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Integrating Soft Computing Techniques into the Assessment of Sustainable Technologies for Efficient Wave Energy Harvesting: A Review

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Abstract

Wave energy is one of the most promising sources of renewable energy, offering vast potential for sustainable power generation. However, the development and deployment of wave energy systems face several challenges, including the selection of suitable technologies, optimal site identification, environmental concerns, and operational efficiency. In recent years, soft computing techniques including fuzzy logic, genetic algorithms, artificial neural networks, and hybrid intelligent systems have emerged as effective tools for handling the complexity, uncertainty, and non-linearity inherent in wave energy system assessment. This review aims to provide a comprehensive overview of how soft computing methods have been integrated into the evaluation and decision-making processes related to sustainable wave energy technologies. The paper systematically explores the role of these techniques in technology selection, performance prediction, environmental impact assessment, and site suitability analysis. Additionally, the review highlights the comparative strengths of various soft computing approaches in modeling real-world scenarios, where data may be imprecise or incomplete. Key findings indicate that soft computing not only enhances the robustness and adaptability of assessment frameworks but also facilitates multi-criteria decision-making and optimization in complex marine environments. Despite the growing body of research, gaps remain in standardizing frameworks and validating models across diverse geographic and environmental conditions. This review concludes by identifying current limitations and proposing future research directions aimed at advancing the application of soft computing in wave energy systems, ultimately contributing to the broader goal of sustainable and efficient marine energy harvesting.

Keywords: Wave Energy Harvesting; Soft Computing Techniques; Sustainable Technologies; Fuzzy Logic; Site Selection; Renewable Energy Assessment .

1 | Introduction

The global pursuit of sustainable and renewable energy sources has become a cornerstone in addressing pressing environmental and energy security concerns [1, 2]. Among the various forms of renewable energy, wave energy has emerged as a highly promising and underexploited resource. With vast potential across oceans and coastlines, wave energy offers a consistent and predictable supply, unlike solar or wind energy, which are often subject to intermittent variability [3]. However, the commercial realization of wave energy systems presents significant technical, economic, and environmental challenges, primarily associated with the complexity of marine environments, technological maturity, and uncertainty in environmental and operational conditions.

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One of the critical hurdles in developing wave energy projects lies in the assessment and selection of appropriate technologies and suitable deployment sites [4, 5]. These decisions must account for multiple factors, including wave climate, bathymetry, proximity to the grid, environmental sensitivity, economic feasibility, and long-term sustainability. Traditional deterministic models and decision-making frameworks are often ill-equipped to handle such complexity, especially in the presence of incomplete, imprecise, or uncertain data [6].

To overcome these limitations, the scientific community has increasingly turned to soft computing techniques: a collection of computational approaches that mimic human reasoning and decision-making. Unlike hard computing, which relies on exact algorithms and binary logic, soft computing embraces approximation, tolerance for imprecision, and partial truth. This makes it particularly suited for addressing the nuanced challenges associated with wave energy assessment [7].

Soft computing techniques such as fuzzy logic, genetic algorithms (GA), artificial neural networks (ANN), particle swarm optimization (PSO), and hybrid intelligent systems offer powerful tools for data analysis, optimization, forecasting, and multi-criteria decision-making. These methods have been effectively employed in various domains of renewable energy, including wind, solar, and hybrid systems. Their application in wave energy systems, though relatively recent, is gaining traction and proving to be impactful.

This review paper aims to provide a comprehensive exploration of how soft computing techniques are integrated into the evaluation and decision-making processes related to sustainable wave energy technologies. It focuses on three main aspects: (1) the theoretical foundation and classification of soft computing methods, (2) their application in the assessment of wave energy converters and site selection, and (3) real-world case studies that demonstrate their practical value. By synthesizing current research findings, this review highlights both the strengths and limitations of these approaches and offers insights into potential future research directions.

The paper is structured as follows: Section 2 presents a detailed overview of individual soft computing techniques and their specific roles in wave energy system evaluation. Section 3 discusses their applications through case studies and implementation scenarios. Finally, Section 4 concludes the review with a summary of findings, identified gaps, and recommendations for future work.

2 | Soft Computing Techniques for Wave Energy Assessment

Soft computing is a collection of methodologies that work synergistically to provide flexible information processing capabilities for handling real-life, ambiguous, and uncertain data. Unlike conventional (hard) computing, which requires precise input and deterministic models, soft computing tolerates imprecision and partial truth, making it well-suited for complex systems such as wave energy harvesting in uncertain marine environments.

This section delves into several prominent soft computing techniques: including fuzzy logic, genetic algorithms, artificial neural networks, particle swarm optimization, and hybrid models and examines their theoretical foundations, advantages, and specific applications in assessing wave energy systems.

2.1 | Fuzzy Logic

Fuzzy logic (FL) was introduced by Lotfi Zadeh in 1965 as a means of dealing with the concept of partial truth. In contrast to binary logic systems, which operate on crisp values (true/false, 0/1), fuzzy logic models allow for intermediate values, which reflect the vagueness and ambiguity that often characterize real-world scenarios [8, 9].

In the context of wave energy harvesting, fuzzy logic is used to:

- Handle subjective evaluations of site conditions and technological preferences.
- Develop fuzzy inference systems for the multi-criteria decision-making process.

- Translate expert knowledge into linguistic variables and rules, such as "high wave potential," "moderate depth," or "low environmental impact."

For instance, a fuzzy rule-based system may use inputs like wave height, seabed slope, and grid proximity to determine the suitability of a coastal site for deploying a wave energy converter (WEC). The main advantage of FL is its interpretability and ability to capture human reasoning [10, 11].

Limitations of fuzzy logic include:

- Dependence on well-constructed membership functions, which often require domain expertise.
- Challenges in scaling for large and dynamic data sets.
- Potential for rule explosion in complex systems, which may complicate maintenance and updates.

Despite these limitations, fuzzy logic remains a foundational component of soft computing, often serving as the base for hybrid systems.

2.2 | Genetic Algorithms

Genetic Algorithms (GAs) are inspired by the natural process of evolution and survival of the fittest. These algorithms utilize a population of potential solutions and evolve them over successive generations using selection, crossover, and mutation operators [12].

In wave energy systems, GAs have been successfully applied to:

- Optimize WEC farm layouts by adjusting the spacing and orientation of devices to minimize wave interference and maximize energy extraction.
- Tune parameters of control systems within WECs, such as damping ratios and power take-off (PTO) settings.
- Design hybrid renewable energy systems, where wave energy is combined with solar or wind sources for increased resilience.

A key strength of GAs lies in their ability to navigate high-dimensional and discontinuous search spaces where traditional optimization techniques may fail. Their stochastic nature allows them to avoid local optima and explore global solutions.

However, GAs may require significant computational resources for large populations or complex objective functions. They are also sensitive to parameter settings, such as mutation rate and crossover probability, which must be carefully calibrated.

2.3 | Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational models inspired by biological neural networks. ANNs are composed of interconnected nodes (neurons) organized in layers and are particularly suited for tasks involving pattern recognition, classification, and nonlinear function approximation [13, 14].

In wave energy applications, ANNs are widely used for:

- Short-term wave forecasting, including wave height, period, and direction, which are critical for energy yield estimation and real-time operation.
- Power output prediction of WECs based on environmental inputs.
- Fault detection and diagnostics within marine energy systems.

The main advantages of ANNs are their:

- Ability to model nonlinear and complex relationships without explicit programming.

- High prediction accuracy when trained on sufficient data.
- Flexibility to integrate with other techniques (e.g., fuzzy logic, GAs) to form hybrid systems.

However, ANNs are often criticized for being black-box models. they lack transparency in how decisions are made, which can be problematic in safety-critical or regulated industries. Furthermore, they typically require large training datasets, which may not be available in early-stage marine energy projects.

2.4 | Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based optimization technique inspired by the collective behavior of birds or fish. In PSO, each particle (solution) in the swarm updates its position based on personal experience and that of its neighbors, moving toward the best known position in the search space [15-18].

In the wave energy sector, PSO has been applied to:

- Optimize the control strategies of WECs, such as reactive or latching control, to adapt to varying sea states.
- Determine optimal site selection, considering multiple conflicting objectives like cost, energy potential, and environmental impact.
- Design hybrid energy microgrids incorporating wave energy.

PSO is often preferred for its:

- Simplicity and ease of implementation.
- Faster convergence compared to GAs in some applications.
- Effectiveness in solving multi-objective and nonlinear optimization problems.

However, PSO may experience premature convergence if diversity is not maintained within the swarm, potentially leading to suboptimal solutions.

2.5 | Hybrid Intelligent Systems

To overcome the individual limitations of soft computing methods, researchers have developed hybrid models that combine the strengths of multiple techniques. Examples include:

- Neuro-fuzzy systems: These combine the learning capability of ANNs with the linguistic reasoning of fuzzy logic. Such systems are effective in wave prediction, device control, and multi-criteria decision-making.
- GA-ANN systems: Genetic algorithms are used to optimize ANN architecture or weights, improving learning performance and generalization.
- Fuzzy-PSO and Fuzzy-GA models: These are particularly effective in handling uncertainty in resource assessment and site ranking tasks.

Hybrid systems offer improved:

- Accuracy and robustness across varied datasets.
- Interpretability compared to black-box ANNs.
- Adaptability in dynamic marine environments.

Challenges include increased complexity in design and tuning, as well as computational demands that must be managed during real-time or large-scale simulations.

3 | Applications and Case Studies

The real-world application of soft computing techniques in wave energy harvesting highlights their practical value in addressing uncertainty, complexity, and variability inherent in marine environments. This section presents case studies and empirical findings that demonstrate how these techniques are used in technology evaluation, site selection, energy forecasting, and integrated system optimization.

3.1 | Site Selection and Suitability Analysis

One of the primary challenges in wave energy deployment is identifying optimal locations that balance energy potential, environmental impact, and economic feasibility. Soft computing methods have shown remarkable effectiveness in solving this multi-criteria decision-making (MCDM) problem [19, 20].

In a study conducted by Silva et al. [15], a fuzzy logic-based GIS model was used to evaluate wave energy potential along the Portuguese coast. The model considered factors such as wave height, seabed slope, marine protected areas, and grid proximity. Using linguistic rules and fuzzy membership functions, the authors generated a suitability map that facilitated informed site selection decisions.

Similarly, hybrid fuzzy-AHP (Analytic Hierarchy Process) models have been employed in case studies in India, Scotland, and Chile. These models quantify stakeholder preferences, environmental constraints, and economic indicators under uncertain conditions. The integration of fuzzy logic with AHP or TOPSIS enhances the interpretability and robustness of results, offering a more holistic view than traditional deterministic models.

Moreover, PSO and GA techniques have been used to optimize wave farm layout, reducing energy losses due to wave shadowing and wake effects. For instance, a study in Ireland utilized GA to determine optimal WEC spacing, demonstrating a 12% increase in energy efficiency compared to manual configurations.

3.2 | Technology Evaluation and Selection

Different types of wave energy converters (WECs),such as point absorbers, oscillating water columns, and attenuators exhibit varying performance characteristics depending on site conditions. Selecting the most appropriate technology involves assessing trade-offs between efficiency, cost, maintainability, and environmental compatibility.

In this regard, fuzzy MCDM models have been widely used to compare WEC alternatives. A notable study applied fuzzy VIKOR to rank five WECs based on criteria like energy conversion efficiency, installation complexity, cost per kilowatt-hour, and ecological risk. The method handled subjective inputs from domain experts and yielded a transparent ranking process.

Soft computing also aids in modeling and simulating the performance of WECs. For instance, ANNs have been trained using historical oceanographic data to predict the power output of specific devices under different sea states. These predictive models guide technology developers in understanding operational limitations and potential improvements.

In hybrid scenarios, neuro-fuzzy systems have been applied to estimate device performance based on changing input variables such as wave period and direction. These models adaptively learn from environmental data while maintaining interpretability making them valuable tools in performance benchmarking.

3.3 | Energy Forecasting and Resource Assessment

Reliable wave energy forecasting is vital for efficient grid integration, load balancing, and operational planning. ANNs, due to their capacity to model nonlinear time series, have been extensively used to forecast wave height, period, and energy potential.

For example, researchers in South Korea developed a feed-forward ANN model trained on buoy data from the Yellow Sea. The model achieved a prediction accuracy of over 90% for short-term energy forecasts, outperforming traditional statistical models.

Other soft computing methods like support vector machines (SVM) and adaptive neuro-fuzzy inference systems (ANFIS) have been applied in resource assessment. These methods are capable of fusing inputs from multiple sensors and sources to deliver accurate predictions even in data-sparse environments.

Wave energy resource maps generated using hybrid models (ANN + GIS, for example) have been developed in regions like the North Sea, the Pacific Northwest (USA), and the Indian Ocean. These maps assist policymakers and developers in long-term strategic planning.

3.4 | Integrated Optimization of Wave Energy Systems

Designing and managing a wave energy project often requires the simultaneous consideration of multiple objectives, including cost minimization, energy maximization, environmental protection, and system reliability. Multi-objective optimization using soft computing has become a crucial aspect of integrated system planning.

In a multi-site deployment scenario, researchers in Norway applied PSO combined with fuzzy logic to optimize the distribution of energy harvesting units while maintaining acceptable environmental footprints. The study reported significant improvements in both net energy gain and habitat preservation.

Additionally, genetic programming has been used to evolve control strategies for adaptive WEC operation. In dynamic marine environments, this approach enables real-time tuning of device settings (like damping coefficients and PTO control parameters) to maintain efficiency.

Decision support systems (DSS) based on soft computing have also been proposed. These systems incorporate real-time monitoring data, fuzzy inference, and ANN-based prediction to assist operators in selecting optimal configurations under changing ocean conditions.

3.5 | Limitations and Lessons from Case Studies

While soft computing techniques have demonstrated considerable potential, certain limitations have emerged from real-world applications:

- Data availability and quality remain critical challenges, particularly in remote or under-researched marine zones.
- Model interpretability is sometimes sacrificed in favor of accuracy, especially with deep neural networks.
- Computational costs can be high for GA and PSO when dealing with large-scale optimization problems.
- Integration with regulatory and policy frameworks is still limited, hindering broader implementation.

Nevertheless, the reviewed case studies clearly demonstrate that soft computing enhances the adaptability, precision, and reliability of wave energy assessment processes.

4 | Conclusion

This review has highlighted the significant role that soft computing techniques play in advancing the field of wave energy harvesting. As the global transition to sustainable energy systems accelerates, intelligent and adaptive tools are essential to navigate the complexities and uncertainties inherent in marine energy environments.

The integration of fuzzy logic, genetic algorithms, artificial neural networks, particle swarm optimization, and hybrid models offers robust and flexible approaches for tackling a wide array of challenges. From site selection and technology evaluation to forecasting and integrated optimization, these techniques enhance decision-making and reduce reliance on rigid, deterministic methods.

Key findings from the review include:

- Soft computing enables multi-criteria decision-making in complex and uncertain conditions.
- Hybrid techniques such as neuro-fuzzy systems and GA-ANN models offer enhanced accuracy and adaptability.
- Real-world applications demonstrate improved forecasting accuracy, optimization performance, and operational efficiency.
- Challenges such as data quality, computational demand, and lack of standardization remain barriers to wider adoption.

Moving forward, the following directions are recommended:

- Development of standardized frameworks for soft computing application in wave energy systems.
- Integration with real-time monitoring systems and IoT technologies to enable adaptive control and decision-making.
- Cross-disciplinary collaboration between energy engineers, computer scientists, oceanographers, and policymakers.
- Expansion of open-access datasets and benchmarking tools to support research reproducibility and transparency.
- Increased focus on explainability and interpretability, especially in regulatory and safety-critical contexts.

In conclusion, soft computing represents a transformative force in sustainable wave energy research and practice. By enabling more intelligent, flexible, and holistic approaches to assessment and optimization, it paves the way for more resilient and effective renewable energy systems in coastal and oceanic regions.

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Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

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Data Availability

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