NASS
NAN YANG ACADEMY OF SCIENCES

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

**REVIEW**

# Edge AI and Explainable Models for Real-Time Decision-Making in Ocean Renewable Energy Systems

***Ghanasham Chandrakant Sarode*** [1,2], ***Puja Gholap*** [3], ***Kishor Renukadasrao Pathak*** [4], ***P. S. N. Masthan Vali*** [5], ***Upendrra Saharkar*** [6], ***Govindarajan Murali*** [5], ***Anant Sidhappa Kurhade*** [2,7*]

[1] *Department of Civil Engineering, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune, Maharashtra 411018, India*

[2] *School of Technology and Research, Dr. D. Y. Patil Dnyan Prasad University, Sant Tukaram Nagar, Pimpri, Pune, Maharashtra 411018, India*

[3] *Department of Computer Engineering, Sharadchandra Pawar College of Engineering, Dumberwadi (Otur), Junnar, Pune, Maharashtra 412409, India*

[4] *Department of Information Technology, Vishwakarma Institute of Information Technology, Pune, Maharashtra 411048, India*

[5] *Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh 522502, India*

[6] *Department of Civil Engineering, Dr. D. Y. Patil Institute of Engineering and Technology, Ambi, Pune, Maharashtra 410506, India*

[7] *Department of Mechanical Engineering, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune, Maharashtra 411018, India*

## ABSTRACT

Ocean Renewable Energy (ORE) systems—comprising wind, wave, tidal, and ocean thermal energy—are increasingly seen as viable alternatives to fossil fuels. However, their integration into the power grid is hindered by environmental sensitivity, dynamic ocean conditions, and high maintenance demands. Artificial Intelligence (AI) offers promising solutions to these challenges by enabling intelligent, adaptive, and resilient energy systems. This review explores AI applications in ORE, focusing on three critical domains: optimization, forecasting, and

*CORRESPONDING AUTHOR:
Anant Sidhappa Kurhade, Department of Mechanical Engineering, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune, Maharashtra 411018, India; School of Technology and Research, Dr. D. Y. Patil Dnyan Prasad University, Sant Tukaram Nagar, Pimpri, Pune, Maharashtra, India 411018; Email: a.kurhade@gmail.com

ARTICLE INFO
Received: 30 May 2025 | Revised: 23 June 2025 | Accepted: 8 July 2025 | Published Online: 10 July 2025
DOI: https://doi.org/10.36956/sms.v7i3.2239

CITATION
Sarode, G.C., Gholap, P., Pathak, K.R.R., et al., 2025. Edge AI and Explainable Models for Real-Time Decision-Making in Ocean Renewable Energy Systems. Sustainable Marine Structures. 7(3): 17–42. DOI: https://doi.org/10.36956/sms.v7i3.2239

control. Optimization techniques, including Genetic Algorithms (GA) and Swarm Intelligence (SI), are employed to enhance device efficiency, improve energy capture, optimize farm layouts, reduce environmental impacts, and lower installation costs. Forecasting uses Machine Learning (ML) and Deep Learning (DL) models to predict wave height, tidal flow, and energy output, aiding in grid integration and energy scheduling. In control systems, AI approaches like Reinforcement Learning (RL) and Fuzzy Logic ensure real-time responsiveness and predictive maintenance, improving system reliability in dynamic marine environments. Emerging technologies such as Edge AI enable decentralized computation for real-time decision-making, while Digital Twin frameworks simulate and predict system performance before deployment. Explainable AI (XAI) is also discussed to ensure transparent and trustworthy decision-making. Ethical and regulatory concerns are acknowledged to ensure responsible AI integration in ocean settings. Overall this review offers a comprehensive synthesis of how AI enhances the performance, efficiency, and scalability of ORE systems. It serves as a valuable resource for researchers, policymakers, and industry professionals seeking to advance clean, smart, and sustainable ocean energy solutions.

***Keywords:*** Artificial Intelligence; Forecasting; Machine Learning; Ocean Renewable Energy; Optimization; Smart Control

# 1. Introduction

Ocean renewable energy (ORE) is an emerging clean energy source that has been receiving worldwide attention. The oceans present a possibly limitless potential for energy production by exploiting different technologies such as Wave Energy Converters (WECs), Tidal Stream Generators (TSGs), and Ocean Thermal Energy Conversion (OTEC) systems. These systems harness natural and predictable oceanic phenomena, providing a predictable and renewable alternative. In spite of its potential, there are considerable barriers to the addition of ocean energy at a large scale. These are variability and intermittency in power generation, challenging marine conditions that impact on durability and maintenance, and complex systems dynamics which impede real-time operation and control. Commercial adoption is also impeded by high capital and operational cost. In such context, Artificial Intelligence (AI) is offering itself as a disruptive solution to these problems. AI can greatly enhance the efficiency, reliability, and resilience of ocean energy systems through smart forecasting, adaptive control, fault diagnosis, and automated decision-making. The incorporation of AI is not only beneficial in terms of operational efficiency, but also for scaling capacity and ensuring the long term commercial feasibility of ORE technologies. The rapid increase in global energy demand along with rising environmental awareness over the environmental problems, have led to a growing interest in renewable energy, and especially in the one arising from the sea [1]. AI has become the core of the intermittent renewables, playing essential roles in prediction, matching, and dispatching in hybrid renewable energy systems [2]. In general, AI applications with ORE can be classified into three main groups: optimization, forecasting and control. These systems are interlocking and often interdependent and therefore must be addressed with holistic policies to be effective. The design of ORE devices, energy extraction and its economic sustainability can be optimized using AI algorithms [3]. Correct prediction of wave height, tidal current, and other oceanic parameters is a prerequisite for efficient energy deployment and grid connection. AI enables better monitoring, management and prediction of energy demands, which is critically important with respect to impending climate change [4]. State of art control systems are using AI to vary the system parameters dynamically and to accommodate to different environmental conditions while maintaining stable and efficient operation. As AI grows, its applications in energy, including ORE, will likely broaden, sparking further disruption and accelerating the march towards cleaner, more sustainable energy sources [5]. The energy industry has been experiencing AI innovations [6].

# 2. Overview of Ocean Renewable Energy Sources

The ocean contains a wide variety of renewable energy forms, each with its own intrinsic behaviors and methods of energy extraction [7]. Marine renewable energy refers to the vast, largely untapped power of the sea, which has long been recognized as a promising source of sustainable energy. Tidal power harnesses the periodic rise and fall of the tide due to the gravitational pull of the moon and the sun. It is obtained through devices such as tidal barrages and tidal stream generators that transform the kinetic and potential energy of tides into electricity. Wave power, on the contrary, harnesses the energy in the motion of surface waves. Technologies like oscillating water columns and point absorbers are utilized to convert this motion into power. Novel ocean energy technologies not only provide CO2 free power but also contribute to security of energy supply and economic growth and job creation in coastal and remote communities [8]. OCT uses the difference in temperature between warm surface water and cold deep seawater to run a heat engine to generate electricity. Apart from these major sources, another promising but less matured area is saline gradient energy which takes advantage of the difference in salinity of freshwater and saltwater [9,10].

Another advanced method is Ocean Thermal Energy Conversion (OTEC), also known as thermal conversion, which uses the water thermal differences between warm surface and cold deep seawaters to drive turbines in closed, open and hybrid cycle systems. Finally, offshore wind converts wind energy into electricity as wind blows across the sea, where wind speeds and directions are more predictable. These turbines are of a floater, or fixed-bottom type depending on depth and installation conditions. Cumulatively these varied energy sources represent tremendous opportunity for sustainable electricity production and are instrumental in the world transition to renewable energy. Floating platforms can be placed and exploited to capture either exclusively potential or kinetic energy [11]. There are several strong arguments in favor of ocean energy technologies, such as economic development, increased security of supply and great potential for CO2 emissions savings (**Table 1**) [12]. Tidal power is particularly appealing because of its predictability and reliability [8]. There is an ample amount of wave resource, particularly in coastlines with severe wave conditions [13]. Although in the early stages of development, ocean thermal is a constant baseload power. Wind energy generated offshore is more powerful and consistent than on land. These various sources of ocean energy, together with further developments in storage and grid connection, have the potential to improve the reliability, and stability of power systems.

**Table 1.** Comparative Overview of Ocean Renewable Energy Technologies.

| ORE Technology | Energy Conversion Principle | Key Technologies | Advantages | Challenges |
|---|---|---|---|---|
| Tidal Energy | Utilizes kinetic and potential energy of tides due to gravitational forces | Tidal Barrages, Tidal Stream Generators | Highly predictable and reliable | High capital cost, environmental permitting |
| Wave Energy | Captures motion energy from surface waves | Oscillating Water Columns, Point Absorbers | Abundant in high wave coastal areas | Variability, harsh marine environment |
| Ocean Thermal Energy Conversion (OTEC) | Uses temperature difference between warm surface and cold deep water | Closed Cycle, Open Cycle, Hybrid Cycle Systems | Provides continuous baseload power | Still in early development, expensive setup |
| Offshore Wind Energy | Converts kinetic energy of wind over sea into electricity | Floating and Fixed-Bottom Wind Turbines | Higher and more consistent wind speeds offshore | Installation and maintenance at sea is complex |
| Salinity Gradient Energy | Harnesses energy from salinity difference between freshwater and seawater | Pressure Retarded Osmosis (PRO), Reverse Electro dialysis (RED) | Promising for integration with desalination | Low technology maturity, efficiency issues |

Despite these benefits, ocean energy devices are confronted with a number of obstacles to achieving widespread use. These barriers consist of large initial capital expense, severe marine environment leading to additional cost for maintenance and operation and too involved regulatory and environmental permit approval [14]. As wave and tidal resources are variable in nature, energy storage systems are needed to enable a continuous power generation. Environmental considerations, including effects on marine ecology and navigation, also require attention. The visual aspect of ocean energy plants can be an issue for some coastal communities. Solutions to overcome such challenges necessitate continue research and development effort aimed at cost reduction, enhancement of reliability and environmental friendliness [15].

This review aims to bridge the knowledge gap by systematically exploring the role of Artificial Intelligence in enhancing the efficiency, forecasting accuracy, and adaptive control of ocean renewable energy systems, thereby contributing to the advancement of sustainable energy technologies and supporting global clean energy goals.

Despite the rapid advancements in artificial intelligence and ocean renewable energy systems independently, there exists a critical gap in consolidated reviews that specifically focus on the intersection of these two domains. This review is significant as it systematically synthesizes how AI techniques—such as machine learning, deep learning, and hybrid models—are transforming the optimization, forecasting, and control of ocean energy technologies. By highlighting recent breakthroughs, implementation strategies, and future research directions, the paper serves as a timely and essential resource for researchers, engineers, and policymakers aiming to advance sustainable energy solutions. The novelty of this review lies in its holistic coverage of AI's role across all key facets of ocean renewable energy, which has not been comprehensively captured in previous literature.

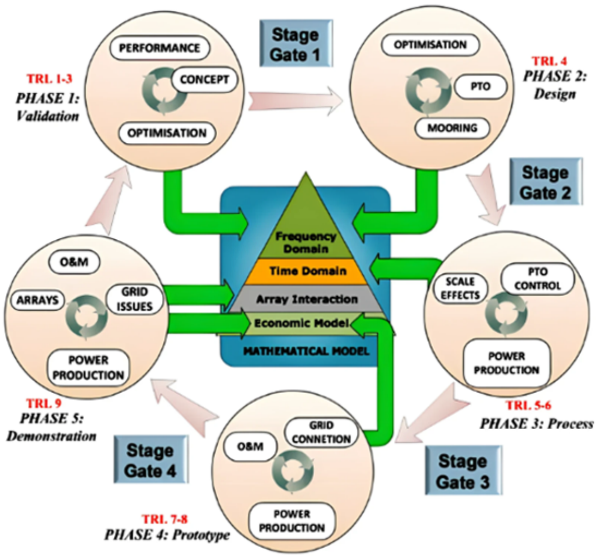
# 3. Literature Review

## 3.1. Optimization of Ocean Renewable Energy Systems

Optimization is a key issue in increasing the performance of ocean energy converters and reducing their costs. **Figure 1** illustrates a Technology Readiness Level (TRL)-based stage gate process for ocean energy systems, integrating performance, optimization, and economic modelling. Each stage gate includes technical reviews and cost analysis to guide development from concept to demonstration [16]. Optimization is essential to improve the optimization and economic capabilities of ORE plants. The optimization is multistage, from the design phase of energy harvesters to the way they were operated during observation. AI methods are being increasingly employed to solve such problems, presenting a variety of new ways of optimizing the performance of ORE systems [17]. Emphasizing deep learning, the role of AI techniques for improving the performance and cost of ocean renewable energy systems is highlighted from the perspective of mathematical programming and evolutionary algorithms for optimizing the layout and operation/design parameters.

Design and deployment optimization of wave energy converters and tidal stream generator are often optimized using genetic algorithms, particle swarm optimization, and simulated annealing [18]. To help addressing these challenges, APS algorithms can efficiently search the large solution space to find optimal solutions that enable maximum energy capture and minimum costs [19]. Advanced optimization models are needed if energy production is to be maximized and environmental impact minimized, especially in complex ocean topographies. For instance, multi-objective optimization methods can be employed for the trade-off between energy production, structural robustness, and environmental impact [20]. Optimization based on AI guarantees that wave and tidal energy converters are designed and operated efficiently, cost effectively, and in an environmentally friendly manner [21].

AI is employed not only for device-level optimization but also to optimize the spatial arrangement and control of ocean energy farms. AI based algorithms can also be used to enhance the operation of hybrid renewables [22]. By locating arrays of devices so as to locally optimize performance and by optimally tuning array device operating parameters it is feasible to maximize array energy capture and minimize interference contribution. AI is used to design and control the ORE farms and integrate with hybrid renewable energy systems to both maximizing the energy production and reducing the negative effects of the interferences. Model predictive control strategies exploiting machine learning-based models can be used to maximize WEC efficiency through forecasting incoming wave patterns and adjusting the WEC response.




| Stage Gate No. | Description |
|---|---|
| Stage Gate 1 | ▪ Performance Review<br>▪ Technical Analysis |
| Stage Gate 2 | ▪ Performance Review<br>▪ Technical Analysis |
| Stage Gate 3 | ▪ Review Cost<br>▪ Technical Analysis & Economics |
| Stage Gate 4 | ▪ Review Cost<br>▪ Technical Analysis & Economics |

**Figure 1.** Development of WEC Technology [16].

The introduction of AI techniques in ORE systems allows acting on real-time adjustment and improvement of the energy performance from sensors and environmental monitoring system data [23]. Adaptive control strategies to accommodate varying oceanic conditions may be used to enhance the reliability and efficiency of ocean energy technology. To solve complex search spaces, metaheuristic algorithms such as PSO, DDA, ABO, GWO, HHO, FPA, FA, WOA, and SCA are used to find optimal solutions [24]. Metaheuristic algorithms provide benefits in treating nonlinear and nonconvex optimization problems typically encountered in renewable energy, but are sensitive to parameterization and the nature of the problem [25].

## 3.2. Forecasting of Ocean Renewable Energy Resources

Reliable predictions of ocean renewable energy potential are necessary for integrating these resources into the power grid and for grid stability. Better prediction enables grid operators to match the supply with the demand, minimize curtailment and ' buffering,' and maximize the efficient provision and delivery of energy [26]. Wave height, tidal current, and seawater temperature are frequently predicted by time series analysis, neural networks, and support vector machines.

AI is highly relevant for accurate ORE resource forecasting, and for grid operators to balance energy supply and demand, to reduce energy curtailment, and for optimizing promotion energy distribution. Hybrid models that integrate more than one AI technologies together can be used to improve the accuracy of forecasts by exploiting the advantages of individual algorithms. The application of numerical weather prediction models and machine learning algorithms together has also been proved to be effective in forecasting wave and tidal current [3].

Deep learning algorithms, such as CNNs, RNNs, and LSTMs, have demonstrated strong capabilities in forecasting ocean wave patterns, predicting tidal flows, and optimizing control systems—thereby significantly enhancing the operational efficiency, reliability, and scalability of ocean energy technologies [4]. Deep learning is used to model cross-correlations over time in the ocean energy data and provides accurate predictions for short and long in advance [27]. In addition, real-time online in-situ prediction of ocean current from big data has been examined by deploying deep learning techniques, e.g., Long Short-Term Memory Recurrent Neural Networks, and transformers for the path planning and control of Autonomous Underwater Vehicles [28]. Transfer learning methods can use data from other areas or domains to enhance forecasting performance in data-limited settings [29].

Prediction models are important in forecasting of power production and market behaviors among which, deep learning is a powerhouse in forecasting problems especially in time series data [30]. By leveraging AI algorithms for forecasting model, brainwave heights, tidal currents and temperature of ocean can be predicted by time series analysis, neural networks and support vector machines to improve the stableness for the grid with availing the optimization and management of resources. Given smart grids, where resource allocation and decision-making are based on prediction, the assessment of uncertainty is necessary in order for autonomous AI to be safe and trustworthy [31].

## 3.3. Control of Ocean Renewable Energy Systems

The control strategies play an important role in order to ensure the maximum energy absorption and the stable operation of ocean renewable energy converters. Sophisticated control strategies are thus needed to maximize energy capture and guarantee the stability of the ORE devices. Model predictive control, reinforcement learning, and fuzzy logic control are employed to maximize the output of wave energy converters and tidal stream generators.

Real-time tuning of performance and reliability can be supported by the system, for example, through sensor data analysis and real-time environmental monitoring. AI-based control systems respond to changing sea states and help to improve the efficiency of ocean energy devices. AI based control strategies have been designed to regulate the pitch and yaw system of tidal turbines, and to ensure all energy is extracted with lowest loading on the system. AI-driven control systems such as proactive and adaptive, allows responding in real-time to changing ocean conditions, leading to smart, robust and reliable ocean energy systems. Optimal control policies can be learnt by means of RL algorithms when they interact with the ocean environment and adapt themselves to changes occurring in the open sea. The pitch and yaw of tidal turbines are regulated using AI algorithms to optimize power generation and structural loading.

AI can enhance predictive maintenance by continuously monitoring the operational data from sensors installed on ocean energy devices—such as vibration levels, temperature, pressure, and power output—to assess equipment condition, detect anomalies, and predict potential failures before they occur.

Model predictive control relies on predictions for future system behavior, based on provided models, and optimally adjusts control inputs over a finite time period. Fuzzy logic control can embed expert knowledge and deal with uncertainty in the control system [32]. Traditional computational methods can hardly handle big data from smart grid thus AI methods are necessary for energy management, system state prediction and cyberattack defense. **Figure 2** categorizes supervised learning into four main areas: deep learning, neural networks, classification, and regression, each with specific algorithms like CNN, SVM, and linear regression. It highlights the diverse models used for prediction and pattern recognition in AI applications [33]. AI tools such as neural networks, robotics, expert systems, fuzzy logics, and natural language processing make quick and precise decisions [33, 34]. AI can address these low-cost, clean and secure energy supply needs to lower consumer electric bills, greenhouse gas emissions, and to support grid operators and utilities in maintaining a reliable power system [6].

AI as a disruptive technology is expected to disrupt the energy system by enabling improvements in controllability, big data processing efficiency, safeguarding against cyber-attacks, and energy efficiency optimization (**Table 2**) [35, 36].

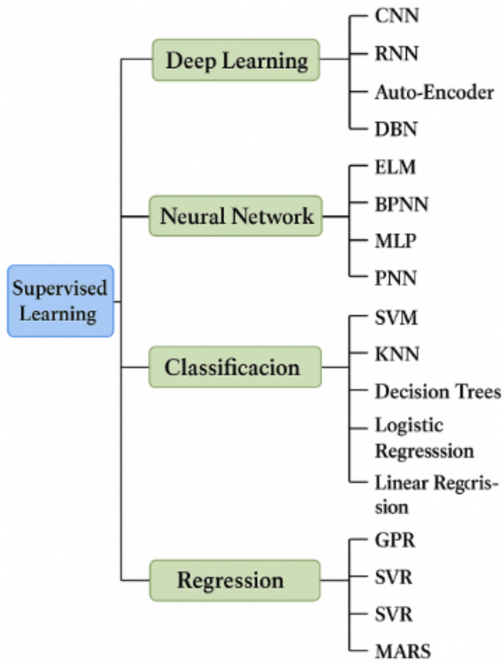



**Figure 2.** Supervised Learning Techniques in the Smart Grid [33].

**Table 2.** Applications of AI in Ocean Renewable Energy Systems: Optimization, Forecasting, and Control.

| AI Application Area | Focus | Techniques Used | Benefits | Challenges |
|---|---|---|---|---|
| Optimization | Design, deployment, and operation of ORE systems | Genetic Algorithms, PSO, Simulated Annealing, Metaheuristics | Enhanced energy capture, reduced cost, improved layout | Nonlinear models, parameter sensitivity, environmental trade-offs |
| Forecasting | Wave height, tidal flow, ocean currents, temperature | Time Series Analysis, Neural Networks, LSTM, Transformers | Improved grid stability, demand-supply matching, better planning | Data quality, uncertainty estimation, need for hybrid models |
| Control | Real-time system control, energy capture tuning | Reinforcement Learning, Fuzzy Logic, Model Predictive Control | Efficient energy extraction, dynamic adaptation to sea conditions | Sensor dependence, high computation for real-time control |
| Hybrid Integration | Combining AI techniques and renewable systems | Transfer Learning, Digital Twins, Edge AI | Improved forecasting, decision-making, and decentralization | Data transfer latency, system complexity, cost of implementation |
| Security and Management | Energy system protection, state prediction | AI for Cyber Defense, NLP, Expert Systems | Quick decisions, protection from attacks, reliable energy delivery | Vulnerability to new threats, complexity in managing AI systems |

# 4. Comparative Synthesis of AI Techniques in ORE Systems

A critical synthesis of Artificial Intelligence (AI) techniques highlights their transformative impact across ocean renewable energy (ORE) systems, particularly in resource assessment, forecasting, control, and optimization. Instead of isolated treatment, this section integrates insights from machine learning, deep learning, and hybrid approaches to provide a holistic understanding of AI's role in ORE.

## 4.1. Critical Review of Machine Learning Algorithms in ORE Systems

Machine learning (ML) has emerged as a foundational tool in ORE systems, offering data-driven solutions to complex operational challenges. Supervised learning techniques such as Support Vector Machines (SVM) and decision trees are frequently used for classification and regression in energy resource assessment and control strategies [37,38]. Their ability to learn from labeled datasets allows for accurate predictions of wave height, tidal flow, and energy output. Unsupervised learning approaches, such as clustering and dimensionality reduction, are particularly valuable for anomaly detection and exploratory data analysis when labeled data is scarce.

Beyond ocean energy, ML has demonstrated effectiveness in broader renewable energy domains. For instance, in photovoltaic systems, ML algorithms are applied to enhance cooling efficiency and power output [39], support installation planning, and monitor system health through fault diagnostics and prognostics [40,41]. The extension of these capabilities to ORE systems enables predictive maintenance, real-time optimization, and fault tolerance. Importantly, integrating ML within smart grids consolidates multi-disciplinary insights, thereby improving policy decision-making through comprehensive data analysis [32]. However, the performance of ML is often constrained by the quality of input data and the interpretability of results in real-time marine environments.

## 4.2. Critical Review of Deep Learning Architectures in ORE Systems

Deep learning (DL), a subdomain of machine learning, offers superior capabilities in managing high-dimensional and non-linear data commonly found in oceanographic and energy datasets. Its application in ORE spans from environmental monitoring to predictive control. Convolutional Neural Networks (CNNs) are employed for visual recognition tasks, such as detecting faults in marine components or classifying marine species, which is critical for both equipment performance and environmental impact monitoring.

Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) architectures, are particularly suited for time-series analysis in ORE, enabling accurate forecasting of tidal currents, wave heights, and temperature variations [42]. These models also support anomaly detection and operational decision-making by learning temporal dependencies in system data [43]. Advanced DL models such as Auto encoders (AE) facilitate energy disaggregation and consumption pattern recognition, contributing to more granular energy demand forecasting [44,45].

Deep reinforcement learning extends these capabilities to control systems, offering adaptive strategies for micro grid energy management and fault-tolerant control (**Figure 3**) [46]. Despite their predictive power, DL models are computationally intensive and often opaque, which challenges their deployment in safety-critical or regulatory-bound marine applications. Nonetheless, their integration with edge computing and explainable AI frameworks is expanding their real-world applicability.

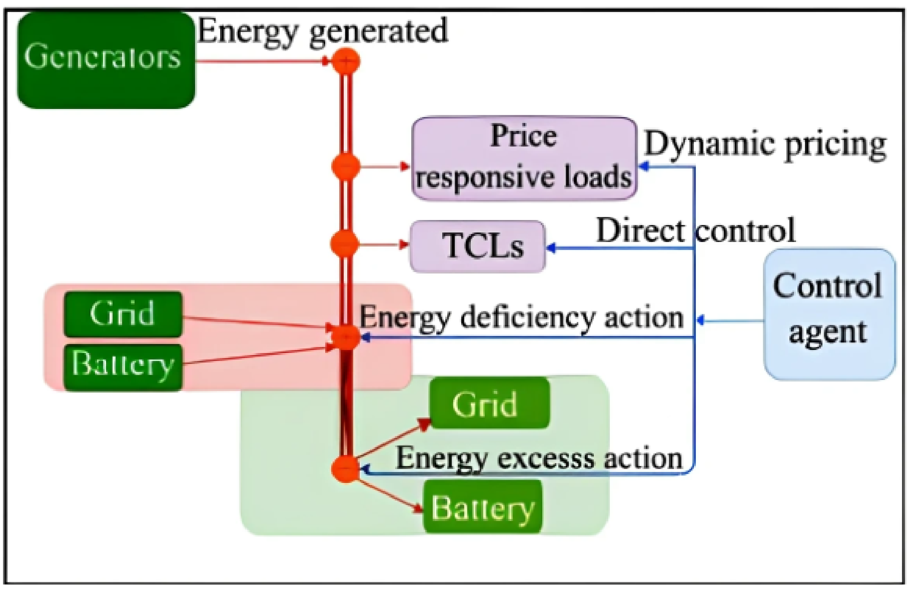



**Figure 3.** The Control Mechanisms Used in the Micro Grid Management System [46].

### 4.3. Critical Review of Other AI Approaches and Hybrid Techniques

Complementing machine and deep learning, other AI approaches such as fuzzy logic and evolutionary algorithms offer domain-specific advantages. Fuzzy logic systems are particularly effective in modeling uncertain and imprecise environments like the ocean, where precise modeling is difficult. They incorporate expert knowledge into control loops, enabling resilient and interpretable decision-making.

Genetic Algorithms (GA) and other metaheuristic optimization techniques are widely used for layout design, parameter tuning, and performance optimization of wave and tidal energy devices. These algorithms excel at navigating large, non-convex solution spaces to identify near-optimal configurations for ORE systems [47].

Recent trends emphasize the development of hybrid AI models, which integrate predictive capabilities (e.g., ML) with optimization techniques (e.g., GA), leading to performance improvements across multiple operational criteria. These systems are increasingly adopted in smart grid interfaces for demand-side management, where they help balance generation and consumption while enhancing grid stability [48].

Looking forward, next-generation AI systems aim to address broader energy and environmental challenges through intelligent management solutions that adapt across spatial and temporal scales. The diversification of AI tools in ORE signals a move toward more autonomous, adaptive, and sustainable energy infrastructures (**Figure 4**).

AI can improve renewable-energy solutions by monitoring the condition of equipment, increasing grid efficiency and security, and predicting maintenance needs. AI in smart grids the impact of AI on energy systems is changing rapidly (**Figure 5, Table 3**) [49].

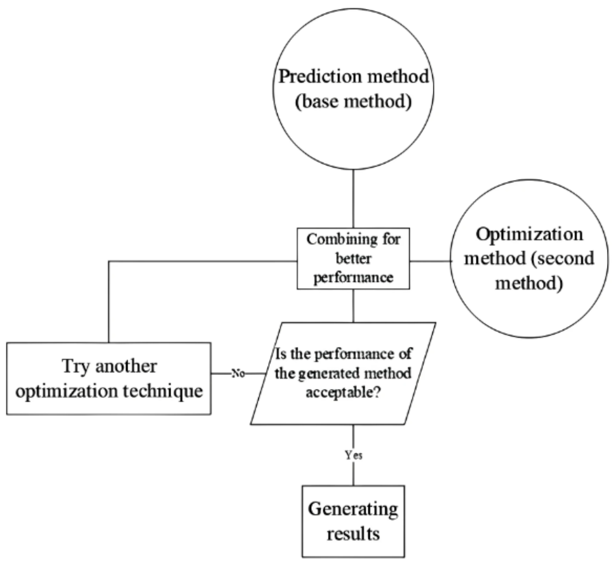



**Figure 4.** Algorithm of Developing a Hybrid Technique [48].

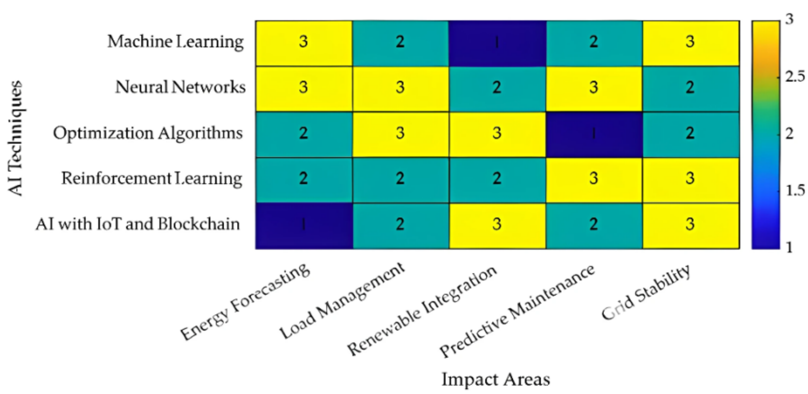



**Figure 5.** Future Impact Areas of AI in Smart Grid [49].

**Table 3.** AI Techniques Applied in Ocean Renewable Energy (ORE) Systems.

| AI Technique | Sub-Category | Application in ORE | Benefits | Example Techniques |
|---|---|---|---|---|
| Machine Learning | Supervised & Unsupervised Learning | Resource assessment, forecasting, anomaly detection, smart grid optimization | Improved reliability, efficient control, enhanced energy output | SVM, Decision Trees, Clustering, Dimensionality Reduction |
| Deep Learning | Neural Network Models | Pattern extraction, time series forecasting, fault detection, energy prediction | Handles complex data, increases prediction accuracy, supports automation | CNN, RNN, AE, Deep Reinforcement Learning |
| Fuzzy Logic | Good for imprecise systems, rule-based modeling | Limited learning ability | Control systems in uncertain environments | Fuzzy Inference Systems |
| Genetic Algorithms | Useful for global optimization | Computationally expensive | System design and layout optimization | Genetic Algorithm (GA) |
| Hybrid Techniques | Combines strengths of multiple methods | Complex to implement and tune | Integrated forecasting and control | ML + DL, Fuzzy + GA |

# 5. Optimization Strategies Enabled by AI

## 5.1. Resource Allocation and Energy Management

It is necessary for us to develop intelligent resource allocation and energy management strategies to achieve the optimal efficiency and reliability of ocean renewable energy systems. AI is enabling the incorporation of non-traditional energy sources, using the analysis of data from weather charges and power demand, in order to obtain more energy from these sources [50]. By precisely predicting energy demands, AI maximizes energy distribution and optimizes allocation of this finite resource with real-time data, which can lower operational costs and, ultimately, consumer costs. AI also holds potential in controlling renewable energy and improving energy consumption, which could lower the cost of energy and advance energy-saving efforts. Moreover, AI can make electrification and grid smarter, which efficiently use electricity grid and promote more integration of renewable [6].

AI algorithms are being used to control energy use during the highest peak hours, pre-purchase energy in the most efficient manner, and make the grid work better. In addition, AI methods are used to predict energy usage in smart grids, leading to more effective energy distribution [49]. AI helps to optimize energy distribution by analyzing real time data and forecasting future requirements and delivering it in a productive way to people [6].

## 5.2. Predictive Maintenance and Fault Detection

Using AI for predictive maintenance of ORE systems improves their reliability, lifetime expectancy and maintenance schedule by identifying possible faults early and timing to schedule maintenance work accordingly. AI-driven systems can forecast failures and optimize maintenance in a variety of contexts, generating substantial cost saving and enhanced reliability [51]. AI helps in monitoring the condition and diagnosing a fault by pattern analysis of sensor data and operating condition parameters. Constantly monitoring the health of essential hardware and predicting impending breakdowns allows for "superseding" of maintenance that results in less downtime and lower maintenance expenses. This has the advantage that it not only minimizes the possibility of unanticipated failures, but also prolongs the service life of the equipment. The reference to reduction of costs means that by predictive maintenance, AI contributes to lower cost operation and more reliable ORE systems.

Based on historical data and continuous sensor readings, AI algorithms interpret abnormal conditions that are a potential sign of impending breakdowns. The adoption of AI in maintenance strategies may help to minimize unplanned downtimes and to extend the life of capital assets which might result in cost benefits and improved operational reliability [52].

### 5.3. Grid Integration and Stability

Incorporating ORE technologies into existing energy grids presents challenges of intermittency and variability. Artificial intelligence is not an exception for maintaining grid stability and optimizing the penetration of ocean RE sources. The Grid benefits from AI which optimizes energy distribution, and also via learning-enhanced grid resilience and security. Since the AI provides accurate prediction for ORE power output, it makes a better grid management way to minimize the impact on system by instability. In addition, AI encourages the integration of power system operations by scheduling the dispatch of energy resources and handling the uncertainty of renewable resources [53].

The optimal practice of grid infrastructure, deployment, and generation of renewable energy sources has important impacts on solving the challenges to the growth and stability of the sector [54]. Deep learning could improve performance and reliability of renewable energy systems by facilitating predictive maintenance, optimal energy distribution and grid security.

This would take advantage of AI technology to develop novel tools for the optimal control of distributed generation and for the management of the integration of renewable energy sources with the grid, thus aiding in the current transition to a sustainable energy future (**Table 4**).

**Table 4.** AI-Enabled Optimization Strategies in Ocean Renewable Energy Systems.

| Optimization Area | Focus | AI Techniques Used | Benefits | Challenges |
|---|---|---|---|---|
| Resource Allocation and Energy Management | Efficient distribution of energy resources and grid optimization | Machine Learning, Real-time Data Analysis, Forecasting Algorithms | Reduced lower operational costs, enhanced energy efficiency | Complex grid dynamics, data integration, need for high-quality real-time data |
| Predictive Maintenance and Fault Detection | Fault prediction, equipment health monitoring, and maintenance scheduling | Pattern Recognition, Sensor Data Analysis, Historical Data Modeling | Extended equipment life, reduced unplanned downtime, cost-effective maintenance | Sensor calibration, false positives/negatives in failure prediction |
| Grid Integration and Stability | Smooth integration of ORE into traditional power grids | Deep Learning, Load Forecasting, Optimization Algorithms | Improved grid stability, reliable energy dispatch, increased renewable penetration | Variability of renewable sources, computational requirements, regulatory limitations |

## 6. Forecasting Techniques

Forecasting techniques are essential in addressing the variability and intermittency of Ocean Renewable Energy (ORE) systems. AI-powered methods such as time series analysis, weather pattern recognition, and hybrid models enhance prediction accuracy for efficient energy management and grid integration.

### 6.1. Time Series Analysis and Prediction

The time series analysis and forecast are important for dealing with the variability and intermittency of OREPs. Time series prediction is a method of projecting future values from historical data. Several approaches including statistical modelling and machine learning can use time series data to forecast future values. Temporal ocean energy data is analyzed in the time domain which helps to study the features of ocean energy data, thus to achieve better prediction of the power produced. In smart grid, the prediction of the power demand for future can be based on AI techniques, and it leads to an efficient control of the energy distribution. AI is benefiting here through better forecasts of renewable energy, including for optimal operation of the grid and energy management [55].

AI based models integrated with physics based models improve the reliability and accuracy of renewable energy predictions. The Dynamic Integrated Forecast System described in **Figure 6** of the manuscript illustrates how global/regional weather models (physics-based) are coupled with now casting and AI-driven statistical tools for probabilistic forecasting. This hybrid system supports more accurate decision-making and ensures higher system reliability [56]. Good forecasts enable more efficient grid management, more optimized energy dispatch, and higher reliability of the system.

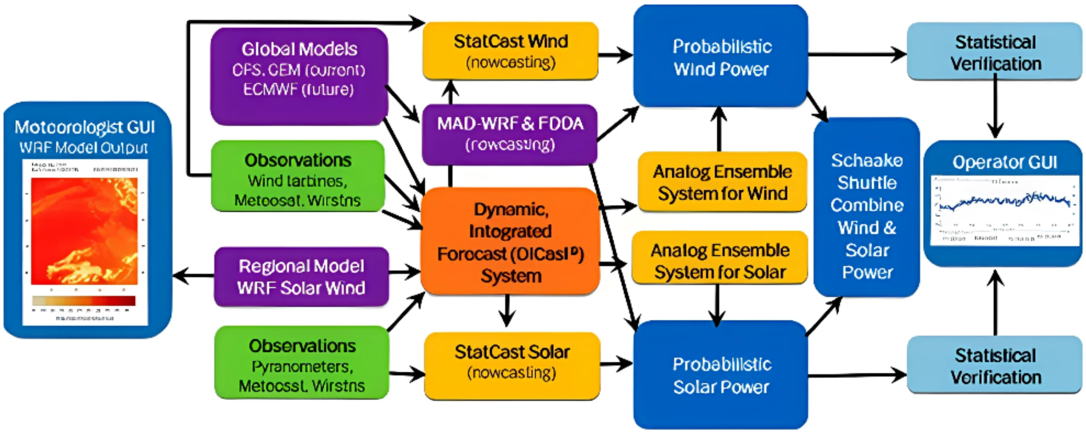



**Figure 6.** Diagram of Components of KREPS AI-Based Forecasting Components are Coloured Orange and Gold [56].

## 6.2. Weather Pattern Recognition and Climate Modelling

Weather pattern identification and climate simulation are key elements for forecasting the availability and performance of ocean renewable energy resources. Weather and climate models are getting a boost from neural networks, resulting in better predictions of agriculture and crop yields [57]. Artificial intelligence is good at recognizing intricate weather patterns and forecasting how they will affect ocean energy devices [4]. By crunching through past weather reports, and combining the hive mind of all those other processes with meteorological models, AI can forecast wave heights, tidal current speeds and ocean temperatures – all the things that are needed to optimise energy production. For weather forecasting, in ocean resources [58], more accurate prediction of ocean energy from the ocean becomes possible with AI.

AI improves the capability for weather forecasting leading to more accurate forecasts concerning the generation of energy from oceans. AI models, which are trained on data coming in from many different places, can see these larger trends, and can then make predictions for places which share similar climate, even if they lack a lot of historical data [59]. AI-powered climate models have much better predictive capacity, providing more accurate and more reliable prediction results to perform climate impact assessment, thereby helping policymakers and decision-makers develop adaptation strategy [60]. AI improves accuracy of weather prediction which allows for more accurate forecasting of available oceanic energy sources [61].

## 6.3. Hybrid Forecasting Models

Hybridizing several forecasting methods can produce stronger and more reliable forecasts for oceanic renewable technologies. Hybrid models that use both statistical and machine learning methods are providing better forecasting accuracy than single-method prediction studies [62]. Hybrid prediction models synthesize different algorithms and improve the overall prediction accuracy more effectively [63]. Combining multiple data sources and algorithms increases the accuracy of a hybrid model. In developing dengue epidemic forecasting models, hybrid models have been reported to exhibit superior solar power forecasting skills. **Figure 7** outlines a machine learning workflow for time series prediction, starting from raw data preprocessing, clustering with Fuzzy C-means, and applying models like SVR, KNN, and XG Boost. It includes hyper parameter tuning for optimization and evaluates performance using RMSE, MAE, and $R^2$-score [64].

For an instance, combining physical and data models can enhance renewable forecasting precision [65]. Occupancy models of ORE systems have improved forecast accuracy by incorporating diverse data sources and techniques to improve ORE systems predictions. Deep learning models are able to learn more complex features from PV power series and achieve better forecasting performance than traditional methods [66]. Reliable energy forecasting is achievable using deep learning.

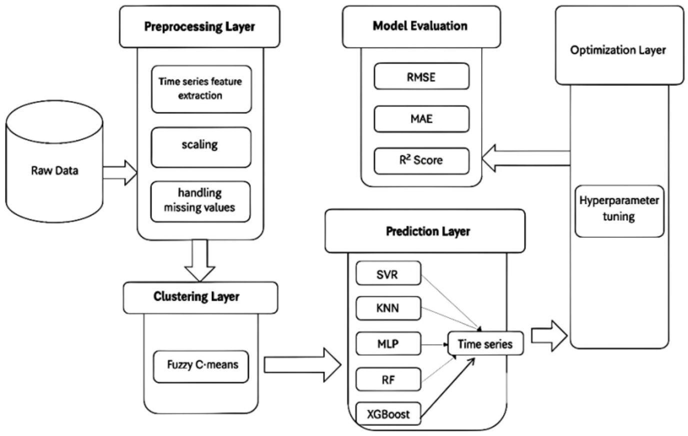



**Figure 7.** Machine Learning Workflow for Time Series Prediction in Renewable Energy Forecasting [64].

# 7. Control Strategies

## 7.1. Real-time Monitoring and Control

Active management and control of ocean energy systems in real time will be critical to achieving the level of performance and reliability required for efficient ocean renewable energy production. Real-time monitoring optimizes ORE systems by constantly adapting the settings in response to the actual real-time situation. Its presence enables ORE systems to be more efficient and reliable by the aid of real-time monitoring and control systems. AI algorithms make real-time updates for the best energy capture and conversion. Artificial intelligence systems analyze sensor data in real time and fine-tune control variables to ensure energy production is maximized. Efficient control and maintenance is one of the main issues of reliability and effectiveness in long-term operation of renewable energy systems. Real time adaptation to maximize energy harvesting and conversion in ORE systems may be achieved due to AI. AI and ML algorithms play an essential role in increasing the level of control and automation in renewable energy systems ultimately increasing efficiency and stability.

## 7.2. Adaptive Control Algorithms

In addition, techniques known as adaptive control algorithms can compensate for changes in system parameters in real time to improve performance in differing ocean conditions. Some ORE systems apply adaptive control techniques, which proportionally actuate systems' parameters in response to instantaneous conditions. The adaptive control algorithms help improve the robust performance and the stability of the ORE systems by updating parameters dynamically. AI-enabled adaptive control solutions can leverage data to learn and to fine tune energy production by controlling the hardware parameters. Adaptive control can improve stability and performance of ORE systems through the adjustment of parameters in the system. The parameters being continuously adjustable by the adaptive control algorithm, catches the real-time state of ORE systems, and guarantees its best performance. Through the usage of methods such as explainable AI and hybrid models, limitations in today's machine learning applications can be brought down and even enable new operational scenarios to make these systems more competitive in the world of energy [67].

## 7.3. Predictive Maintenance and Fault Detection

Preventive maintenance and fault detection are important for the overall long term reliability and availability of ocean renewable energy systems [68]. Predictive maintenance can be a technique used to reduce downtime and maintenance costs and can pre-warn for potential failures with time to spare before they occur [69,70]. The AI predictive maintenance reduces and prevents machinery failures, thus achieving higher efficiency and cost savings [71]. The systems of the automation for predictive maintenance and error identification minimize the delays and the costs to maintain operations. Cognitive AI algorithms process sensor data to search for anomalies and anticipate pending failures – allowing maintenance to be performed proactively. Predictive maintenance is greatly improved with AI, with early identification of possible faults reducing downtime and cost [72]. Predictive maintenance based on AI can remarkably enhance the reliability and minimize the operational costs of renewable energy systems [73].

## 8. Integration of AI and Physics-Based Models for Enhanced Reliability and Accuracy

AI-based models, when integrated with physics-based models, can significantly enhance both the reliability and accuracy of predictions and control strategies in ocean renewable energy (ORE) systems. This hybrid modelling approach combines data-driven insights from AI with the physical interpretability and robustness of physics-based systems, leading to several key advantages:

Physics-based models simulate environmental behavior (e.g., ocean waves, tides) based on fundamental laws. AI enhances these simulations by learning from historical trends and correcting model biases using real-time data. "AI-based models integrated with physics-based models improve the reliability and accuracy of renewable energy predictions" [56]. Physics-based models provide deterministic foundations, while AI offers adaptive capabilities for changing marine conditions. This synergy reduces false predictions and improves operational reliability. AI models can use sensor data to adjust control strategies in real time, while physics-based models ensure that these adaptations remain physically plausible. In situations where high-resolution data is limited, physics-based models fill the gap, while AI refines outputs using learned patterns and statistical correction techniques (e.g., transfer learning). Physics-informed AI can quantify prediction confidence using known physical constraints enhancing safety and decision-making, especially in marine environments where extreme conditions are common.

The integration of AI with physics-based models can be realized through several advanced techniques that bridge data-driven intelligence with physical system understanding. One such approach is the use of Physics-Informed Neural Networks (PINNs), which embed fundamental physical laws—like fluid dynamics or thermodynamics—directly into the training of neural networks. By doing so, these models ensure that predictions are not only data-compliant but also physically realistic, even in regions where data is sparse. Another powerful method is the Hybrid AI-Physics Workflow, where AI and physics-based models operate either sequentially or in parallel [64,67]. In sequential setups, AI can refine or correct the predictions of physics-based models, while in parallel (ensemble) configurations; both outputs are combined to yield more accurate and robust forecasts. A third technique gaining traction is the use of Digital Twins—virtual replicas of physical systems that integrate real-time sensor data with simulations. In this setup, physics models simulate the system's fundamental behavior, while AI dynamically updates the twin to predict faults, optimize operations, and adapt to changing conditions [74]. Together, these integration techniques enable more intelligent, responsive, and resilient ocean renewable energy systems. These integrations enable ORE systems to be smarter, safer, and more adaptive, ultimately improving energy capture efficiency and operational robustness in the complex marine environment.

## 9. Challenges and Future Directions

### 9.1. Data Availability and Quality

Data availability and quality are fundamental challenges in the effective application of AI to ocean renewable energy (ORE) systems. The performance and reliability of AI models depend heavily on access to large volumes of high-quality data, which are often scarce or inconsistently recorded in marine environments. Several types of data are particularly crucial: meteorological data such as wind speed, solar radiation, and atmospheric pressure help predict surface conditions; oceanographic data like wave height, tidal current, salinity, and sea surface temperature are essential for modelling ocean energy dynamics; and hind cast and forecast data provide historical trends and predictive insights necessary for energy scheduling and grid integration. In addition, real-time sensor data from devices such as wave buoys, underwater turbines, and seabed sensors are used to monitor system health and enable adaptive control. Grid-related data, including electricity demand, supply patterns, and load variability, further support AI-driven optimization and forecasting. However, issues such as inconsistent sensor calibration, data fragmentation across legacy platforms, and the lack of standardized acquisition protocols introduce noise and bias, reducing model accuracy. Therefore, data pre-processing, gap filling, and integration from diverse sources become critical tasks. Addressing these concerns through the development of unified data frameworks and real-time acquisition systems is essential to improve the accuracy, adaptability, and overall success of AI-based ORE applications. **Figure 8** illustrates a time series prediction framework involving data pre-processing, clustering, prediction using multiple ML models (e.g., SVR, KNN, RF), and evaluation based on metrics like RMSE and $R^2$-score. Hyper parameter tuning optimizes model performance for accurate renewable energy forecasting [75].

Solving these puzzles is important in the maximal effective use of AI in renewable energy. Data quality and accessibility are major constraints for AI utilization in ORE systems. Pre-processing of data is of paramount importance to obtain high performance in machine learning models [71].

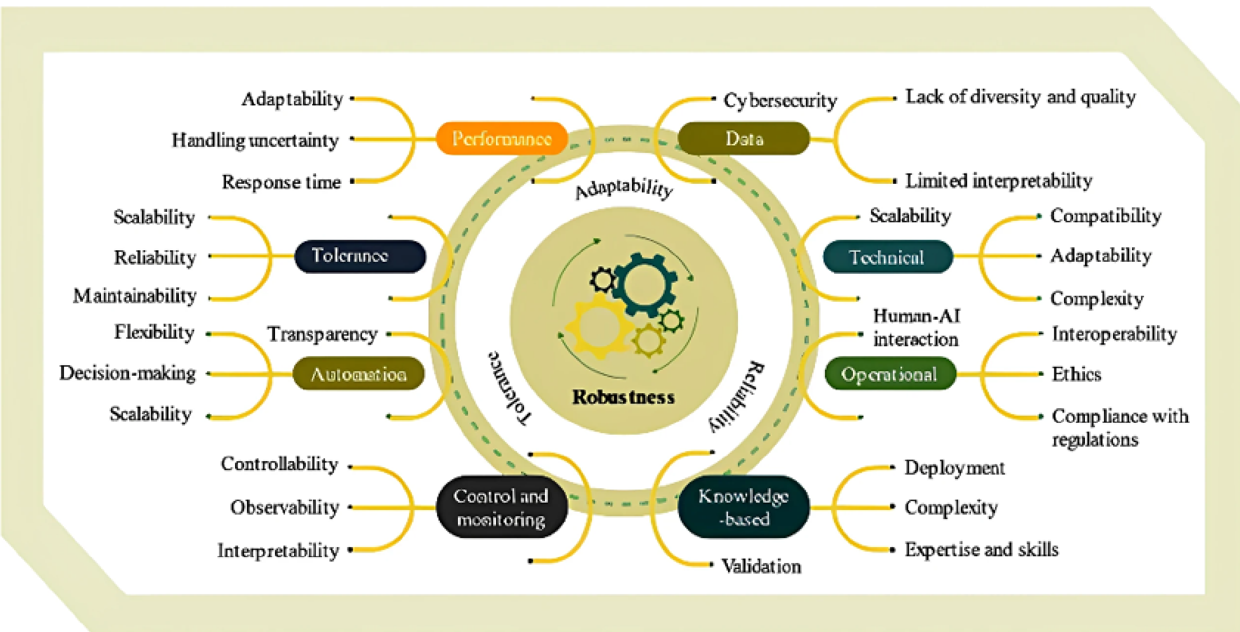



**Figure 8.** AI application in the Energy Systems' Main Challenges and Their Related Factors [75].

## 9.2. Computational Resources and Scalability

The computational demands of training and deploying AI models can be substantial, particularly for large-scale ocean renewable energy systems. Computing is required for the manipulation of extensive dataset and intricate algorithms computerized AI-ORE systems. Scalable to deploy AI models across multiple ORE systems and locations, the scalability of the AI algorithms is important when deploying the solutions to different ORE system and geographical locations. Computational power and scalability of AI methods are crucial to tackle the complexity and scale of ORE systems. The lack of computational resource also blocks the application of AI in ORE facilities.

### 9.3. Ethical and Regulatory Considerations

The ethics and regulation are critical to ensure a responsible and sustainable implementation of AI to ocean renewable energy systems. Transparent regulatory environments will be required to take AI in the right direction, ethically and responsibly.

Building trust and acceptance in AI applications requires a fair, transparent and accountable approach. Ethics involve data privacy, algorithmic bias and impact on employment. Dealing with these ethical and regulatory issues is critical in order to guarantee the responsible development of AI in ocean renewable energy systems. Bringing various actors, such as citizens, policy makers, and experts, into the design and governance of AI systems is essential for ensuring their deployment in line with the values and goals society seeks to promote [26]. Furthermore, standards should cover when and how the AI is developed and applied, for these are at least as critical to success as the methods and data [76]. The new regulations ought to cover the data privacy and availability to safeguard the data owners as well as the usability of the data [32]. The rise of AI and its application in energy may cause some challenges for current legal system, thus policy and regulation may limit the development of AI industry [5]. AI's rapid growth calls for awareness and adherence to ethical principles and legal obligations such as privacy of data, transparency, and fairness of the algorithm [77].

Developing appropriate regulatory mechanisms would be an initial and fundamental effort to regulating the deployment of AI and ensuring ethical and responsible use [78]. Strong regulative standards and the fostering of AI literacy and inclusiveness are quite necessary [79]. AI systems are required to be understandable, and means are to be established to justify decisions to stakeholders [80]. That would allow for accountability and trust in AI systems to be established. Responsible and ethical AI considers creating AI systems that are trustworthy and ethical in design and process, and in motivation and people involved, see, e.g., [81]. To manage the alignment and unintended side effects, entities will need to establish governance to provide oversight and control, and to intervene in AI decision-making in crucial operational situations, to keep it aligned with human values and intent [82]. The general purpose behind the integration of AI systems is to improve learning techniques based on statistics to uncover patterns from large data sets and make predictions based on the observed patterns, which are used in a wide range of applications, with increasing pressure to design and govern AI systems to conform to ethical values [83]. The AI field and its practitioners need to understand some deep shit about ethics in this domain. Given this, there is a need to investigate and comprehend the ethical and regulatory issues of AI that need to be addressed in order to promote responsibly designed and feasibly implemented AI technologies [84,85]. Governments world-wide are currently considering AI regulation because of public pressure, which makes it important to think about what regulation alternatives could be [86].

The EU's determination vis-à-vis AI liability in finance reveals the challenge of regulatory compliance and accountability evaluation, as result of the complexity and opaqueness of AI behavior, as well as its unpredictability [87].

## 10. Future Trends and Research Directions in Artificial Intelligence for Ocean Renewable Energy Systems

Future research directions should focus on developing more robust and reliable AI models that can handle the uncertainties and complexities of ocean environments. This involves incorporating advanced machine learning techniques, such as deep learning and reinforcement learning, to improve the accuracy and efficiency of AI-driven ORE systems. Developing hybrid AI models that combine physics-based models with data-driven approaches can also enhance the performance and reliability of ORE systems. Future trends and research directions in AI for ORE systems include Explainable AI, Edge AI, AI-driven cybersecurity, and digital twins. Research should focus on developing more robust and reliable AI models that can handle the uncertainties and complexities of ocean environments [88]. Explainable AI is a new field seeking to make AI models more open and interpretable. Explainable AI could be leveraged to increase the trust and acceptability of AI-driven ORE systems by offering to understand the decision process of AI models [89]. This would require our field to develop AI models that are able to communicate the rationale and decision-making of their outputs to the operators, to policymakers as well as to the public. The adoption of XAI methods could enhance the interpretability, reliability, and credibility of AI based ORE systems, which contributes to their acceptance and sustainability.

Edge AI refers to the practice of implementing AI models in edge devices, such as sensors and controllers, making real time data processing and decision-making possible [90]. The latency, data privacy and ORE system robustness could be improved through processing data locally by Edge AI. This methodology is especially helpful in far-away or off-shore applications where communication bandwidth is scarce. Edge AI could also facilitate more autonomous and smarter operation of ORE systems, minimizing the need for human interventions. ORE based systems require that such cybersecurity measures be AI-driven. This entails building AI models that could identify and stop a cyberattack and guard against sensitive data and infrastructure. As ORE systems become more interconnected, security becomes very important. AI-enabled cybersecurity would improve the sustainability and security of ORE plants, protecting them against unexpected threats that could compromise safe and reliable operation. Digital twins are virtual representations of physical assets like wave energy converters and tidal turbines. ORE systems may be emulated by digital twins, allowing for the optimization of their behavior and the prediction of possible failures. Combining AI with digital twins will enable ORE systems of the future to be intelligent systems that will learn from and adapt to changes in the operating environment to optimize performance during real time operations." Digital twins can also make predictive maintenance possible, and ORE system downtime can be minimized and efficiency optimized.

Finally, AI offers new transformative approaches in the field of the OR energy systems, covering optimization, forecasting and control. The inclusion of AI in the development of ORE systems holds the promise for them to be markedly more efficient, reliable, and sustainable and by extension to facilitate a cleaner and more sustainable energy future. As we look forward, more emphasis needs to be placed on progressing research into areas such as Explainable AI, Edge AI and AI-driven cybersecurity and digital twins, to continue unlocking the potential of AI in ORE systems [91]. By navigating through the pitfalls and exploiting the opportunities that AI offers, we can lay the path for a robust and sustainable ocean powered energy future. AI is essential for addressing the intermittency of renewable energy sources and energy allocation [2,4]. The mutual penetration of AI and ORE provides an attractive route for the sustainable and secure future energy transformation, with intelligent technologies having the potential to provide novel responses to upcoming energy requirement while mitigating the environmental footprint [1]. AI in renewable energy integration is a critical step towards achieving efficient and greener energy systems [1, 3, 5, and 6]. Deeper investigation and application of AI-driven methods will no doubt enhance the contribution of renewable energy to the global energy supply and contribute to the protection of the environment.

There is currently a digital revolution taking place in the energy industry, and AI is positioned in the focus [6]. Energy companies are already using AI for better supply of energy and minerals, for efficient power generation and transmission, and for consumption [5]. AI can be solution for the energy industry to improve operational performance and efficiency in a competitive market as it is evolving [6]. AI also can greatly promote the optimization of renewable energy systems or equipment in terms of improving their efficiency, reliability, and sustainability [1]. The capability of AI to model consumer behavior and preferences underpins more optimal policy development and stabilizes the equilibrium and efficiency of the energy system [5]. The application of AI is driving a massive transformation of the energy industry that is making it more efficient, clean and robust [26]. This transition should be considered from a holistic viewpoint, not only focusing on the technical aspects but on the social and economic aspects influencing the adoption of AI [54]. Such smart agents based on Smart Grid technologies and AI algorithms on the Energy related sectors needs to analyses the social and economic factors other than the technical dimension that drives the interest [54].

This synergy between AI and renewable energy is certainly encouraging, as AI could help to compensate the inherent variability and unpredictability of renewable resources, like sun, wind and ocean energy [92]. Generative AI can aid in the design of solar-based systems that are more efficient, reliable, and portable [93]. Through the utilization of AI, we can improve the performance of renewable energy systems and lower costs, promoting a transition to a clean energy future [61]. AI has increasingly been used as a tool in the transition to renewable energy and in the better management of the grid [94]. AI also has been used to optimize the distribution of energies, and balance the demand and supply, increase the grid resilience [95]. AI algorithms can leverage historical and present consumption with life patterns to forecast and optimize the production of renewable energy Ulcickas and Yip or analyses past and current data such as the weather, the radiance, the wind speed and the production of energy [26]. Accordingly, grid operators can take decisions on energy storage, distribution, and balancing load to guarantee a stable and reliable power supply [6]. AI is necessary for connecting fluctuating renewable energy supplies with electricity grids through the development of smart grids capable of matching some electricity demand to times when the sun shines and the wind blows [96].

AI has become a disruptive approach for promoting sustainability in multiple domains as well [97]. AI has significantly helped in meeting the sustainable development objectives, particularly in the critical issue of the renewables integration issue [98]. AI improves the implementation of resource utilization efficiency, emission reduction, and energy management [99]. AI will improve energy efficiency, will be able to allocate resources better and foster environmentally friendly decision making. Artificial intelligence supports circularity by improving resource usage and minimizing waste, as well as by creating new, sustainable products and services. New electro catalyst materials to enable efficient and scalable storage and use of renewable energy are being searched using AI [100]. AI can facilitate smarter and more efficient [42], and more sustainable operations across industries, which may lead into a more environmentally friendly and resilient future.

AI in smart energy systems is changing the way we manage, transmit, and consume energy. AI improves the stability and efficiency of the grid by means of real-time prediction, demand response and the incorporation of distributed generations [4]. AI is also integrated into smart energy system to analyzing large amount of data and making smarter decisions at the right time in this sector [101]. In [102], authors discussed that AI enhances building performance and sustainability goals in smart buildings. AI methods can rapidly process data to adjust to changing energy requirements, predict maintenance, and improve grid stability [33]. AI is also applied to enhance the reliability of the power grid through predicting and preventing the equipment failure [33]. AI is reshaping the energy world, driving toward a more sustainable, efficient safer energy future. Critically, AI would also enable the requirements for cheap, clean (low CO2) and secure energy by the accurate interpretation of information from the outside world used to fulfil tasks again through flexible adaptation [6]. Hybrid nan fluids show improved thermal properties for enhanced heat transfer, while AI models like LSTM-AE and RBM optimize energy use in buildings and agriculture [103–105]. Deep learning aids in rock damage detection, and micro-channel heat sink efficiency is improved through geometric optimization [106–109]. Trapezoidal ducts equipped with delta wing vortex generators show improved flow and heat transfer performance, offering passive enhancement techniques for industrial systems [110,111]. Failure and finite element analysis of paddle mixer shafts aid in identifying design improvements, while PCM-based cooling enhances mobile device thermal regulation; additionally, reviews on perforated twisted tapes and AI-driven mining practices highlight advancements in heat transfer and environmental sustainability [112–116].

In the field of ocean renewable energy systems, AI provides a range of applications in optimization, forecasting, and control, and contributes to improving performance, in terms of energy production (cost) and economics (**Table 5**).

**Table 5.** Challenges and Future Directions in AI Applications for Ocean Renewable Energy Systems.

| Challenge/Direction | Description | AI Role | Impact |
|---|---|---|---|
| Data Availability and Quality | Quality data is required for training AI models in ORE systems; availability issues impact model performance. | AI models depend on clean, comprehensive, and preprocessed datasets. | Accurate predictions and system control depend on high-quality data input. |
| Computational Resources and Scalability | AI deployment in ORE systems needs high computational power; scalability is a concern for global use. | AI algorithms must handle large datasets and complex computations efficiently. | Limits real-time AI application across multiple ORE systems without adequate resources. |
| Ethical and Regulatory Considerations | Fair and transparent AI applications require ethical and legal compliance, including privacy and accountability. | Involves governance, data transparency, and inclusive design. | Builds trust and ensures safe and responsible AI integration in ORE systems. |
| Future Trends: Explainable AI (XAI) | Focuses on making AI decision-making transparent and interpretable to users. | Increases trust by explaining model behavior to stakeholders. | Boosts acceptability and clarity of AI-driven decisions in ORE. |
| Future Trends: Edge AI | Executes AI on edge devices (sensors/controllers) for real-time ORE data processing. | Enables fast and localized AI operations even in remote marine environments. | Improves latency, privacy, and autonomy of offshore energy systems. |
| Future Trends: AI-based Cybersecurity | AI guards against cyber threats targeting interconnected ORE infrastructures. | Monitors anomalies, detects breaches, and ensures secure operation. | Protects sensitive energy systems from malicious attacks. |
| Future Trends: Digital Twins | Virtual models replicate physical ORE assets for monitoring and optimization. | Combines AI with real-time simulation for predictive maintenance and performance tuning. | Minimizes downtime and enhances operational efficiency. |

## 11. Conclusions

The AI ocean impact revolution Artificial Intelligence is disrupting ocean renewables to become more efficient for optimizing systems, predict reliability, adapt control? As the precision of AI models increases, and access to marine data becomes widespread, the cross-fertilization of these two domains becomes essential to scale ocean energy technologies and achieve international sustainability targets. "Artificial intelligence is one of the most transformative technologies of our time and it has the power to significantly reshape the energy industry. AI is aiding a cleaner energy transformation by optimizing energy systems and creating better agriculture practices. As a leading technology of the 4 Industrial Revolution, AI brings intelligence for the energy sector in design, operation and maintenance of energy systems. AI is also crucial for efficient power distribution, balancing loads and supply, and hardening the power grid. AI is even being deployed to address climate changes. AI provides more with less and promotes sustainability in the energy industry. More research and resources should be devoted to AI-centered tools to help justly realize the potential of ocean renewables for a clean and secure energy future. AI drives predictive maintenance, smart grids, and efficient power consumption. AI has been used with bioenergy systems over the last decades to tackle issues. AI has the potential to produce data that is difficult to measure directly, enhance existing models on the biomass conversion and end- uses of biofuels, and tackle the limitations of conventional computational methods on bioenergy supply chain design and optimization. This leads to a higher 12 efficiency and lower fuel consumption respecting a save of energy and a reduction of greenhouse gases. The development of AI technologies and the proliferation of big data open up wider possibilities for innovations in ocean renewable energy system design. Statistical and biologically motivated AI models have also been utilized in other work to address shared and future RENEW research goals. Solar PV power systems operational data acquisition accelerate the progress of AI for system learning application in design, control, and maintenance in order to enhance efficiency and shorten response duration. In the last decades, AI has been used in bioenergy systems to deal with problems. AI can improve power generation by increasingly accurate prediction, demand response and control.

## Author Contributions

Conceptualization, G.C.S. and A.S.K.; methodology, G.C.S.; software, P.G.; validation, G.C.S., P.S.N.M.V. and U.S.; formal analysis, K.R.R.P.; investigation, G.C.S.; resources, A.S.K.; data curation, P.G.; writing—original draft preparation, G.C.S.; writing—review and editing, A.S.K.; visualization, G.M.; supervision, A.S.K.; project administration, A.S.K., G.M. and P.S.N.M.V. All authors have read and agreed to the published version of the manuscript.

## Funding

This work received no external funding.

## Institutional Review Board Statement

Not applicable.

## Informed Consent Statement

Not applicable.

## Data Availability Statement

Data are contained within the article.

## Acknowledgments

The authors would like to express their sincere gratitude to Dr. D.Y. Patil Institute of Technology and Dr. D.Y. Patil Dnyan Prasad University, Pune, India, for providing the necessary support and research infrastructure.

## Conflicts of Interest

The authors declare no conflict of interest.

## References

[1] Ukoba, K.O., Olatunji, K.O., Adeoye, E., et al., 2024. Optimizing renewable energy systems through artificial intelligence: Review and future prospects. Energy & Environment. 35(7), 3833–3879. DOI: https://doi.org/10.1177/0958305x241256293

[2] Zhang, X., Khan, K., Shao, X., et al., 2024. The rising role of artificial intelligence in renewable energy development in China. Energy Economics. 132, 107489. DOI: https://doi.org/10.1016/j.eneco.2024.107489

[3] Pachot, A., Patissier, C., 2023. Towards Sustainable Artificial Intelligence: An Overview of Environmental Protection Uses and Issues. Green and Low-Carbon Economy. 3(2), 105–112. DOI: https://doi.org/10.47852/bonviewglce3202608

[4] Pimenov, S., Pimenowa, O., Prus, P., 2024. Challenges of Artificial Intelligence Development in the Context of Energy Consumption and Impact on Climate Change. Energies. 17(23), 5965. DOI: https://doi.org/10.3390/en17235965

[5] Jin, D., Ocone, R., Jiao, K., et al., 2020. Energy and AI. Energy and AI. 1, 100002. DOI: https://doi.org/10.1016/j.egyai.2020.100002

[6] Ahmad, T., Zhang, D., Huang, C., et al., 2021. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. Journal of Cleaner Production. 289, 125834. DOI: https://doi.org/10.1016/j.jclepro.2021.125834

[7] Borthwick, A.G.L., 2016. Marine Renewable Energy Seascape. Engineering. 2(1), 69–78. DOI: https://doi.org/10.1016/j.eng.2016.01.011

[8] Khare, V., Nema, S., Baredar, P., 2020. Fundamental and principles of the ocean energy system. In: Khare, V., Nema, S., Baredar, P. (eds.). Ocean energy modeling and simulation with big data. But-

terworth-Heinemann: Oxford, UK. pp. 1–48. DOI: https://doi.org/10.1016/b978-0-12-818904-7.00001-0

[9] Cohen, R.R., 1982. Energy from the ocean. Philosophical Transactions of the Royal Society of London Series A Mathematical and Physical Sciences. 307(1499), 405–437. DOI: https://doi.org/10.1098/rsta.1982.0119

[10] Cao, J., Liu, J., Liu, X., et al., 2025. A Review of Marine Renewable Energy Utilization Technology and Its Integration with Aquaculture. Energies. 18(9), 2343. DOI: https://doi.org/10.3390/en18092343

[11] Rusu, E., Onea, F., 2018. A review of the technologies for wave energy extraction. Clean Energy. 2(1), 10–19. DOI: https://doi.org/10.1093/ce/zky003

[12] Chowdhury, S., Rahman, K.S., Selvanathan, V., et al., 2020. Current trends and prospects of tidal energy technology. Environment Development and Sustainability. 23(6), 8179–8194. DOI: https://doi.org/10.1007/s10668-020-01013-4

[13] Enferad, E., Nazarpour, D., 2013. Ocean's Renewable Power and Review of Technologies: Case Study Waves. In: Arman, H., Yuksel, I. (eds.). New Developments in Renewable Energy. BoD – Books on Demand: Hamburg, Germany. pp. 273. DOI: https://doi.org/10.5772/53806

[14] Westwood, A., 2004. Ocean power: Wave and tidal energy review. Refocus. 5(5), 50–55. DOI: https://doi.org/10.1016/s1471-0846(04)00226-4

[15] Kumar, D., Sarkar, S., 2016. A review on the technology, performance, design optimization, reliability, techno-economics and environmental impacts of hydrokinetic energy conversion systems. Renewable and Sustainable Energy Reviews. 58, 796–813. DOI: https://doi.org/10.1016/j.rser.2015.12.247

[16] Mwasilu, F., Jung, J., 2018. Potential for power generation from ocean wave renewable energy source: a comprehensive review on state-of-the-art technology and future prospects. IET Renewable Power Generation. 13(3), 363–375. DOI: https://doi.org/10.1049/iet-rpg.2018.5456

[17] Banerjee, S., Duckers, L., Blanchard, R.E., 2013. An overview on green house gas emission characteristics and energy evaluation of ocean energy systems from life cycle assessment and energy accounting studies. Journal of Applied and Natural Science. 5(2), 535. DOI: https://doi.org/10.31018/jans.v5i2.364

[18] Song, Y., Zhang, Z., Xu, Z., 2022. Modular Combined DC-DC Autotransformer for Offshore Wind Power Integration with DC Collection. Applied Sciences. 12(4), 1810. DOI: https://doi.org/10.3390/app12041810

[19] Xie, J., Zuo, L., 2013. Ocean Wave Energy Converters and Control Methodologies. In Proceedings of the ASME 2013 Dynamic Systems and Control Conference, Palo Alto, California, USA, 21–23 October 2013; pp. V002T19A001. DOI: https://doi.org/10.1115/dscc2013-3757

[20] Zhu, W., Guo, J., Zhao, G., et al., 2020. Optimal Sizing of an Island Hybrid Microgrid Based on Improved Multi-Objective Grey Wolf Optimizer. Processes. 8(12), 1581. DOI: https://doi.org/10.3390/pr8121581

[21] Golbaz, D., Asadi, R., Amini, E., et al., 2021. Ocean Wave Energy Converters Optimization: A Comprehensive Review on Research Directions. arXiv (Cornell University). Preprint. DOI: https://doi.org/10.48550/arXiv.2105.07180

[22] Judge, M.A., Franzitta, V., Curto, D., et al., 2024. A Comprehensive Review of Artificial Intelligence Approaches for Smart Grid Integration and Optimization. Energy Conversion and Management X. 24, 100724 DOI: https://doi.org/10.1016/j.ecmx.2024.100724

[23] Bello, S.A., Wada, I., Ige, O.B., et al., 2024. AI-driven predictive maintenance and optimization of renewable energy systems for enhanced operational efficiency and longevity. International Journal of Science and Research Archive. 13(1), 2823–2837. DOI: https://doi.org/10.30574/ijsra.2024.13.1.1992

[24] Alsamia, S., Ibrahim, D.S., Ghafil, H.N., 2021. Optimization of drilling performance using various metaheuristics. Pollack Periodica. 16(2), 80–85. DOI: https://doi.org/10.1556/606.2021.00307

[25] Iacca, G., Santos, V.C., Melo, V.V., 2020. An improved Jaya optimization algorithm with Lévy flight. Expert Systems with Applications. 165, 113902. DOI: https://doi.org/10.1016/j.eswa.2020.113902

[26] Olawade, D.B., Wada, O.Z., David-Olawade, A.C., et al., 2024. Artificial intelligence potential for net zero sustainability: Current evidence and prospects. Next Sustainability. 4, 100041. DOI: https://doi.org/10.1016/j.nxsust.2024.100041

[27] Alkhayat, G., Mehmood, R., 2021. A review and taxonomy of wind and solar energy forecasting

methods based on deep learning. Energy and AI. 4, 100060. DOI: https://doi.org/10.1016/j.egyai.2021.100060

[28] Immas, A., Do, N., Alam, M., 2021. Real-time in situ prediction of ocean currents. Ocean Engineering. 228, 108922. DOI: https://doi.org/10.1016/j.oceaneng.2021.108922

[29] Kumar, N.K., Ramasamy, S., Mamun, A.A., 2018. Ocean wave characteristics prediction and its load estimation on marine structures: A transfer learning approach. Marine Structures. 61, 202–219. DOI: https://doi.org/10.1016/j.marstruc.2018.05.007

[30] Zhu, Y., Lu, S., Dai, R., et al., 2018. Power Market Price Forecasting via Deep Learning. In Proceedings of the IECON 2018-44th annual conference of the IEEE industrial electronics society, Washington, DC, USA, 21–23 October 2018; pp. 4935–4939. DOI: https://doi.org/10.1109/IECON.2018.8591581

[31] Selim, M., Zhou, R., Feng, W., et al., 2021. Estimating Energy Forecasting Uncertainty for Reliable AI Autonomous Smart Grid Design. Energies. 14(1), 247. DOI: https://doi.org/10.3390/en14010247

[32] Xie, L., Huang, T., Zheng, X., et al., 2022. Energy system digitization in the era of AI: A three-layered approach toward carbon neutrality. Patterns. 3(12), 100640. DOI: https://doi.org/10.1016/j.patter.2022.100640

[33] Omitaomu, O.A., Niu, H., 2021. Artificial Intelligence Techniques in Smart Grid: A Survey. Smart Cities. 4(2), 548–568. DOI: https://doi.org/10.3390/smartcities4020029

[34] Simões, M.G., Elmusrati, M., Vartiainen, T., et al., 2023. Enhancing data security against cyberattacks in artificial intelligence based smartgrid systems with crypto agility. arXiv (Cornell University). DOI: https://doi.org/10.48550/arXiv.2305.11652

[35] Kamali, M., Appels, L., Yu, X., et al., 2020. Artificial intelligence as a sustainable tool in wastewater treatment using membrane bioreactors. Chemical Engineering Journal. 417, 128070. DOI: https://doi.org/10.1016/j.cej.2020.128070

[36] Jiao, A., Lu, J., Ren, H., et al., 2024. The role of AI capabilities in environmental management: Evidence from USA firms. Energy Economics. 134, 107653. DOI: https://doi.org/10.1016/j.eneco.2024.107653

[37] Porawagamage, G.D., Dharmapala, K., Chaves, J.S., et al., 2024. A review of machine learning applications in power system protection and emergency control: opportunities, challenges, and future directions. Frontiers in Smart Grids. 3, 1371153. DOI: https://doi.org/10.3389/frsgr.2024.1371153

[38] Zhu, X., Chen, S., Liang, X., et al., 2024. Next-generation generalist energy artificial intelligence for navigating smart energy. Cell Reports Physical Science. 5(9), 102192. DOI: https://doi.org/10.1016/j.xcrp.2024.102192

[39] Jha, S.K., Bilalovic, J., Jha, A., et al., 2017. Renewable energy: Present research and future scope of Artificial Intelligence. Renewable and Sustainable Energy Reviews. 77, 297–317. DOI: https://doi.org/10.1016/j.rser.2017.04.018

[40] Kurukuru, V.S.B., Haque, A., Khan, M.A., et al., 2021. A Review on Artificial Intelligence Applications for Grid-Connected Solar Photovoltaic Systems. Energies. 14(15), 4690. DOI: https://doi.org/10.3390/en14154690

[41] Afridi, Y.S., Ahmad, K., Hassan, L., 2021. Artificial Intelligence Based Prognostic Maintenance of Renewable Energy Systems: A Review of Techniques, Challenges, and Future Research Directions. arXiv (Cornell University). DOI: https://doi.org/10.48550/arXiv.2104.12561

[42] Jathar, L.D., Nikam, K.C., Awasarmol, U.V., et al., 2024. A comprehensive analysis of the emerging modern trends in research on photovoltaic systems and desalination in the era of artificial intelligence and machine learning. Heliyon. 10(3), e25407. DOI: https://doi.org/10.1016/j.heliyon.2024.e25407

[43] Berghout, T., Benbouzid, M., Bentrcia, T., et al., 2021. Machine Learning-Based Condition Monitoring for PV Systems: State of the Art and Future Prospects. Energies. 14(19), 6316. DOI: https://doi.org/10.3390/en14196316

[44] Faustine, A., Mvungi, N.H., Kaijage, S., et al., 2017. A Survey on Non-Intrusive Load Monitoring Methodies and Techniques for Energy Disaggregation Problem. arXiv (Cornell University). DOI: https://doi.org/10.48550/arXiv.1703.00785

[45] Miah, M.S.U., Sulaiman, J., Islam, M.I., et al., 2023. Predicting Short Term Energy Demand in Smart Grid: A Deep Learning Approach for Integrating Renewable Energy Sources in Line with SDGs 7, 9, and 13. arXiv (Cornell University). DOI: https://doi.org/10.48550/arXiv.2304.03997

[74] Ni, Z., Zhang, C., Karlsson, M., et al., 2023. Leverag-

ing Deep Learning and Digital Twins to Improve Energy Performance of Buildings. In Proceedings of the 2023 IEEE 3rd International Conference on Industrial Electronics for Sustainable Energy Systems (IESES), Shanghai, China, 26–28 July 2023; pp. 1–6. DOI: https://doi.org/10.1109/ieses53571.2023.10253721

[46] Nakabi, T.A., Toivanen, P., 2020. Deep reinforcement learning for energy management in a microgrid with flexible demand. Sustainable Energy Grids and Networks. 25, 100413. DOI: https://doi.org/10.1016/j.segan.2020.100413

[47] Ardabili, S., Abdolalizadeh, L., Makó, C., et al., 2022. Systematic Review of Deep Learning and Machine Learning for Building Energy. Frontiers in Energy Research. 10, 786027. DOI: https://doi.org/10.3389/fenrg.2022.786027

[48] Liu, Z., Sun, Y., Xing, C., et al., 2022. Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: Challenges and future perspectives. Energy and AI. 10, 100195. DOI: https://doi.org/10.1016/j.egyai.2022.100195

[49] Arévalo, P., Jurado, F., 2024. Impact of Artificial Intelligence on the Planning and Operation of Distributed Energy Systems in Smart Grids. Energies. 17(17), 4501. DOI: https://doi.org/10.3390/en17174501

[50] Balamurugan, M., Narayanan, K., Raghu, N., et al., 2025. Role of artificial intelligence in smart grid – a mini review. Frontiers in Artificial Intelligence. 8, 1551661. DOI: https://doi.org/10.3389/frai.2025.1551661

[51] Antonopoulos, I., Robu, V., Couraud, B., et al., 2020. Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. Renewable and Sustainable Energy Reviews. 130, 109899. DOI: https://doi.org/10.1016/j.rser.2020.109899

[52] Gowekar, G.S., 2024. Artificial intelligence for predictive maintenance in oil and gas operations. World Journal of Advanced Research and Reviews. 23(3), 1228–1233. DOI: https://doi.org/10.30574/wjarr.2024.23.3.2721

[53] Sirmacek, B., Gupta, S., Mallor, F., et al., 2022. The potential of artificial intelligence for achieving healthy and sustainable societies. arXiv (Cornell University). DOI: https://doi.org/10.48550/arXiv.2202.07424

[54] Șerban, A.C., Lytras, M.D., 2020. Artificial Intelligence for Smart Renewable Energy Sector in Europe—Smart Energy Infrastructures for Next Generation Smart Cities. IEEE Access. 8, 77364–77377. DOI: https://doi.org/10.1109/access.2020.2990123

[55] Feng, C., Liu, Y., Zhang, J., 2021. A taxonomical review on recent artificial intelligence applications to PV integration into power grids. International Journal of Electrical Power & Energy Systems. 132, 107176. DOI: https://doi.org/10.1016/j.ijepes.2021.107176

[56] Haupt, S.E., McCandless, T., Dettling, S., et al., 2020. Combining Artificial Intelligence with Physics-Based Methods for Probabilistic Renewable Energy Forecasting. Energies. 13(8), 1979. DOI: https://doi.org/10.3390/en13081979

[57] Lewis, J.I., Toney, A., Shi, X., 2024. Climate change and artificial intelligence: assessing the global research landscape. Discover Artificial Intelligence. 4(1), 64. DOI: https://doi.org/10.1007/s44163-024-00170-z

[58] Ghannam, R., Klaine, P.V., Imran, M.A., 2019. Artificial Intelligence for Photovoltaic Systems. In: Precup, R.E., Kamal, T., Zulqadar Hassan, S. (eds.). Solar Photovoltaic Power Plants: Advanced Control and Optimization Techniques. Springer, Singapore. pp. 121–142. DOI: https://doi.org/10.1007/978-981-13-6151-7_6

[59] Yadav, K., Malviya, S., Tiwari, A.K., 2025. Improving Weather Forecasting in Remote Regions Through Machine Learning. Atmosphere. 16(5), 587. DOI: https://doi.org/10.3390/atmos16050587

[60] Ukoba, K., Onisuru, O.R., Jen, T., et al., 2025. Predictive modeling of climate change impacts using Artificial Intelligence: a review for equitable governance and sustainable outcome. Environmental Science and Pollution Research. 32, 10705–10724. DOI: https://doi.org/10.1007/s11356-025-36356-w

[61] Lainjo, B., 2024. The Role of Artificial Intelligence in Achieving the United Nations Sustainable Development Goals. Journal of Sustainable Development. 17(5), 1–30. DOI: https://doi.org/10.5539/jsd.v17n5p30

[62] Ritter, G., 2017. Machine Learning for Trading. SSRN Electronic Journal. 1–19. DOI: https://doi.org/10.2139/ssrn.3015609

[63] Han, J., Chen, H., Han, K., et al., 2025. A Physics-guided Multimodal Transformer Path to Weather and Climate Sciences. arXiv. DOI: https://doi.org/10.48550/arXiv.2504.14174

[64] Alsalem, K., 2025. A hybrid time series forecasting approach integrating fuzzy clustering and machine learning for enhanced power consumption prediction. Scientific Reports. 15(1), 6447. DOI: https://doi.org/10.1038/s41598-025-91123-8

[65] Lee, J., Park, E., Lee, S.Y., 2025. Development of a Hybrid Modeling Framework for the Optimal Operation of Microgrids. Energies. 18(8), 2102. DOI: https://doi.org/10.3390/en18082102

[66] Li, P., Zhou, K., Lu, X., et al., 2019. A hybrid deep learning model for short-term PV power forecasting. Applied Energy. 259, 114216. DOI: https://doi.org/10.1016/j.apenergy.2019.114216

[67] Kumar, A., Dubey, A.K., Ramírez, I.S., et al., 2024. Artificial Intelligence Techniques for the Photovoltaic System: A Systematic Review and Analysis for Evaluation and Benchmarking. Archives of Computational Methods in Engineering. 31, 4429–4453. DOI: https://doi.org/10.1007/s11831-024-10125-3

[68] Uçar, A., Karaköse, M., Kırımça, N., 2024. Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends. Applied Sciences. 14(2), 898. DOI: https://doi.org/10.3390/app14020898

[69] Gronfula, M.G., Sayed, K., 2025. AI-Driven Predictive Control for Dynamic Energy Optimization in Flying Cars. Energies. 18(7), 1781. DOI: https://doi.org/10.3390/en18071781

[70] Jigyasu, R., Shrivastava, V., Singh, S., 2021. Prognostics and health management of induction motor by supervised learning classifiers. IOP Conference Series Materials Science and Engineering. IOP Publishing. 1168(1), 012006. DOI: https://doi.org/10.1088/1757-899x/1168/1/012006

[71] Abbas, A., 2024. AI for Predictive Maintenance in Industrial Systems. International Journal of Advanced Engineering Technologies and Innovations. 1(1), 31–51.

[72] Cardoso, D., Ferreira, L., 2021. Application of Predictive Maintenance Concepts Using Artificial Intelligence Tools. Applied Sciences. 11(1), 18. DOI: https://doi.org/10.3390/app11010018

[73] Mammadov, E.E., 2019. Predictive Maintenance of Wind Generators based on AI Techniques [Master's thesis]. University of Waterloo: Waterloo, Ontario, Canada.

[75] Danish, M.S.S., 2023. AI in Energy: Overcoming Unforeseen Obstacles. AI. 4(2), 406–425. DOI: https://doi.org/10.3390/ai4020022

[76] Dignum, V., 2023. Responsible Artificial Intelligence: Recommendations and Lessons Learned. In: Eke, D.O., Wakunuma, K., Akintoye, S. (eds.). Responsible AI in Africa. Social and Cultural Studies of Robots and AI. Palgrave Macmillan: Cham, Switzerland. pp. 195–214. DOI: https://doi.org/10.1007/978-3-031-08215-3_9

[77] Chen, Z., Chen, C.Y., Yang, G., et al., 2024. Research integrity in the era of artificial intelligence: Challenges and responses. Medicine. 103(27), e38811. DOI: https://doi.org/10.1097/md.0000000000038811

[78] Filho, W.L., Gbaguidi, G.J., 2024. Using artificial intelligence in support of climate change adaptation Africa: potentials and risks. Humanities and Social Sciences Communications. 11(1), 1–5. DOI: https://doi.org/10.1057/s41599-024-04223-7

[79] Kalantarinejad, R., Ventresca, M.J., Perez-Crespillo, A., 2024. Future of Innovation by the Impact of AI. SSRN. DOI: https://doi.org/10.2139/ssrn.4884834

[80] Abujaber, A.A., Nashwan, A.J., 2024. Ethical framework for artificial intelligence in healthcare research: A path to integrity. World Journal of Methodology. 14(3), 94071. DOI: https://doi.org/10.5662/wjm.v14.i3.94071

[81] Dignum, V., 2022. Responsible Artificial Intelligence -- from Principles to Practice. ACM SIGIR Forum. 56(1), 1–6. DOI: https://doi.org/10.48550/arXiv.2205.10785

[82] Cath, C., 2018. Governing artificial intelligence: ethical, legal and technical opportunities and challenges. Philosophical Transactions of the Royal Society A Mathematical Physical and Engineering Sciences. 376(2133), 20180080. DOI: https://doi.org/10.1098/rsta.2018.0080

[83] Sigfrids, A., Nieminen, M., Leikas, J., et al., 2022. How Should Public Administrations Foster the Ethical Development and Use of Artificial Intelligence? A Review of Proposals for Developing Governance of AI. Frontiers in Human Dynamics. 4, 858108. DOI: https://doi.org/10.3389/fhumd.2022.858108

[84] Mennella, C., Maniscalco, U., Pietro, G.D., et al., 2024. Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. Heliyon. 10(4), e26297. DOI: https://doi.org/10.1016/j.heliyon.2024.e26297

[85] Khan, A.A., Badshah, S., Liang, P., et al., 2022. Ethics of AI: A Systematic Literature Review of Prin-

ciples and Challenges. In Proceedings of the 26th international conference on evaluation and assessment in software engineering, Gothenburg, Sweden, 13–15 June 2022; pp. 383–392. DOI: https://doi.org/10.1145/3530019.3531329

[86] Percy, C., Dragičević, S., Sarkar, S., et al., 2022. Accountability in AI: From principles to industry-specific accreditation. AI Communications. 34(3), 181–196. DOI: https://doi.org/10.3233/aic-210080

[87] Montagnani, M.L., Najjar, M.C., Davola, A., 2024. The EU Regulatory approach(es) to AI liability, and its Application to the financial services market. Computer Law & Security Review. 53, 105984. DOI: https://doi.org/10.1016/j.clsr.2024.105984

[88] Nishant, R., Kennedy, M., Corbett, J., 2020. Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management. 53, 102104. DOI: https://doi.org/10.1016/j.ijinfomgt.2020.102104

[89] Vinothkumar, J., Karunamurthy, A., 2023. Recent Advancements in Artificial Intelligence Technology: Trends and Implications. Quing International Journal of Multidisciplinary Scientific Research and Development. 2(1), 1–11. DOI: https://doi.org/10.54368/qijmsrd.2.1.0003

[90] Middleton, S.E., Letouzé, E., Hossaini, A.A., et al., 2022. Trust, regulation, and human-in-the-loop AI. Communications of the ACM. 65(4), 64–68. DOI: https://doi.org/10.1145/3511597

[91] Gill, S.S., Golec, M., Hu, J., et al., 2024. Edge AI: A Taxonomy, Systematic Review and Future Directions. arXiv (Cornell University). DOI: https://doi.org/10.48550/arXiv.2407.04053

[92] Lanbaran, N.M., Naujokaitis, D., Kairaitis, G., et al., 2024. Overview of Startups Developing Artificial Intelligence for the Energy Sector. Applied Sciences. 14(18), 8294. DOI: https://doi.org/10.3390/app14188294

[93] Mousavi, R., Mousavi, A.K., Mousavi, Y., et al., 2025. Revolutionizing solar energy resources: The central role of generative AI in elevating system sustainability and efficiency. Applied Energy. 382, 125296. DOI: https://doi.org/10.1016/j.apenergy.2025.125296

[94] Dong, Z., Tan, C., Ma, B., et al., 2024. The impact of artificial intelligence on the energy transition: The role of regulatory quality as a guardrail, not a wall. Energy Economics. 140, 107988. DOI: https://doi.org/10.1016/j.eneco.2024.107988

[95] Tian, L., Li, X., Lee, C.W., et al., 2024. Investigating the asymmetric impact of artificial intelligence on renewable energy under climate policy uncertainty. Energy Economics. 137, 107809. DOI: https://doi.org/10.1016/j.eneco.2024.107809

[96] Vinuesa, R., Azizpour, H., Leite, I., et al., 2020. The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications. 11(1), 233. DOI: https://doi.org/10.1038/s41467-019-14108-y

[97] Qudrat-Ullah, H., 2025. A Thematic Review of AI and ML in Sustainable Energy Policies for Developing Nations. Energies. 18(9), 2239. DOI: https://doi.org/10.3390/en18092239

[98] Massaoudi, M., Refaat, S.S., Abu-Rub, H., 2021. On the Pivotal Role of Artificial Intelligence Toward the Evolution of Smart Grids. In: Refaat, S.S., Ellabban, O., Bayhan, S., et al. (eds.). Smart Grid and Enabling Technologies. John Wiley & Sons: Hoboken, New Jersey, USA. pp. 359–420. DOI: https://doi.org/10.1002/9781119422464.ch15

[99] Uriarte-Gallastegi, N., Landín, G.A., Landeta-Manzano, B., et al., 2024. The Role of AI in Improving Environmental Sustainability: A Focus on Energy Management. Energies. 17(3), 649. DOI: https://doi.org/10.3390/en17030649

[100] Wu, C.J., Raghavendra, R., Gupta, U., et al., 2021. Sustainable AI: Environmental Implications, Challenges and Opportunities. arXiv (Cornell University). DOI: https://doi.org/10.48550/arXiv.2111.00364

[101] Alsaigh, R., Mehmood, R., Katib, I., 2023. AI explainability and governance in smart energy systems: A review. Frontiers in Energy Research. 11, 1071291. DOI: https://doi.org/10.3389/fenrg.2023.1071291

[102] Muniandi, P.K.M.B., 2024. AI-Driven Energy Management Systems for Smart Buildings. Power System Technology. 48(1), 322–337. DOI: https://doi.org/10.52783/pst.280

[103] Maniyar, K., Pawar, P., Kolhe, P., et al., 2024. The comprehensive study of synthesis and characterization of hybrid nano fluids. AIP Conference Proceedings. 3149(1), 030048.

[104] Madhukar, S.R., Singh, K., Kanniyappan, S.P., et al., 2024. Towards Efficient Energy Management of Smart Buildings: A LSTM-AE Based Model. In Proceedings of the 2024 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC), Bengaluru,

India, 02–03 May 2024; pp. 1–6.
[105] Gore, K.B., Chidambararaj, N., Kartheesan, L., et al., 2024. Smart Water Management in Agriculture: Enhancing Crop Productivity with Restricted Boltzmann Machine. In Proceedings of the 2024 First International Conference on Software, Systems and Information Technology (SSITCON), Tumkur, India, 18–19 October 2024; pp. 1–6.
[106] Ramani, P., Reji, V., Sathish Kumar, V., et al., 2025. Deep learning-based detection and classification of moss and crack damage in rock structures for geo-mechanical preservation. Journal of Mines, Metals & Fuels. 73(3), 783.
[107] Chippalkatti, S., Chekuri, R.B., Ohol, S.S., et al., 2025. Enhancing heat transfer in micro-channel heat sinks through geometrical optimization. Journal of Mines, Metals & Fuels. 73(3), 799.
[108] Kurhade, A.S., Siraskar, G.D., Chekuri, R.B., et al., 2025. Biodiesel blends: A sustainable solution for diesel engine performance improvement. Journal of Mines, Metals & Fuels. 73(3), 839.
[109] Kurhade, A.S., Bhavani, P., Patil, S.A., et al., 2025. Mitigating environmental impact: A study on the performance and emissions of a diesel engine fueled with biodiesel blend. Journal of Mines, Metals & Fuels. 73(4), 981–989.
[110] Wakchaure, G.N., Vijayarao, P., Jadhav, T.A., et al., 2025. Performance evaluation of trapezoidal ducts with delta wing vortex generators: An experimental investigation. Journal of Mines, Metals & Fuels. 73(4), 991–1003.
[111] Wakchaure, G.N., Jagtap, S.V., Gandhi, P., et al., 2025. Heat transfer characteristics of trapezoidal duct using delta wing vortex generators. Journal of Mines, Metals & Fuels. 73(4), 1053–1056.
[112] Chougule, S.M., Murali, G., Kurhade, A.S., 2025. Failure investigation of the driving shaft in an industrial paddle mixer. Journal of Mines, Metals & Fuels. 73(5), 1247–1256.
[113] Kurhade, A.S., Sugumaran, S., Kolhalkar, N.R., et al., 2025. Thermal management of mobile devices via PCM. Journal of Mines, Metals & Fuels. 73(5), 1313–1320.
[114] Chougule, S.M., Murali, G., Kurhade, A.S., 2025. Finite element analysis and design optimization of a paddle mixer shaft. Journal of Mines, Metals & Fuels. 73(5), 1343–1354.
[115] Waware, S.Y., Ahire, P.P., Napate, K., et al., 2025. Advancements in heat transfer enhancement using perforated twisted tapes: A comprehensive review. Journal of Mines, Metals & Fuels. 73(5), 1355–1363.
[116] Patil, Y., Tatiya, M., Dharmadhikari, D.D., et al., 2025. The role of AI in reducing environmental impact in the mining sector. Journal of Mines, Metals & Fuels. 73(5), 1365–1378.Ga. Ut repudae voloratem fugitas assint.