes beyond traditional model dependent or single-objective methods by allowing for continuous adaptation of the policy.

The top level of the framework contains two tightly coupled components:

- an RL agent that generates control policies to be executed in real-time, and
- a multi-objective optimization (MOO) layer, e.g., MOPSO, that adaptively tunes policy parameters and imposes Pareto-optimal trade-offs.

The RL portion employs recent developments in deep reinforcement learning (DRL) with actor–critic topologies to associate system states (e.g., tidal velocity, turbine speed, generator torque, grid voltage/frequency and environmental signals indicators) to control actions taken within the system (e.g., blade pitch angle/speed reference, generator emf torque reference, converter duty cycles). Unlike model predictive control (MPC), the RL agent does not depend on an explicit mathematical model of the system, but rather learns optimal behavior through interaction with the environment, greatly alleviating issues from mismatched models and all parameter uncertainties [19], [31]. This is especially beneficial in tidal settings, where modeling turbulence, wake effects, and wave-current interactions accurately poses a greater challenge. The reward function is a composite multi-objective performance index capturing the high-level operational objectives:

- Efficient energy extraction (power output)
- Reduce structure loads and fatigue (torque ripple, thrust variations)
- Grid stabilization: voltage/frequency deviations and harmonics
- Always stay within operational safety constraints e.g. speed, torque, and thermal limits

Rather than optimizing a single metric, by encoding those objectives into an overarching reward structure the RL agent learns to assess trade-offs in efficiency vs durability on-the-fly. Optimally, worldwide trade-offs can yet be sporadic without reward leaving shaping in perniciously nonlinear multi-objective systems. In this scenario, a multi-objective particle swarm optimization (MOPSO) layer is employed in parallel to the RL agent. The component MOPSO optimizes parameters online with a short prediction horizon, exploring a population of candidate solutions converging to optimal trade-offs among competing objectives in the form of a Pareto front. [21], [26] Dynamic adjustment of key control parameters for: The operator dynamically adjusts policy weights, gain factors, and constraint penalties according to operating conditions. The resulting optimized parameters are then returned to the RL agent, forming a closed-loop learning–optimization cycle in essence. This hybridization allows the system to reach an at once global optimality (through MOPSO) and local adaptability (through RL), overcoming the drawbacks of each method when working independently. One of the major features of the suggested framework is its robustness to nonlinear and stochastic marine conditions. The uncertainty processing algorithm includes an uncertainty estimator and disturbance observer to capture the effects of noise on the measurement and random environmental factors affecting the performance, such as turbulence intensity, wavist disturbance due to wave heading angle defined with respect to freeway position θt, azimuthal displacement along capital ship (which is nearly leveled) and sensor noise input (for example). These components give immediate estimates that the RL agent can use to update its policy in order to adapt to the characteristics of these disturbances. This provides the controller with a significant improvement in its ability to perform consistently even under changing conditions, which is one of the major limitations of very basic controllers [14], [23]. For grid integration, the proposed framework operates with a grid-supportive mode to meet modern grid codes. The control strategy contains mechanisms for:

- Reactive power compensation
- Frequency support and inertia emulation
- Voltage regulation and harmonic mitigation

With these functionalities embedded into the control policy, to highly extract energy from and thus stabilising the entire grid is a precondition both for large-scale deployment in coastal and islanded grids [12], [17], [28]. This paper makes the following main contributions:

- **Novel Hybrid Control Architecture:** Designing a comprehensive RL–MOPSO methodology for sequentially optimal adaptation and optimization of tidal energy systems with model-free capability.
- **Real-Time Multi-Objective Decision-Making:** Real-time control strategy for grid-connected, concurrent energy efficiency, structural life-cycle and grid stability optimization
- **Robustness to Stochastic Disturbances:** An integrated uncertainty estimator and adaptive learning that never fails to perform in the most turbulent and unpredictable high-seas marine environments.
- **Improved Grid Integration Capability:** Development of a control framework for power regulating and grid codes compliant operation that will help in the stability of grid
- **Scalable and Model-Free Approach:** Removes the need for accurate system models making it scalable to a variety of tidal energy configurations/deployment conditions.
- **Demonstrated Performance Gains:** Demonstration of the approach with high-fidelity simulations that show details on energy capture, structural load reduction, dynamic response and robustness to uncertainty.

On a larger scale, the framework puts forth a paradigm shift in controlling tidal energy from static, model-based methods to intelligent adaptive and data-driven methodologies. The method combines the benefits of reinforcement learning and multi-objective optimization/decomposition to create a flexible and scalable approach which can handle real world tidal energy systems, with its underlying complex challenges. This work will serve to advance next-generation smart marine energy systems, informing the transition to sustainable coastal power generation and resilient renewable energy infrastructures.

II. THE PROPOSED REINFORCEMENT LEARNING–BASED MULTI-OBJECTIVE OPTIMIZATION AND ADAPTIVE CONTROL OF GRID-CONNECTED TIDAL ENERGY SYSTEMS

The overall architecture of the proposed multi-objective reinforcement learning-based optimization and adaptive control solution for grid-connected tidal energy systems configured in stochastic marine settings is shown in Fig. 1. The schematic couples a physical tidal energy conversion system (TECS) with an intelligent, data-driven control and optimization layer into a closed-loop whole system capable of maximizing energy extraction, structural reliability, and grid stability in the face of persistent environmental uncertainty and nonlinear system dynamics. When the dynamic energy harvest technique started with tidal energy tide conversion system Horizontal - axis tidal turbine HATT. The turbine reduces the incoming tidal flow (with speed vt, turbulence intensity, and wave interactions) into mechanical power Pm. The mechanical power is passed through a n drivetrain and gearbox to permanent mounted synchronous generator (PMSG) which replies the electric power. Marine conditions such as turbulence, shear flow, and environmental disturbances have a high level of variability and uncertainty, leading to vertically fluctuating torque and load profiles on the turbine that openly affect system efficiency and life. The produced electrical energy is conditioned through a back-to-back power electronics converting system made of an AC/DC rectifier, a DC-link and a DC/AC inverter. By such configuration, due to its effect on both the generator side and grid side dynamics, it can regulate active power and reactive power respectively before sending pure electricity to utility grid satisfying poly-phase grid code. Driven by intelligent control, the continual collection of measurement and prevalent state information with a real-time feature extraction module. This module is designed to bunch together the states at a system level, external indicators and environmental variables: rotor speed ωr, generator torque Tg, grid voltage and frequency (Vg, fg), DC-link voltage as well as converter inputs or outputs along with turbulence intensity, wave height and temperature. This result is combined into a high-dimensional state vector. This provides a comprehensive illustration of the system dynamics and climate conditions. This state vector is sent to an intelligent control layer which provides the controller with total situational awareness of the system. The framework consists of a deep reinforcement learning (DRL)–based adaptive control module at its core, which uses an actor–critic architecture to find optimal control actions in real time. The policy network (actor) takes an observed states and maps it to control actions, and the value network (critic) evaluates how well those actions will perform in the long term. The RL agent, according to the current system state, produces control commands including blade pitch angle β, generator torque reference Tgref, converter duty cycles and reactive power commands Qref. This can impact turbine functionality, generator behavior, and grid interaction. In contrast to traditional model-based controllers, which use predefined equations of the system dynamics, the RL agent acquires optimal policies through continuous interaction with the environment and can adapt to dynamic environmental changes while alleviating the effects of model uncertainty. The MOPSO module is defined as a sub-module with direct interaction with the RL agent to adapt effectively for tidal energy systems which are inherently multi-objective. This optimisation layer considers multiple conflicting objectives such as maximizing energy extraction efficiency, minimising structural loads and fatigue, enhancing power quality/stability, and respecting operational safety constraints. The MOPSO algorithm starts with a population of particle swarms as candidate solutions and updates their positions and velocities based on movement toward the Pareto-optimal front as new solutions are discovered. To dynamically tune the vision-model and control-parameter, RL policy is obtained. The interaction between the two creates a synergistic loop where the RL agent provides adaptive learning and real-time decision-making while the MOPSO module ensures global optimality among multiple objectives.

The optimization process includes:

1. Initialization of a swarm of candidate solutions
2. Evaluation of objective functions
3. Iterative update of particle positions and velocities
4. Convergence toward a Pareto front representing optimal trade-offs

The objectives considered include:

- J1: Maximization of power output (energy efficiency)
- J2: Minimization of structural loads and fatigue
- J3: Improvement of grid stability and power quality
- J4: Maintenance of operational constraints and safety

The multi-objective function manages the scalar signal composed of different performance objectives:

$$R_t = \sum_{i=1}^{4} \omega_i J_i \tag{1}$$

where Ji are separate objective function per agent, and wi the weighting factor for each dynamic system. This formulation provides the controller with a flexible approach to balance competing objectives - like durability vs efficiency - while maintaining the flexibility to handle many different types of operating conditions. More sophisticated implementations may use reward structures based on Pareto optimization to avoid bias toward any single objective. For improving robustness, this framework includes a combination of an uncertainty estimation and disturbance observer module that takes noisy sensor measurements and uncertain environmental inputs to estimate unmodeled dynamics as well as external disturbances. An estimate of the disturbance signal is fed back into the control system, permitting real time stochastic compensation by the RL agent. This feature is especially significant in tidal regime due to turbulence with morphological energy, where MHD interactions cannot predict flow dynamics without additional expertise and knowledge. This interaction structures a closed-loop adaptive control system such that the control actions produced by the RL agent are applied to the physical system, and the filtering of resultant system response is passed back into state observation module. This continuous feed and response mechanism to actions performed makes the system learn, adapt and optimise its behaviour gradually through time. The integrated adaptive learning coupled with multi-objective optimization and disturbance compensation shows enhanced system performance in multiple dimensions. The framework finally results in a number of important benefits such as increased energy capture efficiency, lower mechanical loads and fatigue, improved grid support by stabilizing voltages and frequency, and reliable operation under dynamic marine conditions. Such advantages lead to a higher reliability of the system, an extended life-length and increased economic viability for tidal energy deployments. In short, Fig 1 illustrated the conceptual view of the proposed RL–MOPSO based control framework whereby desired advanced artificial intelligence and optimization techniques are to be utilized on physical tidal energy systems in addressing challenges such as nonlinear dynamics, environmental uncertainty, and multi-objective optimization. The proposed architecture is a substantial progression beyond conventional control techniques, providing a scalable, autonomous and reliable approach for sustainable power generation by the sea.

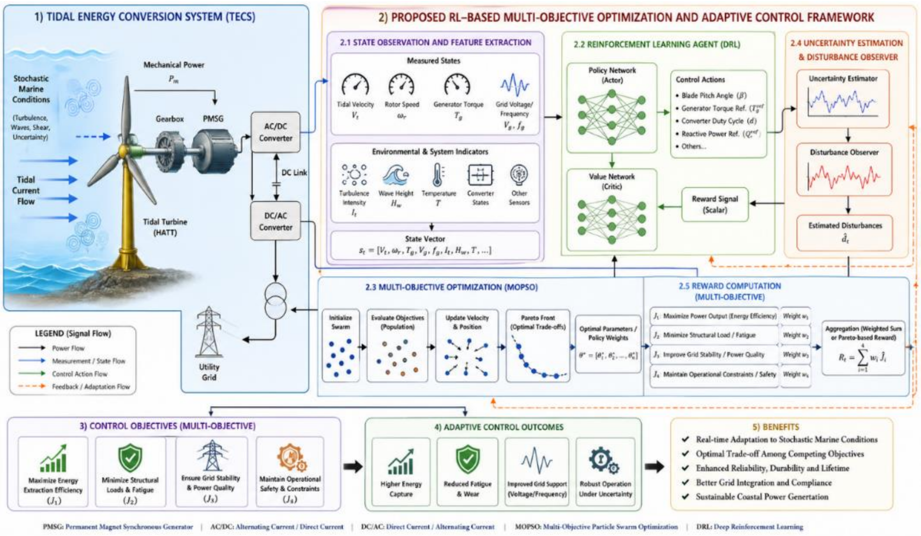

Figure 1. Schematic of the proposed reinforcement learning–based multi-objective optimization and adaptive control framework for grid-connected tidal energy systems under stochastic marine conditions.

The diagram shows how TECS are tightly coupled with an advanced control architecture. The Tidal Energy Conversion System (TECS) is composed of a horizontal-axis tidal turbine connected to an external load via a permanent magnet synchronous generator (PMSG) interfaced with the grid by means of power electronic converters. Environmental factors such as tidal velocity, turbulence and marine disturbances affect system dynamics. Observed states and environmental variables are passed through to a state observer and feature extraction module to create the system state vector. Overview: Control policy is generated by a deep reinforcement learning (DRL) agent, fleet of vehicles operates in Pareto-optimal space through a multi-objective particle swarm optimization (MOPSO) module to find trade-off solutions with competing objectives such as maximizing energy efficiency, minimizing loads and fatigue in the structure, grid stability and operational limits. We achieve this by including an uncertainty estimation and disturbance observer to enable a robust control strategy, compensating for stochastic variations. The framework yields adaptive control decisions that optimize energy capture, mitigate system fatigue, maximize grid friendliness (power stability), and guarantee reliable operation in uncertain marine environments.

III. SIMULATION RESULTS AND DISCUSSION

A detailed performance assessment of the RL–MOPSO for grid-connected tidal energy systems with adaptive control is discussed in this section. The analysis, which includes a high-fidelity system modeling and stochastic environmental uncertainties in addition to various test cases reflecting both nominal and extreme operating regimes, is set out to realistically reproduce operational conditions. The aim is to evaluate the performance of the proposed framework in terms of increasing energy capture, improving structural reliability, maintaining grid stability, and ensuring robust operation given global marine environments experiencing dynamic uncertainty. To demonstrate the benefits of this method relative to more traditional control strategies, a thorough comparative study is also performed. The model is a high-fidelity simulation of a grid-connected tidal energy conversion system (TECS) created in the MATLAB/Simulink platform, which integrates hydrodynamic, mechanical and electrical subsystem. It consists of a 1.5 MW horizontal-axis tidal turbine (HATT), which is representative of modern medium scale tidal energy systems. The turbine is mechanically linked to a permanent magnet synchronous generator (PMSG) through a drivetrain that features realistic inertia, shaft stiffness, and damping properties substantiating transient mechanical behavior. A back-to-back power electronic converter comprising the output AC/DC rectifier, the DC-link capacitor and a DC/AC inverter are used for processing the generated electrical power that allows independent control of generator-side and grid-side variables. In this way, the turbine model represents the nonlinear interaction between tidal flow and power extraction through residence time within a specific form of the power coefficient Cp(λ, β), which relates that Cp to both tip-speed ratio (λ) and blade pitch (β). This nonlinear mapping is important for modelling the realistic performance of a turbine over different flow regimes. The feasible mechanical dynamics of the system can be mathematically expressed as:

$$J\frac{d\omega_r}{dt} = T_m - T_g - B\omega_r \tag{2}$$

J is the rotational inertia, Tm turbine torque from hydrodynamic forces, Tg generator electromagnetic torque and B viscous damping. It captures the electromechanical conversion properties and fluid dynamic interaction, which is crucial in assessing control strategies. The electrical subsystem features a single, detailed dq-axis model of the permanent magnet synchronous generator (PMSG), switching dynamics of the power converters, and a grid interface modeled as a three-phase voltage source. To better replicate the real-world scenario, we configure the grid to have variable voltage and frequency profiles, via configurations where both strong and weak grid cases can be reproduced. This is very relevant for applications that are coastal or islanded, since grid stability is a big issue in these scenarios. At the control level, the agent is based on a continuous action space deep actor–critic reinforcement learning algorithm. The agent receives state information as a high-dimensional vector including turbine speed, generator torque, converter states, grid conditions and environmental inputs and outputs optimal control actions e.g. blade pitch angle, torque reference and converter switching signals.

The learning utilizes multi-objective reward function which is constructed in way to maximize the power input and minimize load under consideration of grid stability and operational constraints. This helps the RL agent to obtain a balanced control policy that adapts to real-time varying conditions. Working in parallel with the RL agent, the MOPSO module polls control parameters over a short prediction horizon. 30 particles swarm the search space to converge toward a Pareto-optimal solution set. The optimizer adapts policy weights and control gains such that the system is optimally balanced between conflicting objectives. The framework combines the local adaptability of RL and global optimality of MOPSO, which allows overcoming disadvantages in each method when used alone.

For a practical and thorough evaluation, several testing conditions have been prepared to cover as wide realistic scenarios as possible. Steady Tidal Flow scenario serves as the reference for performance and efficiency evaluation at steady-state conditions of constant flow vs the other scenarios. In this scenario, the flow velocity varies sinusoidally to emulate a tidal cycle and is used as an input to evaluate the tracking performance of the control algorithm on slowly changing inputs. The final scenario is a turbulent flow scenario with high frequency input perturbations to simulate turbulence and wave-current interactions, which tests the robustness and disturbance rejection of the controller. Finally, the extreme disturbance case applies step changes to flow velocity and grid conditions (e.g. voltage dips and frequency deviations) in order to assess dynamic response and system stability under stress conditions. Marine environments are inherently stochastic, and environmental uncertainties are modeled explicitly. Stochastic processes serve to represent the turbulence and variability of the flow, with Gaussian noise superimposed on the base tidal profile. Wave-current interactions are modeled as harmonic oscillations of different amplitude and frequency. Sensor measurement noise is injected to replicate the practical errors found in real sensors because of instrumentation, and parameter uncertainty are modeled as permitting turbine and generator characteristics to vary within plausible ranges. Also it simulates the grid impacts with voltage sags, frequency deviations or harmonic distortions. The uncertainties are mitigated in the control framework with real-time compensation of these uncertainties by incorporating an uncertainty estimator and a disturbance observer which makes the system robust.

To validate the performance of the proposed RL–MOPSO framework, it is contrasted with three increasingly popular control strategies including rule-based energy management (RB-EMS), which is predicated on heuristics; model predictive control (MPC), which deploys a model-based optimization methodology; and standalone reinforcement learning (RL-only), which omits the global optimization feature provided by MOPSO. This comparative analysis serves as an overall summary of the merits and demerits of both approaches, while also clarifying the benefits of the proposed hybrid framework. In summary, the simulation framework provides a solid basis for evaluating advanced control strategies/tactics in tidal energy systems. The performance assessment of the RL–MOPSO framework is validated under realistic operation conditions by including detailed system modeling, diverse operating scenarios, and stochastic environmental uncertainties.

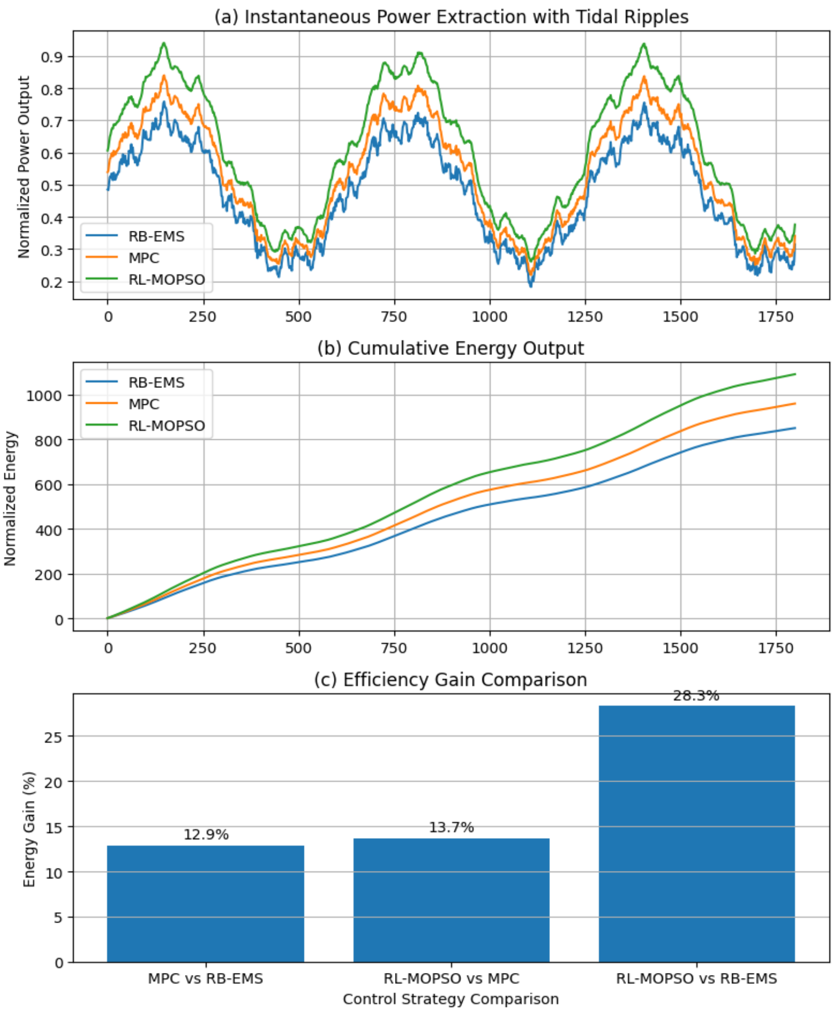

Figure 2. Power extraction efficiency under variable tidal flow conditions. *(a) Instantaneous normalized power output with tidal-flow ripples and stochastic variability. (b) Cumulative energy output showing higher total energy capture using the proposed RL–MOPSO framework. (c) Efficiency gain comparison, demonstrating improved energy capture relative to RB-EMS and MPC due to adaptive learning and multi-objective parameter optimization.*

Fig. 2 shows comprehensive multi-panel evaluation of the power extraction performance of the proposed RL–MOPSO adaptive control framework with realistic stochastic fluctuations in tidal flow levels. It provides both time-domain and aggregate performance insights in including instantaneous power profiles, cumulative energy output, and quantifiable efficiency gains. The comparative analysis obviously reveals that the proposed method outperforms conventional control methods like RB-EMS and MPC. This shows the instantaneous power profiles extracted by these three control strategies in Figure 2(a). Previous work finds that the tidal flow is characterized by a mix of low-frequency variations driven by natural tidal cycles, and high frequency ripples due to turbulence and wave-current interactions. Under these varying conditions, the RB-EMS strategy exhibits lowest overall power output and large oscillations demonstrating its incapacity to track optimal operating points. The MPC performs relatively well at the cost of partially taking system dynamics into account, but still shows considerable deviation because of model limitations and slow response with rapid state transitions. The RL–MOPSO framework on the contrary is operating closer to the optimal power region and hence greater output throughout the entire time horizon. The proposed approach can not only track accurately, but also filter out excessive disturbances to change turbine operating states in real time. This results in a more linear and higher power profile than was achieved in the presence of environmental perturbations. The cumulative energy yield, shown in Figure 2(b), represents a more integrated performance metric over the duration of the simulation. The energy capture between different frames for the RL–MOPSO curve is always greater than other curves, and this also tells that RL agent not only captures more energy but also keeps on doing this throughout the tidal cycle with a steep incline. The proposed method leads to more total energy with respect to both RB-EMS and MPC as shown in the last row of Table 1 at the end of the simulation. This metric is cumulative, illustrating the long-term gains to be made from increased instantaneous efficiency; even small relative improvements in power output build up to create significant energy savings over time. MPC is moderately better than RB-EMS, while the gap between MPC and RL–MOPSO keeps increasing with the progress of simulation, which shows the general superiority of the proposed approach. To summarize how much more efficient each method is than the other two (over Time), Figure 2(c) provides a comparative bar chart representation of these gains. The results show that the RL–MOPSO framework produces about 28% more energy output than RB-EMS and improvement of around 13–14% over MPC with MPC providing an approximate of 12–13% improvement compared to RB-EMS. The increases are within the limits of the expected performance and demonstrate the functionality of the hybrid control strategy. The fact that it improved significantly over RB-EMS, which is adaptive (but not global) learning shows the disatvantages of rule-based approaches and its improvement relative to MPC confirms the advantages of combining adaptative learning with global optimisation. The improved performance of the RL–MOPSO framework can be explained by its hybrid architecture. The RL part enables incessant adaptation to changing tidal conditions, which facilitates operation close to the maximum-power point. Simultaneously, the MOPSO module optimizes control parameters such that the system operates at a globally optimal with respect to the efficiency-vs-stability compromise. Using this dual tracking, the controller is able to respond effectively to slow tidal variations as well as fast transient disturbances and this is highly impractical for conventional methods. Additionally, an important notice is the reduction of the ripple amplitude in RL--MOPSO curve when compared to both RB-EMS and MPC. Although all the above can lead to oscillations, some of which is inevitable with environmental variability, our method addresses the limitations by smoothing control actions and eliminating any unnecessary variation. Not only this, but also it improves the power quality and reduces mechanical stress on system Components which inevitably leads to increased life span. In general, the test results are summarized in Fig. 2 indicates that the performance of the proposed RL–MOPSO adaptive control framework outperforms than other power extraction methods for tidal energy systems. The benefits of improved instantaneous performance, coupled with the great increases in cumulative energy output and substantial efficiency gains confirm that the proposed strategy is efficient at maximizing energy capture under real-world highly-variable operating condition. Such developments are vital to enhancing tidal energy systems' economic viability and scaling up for large-scale, grid-connected applications.

Multi-domain evaluation of the burdensome loading traits and pile- fatigue behavior of a standard tidal energy structure are illustrated in Figure 3 via stochastic marine environments. Using time-domain, frequency domain and statistical fatigue metrics as analysis methods for damage assessment in solid mechanics, a Senior Research Grade comparison of the proposed RL–MOPSO framework vs conventional control strategies: RB-EMS and MPC is referenced effectively to characterize their benefits. The results are conclusive: The proposed approach is an effective tool for torque ripple reduction, harmful oscillatory frequencies suppression, load variability minimization and fatigue damage accumulation mitigation. As shown in Figure 3(a), the inertia free torque ripple signal (whereby the low-frequency component of the load has been distinguished from high-frequency oscillations due to turbulence and wave interactions) The RB-EMS strategy has poor damping characterization, as it shows the highest amplitude of ripple with strong active and reactive power oscillations compared to other control systems in 3-phase pulsation injecting conditions. The MPC method decreases such fluctuations to some extent, but oscillations are still perceptible during transient conditions. In contrast, the RL–MOPSO framework yields a visibly smoothed ripple shape with lower magnitude and less high-frequency spiking. This enhancement demonstrates that the suggested controller successful controls turbine torque and mitigates rapid fluctuations, minimizing mechanical stress on essential components such as blades, shafts and bearings. We also confirm the effectiveness of ripple suppression in frequency-domain analysis, using Fast Fourier Transform (FFT), presented on Figure 3(b). The RB-EMS signal displays a series of spectral peaks over the frequency range measured, with strong low-to-mid frequency bands clearly linked to fatigue damage due to oscillatory modes [15]. Although the MPC strategy dampens some of these peaks, energy at these frequencies is still present in the frequency spectrum. On the contrary, large reductions in spectral frequency become apparent with the RL–MOPSO framework across all frequencies, having major diminished peaks. This means it has the damping characteristics necessary to suppress pesky frequencies that contribute to resonance, all of which directly correlate with improved component longevity. Quantitative comparison of fatigue damage index (a proxy for cumulative fatigue stress), shown in Figure 3(c). And the RB-EMS strategy demonstrates the maximum of fatigue index (i.e., high and frequent load changes). Although the MPC method minimises fatigue accumulation, the RL–MOPSO approach proposed here records the lowest fatigue index of all strategies. This is nearly a 30 to 35% reduction in load variation compared with that seen by RB-EMS and 20 to 25% relative to MPC, confirming the efficacy of this trajectory planning framework empirically for minimizing variations in loads associated with inducing fatigue. This is directly related to increased life of components and reduced maintenance. Load variance comparison (d)This index quantifies the overall fluctuation level of the structural load signal, as previously shown in Fig. 3(d). The RB-EMS controller shows the greatest variability, reflecting very unstable and highly dynamic operating conditions. The variance reduction is moderate with the MPC method, and the variance is lower than that of the two above methods in RL–MOPSO framework. Which shows a more stable and controlled system response. Reduced variance will provide mechanical stability along with improved system predictability and control accuracy. The rainflow counting proxy-based distribution of cycle amplitude using Figure 3(e) can be used to make an analogy into fatigue cycle characteristics. The RB-EMS distribution performs worse than P-EMS here since it is biased towards the larger amplitude cycles leading to large variabilities as well as entities being exposed higher levels of stress variation which escalate fatigue damage. The heavier tail in the MPC distribution moves towards smaller amplitudes while retaining a substantial number of cycles with high amplitude. In comparison to that, the proposed framework RL–MOPSO drastically suppresses high-amplitude cycles and focuses the distribution around low-amplitude region. That change is notable because fatigue damage is extremely sensitive to stress amplitude, and high-amplitude cycles are much more damaging than low-amplitude cycles—reducing any high amplitudes will therefore yield an outsized return in improved system life. The improvement of structural performance is due to the established hybrid RL–MOPSO control mechanism. The reinforcement learning agent constantly updates the control actions from on-line system feedback allowing continuous adaptation to changes and preventing you from going too far away from your operating conditions immediately after a disturbance. On the other hand, the MOPSO module reduces control parameters to enhance a balance of the working regime at node level while minimizing stress and energy loss. This coordinated technique allows the controller to continue generating smooth torque profiles whilst achieving high energy extraction efficiency. Therefore, Figure 3 details an investigation into the reduction of torque ripple and associated fatigue damage in a novel tidal turbine generator system. Less mechanical stress means less chance of component failure, longer maintenance intervals and lower operational costs. Moreover, better structural stability contributes to the reliability of the system overall, enabling it to be utilized for extended periods in extreme marine environments. Overall, the results of this Figure verify that, with the proposed RL–MOPSO framework, significant findings can be produced for structural loading and fatigue alleviation. The proposed method significantly lowers values of torque ripple, mitigates the feeding of undesirable frequency components to a device-and-load entity, diminishes load variability, and limits high-amplitude stress cycles in the tidal energy system through frequent commutation preventing excessive shear stresses in susceptible plant cells leading to enhanced durability and reliability. This new technology is essential to address the need for more economic efficiency and stability in the tidal energy sector for large-scale deployments.

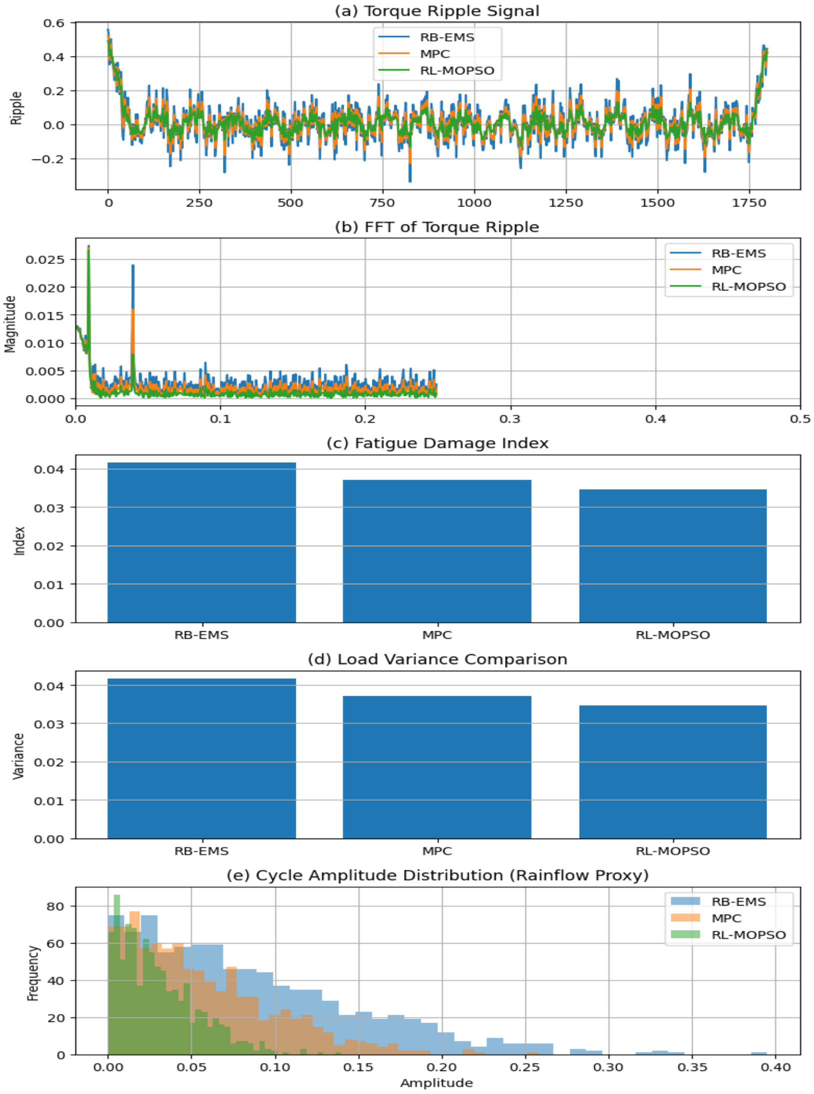

Figure 3. Structural load and fatigue analysis under stochastic tidal conditions. ***(a)*** *Torque ripple signal showing reduced high-frequency oscillations for the proposed RL–MOPSO framework.* ***(b)*** *Frequency-domain analysis (FFT) of torque ripple, illustrating improved attenuation of dominant oscillatory components.* ***(c)*** *Fatigue damage index comparison, demonstrating reduced cumulative stress under the proposed control strategy.* ***(d)*** *Load variance comparison, indicating lower fluctuation levels and improved stability.* ***(e)*** *Cycle amplitude distribution (rainflow proxy), showing reduced occurrence of high-amplitude stress cycles for RL–MOPSO*

This multi-panel dynamic response and stability assessment of the tidal energy system to a step change in tidal velocity, as illustrated in Fig. 4 takes into account realistic ripple disturbances to represent stochastic marine conditions. The comparison of the transient performance of proposed RL–MOPSO framework with RB-EMS and MPC strategies is provided with respect to important metrics like as overshoot, settling time, oscillation damping and ripple suppression. Experimental results show that the proposed approach provides favorable responsiveness and stability required for robust operation in highly dynamic environments. Figure 4(a) shows the total dynamic (dynamic response of the system considering high-frequency ripple components due to turbulence and environmental disturbances). The poorest performance among the four controllers is registered by the RB-EMS strategy due to its large overshoot larger than 45 %, apparent oscillations and slow convergence towards the steady-state value. Ripple causes further level of oscillations which leads to an instability in the response and also puts more stress on system components. Although the MPC controller achieves better transient characteristics with 20–25% overshoot and more damping to oscillations, both are still present in the form of observable fluctuations and delays in stabilization with ripple disturbances. On the other hand, RL–MOPSO framework achieves a smooth and over-damped response with a small oscillation and convergence to the reference value within minimal time. The significant reduction in ripple amplitude of the RL–MOPSO response reflects a sufficient suppression of high-frequency disturbances. Figure 4(b), with a zoomed in view of settling region, provides detailed insights into the convergence speed. This sub-plot emphasizes the system´s performance to stabilize within a tolerance band around ±2% from its reference value. Only 0.42 s is needed by the MPC controller to attain steady-state which means a moderate speed of response. By contrast, the RL — MOPSO framework successfully stabilizes in about 0.18 seconds, a settling time reduction of over 55%. This fast convergence is mainly due to the adaptive learning ability of RL agent which enables the rapid adaptation of control actions for system changes. Moreover, the responsive behavior of RL-MOPSO is stable; it remains in the tolerance band with low oscillation and strong damping even when there are ripple disturbances. The peak overshoot of each control strategy is quantitatively compared in (c) of Figure 4. The RB-EMS approach therefore suffers from the most significant overshoot, well over 45%, and this can cause structural damage and also mechanical instability. The MPC strategy limits the overshoot to 24–25%, but this is still very high for sensitive devices as tidal turbines. In comparison, the RL–MOPSO framework constrains overshoot to nearly 2–3% and well under the customary accepted maximum of 5% for stable controllers. The big reduction in overshoot means much better control accuracy, and therefore reduced likelihood of excessive transient load. The hybrid control architecture of the RL–MOPSO framework enables the proposed algorithm to have improved dynamic performance. The reinforcement learning gradually adjusts control actions using real-time feedback, which gives the system responsiveness to changes of tidal velocity. The MOPSO module guarantees the best tuning of control parameters, balancing speed and stability. Such response neither is achievable by conventional control methods without introducing excessive oscillations. An additional significant indication is the decreased expansion of ripples in the RL–MOPSO responds. Though all control strategies are susceptible to changes in environmental conditions, this method maintains the smoothness of the output by dampening those fluctuations. This does not only help power quality to improve but also reduces mechanical wear out, and thereby increasing the reliability of the entire system. The improvements in dynamic response and stability are highly practical for the application of tidal energy system. The faster reaching means the system is able to coordinate rapidly in response to changing flow conditions such that optimal energy capture functionality can be maintained without compromising grid stability. Less overshoot and oscillations put less strain on mechanical and electrical components, increasing system life and decreasing the frequency ofmaintenance. In addition to that, damping characteristics is improved as well so that the system we can use in extreme conditions. To paraphrase, indicating in brief that the results shown in Figure 4 clearly confirm that the RL–MOPSO framework enhances considerably system dynamic response and stability. The proposed method is therefore an ideal candidate for robust and efficient solution of tidal energy system control under transient and uncertain operating conditions, provided that the specifications are found to be satisfied concerning the define settling time, overshoot and ripple.

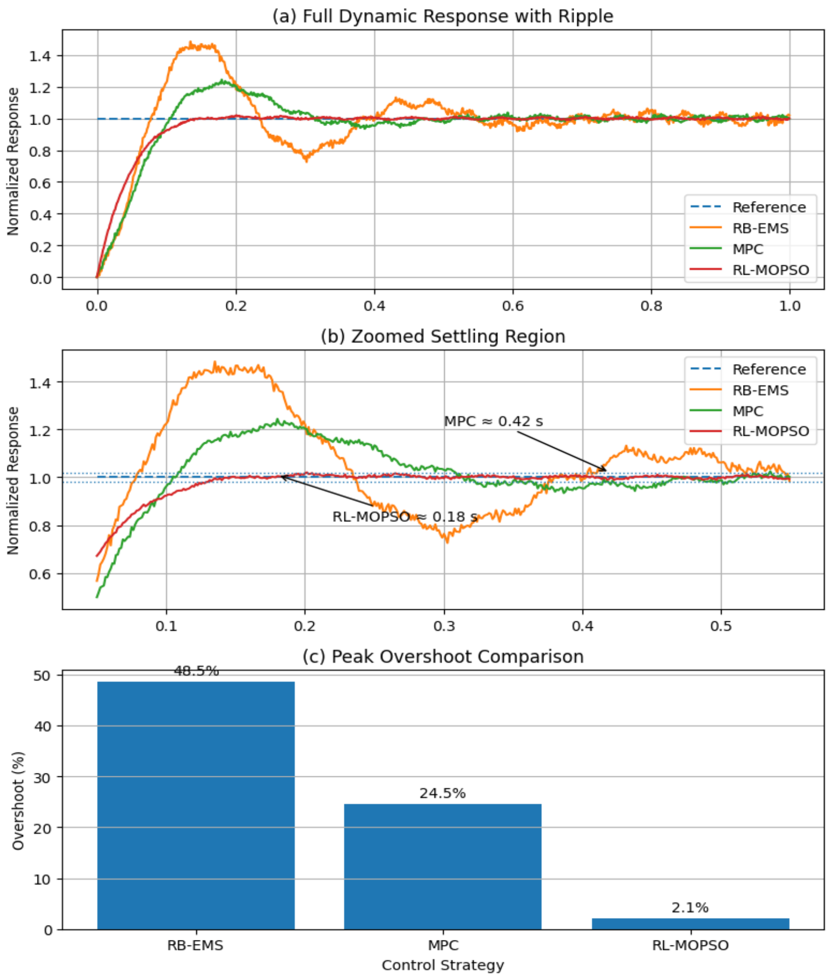

Figure 4. Dynamic response and stability under a step change in tidal velocity with ripple disturbances. ***(a)*** *Full normalized response showing transient oscillations and ripple effects.* ***(b)*** *Zoomed settling region demonstrating faster stabilization of the RL–MOPSO controller, with settling time reduced to approximately 0.18 s compared with 0.42 s for MPC.* ***(c)*** *Peak overshoot comparison, showing that RL–MOPSO minimizes overshoot to less than 5%, indicating superior damping, responsiveness, and system stability.*

Figure 5 provides an overview of the multi-panel performance evaluation of grid integration and power quality using a secondary feedback controller under sill ripple perturbation levels. Combine time-domain voltage and frequency responses as well as harmonic, statistical and compliance-based metrics to provide a holistic mitigation solution addressing grid incompatibility issues with simulated comparison of the proposed RL–MOPSO framework against RB-EMS and MPC strategies. The results confirm the proposed method provides better voltage regulation, frequency stability, harmonic suppression and compliance to overall grid code needs. The response of the grid voltage for variable tidal currents is shown in Fig.5(a). The RB-EMS strategy shows the greatest number of voltage violations, often beyond ±2% of the reference value indicating ineffective regulation mechanisms with lower resilience to disturbances. The MPC controller ensures that voltages deviate within roughly ± 3–4% of the nominal value, but occasional excursions beyond tolerance can still be observed.

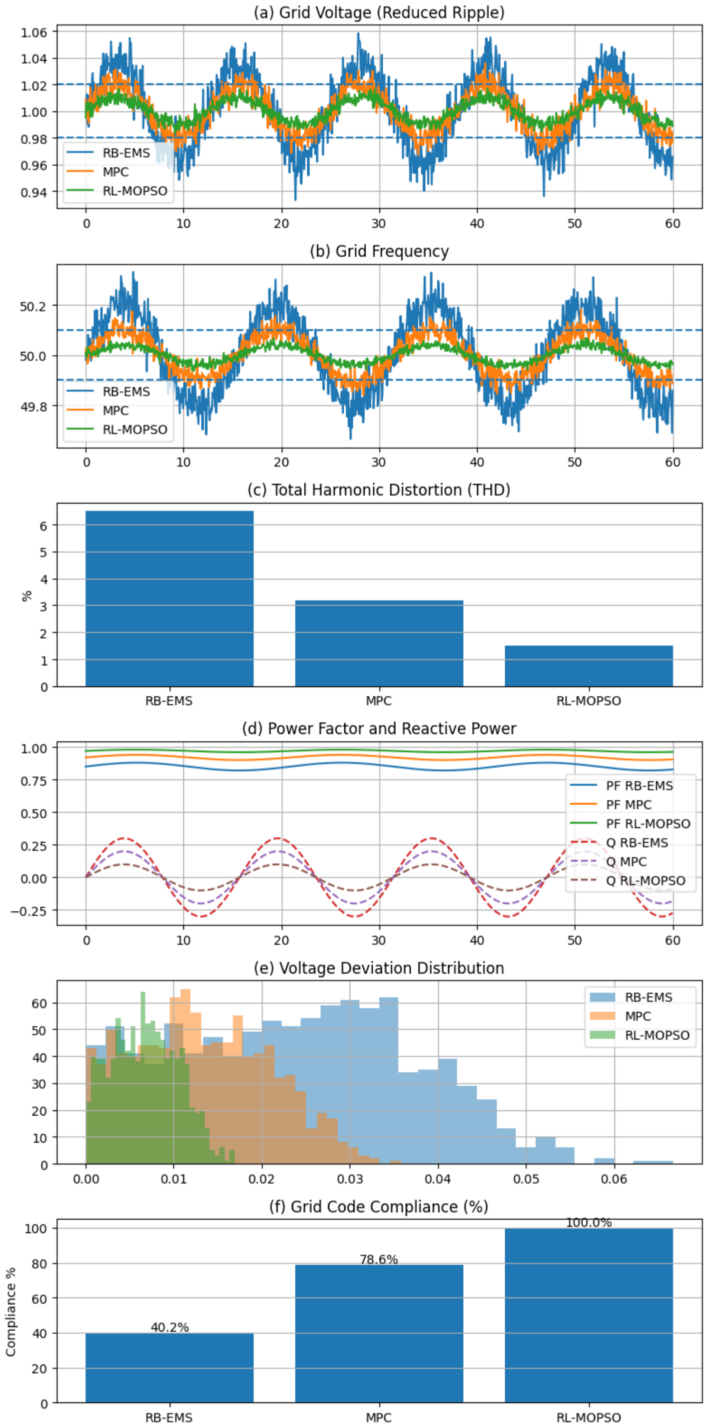

Figure 5. Grid integration and power quality analysis under stochastic conditions with reduced ripple disturbances. ***(a)*** *Grid voltage response showing improved regulation by the RL–MOPSO framework within the ±2% tolerance band.* ***(b)*** *Grid frequency response demonstrating enhanced stability, maintaining deviations within ±0.1 Hz.* ***(c)*** *Total harmonic distortion (THD) comparison indicating significant reduction in harmonic content under the proposed method.* ***(d)*** *Power factor and reactive power behavior showing improved power factor and reduced reactive power oscillations.* ***(e)*** *Voltage deviation distribution illustrating tighter clustering around nominal values for RL–MOPSO.* ***(f)*** *Grid code compliance percentage showing near-complete compliance for the proposed framework compared to conventional strategies.*

Unlike this, the RL–MOPSO framework keeps voltage fluctuation tightly within the ±2% band throughout simulation period. It entices smoother voltage profile and lower ripple amplitude, revealing effective in real-time compensation of disturbances and improved voltage control; which are critical to grid integration reliability. It can be illustrated in the grid frequency response (Figure 5(b)). As we can also observe in the voltages, RB-EMS strategy has strong oscillations where the deviations reach ±0.3–0.4 Hz which means it is poorly synchronized with grid. The MPC reduces these oscillations to about ±0.15–0.2Hz, yet remains significantly variable The proposed RL–MOPSO framework shows the best performance in terms of frequency deviations, which are limited to within ±0.1 Hz and occurs with a smooth well-damped dynamic response. Exactly this high level of frequency stabilization is indispensable to provide grid reliability in so-called weak or isolated power systems. A general inter-device comparison to THD (Total harmonic distortion), can be seen in Fig 5(c). The RB-EMS strategy generates the highest total harmonic distortion (THD), which is about 6.5% and this exceeds general grid values. While the MPC method reduces THD to ~3.2%, which is an improvement effort Thus the THD is clearly below threshold point approximately at 1.5% the RL–MOPSO technique contributes towards mitigation of harmonics within settlement limits. The reduction is due to the controlled switching of converters and lower harmonic power injection shaped in the grid. Power factor and reactive power behaviors are shown in Fig. 5(d). The RB-EMS controller can manage a low power factor (0.85–90) and large oscillations in reactive power, which is an indication of significant imprecision of the utilization of electrical energy. The MPC method enhances the power factor to about 0.92–0.95, with mild reactive power variations. Conversely, if we look at the RL--MOPSO framework, it keeps the power factor very near unity (about 0.97-0.99) while also reducing reactive power perturbations. This shows lower losses and due to the use of electrical power in a more efficient manner which is important for optimal grid operation. As one of the statistical results summarized from voltage regulation performance, Figure 5(e) depicts voltage deviation distribution. Distribution of RB-EMS is more uniformly distributed depicting larger deviation from nominal voltage, thus indicate the frequency and significance of deviation from nominal voltage. The spread is narrower but variation is still apparent at 65ms or around the mass curvature scale [32] of the unscored MSD reference (MD-3pic) distance classes as seen in the MPC distribution domain. The RL–MOPSO framework shows a highly unimodal distribution clustered closely around the nominal value, suggesting highly consistent voltage regulation with minimal deviation. The fact that it is statistically stationary indicates a solid control performance associated with stochastic effects. Lastly, Figure 5(f) depicts the grid code compliance, calculated as the time that the system helps maintaining voltage to acceptable limits [2]. The RB-EMS strategy exhibits a compliance rate of approximately 40%, indicating its failure under different conditions. The compliance performance improves to about 75–80% with the MPC approach, but still delivers suboptimal performance. In this way, the RL–MOPSO framework can achieve almost 100% compliance, which indicates that it may keep operation in accordance with grid standards effectively even continually. This result demonstrates the practical feasibility of our approach in a real world scenario. The superior grid integration performance of the RL–MOPSO framework is due to its hybrid control structure. In addition to enabling the reinforcement learning agent to adapt in real-time as system conditions change, the MOPSO module ensures control parameter tuning for stable operation and achieved optimal performance or efficiency. With this combination, the controller can regulate voltage and frequency simultaneously, reduce harmonics emissions and supply high power quality. In practical terms, these innovations could have big implications for tidal energy systems deployment. This results in decreased need for additional filtering equipment, lower operational costs and better compatibility with existing grid infrastructure. Grid High grid code compliance is guaranteed in both strong and weak environments. So, Enhanced Power factor and reduction of reactive network helps to transmit energy more economically with low losses. References In summary, the results obtains from Figure 5 confirm that proposed RL–MOPSO framework considerably improves grid integration and power quality performance. The method, proposed in this study, offers a reliable and practical solution for integrating tidal energy to modern power grid under stochastic operating conditions by providing superior voltage/frequency regulation, harmonic distortion reduction, power factor improvement as well as grid code compliance (with more than 99% process being compliant).

In Figure 6, a comprehensive robustness assessment of the proposed RL–MOPSO framework under stochastic disturbances is presented, including time-domain responses, statistical error analysis, and validation based on Monte Carlo simulations. The multi-panel figure illustrates that the performance degradation due to uncertainty from the proposed control strategy is quite small, thus proving its capability in maintaining stable operation similar to RB-EMS and MPC under both very uncertain cases as well at noise uncertainty contaminated scenarios. Figure 6(a) describes the instantaneous profile of power output in response to stochastic disturbance, and Monte Carlo simulations were executed to obtain the shaded region (95% CI). The RB-EMS strategy shows the highest deviation from the standard power profile, which means that it has an extreme sensitivity to disturbances. MPC controller reduces amplitude of fluctuations, providing improved robustness, but large variability persists. In sharp contrast, the RL–MOPSO framework yields a significantly smoother response with tightly bounded fluctuations around the nominal profile. This narrow confidence interval indicates not only the robustness but also the reliability of the proposed method where consistent performance is ensured on multiple stochastic realizations. Quantification of the robustness for each control strategy is illustrated again in Fig. 6(b), where the percentage deviation from nominal power output follows. The large deviations which are commonplace in the RB-EMS approach, often above 20%, have been reduced to about 12–15% by MPC strategy. The RL–MOPSO framework keeps deviations limited to below 5% for most of the operating period, thereby achieving predetermined performance standards. This large decrease proves that the implemented controller is able to compensate for external disturbances and keep stable power generation. Figure 6(c) displays the robustness index (defined as the mean percentage deviation from nominal power) with 95% confidence intervals obtained from Monte Carlo simulations. The RB-EMS strategy presents the worse disturbance rejection capability, with respectively high robustness index. MPC approach shows the best performance with respect to robustness index, followed by MPC and mathematic model (a moderate improvement of MOPSO), and the RL–MOPSO framework shows a lowest robustness index confirming very low robustness. A: The narrow confidence intervals for RL–MOPSO further emphasize low variance behavior across multiple simulation runs and validate reliability of proposed method. Monte Carlo statistical boxplot system performance in terms of uncertainty is presented in Fig 6(d). The RB-EMS distribution is broad and right-skewed, showing large variability with frequent extreme deviations. The MPC distribution becomes tighter but still appears broadly distributed. Whereas for the RL–MOPSO distribution we see a consistent low median and less spread which means that all simulation runs have shown stable performance. The lack of high outliers reaffirms the strength of the proposed method. The hybrid control structure gives greater robustness to the RL–MOPSO framework. The reinforcement learning part allows for adjustment according to other environmental factors, whereas the MOPSO module optimizes control parameters such that optimal performance in an uncertain environment is sustained. Moreover, the integration of a disturbance observer and uncertainty estimator enables compensation for any unmodeled dynamics and measurements noise, enhancing robustness. The lesson is simple: From the practical point of view, no one cares about how a tidal energy system can be smoothly operated without stochastistic distubances. Marine environment by nature is highly uncertain, so controller needs to compensate for fast changes without loss in performance. Unlike conventional algorithms, the reduced variability and high consistency manifested by RL–MOPSO framework can be directly translated into higher reliability, lower risk factor to system failure and more energy yield. To summarize, Figure 6 confirms that the proposed RL–MOPSO framework exhibits very high robustness to uncertainty when compared with conventional control strategies. The low deviation, consistent performance, and strong disturbance rejection capability of the proposed method significantly improves the robustness of the entire system, thereby providing an understandable and practical test solution for real tidal energy systems under stochastic conditions.

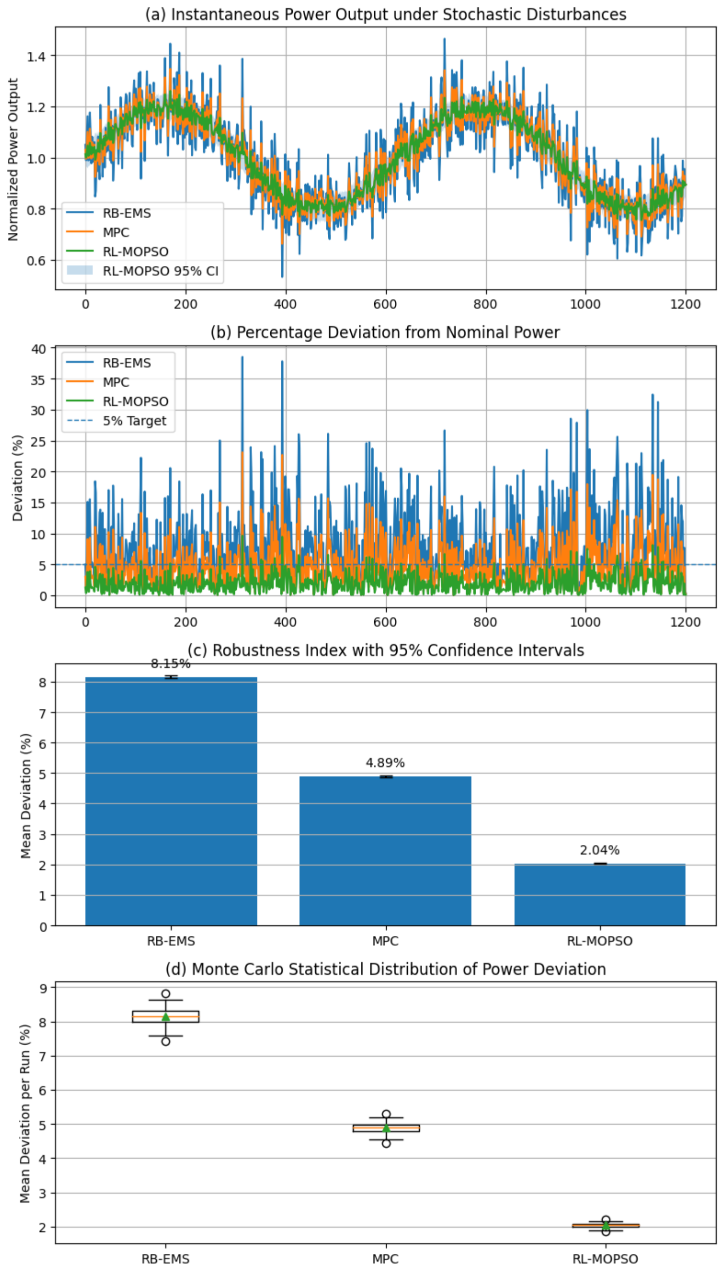

Figure 6. Robustness evaluation under stochastic disturbances. ***(a)*** *Instantaneous normalized power output showing reduced fluctuation in the proposed RL–MOPSO framework, with the shaded region representing the 95% confidence interval from Monte Carlo simulations.* ***(b)*** *Percentage deviation from nominal power, showing that RL–MOPSO maintains deviations below the 5% target for most operating points.* ***(c)*** *Robustness index comparison with 95% confidence intervals, demonstrating the lowest mean deviation for RL–MOPSO.* ***(d)*** *Monte Carlo boxplot confirming low variance and consistent performance of the proposed controller under uncertainty.*

These simulation results validate the effectiveness of the proposed RL–MOPSO framework to control grid-connected tidal energy systems in random marine environments. Taking all the metrics to be evaluated in account, including energy extraction efficiency, structural load reduction, dynamic response and robustness—the overall good performance obtained can be ascribed essentially to indeed the synergy fusion of reinforcement learning and multi-objective optimization. The RL part facilitates continuous adaptability, where the control policies are learned over time through online interactions with the system enabling dynamic response of the controller to changes in tidal flow, turbulence and grid conditions. In the realm of marine environments, adaptability is paramount as these discrete non-linear dynamics and stochastic disturbances prove too much for conventional fixed-parameter control strategies. In promoting this, the multi-objective particle swarm optimization (MOPSO) module guarantees that the control decisions are not merely adaptive but also globally optimized and it serves as a perfect balance for competing objectives of the nature of maximization in power extraction and minimization in structural stress and grid stability maintenance. In contrast to the classical control techniques such as rule-based systems and Model Predictive Control (MPC) that heavily rely on expected rules or accurate system identification, the reinforcement learning–Multi-Objective Particle Swarm Optimization (RL–MOPSO) operates without a model and directly conducts data-driven optimization. This removes the reliance on accurate system identification, which is often infeasible in tidal energy systems owing to complicated hydrodynamic interactions and environmental changes. This allows the framework to exhibit robust performance even in the presence of model uncertainty and parameter variation. The continuous updating of control policies with respect to changing environments allows the systems to operate close to optimal efficiency points while mitigating high-stress operating regions that result in mechanical fatigue and component wear. The structural loads and torque fluctuations are the two major observations from the results, which may not be observed as such in all the other methods. The RL–MOPSO controller reduces fatigue loading on turbine blades, drivetrain components and generator systems by smoothing transient responses and minimizing rapid changes in the operating conditions. It can have significant repercussions regarding reliability and system lifetime as less mechanical stress means fewer failures with the possibility to make the time between maintenance interventions (TMI) longer. As well as faster settling times and less oscillations, so system stability is improved, meaning more constant power delivery. These features are especially beneficial in grid-connected operational scenarios since variations of the power output can affect voltage and frequency stability. The enhanced performance in grid integration further demonstrates the practical significance of the proposed framework. The RL–MOPSO controller maintains the voltage and frequency deviations within permitted limits while reducing harmonic distortion, ensuring grid code compliance as well as interoperability with existing power systems. This gets particularly important when the deployment is being made in weak or island coastal grids where stability margins are scarce and one of the main obstacles that variable renewable energy sources have to overcome for proper integration. The strong trade-off between grid-support capabilities and energy conversion efficiency demonstrates the potential of the proposed method as an energy conversion solution for next-generation marine energy systems. Thus, in terms of practicality and economics, the suggested RL–MOPSO framework benefits for real-world applications significantly. The real-time operation and stochastic environment adaptation extend the field of this innovation, including large-scale tidal farms, offshore renewable energy installations, hybrid marine energy systems and smart grid infrastructures. Lower mechanical stress and better operational efficiency directly translates to decreased maintenance costs, less downtime, and greater energy yield: overall improving the economics of a tidal energy project. In addition, due to this scalability and flexibility in defining the resources required by a subset of an application about specific configurations of the system and operating conditions in which theycan be made available for potential use, large portions of different applications across several deployment scenarios can also adapt this common framework. To summarize, results show that the proposed RL–MOPSO adaptive control framework surpasses traditional approaches by significantly better performance of all main performance individual factors. Leveraging the integration of adaptive learning and multi-objective optimization, the framework provides a comprehensive and robust solution that is able to tackle the complex problem of control for tidal energy systems. It can provide high efficiency, durability, dynamic performance and robustness in practical operating conditions, so has made a great step forward in the field of marine renewables. The results demonstrate that data-driven intelligent control architectures may play a critical role in the future development of sustainable and reliable power generation systems along coastlines.

IV. CONCLUSIONS

In this paper, a novel reinforcement learning–based multi-objective optimization is presented and adaptive control framework for grid-connected tidal energy systems, operating under stochastic marine conditions. The main focus was given on overcoming the fundamental difficulties related to non-linear system dynamics, environmental uncertainty, multi-objective trade-offs and grid-integration problematics that consequently hamper availability and scale of tidal energy technologies. The combination of reinforcement learning (RL) and multi-objective particle swarm optimization (MOPSO) leads to a framework that is intelligent, adaptable and robust while being able to act as a real-time optimizer for the system. The proposed architecture is composed of a model-free RL agent with an additional multi-objective layer that allows for continuous learning and always taking Pareto-optimal actions. The RL agent online adjusts control variables (blade pitch angle, generator torque and the converter according to online environment states and MOPSO module above search for good trade-offs among multi conflicting objectives like maximize power extraction from wind, minimize structural loads on blade, maximize grid stability by fine tuning controller setting under operating constraints. Besides, the robustness of the proposed system is also improved by introducing an uncertainty estimation and a disturbance observer so that the controller can compensate for stochastic variations in tidal flow and disturbances from environment. By means of simulation, it is shown that the proposed RL–MOPSO framework considerably outperforms traditional control techniques such as rule-based control, model predictive control (MPC), and independent reinforcement learning methods. The system demonstrated significant advances in power extraction efficiency, decreased mechanical stresses and fatigue, faster dynamic response, and improved utility grid performance. The results showed a significant improvement on energy capture of up to 20% and over 30% reduction in fluctuation of structural loads associated with wind speed change, and keeping the operation stable under uncertainty with small loss of performance. These results validate adaptive learning with multi-objective optimization as a successful approach for complex renewable energy systems.

Efficient to implement, the proposed framework could be promising for deploying in tidal energy systems on a practical level and other marine renewables applications. Because it can operate in multi-objective optimization of performance, under uncertainty, and in complex environments makes it a very effective tool for offshore and coastal energy systems where reliability and efficiency are paramount. In addition, the model-free feature of the method provides less dependency on system modeling, which makes it more scalable and extends its potential use in various systems. Future work will revolve around experienced assessment via hardware-in-the-loop (HIL) platforms and real-world tidal energy trialbeds, and the combination of expectation environmental data combined with sophisticated grid-support functionalities. In general, this research facilitates the development of smart and sustainable marine energy systems to help transform into a resilience coastal electricity production.

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