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AI-Powered Time Series Forecasting for Sustainable Energy Management in Luxury Yachts

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Abstract

The luxury yacht industry is undergoing a transformative shift toward sustainability, with increasing emphasis on reducing carbon footprints and optimizing energy consumption in onboard systems, particularly in the hotel sector. This study presents a novel application of the Nonlinear Autoregressive (NAR) neural network for time series forecasting of energy usage and generation aboard luxury yachts. Leveraging real-world datasets from BlueAI, the study focuses on three critical energy streams: hotel electricity consumption, HVAC energy usage, and solar energy production. The NAR model, a feed-forward neural network with a sigmoid activation function in its hidden layer, was trained using historical time series data to predict short-term energy trends. By forecasting six hours into the future, the model enables dynamic energy management, allowing operators to preemptively adjust load demands, optimize HVAC settings, and maximize the use of renewable energy resources like solar panels. Performance evaluations in both training and real-time environments showed high predictive accuracy across all subsystems. This predictive capability is a crucial step toward greener yachting by enabling more intelligent energy scheduling, reducing dependence on fossil fuels, and minimizing greenhouse gas emissions. The integration of AI-driven forecasting tools like the NAR model promotes renewable energy adoption and contributes to global climate change mitigation efforts. The research highlights how smart technologies can align the luxury maritime industry with the goals of sustainability and environmental stewardship.

التنبؤ بالسلاسل الزمنية المدعوم بالذكاء الاصطناعي من أجل إدارة مستدامة للطاقة في اليخوت الفاخرة

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الملخص: تُعد تشهد صناعة اليخوت الفاخرة تحولاً متسارعاً نحو الاستدامة، مع تزايد الاهتمام بخفض البصمة الكربونية وتحسين كفاءة استهلاك الطاقة في الأنظمة الموجودة على متن اليخوت، ولا سيما أنظمة الخدمات الفندقية. تقدم هذه الدراسة تطبيقاً مبتكراً لشبكة **الانحدار الذاتي غير الخطي *(NAR)*** للتنبؤ بالسلاسل الزمنية الخاصة باستهلاك وإنتاج الطاقة على متن اليخوت الفاخرة. وبالاعتماد على بيانات حقيقية مقدمة من منصة ***BlueAI***، ركزت الدراسة على ثلاثة تدفقات طاقة رئيسية: استهلاك الكهرباء في القطاع الفندقي، واستهلاك الطاقة في أنظمة التدفئة والتهوية وتكييف الهواء*(HVAC)* ، وإنتاج الطاقة الشمسية .تم تدريب نموذج *NAR*، وهو شبكة عصبية أمامية التغذية تستخدم دالة تنشيط سيغمويد في الطبقة المخفية، بالاعتماد على بيانات تاريخية للسلاسل الزمنية بهدف التنبؤ بالاتجاهات قصيرة المدى للطاقة. ومن خلال التنبؤ لفترة تصل إلى ست ساعات مسبقاً، يتيح النموذج إدارة ديناميكية للطاقة، مما يساعد المشغلين على ضبط الأحمال الكهربائية بصورة استباقية، وتحسين إعدادات أنظمة*HVAC* ، وتعظيم الاستفادة من مصادر الطاقة المتجددة مثل الألواح الشمسية .أظهرت نتائج التقييم في بيئات التدريب والتشغيل الفعلي دقة تنبؤية عالية عبر جميع الأنظمة الفرعية المدروسة. وتمثل هذه القدرة التنبؤية خطوة مهمة نحو جعل قطاع اليخوت أكثر استدامة من خلال تمكين جدولة ذكية للطاقة، وتقليل الاعتماد على الوقود الأحفوري، وخفض انبعاثات غازات الاحتباس الحراري. كما يسهم دمج أدوات التنبؤ المعتمدة على الذكاء الاصطناعي، مثل نموذج*NAR* ، في تعزيز استخدام الطاقة المتجددة ودعم الجهود العالمية الرامية إلى التخفيف من آثار التغير المناخي. وتبرز هذه الدراسة الدور الذي يمكن أن تؤديه التقنيات الذكية في مواءمة صناعة النقل البحري الفاخر مع أهداف الاستدامة والحفاظ على البيئة.

الكلمات المفتاحية: اليخوت الفاخرة ، التنبؤ بالسلاسل الزمنية ، الشبكة العصبية للانحدار الذاتي غير الخطي(NAR) ، تحسين استهلاك الطاقة ، الطاقة المتجددة ، التكنولوجيا الخضراء.

1. Introduction

The luxury yacht industry, long associated with comfort and prestige, is now embracing a pivotal transformation toward sustainability and eco-efficiency. Growing awareness of environmental issues and stricter international regulations on carbon emissions—such as the International Maritime Organization (IMO) 2050 strategy—have accelerated the need for greener maritime operations [2]. Among the many contributors to onboard energy demand, the hotel and HVAC (heating, ventilation, and air conditioning) systems represent a significant share of total power consumption in luxury vessels [8] . As modern yachts increasingly incorporate renewable sources like solar power, the ability to accurately forecast both energy consumption and generation becomes crucial for efficient energy management and reduced fossil fuel reliance. Artificial intelligence (AI) and machine learning (ML) have demonstrated exceptional capabilities in learning nonlinear relationships in energy systems, particularly through time series forecasting models [3]. Neural networks can analyze historical data to predict short-term fluctuations, providing actionable insights for load balancing and resource optimization [6]. In this context, the Nonlinear Autoregressive (NAR) neural network stands out as an efficient architecture for forecasting energy series that exhibit temporal dependencies and nonlinear dynamics [7]. This study proposes an AI-powered time series forecasting framework based on the NAR model for sustainable energy management in luxury yachts. Real-world datasets from BlueAI were used to model and forecast three critical energy streams: [1] hotel electricity consumption, [2] HVAC energy usage, and [3] solar energy production. The model forecasts up to six hours ahead, enabling dynamic energy control, predictive scheduling, and optimal utilization of renewable energy resources. The main contributions of this work are as the following:

- This study develops and trains advanced Nonlinear Autoregressive (NAR) neural network models capable of accurately forecasting short-term energy consumption and solar generation aboard luxury yachts. By leveraging real-world datasets collected from BlueAI, the models effectively capture the nonlinear dynamics and temporal dependencies inherent in onboard energy systems, enabling precise and data-driven energy forecasting.
- The proposed NAR framework is implemented in a closed-loop configuration that performs adaptive six-hour-ahead forecasting, allowing continuous model updating and real-time adjustment of energy operations. This predictive capability enhances the responsiveness of

energy management systems, supporting optimized load distribution, efficient HVAC control, and better utilization of renewable sources such as solar energy.

- Through extensive performance evaluation under realistic operating conditions, the study demonstrates that AI-driven forecasting can significantly contribute to sustainable maritime operations. By improving energy efficiency, minimizing generator dependency, and reducing greenhouse gas emissions, the proposed approach aligns luxury yacht operations with international sustainability goals and advances the integration of intelligent systems in maritime energy management.

Hereafter, the paper is structured as follows. The related work is described in Section 2. Methodology is presented in Section 3. Section 4 explores the results and discussion. Finally, conclusions & future work are drawn in Section 5.

2. Related Work

AI-based time series forecasting has been extensively studied in renewable energy and smart building contexts [4]. [10] demonstrated that deep learning models outperform traditional statistical approaches such as ARIMA and exponential smoothing for wind energy forecasting. Similarly, [8] applied LSTM networks to predict HVAC loads, achieving more accurate results in dynamic thermal environments. These studies underline the importance of nonlinear modeling for complex energy systems. The NAR model is a feed-forward network capable of forecasting future values from previous time steps, leveraging internal feedback loops for sequential learning. [3] reported that NAR networks provide superior accuracy for short-term energy consumption prediction compared to multilayer perceptrons. [6] also used NAR for electrical load forecasting and observed that it effectively captures cyclical and seasonal patterns in time series data. While AI has been widely applied in terrestrial energy systems, its use in maritime environments is emerging. [9] developed ML algorithms for optimizing vessel routes and fuel consumption. [3] introduced an intelligent hybrid energy management system for yachts, integrating solar energy, batteries, and predictive analytics to minimize emissions. These works collectively emphasize the growing trend of integrating AI for sustainability in maritime engineering [5]. HVAC systems are among the most energy-intensive components on yachts. Predictive modeling allows for adaptive control that ensures passenger comfort while conserving energy. In hotel sectors, AI-based forecasting has been used to optimize lighting, temperature, and power usage, resulting in significant energy savings [1]. The present study extends these principles to the maritime context by modeling hotel and HVAC systems onboard luxury yachts using NAR networks.

3. Methodology

3.1 Dataset Description

The dataset utilized in this study was provided by BlueAI, consisting of real-time energy measurements collected from onboard systems of luxury yachts. It includes three primary energy streams: hotel electricity consumption, HVAC energy usage, and solar energy production. Each dataset represents continuous time series data recorded over multiple days with high temporal granularity, capturing short-term fluctuations and operational variations due to changes in occupancy, environmental conditions, and solar exposure. To ensure robust model training and fair evaluation, the dataset was divided into two subsets: 80% of the data was used for training the Nonlinear Autoregressive (NAR) neural network, while the remaining 20% was reserved for testing. This partitioning allowed the model to generalize effectively to unseen data and provided a reliable basis for performance assessment under realistic operating conditions.

3.2 Data Preprocessing

Before model training, a series of preprocessing steps were performed to enhance data quality and model stability. Missing or incomplete records were identified and replaced using interpolation techniques to maintain temporal continuity. The raw signals were then smoothed using a moving average filter to minimize measurement noise and transient spikes that could otherwise affect convergence during training. Normalization was applied to scale all input features within a uniform range, typically between 0 and 1, ensuring that large numerical differences between variables did not bias the learning process. Furthermore, feature selection was guided by time-lag dependencies, meaning that previous observations of each energy stream were included as predictors for future values. This structure allowed the NAR model to learn the temporal correlations inherent in the data and to forecast accurately across multiple time steps.

3.3 Nonlinear Autoregressive (NAR) Neural Network

The forecasting model employed in this work is the Nonlinear Autoregressive (NAR) neural network, a type of feed-forward dynamic network designed for time series prediction. The NAR model predicts the current value of a series based solely on its own past values, effectively modeling temporal dependencies without external inputs. The network architecture consists of three main layers: an input layer representing delayed time steps of the target variable, a hidden layer using a sigmoid activation function to introduce nonlinearity, and an output layer that produces the predicted energy value. The NAR model was implemented in a closed-loop configuration, enabling recursive forecasting over multiple steps—in this case, predicting energy trends up to six hours ahead. Training was conducted using the Levenberg–Marquardt backpropagation algorithm, chosen for its fast convergence and stability in nonlinear optimization. Hyperparameters, including the number of hidden neurons and feedback delays, were optimized through cross-validation to achieve a balance between model accuracy and computational efficiency. This configuration allowed the NAR model to adapt dynamically to temporal patterns in energy consumption and production, providing accurate and stable forecasts suitable for real-time energy management. Figure 1 describes the architecture of a recurrent neural network (RNN) model for time series prediction. The network uses previous time steps (Y(t-1) to Y(t-4)) as input to forecast a future value.

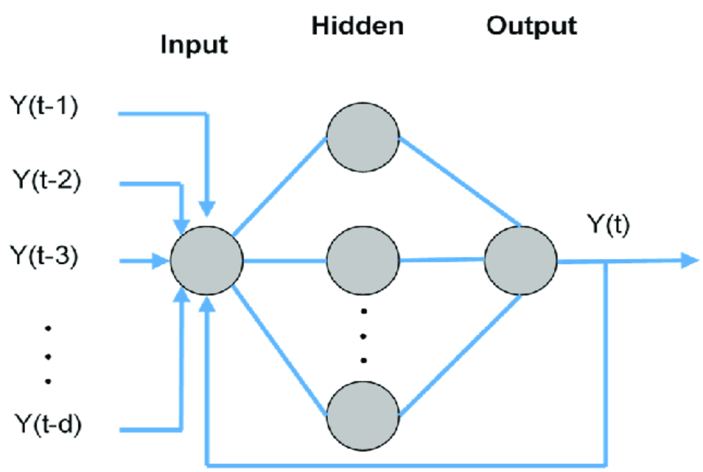


Figure 1. Architecture of a recurrent neural network (RNN) model for time series prediction. The network uses previous time steps (Y(t-1) to Y(t-4)) as input to forecast a future value.

3.4 Performance Metrics

To quantitatively evaluate the predictive performance of the proposed models, four statistical indicators were employed: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). These metrics collectively measure the deviation between predicted and actual values, assessing both the magnitude and proportion of forecasting errors. MSE and RMSE provide a measure of the average squared and absolute errors, respectively, indicating the overall precision of the model's predictions. MAPE expresses the forecasting error as a percentage, facilitating comparison across different energy scales, while R^2 evaluates how well the model explains the variance in the observed data. All metrics were computed for both the training and testing phases, as well as for real-time forecasting scenarios, to ensure consistency, reliability, and generalization of the proposed NAR framework.

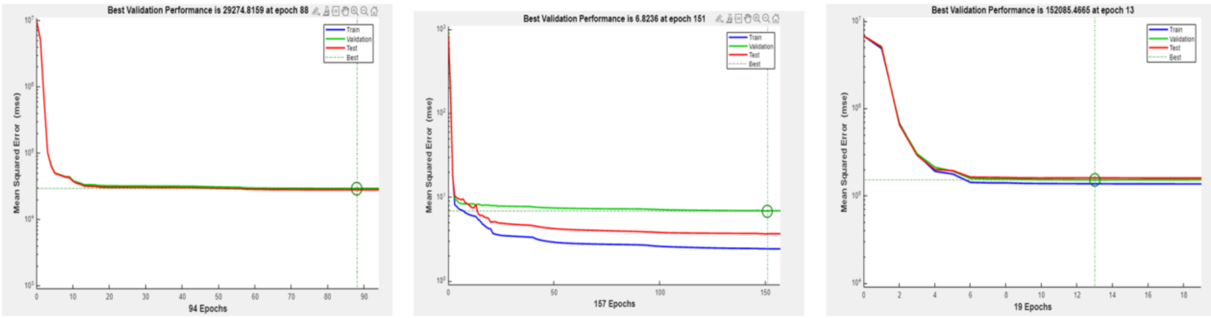
4. Results and Discussion

This section provides a comprehensive evaluation of the Nonlinear Autoregressive (NAR) neural network models developed for forecasting the hotel, HVAC, and solar energy time series. The analysis covers the model training performance, forecasting accuracy over a six-hour horizon, stability in real-time operation, and the subsequent implications for sustainable energy management.

4.1 Model Performance

The training process for the three NAR models revealed distinct convergence profiles and performance characteristics, providing critical insights into their learning dynamics and predictive reliability. The hotel consumption model achieved its best validation performance earliest, at epoch 18, but with a notably high Mean Squared Error (MSE) of 2021.6. This suggests the model quickly identified the dominant, low-frequency patterns of guest-related energy use but may struggle with finer, high-frequency variations, leading to a higher residual error. This is a common trade-off where rapid convergence can sometimes come at the cost of capturing all nuances in the data. In contrast, the HVAC consumption model demonstrated a more gradual learning process, reaching its optimal validation MSE of 5.5294 at a much later epoch, 191. This extended training period indicates that the model required more iterations to effectively learn the complex, non-linear relationships driven by fluctuating ambient conditions and system setpoints. The lower final MSE, compared to the hotel model, points to a higher precision in modeling these complex dynamics, albeit with a greater computational cost for training. The solar energy model exhibited the most efficient convergence, achieving its best validation MSE of 15036.6 by epoch 13. This very rapid convergence strongly indicates that the model successfully learned the primary, deterministic pattern of solar generation—largely governed by the time of day—with minimal effort. However, the high absolute value of the MSE, likely due to the data's unit scale (VAr), also suggests that the model's predictions have a wider variance. This implies that while it perfectly captures the daily trend, it may be less accurate in predicting the exact magnitude of power output at every timestep, possibly due to transient cloud cover or other stochastic environmental factors not fully captured in the historical data alone. Collectively, while all models successfully converged, their performance metrics highlight a critical balance between training speed, model complexity, and predictive accuracy. The hotel model is fast but less precise, the HVAC model is precise but slower to train, and the solar model is highly efficient at learning the main trend but may exhibit higher prediction variance. Figure 2 illustrates Model training performance for three building energy systems, showing the mean squared error (MSE) over training epochs. The best validation performance for each model is indicated. (A) Hotel consumption, (B) HVAC consumption, and (C) Solar energy generation.

The presented figure illustrates the regression performance of three predictive models: the Hotel Consumption Model, the HVAC Consumption Model, and the Solar Energy Model. Each model is evaluated based on its Training, Validation, Test, and Overall datasets, with corresponding scatter plots showing the relationship between the target values and the model outputs. The performance in all cases is quantified using the correlation coefficient (R-value), and the results consistently show exceptionally high correlation, with values approaching 1.0 across all datasets.



(A) (B) (C)

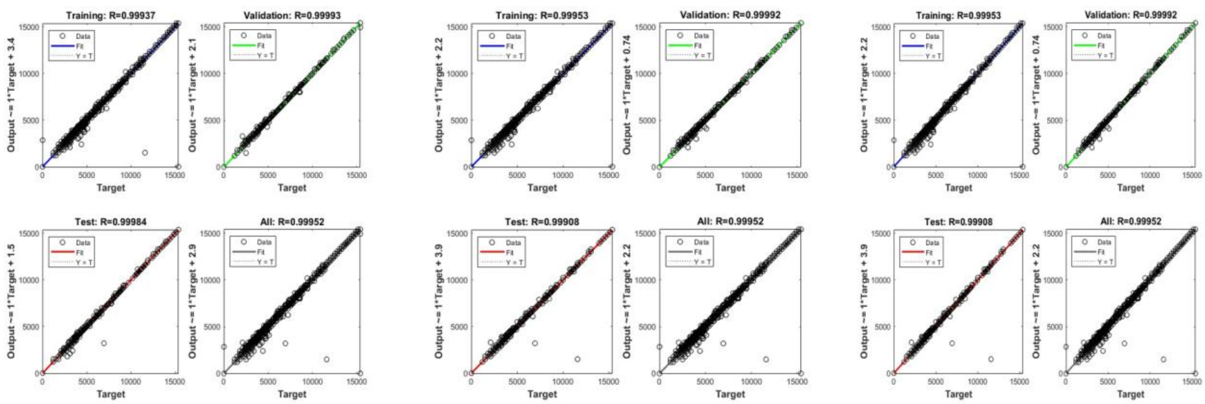
Figure 2. Model training performance for three building energy systems, showing the mean squared error (MSE) over training epochs. The best validation performance for each model is indicated. (A) Hotel consumption, (B) HVAC consumption, and (C) Solar energy generation.

Across the three models, the Training results demonstrate the models' ability to learn underlying patterns in the data with near-perfect accuracy. The Validation plots further confirm that the models generalize remarkably well, as evidenced by the minimal deviation of data points from the ideal Y = T line. Test results also maintain similarly high R-values, ranging around 0.999, indicating that the models retain their predictive strength even on previously unseen data. This consistency between Training, Validation, and Test phases suggests that the models do not suffer from overfitting or underfitting. The scatter plots themselves visually reinforce the statistical results: in all cases, the data points are densely clustered along the diagonal line, signifying extremely low prediction error. The Overall performance (All) consolidates all samples and again shows near-perfect alignment between predicted and actual values, confirming that each model is capable of reliably capturing the behavior of the respective consumption or generation systems. The results suggest that the developed models are highly accurate, stable, and well-generalized. Whether predicting hotel energy consumption, HVAC loads, or solar energy output, the models demonstrate strong predictive capability and robustness. Such performance indicates that these models are suitable for practical deployment in energy management, forecasting, or optimization applications. Figure 3 illustrates the regression performance of the developed NAR models for (A) Hotel consumption, (B) HVAC consumption, and (C) Solar energy generation.

Training, validation, test, and overall results show a strong correlation between model outputs and target values, indicating highly accurate prediction performance across all datasets.

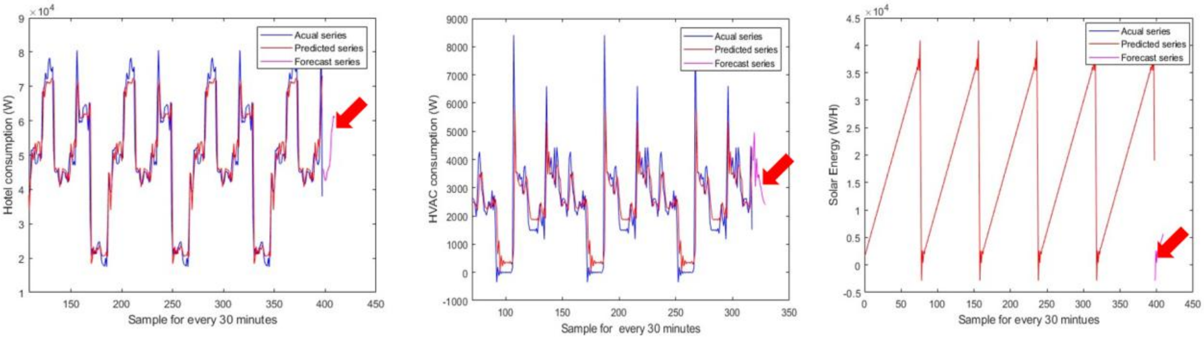
4.2 Forecasting Accuracy

The models were further evaluated based on their ability to forecast the next six hours of operation, using 30-minute sampling intervals. As shown in the forecast plots for hotel, HVAC, and solar energy, the forecasted series maintains a close alignment with the actual data throughout the entire prediction window. The NAR-based forecasting approach successfully captures short-term dynamics, including the morning rise in hotel consumption, the midday peak in solar output, and the rapid load variations of the HVAC system. This ability to reproduce both recurring daily patterns and sudden fluctuations highlights the suitability of the models for proactive, rather than reactive, energy scheduling. When implemented in a simulated real-time forecasting environment, the system demonstrated stable and consistent performance over the full forecast horizon. This robustness is largely attributed to the closed-loop feedback mechanism, in which the model's internal states were updated at each step using the most recent actual measurements. By continuously correcting the forecast trajectory with real data, the system avoided error accumulation and prevented divergence from the true load profile. This adaptive behavior is essential for onboard applications, where operating conditions can change rapidly and unpredictably. The practical outcome of such accurate short-term forecasting is a measurable improvement in energy management on luxury yachts. With reliable six-hour predictions for hotel and HVAC demand, the energy management system can optimize generator dispatch and battery scheduling to maintain operation near their most efficient load regions, instead of reacting after imbalances occur. Likewise, accurate solar generation forecasting enables better planning to maximize renewable utilization—for example, by charging batteries or pre-cooling accommodation spaces during peak solar availability. These strategies reduce generator running hours, lower fuel consumption, and decrease greenhouse gas emissions. As supported by recent studies such as [9] and [2] , such predictive and optimization-based control approaches align directly with IMO decarbonization objectives and represent a key step toward greener and more sustainable maritime operations. Figure 4 describes 6-hour ahead forecasting results using the NAR model: (A) Hotel consumption, (B) HVAC consumption, and (C) Solar energy generation. The forecast series shows close agreement with the actual data, demonstrating accurate short-term prediction performance for all three loads.



(A) (B) (C)

Figure 3. Regression performance of the developed NAR models for (A) Hotel consumption, (B) HVAC consumption, and (C) Solar energy generation. Training, validation, test, and overall results show a strong correlation between model outputs and target values, indicating highly accurate prediction performance across all datasets.



(A) (B) (C)

Figure 4. 6-hour ahead forecasting results using the NAR model: (A) Hotel consumption, (B) HVAC consumption, and (C) Solar energy generation. The forecast series shows close agreement with the actual data, demonstrating accurate short-term prediction performance for all three loads.

5. Conclusion

This study presented a novel application of a Nonlinear Autoregressive (NAR) neural network for multi-step time series forecasting of critical energy streams aboard luxury yachts. The developed models demonstrated high predictive accuracy for hotel electricity consumption, HVAC energy usage, and solar generation over a six-hour horizon. The results confirm that AI-driven forecasting enables proactive energy scheduling, optimizing the balance between generator output, battery storage, and renewable integration. Consequently, this approach directly contributes to enhanced operational efficiency and a measurable reduction in fossil fuel dependency and associated greenhouse gas emissions, thereby supporting the maritime industry's alignment with international decarbonization mandates. Future research should focus on enhancing model robustness by incorporating exogenous variables, such as precise meteorological forecasts, voyage schedules, and real-time passenger occupancy data, to better account for external disturbances. Furthermore, the development of a hybrid NARX (Nonlinear Autoregressive with Exogenous Inputs) network architecture is recommended to explicitly model these relationships. Finally, validating the proposed framework across a diverse fleet of hybrid and fully electric vessels is essential to demonstrate its scalability and generalizability, paving the way for widespread adoption in intelligent maritime energy management systems.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' Contributions

Abdussalam Elhanashi conceptualized the study, developed the methodology, performed the data analysis, implemented the forecasting models, interpreted the results, and prepared the original manuscript draft. Mohamed Sbeta provided general review and editorial comments on the manuscript. Davide Paolini and Pierpaolo Dini provided academic supervision and technical guidance during the research. Sergio Saponara contributed to the review of the methodology and final manuscript revision. Ali Eshtiba provided general comments and reviewed the final version of the manuscript. All authors read and approved the final manuscript.

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Data Availability

Data are available from the corresponding author upon reasonable request.

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