Journal of Mines, Metals and Fuels, *73(11): 3401-3423; 2025. DOI: 10.18311/jmmf/2025/50086*

Print ISSN : 0022-2755

Journal of Mines, Metals and Fuels

Contents available at: *www.informaticsjournals.co.in/index.php/jmmf*

Artificial Intelligence Applications in Ocean Renewable Energy Systems: Optimisation, Forecasting, and Control

Manjusha Tatiya[1*], Pragati Choudhari[2], Hemantkumar Balasaheb Jadhav[3], Puja Gholap[4], Yogendra Patil[5], Rupesh Gangadhar Mahajan[6,8] and Anant Sidhappa Kurhade[7,8]

[1]Department of Artificial Intelligence and Data Science, Indira College of Engineering and Management, Indira Chanakya Campus (ICC), Parandwadi, Pune - 410506, Maharashtra, India
[2]School of Computer Science Engineering and Applications, D Y Patil International University, Akurdi, Pune - 411044, Maharashtra, India
[3]Department of Computer Engineering, Adsul Technical Campus, Ahmadnagar - 414005, Maharashtra, India
[4]Department of Computer Engineering, Sharadchandra Pawar College of Engineering, Dumberwadi (Otur), Junnar, Pune - 412409, Maharashtra, India
[5]Department of Computer Engineering, Marathwada Mitra Mandal's Institute of Technology, Lohgaon, Pune - 411047, Maharashtra, India
[6]Department of Computer Engineering, Dr. D. Y. Patil Institute of Technology, Pune - 411018, Maharashtra, India
[7]Department of Mechanical Engineering, Dr. D. Y. Patil Institute of Technology, Pune - 411018, Maharashtra, India
[8]School of Technology and Research, Dr. D. Y. Patil Dnyan Prasad University, Pune - 411018, Maharashtra, India; a.kurhade@gmail.com

Abstract

Ocean Renewable Energy Systems (ORES) represent a promising solution for sustainable energy generation, yet they face challenges related to forecasting accuracy, system optimisation, and adaptive control in highly dynamic marine environments. Although recent developments have advanced ORES technology, the absence of intelligent, responsive systems limits their efficiency and scalability. This study explores the integration of Artificial Intelligence (AI) techniques—including machine learning, deep learning, fuzzy logic, and hybrid models—to overcome these limitations. By reviewing recent literature, the study highlights how AI improves energy forecasting, enables structural and thermal optimisation, supports predictive maintenance, and enhances real-time decision-making. The findings indicate that AI-driven approaches significantly boost system performance, adaptability, and reliability. Ultimately, the integration of AI in ORES holds transformative potential, enabling cost-effective, automated, and environmentally friendly ocean energy solutions.

Major Findings: *It is concluded that AI technology greatly increases the efficiency, reliability and flexibility of ORES thanks to intelligent prediction, optimal purchasing and intelligent control. AI algorithms like ANN, SVM, and Deep Learning models enhance the prediction of energy output, faulty diagnosis and real-time decision-making. Optimisation algorithms like GA and PSO for improved design parameters and AI-based SCADA systems for predictive maintenance and fault detection. Collectively, the AI combination minimises the operation cost, maximises the energy production, and facilitates a wide attainment of ocean energy.*

**Author for correspondence*

Keywords: *Adaptive Control, Artificial Intelligence, Forecasting, Intelligent Systems, Ocean Renewable Energy, Optimisation, Predictive Maintenance, Smart Grids*

1.0 Introduction

Artificial intelligence is applied to address technical, economic and social challenges of the global energy transition[1]. With the growing significance of renewable energy as a global energy source, AI can benefit grid stability and energy forecasting accuracy[2]. Through AI, huge databases can be analysed to improve the performance of the renewable energy systems, to minimise environmental impact; AI can be used to predict energy demand, and the utilisation of renewable energy instead of the use of fossil fuels[3]. AI and smart systems are now being used to optimise power usage in different domains, enabling better efficiency and sustainability[4]. AI concepts like fuzzy expert systems, fuzzy logic, meta-heuristic methods, and machine learning are utilised to solve the problems in design, control, and maintenance in renewable energy systems[5,6]. AI may make decisions, perform tasks to order and operate equipment for you, reducing your burden[7]. AI can predict power generation and manage the location and operation of renewable plants[8,9]. AI, which was historically a subfield of computer science, has gained its discipline status due to its broad application in a variety of industries, such as sustainable energy[10]. Renewable energy systems in conjunction with other trends are shaping the future of the energy sector with smart energy systems; artificial intelligence and complex data processing to make smarter decisions are being implemented[11]. Predictions regarding energy demand and optimal energy policies[10] are important for establishing an efficient and intelligent energy system, AI being a key ingredient in this process. AI applications in renewable energy, mainly prediction, maintenance, and fault detection, have a mature solution[12]. Utilities require smart devices that can help them integrate renewable resources more effectively and equally alongside traditional resource generation[13]. AI improves the operational performance and efficiency of the competitive energy market[14]. AI is therefore an enabler of sustainable development, allowing resource allocation to be optimised, decision making to be improved, and efficiencies to be achieved across sectors[9]. Because the technological progress in IT, AI and data analysis is fast, the regulatory approval for new services and products in a digital energy market can be done more effective[15]. AI is necessary to optimise the exploitation of available resources, reduce emissions and overall support energy management[16]. As AI is becoming more crucial, understanding its application in the power industry is crucial[17]. Smart software to manage the seamless integration of energy supply, demand and renewables within the grid will make its own decisions and run operations[15].

Figure 1 illustrates the diverse applications of AI in the renewable energy sector, including optimisation, fault detection, maintenance, emissions reduction, energy forecasting, and smart grid management. AI supports improved efficiency, decision-making, and sustainability across power generation, policy formulation, and integration of renewable systems. Artificial intelligence is important for optimal creation and effective management of a portfolio, particularly as green projects grow in both scale and complexity[18]. AI is also important for the integration of variable renewables that could be connected based on the intelligence of electrical demand to renewable (intelligently coupling of electrical demand and renewable energy availability[19]). These advanced technologies enable real-time simulation, adaptive control, and intensified human–machine interaction to smart devices, which enables dynamic energy distribution and a proactive risk control[20]. AI-enabled policy making is also a crucial measure to facilitate carbon neutrality in the electricity sector[21]. New regulation, however, is required for oversight of AI in critical infrastructure, reliability and privacy, and interpretability for easy human oversight[21].

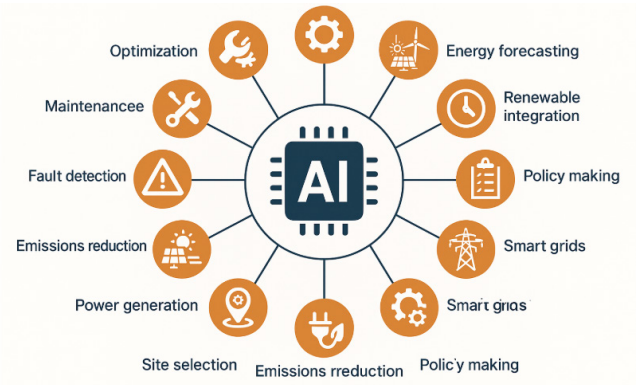


Figure 1. AI in renewable energy.

AI-enablement and digitisation of the electric grid is necessary to enable the management of the electrification the decarbonisation of the power industry[22]. AI can also enhance the reliability and robustness of power systems[23]. AI enables the generation of scenarios, the prediction of incidents, the assessment of risks and the grading of severity, to handle increasing complexities added by renewable energy penetration and digital grid technologies[24]. These AI tools improve our prediction and perform optimisation; they can optimise the offline plans as well as the online operation adjustment of the grid[21]. The fusion of AI and IoT is one of the drivers behind this, which allows for real-time monitoring, predictive maintenance, and dynamic demand response methods[25]. However, quite a lot of grid systems deploy manual operations, as a result of the unavailability of sufficient advanced intelligent control resources[26]. To stay competitive, the energy sector might have to bring AI technologies to the forefront[15]. AI can even create smart grids that can better match electricity demand with renewable energy availability[19]. AI-based smart grids are designed to combine power generation, distribution and consumption into a single integral system, to deliver efficient energy from production to consumption via intuitive communication, highly sensitive sensing technologies and AI-based algorithms in a real-time manner[27]. The State Grid Corporation of China has acknowledged the significance of AI and proposed enormous investment to promote the construction of the smart grid, which is also embedded in the Chinese government's strategic guideline for AI development[28]. Smart grids are intelligent infrastructures having characteristics such as wireless Automatic Meter Reading (AMR), power system stability monitoring, and demand response system[29]. In the power systems, AI has been widely applied to handle large volumes of power data from intelligent devices, so that service providers could enhance load forecasts, optimise profit, and learn the strategies for demand management and grid operation[12,30]. Power electronics systems, combined with AI and machine learning, and are essential to improve flexibility, reliability, and controllability of power systems, which allow the micro grids and smart grids to operate optimally[31]. These are such smart grids that make a power distribution system more reliable, efficient, and sustainable through smart technologies[32]. Grid modernisation is changing traditional electric power systems and requires the incorporation of new technology such as advanced data analytics and communications technologies[33,34]. These aberrations are important due to the increasing demands for energy and the incorporation of green technologies, making grid study more complex[35,36]. AI also provides advanced smart grid operation functions using intelligent monitoring and control equipment to report electric parameters and raise network alarms[37]. AI can also reduce power usage, most notably in retail, generation, and transmission[4]. AI for prediction of energy supply and demand, optimisation and control of grid operations, as well as for sustainable energy distribution, is especially beneficial for mini-grids that may function independently or interconnected to the national power grid to provide affordable electricity to off-grid communities[38]. AI technologies are essential for dealing with the complexities of the smart grid and enhancing grid operation and reliability[39]. Efficient energy management, with the help of AI, is closely linked to sustainable and smart cities that can promote resource efficiency, environmental protection, and human well-being[40]. Smart grids are also crucial for the integration of distributed renewable generation and energy storage solutions that allow smooth and smart energy curtailment[41,42]. These systems leverage sophisticated electronics and control to advance beyond traditional bulk forms to flexible smart networks[43]. Adoption of computational intelligence, such as AI, at all levels of the smart grid is essential to accommodate uncertainties and to enhance energy utilisation[44]. Table 1 presents the Summary of Artificial Intelligence Applications in Renewable Energy Systems

In summary, the integration of Artificial Intelligence into the energy sector—especially within ORES—presents a transformative opportunity to address critical technical, environmental, and operational challenges. By leveraging AI techniques such as machine learning, fuzzy logic, and neural networks, the energy industry can achieve greater forecasting accuracy, intelligent control, and sustainable grid integration. This foundational understanding sets the stage for exploring AI's specific applications in optimisation, forecasting, and intelligent control of ocean energy systems.

2.0 Why AI in Ocean Energy?

There is a significant transformative potential through the incorporation of AI in ORES, which is to overcome

Table 1. Summary of AI applications in renewable energy systems

Application Area	AI Technique/Tool	Purpose	Key Benefit
Grid stability and forecasting	Machine learning	Predict energy demand/ supply	Improves prediction accuracy
Smart systems optimisation	Fuzzy logic, metaheuristics	Optimise control/ maintenance	Enhances efficiency and reliability
Power plant operations	Decision systems	Automate equipment operation	Reduces manual burden
Energy policy and regulation	AI-enabled policy making	Support carbon neutrality goals	Enables informed policy decisions
Smart grid integration	AI +IoT + sensors	Real-time control and fault detection	Improves grid resilience
Power electronics and control	AI-based algorithms	Control smart/micro grids	Enhances flexibility and stability
Smart city energy management	Computational intelligence	Efficient urban energy use	Promotes sustainability
Data analytics for grid	Big data, predictive models	Scenario generation, risk analysis	Handles operational complexity
Mini-grid support	AI planning tools	Ensure energy access in off-grid areas	Affordable rural electrification
Grid modernisation	Advanced analytics and communication	Replace legacy systems	Supports green tech integration

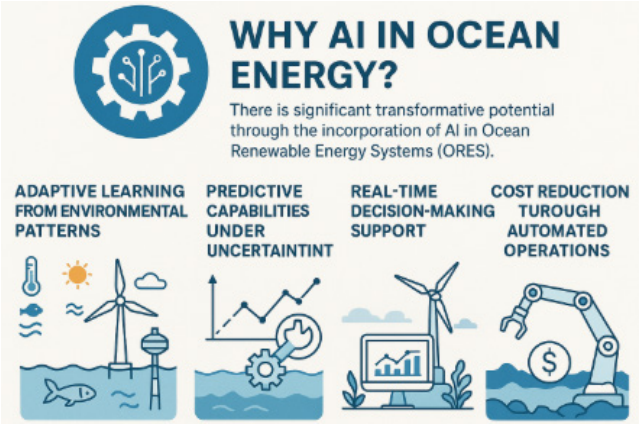


Figure 2. Key advantages of AI integration in ocean renewable energy systems.

many of the operational, environmental challenges in harvesting energy from the ocean. AI makes machines more intelligent for decision making, predictive analytics, and automation to improve system performance, efficiency and reliability. AI-based algorithms are capable of analysing the large volume of data sources and help to optimise the water distribution, estimate equipment failure states and improve the operational efficiency[2,45]. AI also presents potential in scarfing in water treatment and desalination processes, wherein it has learned to handle tremendous amounts of data and project futures while higher-order optimisation of complicated systems is envisaged[46]. The Figure 2 highlights the importance of AI in ORES by enabling adaptive learning from environmental data, predictive modelling under uncertainty, real-time decision support, and cost reduction through automation. These capabilities enhance efficiency, reliability, and sustainability in ocean energy operations.

1.1 Adaptive Learning from Environmental Patterns

The oceans are in constant motion, with fluctuating wave heights, currents, temperatures, and salinity. AI models, particularly those of ML and DL, are able to learn from historical and real-time environmental data to automatically optimise energy conversion processes. AI also assists in optimising control systems and maximising energy capture efficiency by recognising trends in oceanographic conditions. This flexibility makes these devices less sensitive to environmental conditions and

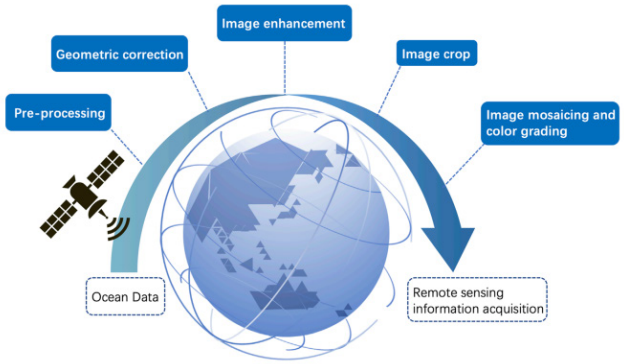


Figure 3. Remote sensing data acquisition process[47].

keeps the devices always work efficiently. The Figure 3 demonstrates how satellite-acquired ocean data undergoes a series of image processing steps—such as pre-processing, geometric correction, and enhancement—to enable intelligent systems to adaptively learn from environmental changes. These processed data help AI models recognise spatial and temporal patterns for accurate decision-making in ocean monitoring and management[47].

In addition, AI improves the prediction of soil moisture that could be utilised in irrigation planning[48]. AI's predictive mapping also assists land managers to locate potential degradation areas[48]. Predictive maintenance and fault diagnosis AI's ability to predict hardware breakdowns before they manifest enables anticipatory maintenance which cruises in breakdowns and the life of vital maritime infrastructure[49]. Through real-time condition-based monitoring, and predictive maintenance, AI reduces downtime and operational costs[50].

1.2 Predictive Capabilities under Uncertainty

Variability in oceanic behaviour is a challenge to power production and safety equipment. It has been proven that AI algorithms, as the Artificial Neural Networks (ANN)[1], Support Vector Machines (SVM)[2], reinforcement learning[3], *etc.* can be used to model non-linear and uncertain systems with an accurate way. Such tools can predict energy production, identify anomalies, and predict service so that maintenance can be scheduled rather than done until something breaks, improving project-level planning and minimising unexpected downtime. Further, AI can process data collected from sensors in real-time identifying pollutants and contaminants to be vigilant of public health crisis and work towards prevention[45]. AI also underpins better decisions and strategies for water management[51]. AI systems can process enormous data from a wide variety of sources, thereby enabling support for complex and multifaceted decision-making while comparing to the conventional approaches is behind to maintain multi-dimensional data without a significant loss of essential details[52]. With the use of real time information and historical data trends, AI enables better estimation and responses which is vital to maximise operations and to minimise risk in the ocean energy[45,53]. Data can be handled on real-time basis by the AI systems and they possess the capability to take prudent decisions, which motivates the maritime industry into a safer, cheaper and greener environment[49]. AI algorithms process available data to identify the core factors that might be associated with future failures, based on past occurrences, and forecast natural wear and tear, anomalies, and remaining useful life of equipment[54]. Figure 4 illustrates the essential components of an AI-based Predictive Maintenance (PdM) system, starting from sensor data collection and preprocessing to AI algorithm application and decision-making. The system ensures communication, integration, and user-friendly reporting for effective maintenance planning.

AI's predictive nature expects issues and failures whilst monitoring data from sensors and detecting slight changes, and recommending logistical alterations[55].

1.3 Real-Time Decision-Making Support

AI based control systems monitor in real-time the environment and can react autonomously to unexpected changes to the environment. For example, control systems that utilise AI can change the angle of turbine blades or the position of buoys based on the current wave pattern and maximise efficiency. This responsiveness that sustains power production as well as the system during extreme conditions.

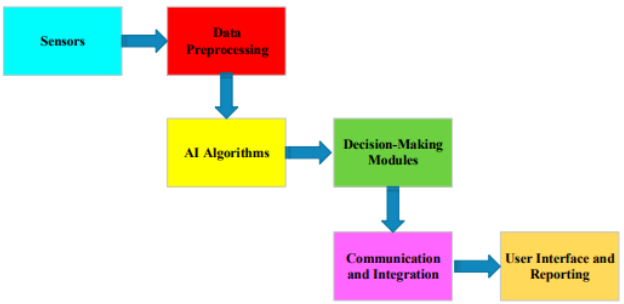


Figure 4. Key components of an AI-based PdM system[54].

This rapid agility makes the ocean energy systems secure, reliable and robust, and minimises the sudden changes in waves or currents, and thus more reliable renewable cleaner sources of energy[56]. Real-time data gathering and sharing with the help of a diverse range of algorithms for decision making are also other strength of AI systems[57]. With AI being capable of processing data, identifying patterns and even auto-responding, better performances and real-time control becomes possible, which is necessary for performance optimisation and assets longevity of ocean renewable energy[58]. AI technologies can also be implemented to stabilise and optimise the renewable energy supply and consumption in a power network by accurately predicting supply and demand, as well as coordinating the Distributed Energy Resources (DER)[18].

1.4 Cost Reduction through Automated Operations

Manual observation and remediation in an offshore environment are costly and time-consuming. AI-driven automation reduces the requirement of human intervention by providing remote system monitoring, autonomous fault diagnosis, and predictive maintenance. This lowers operational costs and increases safety and system lifetime, which together improve ocean energy economics. For instance, cloud-based AI systems incurred significantly lower service outages, quicker service restoration and also significantly higher overall system reliability when compared to the traditional process[59]. AI deployment in maintenance strategies may result in lower downtime and longer life of capital assets, thereby providing potential to save costs and improve operational reliability[60]. It further automates repetitive tasks and minimises opportunities for human error, thereby achieving high accuracy and timeliness of the obtained data[61]. The inclusion of AI does not merely resolve technical challenges; it also sets a direction for a more sustainable and energy-efficient 33 future[62]. AI-based predictive maintenance further improves operational efficiency by predicting maintenance and optimal resources allocations[2]. AI-based approaches also increase the protection of renewable energy systems from cyber-attacks[63]. Table 2 presents summary of AI capabilities in ocean renewable energy systems.

In conclusion, AI stands out as a vital enabler in overcoming the inherent complexities of ocean renewable energy systems. Its ability to process vast and diverse datasets, predict environmental behaviours, automate operations, and enhance decision-making transforms the way energy is harvested from marine environments. By integrating AI into ORES, stakeholders can ensure smarter resource utilisation, improved system performance, and accelerated progress toward sustainable and resilient marine energy infrastructures.

3.0 AI Techniques used in Ocean Energy Systems

Different methodologies of AI have been employed to improve the accuracy, reliability and versatility of ORES. Such methods comprise machine learning, neural networks, genetic algorithms, and fuzzy logic offering different advantages with respect to certain issues in

Table 2. Summary of AI capabilities in ocean renewable energy systems

Section	AI techniques used	Functionality	Key benefits	Applications
Adaptive learning from environmental patterns	Machine Learning (ML), Deep Learning (DL)	Learning from environmental data for energy optimisation	Enhanced energy capture and soil moisture prediction	Wave, current, salinity-based renewable systems
Predictive capabilities under uncertainty	ANN, SVM, Reinforcement learning	Modeling non-linear systems under uncertainty	Improved planning, risk mitigation, public health alert	Energy output prediction, sensor-based diagnostics
Real-Time decision-making support	AI-based control systems, Pattern recognition	Autonomous reaction to environmental changes in real-time	Stable energy production and asset longevity	Turbine blade adjustment, real-time energy supply
Cost reduction through automated operations	Cloud-based AI, Predictive maintenance systems	Automation of operations and remote monitoring	Reduced cost, improved reliability, fewer human errors	Remote diagnostics, cyber-attack prevention

the field of ocean energy[64,65]. These AI are relied on for optimisation, forecasting, as well as control and control management, thus making them part of a system for an effective and sustainable ocean energy technologies[66]. AI techniques synergise with dynamical/physical models to enrich predictive systems and the emergence of fully-integrated forecasting systems for renewable energy is a possibility[67]. These AI-based prognostics deal with data availability, data quality, feature engineering, interpretability and security, all leading to reliable operation of renewable energy systems[68]. AI is also applied for the development of tools based on machine learning for fault detection in naval auxiliary systems in order to predict trends of failures of system components and to enhance the maintenance planning[69]. AI is also applied to develop intelligent water management strategies to address water problems, to enhance the advanced changes of industrial sectors and to make smarter decisions[70]. AI and ML are also crucial in the automating of complex tasks, optimising designs, and enhancing decision-making in various applications, such as optimisation of renewable energy systems[71]. AI can also play an important role in creating data that is difficult to measure directly, extending the classical models, transmitting (eX3 technology) and compensating for the limitations that have the traditional methods of calculation and design for supply chain[6].

These techniques are designed to tackle particular problems such as environmental fluctuations, fault detection, control optimisation, and prediction. Table 3 represents summary of popular AI approaches and their domains of application:

These AI methods significantly improve ORES by enabling smarter decision-making, efficient energy conversion, and predictive maintenance, ultimately making ocean energy systems more viable and cost-effective.

In conclusion, the diverse array of AI techniques—ranging from artificial neural networks and support vector machines to fuzzy logic, genetic algorithms, and deep learning models—offers tailored solutions for various challenges in ocean renewable energy systems. These methods enhance forecasting, fault detection, system control, and optimisation, making ORES more adaptive, reliable, and efficient. Their strategic deployment ensures smarter energy generation, reduced operational risks, and supports the development of intelligent, data-driven marine energy infrastructures.

Table 3. AI techniques used in ocean energy systems

AI Technique	Application Area
ANN (Artificial Neural Networks)	Forecasting ocean energy resources and estimating power output based on historical and real-time data patterns.
SVM (Support Vector Machines)	Used for classifying operational states and identifying wave patterns or system faults.
Fuzzy Logic	Handles imprecise marine data for decision-making in uncertain conditions, enhancing control system responsiveness.
Genetic Algorithms (GA)	Optimises design parameters, control strategies, and system configurations for better efficiency and adaptability.
Deep Learning (CNN, LSTM)	Facilitates long-term prediction and image-based monitoring of ocean environments using time-series and visual data.
Reinforcement learning	Enables adaptive, real-time autonomous control of ocean devices by learning optimal strategies through environmental interaction.

4.0 Forecasting in Ocean Renewable Energy Systems

Reliable prediction of wave power is essential in performance enhancement and scheduling of ORES. With AI techniques, especially Machine Learning (ML) and Deep Learning (DL), accurately predicting ocean parameters such as wave height, tide level, and temperature difference become feasible. Such predictions lead to better estimates of energy production, grid connection, and equipment maintenance.

4.1 Wave and Tidal Energy Forecasting

4.1.1 AI Models Trained on Marine Datasets

Wave and tide power systems require an accurate forecasting of sea conditions such as wave height, wave period, wave direction and tidal flow velocity. Machine learning models, such as ANNs and SVMs are developed on historical and real-time ocean data to predict energy production and to determine the performance of the system. These data-informed techniques improve the

planning and performance of wave and tidal farms[64]. Such AI models are able to model the non-linear relations, learn in time-varying world and are appropriate to develop based on the dynamic sea environment[70]. The capability of AI to analyse the unstructured data like weather trends, as well, means more accurate forecasting[72]. Such integration of multiple data sources using AI technologies will suggest a potential direction, as AI techniques, including deep learning, are strong in processing complex and large-scale datasets and reveal subtle patterns[73]. Artificial intelligence-based prediction models can be further set as benchmarks to measure process parameters deviations in individual elements and the system[74]. The application prospect of DL in different application has inspired many researchers, as can be seen from the wealth of proposed methods and the growing number of publications[75]. Prediction of ocean states is essential not only for air-sea interaction but also for mitigating the effects of ocean anomalies or extreme phenomena[76]. As well, deep learning models are utilised to predict wave-induced loads on ocean structures with historical data, which makes estimation of wave properties in favourable areas[77]. Figure 5 represents AI-powered forecasting approaches in ocean renewable energy systems.

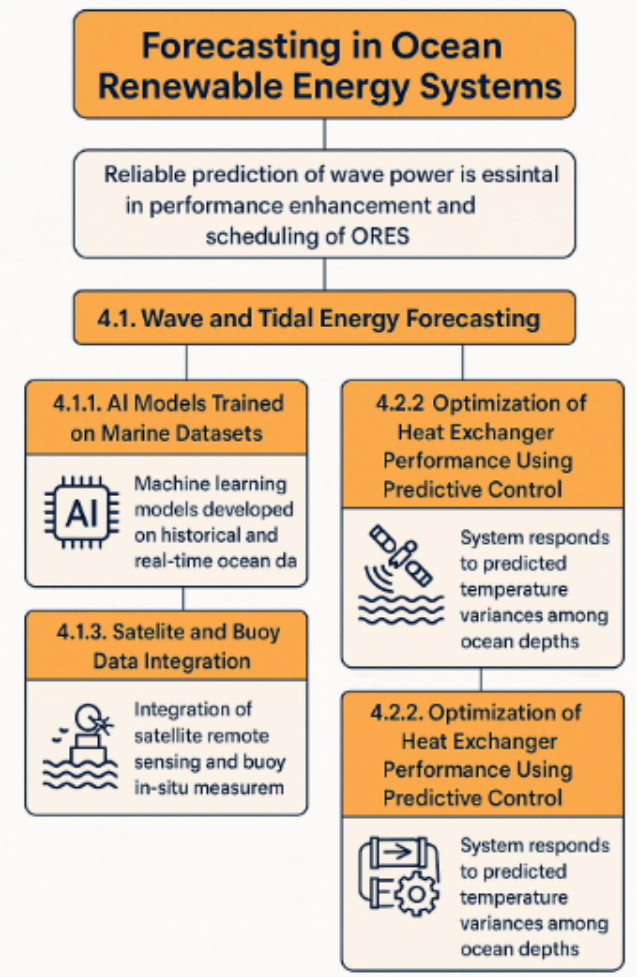


Figure 5. AI-powered forecasting approaches in ocean renewable energy systems.

4.1.2 Use of LSTM and CNN for Spatiotemporal Prediction

LSTM networks, while CNN are good at managing temporal and spatial data, respectively. The LSTM models learn the temporal dependency in wave and tide observations and the CNNs capture the spatial feature from satellite images and oceanic maps. They can be used to dynamically predict spatiotemporal information, to assist real-time operational decisions. This is very useful for path planning and AUV autonomous control[78]. These models provide advance-warning information essential for motion prediction and offshore operations[79]. AI also enhances forecast accuracy in predicting daily streamflow over a 7-d forecast horizon using long short-term memory networks[80]. Neural networks have also been used as one of the popular techniques to address some of the drawbacks of the classical methods and have shown to perform well in time-series prediction[81]. Prediction of the full time-series evolution of storm surge with neural networks can improve tools for decision-making in emergency response and regional planning[82]. Deep learning approaches are particularly applicable due to their capability of identifying complex patterns buried in large data, which is crucial for accurate prediction of ocean phenomena[83].

4.1.3 Satellite and Buoy Data Integration

Integration of satellite remote sensing measurements with buoy in-situ measurements improves the forecast. Buoys supply real-time wave information in a local area, and satellites provide broad spatial coverage. The AI models incorporate both data to form a stable model that can predict wave and tidal systems in the near term and the long term. Convolutional Neural Networks have also shown to be very successful in image and pattern recognition, as well as physics-based simulations such as structural analysis and computational fluid dynamics, suggesting the strong capabilities of a CNN to deal with

data coming from tsunami or geodetic observation networks to achieve an outstanding forecasting performance[84]. Such networks train the relationship between observation data and generated tsunami waveforms, and are applicable to predict inundation tsunami waveforms at onshore forecasting sites based on observation data[84]. Artificial Neural Networks present a data driven approach, learning the relationships between provided variables by means of training algorithms conducted on available data, being useful tools for the analysis of complex scenarios, where the purpose is to analyse the outcome not the underlying phenomena[85]. AI techniques, such as fuzzy logic and artificial neural networks, are frequently used in a joint framework to increase forecasting accuracy and flexibility particularly when using non-linear and noisy data[86]. For example, artificial neural networks are growing up and growing fast, especially in terms of forecasting spatiotemporal models, because they are good at predicting non-linear functions without the need for any data assumptions[87]. With a large enough dataset that records specific surface wave and current distributions, a deep learning network could be trained to produce an optimal mode solution through minimising a loss function, and the computed solution is generic and has a very low computational cost[88]. Such models are as close to natural ontogeny as possible and are able to incorporate large amounts of characteristic data[83]. The development of algorithms aiming at the dynamic monitoring of algal blooms involving AI-driven analysis of the high-resolution satellite imagery (such as by using NIR and SWIR bands of the Sentinel-2 imagery, altitude, temperature, wind, longitude and latitude) shows that such deep learning models have the capability to employ various remote sensing inputs for solving environmental issues of high interest[89]. Large success of artificial neural networks for modelling complex issues mainly justified by their high capability in approximating nonlinear relationships and in managing time series[90].

4.2 Ocean Thermal Gradient Prediction

4.2.1 Application of ANN and Fuzzy Models

Ocean Thermal Energy Conversion (OTEC) has temperature differentials between surface and deep ocean waters. The thermal gradients are modelled using according to a neural network and a fuzzy logic system, taking into account parameters such as depth, solar radiation and ocean currents. These models can be used to estimate thermal energy extraction performance and ability in various sites. Using the time-lagged input-output data into such models, they can accurately forecast the algae alert levels and hence early warning of the cyanobacterial bloom is expected in freshwater reservoirs[91]. Besides artificial neural network approaches, linear regression, support vector regression and neuro-fuzzy network methods have also been applied for the prediction of change of pollutant concentration[92]. These approaches provide great practical interest in predicting water quality changes at high-density aquaculture, which may help in the process of avoiding water quality deterioration and outbreak of diseases[93]. Artificial neural networks can be designed without explicit knowledge of the kinetics of the system and can be updated on-line with a small sampling effort, making them appropriate to real-time control situations[94]. Such models are easy to construct and utilise, but generally require a large volume of high-quality data for training[95]. They can be a valuable as a tool for forecasting of hydrology and water quality in agricultural watershed, in which traditional models face limitations caused by the intricate physical rates[96]. Long short-term memory networks- another type of neural network- have been also employed for discharge-level prediction providing increased efficiency in capturing temporal dependence of hydrological data when compared to classical methods[97]. These networks have demonstrated the potential to deal with the problem of long-term dependency in traditional numerical schemes and other neural networks[97,98].

4.2.2 Optimisation of Heat Exchanger Performance using Predictive Control

Use of Artificial Intelligence based predictive controllers for Heat exchanger control in OTEC systems. The system can respond to predicted temperature variances among ocean depths by making changes in flow rates and configurations to optimally convert energy to electricity. This results in a lower thermal loss and better system performance. Predictive models are also making it easier to interpret variability in process parameters, which helps improve operational and sustainability aspects of resource management[74]. Predictive tools have progressed in a substantial way, focusing issues like data loss or stability analysis, and involving applications including drinking water networks and building systems[99]. In addition, the

ensemble modelling that uses the methods such as simple and weighted average and the ensemble of the neural network improves the prediction of single model[100]. Another type of recurrent neural network, LSTM networks, have also been applied to pressure forecasting in water networks, and showed their potential in such tasks as gas and oil pipeline monitoring[74]. Naive approaches are increasingly applicable, thanks to neural networks, which can be trained to run in parallel on processors such as GPUs, simplifying approach adaptation and system scale-up[101]. Regarding the water supply system, the performance and accuracy of prediction have been improved by LSTM models compared to the conventional methods[102]. These should lead to better prevention and response on water supply systems and other sectors, such as gas and heat supply[74]. Table 4 presents Summary of Forecasting Applications using AI in Ocean Renewable Energy.

In summary, AI-based forecasting has revolutionised the ability to predict critical ocean parameters such as wave height, tidal flow, and thermal gradients with greater accuracy and reliability. Techniques like ANN, SVM, LSTM, CNN, and fuzzy logic enable dynamic, real-time insights that improve energy production planning, operational efficiency, and risk mitigation. By integrating satellite and buoy data, these AI models support smarter, more resilient decision-making in the deployment and operation of ocean renewable energy systems.

5.0 Optimisation Techniques

Optimisation techniques are essential for improving the design, efficiency, and deployment strategies of ORES. AI-powered methods like Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), and hybrid models play a crucial role in solving complex, multi-variable engineering problems in ocean energy harvesting.

5.1 Energy Conversion Efficiency

5.1.1 Use of GA and PSO for Optimising Turbine Blade Shape and WEC Damping Factors

Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO) are accordingly effective tools to optimise design parameters including turbine blade profiles and wave energy converter (WEC) damping

Table 4. Summary of forecasting applications using AI in ocean renewable energy

Section	Forecasting scope	AI Techniques used	Functionality	Key benefits	Applications
AI models trained on marine datasets	Wave and tidal energy output	ANN, SVM, DL, CNN	Model wave/tidal parameters using marine datasets	Improved planning and performance of ORES	Wave/tide farms, ocean monitoring
Use of LSTM and CNN for spatiotemporal prediction	Real-time ocean condition	LSTM, CNN	Predict spatial-temporal ocean conditions in real-time	Enhanced real-time decision support and forecasting	AUV navigation, emergency planning
Satellite and buoy data integration	Wave/tide behavior with multi-source data	CNN, ANN, Fuzzy Logic	Combine satellite and buoy data for wave/tide forecasting	Higher accuracy and reliability in forecasting	Disaster alert systems, climate analysis
Application of ANN and fuzzy models	Thermal gradients and water quality	ANN, Fuzzy Logic, LSTM, SVR	Forecast ocean thermal gradients and algal blooms	Accurate estimation of energy and environmental safety	OTEC, freshwater monitoring, aquaculture
Optimisation of heat exchanger performance using predictive control	Energy efficiency in OTEC systems	Predictive Controllers, LSTM, Ensemble NN	Optimise OTEC heat exchangers based on temperature variance	Better conversion efficiency and thermal control	OTEC plants, water/gas pipeline management

coefficients. By simulating through many different configurations, these algorithms find the optimal shapes and operation settings in order to maximise the energy conversion and minimise the hydrodynamic losses. These optimisations tend to lead to a higher value and cost-efficient energy extraction[103]. They are also proposed for design and tuning devices to increase efficiency, reliability, and cost-effectiveness that should make, in the long terms, ORE more competitive and sustainable[104]. Hybrid AI Models for Rapid Adaptation Hybrid AI models utilise a plethora of optimisation approaches to manage real-time adjustment of ORE systems. Using coupling with predictive prediction and adaptive control algorithms, these models make it possible to take dynamically into account varying oceanic conditions (wave elevations, tidal currents, water temperature, and so forth)[105]. These modifications maximise energy uptake and decrease mechanical load on the apparatus[106]. Genetic Algorithms (GAs), inspired by natural selection, are very good at solving multi objective optimisation problems in which efficient solutions are sought[107]. PSO, which is based on social behaviour, is a powerful for optimisation of complex engineering problems[108]. Figure 6 presents AI-driven optimisation techniques for ocean renewable energy systems.

5.1.2 Multi-Objective Optimisation for Energy Yield vs. Structural Stability

Marine devices need to compromise between maximum energy uptake and maintaining a safe structure in the harsh marine environment. B E RICNS Multi-objective optimisation methods compare trade-offs between objectives including power, fatigue life, and material cost. This results in designs, which are robust and efficient, thus being productive, but also solid and economically viable. AI algorithms can maximise energy density and economic indicators, e.g., net present value, thus solutions that are coherent with the demands from the regulators can be obtained[109]. In particular, in multi-objective optimisation, Pareto optimal points trade-offs are considered by taking into account the complex nature of energy systems characterised by multi-scale, distributed and nonlinear models[110]. Location of Power Plants Using AI algorithms AI-based algorithm can analyse the Geographical and Topographical Data, Environmental factors, conditions and then predict the best locations for setting up renewable energy plants, thereby enhancing

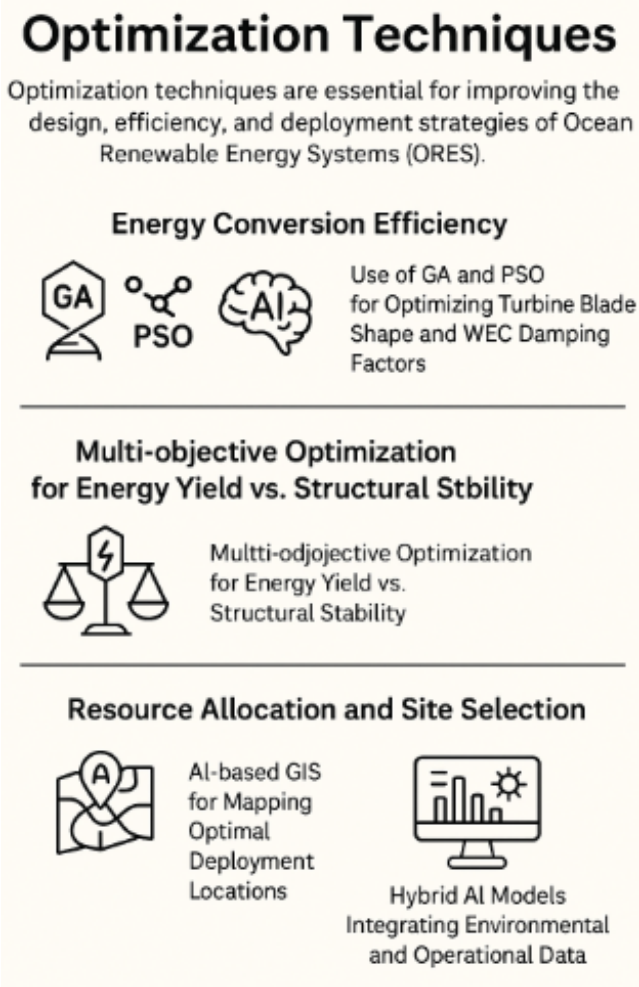


Figure 6. AI-driven optimisation techniques for ORES.

power generation and minimising environmental impact and cost[9]. These approaches are necessary to cope with the increasing need for renewable and sustainable energy sources, also not to be underestimated from an economic point of view[2]. Hybrid algorithms which are comprised of several heuristic methods that further improve solution variety and the rate of convergence of single method are also becoming more and more fashionable that are applicable to solve a few conflicting objective problems[111,112]. AI has been widely benefiting from nature inspired optimisation algorithms that are actually stochastic search points that are very effective in finding and navigating the design space while adapting to the changes and improving the higher education and personalisation of teaching management[113]. These algorithms treat optimisation problems as a black box, dynamically adapting their output according to the input with no mathematical models of the search landscape,

which resulting in high flexibility[114]. These approaches are also being able to outperform at the global or near-global optima with less information for problems[115,116].

5.2 Resource Allocation and Site Selection

5.2.1 AI-Based Geographic Information Systems (GIS) for Mapping Optimal Deployment Locations

AI-driven geospatial tools support pinpointing high potential sites to deploy OES. These AI-GIS models use data on bathymetric features, wave/tide patterns, ecological impact zones, and proximity to grid infrastructure to suggest high-sustainability potential sites for development. AI algorithms determine whether a renewable energy project is optimally located based on a range of environmental and logistical variables to optimise the output of energy and minimise its cost to the environment[18]. ARM Datacentre Predictive Modelling for Resource Availability and Variability Accurate prediction of resource availability and variability of metal cast ocean energy is highly desirable[1]. There are survey models based on historical and real-time observational data that predict wave elevations, tidal currents and temperature gradients, all of which are critical for resource management and resource planning[8].

5.2.2 Hybrid AI Models Integrating Environmental and Operational Data

By integrating with physical simulations, machine learning models can be used in hybrid optimisation frameworks considering both operating constraints (*e.g.*, maintenance schedules, accessibility) and environmental conditions (*e.g.*, sea state, temperature, salinity). Such unified approaches can assist developers to make proper choices of the most effective sites and system design for the best long-term performance. AI can be used to manage resources more efficiently, take better decisions and offer personalised learning experience, these are all the requirements of a futuristic educational prospective[113]. Your submission promises to be a valuable tool to solve the resource allocation and site selection problem in ocean renewable energy systems due to the flexibility of AI optimisation methods[11,13]. AI technologies such as graph neural networks, recurrent neural networks are essential for addressing the scaling of optimisation problems and their model complexity in practical AI applications[117]. These models can process large datasets to improve the performance of ocean renewable energy devices and minimise their environmental impact[3]. AI has the potential for optimising energy systems, reducing greenhouse gas emissions, and contributing to a climate-resilient future by analysing energy usage patterns to identify energy conservation measures and energy optimisation measures[9]. Table 5 represents summary of AI-based optimisation techniques in ocean renewable energy.

In conclusion, AI-powered optimisation techniques such as GA, PSO, and hybrid models play a critical role in enhancing the performance, efficiency, and sustainability of ocean renewable energy systems. These methods

Table 5. Summary of AI-based optimisation techniques in ocean renewable energy

Section	AI techniques used	Functionality	Key benefits
Use of GA and PSO for optimising turbine blade shape and WEC damping factors	Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), hybrid ai models	Optimise design profiles and configurations under hydrodynamic constraints	Enhanced energy conversion and cost-effectiveness
Multi-objective optimisation for energy yield vs. structural stability	Multi-objective optimisation, pareto analysis, hybrid algorithms	Analyse trade-offs between energy output, fatigue life, and economic feasibility	Improved system reliability and economic sustainability
AI-based GIS for mapping optimal deployment locations	AI-GIS tools, predictive modelling	Analyse environmental and topographical factors to select optimal sites	Efficient resource use, minimised environmental impact
Hybrid AI models integrating environmental and operational data	Hybrid ML models, GNN, RNN, physical simulations	Integrate operational and environmental data for informed deployment decisions	Holistic planning and improved long-term performance

enable multi-objective decision-making, precise control tuning, and intelligent site selection by analysing complex environmental and operational parameters. As a result, AI-driven optimisation ensures robust, cost-effective designs that maximise energy output while minimising structural stress and ecological impact.

6.0 Intelligent Control Systems

Intelligent control systems powered by AI are crucial for the efficient, reliable, and autonomous operation of ORES. These systems enable real-time decision-making, predictive maintenance, and adaptive responses to dynamic marine environments.

6.1 Real-Time Monitoring and Fault Diagnosis

6.1.1 Use of SVM and ANN for Predictive Maintenance and Anomaly Detection

SVMs and ANN are the most frequently deployed to detect anomalies and predict faults in ocean energy devices. These models are developed on top of sensor data viz vibration, temperature, and pressure to predict the early signs of component wear or failure. Early failure detection enables proactive maintenance, which helps minimising downtime and maximising equipment life. Similar AI practices are applied (called AI Grid Health Monitoring – AGHM) in article[118] as a tool for modelling, prediction, and fault detection described to be beneficial for traditional physical modelling in the above points "Guide to Feature Extraction", meaning AI is an appropriate tool for these[118]. AI-enhanced Monitoring for Grid Stability and Power Quality AI algorithms provide grid stability fulfilment by continuously monitoring the power quality and conditions of the grid. These systems can respond to disturbances in real-time, utilising data that already exists over the network to provide grid stabilising (reliable) ocean renewable energy power supply[7]. These AI-based monitoring systems are crucial in integrating VRE sources into the grid while ensuring the overall grid stability[24]. AI enhances fault detection by studying the interactions of input variables and output responses, allowing quick isolating a fault by detecting deviations from expected performance[119]. Water Quality and Consumption Ensuring water quality, predicting users' water[45] consumption, and estimating the exact amount of water required by users for effective water resources allocation are some of the applications of AI as well as intelligence for water quality and consumption. - Operation Optimisation of Renewable Energy (Solar, Wind) for Predictive Maintenance AI and machine learning form an essential component of addressing high capital costs and advancing the 2. Intelligent Maintenance based on AI and Industrial IoT implements a framework to combine real-time data collection, transferring, and storage through wireless sensors with Big Data techniques to online train and deploy the machine learning models for decision support[120]. These models are taken through the process of training, involving historical data that captures the normal and fault states of the equipment, and then are used to make predictions on the state of the equipment with new data[121]. Deep learning technology is also used in the fault diagnosis and prediction of system health management, from the traditional monitoring of mechanical equipment to electrical systems and power system[122]. Artificial intelligence algorithms can identify and even anticipate faults before they present, conditioning or predictive maintenance that minimises reactive maintenance and ensures the reliability of machinery will be achieved[123]. Figure 7 represents intelligent control systems in ocean renewable energy systems.

6.1.2 AI-Enabled SCADA Systems for Autonomous Fault Reporting

SCADA systems with AI drive independent fault detection and reporting. These intelligent systems are constantly watching over and assessing the operations and conditions in real time, alarm us if things aren't

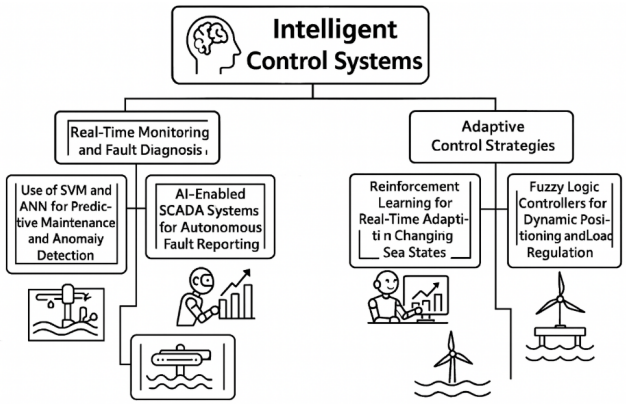


Figure 7. Intelligent control systems in ocean renewable energy systems.

working as expected, give us suggestions on what to change and process the changes without human intervention. This makes the system safer, particularly at offshore installations in remote locations. Predictive analytics to predict asset failures using machine learning and data analysis to undertake preventative maintenance that prevent outages and extend the life of key maritime infrastructure are one of the significant benefits of AI[49]. Predictive maintenance based on AI is both a choice and a necessity, providing a competitive benefit for them with its enhanced efficiency, economy and sustainability[124]. Predictive analytics employs statistical modelling to uncover strategic insights from historical data for real-time decision support for select equipment[125]. Operationally, AI technologies optimise equipment utilisation thus reducing downtime and waste[126]. AI approaches also aid enhancing maintenance through predictions of possible failures and promoting conditions-based maintenance, supported by digital twins in Industry 4.0[127]. Through automation of hazard detection and resource allocation, AI can greatly improve the situation awareness and response in emergency cases[53].

6.2 Adaptive Control Strategies

6.2.1 Reinforcement Learning for Real-Time Adaptation to Changing Sea States

Also, RL-based approaches facilitate ocean energy conversion devices to learn through interacting with the environment and optimising the control input. For instance, a wave energy converter can dynamically control the damping behaviour to track the wave height and period to increase the efficiency of energy capture. This adaptive controller improves energy production and system robustness in varying marine environments[124]. The power production of tidal turbines can be enhanced by using intelligence techniques such as machine learning to control the blade pitch and the yaw angle in real time in order to maximise the power extraction[50]. AI agents could analyse large volumes of the real-time data for informed decision making which would improve safety and efficiency[49]. These algorithms examine data to identify characteristics known to be associated with potential failures that have learned from historical events how to predict equipment failures and estimate remaining useful life[54]. AI algorithms process data from sensors, monitor variations, and suggest corrections to logistics, project specificity, production flow maintenance, system performance, and product quality[55]. AI can also anticipate the specific water demands of users, enabling dam controllers to allocate water resources more efficiently[45]. Compared with other methods of handling multi-dimensional data, AI systems are able to process large and variable data for more accurate decision-making[52]. AI's generalisation and learning from past experience make it an invaluable instrument for forecasting parameters required in complex systems[56]. AI can also enhance estimation of soil moisture, being critical for irrigation and drought tracking[48].

6.2.2 Fuzzy Logic Controllers for Dynamic Positioning and Load Regulation

Controllers based on fuzzy logic are capable of effectively coping with uncertain and vague inputs, such as sea currents or wave patterns. These controllers provide dynamic positioning of the floating structures and control the electrical load when the energy generation is irregular in order to maintain proper performance and stability of the system. AI algorithms can also improve the integration of renewable energy resources in the power grids, as well as tackle the "intermittency problem" of solar and wind power[18]. AI can greatly enhance wind-farm performance by considering meteorological data and its relation to the turbines, maximising electricity generation[128]. AI can promote a shared renewable future through the development of smart grids, matching demand with the supply of electricity[19]. The use of AI allows proper energy prediction and optimum energy distribution, particularly for mini-grids that work standalone or with national grids[38]. Furthermore, AI enables high availability thanks to smart load balancing, which guarantees that the resources are efficiently shared in order to provide the service under all circumstances, even in the presence of peak loads or failures[59]. Renewable energy production forecasting can, for example, allow for more efficient energy use as well[58]. Moreover, AI algorithms can help optimise energy consumption through energy demand forecasting and dynamic adjusting of energy supply on the fly[16,45]. AI is also used to solve water treatment and desalination problems, optimising the complex systems in order to minimise energy consumption and operational costs, and thus sustainability[46]. AI encompasses a plethora of tools, techniques and algorithms (*e.g.*, robotics, autonomous vehicles, neural networks, and machine learning) that offer the ability to allow intelligent systems to think and

Table 6. AI in intelligent control systems

Content	AI techniques used	Applications	Key benefits
Use of SVM and ANN for predictive maintenance and anomaly detection	SVM, ANN, Deep learning, AI Grid Health Monitoring (AGHM)	Early fault detection, condition monitoring, grid stability, predictive water demand estimation	Reduced downtime, extended equipment life, improved grid reliability
AI-Enabled SCADA systems for autonomous fault reporting	Machine learning, predictive analytics, digital twins, statistical modelling	Real-time system monitoring, hazard detection, preventive maintenance, and decision support	Improved safety, minimised outages, extended infrastructure lifespan
Reinforcement learning for real-time adaptation to changing sea states	Reinforcement learning, real-time sensor data analytics, predictive modelling	Blade pitch/yaw optimisation, adaptive wave tracking, failure prediction, irrigation demand estimation	Maximised energy capture, increased operational safety and efficiency.
Fuzzy logic controllers for dynamic positioning and load regulation	Fuzzy logic, neural networks, smart load balancing, AI forecasting	Dynamic system stability, renewable grid integration, smart grid management, energy optimisation	Enhanced system robustness, balanced energy supply, and sustainability

Table 7. Case studies: AI applications in ocean renewable energy systems

Case Study	Technology	AI technique used	Key outcome
Wave Energy Converter (WEC) – Portugal	Wave energy	AI-based forecasting (ANN/ CNN)	Improved wave energy prediction accuracy by 20% compared to traditional models.
Tidal turbines – Scotland	Tidal energy	Reinforcement learning	Optimised blade pitch control, resulting in an 8% increase in power output.
OTEC facility – Japan	Ocean thermal energy	ANN-based control systems	Enhanced control of condenser operations, reducing energy losses significantly.

learn for itself[129-131]. Table 6 represents details of AI in intelligent control systems.

In conclusion, intelligent control systems powered by AI enable real-time responsiveness, predictive maintenance, and adaptive operation in ocean renewable energy systems. Techniques such as ANN, SVM, reinforcement learning, and fuzzy logic provide advanced capabilities for monitoring, fault diagnosis, and autonomous control. These AI-driven systems enhance the reliability, safety, and efficiency of ORES, allowing them to operate optimally in dynamic and uncertain marine environments while reducing downtime and operational costs.

7.0 Case Studies

Real-world implementations of AI in ORES demonstrate significant improvements in forecasting accuracy, operational efficiency, and energy output. Table 7 represents the case studies highlighting AI applications across different ocean energy technologies.

These case studies validate the potential of AI in enhancing ORES's intelligence, autonomy, and efficiency, thereby contributing to its scalability and long-term sustainability.

8.0 Research Gaps and Future Directions

Despite promising advancements in integrating AI with ORES, several critical research gaps must be addressed to enable robust, scalable, and trustworthy deployment. Future efforts should focus on the following key areas:

8.1 Need for More Labelled Datasets for AI Training in Ocean Environments

Well-labelled datasets are vital for training supervised machine learning models. However, marine data are generally characterised by scarcity, fragmentation or lack of labels, and this is because of the complexity and costs that are involved in their collection. There is an urgent need to establish open-access and richly annotated oceanic datasets that span multiple regions and oceanographic features that could benefit from AI training and validation.

8.2 Fusion of Hybrid AI Models and IoT and Edge Computing

For making real-time decisions in extreme marine environmental condition, the AI model should be deployed with IoT sensors and edge computing platform. This results in distributed processing of the data, minimisation of latency and system control without intervention. Future work should construct lightweight and power efficient hybrid AI models for the edge deployment.

8.3 Designing Performance Metrics for AI Models

As of now, there is no comprehensive evaluation framework for AI algorithms in ORES applications. Benchmarking AI models across different MET is a niche that not only needs, but also requires standardised performance metrics that account for an intelligent balancing between accuracy, robustness, energy efficiency and adaptability.

8.4 Increasing Interpretability and Trust in AI-Based Decision Making

The black-box behaviour of most of the AI models, and specifically Deep Learning (DL), restricts their potential for safety-critical tasks such as those found in offshore energy. A shift toward explainable AI (XAI) approaches has been increasingly demanded to enhance transparency, increase trust from stakeholders, and meet regulatory requirements.

8.5 Quantum AI for Real-Time Marine Systems Modelling

One motivation of quantum computing is the ability to solve high-dimensional problems in real time, which are costly to solve using classical techniques. Mechanisms such as quantum machine learning and quantum neural networks could be further examined for real-time modelling, forecasting and optimisation of ocean systems.

In conclusion, while AI has significantly advanced the capabilities of ocean renewable energy systems, several research gaps remain that must be addressed to ensure robust and scalable implementation. These include the need for high-quality labelled datasets, integration with edge computing and IoT, development of standardised performance metrics, and enhanced model interpretability through explainable AI. Additionally, the emerging potential of Quantum AI offers a promising frontier for real-time, high-dimensional marine system modelling. Addressing these challenges will be vital for unlocking the full potential of AI in achieving sustainable and intelligent ocean energy solutions.

9.0 Conclusion

The integration of AI in ORES marks a significant technological leap toward achieving a reliable, efficient, and sustainable marine energy infrastructure. This review has established that AI techniques—ranging from machine learning algorithms and deep learning networks to hybrid optimisation models—are instrumental in addressing the inherent challenges of ocean energy harvesting, including environmental variability, system unpredictability, and high operational costs. By enabling intelligent forecasting of wave, tidal, and thermal patterns, AI supports more accurate energy resource estimation and system planning. AI-driven predictive maintenance frameworks ensure operational reliability by identifying faults and potential failures before they occur, significantly reducing system downtime and maintenance costs. Furthermore, AI-enhanced control systems allow for real-time decision-making and dynamic responses to fluctuating marine conditions, ensuring continuous and optimised energy generation.

Optimisation methods such as Genetic Algorithms and Particle Swarm Optimisation, along with hybrid AI models, contribute to the improved efficiency and structural stability of ocean energy devices. These technologies facilitate the design of robust systems that balance energy yield with material and environmental considerations. AI's integration with Geographic Information Systems (GIS) has also proven effective

in site selection and resource allocation, promoting environmentally responsible development. Despite these advancements, several challenges persist. There is a pressing need for more comprehensive and labelled datasets specific to ocean environments, the adoption of hybrid AI-edge computing frameworks for remote operations, and the development of standardised metrics to evaluate AI model performance in ORES. Additionally, enhancing the transparency and explainability of AI decisions is essential to ensure safety, stakeholder trust, and regulatory compliance. Looking forward, emerging paradigms such as Quantum AI hold the potential to further revolutionise real-time modelling and control of complex marine systems. By bridging current research gaps and leveraging the full capabilities of AI, future ocean energy systems can become more autonomous, scalable, and adaptive—playing a crucial role in the transition to a low-carbon global energy landscape.

10.0 Author Contributions

Manjusha Tatiya: Conceptualisation, Methodology, Investigation, Writing – Original Draft, Supervision. Pragati Choudhari: Formal Analysis, Data Curation, Visualisation, Writing – Review and Editing. Hemantkumar Balasaheb Jadhav: Software, Validation, Writing – Review and Editing. Puja Gholap: Resources, Literature Review, Writing – Original Draft. Yogendra Patil: Investigation, Methodology, Figures and Tables Preparation. Rupesh Gangadhar Mahajan: Writing – Review and Editing, Supervision, Project Administration. Anant Sidhappa Kurhade: Technical Review, Domain Expertise, Writing – Review and Editing, Validation.

11.0 References

1. Wang Q, Li Y, Li R. Integrating artificial intelligence in energy transition: A comprehensive review. Energy Strat Rev. 2025; 57:101600. https://doi.org/10.1016/j.esr.2024.101600
2. Bello SA, Wada I, Ige OB, Chianumba EC, Adebayo SA. AI-driven predictive maintenance and optimization of renewable energy systems for enhanced operational efficiency and longevity. Int J Sci Res Arch. 2024; 13(1):2823-2837. https://doi.org/10.30574/ijsra.2024.13.1.1992
3. Pachot A, Patissier C. Towards sustainable artificial intelligence: An overview of environmental protection uses and issues. Green and Low-Carbon Econ. 2023; 3(2):105-112. https://doi.org/10.47852/bonviewglce3202608
4. Biswas P, Rashid A, Biswas A, Nasim MAA, Gupta KD, George R. AI-driven approaches for optimizing power consumption: A comprehensive survey. arXiv (Cornell University). 2024. Available from: http://arxiv.org/abs/2406.15732
5. Zhao S, Blaabjerg F, Wang H. An overview of artificial intelligence applications for power electronics. IEEE Trans Power Electron. 2020; 36(4):4633-4658. https://doi.org/10.1109/tpel.2020.3024914
6. Liao M, Yao Y. Applications of artificial intelligence-based modeling for bioenergy systems: A review. GCB Bioenergy. 2021; 13(5):774-802. https://doi.org/10.1111/gcbb.12816
7. Antonopoulos I, Robu V, Couraud B, Kirli D, Norbu S, Kiprakis A, *et al.* Artificial Intelligence and machine learning approaches to energy demand-side response: A systematic review. Renew Sust Energ Rev. 2020; 130:109899. https://doi.org/10.1016/j.rser.2020.109899
8. Yadav M, Singh G. Environmental sustainability with Artificial Intelligence. Int J Multidiscip Res. 2023; 9(5). https://doi.org/10.36713/epra13325
9. Olawade DB, Wada OZ, David-Olawade AC, Fapohunda O, Ige AO, Ling J. Artificial Intelligence potential for net zero sustainability: Current evidence and prospects. Next Sustainab. 2024; 4:100041. https://doi.org/10.1016/j.nxsust.2024.100041
10. Jin D, Ocone R, Jiao K, Xuan J. Energy and AI. Energy AI. 2020; 1:100002. https://doi.org/10.1016/j.egyai.2020.100002
11. Alsaigh R, Mehmood R, Katib I. AI explainability and governance in smart energy systems: A review. Front Energy Res. 2023; 11. https://doi.org/10.3389/fenrg.2023.1071291
12. Heymann F, Quest H, Garcia T, Ballif C, Galus MD. Reviewing 40 years of Artificial Intelligence applied to power systems – A taxonomic perspective. Energy AI. 2023; 15:100322. https://doi.org/10.1016/j.egyai.2023.100322
13. Sirmacek B, Gupta S, Mallor F, Azizpour H, Ban Y, Eivazi H, *et al.* The potential of artificial intelligence for achieving healthy and sustainable societies. arXiv (Cornell University). 2022. https://arxiv.org/abs/2202.07424
14. Kabir M, Ekici S. Energy-agriculture nexus: Exploring the future of Artificial Intelligence applications. Energy Nexus. 2023; 13:100263. https://doi.org/10.1016/j.nexus.2023.100263

15. Ahmad T, Zhang D, Huang C, Zhang H, Dai N, Song Y, Chen H. Artificial Intelligence in sustainable energy industry: Status Quo, challenges and opportunities. J Clean Prod. 2021; 289:125834. https://doi.org/10.1016/j.jclepro.2021.125834
16. Uriarte-Gallastegi N, Landín GA, Landeta-Manzano B, Laskurain-Iturbe I. The role of AI in improving environmental sustainability: A focus on energy management. Energies. 2024; 17(3):649. https://doi.org/10.3390/en17030649
17. Franki V, Majnarić D, Višković A. A comprehensive review of Artificial Intelligence (AI) companies in the power sector. Energies. 2023; 16(3):1077. https://doi.org/10.3390/en16031077
18. Stern N, Romani M, Pierfederici R, Braun M, Barraclough D, Lingeswaran S, *et al*. Green and intelligent: The role of AI in the climate transition. npj Clim Action. 2025; 4:56. https://doi.org/10.1038/s44168-025-00252-3
19. Vinuesa R, Azizpour H, Leite I, Balaam M, Dignum V, Domisch S, *et al*. The role of artificial intelligence in achieving the sustainable development goals. Nature Comm. 2020; 11(1):233. https://doi.org/10.1038/s41467-019-14108-y
20. Rajaperumal TA, Columbus CC. Transforming the electrical grid: The role of AI in advancing smart, sustainable, and secure energy systems. Energy Inform. 2025; 8:51. https://doi.org/10.1186/s42162-024-00461-w
21. Xie L, Huang T, Zheng X, Liu Y, Wang M, Vittal V, *et al*. Energy system digitization in the Era of AI: A three-layered approach towards carbon neutrality. arXiv (Cornell University). 2022. Available from: https://arxiv.org/abs/2211.04584
22. Xie L, Zheng X, Sun Y, Huang T, Bruton T. Massively digitized power grid: Opportunities and challenges of use-inspired AI. Proc IEEE. 2022 Jun; 111(7):762-787. https://doi.org/10.1109/jproc.2022.3175070
23. Safari A, Daneshvar M, Anvari-Moghaddam A. Energy intelligence: A systematic review of Artificial Intelligence for energy management. Appl Sci. 2024; 14(23):11112. https://doi.org/10.3390/app142311112
24. Zhang R. Artificial intelligence in power system security and stability analysis: A comprehensive review. arXiv (Cornell University). Cornell University. 2024. Available from: http://arxiv.org/abs/2408.08914
25. Campana P, Censi R, Ruggieri R, Amendola C. Smart grids and sustainability: The impact of digital technologies on the energy transition. Energies. 2025; 18(9):2149. https://doi.org/10.3390/en18092149
26. Ali SS, Choi BJ. State-of-the-art Artificial Intelligence techniques for distributed smart grids: A review. Electronics. 2020; 9(6):1030. https://doi.org/10.3390/electronics9061030
27. Bousbiat H, Bousselidj R, Himeur Y, Amira A, Bensaali F, Fadli F, *et al*. Crossing roads of federated learning and smart grids: Overview, challenges, and perspectives. arXiv (Cornell University). 2023. Available from: https://arxiv.org/abs/2304.08602
28. Zhang X, Khan K, Shao X, Oprean-Stan C, Zhang Q. The rising role of Artificial Intelligence in renewable energy development in China. Energy Econ. 2024; 132:107489. https://doi.org/10.1016/j.eneco.2024.107489
29. Alfiah F, Prastiwi NR. Cyber security in smart grid technology: A systematic review. Int J Cyber IT Serv Manag. 2022; 2(1):48-54. https://doi.org/10.34306/ijcitsm.v2i1.79
30. Husnoo MA, Anwar A, Hosseinzadeh N, Islam SN, Mahmood AN, Doss R. A secure federated learning framework for residential short term load forecasting. arXiv (Cornell University). 2022. Available from: https://arxiv.org/abs/2209.14547
31. Wong M, Lam C, Wang L, Choi W. Smarter solutions based on power electronics. Elsevier eBooks, Elsevier BV; 2019. https://doi.org/10.1016/b978-0-08-102592-5.00009-0
32. Butt OM, Zulqarnain M, Butt TM. Recent advancement in smart grid technology: Future prospects in the electrical power network. Ain Shams Eng J. 2020; 12(1):687-695. https://doi.org/10.1016/j.asej.2020.05.004
33. Agüero JR, Takayesu E, Novosel D, Masiello R. Grid modernization: Challenges and opportunities. Electricity J. 2017; 30(4):1-6. https://doi.org/10.1016/j.tej.2017.03.008
34. Shashank S, Thirumalai S, Selvan MP. Realization of self-demand response through non-intrusive load monitoring algorithm. arXiv (Cornell University). 2020. Available from: https://arxiv.org/abs/2002.06340
35. Anwar A, Mahmood AN. Cyber security of smart grid infrastructure. arXiv (Cornell University). 2014. Available from: https://arxiv.org/abs/1401.3936
36. Çolak İ, Sağıroğlu Ş, Fulli G, Yeşilbudak M, Covrig C. A survey on the critical issues in smart grid technologies. Renew Sustain Energy Rev. 2015; 54:396-405. https://doi.org/10.1016/j.rser.2015.10.036
37. Cheema JA, Clark A, Kilimnik J, Pavlovski CJ, Redman D, Vu M, *et al*. Towards smart grid dynamic ratings. AIP Conf Proc. 2011; 1373:3-17. https://doi.org/10.1063/1.3627190
38. Pirie C, Kalutarage H, Hajar MS, Wiratunga N, Charles S, Madhushan GS, *et al*. A survey of AI-powered mini-grid solutions for a sustainable future in rural communities.

arXiv (Cornell University). 2024. Available from: http://arxiv.org/abs/2407.15865
39. Shi D, Zhang Q, Hong M, Wang F, Maslennikov S, Luo X, *et al*. Implementing deep reinforcement learning-based grid voltage control in real-world power systems: Challenges and insights. arXiv (Cornell University). 2024. Available from: http://arxiv.org/abs/2410.19880
40. Azad MI, Rajabi R, Estebsari A. Non-Intrusive Load Monitoring (NILM) using deep neural networks: A review. 2022 IEEE Int Conf Environ Elect Eng 2022 IEEE Ind Comm Power Sys Europe (EEEIC/I&CPS Europe), 2023 Jun 6-9, Spain: Madrid. 2023. https://doi.org/10.1109/eeeic/icpseurope57605.2023.10194770
41. Munonye WC. Circular economy meets smart energy grids: designing systems for resource optimization and carbon reduction. Front Sustain. 2025. https://doi.org/10.3389/frsus.2025.1568254
42. Ethirajan V, Mangaiyarkarasi SP. An in-depth survey of latest progress in smart grids: Paving the way for a sustainable future through renewable energy resources. J Electr Syst Inf Technol. 2025; 12:9. https://doi.org/10.1186/s43067-025-00195-z
43. Özcanlı AK, Yaprakdal F, Baysal M. Deep learning methods and applications for electrical power systems: A comprehensive review. Int J Energy Res. 2020. https://doi.org/10.1002/er.5331
44. Bitencourt HV, Souza LAF de, Santos MC dos, Silva PC de L e, Guimarães FG. Combining embeddings and fuzzy time series for high-dimensional time series forecasting in internet of energy applications. arXiv (Cornell University). 2021. Available from: https://arxiv.org/abs/2112.02140
45. Moreno-Rodenas A, Verbist K, Mertens A, Gerritsma I, Deng J, *et al*. Applications of AI for water management. 2025. UNESDOC. https://doi.org/10.54677/vgvl7976
46. Alenezi A, Alabaiadly Y. Artificial intelligence applications in water treatment and desalination: A comprehensive review. Water. 2025; 17(8):1169. https://doi.org/10.3390/w17081169
47. Song T, Pang C, Hou B, Guangxu X, Xue J, Sun H, *et al*. A review of artificial intelligence in marine science. Front Earth Sci. 2023; 11. https://doi.org/10.3389/feart.2023.1090185
48. Biazar SM, Golmohammadi G, Nedhunuri RR, Shaghaghi S, Mohammadi K. Artificial intelligence in hydrology: Advancements in soil, water resource management, and sustainable development. Sustain. 2025; 17(5):2250. https://doi.org/10.3390/su17052250
49. Durlik I, Miller T, Kostecka E, Kozlovska P, Ślączka W. Enhancing safety in autonomous maritime transportation systems with real-time AI agents. Appl Sci. 2025; 15(9):4986. https://doi.org/10.3390/app15094986
50. Ou L, Lu L, Wei-guo Q, Liu B. Application of artificial intelligence in fish information identification: A scientometric perspective. Front Marine Sci. 2025; 12. https://doi.org/10.3389/fmars.2025.1575523
51. Kamyab H, Khademi T, Chelliapan S, Kamarposhti MS, Rezania S, Yusuf M, *et al*. The latest innovative avenues for the utilization of artificial Intelligence and big data analytics in water resource management. Results Eng. 2023; 20:101566. https://doi.org/10.1016/j.rineng.2023.101566
52. Shah M, Wever M, Espig M. A Framework for assessing the potential of Artificial Intelligence in the circular bioeconomy. Sustain. 2025; 17(8):3535. https://doi.org/10.3390/su17083535
53. Bajwa A. AI-based emergency response systems: A systematic literature review on smart infrastructure safety. SSRN Electronic Journal. 2025. https://doi.org/10.2139/ssrn.5171521
54. Uçar A, Karaköse M, Kırımça N. Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. Appl Sci. 2024; 14(2):898. https://doi.org/10.3390/app14020898
55. Shiboldenkov VA, Nesterova K. The smart technologies application for the product life-cycle management in modern manufacturing systems. MATEC Web of Conferences. 2020; 311:2020. https://doi.org/10.1051/matecconf/202031102020
56. Kamali M, Appels L, Yu X, Aminabhavi TM, Dewil R. Artificial Intelligence as a sustainable tool in wastewater treatment using membrane bioreactors. Chem Eng J. 2020; 417:128070. https://doi.org/10.1016/j.cej.2020.128070
57. Matloob S, Li Y, Khan KZ. Safety measurements and risk assessment of coal mining industry using artificial intelligence and machine learning. Open J Bus Manag. 2021; 9(3):1198-1209. https://doi.org/10.4236/ojbm.2021.93064
58. Wu CJ, Raghavendra R, Gupta U, Acun B, Ardalani N, Maeng K, *et al*. Sustainable AI: Environmental implications, challenges and opportunities. arXiv (Cornell University). 2021. Available from: https://arxiv.org/abs/2111.00364
59. Chaudhari BP, Kabade S. AI-driven cloud services for guaranteed disaster recovery, improved fault tolerance, and transparent high availability in dynamic cloud systems. Int J Sci Res Sci Eng Technol. 2023; 10(6):437-458. https://doi.org/10.32628/ijsrset25122169

60. Gowekar GS. Artificial Intelligence for predictive maintenance in oil and gas operations. World J Adv Res Rev. 2024; 23(3):1228-1233. https://doi.org/10.30574/wjarr.2024.23.3.2721
61. Li J. Optimization strategy of property energy management based on Artificial Intelligence. Energy Inform. 2024; 7:79. https://doi.org/10.1186/s42162-024-00383-7
62. Li JX, Zhang T, Zhu Y, Chen Z. Artificial general intelligence for the upstream geoenergy industry: A review. Gas Sci Eng. 2024; 131:205469. https://doi.org/10.1016/j.jgsce.2024.205469
63. Ige AB, Kupa E, Ilori O. Analyzing defense strategies against cyber risks in the energy sector: Enhancing the security of renewable energy sources. Int J Sci Res Arch. 2024; 12(1):2978-2995. https://doi.org/10.30574/ijsra.2024.12.1.1186
64. Jha SK, Bilalovic J, Jha A, Patel N, Zhang H. Renewable energy: Present research and future scope of Artificial Intelligence. Renew Sust Energ Rev. 2017; 77:297-317. https://doi.org/10.1016/j.rser.2017.04.018
65. Ghahramani M, Zhou M, Mölter A, Pilla F. IoT-based route recommendation for an intelligent waste management system. IEEE Internet of Things J. 2021; 9(14):11883-11892. https://doi.org/10.1109/jiot.2021.3132126
66. Lee J, Park E, Lee SY. Development of a hybrid modeling framework for the optimal operation of microgrids. Energies. 2025; 18(8):2102. https://doi.org/10.3390/en18082102
67. Haupt SE, McCandless T, Dettling S, Alessandrini S, Lee JA, Linden S, *et al*. Combining Artificial Intelligence with physics-based methods for probabilistic renewable energy forecasting. Energies. 2020; 13(8):1979. https://doi.org/10.3390/en13081979
68. Mammadov EEo. Predictive maintenance of wind generators based on AI techniques. 2019. Available from: https://uwspace.uwaterloo.ca/bitstream/10012/15335/3/Mammadov_Emin.pdf
69. Simion D, Postolache F, Fleacă B, Fleacă E. AI-driven predictive maintenance in modern maritime transport—Enhancing operational efficiency and reliability. Appl Sci. 2024; 14(20):9439. https://doi.org/10.3390/app14209439
70. AL-Zubaidi YAT, Al-Gabri HK, Gaikwad SS, Kamat RK. An Integrated Expert Water Management (IEWM) with IoT. Int J Innov Technol Explor Eng. 2019; 9(2):3835-3839. https://doi.org/10.35940/ijitee.b7269.129219
71. Sargiotis D. Advancing civil engineering with AI and machine learning: From structural health to sustainable development. 2024. Available from: https://doi.org/10.2139/ssrn.4883999
72. Cohen G, Aiche A. Predicting the Bitcoin's price using AI. Front Artif Intell. 2025; 8. https://doi.org/10.3389/frai.2025.1519805
73. Zhang Y, Congcong W, Sornette D, Chengxiang Z. Integrating artificial intelligence and geophysical insights for earthquake forecasting: A cross-disciplinary review. arXiv (Cornell University). Cornell University; 2025. Available from: http://arxiv.org/abs/2502.12161
74. Kapanski A, Hruntovich N, Klyuev RV, Boltrushevich AE, Sorokova SN, Efremenkov EA, *et al*. Intelligent methods of operational response to accidents in urban water supply systems based on LSTM neural network models. 2025; 8:59. https://doi.org/10.20944/preprints202502.0536.v1
75. Alkhayat G, Mehmood R. A review and taxonomy of wind and solar energy forecasting methods based on deep learning. Energy AI. 2021; 4:100060. https://doi.org/10.1016/j.egyai.2021.100060
76. Wang G, Hou M, Qin M, Wu X, Gao Z, Chao G, *et al*. TSformer: A non-autoregressive spatial-temporal transformers for 30-day ocean eddy-resolving forecasting. arXiv (Cornell University). 2024. Available from: http://arxiv.org/abs/2412.17392
77. Kumar NK, Ramasamy S, Mamun AA. Ocean wave characteristics prediction and its load estimation on marine structures: A transfer learning approach. Mar Struct. 2018; 61:202-219. https://doi.org/10.1016/j.marstruc.2018.05.007
78. Immas A, Do N, Alam M. Real-time in situ prediction of ocean currents. Ocean Eng. 2021; 228:108922. https://doi.org/10.1016/j.oceaneng.2021.108922
79. Guo X, Zhang X, Tian X, Li X, Lu W. Predicting heave and surge motions of a semi-submersible with neural networks. Appl Ocean Res. 2021; 112:102708. https://doi.org/10.1016/j.apor.2021.102708
80. Nearing G, Cohen D, Dube V, Gauch M, Gilon O, Harrigan S, *et al*. Global prediction of extreme floods in ungauged watersheds. Nature. 2024; 627(8004):559-563. https://doi.org/10.1038/s41586-024-07145-1
81. Zhang C, Hu P, Zhang R, Wu Q, Yang A. Modeling of coupling effects in neural networks for ship motion prediction. 2021. https://doi.org/10.36227/techrxiv.14945544
82. Adeli E, Sun L, Wang J, Taflanidis AA. An advanced spatio-temporal convolutional recurrent neural network for storm surge predictions. arXiv (Cornell University). 2022. Available from: https://arxiv.org/abs/2204.09501

83. Zhao Q, Peng S, Wang J, Li S, Hou Z, Zhong G. Applications of deep learning in physical oceanography: A comprehensive review. Front Mar Sci. 2024; 11. https://doi.org/10.3389/fmars.2024.1396322
84. Makinoshima F, Oishi Y, Yamazaki T, Furumura T, Imamura F. Early forecasting of tsunami inundation from tsunami and geodetic observation data with convolutional neural networks. Nature Comm. 2021; 12(1):2253. https://doi.org/10.1038/s41467-021-22348-0
85. Wünsch A, Liesch T, Broda S. Forecasting groundwater levels using Nonlinear Autoregressive Networks with Exogenous input (NARX). J Hydrol. 2018; 567:743-758. https://doi.org/10.1016/j.jhydrol.2018.01.045
86. Weighuo H, He H. Flood forecasting model using the combination approach. Comput Sci IT Res J. 2020; 1(2):59-64. https://doi.org/10.51594/csitrj.v1i2.136
87. Yasin H, Warsito B, Santoso R, Hakim AR. Forecasting of rainfall in Central Java using hybrid GSTAR-NN-PSO model. E3S Web Conf. 2019; 125:23015. https://doi.org/10.1051/e3sconf/201912523015
88. Li T, Xuan A, Shen L. Study of nonlinear interaction between waves and ocean currents using high-fidelity simulation and machine learning. arXiv (Cornell University). 2021. Available from: https://arxiv.org/abs/2101.03439
89. Nasios I. AI-driven multi-source data fusion for algal bloom severity classification in small inland water bodies: Leveraging Sentinel-2, Dem, and Noaa Climate Data. SSRN. 2024. Available from: https://doi.org/10.2139/ssrn.5029812
90. Hofmann J, Schüttrumpf H. floodGAN: Using deep adversarial learning to predict pluvial flooding in real time. Water. 2021; 13(16):2255. https://doi.org/10.3390/w13162255
91. Park Y, Lee HK, Shin JK, Chon K, Kim S, Cho KH, *et al*. A machine learning approach for early warning of cyanobacterial bloom outbreaks in a freshwater reservoir. J Environ Manage. 2021; 288:112415. https://doi.org/10.1016/j.jenvman.2021.112415
92. Cheng Q, Chunhong Z, Qianglin L. Development and application of random forest regression soft sensor model for treating domestic wastewater in a sequencing batch reactor. Sci Rep. 2023; 13(1): 9149. https://doi.org/10.1038/s41598-023-36333-8
93. Yang H, Liu S. A prediction model of aquaculture water quality based on multiscale decomposition. Math Biosci Eng. 2021; 18(6):7561-7579. https://doi.org/10.3934/mbe.2021374
94. El-Din AG, Smith DW, El-Din MG. Application of artificial neural networks in wastewater treatment. J Environ Eng Sci. 2004; 3(1):S81-S95. https://doi.org/10.1139/s03-067
95. Sun Y, Nathan-Roberts W, Pham T, Otte E, Aickelin U. Multi-fidelity Gaussian process for biomanufacturing process modeling with small data. arXiv (Cornell University). 2022. Available from: https://arxiv.org/abs/2211.14493
96. Yu C, Northcott WJ, McIsaac GF. Development of an artificial neural network for hydrologic and water quality modeling of agricultural watersheds. Am Soc Agr Biol Eng. 2004; 47(1):285-290. https://doi.org/10.13031/2013.15853
97. Sudriani Y, Ridwansyah I, Rustini HA. Long Short Term Memory (LSTM) Recurrent Neural Network (RNN) for discharge level prediction and forecast in Cimandiri river, Indonesia. IOP Conference Series Earth and Environmental Science. 2019. https://doi.org/10.1088/1755-1315/299/1/012037
98. Eze E, Kirby S, Attridge J, Ajmal T. Time series Chlorophyll-A concentration data analysis: A novel forecasting model for aquaculture industry. 2021; 5(1):27. https://doi.org/10.3390/engproc2021005027
99. Mishra PK, Chatterjee D, Quevedo DE. Stochastic predictive control under intermittent observations and unreliable actions. Automatica. 2020; 118:109012. https://doi.org/10.1016/j.automatica.2020.109012
100. Nourani V, Elkiran G, Abba SI. Wastewater treatment plant performance analysis using artificial intelligence – An ensemble approach. Water Sci Technol. 2018; 78(10):2064-2076. https://doi.org/10.2166/wst.2018.477
101. O'Shea TJ, Clancy TC, McGwier R. Recurrent neural radio anomaly detection. arXiv (Cornell University). 2016. Available from: https://arxiv.org/abs/1611.00301
102. Xu Z, Ying Z, Li Y, He B, Chen Y. Pressure prediction and abnormal working conditions detection of water supply network based on LSTM. Water Sci Technol: Water Supply. 2020; 20(3):963-974. https://doi.org/10.2166/ws.2020.013
103. Kumar P, Arya SR, Mistry KD. Optimized neural network and adaptive neuro-fuzzy controlled dynamic voltage restorer for power quality performance. Int J Emerg Electr Power Syst. 2021; 22(4). https://doi.org/10.1515/ijeeps-2020-0256
104. Zerara M. Machine learning and statistical methods for time series forecasting: A case study with water demand. TechRxiv. 2021. https://doi.org/10.36227/techrxiv.15019698.v1

105. Gronfula MG, Sayed K. AI-driven predictive control for dynamic energy optimization in flying cars. Energies. 2025; 18(7):1781. https://doi.org/10.3390/en18071781
106. Iacca G, dos Santos Jr VC, de Melo VV. An improved Jaya optimization algorithm with Lévy flight. Expert Syst Appl. 2020; 165:113902. https://doi.org/10.1016/j.eswa.2020.113902
107. Erdoğdu A, Dayı F, Yanik A, Yildiz F, Ganji F. Innovative solutions for combating climate change: Advancing sustainable energy and consumption practices for a greener future. Sustainability. 2025; 17(6):2697. https://doi.org/10.3390/su17062697
108. Khoshahval F, Minuchehr A, Zolfaghari A. Performance evaluation of PSO and GA in PWR core loading pattern optimization. Nucl Eng Des. 2011; 241(3):799-808. https://doi.org/10.1016/j.nucengdes.2010.12.023
109. Áquila G, Rocha LCS, Rotela Jr P, Saab Jr JY, Lima JdB, Balestrassi PP. Economic planning of wind farms from a NBI-RSM-DEA multiobjective programming. Renew Energy. 2020; 158:628-641. https://doi.org/10.1016/j.renene.2020.05.179
110. Thebelt A, Tsay C, Lee RM, Sudermann-Merx N, Walz D, Tranter TG, *et al*. Multi-objective constrained optimization for energy applications via tree ensembles. Appl Energy. 2021; 306(Part B):118061. https://doi.org/10.1016/j.apenergy.2021.118061
111. Guo S, Liu Q, Sun J, Jin H. A review on the utilization of hybrid renewable energy. Renew Sustain Energy Rev. 2018; 91:1121-1147. https://doi.org/10.1016/j.rser.2018.04.105
112. Dankolo NM, Radzi NHM, Mustaffa NH, Arshad NI, Nasser M, Gabi D, *et al*. Optimizing resource allocation for IoT applications in the edge cloud continuum using hybrid metaheuristic algorithms. Sci Rep. 2025; 15(1):11409. https://doi.org/10.1038/s41598-025-97648-2
113. Xu X. AI optimization algorithms enhance higher education management and personalized teaching through empirical analysis. Sci Rep. 2025; 15(1):10157. https://doi.org/10.1038/s41598-025-94481-5
114. Mohammad S, Nasir ANK, Ghani NMA, Kamil R, Razak AAA, Jusof MFM, *et al*. Hybrid bacterial foraging sine cosine algorithm for solving global optimization problems. IOP Conf Ser Mater Sci Eng. 2020; 917:12081. https://doi.org/10.1088/1757-899x/917/1/012081
115. Rao RV, Saroj A. A self-adaptive multi-population based Jaya algorithm for engineering optimization. Swarm Evol Comput. 2017; 37:1-26. https://doi.org/10.1016/j.swevo.2017.04.008
116. Abdel-Basset M, Zhou Y, Smarandache F. Special issue on recent advances in intelligent algorithms and its applications. Concurr Comput Pract Exp. 2019; 32(4):e5417. https://doi.org/10.1002/cpe.5417
117. Fan Z, Ghaddar B, Wang X, Xing L, Zhang Y, Zhou Z. Artificial Intelligence for operations research: Revolutionizing the operations research process. arXiv (Cornell University). 2024. Available from: https://arxiv.org/abs/2401.03244
118. Mellit A, Kalogirou SA. A survey on the application of Artificial Intelligence techniques for photovoltaic systems. Elsevier eBooks; 2017. https://doi.org/10.1016/b978-0-12-809921-6.00019-7
119. Salazar-Peña N, Tabares A, González-Mancera A. AI-powered dynamic fault detection and performance assessment in photovoltaic systems. arXiv (Cornell University). 2024. Available from: http://arxiv.org/abs/2409.00052
120. Zheng H, Paiva ARC, Gurciullo CS. Advancing from predictive maintenance to intelligent maintenance with AI and IIoT. arXiv (Cornell University). 2020. Available from: https://arxiv.org/abs/2009.00351
121. Nithin AH, Hobbs M, Sriramula S, Sripada S. An approach to improve asset maintenance and management priorities using machine learning techniques. Saf Reliab. 2022; 41(3):151-169. https://doi.org/10.1080/09617353.2022.2142011
122. Khan S, Yairi T. A review on the application of deep learning in system health management. Mech Syst Signal Process. 2018; 107:241-265. https://doi.org/10.1016/j.ymssp.2017.11.024
123. Yuan Y, Ma G, Cheng C, Zhou B, Zhao H, Zhang H, *et al*. Artificial Intelligent diagnosis and monitoring in manufacturing. arXiv (Cornell University). 2019. Available from: https://doi.org/10.1093/nsr/nwz190
124. Abbas A. AI for predictive maintenance in industrial systems. OSFPreprints. 2024. https://doi.org/10.31219/osf.io/vq8zg
125. Dube E. Predictive asset management. AusRAIL PLUS 2007, 2007 Dec 4-6, Australia: Sydney, NSW; 2007. Available from: https://trid.trb.org/view.aspx?id=1300763
126. Patil DT. Artificial Intelligence-Driven predictive maintenance in manufacturing: Enhancing operational efficiency, minimizing downtime, and optimizing resource utilization. 2025. SSRN. https://doi.org/10.2139/ssrn.5057406
127. Rojek I, Jasiulewicz–Kaczmarek M, Piechowski M, Mikołajewski D. An Artificial Intelligence approach for

improving maintenance to supervise machine failures and support their repair. Appl Sci. 2023; 13(8):4971. https://doi.org/10.3390/app13084971

128. Chougule SM, Murali G, Kurhade AS. Design and analysis of industrial material handling systems using FEA and dynamic simulation techniques: FEA and simulation-based design of material handling systems. J Sci Ind Res. 2025; 84(6):645-653. https://doi.org/10.56042/jsir.v84i6.17512
129. Bao Y, Gong W, Yang K. A literature review of human–AI synergy in decision making: From the perspective of affordance actualization theory. Systems. 2023;11(9):442. https://doi.org/10.3390/systems11090442
130. Chaudhari SS, Shahakar M, Gholap P, Dhamdhere PB, Agrawal SS, Mahajan RG, *et al*. Enhancing energy efficiency in metallurgical operations using AI: A state of the art review. J Mines Met Fuels. 2025; 73(6):1595-1616. https://doi.org/10.18311/jmmf/2025/48703
131. Waware SY, Ahire PP, Ghutepatil PR, Biradar R, Kadam AA, Kore SS, *et al*. Enhancing heat transfer in tubular heat exchanger using Minijet technology. J Mines Met Fuels. 2025; 73(6):1699-1706. https://doi.org/10.18311/jmmf/2025/49028