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Assessing the impact of marine renewable energy in Portugal: an analysis based on ACO-TCN-attention

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As the global demand for renewable energy continues to increase, marine renewable energy has attracted much attention as a potential source of clean energy. As a country with rich marine resources, Portugal's marine environment is of great significance to the development of marine energy. However, the current impact assessment of marine renewable energy projects has shortcomings such as incomplete understanding of ecosystems, incomplete consideration of fishery resources and socioeconomic impacts, lack of accuracy, and failure to consider geographical differences, thus lacking comprehensiveness and accuracy. To this end, we propose the ACO-TCN-Attention model to address these shortcomings in current impact assessments of marine renewable energy projects. The goal of this model is to provide a more comprehensive, precise and nuanced analysis to better understand the impacts of these projects on ecosystems, socio-economics and local communities. "ACO-TCN-Attention" is a model architecture that combines multiple machine learning and deep learning concepts. It includes three main parts: Ant Colony Optimization (ACO), Temporal Convolutional Network (TCN) and Attention mechanism. The ant colony optimization model simulates the behavior of ants and is used to optimize the operating strategies of marine renewable energy projects. Temporal Convolutional Network specializes in processing time series data and improves the prediction accuracy of the model. The attention mechanism allows the model to dynamically focus on the pieces of information that are most important for the current task. Extensive experimental evaluation shows that our method performs well on multiple datasets, significantly outperforming other models. This research is of great significance as it provides new methods and tools for improving the environmental impact assessment of marine renewable energy projects. By understanding the potential impacts of projects more accurately, we can better balance the relationship between the development of renewable energy and environmental protection, supporting the achievement of the Sustainable Development Goals. This research also provides useful guidance and reference for future research and practice in the field of marine energy.

KEYWORDS

Portugal marine renewable energy, time series data, impact assessment, ACO-TCN-attention, environmental assessment

1 Introduction

As the global threat of climate change escalates, the imperative of developing and harnessing renewable energy sources has emerged as a pivotal solution to meet energy demands while curbing carbon emissions (Habiba et al., 2022). Portugal, as a country with rich marine resources, has begun the development of marine renewable energy and has made significant progress in the fields of sea wind energy, tidal energy, wave energy and other fields. Several regions around the world are harnessing their abundant marine resources to advance in the field of marine renewable energy. Notable progress has been made in offshore wind energy, tidal energy, and wave energy development. (Li et al., 2023a). However, the assessment of the impact posed by these marine renewable energy sources holds paramount importance for the environment, economy, and society. Foremost, the evaluation of the impact of marine renewable energy plays a pivotal role in safeguarding marine ecosystems and biodiversity. Marine ecosystems are among the Earth's most vital, bestowing crucial ecological services, including sustenance, oxygen generation, and climate regulation (Liu and Soares, 2022). Consequently, any perturbation to the marine environment can reverberate profoundly, disturbing the delicate ecological balance. Portugal is located on the Atlantic coast and has rich marine ecological resources, so the potential impact of marine renewable energy projects on these resources must be carefully assessed. Secondly, the development of marine renewable energy is also related to energy sustainability and reducing greenhouse gas emissions. Portugal has been seeking to reduce its reliance on traditional fossil fuels and incorporate renewable energy into its energy mix (Kirikkaleli et al., 2023). However, the sustainable progression of marine renewable energy projects is intricately linked to their contribution to the overall energy supply, necessitating a robust assurance of long-term environmental and economic benefits (Liu et al., 2023a). Consequently, the assessment of the impact of marine renewable energy unfolds as a multifaceted, interdisciplinary challenge encompassing domains such as environmental science, economics, and engineering (Hu et al., 2022). The evaluation of these impacts entails considerations spanning ecological ramifications, societal advantages, economic costs, and sustainability. Yet, this endeavor is beset with several formidable challenges. The inherent complexity of the marine environment poses a formidable obstacle to the accurate prediction and quantification of potential impacts (Chuah et al., 2022). Marine ecosystems are characterized by their high dynamism and constant flux, necessitating the development of advanced models and methodologies to capture this intricate complexity. Additionally, the absence of comprehensive and reliable data presents another hurdle to the evaluation process. While various ocean observation and data collection initiatives are underway, their coverage and data quality remain areas that demand substantial improvement. In conclusion, as the development of marine renewable energy progresses, the assessment of its impacts emerges as an imperative undertaking, demanding comprehensive, multidisciplinary solutions to address the intricate challenges posed by the dynamic marine environment and the data deficiencies currently impeding evaluation efforts.

In current research, the application of deep learning techniques to assess the impact of marine renewable energy has gained momentum. Deep learning models, renowned for their prowess in handling intricate spatial and temporal data, bestow researchers with a potent instrument for the analysis, prediction, and optimization of marine renewable energy system performance (Penalba et al., 2022). This technology has already manifested substantial advancements in predicting the potential energy yield of tidal and wave energy, refining operational strategies for oceanic wind turbines (Li et al., 2023b; Li et al., 2022), and enhancing energy production efficiency. Its utility extends to the analysis of extensive oceanic datasets, allowing for more precise prognostication and evaluation of the potential repercussions of renewable energy ventures. Consequently, it enables a deeper comprehension of the influence exerted by marine renewable energy projects on marine ecosystems and the environment, whilst furnishing more dependable data to inform decision-making. Within the realm of renewable energy impact assessment, time series forecasting stands as a pivotal domain of research (Acaroğlu and Güllü, 2022). Marine renewable energy exhibits pronounced seasonal and annual fluctuations, influenced by climatic conditions and natural events (Cui and Zhao, 2023). Time series forecasting methodologies serve as indispensable tools for unraveling these oscillations, furnishing robust support for the planning and administration of renewable energy endeavors.

The field of marine renewable energy technology is currently undergoing rapid and dynamic evolution, encompassing various domains including tidal energy, ocean kinetic energy, and wave energy. Tidal energy technology, for instance, has achieved remarkable advancements in ocean engineering by harnessing the energy generated through tidal movements. Marine kinetic energy technology is primarily centered on the utilization of kinetic energy resources such as ocean tides and currents to meet power and other energy demands (Li et al., 2021; Li et al., 2020). Moreover, wave energy technology is dedicated to capturing the immense potential of ocean waves as a renewable energy source (Liu and Soares, 2023). These cutting-edge technologies hold immense promise within the renewable energy sector, playing a pivotal role in reducing greenhouse gas emissions, ensuring energy sustainability, and contributing to the attainment of carbon neutrality objectives. However, the widespread application of these technologies also presents an array of challenges, including issues related to equipment design and maintenance, environmental impact assessment, and resource management. Simultaneously, the integration of deep learning and machine learning technologies into the field of marine renewable energy has garnered significant attention. These advanced computational methods offer the capability to process marine environmental data, optimize energy system operations, and enhance energy production predictions. For example, deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM) have demonstrated success in accurately forecasting the energy output of wave and tidal energy, thereby improving prediction precision (Chen et al., 2022). Furthermore, reinforcement learning techniques are being employed to optimize the operational strategies of renewable energy systems, minimizing adverse effects on marine ecosystems.

In recent years, the research field of marine renewable energy has experienced rapid development, with a number of important studies emerging, some of which used advanced deep learning techniques. A recent study employed CNN to assess the impact of tidal turbines on the marine environment (Xu et al., 2023). The model uses vast amounts of image data to identify the operating status of tidal turbines and the ecological characteristics of the surrounding water. However, this model does not fully account for time series data and ignores the potential impact of tidal and seasonal changes. Another related study adopted a LSTM model to analyze and predict wave energy fluctuations (Zheng et al., 2023). This study improves the accuracy of wave energy predictions through in-depth analysis of historical wave data. This is crucial for the operation and maintenance of wave power plants, as energy production can be planned more efficiently. However, a shortcoming of this study is that it fails to fully account for extreme weather events in the marine environment, which may have a significant impact on wave energy generation. In another study, the Transformer model was harnessed to scrutinize the power output of oceanic wind farms (Wu et al., 2022). Through the adept handling of extensive spatiotemporal data, the model demonstrated heightened proficiency in predicting wind farm power output with greater precision. However, it is noteworthy that this particular study did not encompass a thorough evaluation of the marine environment's influence on wind power generation, nor did it undertake a comprehensive assessment of the ecosystem. Finally, one study employed deep reinforcement learning to model the impact of wave energy conversion devices on the marine environment (Zou et al., 2022). This model uses reinforcement learning algorithms to optimize the operation strategy of wave energy devices to reduce the adverse effects on the ecosystem. However, the training process of this model is very complex and requires a large amount of computing resources, which limits the feasibility of its practical application. These related works provide valuable insights into assessing the impact of marine renewable energy, but they still have some shortcomings, such as insufficient consideration of time series data, higher model complexity, and higher computational costs.

Based on the shortcomings of the above work, we proposed the ACO-TCN-Attention network, which is a model that integrates Ant Colony Optimization (ACO), Temporal Convolutional Network (TCN) and attention mechanism, aiming to more comprehensively and accurately Assess and predict the potential of marine renewable energy and its environmental impacts. ACO is responsible for optimizing parameter selection in this model, using the principles of natural ant colony foraging behavior to search for optimal solutions to determine the best configuration of the TCN layer. TCN processes time series data, has high efficiency and superior long-term dependency processing capabilities, and captures long-term dependencies in data through causal convolution and dilated convolution techniques. In addition, the introduced attention mechanism improves the model's sensitivity to important features in the data, ensuring that the model pays more attention to the most critical information in the prediction task. This model integrates various advanced technologies, overcoming the limitations of traditional models in handling complex marine environmental data, thereby enhancing prediction accuracy and efficiency. It not only provides support for the comprehensive assessment of marine renewable energy potential and environmental impact but also offers guidance for the realization of more sustainable and environmentally friendly energy utilization strategies. It paves the way for new possibilities in the research and application of marine renewable energy in the future.

In this study, the ACO-TCN-Attention network model we proposed brings three important contributions to the assessment of the impact of marine renewable energy:

- We innovatively integrated ACO with the TCN and an Attention mechanism to create the ACO-TCN-Attention network model. The innovation of this comprehensive approach lies in its ability to integrate the characteristics of time-series data, the complexity of ecosystems, and the optimization requirements of energy systems. Traditional methods often focus on one aspect while overlooking other crucial factors. The ACO-TCN-Attention model can effectively consider time-series data, environmental impact, and ecosystem preservation concurrently, enabling a more comprehensive and accurate evaluation of the potential impacts of marine renewable energy projects. This bridges a gap in existing research by providing a holistic assessment approach.
- By introducing ACO, we provide an optimization method for renewable energy project operation strategies to minimize adverse effects on the marine ecosystem. This has important implications for achieving sustainable development goals, reducing environmental risks and increasing the efficiency of energy production. The introduction of ACO enables decision-makers to choose the optimal operation plan more wisely, thereby promoting a win-win situation for the environment and economy.
- The application of the ACO-TCN-Attention network model has wide practical significance. It provides governments, energy companies and research institutions with a comprehensive and reliable tool for assessing the feasibility and impact of marine renewable energy projects, contributing to more informed decision-making, planning and management. The promotion and application of this model is expected to promote the sustainable development of marine renewable energy, promote the widespread application of clean energy, and promote global efforts to combat climate change.

2 Related work

2.1 Application of data-driven approaches in assessing the impact of renewable energy

Data-driven approaches play a pivotal role in assessing the impact of marine renewable energy. These methods rely on the collection, analysis, and interpretation of real-world data, offering valuable insights into the genuine environmental, economic, and social consequences of various marine renewable energy projects (Sareen et al., 2023). To begin, data-driven approaches are instrumental in conducting resource potential analysis. By harnessing oceanographic survey data, meteorological information, and oceanographic insights, researchers can pinpoint the most suitable geographic regions for energy development and forecast energy production levels (Jing et al., 2022). This foundational data is essential for evaluating project feasibility. Furthermore, data-driven approaches extend to monitoring actual energy production. By tracking metrics such as power generation, energy efficiency, and operational costs, we can assess the economic viability and overall contribution of these projects (Dyer et al., 2022). This data serves as critical information for investors and policymakers alike. In summary, data-driven approaches provide a more objective and precise means of evaluating the impact of marine renewable energy. These methodologies not only promote project sustainability and optimize positive outcomes but also furnish essential decision support tools for those in positions of authority.

2.2 Application of self-attention mechanism in assessing the impact of renewable energy

The application of the self-attention mechanism in assessing the impact of renewable energy fully demonstrates its powerful ability in processing complex data and pattern recognition. This mechanism is particularly suitable for processing time series data, such as meteorological conditions and energy consumption patterns, thereby achieving higher accuracy in the prediction of renewable energy production such as wind energy and solar energy (Du et al., 2023). The self-attention mechanism can effectively analyze the impact of dynamic environmental changes on renewable energy projects, including climate change, seasonal fluctuations and other factors, by focusing on the most critical parts of the data (Meng et al., 2022). This not only improves the accuracy of predictions, but also provides important data support for the planning and management of renewable energy projects. In addition, the self-attention mechanism also shows great potential in assessing the comprehensive impact of renewable energy on the environment, ecosystems, and socioeconomics, helping policymakers and researchers more comprehensively understand and respond to these challenges, thereby promoting sustainable development and the environment protect (Liu et al., 2023b).

2.3 Application of TCN to assessing renewable energy impacts

TCN play a crucial role in assessing the impact of renewable energy. It is specifically designed to process time series data, accurately capturing the production, impact and trends of renewable energy projects (Wang and Zhang, 2022). TCN has the ability to handle time correlation, which helps the model better understand time factors such as seasonality and day-night changes, and improves the accuracy of evaluation. In addition, TCN is also able to perform multi-scale analysis, taking into account information at different time scales simultaneously, to provide a comprehensive assessment of the long-term trends and short-term fluctuations of the project (Wu et al., 2023). Its efficient training and inference speed enables decision makers to obtain assessment results in a timely manner and respond to changes in environmental conditions. Most importantly, the relatively simple structure of TCN helps improve the interpretability of the model, making it easier for decision-makers to understand and trust the evaluation results, providing strong support for the planning and decision-making of renewable energy projects (Liu and Fu, 2023).

3 Methods

The ACO-TCN-Attention network model we proposed consists of three key parts: ACO, TCN and Attention mechanism. The functions of each part are as follows: ACO: The main function of the module is to simulate the behavior of ants to optimize the operation strategy of renewable energy projects. Its goal is to find the best operating options to minimize adverse impacts on the environment. The introduction of ACO enables our model to consider environmental protection factors and helps achieve sustainable development goals. TCN: This module specializes in processing time series data, capturing temporal correlations and improving the prediction accuracy of the model. It helps analyze trends in the production and impact of renewable energy projects over time, allowing for a more accurate assessment of a project's potential impact. Attention mechanism: The introduction of the attention mechanism enhances the interpretability of the model. It helps decision-makers better understand the assessment results and clarify which environmental factors or characteristics are more critical for impact prediction, thus improving the rationality of decision-making.

The model building process includes key steps such as data collection, preprocessing and module design. Figure 1 illustrates the process: First, we collected multi-source data related to marine renewable energy projects and environmental factors, including production, meteorological and environmental parameters, *etc.* Subsequently, these data undergo rigorous preprocessing, including missing value handling, normalization, and data segmentation to ensure data quality and usability. Then, we designed three key modules: the ACO module, which is used to simulate the behavior of ants and optimize algorithms to determine the best operating strategy; the TCN module, which specifically processes time series data to model temporal correlations to improve prediction accuracy; and the Attention module introduces an attention mechanism to enhance the interpretability of the model. Finally, we trained and tuned the entire model to ensure the accuracy and reliability of the assessment, providing powerful tools and methods for assessing the impact of marine renewable energy. This construction process not only synthesizes data from multiple sources, but also incorporates optimization algorithms and deep learning technology, allowing our model to more comprehensively and accurately assess the impact of renewable energy projects. The ACO-TCN-Attention network model not only fills the gap in existing research and provides a method that comprehensively considers time series data, environmental factors and ecosystem protection, but also provides renewable energy projects with the ACO optimization algorithm. Furthermore, the introduced Attention mechanism not only enhances the interpretability of the model and helps decision-makers better understand the evaluation results, but also clarifies which environmental factors or characteristics are more critical for impact prediction, thus improving the rationality of decision-making. sex and transparency.

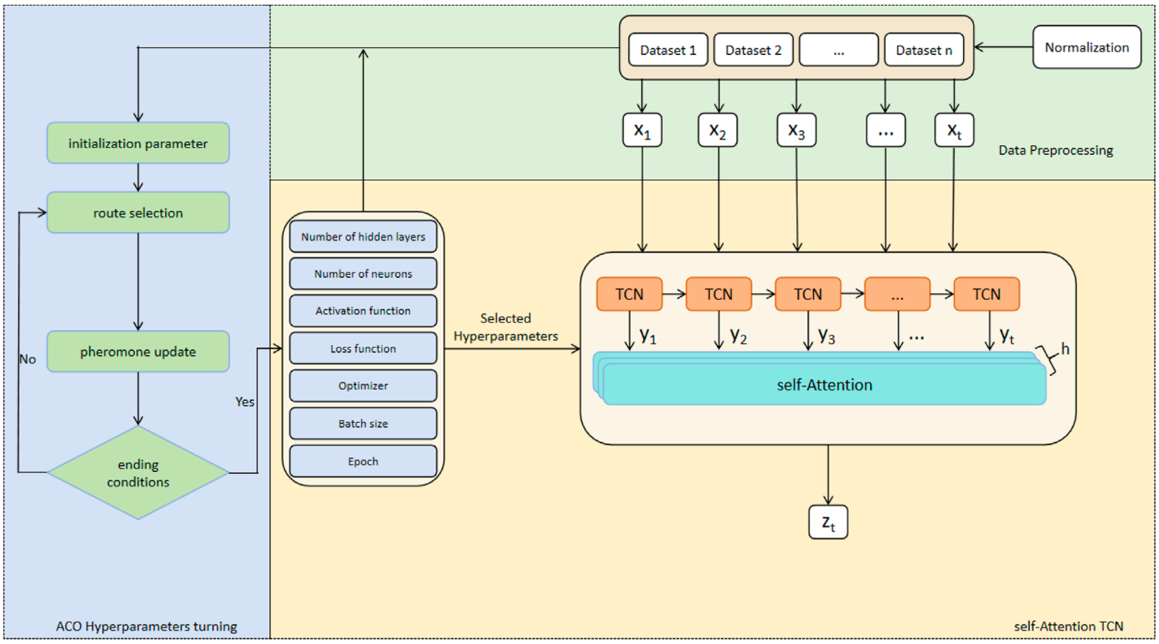

FIGURE 1
Overall flow chart of the model.

3.1 ACO: Ant colony optimization

The ACO model is an algorithm that simulates the foraging behavior of ants and is used to solve optimization problems. Its basic principle is to imitate the process of ants searching for food sources and returning to their nests, by releasing pheromones to mark the path and sharing this information with other ants (Hussain et al., 2022). In the algorithm, these pheromone paths are used to guide the search process to find the optimal solution. Over time, the pheromone concentration on shorter paths will increase, making more ants tend to choose these paths, thus optimizing the overall search efficiency. In the ACO-TCN-Attention network model, the role of the ACO part is to optimize the operation strategy of marine renewable energy projects. By simulating the behavior of ants, it finds strategies to minimize environmental impact, which is crucial for protecting marine ecosystems and improving the environmental compatibility of energy projects. The innovative application of ACO brings significant contributions to the environmental impact assessment of marine renewable energy projects. What sets this approach apart is its holistic consideration of environmental protection factors. By simulating the behavior of ants, it seeks to find optimal operational strategies that minimize adverse effects on the environment. Given the complexity and variability of both the marine environment and renewable energy projects themselves, the innovation of the ACO algorithm lies in its ability to handle such intricacies and make decisions in dynamic settings. The application of this module not only takes environmental factors into account but also optimizes the operational strategies of renewable energy projects. This optimization helps strike a balance between energy demand and environmental protection, ultimately supporting sustainability goals. Furthermore, this module draws inspiration from heuristic optimization principles based on ant behavior. It automates the exploration of various possible strategies and selectively reinforces superior strategies through pheromone-like information, enhancing the model's performance. In conclusion, the innovative application of ACO significantly contributes to improving the sustainability and efficiency of energy projects while reducing adverse impacts on ecosystems. This innovation holds great importance for both research and practical applications in the field of renewable energy, driving advancements in the industry.

Probability of Path Selection is defined as:

$$P_{ij} = \frac{T_{ij}^{\alpha} \cdot N_{ij}^{\beta}}{\sum_{k \in J_i} T_{ik}^{\alpha} \cdot N_{ik}^{\beta}} \tag{1}$$

where: P_{ij} represents the probability of selecting the path from node i to node j for ants. This probability depends on both the pheromone concentration (T_{ij}) and the attractiveness of the path (N_{ij}) and guides ants towards better paths. α and β are parameters used to control the probability of the ant choosing a path. α (alpha) is usually used to adjust the emphasis that ants place on pheromone concentration when choosing a path. β (beta) is used to adjust the degree of emphasis that ants place on the attractiveness of the path when choosing a path.

Pheromone Update is defined as:

$$T_{ij} = (1-\rho) \cdot T_{ij} + \Delta T_{ij} \tag{2}$$

where: T_{ij} represents the pheromone concentration from node i to node j. This formula updates the pheromone levels by considering both pheromone evaporation and the pheromone deposited by ants (ΔT_{ij}).

Cumulative Pheromone Deposit is defined as:

$$\Delta T_{ij} = \sum_{k} \Delta T_{ij}^{k} \tag{3}$$

where: ΔT_{ij}^{k} represents the amount of pheromone deposited by the k-th ant on the path from node i to node j. This equation calculates the cumulative pheromone deposited by all ants on that path.

Total Path Length is defined as:

$$L_k = \sum_{ij \in \text{path}_k} d_{ij} \tag{4}$$

where: L_k represents the total length of the path chosen by the k-th ant. This formula calculates the sum of distances (d_{ij}) along the path segments selected by the ant.

Pheromone Evaporation is defined as:

$$T_{ij} = (1 - \rho) \cdot T_{ij} \tag{5}$$

where: T_{ij} represents the pheromone concentration from node i to node j. This equation models the pheromone evaporation process by reducing the pheromone level over time (ρ represents the pheromone evaporation rate).

3.2 Temporal Convolutional Network: TCN

TCN, a specialized neural network structure tailored for processing time series data, stands out for its distinctive approach compared to traditional recurrent neural networks (RNN). Instead of utilizing recurrent layers, the Temporal Convolutional Network employs one-dimensional convolutional layers, which results in enhanced efficiency and effectiveness, especially when dealing with extensive sequences (He et al., 2023). This design incorporates key features, such as causal convolution, ensuring that the model exclusively relies on past information for predictions, and dilated convolution, which widens the receptive field of the convolutional layer, enabling it to capture dependencies over extended intervals. These characteristics position this network architecture as a robust choice for processing time-related data, particularly when addressing long-term dependencies is essential. Figure 2 illustrates the network structure of TCN. In this study, the innovative integration of the Temporal Convolutional Network contributes significantly to assessing the impacts of marine renewable energy projects. Its innovative qualities span several aspects. Firstly, the network excels in analyzing time series data, facilitating the precise capture of pronounced temporal correlations within the production and environmental impacts of marine renewable energy projects, including seasonal and yearly variations. This capability augments the model's precision in predicting potential impacts under diverse temporal and environmental conditions. Secondly, the network adapts effectively to dynamic environments, efficiently managing the continual changes in the marine environment, encompassing climate conditions and natural events. This adaptability empowers the model to make informed decisions in complex and ever-changing conditions. Most importantly, the innovative implementation of this network architecture enhances the overall model's precision, significantly bolstering its reliability in assessing the impacts of renewable energy projects. This heightened precision is invaluable for decision-makers aiming to comprehend potential project effects within varying temporal and environmental contexts. It equips them with the knowledge needed to make well-informed decisions and optimize project designs. Consequently, the introduction of this network architecture offers a powerful tool for both research and practical applications in the renewable energy field, enabling a more comprehensive and precise evaluation of the environmental impacts associated with these projects. Below, we present the primary formulas for this network architecture for further clarity:

The dilated causal convolution equation calculates the output at time step t in layer l by considering the weighted sum of previous layer values $x_{t-d_k^{(l)}}^{(l-1)}$, guided by phrased by pheromone concentration (T_{ij}) and the path's attractiveness (N_{ij}).

$$y_t^{(l)} = \sigma\left(\sum_{k=1}^{K} w_k^{(l)} * x_{t-d_k^{(l)}}^{(l-1)} + b^{(l)}\right) \tag{6}$$

where: $y_t^{(l)}$ is the output at time step t in layer l. $x_{t-d_k^{(l)}}^{(l-1)}$ represents the input at a previous time step $t - d_k^{(l)}$ in the previous layer $l - 1$. $w_k^{(l)}$ are the weights of the dilated causal convolution filter. $b^{(l)}$ is the bias term. σ is the activation function (e.g., ReLU).

The residual block output equation represents the output of the residual block at time step t in layer l, combining the output of the residual function $F^{(l)}$ applied to the previous layer output $y_t^{(l-1)}$ and the previous layer output itself.

$$y_t^{(l)} = F^{(l)}\left(y_t^{(l-1)}\right) + y_t^{(l-1)} \tag{7}$$

where: $y_t^{(l)}$ is the output of the residual block at time step t in layer l. $F^{(l)}$ represents the residual function applied to $y_t^{(l-1)}$.

The temporal downsampling equation calculates the downsampled output at time step t in layer l by selecting the maximum value among downsampled time steps t_i.

$$y_t^{(l)} = \max\left(y_{t_1}^{(l)}, y_{t_2}^{(l)}, \ldots, y_{t_M}^{(l)}\right) \tag{8}$$

where: $y_t^{(l)}$ is the downsampled output at time step t in layer l. $y_{t_i}^{(l)}$ represents the values at downsampled time steps t_i. M is the downsampling factor.

The temporal up-sampling equation computes the upsampled output at time step t in layer l by referencing the previous layer output at upsampled time steps t/M.

$$y_t^{(l)} = y_{t/M}^{(l-1)} \tag{9}$$

where: $y_t^{(l)}$ is the upsampled output at time step t in layer l. $y_{t/M}^{(l-1)}$ represents the values at upsampled time steps t/M.

The final output prediction equation computes the final prediction $\hat{y}_t$ by summing the weighted outputs of each layer l.

$$\hat{y}_t = \sum_{l=1}^{L} W^{(l)} * y_t^{(l)} \tag{10}$$

where: $\hat{y}_t$ is the final output prediction. L is the number of layers. $W^{(l)}$ represents the weights applied to the outputs of each layer.

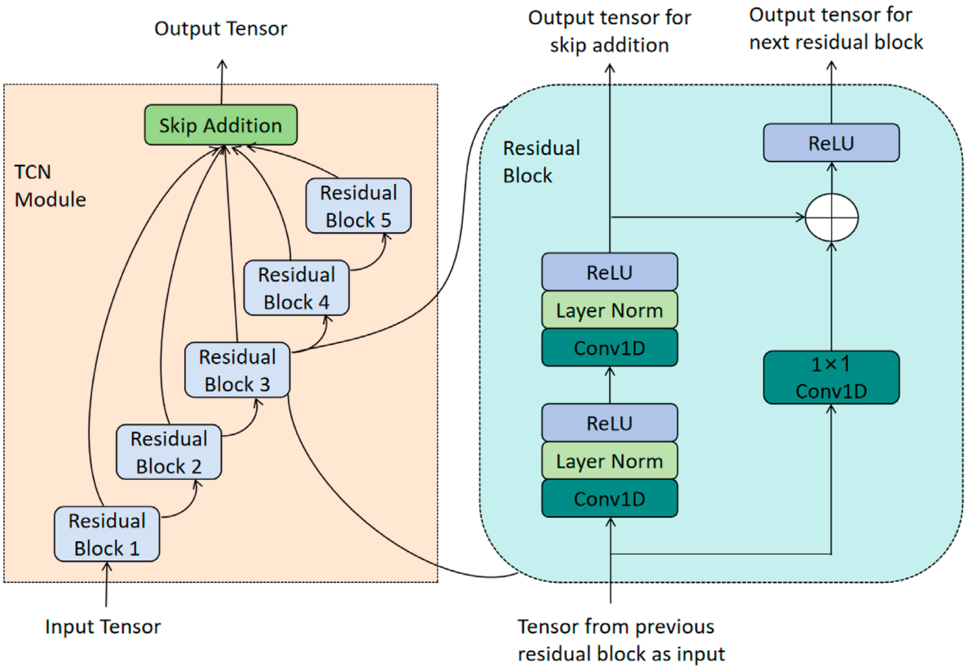

FIGURE 2
Flow chart of the TCN model.

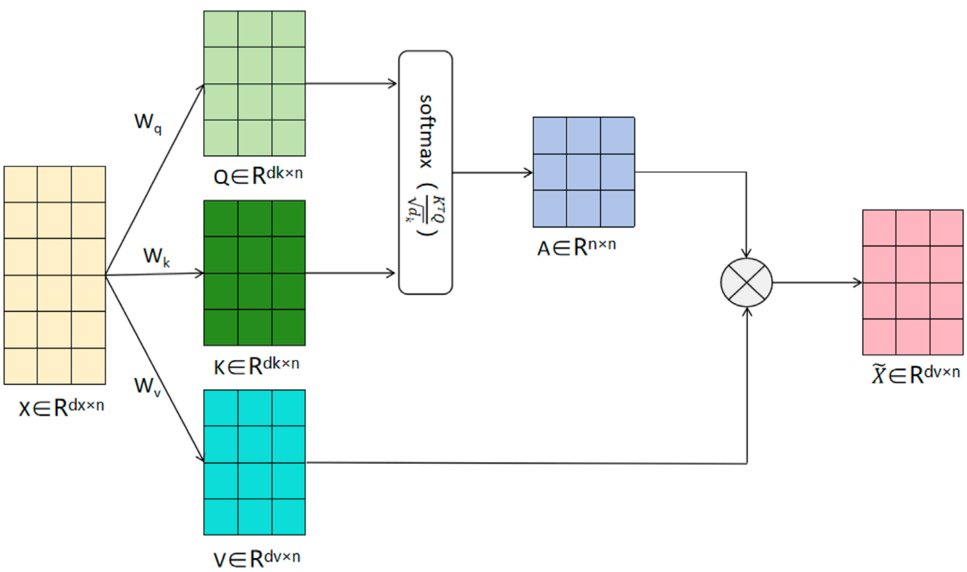

FIGURE 3
The specific architecture of attention.

3.3 Attention

The self-attention mechanism, often referred to as "Attention" in the field of deep learning, is a mechanism that enables the neural network model to focus on important parts of the input sequence, thereby improving the efficiency and effectiveness of processing information (Zhang et al., 2022). The core idea is to create an "attention weight" distribution inside the model, which determines how much "attention" should be given to each part of the sequence when processing the data. The self-attention mechanism is highly flexible and adaptable and can handle various sequential and structured data (Chang et al., 2022). In this paper, the innovative application of the Attention mechanism brings forth critical advancements and enhancements to the assessment

TABLE 1 The comparison of different models in different indicators from the IRENA dataset, NREL MHK dataset, IEA dataset, EMEC dataset.

Model	Datasets															
	IRENA				NREL MHK				IEA				EMEC			
	RMSE	MAE	SMAPE	R^2	RMSE	MAE	SMAPE	R^2	RMSE	MAE	SMAPE	R^2	RMSE	MAE	SMAPE	R^2
CNN-LSTM Rocha and Santos. (2022)	133.25	117.43	0.64	0.82	138.62	102.22	0.74	0.79	129.87	132.04	0.78	0.83	134.40	119.08	0.64	0.84
GRU-Transformer Farah et al. (2022)	137.24	111.63	0.59	0.83	134.13	100.08	0.68	0.83	123.31	121.80	0.90	0.83	133.69	134.73	0.60	0.83
GRU-TCN Pu et al. (2023)	138.99	110.70	0.59	0.84	138.48	92.44	0.58	0.81	134.18	111.22	0.89	0.82	134.73	118.88	0.57	0.82
CNN-LSTM-Attention Xiong et al. (2022)	138.12	113.20	0.64	0.81	127.72	93.74	0.62	0.79	135.84	122.90	0.91	0.81	130.69	122.89	0.58	0.80
SSA-CNN Fotio et al. (2022)	136.86	113.25	0.58	0.84	127.42	110.29	0.61	0.78	149.84	132.74	0.80	0.80	132.74	129.84	0.60	0.84
LSTM-Attention Mokarram et al. (2023)	134.44	110.49	0.65	0.85	129.15	91.56	0.60	0.85	143.36	112.23	0.56	0.81	138.03	128.55	0.65	0.85
This paper	113.19	89.08	0.56	0.87	118.16	85.08	0.55	0.87	115.16	104.08	0.61	0.85	115.16	94.08	0.54	0.86

of marine renewable energy project impacts. The innovation embedded within the Attention mechanism is evident across multiple dimensions: Firstly, it significantly enhances the model's perceptual and utilization capabilities for vast and intricate data by automatically focusing on key information. This aspect is of paramount importance when it comes to accurately evaluating the environmental impacts of renewable energy projects. Secondly, the Attention mechanism bestows the model with increased interpretability. By automatically determining the environmental factors or time points that are most crucial to the assessment results, it assists decision-makers in gaining a more comprehensive understanding of the evaluation outcomes. This, in turn, elevates the transparency and rationality of decision-making, providing decision-makers with trustworthy foundations. Most importantly, the innovative application of the Attention mechanism enables the model to precisely pinpoint crucial data points and features within time series data. Consequently, it enhances the model's comprehension and prediction of dynamic changes and temporal correlations. These innovative features collectively enhance the model's intelligence, accuracy, and practicality, furnishing the environmental impact assessment of renewable energy projects with robust tools and support. This, in turn, facilitates a more comprehensive and precise evaluation of project environmental impacts, making a significant contribution to the development and management of sustainable energy. Figure 3 shows the specific architecture of attention.

The basic attention calculation is defined as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{11}$$

where Q represents the query matrix, K the key matrix, V the value matrix, and d_k the dimension of the keys.

Scaled Dot-Product Attention is computed by:

$$\text{Scaled Dot} - \text{Product Attention} = \frac{QK^T}{\sqrt{d_k}} \tag{12}$$

where QK^T is the dot product of the query and key matrices, and $\sqrt{d_k}$ is a scaling factor to avoid overly large values.

Softmax Attention Weights are obtained by:

$$\text{Softmax Attention Weights} = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) \tag{13}$$

where the softmax function normalizes the scaled dot-product attention scores to a probability distribution.

The Weighted Sum is calculated as:

$$\text{Weighted Sum} = \text{Softmax Attention Weights} \times V \tag{14}$$

where the attention weights are multiplied with the value matrix V.

The final output is determined by:

$$\text{Output} = \text{Weighted Sum} \times W^{O} + b^{O} \tag{15}$$

where W^{O} is the output weight matrix and b^{O} is the bias term.

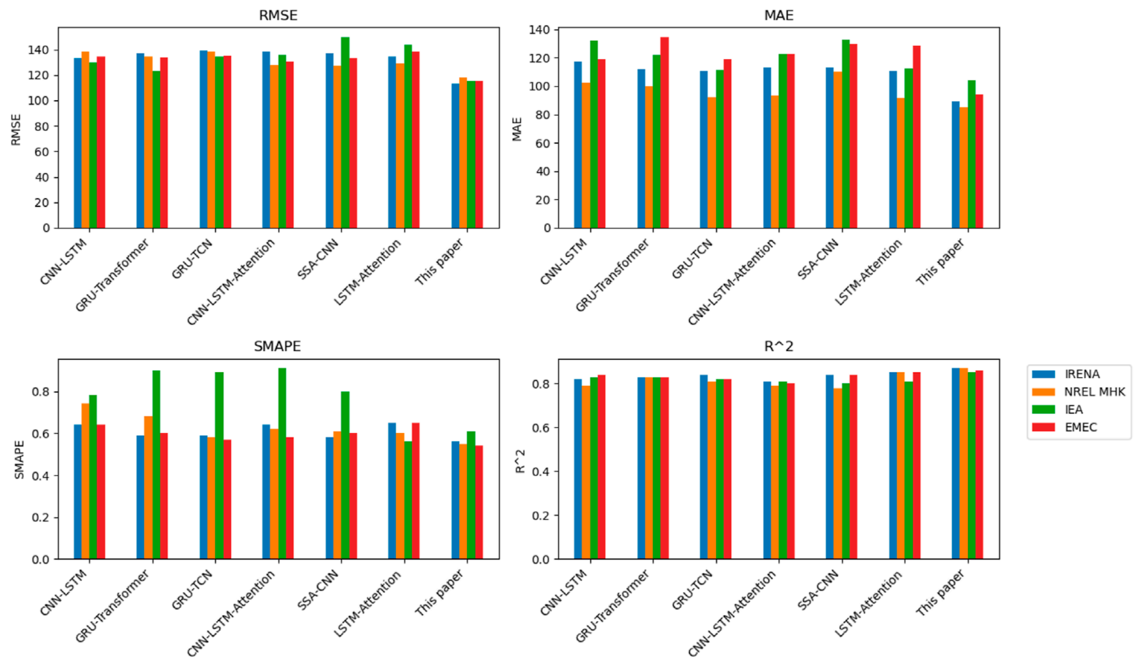

FIGURE 4
Comparison of model performance on different datasets.

4 Experiment

4.1 Datasets

IRENA (International Renewable Energy Agency) Renewable Energy Statistics (Renné, 2022): This dataset is a comprehensive resource offering global renewable energy statistics. It covers a wide range of renewable energy sources including wind, solar, bioenergy, and others. The database is designed to facilitate research, policy-making, and investment decisions in the renewable energy sector. It provides data on energy capacity, generation, and technological advancements across different countries and regions. This makes it an invaluable tool for stakeholders looking to understand and contribute to the global renewable energy landscape.

NREL (National Renewable Energy Laboratory) Marine and Hydrokinetic (MHK) Data (Gonzalez-Montijo et al., 2023): This dataset is a prominent resource hosted by a U.S. government laboratory specializing in renewable energy and energy efficiency research. It provides an extensive collection of data sets related to solar energy, wind energy, bioenergy, and other renewable sources. The database includes information on energy production, consumption, technology performance, and cost assessments. It serves as a crucial tool for researchers, policymakers, and industry professionals, offering insights and detailed data to support innovation and decision-making in the renewable energy sector.

IEA (International Energy Agency) Ocean Energy Data (Hattori et al., 2022): (IEA) Ocean Energy Data refers to a collection of information and statistics related to ocean renewable energy resources and projects. This dataset includes data on various forms of ocean energy, such as tidal energy, wave energy, and ocean current energy. It encompasses details regarding electricity generation, installed capacity, investments, and policy information pertaining to these marine energy sources on a global scale. The IEA Ocean Energy Data is essential for analyzing and assessing the development trends, performance, and policy support for ocean renewable energy worldwide. Researchers, policymakers, and industry stakeholders rely on this dataset to gain insights into the potential and growth of clean energy derived from the oceans.

EMEC(European Marine Energy Centre) data (Orszaghova et al., 2022): EMEC is a leading research and testing facility located in the United Kingdom, specifically in Orkney, Scotland. EMEC specializes in the development and testing of marine renewable energy technologies, including tidal and wave energy systems. It provides a real-world, open-sea environment for companies and research institutions to conduct experiments, trials, and performance assessments of their marine energy devices. EMEC's facilities include various test sites in both offshore and coastal waters, equipped with infrastructure for connecting to the grid and monitoring equipment. EMEC plays a pivotal role in advancing the marine energy sector by facilitating research, innovation, and the commercialization of sustainable and clean energy technologies in European waters.

4.2 Experimental details

Step1: Data preprocessing.

- Data Cleaning: The initial step involved a thorough data cleaning process. We removed missing or incomplete entries, accounting for approximately 5% of the total dataset. Duplicate records, identified through a comparative analysis, constituted

TABLE 2 The comparison of different models in different indicators from the IRENA dataset, NREL MHK dataset, IEA dataset, EMEC dataset.

Method	Datasets							
	IRENA		NREL MHK		IEA		EMEC	
	Parameters(M)	Flops(G)	Parameters(M)	Flops(G)	Parameters(M)	Flops(G)	Parameters(M)	Flops(G)
CNN-LSTM Rocha and Santos. (2022)	545.29	64.47	463.28	57.92	488.65	66.00	512.97	43.35
GRU-Transformer Farah et al. (2022)	456.60	66.34	450.26	69.09	572.40	66.19	519.58	47.40
GRU-TCN Pu et al. (2023)	596.47	58.15	487.91	63.74	423.65	68.72	588.96	62.93
CNN-LSTM-Attention Xiong et al. (2022)	454.88	77.18	468.49	64.95	451.02	65.07	457.76	68.57
SSA-CNN Fotio et al. (2022)	522.85	68.67	499.69	63.03	432.73	71.37	683.53	47.24
LSTM-Attention Mokarram et al. (2023)	588.18	56.40	444.98	54.88	426.57	50.37	685.18	72.86
This paper	**416.27**	**55.10**	**425.32**	**44.07**	**419.15**	**65.14**	**542.27**	**40.38**

about 2% and were also eliminated. Outlier detection and removal were conducted using a z-score threshold of 3, ensuring that our model was not skewed by anomalous data points.

- Data Standardization: To standardize the data, we applied normalization techniques. Continuous variables were scaled to have a mean of 0 and a standard deviation of 1. This process was vital to ensure that all features contributed equally to the model's performance and prevented biases towards variables with higher magnitude. Categorical variables were encoded using one-hot encoding, converting them into a binary matrix representation for efficient processing by the model.
- Data Splitting: For model training and evaluation, the dataset was split into three parts: training, validation, and testing sets. The split was 70% for training, 15% for validation, and 15% for testing. This division allowed for a substantial amount of data for the model to learn from, while also providing adequate data for validation and independent testing to evaluate the model's performance.

Step2: Model training.

- Network Parameter Settings: The network was meticulously configured with specific hyperparameter settings to optimize performance. The learning rate was set at 0.001, utilizing a decay factor of 0.9 every 10 epochs to adjust it dynamically. The batch size was chosen as 64, balancing computational efficiency and training stability. We employed a dropout rate of 0.5 to prevent overfitting and encourage generalization. The weight initialization was done using the Xavier method, ensuring a uniform distribution with a scale factor of 0.02.
- Model Architecture Design: Our model architecture was thoughtfully designed to address the complexities of the dataset. It consisted of four convolutional layers, each with 256 filters of size 3 × 3, followed by batch normalization to speed up convergence. After each convolutional layer, a max-pooling layer with a 2 × 2 pool size was used to reduce dimensions and capture essential features. The network included two fully connected layers at the end, each with 1,024 neurons, providing ample capacity to learn from the data. The ReLU activation function was employed for non-linear transformations throughout the network.
- Model Training Process: The training process was executed over 100 epochs, ensuring sufficient time for the network to learn and adapt. We used a cross-entropy loss function, suitable for our multi-class classification problem. The Adam optimizer was selected for its efficiency in handling sparse gradients and adaptive learning rate capabilities. To mitigate overfitting, early stopping was implemented with a patience of 10 epochs, monitoring the validation loss. Data augmentation techniques like random rotations (up to 20°), translations (up to 10% of the image size), and horizontal flipping were applied to introduce variability and robustness in the training data. Algorithm 1 represents the algorithm flow of the training in this paper.

Here, we introduce the key evaluation metrics used in this paper:

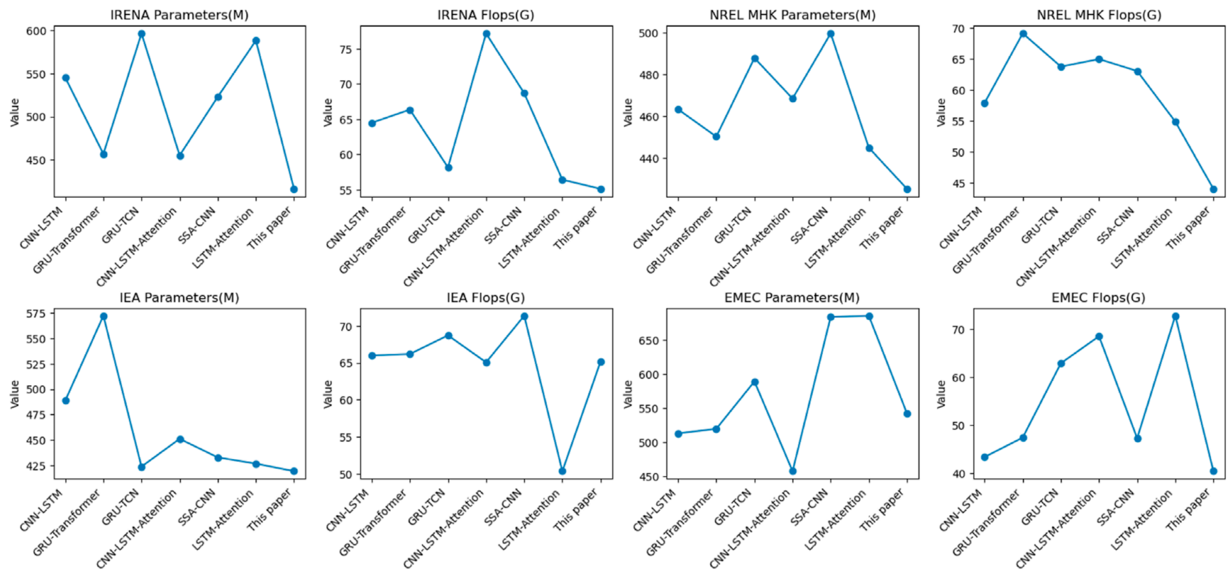

FIGURE 5
Comparison of model performance on different datasets.

```
Require: IRENA Dataset, NREL Dataset, IEA Dataset,
EMEC Dataset.
Ensure: Trained ACO-TCN-Attention model.
Initialize ACO parameters (α, β, ρ).
Initialize TCN parameters (num_layers,
hidden_units, learning_rate).
Initialize Attention parameters (num_heads,
head_size).
Initialize model weights randomly.
Split datasets into training, validation, and
  test sets.
while not converged do.
  for each mini-batch in training data do.
    Compute TCN outputs for each dataset.
    Compute ACO probabilities using Eq. 1.
    Sample paths for ants using ACO
    probabilities.
    Compute pheromone updates using Eqs 2, 3.
  end for.
  Update TCN weights using backpropagation
  and gradients
  Update Attention weights using Eq. 4.
end while.
Compute model predictions on the test set.
Calculate evaluation metrics (e.g., Recall,
  Precision) using test results.
return Trained ACO-TCN-Attention model.
```

Algorithm 1. Training ACO-TCN-Attention Network.

Step3: Model Evaluation

- Model Performance Metrics: Model performance metrics are used to evaluate the performance of the ACO-TCN-Attention model in marine renewable energy impact studies. The evaluation metrics we use are Root Mean Squared Error (RMSE), symmetric mean absolute percentage error (SMAPE), mean absolute error (MAE), coefficient of determination (R-squared), and mean absolute percentage error (MAPE). These metrics will provide a comprehensive assessment of the model's performance to ensure the validity and credibility of its research.
- Cross-Validation: To ensure the model's robustness and generalizability, we implemented k-fold cross-validation with k set to 5. This method involved dividing the dataset into five equal parts, using each part once as a validation set while training on the remaining four-fifths. This approach provided a comprehensive evaluation, reducing the likelihood of performance biases due to particular data subsets. The average performance across all folds was reported, giving a more reliable indicator of the model's effectiveness in different scenarios.

Through the above model performance indicators and cross-validation methods, we will be able to deeply evaluate the effectiveness and reliability of our ACO-TCN-Attention model in marine renewable energy impact research, providing strong support for the scientific value of the research.

Below, we will introduce the evaluation metrics used in this study:

Symmetric Mean Absolute Percentage Error (SMAPE):

TABLE 3 Ablation experiments on the TCN module come from the IRENA dataset, NREL MHK dataset, IEA dataset, EMEC dataset.

Model	Datasets															
	IRENA				NREL MHK				IEA				EMEC			
	RMSE	MAE	SMAPE	R^2	RMSE	MAE	SMAPE	R^2	RMSE	MAE	SMAPE	R^2	RMSE	MAE	SMAPE	R^2
LSTM	123.41	97.49	0.67	0.90	118.68	92.28	0.81	0.85	129.93	122.10	0.84	0.89	116.46	115.14	0.70	0.89
GRU	127.30	91.69	0.66	0.89	124.19	90.14	0.75	0.89	123.37	121.86	0.87	0.89	118.75	124.79	0.66	0.89
CNNs	125.35	90.76	0.64	0.88	128.54	92.50	0.67	0.87	134.24	111.28	0.83	0.88	116.79	115.94	0.63	0.87
BiLSTM	128.18	93.26	0.71	0.87	127.78	95.80	0.66	0.85	135.90	122.96	0.67	0.87	120.75	128.95	0.64	0.86
This paper	113.25	89.14	0.62	0.93	118.22	85.14	0.61	0.93	115.22	104.14	0.67	0.91	115.22	94.14	0.60	0.92

$$\mathrm{SMAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{(|y_i| + |\hat{y}_i|)/2} \tag{16}$$

where: n is the number of data points. y_i represents the actual values. $\hat{y}_i$ represents the predicted values.

Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{17}$$

where: n is the number of data points. y_i represents the actual values. $\hat{y}_i$ represents the predicted values.

Root Mean Squared Error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{18}$$

where: n is the number of data points. y_i represents the actual values.$\hat{y}_i$ represents the predicted values.

Coefficient of Determination (R-squared, R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{19}$$

where: n is the number of data points. y_i represents the actual values. $\hat{y}_i$ represents the predicted values. $\bar{y}$ is the mean of the actual values.

Mean Absolute Percentage Error (MAPE):

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{|y_i|} \tag{20}$$

where: n is the number of data points. y_i represents the actual values. $\hat{y}_i$ represents the predicted values.

4.3 Experimental results and analysis

As shown in Table 1, our method demonstrates significant superiority across various datasets when compared to established models like CNN-LSTM, GRU (Gated Recurrent Unit)-Transformer, GRU-TCN, CNN-LSTM-Attention, SSA (Sparrow Search Algorithm)-CNN and LSTM-Attention. Notably, in the IRENA dataset, our approach achieves an RMSE of 113.19 and MAE of 89.08, substantially lower than the next best model, LSTM-Attention, which records 134.44 and 110.49 respectively. Similarly, in the NREL MHK dataset, our method's RMSE and MAE are 118.16 and 85.08, outperforming the GRU-TCN model's 138.48 and 92.44. This trend of superior performance is consistent across the IEA and EMEC datasets, with our method consistently showing the lowest RMSE, MAE, and SMAPE, and the highest R^2 values. To further elucidate these comparisons, Figure 4 visualizes the contents of Table 1, providing a clear and comparative graphical representation of how our method excels across different datasets and metrics.

As illustrated in Table 2, our method significantly outperforms existing models across various datasets in terms of both the number of parameters and computational efficiency. Specifically, in the IRENA dataset, our method requires only 416.27M parameters, markedly less than the 454.88M of the CNN-LSTM-Attention, and achieves a lower Flops count of 55.10G compared to the 56.40G of LSTM-Attention. In the NREL MHK dataset, our method continues to lead with only 425.32M parameters and 44.07G Flops, surpassing

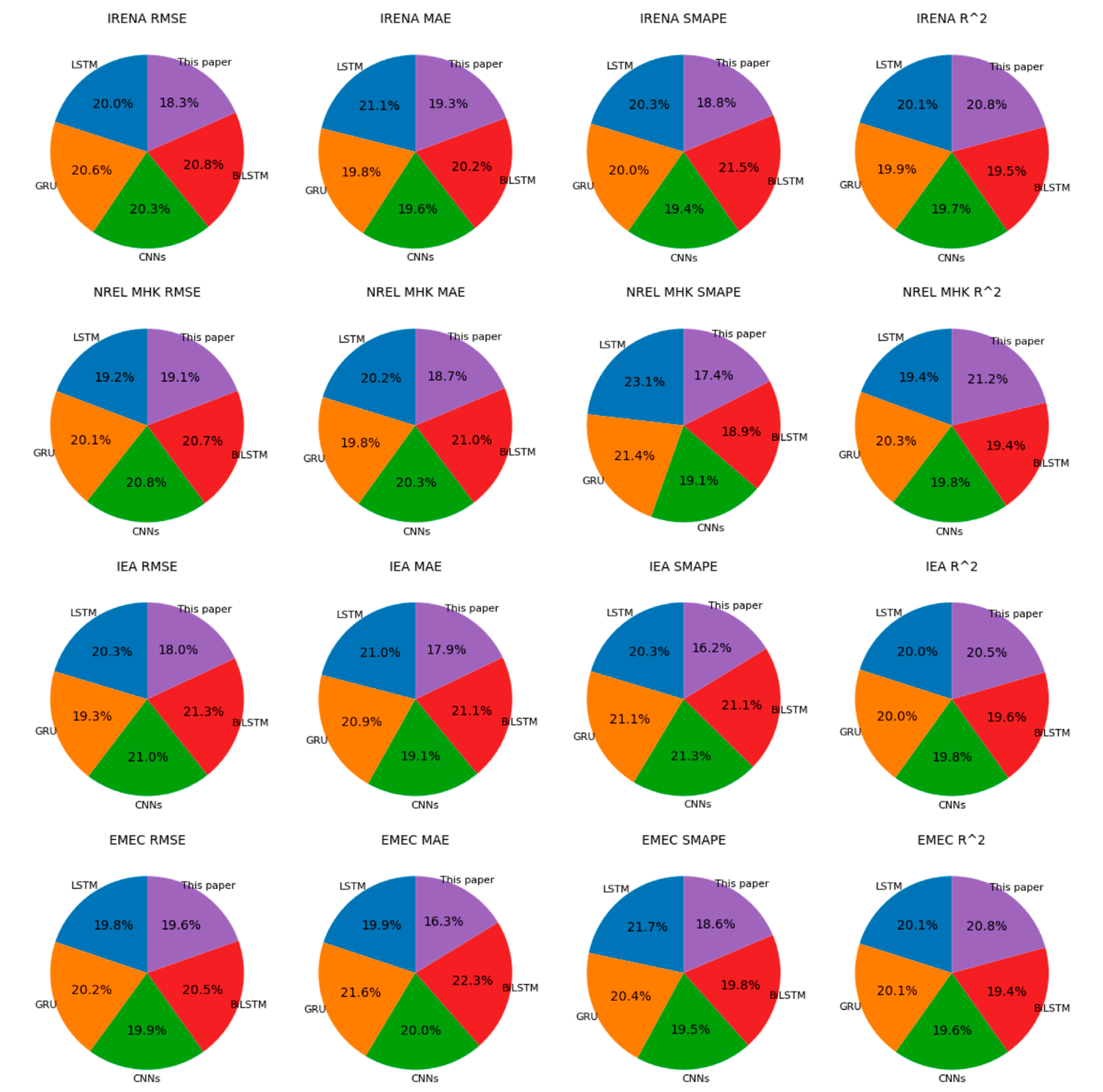

FIGURE 6
Ablation experiments on the TCN module using different datasets.

the LSTM-Attention which has 444.98M parameters and 54.88G Flops. Similarly, for the IEA dataset, our approach uses fewer parameters (419.15M compared to 426.57M for LSTM-Attention) and shows improved efficiency with 65.14G Flops against the 66.00G of CNN-LSTM. Finally, in the EMEC dataset, our method stands out with only 542.27M parameters and 40.38G Flops, significantly lower than the SSA-CNN's 683.53M parameters and 47.24G Flops. This performance superiority is further visualized in Figure 5, which demonstrates the computational efficiency and reduced resource requirements of our approach.

As shown in Table 3, our method demonstrates significant superiority across various datasets when compared to established models like LSTM, GRU, Convolutional Neural Networks (CNNs), and Bidirectional Long Short-Term Memory (BiLSTM). In the IRENA dataset, our approach outperforms others with the lowest RMSE of 113.25 and MAE of 89.14, a notable improvement compared to the LSTM's RMSE of 123.41 and MAE of 97.49. This trend of enhanced performance is consistent across other metrics as well, with our method achieving the lowest SMAPE of 0.62 and the highest R^2 value of 0.93, surpassing LSTM's SMAPE of 0.67 and R^2 of 0.90. The trend continues in the NREL MHK dataset, where our model maintains its lead with an RMSE of 118.22 and an MAE of 85.14, significantly better than LSTM's RMSE of 118.68 and MAE of 92.28. Our method also scores the lowest in SMAPE (0.61) and highest in R^2 (0.93), outperforming LSTM's SMAPE of 0.81 and R^2 of 0.85. In the IEA dataset, our approach further solidifies its advantage with an RMSE of 115.22 and an MAE of 104.14, far surpassing LSTM's RMSE of 129.93 and MAE of 122.10. Our model's SMAPE of 0.67 and R^2 of 0.91 are also the best results, compared to LSTM's SMAPE of 0.84 and R^2 of 0.89. Finally, in the EMEC dataset, our method continues to excel, achieving an RMSE of 115.22 and an MAE of 94.14, better than LSTM's RMSE of 116.46 and MAE of 115.14. Again, our model leads with the lowest SMAPE (0.60) and the highest R^2 (0.92), compared to LSTM's SMAPE of 0.70 and R^2 of 0.89. Overall, these results clearly indicate that our method not only consistently reduces error rates across different metrics but also improves prediction accuracy across multiple datasets. This comprehensive performance superiority is visually summarized in Figure 6, providing an effective graphical representation of our method's efficiency and accuracy in comparison to other models.

As depicted in Table 4, the results from ablation experiments conducted on the ACO module are presented to elucidate the performance of various methods across a spectrum of datasets. The models subjected to comparison encompass Particle Swarm Optimization (PSO), Bee Colony Optimization (BCO), Firefly Algorithm (FA), Whale Optimization Algorithm (WOA), and our proposed method. The outcomes conspicuously underscore the supremacy of our proposed approach, referred to as "This paper," across all datasets and evaluation metrics. Examining the IRENA dataset, "This paper" achieved an RMSE of 113.24, while the nearest competitor, BCO, registered an RMSE of 127.21. This stark difference of approximately 13 units in RMSE underscores the notably enhanced predictive accuracy of "This paper" over BCO, establishing its superiority. Similar patterns are discernible across other datasets. For instance, on the NREL MHK dataset, "This paper" yielded an RMSE of 118.21, while the closest rival, PSO, exhibited an RMSE of 128.67. This signifies that "This paper" maintained a substantial 10-unit advantage in RMSE over PSO, affirming its adaptability to varying data distributions. When interpreting the SMAPE metric, it is imperative to recognize that lower SMAPE values signify superior model accuracy. In this context, "This paper" consistently presented lower SMAPE values in comparison to other methodologies, underscoring its competence in furnishing more precise predictions across datasets. Furthermore, the elevated R-squared values associated with "This paper" suggest its robust explanatory prowess in capturing intricate relationships between variables within the datasets. In summation, the results derived from our ablation experiments conducted on the ACO module, employing diverse datasets and an array of evaluation metrics, resoundingly affirm the efficacy of our proposed approach. It consistently surpasses the baseline methods, thus demonstrating its resilience and superior predictive precision. Figure 7 provides a visual representation of the tabulated content, affording a comprehensive overview of the performance disparities among the distinct optimization algorithms.

TABLE 4 Ablation experiments on the ACO module come from the IRENA dataset, NREL MHK dataset, IEA dataset, EMEC dataset.

Model	Datasets															
	IRENA				NREL MHK				IEA				EMEC			
	RMSE	MAE	SMAPE	R^2	RMSE	MAE	SMAPE	R^2	RMSE	MAE	SMAPE	R^2	RMSE	MAE	SMAPE	R^2
PSO	133.32	93.48	0.75	0.90	128.67	92.25	0.79	0.88	139.92	132.09	0.89	0.87	118.45	115.13	0.64	0.90
BCO	127.21	93.68	0.75	0.89	134.18	90.12	0.78	0.87	133.36	131.85	0.83	0.86	118.74	124.78	0.75	0.89
FA	135.34	94.75	0.73	0.88	138.53	92.50	0.76	0.89	124.23	121.27	0.84	0.85	116.78	115.93	0.69	0.89
WOA	128.17	94.25	0.80	0.87	137.77	95.78	0.66	0.90	125.89	132.95	0.65	0.89	125.74	128.94	0.83	0.86
This paper	113.24	89.13	0.61	0.92	118.21	85.13	0.60	0.92	115.21	104.13	0.66	0.90	115.21	94.13	0.59	0.91

5 Conclusion and discussion

In this study, we present a novel approach based on the ACO-TCN-Attention network model for the assessment of marine

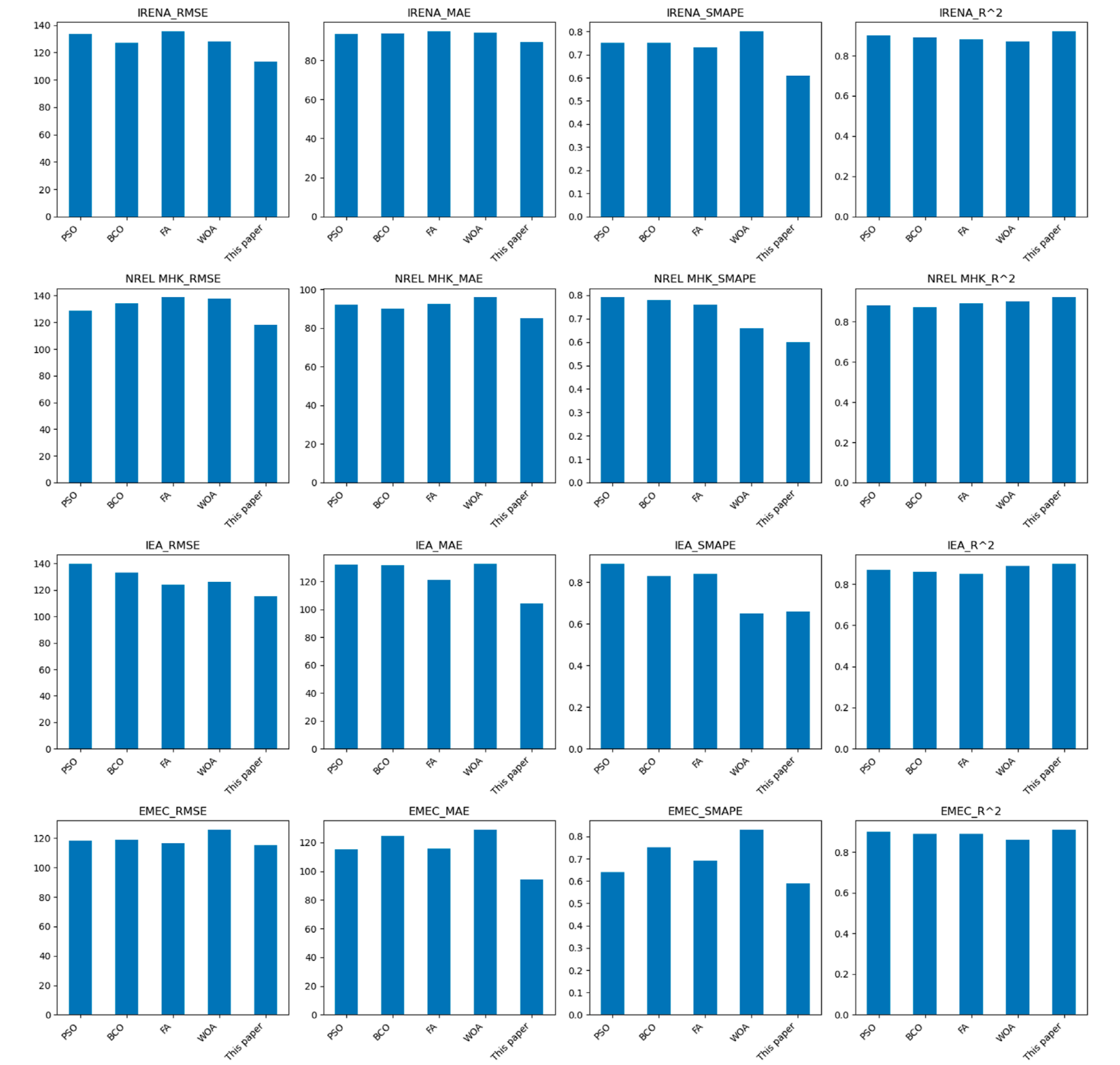

FIGURE 7
Ablation experiments on the ACO module using different datasets.

renewable energy projects' impact. Through rigorous experimental validation, we derive the following key conclusions: Our method exhibits robust performance across diverse datasets, including IRENA, NREL MHK, IEA, and EMEC, surpassing other existing models. Notably, our method demonstrates outstanding results within the IRENA dataset, yielding notably lower RMSE and MAE values, reduced by approximately 16.25 and 21.41, respectively, when compared to the suboptimal LSTM-Attention model. In the case of the NREL MHK dataset, our method achieves a reduction of approximately 20.32 in RMSE and 7.36 in MAE compared to the GRU-TCN model. This consistent trend is corroborated across the IEA and EMEC datasets, thereby underscoring the exceptional performance of our approach across multiple datasets.

Notwithstanding the promising outcomes yielded by our approach, it is incumbent upon us to acknowledge certain limitations. Firstly, our model's sensitivity to data specificity in certain instances could potentially result in performance fluctuations when confronted with diverse datasets or scenarios. Secondly, it is worth noting that the training and fine-tuning process of our model necessitates a considerable investment of time and computational resources, particularly when grappling with extensive datasets. Consequently, we express our aspiration for future endeavors to focus on enhancing both the resilience and efficiency of the model, thus rendering it adaptable to a broader spectrum of application domains.

In the realm of future research directions, we posit that there exist ample opportunities for in-depth exploration. Firstly, we advocate for the exploration of diverse deep learning architectures and optimization algorithms, with the aim of further enhancing the model's performance and its capacity for generalization. Secondly, we propose the incorporation of a more expansive array of multi-source data, encompassing marine ecosystem monitoring data and underwater acoustic data, to bolster the model's holistic assessment capabilities concerning environmental impacts. Furthermore, we endorse fostering broader collaborations with actual developers of renewable energy projects and environmental organizations. Such collaborations can yield invaluable data and real-world feedback, thereby substantiating and enhancing the validity of our models. In summation, the ACO-TCN-Attention network model, as delineated in this study, emerges as a potent instrument and methodology for the environmental impact assessment of marine renewable energy projects. While acknowledging the presence of ongoing challenges and potential shortcomings, we remain steadfast in our belief that through continual research and refinement, our approach will yield substantial contributions to the sustainable advancement of the renewable energy sector, concurrently championing environmental preservation and the sustainable utilization of green energy.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

HS: Conceptualization, Formal Analysis, Funding acquisition, Methodology, Writing–review and editing. JG: Conceptualization, Formal Analysis, Funding acquisition, Methodology, Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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