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A Review of Hybrid Energy Management Systems for Ships

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Abstract

To support the International Maritime Organization's (IMO) 2050 greenhouse gas reduction targets, hybrid propulsion energy management systems (EMS)—which integrate multi-energy coordination and dynamic scheduling—have become a critical pathway for enabling low-carbon transitions and improving energy efficiency in the maritime sector. This paper conducts a comprehensive and structured analysis of EMS technologies applied to ship hybrid propulsion systems. It evaluates the functional roles of EMS under varying system architectures, synthesizes mainstream energy management strategies, and identifies current technological bottlenecks, thereby contributing theoretical foundations for the green transformation of the shipping industry.

The study first examines representative hybrid propulsion architectures, detailing their technical characteristics to clarify the functional positioning and optimization priorities of EMS in each configuration. It then reviews prevailing energy management and control strategies, with a focus on their integration with artificial intelligence (AI) and the emergence of adaptive and data-driven approaches. Finally, the paper identifies key challenges in hybrid propulsion EMS, proposes future research directions, and offers practical recommendations to support the advancement and implementation of intelligent energy management technologies in maritime applications.

Keywords: Hybrid Propulsion; Energy Management; Artificial Intelligence

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1. Introduction

Global shipping, as the cornerstone of the world economy, carries over 80% of international trade volume, making its energy transition a strategic issue for global climate governance and supply chain stability (Qiu, 2024). Currently, ship propulsion systems remain heavily reliant on traditional diesel engines. While diesel engines offer advantages in propulsion efficiency and reliability, they emit pollutants such as nitrogen oxides (NOx), sulfur oxides (SOx), and particulate matter (PM), along with continuous releases of greenhouse gases like carbon dioxide (CO_2), posing systemic threats to marine and atmospheric environments (Barkhordarian, 2022). Research indicates that without effective technological innovation and policy intervention, shipping's CO_2 emissions are projected to account for 12%－18% of total global anthropogenic emissions by 2050. This proportion may further increase due to the opening of Arctic routes and growing global trade volume (Zou, 2022).

To address this severe challenge, the International Maritime Organization (IMO) has enacted regulations such as the International Convention for the Prevention of Pollution from Ships (MARPOL), the mandatory Energy Efficiency Design Index (EEDI), the Ship Energy Efficiency Management Plan (SEEMP), and the Energy Efficiency Existing Ship Index (EEXI) (Jaramillo Jimenez, 2022). These regulations establish a full-cycle carbon reduction framework for ship design, construction, and operation, compelling the shipping industry to accelerate its transition toward low-carbon technology pathways. This shift has led to the adoption of a multi-energy synergy model integrating various energy forms, including traditional fossil fuels, electricity, hydrogen, ammonia, and methanol.

However, ship sailing conditions are extremely complex, and ensuring efficient power output under a multi-energy cooperative mode presents significant technical challenges (Lee, 2024). In this regard, the Ship Energy Efficiency Management Plan requires ships to be equipped with EMS capable of real-time monitoring, optimized scheduling, and efficiency assessment. Such systems not only handle complex sailing conditions by enabling full-voyage energy consumption tracking and quantified emission reduction targets but also construct mathematical models and control algorithms to allocate power output among engines, motors, and energy storage devices according to varying operational demands, significantly reducing energy consumption while improving power performance (Fan, 2020).

A hybrid propulsion system serves as a multi-energy integration framework, enabling efficient and clean power output through the coordinated control of engines, electric motors, and energy storage devices. The EMS plays a key role as a “centralized energy management unit” by: (1) achieving seamless multi-energy coordination; (2) dynamic power matching (Fan, 2022): intelligently coordinating diesel engines and motors to jointly output power under high-speed, heavy-load conditions; and (3) full-voyage efficiency optimization: continuously improving the overall system efficiency through real-time data acquisition and algorithmic optimization.

This advanced energy management paradigm not only addresses the high pollution and low energy efficiency of traditional systems but also provides technical support for the intelligent upgrading of ship propulsion systems (Fan, 2023). By precisely scheduling energy, ship operation shifts from a resource-intensive mode that ignores emissions to an intelligent mode that prioritizes energy efficiency. Thus, the EMS of a ship hybrid system with micro-grid characteristics is crucial: it not only maximizes the energy-saving and emission reduction advantages of the hybrid system but also serves as the core technological support driving ship propulsion systems toward intelligence and greenness.

Currently, some commercial vessels have begun to apply EMS to hybrid propulsion systems. Practice shows that during port operations or low-speed cruising, a pure electric drive mode is used preferentially to eliminate exhaust emissions, whereas under high-load conditions propulsion power is supported by a combined supply from diesel engines and energy storage systems. This approach raises the diesel engine's average load to 75% (within its optimal efficiency range) and reduces fuel consumption by 22% (D. Park, 2021). Notably, new clean energy technologies such as hydrogen fuel, wind-assisted propulsion, and integrated photovoltaic generation are expanding the boundaries of traditional energy systems (Chen, 2023).

For example, Norway's “MF Hydra” ferry has successfully commercialized liquid hydrogen fuel cells, and with an 80 m^3 hydrogen storage tank, it reduces its annual carbon emissions by up to 95% (Corvus Energy, 2023). Japan's "Wind Challenger" project uses a telescopic hard sail to convert wind energy into propulsion, expected to reduce fuel consumption and greenhouse gas (GHG) emissions by approximately 7%–16%. These innovations validate the potential of wind–solar complementary systems in ocean-going vessels. Such practices indicate that the low-carbon evolution of hybrid power systems has advanced from single energy substitution to multi-energy complementary integration.

However, large-scale deployment of hybrid power systems still faces multiple technical bottlenecks and industrialization barriers (Xie, 2021). First, the complexity of multi-energy coordinated control imposes extremely high requirements on the system's dynamic response capability: under frequently changing navigation conditions (such as sudden load increases, emergency braking, or rough seas), the power distribution strategy among diesel engines, batteries, and fuel cells must balance multiple objectives, including optimal efficiency, minimal emissions, and extended equipment lifespan. Existing rule-based control algorithms (such as state-machine control) and optimization algorithms (such as dynamic programming) often experience scheduling lags due to computational latencies or model mismatches, leading to a 5%–10% reduction in overall system efficiency (Fan, 2022).

Second, the applicability of clean energy sources like hydrogen remains constrained: for example, liquid hydrogen storage requires maintaining extremely low temperatures of −253 °C, posing severe challenges for ship compartment insulation design and safety monitoring systems. Renewable sources like wind and solar are inherently limited by low energy density and intermittency, making it difficult for them to serve as primary energy sources for long-range voyages. More critically, the EMS—considered the "brain" of the hybrid power system—has a testing and validation framework that seriously lags behind technological innovation (Xie, 2022a).

In the automotive industry, EMS testing has developed complete processes, including hardware-in-the-loop (HIL), software-in-the-loop (SIL), and full-vehicle calibration, and has established functional safety standards such as ISO 26262 (Guillemin, 2024). In contrast, the maritime industry lacks a unified library of test scenarios, performance evaluation metrics, and reliability verification protocols. This results in poor compatibility between different vendors' EMS systems, insufficient fault diagnosis coverage, and a lack of effective evaluation of algorithm robustness in real maritime environments (e.g., resistance to electromagnetic interference and salt fog corrosion) (Zeng, 2024). These technical shortfalls not only raise system development and maintenance costs but also delay the commercial deployment of hybrid ships.

In summary, ship hybrid propulsion systems, as key technological enablers of the shipping industry's low-carbon transition, exhibit dual characteristics (Maloberti, 2025). On one hand, innovative practices in multi-energy coupled architectures have broken the energy efficiency limitations of traditional propulsion systems, demonstrating great potential in reducing carbon emissions (Rajendran Sai Sasidhar, 2025). On the other hand, challenges in dynamic control algorithms, clean energy integration, and testing and validation frameworks hinder the large-scale application of these systems (Li, 2025). Facing this confluence of opportunities and challenges, a systematic technical review is highly necessary.

Accordingly, this paper is structured around three main dimensions: (1) a review of the principal hybrid power architectures based on power transmission paths; (2) a summary of current mainstream energy management strategies; (3) a discussion of various challenges in ship energy management and operation, including dynamic environmental adaptability issues, multi-objective conflicts, and hardware constraints. In the following sections, we present a structured exposition of hybrid power system architectures, energy management strategies, and current challenges, aiming to provide a theoretical reference for the development of next-generation low-carbon ship propulsion systems.

2. Basic Types of Hybrid Power Systems

In the field of ship hybrid power systems, the category of system architecture is a key factor influencing the design and optimization of energy management strategies. From the perspective of power transmission paths, the major architectures can be divided into three categories: series, parallel, and series-parallel.

2.1 Series Hybrid Power Architecture

The block diagram of a series hybrid power system is shown in Fig. 1. In this architecture, multi-energy co-supply is achieved in a full electric propulsion mode, with a diesel generator set driving a synchronous generator (Anton, 2020). Its output is rectified by an AC/DC converter and connected to the DC bus. To achieve power fluctuation smoothing and energy buffering, a battery pack and super-capacitor are connected to the DC bus through bidirectional DC/DC converters, while fuel cells and photovoltaic units are integrated into the bus via unidirectional DC/DC boost converters. The DC bus then converts electrical energy back to AC via a DC/AC inverter to supply the propulsion motor and onboard equipment (Yuan, 2020).

The advantage of this architecture is that the internal combustion engine can always operate within its high-efficiency speed range, significantly reducing fuel consumption and emissions. This makes it especially suitable for scenarios with high demands for low-speed maneuverability, such as port-operating vessels or inland ferries (P, 2024).

However, the series configuration requires energy to undergo multiple conversions (“mechanical→electrical →mechanical”), which significantly reduces overall efficiency under high-speed cruising conditions. Additionally, this architecture requires a high battery capacity, thus escalating the system cost (Benevieri, 2021). Because energy conversion in this architecture depends on the electrical system, the core of energy management for the series architecture lies in optimizing the operating range of the power generation unit. Although the control logic for this architecture is relatively simple, energy conversion losses are inevitable.

Machine learning can address the energy conversion loss in series architectures by modeling the battery’s state of charge (SOC) and state of health (SOH) and dynamically adjusting the coordination strategy between the diesel engine and energy storage devices. For example, Wang et al. (2024) proposed an improved firefly algorithm (IFA) to optimize the hyperparameters of a Gaussian Process Regression (GPR) model, which enhanced the model’ s predictive performance. After hyperparameter optimization with four swarm intelligence algorithms, an IFA-GPR model was constructed. Compared with the traditional conjugate gradient method, this model improved SOC estimation accuracy by 6.75% and 3.12% under two conditions and increased SOH prediction accuracy by 91.64% and 78.12% in two SOH prediction schemes.

Li et al. (2024) used a genetic algorithm (GA)-optimized long short-term memory (LSTM) model to build a ship energy consumption prediction model that comprehensively considers factors such as route, speed, trim, and various environmental factors. They further innovatively proposed a multi-objective collaborative optimization method based on the Non-dominated Sorting Genetic Algorithm III (NSGA-III). Empirical analysis showed that compared with traditional operation modes, this collaborative optimization strategy can achieve up to 4.54% fuel savings. Hou Hui et al. (2025) applied a series configuration with a super-capacitor plus diesel generator to an electric cargo ship on the Yangtze River, facilitating rapid charge/discharge to meet the frequent start-stop requirements of inland river conditions.

Currently, energy management research for hybrid systems has expanded beyond the maritime and automotive fields; in the agricultural domain, research on energy management for hybrid tractors has also begun, with the core goal of reducing fuel consumption while maximizing engine efficiency (Curiel-Olivares, 2024). For example, Manuel Antonio Perez Estevez et al. (2024) constructed a series hybrid power system model for vineyard/orchard tractors, using dynamic programming and exhaustive search methods together with real-world data to optimize control strategies and component sizing, considering environmental, economic, and volume factors.

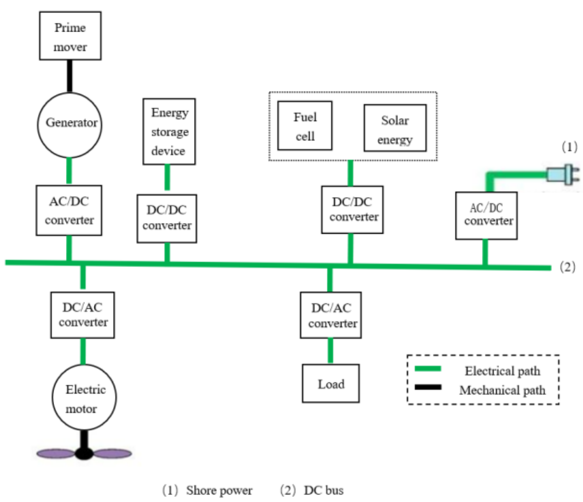

Fig. 1. Schematic of the Series Hybrid Architecture

2.2 Parallel Hybrid Power Architecture

The block diagram of a parallel hybrid power system is shown in Fig. 2. In this architecture, the internal combustion engine and the electric motor cooperatively drive the propeller shaft through mechanical coupling devices such as clutches and planetary gears (Kurt, 2025). Under this architecture, the internal combustion engine and the electric motor can operate independently or in coordination to output power. In high-speed navigation conditions, the system can directly leverage the efficient power output of the internal combustion engine, effectively reducing energy conversion losses (Zhao, 2025).

Since the parallel architecture relies on mechanical coupling to coordinate multiple power sources, its energy management strategy requires precise control of torque distribution and operating mode switching. Although this architecture has higher efficiency, it proportionally increases the complexity of the control strategy. Therefore, this architecture is widely used in long-distance ocean-going cargo ships or roll-on/roll-off vessels that require long-term stable navigation. However, this architecture has a limitation: its power distribution logic is relatively fixed, making it difficult to achieve dynamic coordination of multiple energy sources. Moreover, its optimization potential is limited under complex conditions (such as frequent speed changes or sudden load fluctuations).

Zhou Jianhua et al. (2023) analyzed power demands under different sailing conditions of yachts and explored how to utilize a parallel structure to achieve the complementary advantages of engines and motors, improving yacht propulsion performance and energy utilization efficiency. Similarly, Sun Xiaojun et al. (2022) adopted a parallel architecture for the ferry “Prinsesse Benedikte”; under different navigation conditions, it can flexibly switch between pure electric, hybrid, and other modes according to demand, solving the energy loss issue caused by secondary power conversions.

Currently, parallel hybrid systems face many challenges, including hybrid system torque distribution, decoupling between the main engine and the load, and dynamic switching of operating modes (Yuan, 2020). Convolutional Neural Networks (CNNs) play an important role in addressing these issues: they can recognize ship navigation conditions (e.g., high-speed cruising or port maneuvering) and automatically switch to the optimal control mode, effectively improving the system’s response speed (Chen, 2025).

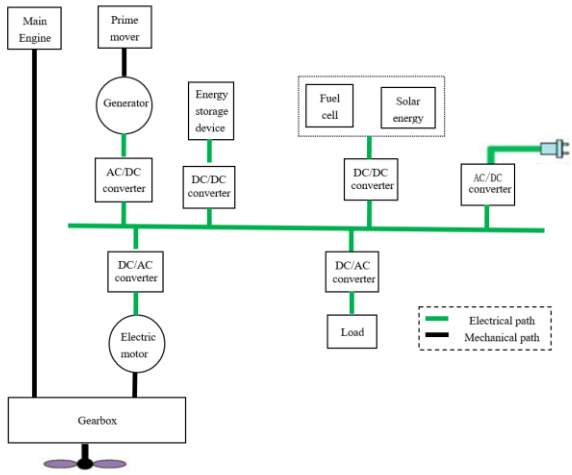

Fig. 2. Schematic of the Parallel Hybrid Architecture

2.3 Series-Parallel Hybrid Power Architecture

The block diagram of a series-parallel hybrid power system is shown in Fig. 3. The series‑parallel (mixed) architecture combines the advantages of the series and parallel architectures, allowing flexible adjustment of energy flow paths, but it imposes higher requirements on real-time optimization algorithms; energy management must balance global energy efficiency with system response speed (Sun, 2024).

In this configuration, there are two coupling devices: on the mechanical propulsion side, mechanical and electrical propulsion can run in parallel to drive the propeller. The main engine can directly drive a generator through a coupling to supply the DC bus (Soma, 2016). On the electrical propulsion side, multiple energy sources are integrated into the DC bus through converters, from which the DC grid supplies power to electrical loads and motors, thus constituting a multi-energy hybrid power system (Yuan, 2020).

This architecture excels in dynamic adaptability, as it can optimize energy flow paths in real time according to speed and load, making it especially suitable for special ships with stringent comfort and environmental requirements, such as research vessels and luxury cruise ships. However, the mechanical structure and control algorithm complexity of the series-parallel system increase significantly, which not only raises manufacturing costs but also imposes higher demands on system reliability.

In current research, the engineering application of the series-parallel architecture is still limited by the development and verification cost of high-precision energy management strategies, but its potential for balancing emission reduction and energy efficiency makes it a key development direction for future green ships (Yuan, 2023).

Due to the complexity and high cost of the series-parallel architecture, its application on ships is currently limited. However, its complex energy flow paths provide ample opportunities for artificial intelligence and machine learning (AI/ML) techniques. For example, graph neural networks (GNNs) can model multi-energy coupling relationships, effectively capturing the nonlinear interactive characteristics between mechanical and electrical paths (Ngo, 2025), thereby assisting model predictive control (MPC) in generating multi-step future optimization trajectories (Li, 2023).

Additionally, generative adversarial networks (GANs) can simulate energy flow characteristics under extreme conditions (such as sudden loads or rough seas) to verify the robustness of control strategies, thereby reducing the risk of real-ship testing (Jia, 2023).

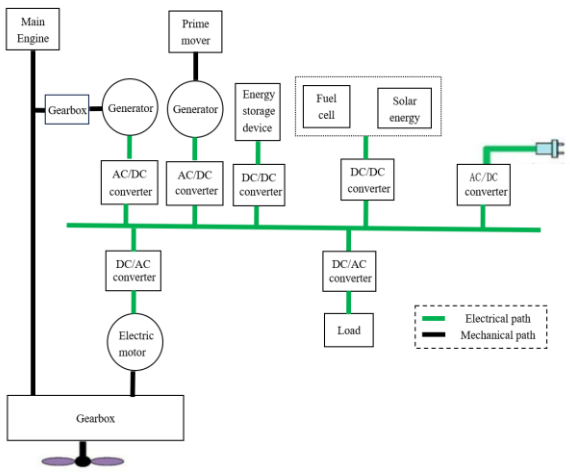

Fig. 3. Schematic of the Series-Parallel Hybrid Architecture

In summary, each of the three hybrid power architectures has its own advantages and disadvantages. Among the hybrid power system architectures currently used on ships, the series architecture is the most mature and comparatively more widely applied.

3. Energy Management Strategies

Energy management strategies for hybrid power systems have developed along three technical routes: rule-based strategies, optimization-based strategies, and intelligent algorithms (Ma, 2025). Rule-based strategies rely on preset logic (such as fuzzy control and state machines) to achieve rapid energy allocation, offering advantages of strong real-time capability and high engineering convenience. However, they struggle with multi-objective cooperative optimization under complex dynamic conditions.

Optimization-based strategies (such as model predictive control and dynamic programming) enhance energy efficiency and environmental performance through global or receding-horizon optimization. Their multi-objective hierarchical structures can flexibly coordinate economic costs and emissions constraints, but they face bottlenecks of high computational complexity and heavy hardware dependency. Intelligent algorithms (such as reinforcement learning and deep neural networks) break through the limitations of traditional models through data-driven and autonomous learning approaches, exhibiting significant adaptability in highly nonlinear and strongly coupled scenarios. However, most research is still limited to the simulation verification stage, and in real ship applications, these methods face challenges of insufficient real-time performance and poor model generalization.

3.1 Rule-Based Strategies

In the context of ship propulsion systems, rule-based strategies are widely used for energy management (Lü, 2022). In these systems, rule-based strategies use various techniques to allocate and manage energy based on ship operating states and energy characteristics, thereby improving system performance and efficiency (Song, 2024).

Tsitsilonis et al. (2018) proposed a systematic approach for energy management of ship propulsion engines that employs statistical analysis, compressor modeling, and energy and exergy analysis tools to determine engine operating curves and points, assess the quality of measurement parameters, identify components with significant deviations from baseline conditions, and propose energy-saving measures. Nivolianiti et al. (2024) compared a fuzzy logic rule-based strategy with other methods under typical river navigation conditions. They evaluated its performance in optimizing fuel efficiency and reducing hydrogen consumption in a small hydrogen-powered passenger ship hybrid fuel-cell propulsion system. Simulations showed that the energy management system under this strategy, by adaptively distributing power, performed best in reducing fuel consumption.

Currently, energy management research in the maritime field lags behind the automotive field, and some cutting-edge ideas from the automotive sector can be borrowed. For example, in the automotive domain, researchers focus on hybrid energy storage systems (HESS) composed of batteries and super-capacitors, exploring rule-based strategies such as logic rules and fuzzy logic. These strategies can formulate energy distribution rules based on the states of charge of the battery and super-capacitor, as well as driving conditions, to optimize system performance.

In the automotive field, fuzzy logic rule-based strategies have also been combined with global optimization algorithms such as dynamic programming (DP): the fuzzy logic controller makes quick preliminary energy distribution decisions based on real-time vehicle operating parameters and energy storage states, while the DP algorithm is used at a higher level for energy management optimization to find the global optimum (Zhou, 2024).

At present, as ship operating conditions become more complex, traditional EMS approaches based on rules or static models are unable to meet the demands of nonlinear, strongly coupled multi-energy scheduling. In recent years, breakthroughs in artificial intelligence (AI) and machine learning (ML) have brought innovation to EMS: through data-driven modeling, autonomous optimization learning, and real-time decision-making, they significantly improve energy distribution precision and system robustness in complex scenarios. For example, deep reinforcement learning (DRL) can dynamically optimize multi-energy power allocation through a “state－action－reward” mechanism, extending equipment life while meeting efficiency targets (Zhang, 2024).

3.2 Optimization-Based Strategies

In the field of ship energy management, optimization-based strategies are system-level approaches and methods that plan and control stages of energy generation, distribution, storage, and consumption to achieve goals such as efficient energy utilization, cost reduction, and emission reduction. These strategies focus on making macro-level optimization decisions about system operating modes and energy distribution ratios, encompassing various specific strategies applied to different ship energy system scenarios.

Currently, model predictive control (MPC) algorithms and multi-objective optimization algorithms are most widely used in this field, with MPC being particularly prevalent in ship energy management (Liu, 2025).

For example, Ji Zhongping et al. (2025) applied an MPC algorithm to a ship’s automatic steering system by constructing a ship dynamic model (including environmental disturbances such as wind, waves, and currents). In each control cycle, they predicted the ship’s motion state over multiple future time steps and performed rolling optimization to generate an optimal rudder angle instruction sequence, minimizing the heading tracking error.

Hanyou Liu (2024) proposed a multi-objective hierarchical energy management strategy for a fuel-cell hybrid propulsion ship. This strategy uses multiple objectives such as economic cost, environmental impact, and system stability and coordinates different layers of energy management tasks through a hierarchical framework. Zhi-Hong Zhao (2022) optimized the performance of photovoltaic (PV) systems by using maximum power point tracking (MPPT) algorithms. Simultaneously, an improved fuzzy logic controller based on dynamic programming was combined with wavelet analysis and PI control to achieve optimal power distribution and online control. Fabio D’Agostino et al. (2025) proposed an MPC method to optimize the efficiency of a ship’s hybrid onboard power system (shipboard power system, SPS) while ensuring safe operation.

Compared to traditional single-objective optimization strategies, multi-objective optimization strategies can better meet the diverse demands of ships under different operating conditions and improve the overall performance and competitiveness of vessels (Wu, 2024). Such strategies can flexibly adjust the weights of various objectives based on the ship’s actual operational conditions and mission requirements, achieving personalized energy management and providing strong support for the sustainable development of the shipping industry.

3.3 Intelligent Algorithms

In the field of ship energy management, intelligent algorithms are technical tools based on mathematical models, computer science, and AI theories that automatically search for optimal or near-optimal solutions through specific computational steps and logic —examples being genetic algorithms, particle swarm optimization (PSO), and neural networks (Wen, 2024). These algorithms are widely applied in areas such as energy management, condition monitoring, and fault diagnosis.

In energy management, they help optimize energy distribution and scheduling; in condition monitoring and fault diagnosis, they enable accurate identification of equipment status and faults, improving ship operational safety and reliability. For instance, the PSO algorithm simulates the foraging behavior of bird flocks to search for optimal solutions in the solution space (Lan, 2024). It can optimize the capacity ratio between batteries and supercapacitors based on ship load characteristics, energy demand, and the performance parameters of storage devices, thereby achieving the best energy storage efficiency and overall system performance (Chen, 2020).

However, although PSO has certain advantages in finding optimal solutions, it also suffers from high computational complexity and therefore has not become a mainstream algorithm in ship energy management.

Teng Fei et al. (2020) proposed a distributed optimization dispatch method for intelligent ship integrated energy systems based on reinforcement learning and related theories. Ying Yulong et al. (2012) used system simulation and modular modeling to build a simulation model of a ship gas turbine power generation system, allowing it to learn from large amounts of historical operation data. The neural network then established a complex relational model among the power system’s parameters, enabling accurate prediction of Wei Donghui et al. (2024) constructed a ship electrical equipment state recognition network based on spectral clustering and deep neural networks. This model is trained on fused multi-source data and uses real-time operation data from electrical equipment to identify equipment states. Lin Zhu et al. (2024) proposed a Deep Q-Learning (DQL)-based energy management strategy for fuel cells: by discretizing the fuel cell power action space to avoid adverse conditions such as on-off cycling and high load, they designed a reward function incorporating sailing cost, battery SOC maintenance, and fuel cell load fluctuation penalties.

This strategy significantly extended the fuel cell lifespan while ensuring economic sailing (achieving 92.6% of the performance of a DP algorithm) and minimized system life-cycle cost through weight optimization.

To reduce fuel consumption of commercial inland ships, Derollepot et al. (2019) proposed a global resizing method combining genetic algorithms and dynamic programming; the results indicated a potential fuel consumption reduction of about 10%. Jiang Jiawei et al. (2023) presented a feature selection method based on relative entropy: by calculating the degree of disorder between features and labels to select key features and reduce data redundancy. On this basis, they trained support vector machines for each category to improve classification speed and accuracy in a multi-class problem, achieving a fault identification accuracy of 94.46% and reducing classification time by up to 77.8%.

3.4 Summary of Energy Management Strategies

Table 1 compares the key characteristics of different energy management strategies. From the literature surveyed above, it is evident that in recent years the application of intelligent algorithms in the maritime field has made significant progress, especially in addressing complex multi-dimensional optimization problems and enhancing the intelligent level of ship systems (Meng, 2025).

Currently, most optimization and intelligent algorithms are still at the software simulation or hardware-in-the-loop stage, and there remains a considerable gap before practical implementation on real ships, necessitating much deeper research. Rule-based energy management strategies can improve the performance and economy of hybrid systems to some extent, but their effect is limited, and they cannot achieve multi-objective optimized energy management.

As research on energy management strategies for ship hybrid systems continues to deepen, more advanced algorithms are expected to be applied on actual vessels in the future. In embedded system development, effectively balancing the optimization performance of the EMS with real-time implementation performance has become a core challenge. This balance is a key aspect for the broad application of intelligent algorithms in the maritime field and is of great significance for promoting the intelligent development of the shipping industry (Sun, 2024).

Table 1: Comparison of energy management strategies

Strategy Type	Advantages	Disadvantages	Applicable Scenarios
Rule-based Strategy	①Simple to implement with clear logic ②Small computational load and high real-time performance ③High reliability and easy to debug and maintain	① Relies on expert experience with low flexibility ② Difficult to cope with complex and variable operating conditions ③May have relatively low energy utilization rate	①Scenarios with high real-time requirements ②Ships with relatively fixed operating conditions
Optimization -based Strategy	①Better energy distribution and high efficiency ② Can be dynamically adjusted in combination with objective functions (such as fuel consumption, emissions) ③ Suitable for multi-objective optimization problems	① High computational complexity, which may affect real-time performance ② Relies on accurate mathematical models ③ Requires high hardware computing power	① Scenarios with strict energy-efficiency requirements ② Ships with frequently changing but predictable operating conditions
Intelligent Algorithm	① Strong adaptability, capable of learning complex nonlinear relationships ②Does not rely on accurate mathematical models ③Suitable for multi-source heterogeneous data fusion	①Requires a large amount of training data ② Risks of overfitting or poor generalization ability ③Low interpretability	① Environments with high uncertainty or dynamic changes ② Complex systems for multi-energy collaborative management

4. Current Challenges

In the field of hybrid ship energy management and operation, there are numerous challenges, including dynamic environmental adaptability, multi-objective conflicts, and hardware limitations. These challenges affect a ship's performance, cost, and sustainability (Yang, 2025). This paper summarizes them in terms of dynamic environmental adaptability (e.g., wave-induced load variations), multi-objective conflicts (economic efficiency/environmental requirements), and hardware constraints.

4.1 Dynamic Environmental Adaptability

Compared with land-based microgrids, ship microgrids have features such as smaller power plant capacity, large load-startup impacts, centralized power equipment, short transmission lines with multiple redundancies, long-term islanded operation, and harsh operating environments (Alam, 2025). When a ship is at sea, environmental factors such as waves cause the vessel to roll and pitch, leading to sudden changes in load demand (Wen, 2024).

When a ship encounters large waves, to maintain stable navigation, the propulsion system must rapidly adjust its power output, which places high demands on the dynamic response capability of the ship's EMS (Du, 2021). If the EMS cannot respond promptly to load changes, it may result in insufficient propulsion power or energy waste (Zhou, 2022).

To address this challenge, it is necessary to develop technologies that can monitor and predict load changes in real time, allowing the energy distribution strategy to be adjusted in advance. By establishing ship load prediction models and using multi-level predictive control methods or short-term forecasting models based on multi-resolution wavelet neural networks, one can predict the trend of load changes in advance, enabling the EMS to respond in a timely manner and ensure stable ship operation under dynamic conditions (Sun, 2022).

Some researchers have also studied environmental disturbances during navigation. For example, Kai Feng et al. (2024) proposed a strong tracking variational Bayesian unscented Kalman filter algorithm based on multiple fading factors and applied it to a DP-based speed control system. The results showed that the proposed adaptive filter effectively improved estimation accuracy and stability under time-varying environmental disturbances and significantly enhanced the adaptability and robustness of the DP system.

Xi Luo et al. (2024) developed a new method for ship voyage speed optimization that incorporates dynamic weather conditions. Practical tests verified that using this method significantly reduced ship fuel consumption by 5.35%, and compared to a static speed optimization model, fuel consumption was reduced by up to 7.34%.

4.2 Multi-Objective Conflicts

During ship voyages, it is necessary to consider not only various costs but also to meet environmental requirements in different regions. In terms of energy use, traditional fossil fuels offer relatively low energy costs but lead to higher carbon emissions, whereas using clean energy reduces carbon emissions but requires higher equipment investment and maintenance costs (Hou, 2025). Therefore, there is a need to balance these conflicting objectives.

Teng Fei et al. (2020) built an optimization dispatch model for an intelligent ship integrated energy system, taking into account constraints such as the ship's Energy Efficiency Design Index (EEDI), to minimize total voyage energy cost while reducing navigation-related emissions. Peng Dengchao et al. (2024) proposed a parallel equal current control method for energy storage modules on a DC bus, enabling pure electric ships to select the number of grid-connected DC/DC converters based on the voyage and operating conditions.

The system can automatically monitor, via PLC, the communication frequency of the on-board power supplies and perform real-time equal-current control based on the bus voltage and total DC current, making the ship more economical and energy-efficient.

Xia et al. (2024) proposed an integrated energy utilization system for LNG-powered ships aimed at zero carbon emissions by employing oxy-fuel combustion with carbon capture. Through modeling analysis, parameter studies, and multi-objective genetic algorithm optimization, they showed that under zero carbon emissions, the system achieves an energy efficiency of 51.71% and a net output power of 511 kW, with low investment and power-generation costs and excellent environmental and economic benefits.

Route planning is also crucial for ship navigation. Scientific route planning can guide a ship to avoid various risks efficiently, ensuring a smooth and orderly voyage, which improves navigation efficiency and ensures safety. At the same time, it can reduce fuel consumption and the pollutant emissions generated by fuel combustion, helping to alleviate the environmental impact of shipping activities and playing an indispensable role in promoting green and sustainable development of the shipping industry.

Man Zhu et al. (2025) formulated the route planning problem as a multi-objective optimization model and utilized Constraint Pareto Optimization (CPO) to explore Pareto-optimal paths. Their method outperformed NSGA-II and MOEA/D-based methods in terms of path length and energy consumption in tests under four different environmental scenarios, achieving the shortest path (261.89 m) and the lowest energy consumption (1.10×10^6 J), while maintaining the best Pareto front and demonstrating significant advantages in complex environments.

4.3 Hardware Limitations

Clean energy, such as hydrogen-based green fuels and synthetic fuels like ammonia and methanol, demonstrates excellent low-carbon emission characteristics during the combustion and power supply processes. By pre-storing such green electricity, its adaptability to complex working conditions can be significantly enhanced. However, the storage of green electricity highly depends on the energy storage system (Hassan, 2025), making the energy storage system the core part of the hybrid power energy management for ships.

Currently, the development of the energy storage system still faces several key challenges (Sun, 2022):

1. Economic bottleneck: The introduction of the energy storage system significantly increases the construction cost of ships.

2. Performance and safety limitations: The deep discharge and frequent use of storage batteries not only shorten their service life but also may cause potential safety hazards.

These factors jointly restrict the efficient regulation of the energy storage unit by the energy management system, and technical breakthroughs are urgently needed. To promote the development of energy storage technology, various countries have successively introduced supportive policies to drive industry innovation. Against this backdrop, the academic community has conducted in-depth research on key issues such as the optimized design, power management, and capacity configuration of the energy storage system:

Large-capacity energy storage system access technology: An Feng et al. (2024) proposed a cascaded energy storage system architecture based on a DC collector, which is applicable to medium-voltage DC power grids and improves the integration efficiency of energy storage units.

Optimization of ship photovoltaic power generation and hybrid energy storage: Shuli Wen et al. (2017) established a mathematical model of a photovoltaic (PV) power generation system considering the influence of ship rolling, and used the Discrete Fourier Transform (DFT) to decompose the balanced power, converting it into time-varying periodic components. Furthermore, by combining with the Particle Swarm Optimization (PSO) algorithm for cost capacity optimization, the simulation results show that this scheme can significantly improve the configuration efficiency of the energy storage system (ESS).

Frequency response modeling of the energy storage system: Zhang Jinjia et al. (2025) proposed a new equivalent frequency response model of the ESS, which can be used to evaluate the lowest frequency point and the maximum frequency deviation in a synchronous generator (SG)-dominated system, thus optimizing the energy storage capacity and droop control strategy.

These studies provide important theoretical support and engineering practice references for the energy storage technology of ship hybrid power systems. However, it is still necessary to further explore more economical, reliable solutions that are adaptable to complex working conditions.

5. Conclusion and Outlook

This study focuses on the energy management system (EMS) of ship hybrid propulsion systems, providing a systematic examination of how different system architectures influence EMS performance. It analyzes the challenges faced by EMS in supporting the maritime industry's low-carbon transition, discusses strategic and hardware-related constraints, and highlights research gaps, particularly in the standardization of testing methodologies. The main findings are summarized as follows:

(1) Ship hybrid power EMS faces multiple challenges, including limited adaptability to dynamic marine environments, multi-objective conflicts, and hardware performance bottlenecks. These issues hinder operational efficiency and limit large-scale deployment.

(2) The series configuration remains prevalent due to its technological maturity and operational simplicity. In contrast, parallel and series‑parallel architectures offer advantages in high-speed operational efficiency and dynamic adaptability, respectively. However, the

widespread application of series–parallel systems is constrained by their complex control requirements and elevated costs.

(3) Rule-based strategies rely on heuristic logic, while optimization-based methods—such as model predictive control (MPC) and multi-objective optimization—and intelligent algorithms, including reinforcement learning and neural networks, enhance control precision. Nevertheless, real-time implementation is impeded by high computational burdens and system latency.

(4) The limited lifespan of energy storage systems, high capital investment, and the cost-effectiveness of clean energy technologies remain key obstacles to large-scale EMS integration.

(5) Current research predominantly emphasizes control strategy development and system-level performance optimization, with insufficient attention to systematic testing frameworks. Given its critical role in validating EMS functionality and ensuring reliable deployment, the absence of a well-defined theoretical and methodological foundation for EMS testing constitutes a major research gap. The development of comprehensive testing protocols and scenario-based benchmarks is essential to support algorithm verification, system safety, and performance robustness.

To address these limitations, future research should prioritize the following directions:

(1) Intelligent Energy Management Algorithms: Design EMS algorithms with adaptive and autonomous learning capabilities through the integration of artificial intelligence, such as reinforcement learning and digital twins. These algorithms should support coordinated multi-timescale optimization—spanning real-time power allocation to mid-term energy planning—thereby enhancing system responsiveness under complex and variable operating conditions (Guo, 2024).

(2) Clean Energy Technology Innovation: Accelerate the development and integration of advanced clean energy technologies for maritime applications. Key areas include high-density, low-temperature hydrogen storage, intelligent grid-connection solutions for hybrid wind–solar–diesel systems, and digital twin-based platforms informed by large-scale vessel operational data.

(3) Standardized EMS Testing Framework: Establish a multi-level EMS testing framework encompassing laboratory validation, dockside trials, and full-scale ship testing. The framework should draw upon established models, such as the automotive V-model development process, and include maritime-adapted functional safety standards—such as fault injection protocols and boundary condition coverage. A standardized database of representative multi-energy operational scenarios is also needed to support iterative algorithm refinement (Longva, 2024).

In conclusion, the realization of large-scale deployment and industrialization of ship hybrid power systems requires the integrated advancement of intelligent control technologies, clean energy solutions, and standardized testing protocols. Only through this holistic approach can the maritime sector achieve the IMO's 2050 target of a 50% reduction in greenhouse gas emissions.

References

1.Qiu, C.G., Zhao, G. (2024),Shipping Industry Carbon Inventory: Carbon Accounting Status, Decarbonization Challenges and Follow-up Thinking, China Sustainability Tribune12,27-30.

2.Barkhordarian, A., Nielsen, D.M. & Baehr, J. (2022), Recent marine heatwaves in the North Pacific warming pool can be attributed to rising atmospheric levels of greenhouse gases, Commun Earth Environ 3, 131.

3.Zou, X.L.(2022),The impact of carbon tax on global shipping costs and maritime trade and the research on shipping enterprises' coping strategies, South China University of Technology.

4.Jaramillo Jimenez, V., Kim, H., Munim, Z. H. (2022), A review of ship energy efficiency research and directions towards emission reduction in the maritime industry. Clean 366(8), 132888.

5.Sun, C., Weng, S. W., Du, S. Z., et al. (2025), Current Situation and Prospects of the Digital and Intelligent Development of Ships under the Background of "Carbon Peaking and Carbon Neutrality",Journal of Shanghai Ship and Shipping Research Institute 33(02), 14-18.

6.Lee, S.S. (2024), Analysis of the effects of EEDI and EEXI implementation on CO2 emissions reduction in ships, Ocean Engineering 295, 116877.

7.Fan, A., Yan, X., Bucknall, R., Yin, Q, Ji, S., Liu, Y., et al. (2020),A novel ship energy efficiency model considering random environmental parameters, Marine Eng Technol 19,215-28.

8.Fan, A., Yang, J., Yang, L., Wu, D., Vladimir, N. (2022), A review of ship fuel consumption models, Ocean Eng 264,112405.

9.Fan, A., Li, Y., Fang, S., Li, Y., Qiu, H.(2023), Energy management strategies and comprehensive evaluation of parallel hybrid ship based on improved fuzzy logic control. IEEE Trans Transp Electrific:1.

10.D. Park, F. Perabo, M. Choi, E. Skjong and M. Zadeh. (2021), An Optimal Energy Management System for Marine Hybrid Power Systems, IEEE 22nd Workshop on Control and Modelling of Power Electronics (COMPEL), Cartagena Colombia,1-8.

11.Chen, W., Tai, K., Lau, MWS., Abdelhakim, A., et al. (2023), Optimal power and energy management control for hybrid fuel cell-fed shipboard DC microgrid, IEEE Trans Intell Transp Syst, 1-18.

12.Corvus Energy, (2023), MF Hydra: The World’s First Liquid Hydrogen Ferry, Corvus Energy.

13.Xie, P., Guerrero, J. M., Tan, S., et al. (2021),Optimization-Based Power and Energy Management System in Shipboard Microgrid: A Review, IEEE Systems Journal, pp(99):1-13.

14.Fan, A., Yang, J., Yang, L., Wu, D., Vladimir, N. (2022), A review of ship fuel consumption models, Ocean Eng 264,112405.

15.Xie, P., Guerrero, J.M., Tan, S., Bazmohammadi, N., Vasquez, J.C., Mehrzadi, M., AlTurki, Y.(2022a), Optimization-based power and energy management system inshipboard microgrid: a review. IEEE Syst 16, 578-590.

16.Guillemin, S., Choulet, R., et al. (2024), Electrical Vehicle Smart Charging Using the Open Charge Point Interface (OCPI) Protocol, Energies.

17.Zeng, Y.J., Zhang, Q.J., et al. (2024), Bilayered Real-Time Energy Management Strategy for Hybrid Power Systems in Hydrogen Fuel Cell Vessels, IEEE Transactions on Transportation Electrification, vol. 10, No. 4, pp. 7954-7970.

18.Maloberti, L., Zaccone, R., De Gaetano, J., Campora, U. (2025), A comparison among innovative hybrid propulsion systems to reduce the environmental impact of a small passenger ship, Sustainable Energy Technologies and Assessments, vol. 75,104194.

19.Rajendran Sai Sasidhar, P., Gebremedhin, A., Norheim, I. (n.d.) (2025), Multi-energy microgrid design and the role of coupling components—A review, Renewable and Sustainable Energy Reviews, vol 216,115540.

20.Li, M., Liu, H., Yan, M., Guo, B., Wu, J., Jiang, G., Fu, X. (2025), Traffic scenario frozen callback and adaptive neuro-fuzzy inference system based energy management strategy for connected fuel cell buses, Applied Energy 387, 125605.

21.Anton, B., Florescu, A. (2020), Design and Development of Series-Hybrid Automotive Powertrains, IEEE Access, vol. 8, pp. 226026-226041.

22.Yuan, Y., Wang, J., Yan, X., et al. (2020), A review of multi-energy hybrid power system for ships, Renewable and Sustainable Energy Reviews, vol 132,110081.

23.Y.Z., P, B. (2024), Optimization Method of Energy for Series Hybrid Electric System, Internal Combustion Engine & Parts 09, 16-18.

24.Benevieri, A., Carbone, L., Cosso, S., Kumar, K., Marchesoni, M., Passalacqua, M., Vaccaro, L. (2021), Series Architecture on Hybrid Electric Vehicles: A Review, Energies 14(22), 7672.

25.Wang, C.C., Su, Y.Y., Ye, J.L., Xu, P.H, Xu, E.Y., Ouyang, T.C.(2024), Enhanced state-of-charge and state-of-health estimation of lithium-ion battery incorporating machine learning and swarm intelligence algorithm, Journal of Energy Storage, vol 83.

26.Li, Z.W., Wang, K., Hua, Y., Liu, X., Ma, R.Q., Wang, Z., Huang, L.Z.(2024), GA-LSTM and NSGA-III based collaborative optimization of ship energy efficiency for low-carbon shipping, Ocean Engineering, vol 312.

27.Hou, H., Xie, Y.B., Yan, Y.L., et al. (2025), Collaborative Scheduling of Multi-Port Integrated Energy Systems based on Shared Berths and P2P Tading, Proceedings of the CSEE,1-13.

28.Curiel - Olivares, G., Escobar, G., Johnson, S., et al. (2024), MPC - Based EMS for a Series Hybrid Electric Tractor, IEEE Access 12, 135999 - 136010.

29.Estevez, M. A. P., Frigola, J. M., Llobet, J. A., et al. (2024), Optimal design of a series hybrid powertrain for an agricultural tractor, Energy Conversion and Management: X, vol 24,100789.

30.Kurt, E., Arabul, A. Y., Arabul, F. K., Senol, I. (2025), Parallel hybrid propulsion system with integration of designed electric machine for medium altitude long endurance UAV, Heliyon, vol 11.

31.Zhao, Y., Wang, H.T. (2025), Engine Operating Conditions and Optimization Measures for Commercial Vehicle Hybrid Systems, Internal Combustion Engine & Parts 05,24-26.

32.Zhou, J.H., Guo, J.C., Tang, Q., Wu, Z.H.(2023), Design of the smart midsize yacht hybrid system, Design Of The Smart Midsize Yacht Hybrid System 02, 67-76.

33.Sun, X.J., Song, E.Z.(2022), Research Status of Key Technologies for Energy Management System of Marine

Hybrid Propulsion Systems, China Mechanical Engineering 33(04), 469-495.

34.Chen, X.Q., Hu, R.Y, Luo, K, et al. (2025), Intelligent ship route planning via an A∗ search model enhanced double-deep Q-network, Ocean Engineering 327, 120956.

35.Sun, X., Xin, F., Gao, K. (2024), Energy efficiency research of propulsion system for series-parallel hybridization of amphibious vehicles, Heliyon.

36.Soma, A., Bruzzese, F., Mocera, F., Viglietti, E. (2016), Hybridization factor and performance of hybrid electric telehandler vehicle, IEEE Transactions on Industry Applications, 52, 5130-5138.

37.Yuan, Y., Ye, T., Tong, L., et al. (2023), Optimizing energy management strategies for hybrid electric ships based on condition identification and model predictive control, International Journal of Green Energy, 20(15).

38.Ngo, Q.H., Nguyen, B.L.H., Zhang, J.H., et al. (2025), Deep graph neural network for fault detection and identification in distribution systems, Electric Power Systems Research 247, 111721.

39.Li, S.L., Zhu, Y.K., Bai, J.G., et al. (2023), Dynamic obstacle avoidance of unmanned ship based on event-triggered adaptive nonlinear model predictive control, Ocean Engineering 286(Part 2), 115626.

40.Jia, C.F., Ma, J., Yang, X., et al. (2023), RAGAN: A Generative Adversarial Network for risk-aware trajectory prediction in multi - ship encounter situations, Ocean Engineering 289(Part 1), 116188.

41.Ma, B., Li, P.-H. (2025), Optimal flexible power allocation energy management strategy for hybrid energy storage system with genetic algorithm based model predictive control, Energy 324, 135958.

42.Lü, X., Li, S., He, X., Xie, C., He, S., et al. (2022), Hybrid electric vehicles: A review of energy management strategies based on model predictive control, Journal of Energy Storage 56(B), 106112.

43.Song, K., Li, Z., Zhang, Y., Wang, X., Xu, G., Zhang, H. (2024), A rule-based online energy management strategy for long-endurance stratospheric airships, Aerospace Science and Technology, vol 151.

44.Tsitsilonis, K., Theotokatos, G. (2018), A novel systematic methodology for ship propulsion engines energy management, Journal of Cleaner Production 204, 212-236.

45.Nivolianiti, E., Karnavas, Y. L., et al. (2024), Fuzzy Logic-Based Energy Management Strategy for Hybrid Fuel Cell Electric Ship Power and Propulsion System, Journal of Marine Science and Engineering.

46.Zhou, J., Zhao, J., Wang, L. (2024), Cost-Based Research on Energy Management Strategy of Electric Vehicles Using Hybrid Energy Storage System, TsingHua Science and Technology.

47. Zhang, X.X., Sun, T.T.(2024), Deep reinforcement learning for collision avoidance of autonomous ships in inland rivers, Proceedings of the Institution of Civil Engineers-Transport.

48.Liu, H., Fan, A., et al. (2025), Multi-objective hierarchical energy management strategy for fuel cell hybrid ships based on deep reinforcement learning, Applied Energy.

49.Ji, Z.P., Wang, Y.W. (2025), Mathematical model based on improved ship automatic rudder design, Ship Science and Technology 47(04), 91-95.

50.Liu, H., Fan, A., Li, Y., et al. (2024), Testing methods for multi-energy ship energy management system: A systematic review, Ocean Engineering.

51.Zhao, Z.H. (2022), Improved fuzzy logic control-based energy management strategy for hybrid power system of FC/PV/battery/SC on tourist ship, International Journal of Hydrogen Energy 47(16), 9719-9734.

52.D'Agostino, F., Gallo, M., et al. (2025), A Model Predictive Control-Based Energy Management Strategy for Secure Operations in Shipboard Power Systems, IEEE Transactions on Transportation Electrification.

53.Wu, N., Zhang, F., Zhang, F., Jiang, C., et al. (2024), An integrated multi-objective optimization, evaluation, and decision-making method for ship energy system, Applied Energy 373, 123917.

54.Wen, J., Lu, J., Spataru, C., et al. (2024), Coordinated intelligent control strategy and power management for marine gas turbine under pulsed load using optimized neural network, Energy 313.

55.Lan, T., Huang, L. Z., Ma, R. Q., Wang, K., et al. (2024), A robust method of dual adaptive prediction for ship fuel consumption based on polymorphic particle swarm algorithm driven, Applied Energy, vol 379, 124911.

56.Chen, H., Zhang, Z., Guan, C., Gao, H. (2020), Optimization of sizing and frequency control in battery/supercapacitor hybrid energy storage system for fuel cell ship, Energy, 197, 117285.

57.Teng, F., Shan, Q.H., Li, T.S. (2020), Intelligent Ship Integrated Energy System and Its Distributed Optimal Scheduling Algorithm, Acta Automatica Sinica 46(09), 1809-1817.

58.Ying, Y.L., Li, L.L., Wang, Z.T., et al. (2012), Research on the Design of a Simulation Software for Marine Power

Generation System Based on MATLAB/GUI, Gas Turbine Technology 25(02), 37-42.37-42.

59.Wei, D.H., Li, H.Z. (2024), The state recognition method of ship electrical equipment based on multi source information fusion, Ship Science and Technology 46(10),186-189.

60.Zhu, L., Liu, Y., Zeng, Y., Guo, H., Ma, K., Liu, S., Zhang, Q. (2024), Energy management strategy for fuel cell hybrid ships based on deep reinforcement learning with multi-optimization objectives, International Journal of Hydrogen Energy 93, 1258-1267.

61.Derollepot, R., Vinot, E. (2019), Sizing of a combined series-parallel hybrid architecture for river ship application using genetic algorithm and optimal energy management, Mathematics and Computers in Simulation, 158, 248-263.

62.Jiang, J. W., Hu, Y. H., Ding, M. H., et al. (2023), Intelligent condition monitoring and fault diagnosis of marine fans based on feature selection of relative chaos, Journal of Shanghai Maritime University 44(1), 88-94.

63.Meng, N. J., Mei, J. H. (2025), A Review of Research on Ship-Related Intelligent Algorithm, Pearl River Water Transport 4, 72-75.

64.Yang, G. Y., Zhao, H. J., Wu, J. J. (2025), Design and Implementation of Distribution Network Dispatching and Energy Management System Based on Distributed Intelligent Collaboration, Appliance Maintenance 3, 137-139.

65.Alam, F., Zaidi, S. H., Rehmat, A., Khan, B. M. (2025), Model predictive controller based design for energy optimization of the hybrid shipboard microgrids, Ocean Engineering 323, 120545.

66.Wen, J., Lu, J., Zhang, S., Liu, R., Spataru, C., Weng, Y., Lv, X. (2024), Intelligent control for rapidity and security of all-electric ships gas turbine under complex mutation load using optimized neural network, Applied Thermal Engineering, 248(Pt A), 123120.

67.Du, J.W., Sui, Y.F., Wen, S.X., Hao, G.C., Du, X., Sun, X.M. (2021), Bumpless Transfer Control for Gas Turbine IFAC-PapersOnLine 54(10), 488-493.

68.Zhou, L.D., Xu, J., Yao, G. (2022), Review of integrated energy management systems for a marine microgrid, Power System Protection and Control 50(13), 171-186.

69.Feng, K., Wang, J., Wang, X., et al. (2024), Adaptive state estimation and filtering for dynamic positioning ships under time-varying environmental disturbances, Ocean Engineering 303, 117798.

70.Luo, X., Yan, R., Wang, S. (2024), Ship sailing speed optimization considering dynamic meteorological conditions, Transportation Research Part C: Emerging Technologies 167, 104827.

71.Peng, D.C., Wang, Y.G. (2024), Current Sharing Control of Parallel Energy Storage on Ship DC Bus, Journal of Shanghai Ship and Shipping Research Institute 47(04), 30-38.

72.Xia, M., Yao, S., Li, C., et al. (2024), Exergy, energy, economy analysis and multi-objective optimization of a comprehensive energy utilization system for LNG-powered ships based on zero-carbon emissions, Case Studies in Thermal Engineering 53, 103783.

73.Zhu, M., Kong, M., Wen, Y., et al. (2025), A multi-objective path planning method for ships based on constrained policy optimization, Ocean Engineering 319, 120165.

74.Hassan, A. A., Awad, M. M., Nasser, M., et al. (2025), Towards clean energy independence: Assessing MENA region hybrid PV-wind solutions for green hydrogen generation and storage and 24/7 power production, Sustainable Energy Technologies and Assessments 73, 104158.

75.Feng, A., Biao, Z., Bin, C., et al. (2024), DC Cascaded Energy Storage System Based on DC Collector With Gradient Descent Method, IEEE Transactions on Industrial Electronics 71(2), 1594-1605.

76.Wen, S., Lan, H., Yu, D. C., Fu, Q., Hong, Y.-Y., Yu, L., Yang, R. (2017), Optimal sizing of hybrid energy storage sub-systems in PV/diesel ship power system using frequency analysis, Energy 140(Pt 1), 198-208.

77.Zhang, J., Xue, Y., Tang, Y., Chen, Y., Chen, M., He, X., Lin, S. (2025), Equivalent system frequency response model with energy storage, Electric Power Systems Research 239, 111211.

78.Guo, X.D., Lang, X., Yuan, Y., Tong, L., Shen, B., Long, T., Mao, W. (2024), Energy management system for hybrid ship: Status and perspectives, Ocean Engineering 310(Pt 1), 118638.

79.Longva, T., Eide, M. S., Endresen, Ø., Sekkesæter, Ø., Helgesen, H., Rivedal, N. H. (2024), Marginal abatement cost curves for CO_2 emission reduction from shipping to 2050, Maritime Transport Research 6, 100112.

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