Research on Intelligent Energy Management Algorithm for Ship Hybrid Power System

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Abstract

In response to the green and low-carbon transformation demands of the shipping industry, ship hybrid power systems, with their significant advantages in reducing fuel consumption and controlling pollutant emissions, have become a research hotspot in the field of ship power. In order to lay a theoretical foundation for subsequent research, identify the research entry point, and prove the necessity and innovation of the research. Based on the relevant research achievements in the field of ship hybrid power energy management, this paper compares the existing energy management strategies from the perspectives of rule-based, optimization-based and intelligent algorithm-based energy management, comprehensively and deeply analyzes the advantages and disadvantages of the research on these energy management strategies and their application conditions, and prepares for subsequent research. Finally, the deficiencies of the current research and the future development direction were pointed out, providing a reference for the design optimization and engineering application of ship hybrid power systems.

Keywords

Green Ship; Ship Hybrid Power System; Energy Management Strategy.

1. Introduction

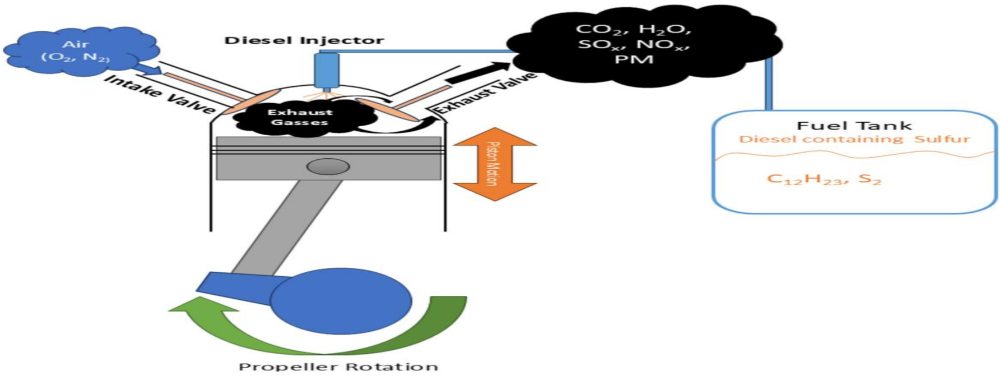

Figure 1. Exhaust gases generated during the combustion process [4]

The transportation industry is a fundamental sector of the national economy, and shipping is a crucial carrier of global trade: globally, approximately 80% of trade is accomplished by sea transportation [1]. Driven by the global emission reduction targets and stricter environmental regulations, the International Maritime Organization (IMO) has continuously strengthened the supervision of ship emissions and energy efficiency, for instance, starting from 2020, the global fuel sulfur content was set at a maximum of 0.50% (0.10% in the ECA area) [2], and through energy efficiency and carbon intensity requirements such as EEXI/CII, it promoted emission reduction in the shipping industry [3]. Moreover, the transformation of shipping power needs to take into account multiple goals. Not only should greenhouse gas emissions be reduced to mitigate global warming, but also the pollutants such as sulfur dioxide and particulate matter generated by the combustion of fossil fuels should be controlled simultaneously to achieve the coordinated advancement of climate governance and air quality and human health protection (see Figure 1) [4]. At the same time, in 2023, the IMO updated its greenhouse gas strategy, proposing to achieve net zero emissions in international shipping by around 2050, and setting phased emission reduction and zero/near-zero energy proportion targets for 2030/2040 [5]. Under the dual pressure of policies and the market, the transformation of ship power systems towards cleanliness and efficiency has become the core issue in the industry.

The hybrid propulsion system operates through the coordinated work of multiple power sources such as engines/generators, energy storage, and electric propulsion, enabling reasonable power distribution and energy efficiency improvement while meeting the speed and maneuverability requirements. Thus, it is widely regarded as one of the important technical paths for the low-carbon transformation of ships [6]. With the continuous development of multi-energy combinations such as diesel-battery, LNG-battery, hydrogen-battery, methanol-battery, and the introduction of solar energy, the system topology and operation mode have significantly increased, and the system complexity and control difficulty have also risen simultaneously [7]. The energy management strategy (EMS/PMS) as the "hub" of the hybrid power system is responsible for power distribution and constraint coordination among multiple energies, and its performance directly affects fuel economy, emission control, and system reliability [6][7]. However, in actual navigation, the propulsion load and on-board electrical load will be subject to the influence of navigation conditions, maneuvering requirements, and sea conditions (wave disturbances, propeller entering and leaving water, etc.) and show strong fluctuations and uncertainties, which pose higher requirements for real-time control and global optimization [8][9].

In recent years, a large number of studies have been conducted on energy management of ship hybrid power systems at home and abroad. The existing literature usually classifies EMS into three types: rule-based (rule-based), optimization-based (optimization-based), and learning/ intelligent-based (learning-based / AI) [10]. Rule-based strategies are simple to implement and have good real-time performance, but they are often limited by artificial experience rules and have insufficient adaptability to complex and variable conditions [10]; optimization-based strategies can explicitly incorporate energy consumption/emission targets and engineering constraints into the solution, and have more systematic performance, but are sensitive to model accuracy and online computing resources [11]; learning/ intelligent-based strategies demonstrate potential in handling complex nonlinear and multi-objective trade-offs, but still face challenges in training data, interpretability, and engineering deployment [12][13]. Based on this, this paper will start from different hybrid power energy combinations and their application scenarios, systematically review and compare the core principles, application effects, advantages and disadvantages, and applicable conditions of the three energy management strategies, further summarize the shortcomings of existing research, and combine multi-source perception and algorithm lightweighting trends to look forward to future directions, in order to provide references for the system design optimization and engineering application of hybrid power ships.

2. Overview of Hybrid Ships

Under the backdrop of energy conservation and emission reduction, the ship power system is undergoing a transformation from the traditional single fossil energy-driven mode to a multi-energy collaborative driving mode. With the increasing maturity of the ship hybrid power system, based on the energy combination, it can be classified into the following types: diesel-battery hybrid, LNG-battery hybrid, hydrogen-battery hybrid, methanol engine-battery hybrid, solar energy-wind energy-battery hybrid, etc.

In the diesel-battery hybrid aspect, Banaei, A et al. [14] proposed an efficient energy management strategy applicable to diesel-electric hybrid-powered ships. This strategy takes into account the influence of emission policies, ship resistance, wind direction and sea conditions, explores the feasibility and role of the charging and discharging of the electric vehicle batteries carried by the ship, builds a system mathematical model and combines real ship data, and uses MATLAB genetic algorithm to solve the optimal plan for a specific voyage. The diesel-electric hybrid-powered ship is shown in Figure 2.

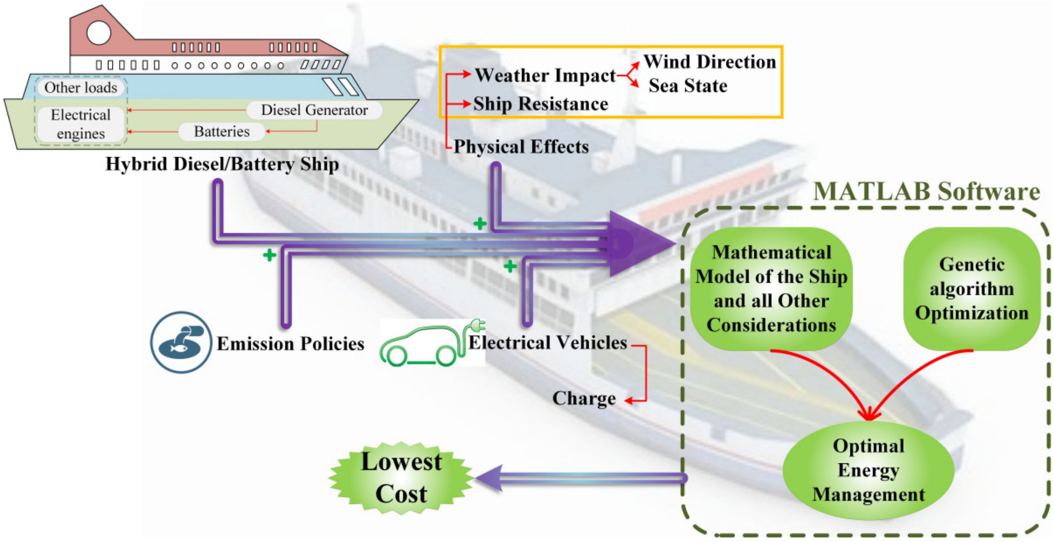

Figure 2. Schematic diagram of diesel-electric hybrid-powered vessel [14]

In the field of LNG-battery hybrid propulsion, Roslan S B et al. [15] conducted modeling and testing on the LNG-battery hybrid power system of tugboats and the corresponding energy management strategy, confirming that it can reduce emissions by 67.2% and costs by 64.0% compared to the diesel system. The optimal strategy can achieve an additional 23.8% reduction in emissions and 22.3% reduction in costs. The schematic diagram of the liquefied natural gas-battery hybrid power system for the vessel is shown in Figure 3.

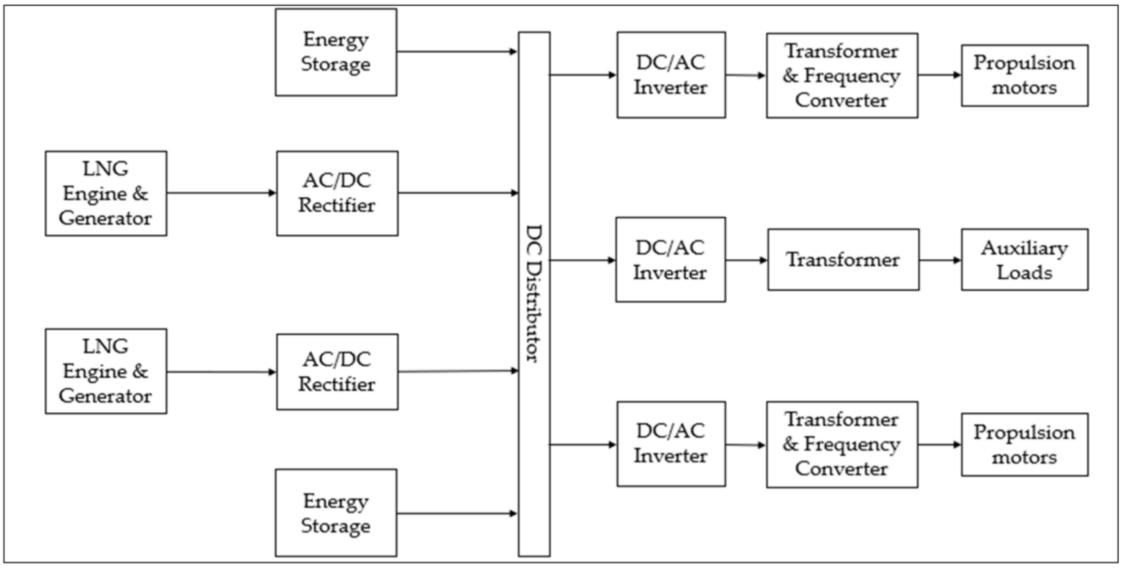

Figure 3. Diagram of LNG–battery hybrid vessel power system.[15]

In the field of hydrogen-battery hybrid power systems, Manias P et al. [16] conducted a study using a 1700-passenger ferry as the subject. By comparing the time-domain power data with a Python model, they evaluated four hydrogen hybrid configurations and a diesel direct drive scheme. They concluded that the efficiency of the hydrogen fuel - battery system could be reduced by up to 72% in terms of battery parameters without sacrificing efficiency. The hydrogen-battery power system is shown in Figure 4.

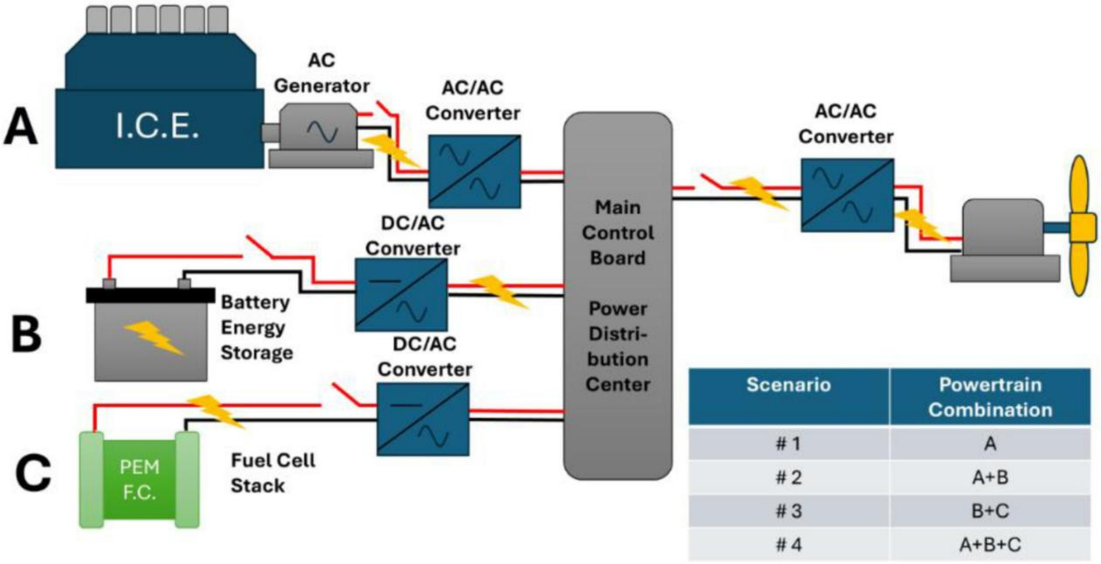

Figure 4. Hydrogen-Electric Battery Power System Diagram [16]

In the field of methanol engine-battery hybrid power systems, Li Z et al. [17] proposed a methanol-electric hybrid power system and an energy management strategy that combines global optimization through dynamic programming with real-time adaptation using an adaptive neural fuzzy inference system. Through simulation modeling and hardware-in-the-loop testing, it was confirmed that this strategy significantly reduces energy consumption and emissions compared to the conventional strategy and is practical. The simulation model of the marine methanol-electric hybrid propulsion system and the schematic diagram of the methanol-electric hybrid power system architecture are shown in Figure 5.

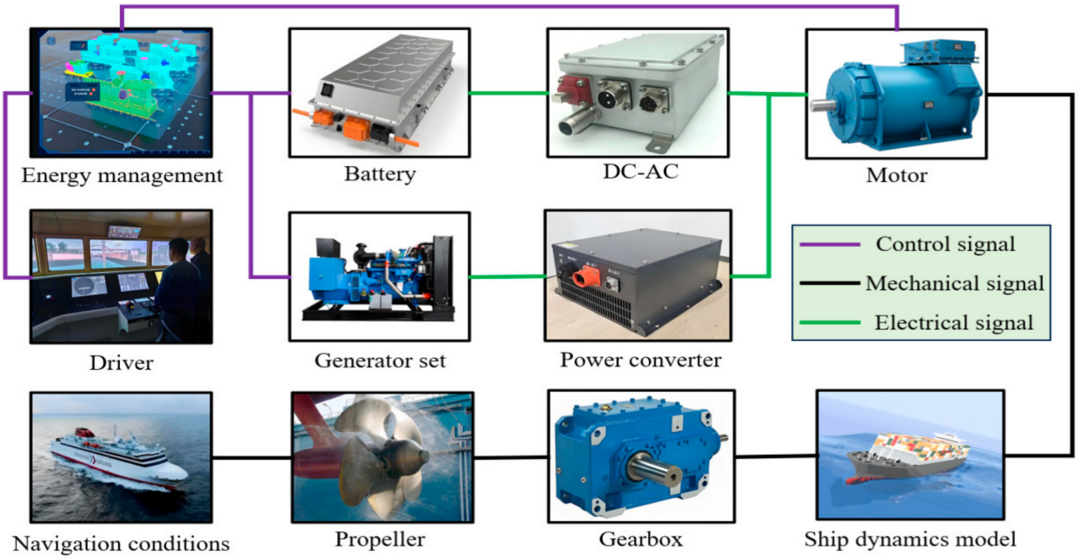

Figure 5. Simulation model of the marine methanol-electric hybrid propulsion system [17]

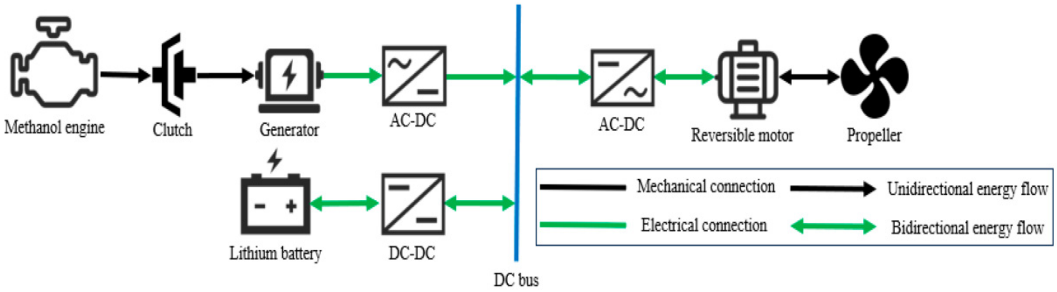

Figure 6. Schematic diagram of the methanol-electric hybrid power system architecture [17]

Regarding solar energy, Yu et al. developed a multi-energy ship micro-grid energy control system based on solar batteries and diesel generators, and proposed an energy distribution control strategy in accordance with the requirements for safe and stable operation, and verified its feasibility in actual ships [8][19]. Banaei et al. conducted research on all-electric propulsion ships, which consist of fuel cells, batteries, photovoltaic systems and two diesel generators [20].

Figure 7. “ShangDeGuoSheng” solar cruise ship[21]

Figure 8. “Planet Solar” solar ship.[21]

The operation methods, advantages and disadvantages, applicable scenarios of various types of hybrid power systems are summarized in Table 1 based on the energy type:

3. Energy Management Strategy

Figure 9 shows the three categories of energy management strategies for hybrid ships, including rule-based types based on engineering or practical experience, optimization-based types based on different optimization goals, and intelligent algorithm-based types that rely on autonomous learning and adaptive capabilities.

Table 1. Comparison of Ship Hybrid Power Systems

Type	Operation Mode	Advantages	Disadvantages	Application Scenarios
Diesel-battery	All-electric in port; peak boosting; diesel as main supply during cruising	Mature and easy to retrofit; peak shaving and valley filling to reduce fuel consumption	Short battery lifespan	Ferries, port operations, offshore operations
LNG-battery	LNG as main supply during navigation; increase battery proportion in sensitive areas	Low SO_x/PM emissions; strong endurance	Complex gas supply system; methane leakage risk	Coastal transport, ro-ro passenger ships, offshore engineering
Hydrogen-battery	Fuel cells for steady-state operation; batteries handle transient and peak loads	Local zero emissions; low noise and vibration	Complex gas supply system; methane leakage risk	Coastal transport, ro-ro passenger ships, offshore engineering
Solar-wind-battery	Renewable energy priority; batteries compensate for night/windless/sunless conditions	Zero fuel consumption; improved self-sustainability	Low energy density; limited by weather and space	Hotel loads, yachts/platforms, auxiliary power supplies
Methanol engine-battery	Methanol engine as main supply; batteries for peak shaving/low-noise operation in port	Convenient liquid fuel supply; potential for carbon reduction	Low safety	Feeder transport, offshore operations

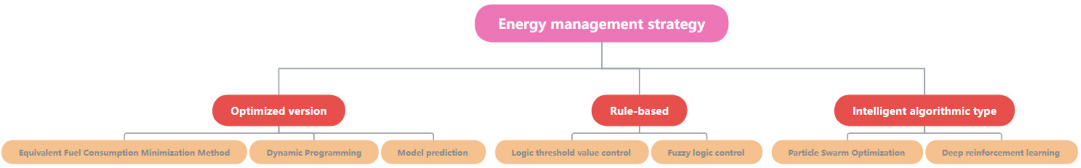

Figure 9. Classification of energy management strategies.

3.1. Rule-based Energy Management Strategy

3.1.1. Core Principles and Typical Applications

The rule-based energy management strategy is based on preset logical rules/expert experience and achieves the coordinated operation of multiple power sources through mode switching and power distribution. Its prominent feature is that it does not require precise system models and complex online optimization calculations, thus having a simple structure, strong real-time performance, and relatively easy implementation and verification, and is widely used in engineering applications [6][31]. In the scenario of ship hybrid power, common rule-based methods mainly include logic threshold value control (threshold/state machine) and fuzzy logic control [6][22]. Logic threshold value control usually sets thresholds around variables such as battery state of charge (SoC), load power demand, and engine/generator efficiency range, and accordingly stipulates the start/stop of power sources and mode switching: for example, in the low-load zone, the energy storage unit supplies power or the main source operates at low load, and in the high-load zone, the main source and the energy storage unit supply power collaboratively (peak shaving and valley filling) to meet the dynamic power demands of propulsion and the ship's power system [6][11]. Fuzzy logic control performs fuzzyization on input variables such as load, SoC, and speed, and outputs control quantities based on rule tables, thereby achieving smoother energy distribution in uncertain conditions. This idea has been applied in the strategy design and performance evaluation for typical navigation conditions in hybrid fuel cell ship propulsion systems [22].

3.1.2. Analysis of Advantages and Disadvantages

The advantages of rule-based strategies mainly lie in: good real-time performance and robustness. When facing the high dynamics and disturbances of ship loads (such as sea conditions, operation, and power fluctuation of propulsion), rule-based strategies can respond quickly according to logic [30]. Additionally, their engineering implementation threshold is low, they have weak dependence on models, and are easy to deploy and verify in ship control systems [6][31]. Moreover, the cost is relatively low. However, their limitations are also prominent: they highly rely on experience and parameter tuning. Thresholds and rule tables often need to be repeatedly adjusted according to ship type, mission profile, and equipment characteristics. Their generalization ability across operating conditions is limited [6][31]. Furthermore, they are difficult to ensure global optimality. When multiple objectives (fuel consumption/ emission/ lifespan/ comfort) coexist, rule-based strategies often only achieve average results rather than the optimal compromise [6]. Lastly, in the engineering of mode switching, if there is a lack of hysteresis/ suppression strategies, fixed thresholds may cause the main power source to frequently start and stop or power to switch back and forth, thereby leading to efficiency decline and component lifespan impact (engineering often alleviates this through hysteresis bands, minimum start-stop time, penalty terms, etc.). These types of issues have been repeatedly emphasized in discussions on ship hybrid power systems control [6][11].

3.2. Optimized Energy Management Strategy

3.2.1. Core Principles and Typical Applications

The optimized energy management strategy is guided by a clear objective function (such as minimizing fuel consumption, emissions, operating costs, and maximizing lifespan, etc.) under constraints (SoC boundaries, power/slope rate limits, equipment safety constraints, etc.), and solves the optimal power allocation through system modeling [24][27]. This type of method is more suitable for making interpretable trade-offs among multiple objectives [24]. Typical methods include dynamic programming (DP), equivalent consumption minimization strategy (ECMS), and model predictive control (MPC) [24][27]. In the study by Kanellos et al. [33], the dynamic programming (DP) clearly explains the concept of DP and how to use DP to obtain the best power management to minimize operating costs and limit greenhouse gas emissions. The operating costs were reduced by 3%, and the EEOI was maintained within the limit of 23 grams of carbon dioxide per ton of cargo. The DP results calculated by Kalikatzarakis et al. [32] were taken as the global optimum, and it was found that the fuel consumption was the lowest, with an average reduction of 8.6% compared to the RB strategy. Model predictive control (MPC) was used by Hou et al. [34] to effectively optimize the load fluctuations of all-electric ships. It was reported that the voltage variation decreased by 38%, and the energy storage loss increased by 65%. Haseltalab [35] et al. used MPC to control the ship speed and the load required by the propeller, while optimizing the power allocation among different energy sources. MPC control can provide the energy required by the hybrid power system, even in the presence of disturbances. Dynamic programming (DP) can obtain the theoretical global optimal energy allocation trajectory by discretizing the state/control variables and backtracking for the entire voyage conditions, and is often used to provide performance upper bounds and benchmarking for other strategies [26][27]. The equivalent consumption minimization strategy (ECMS) converts the battery charging and discharging power into equivalent fuel consumption, converting the multi-source energy allocation problem into a real-time optimization with the minimum equivalent consumption; in the scenario of hybrid electric propulsion of ships, there is also an adaptive ECMS design for lifespan/decay factors, used to alleviate the SoC drift and lifespan loss caused by the fixed equivalent factor [23][27]. Model predictive control (MPC) uses a closed-loop mechanism of "prediction - rolling optimization - feedback correction", continuously updating the optimal control sequence within a limited prediction time domain, and can explicitly handle constraints such as SoC, power, and slope rate, and has been used for energy management and power control problems in hybrid power systems of ships and ship power systems [24][25].

3.2.2. Analysis of Advantages and Disadvantages

The advantages of the optimized strategy lie in: clear objectives, achievable and verifiable optimality: Dynamic Programming (DP) can provide a global optimal benchmark, and Equivalent Consumption Minimization Strategy (ECMS) and Model Predictive Control (MPC) can achieve online optimization to varying degrees [26][24]. Strong constraint handling capability: especially MPC, it can incorporate SoC safety boundaries and power/dynamic constraints into a unified framework [24][25].

The limitations mainly lie in: Dynamic Programming (DP) requires full flight/forecasting information and is difficult to directly be used for real-time control; the performance of Model Predictive Control (MPC) is highly correlated with the quality of the prediction model [26][24]. Model Predictive Control (MPC) may bring a high online computational burden in high-dimensional constraints; Dynamic Programming (DP) has a significant increase in computational cost when the state dimension and flight duration increase [24][27]. The parameters of the ship power system will change over time (such as battery capacity degradation, internal resistance changes, generator efficiency drift), which will weaken the optimization effect based on fixed model parameters. In engineering, online identification or robust/adaptive mechanisms are often needed to be combined [24][23]. The flowchart of the Equivalent Consumption Minimization Strategy (ECMS) considering mode switching is shown in Figure 10.

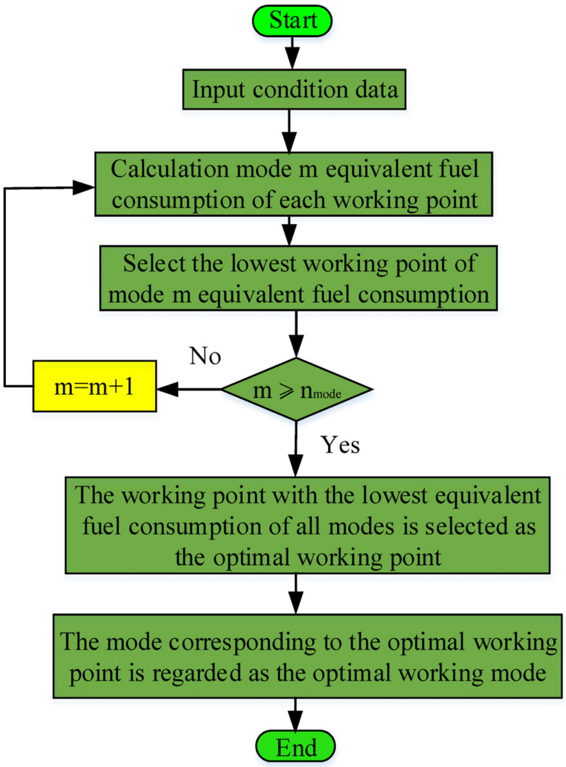

Figure 10. ECMS Flowchart [37]

3.3. Intelligent Algorithm-Based Energy Management Strategy

3.3.1. Core Principles and Typical Applications

The intelligent algorithm-based energy management strategy utilizes machine learning, reinforcement learning, or evolutionary/ swarm intelligence algorithms to achieve adaptive optimization for complex operating conditions through data training or online interactive learning mappings [29][30]. Compared with optimization methods, its advantages often stem from its learning ability in dealing with strong nonlinearity, strong coupling, and uncertain environments [11]. Typical routes include: evolutionary/swarm intelligence algorithms for parameter optimization: for instance, particle swarm optimization (PSO) can be used for global optimization of energy management strategy parameters (weights, rule parameters, power allocation coefficients, etc.), and there are already optimization frameworks and simulation validations based on PSO in fuel cell hybrid ships energy management [28]. Deep reinforcement learning (DRL) directly learns the strategy: through interaction between the intelligent agent and the environment to learn the optimal action. In hybrid electric propulsion ships and fuel cell hybrid ships, DRL and deep Q-learning forms have been used for multi-objective energy management and compared with DP and other strategies [29][30]. The overall framework of reinforcement learning is shown in Figure 11.

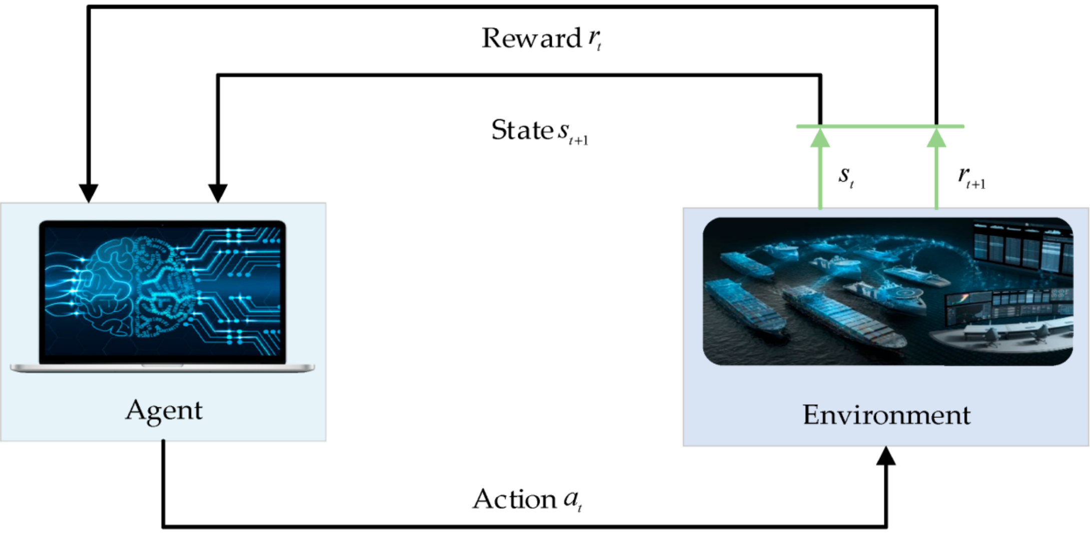

Figure 11. The overall framework of reinforcement learning [36]

3.3.2. Analysis of Advantages and Disadvantages

The advantages of intelligent algorithm-based strategies mainly lie in the following aspects: strong adaptability. Under conditions such as sea state disturbances, uncertain loads, and changes in task profiles, the learning-based strategies can acquire better performance adaptation capabilities through learning [29][30]. It can balance multiple objectives and complex constraints. Through reward functions/cost design, economic, lifespan, and SoC constraints can be unified into the optimization objective, making it suitable for comprehensive trade-offs of complex systems [30]. The limitations mainly include: high data and training costs. The cost of collecting and annotating high-quality navigation data is high. The training process is highly dependent on the simulation platform and data coverage. Challenges in engineering safety and verifiability. Reinforcement learning strategies need to handle safety constraints, extreme conditions, and generalization risks. Engineering deployment usually requires safety layers/constraint corrections/interpretability design [29][30].

In conclusion, the rule-based strategy serves as the fundamental guarantee for the stable operation of the system, and is suitable for scenarios with high requirements for real-time performance and reliability as well as simple working conditions; the optimization-based strategy is currently the mainstream choice that balances economic efficiency and practicality, and can meet the energy-saving needs of most medium and large-sized ships; the intelligent algorithm-based strategy is the development direction for future application in new energy vessels and complex navigation requirements, and has broad application prospects.

4. Summary

In terms of energy types, the marine hybrid power systems have developed diversified technical routes such as diesel-battery, LNG-battery, hydrogen-battery, methanol-battery, and solar-wind-battery. Each system presents significant differences in operation mechanisms, advantages, and applicable scenarios: Diesel-battery hybrid power, with its mature and easily-modifiable characteristics, is suitable for port operation vessels and offshore operations; LNG-battery hybrid power, with its low emissions and long range advantages, is applied in offshore transportation and passenger-cargo ships; Hydrogen-battery hybrid power achieves local zero emissions and becomes a green option for short-haul and inland vessels; Methanol-based hybrid power, relying on the convenience of fuel supply, is gradually promoted in feeder transportation and demonstration vessels. A large number of benchmark applications have emerged both domestically and internationally, verifying the engineering feasibility of different technical routes and providing practical support for industry transformation.

In terms of energy management strategies, existing research has formed three core systems: rule-based, optimization-based, and intelligent algorithm-based. Rule-based strategies are represented by logical threshold values control and fuzzy logic control, with advantages of simple structure, strong real-time performance, and high reliability, making them the basic choice for small near-shore vessels, but they have limitations such as reliance on expert experience and insufficient self-adaptive ability; Optimization-based strategies use methods such as equivalent fuel consumption minimization, dynamic programming, and model predictive control to achieve optimal solutions for clear goals such as fuel consumption and emission control, and are the mainstream solutions for medium and large ocean-going ships and fixed-route vessels, but their performance is constrained by the ability to predict working conditions and model accuracy; Intelligent algorithm-based strategies (such as particle swarm optimization, deep reinforcement learning) have strong adaptability and global optimization capabilities, and can adapt to complex sea conditions without relying on precise models, providing innovative solutions for large new energy vessels. However, problems such as high data dependence and high hardware computing power requirements hinder their engineering implementation. The three types of strategies have their own focuses and complement each other, jointly forming the technical system for marine hybrid power energy management.

Currently, there are two major challenges: 1) The dynamic adaptability of energy management strategies is insufficient. Most existing strategies cannot simultaneously take into account the steady state, dynamic, and extreme conditions during ship navigation, and their optimization effects are limited in complex sea conditions and load sudden changes scenarios; 2) There are obstacles in the engineeringization transformation of technologies, such as insufficient lightweight design of intelligent algorithms, high costs of data collection and annotation, and mismatch between hardware configuration and actual ship requirements, which restrict the practical application of advanced strategies.

Future research directions: 1) Develop adaptive energy management strategies that integrate multi-source sensing technologies, by integrating real-time data such as speed, sea conditions, load power, and battery status, to enhance the dynamic response ability of strategies to complex conditions and environmental changes; 2) Promote the engineering optimization of intelligent algorithms, through lightweight design to reduce the requirements for hardware computing power, combined with actual navigation data to build a low-cost training sample library, to solve technical bottlenecks in the implementation process.

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