State-of-Art Energy Management Strategies for Hybrid Fuel Cell Applications for Ships

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1 Introduction

The global carbon dioxide (CO_2) emissions of shipping alone were, in 2018, equal to 1,056 million tonnes [1]. This represents a share of about 2.89% of the total global CO_2 emissions. As the emissions caused by ships are expected to be 90–130% of the 2008 greenhouse gas (GHG) emissions in 2050, the International Maritime Organization (IMO) aims to reduce this number to at least 50% [1]. Hydrogen, renewable energy sources like wind and solar, and carbon capture technologies are being extensively researched to help meet global decarbonization goals and achieve net-zero emissions by 2050. Hydrogen, in particular, could contribute to reducing 20% of annual global CO_2 emissions by 2050 through its applications in industries such as steelmaking, transportation, and power generation, complementing renewable energy technologies [2, 3]. The operating profiles of ships have diversified significantly, leading to a notable evolution in power and propulsion architectures, as vessels adapt to varying mission requirements and technological advancements, such as hybrid propulsion systems and dynamic EMS [4]. This adaptation not only enhances efficiency but also ensures that ships are better suited to varied operational demands. As outlined by [1], the development of these sophisticated architectures necessitates precise design and control systems. Properly implemented, these systems can result in substantial fuel savings, thereby making ships both greener and

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C. O. Colpan et al. (eds.), *Fuel Cell and Hydrogen Technologies in Maritime Transportation*, https://doi.org/10.1007/978-3-031-86110-9_6

safer, as discussed in [5]. Moreover, recent advancements in maritime propulsion, particularly with the integration of electric and hybrid-electric systems, have opened up new possibilities for control strategies. These systems allow for more precise control over power distribution, enabling optimization based on operational needs, such as load demand and environmental factors. However, further research is required to fully understand and develop these strategies, especially in large-scale and ocean-going vessels, where system complexity and operational requirements pose significant challenges [6, 7]. The evolution of ship design, particularly in response to stricter environmental regulations like the Energy Efficiency Design Index and the Carbon Intensity Indicator, is driving innovation aimed at improving energy efficiency and reducing emissions [8, 9, 10, 11]. Advances in propulsion systems, hull optimization, and the incorporation of low-carbon fuels are examples of how ship design adapts to meet the increasing demands for sustainability and compliance with international maritime standards [12].

However, many existing maritime architectures continue to rely heavily on classical control theories. While these systems often incorporate advanced components and modern architectures, they frequently fail to significantly improve fuel efficiency and emission reductions. Proportional-Integral-Derivative (PID) controllers are recognized as one of the most widely used control mechanisms in industrial applications, including ship propulsion and power management systems. The popularity of PID controllers stems from their simplicity, robustness, and proven reliability in managing dynamic systems, making them particularly suited for applications where real-time stability is critical. They are frequently favored because they require relatively simple tuning compared to more advanced controllers and provide satisfactory performance for most control tasks, including in maritime environments. PID controllers are extensively utilized due to their ability to manage single-input, single-output systems, such as those found in propulsion systems, with high reliability. Despite the rise of more complex, model-based controllers, the PID's balance of practicality and effectiveness ensures its continued dominance in various fields, including marine engineering. Despite their strengths, these classical systems encounter limitations, particularly in dynamic and complex environments where advanced, data-driven control strategies—such as neural networks and fuzzy logic—could provide more flexibility and efficiency. The slow transition to these advanced technologies is exacerbated by the conservative nature of the maritime industry, where safety and regulatory compliance are prioritized, often at the expense of adopting newer control methods [13, 14]. Additionally, as highlighted by Nguyen et al. [15], the integration of traditional control systems into modern architectures increases both system complexity and costs. This mismatch between outdated control strategies and the growing demand for technological advancement creates a critical gap in achieving optimal energy efficiency and environmental sustainability in maritime operations. The systems discussed here are typically classified as hybrid powerplants or hybrid ships, emphasizing the need for better integration between conventional and cutting-edge technologies [6].

Integrating Energy Storage Systems (ESS) is a key point for hybrid ships [16]. From the storage point of view, lead-acid batteries have not been considered for large-scale present and future applications due to limited power and energy density capacity. Lithium-ion batteries (LIBs) are widely used as ESS for hybrid ships due to their high energy density and efficiency. However, producing these batteries is highly energy-intensive, often relying on high-heat processes primarily using fossil fuels, such as coal. As a result, manufacturing these batteries contributes significantly to GHG emissions, with estimates showing that for each ton of lithium extracted, approximately 15 tons of CO_2 are emitted. Furthermore, around 77% of LIBs are produced in China, where coal dominates the energy supply, exacerbating the carbon footprint of their production [17, 18].

To put this into perspective, authors of [19] have reviewed 79 papers on the environmental impact of the production of LIBs, concluding that the average cumulative energy demand and GHG emissions for battery production are 328 kWh and 110 kg CO_2 equivalent per kWh of storage capacity, respectively. And with that, the impact (both environmental and social) on the areas where lithium is mined is not even discussed. As we all strive to solve the global crisis problems and not reallocate them, the lifetime of these batteries should be extended as much as possible. The second focus in hybrid propulsion layouts of ships is using alternative fuels. One of those alternative fuels is hydrogen, which can be used via fuel cells [20]. Integrating component health awareness into the Energy Management System (EMS) plays a critical role in enhancing the overall performance and lifetime of energy systems, particularly in hybrid propulsion systems. Neglecting health adaptation mechanisms can lead to significant inefficiencies. For example, hydrogen consumption can increase dramatically, from around 6.5% to as much as 24%, as demonstrated in studies focused on fuel cell-battery systems, depending on how well the EMS adapts to the evolving health of components during operation [21]. The health of key components such as fuel cells and batteries affects not only the energy efficiency but also the overall lifespan of the system. This is crucial because the limited lifetime of components, such as fuel cells, remains one of the major barriers to the widespread adoption of hybrid propulsion technologies. In such systems, taking health factors into account ensures more consistent performance and reduces wear, thereby extending the lifetime of the components. However, the challenge of effectively integrating health-aware mechanisms into EMS design remains significant. Although research has highlighted the importance of component health monitoring in prolonging system lifespan and improving efficiency, much work is still needed to develop comprehensive EMS models that adapt to real-time health indicators of the system's components. This calls for advancements in both monitoring technologies and algorithmic strategies to ensure that the system can make informed decisions based on the current health of its components, paving the way for a more reliable and efficient transition to hybrid propulsion systems. However, integrating health awareness factors into the EMS design still has a long way to go [21].

Hybrid fuel cell applications for ships refer to integrating fuel cell technology with one or more other energy sources to power a vessel's propulsion and onboard systems. Hybrid fuel cell systems represent a forward-looking solution for the maritime industry. They aim to meet stricter environmental regulations while maintaining operational efficiency and performance, and they are increasingly recognized as a promising solution for reducing GHG emissions and pollutants in the maritime industry. These systems offer significant environmental benefits by generating electricity without harmful emissions, making them a cleaner alternative to traditional diesel-powered propulsion systems. Hybrid fuel cell systems combine fuel cells, typically powered by hydrogen or other alternative fuels, with energy storage devices like batteries and, in some cases, traditional internal combustion engines. These components work together to ensure optimized power delivery, improved fuel efficiency, and reduced emissions. The hybrid system aims to maximize efficiency, reduce emissions, and improve energy management onboard ships. Key Components of hybrid fuel cell systems for ships are

- **Fuel Cells**: to convert chemical energy from fuels directly into electricity through an electrochemical reaction with oxygen or another oxidizing agent, favored for their high efficiency and low emission levels.
- **Energy Storage Systems**: batteries or supercapacitors that store excess energy generated by the fuel cells. This stored energy can be used during peak power demands or when the fuel cell is off.
- **Power Management System**: to control how power is distributed between the fuel cells, energy storage, and the ship's propulsion and electrical systems, ensuring optimal performance and efficiency.
- **Auxiliary Power Units**: include traditional internal combustion engines that can work in conjunction with the fuel cells to provide additional power when needed.

Recent projects demonstrate how fuel cell technology, combined with renewable fuels like hydrogen and methanol, can substantially decarbonize maritime operations, supporting the IMO's goals to reduce emissions by 50% by 2050 [22, 23]. Moreover, fuel cells have intrinsic higher efficiency compared to traditional internal combustion engines [24]. By combining different energy sources, hybrid fuel cell systems increase the ship's energy system flexibility and adaptability to different operating conditions while complying with stringent regulatory frameworks. Furthermore, the silent operation of fuel cells significantly reduces noise pollution, which benefits marine life and crew comfort on board vessels [23]. Among different fuel cell types, polymer electrolyte membrane fuel cells (PEMFCs) powered by hydrogen have been the most applied technologies in projects involving fuel cells on ships [25]. PEMFCs are usually integrated with an ESS, creating a hybrid PEMFC/ESS powertrains configuration that allows zero-emission propulsion.

This chapter targets maritime engineers, policymakers, and researchers interested in the evolution and implementation of EMS within hybrid PEMFC/ESS systems. This chapter gathers and synthesizes the latest developments in EMS for hybrid fuel cell applications in ships, an area characterized by technological innovation and potential environmental impact. For this reason, we begin by recalling the preliminaries related to the fundamentals of hybrid fuel cell systems and EMS, providing an overview of key international research projects that have advanced the application of fuel cell technologies in the maritime sector. The chapter explains the architecture of hybrid PEMFC/ESS powertrains, examining the specific components of the PEMFC system, including its structure, operational principles, and factors influencing performance. Then, we further dissect the ESS, which plays a crucial role in complementing PEMFCs by managing the balance between power generation and energy demands. The combined benefits of hybrid PEMFC/ESS systems, such as improved efficiency, reduced emissions, and fuel flexibility, are weighed against their challenges, including technical complexity, costs, and durability concerns. Then, the focus shifts to EMS, which governs how power is distributed between the PEMFC and ESS. These strategies are broken down into three main approaches: (i) rule-based (RB), (ii) optimization-based (OB), and (iii) learning-based methods (LB). Each type of EMS is explained in detail, starting with RB approaches that use pre-defined rules for power distribution, followed by OB methods, which utilize algorithms to optimize fuel cell efficiency and energy use. The final approach discussed, LB EMS, involves using machine learning techniques to dynamically adapt and optimize the system based on operational data. The actual state-of-the-art EMS provides a more focused discussion on the most current advancements in each of the three EMS categories. RB strategies, though simple, are evaluated for their limitations in flexibility, while OB strategies are praised for their ability to achieve greater energy savings through more complex algorithms. LB strategies, being the most advanced, hold significant promise for future applications due to their adaptability and ability to handle complex maritime operations. A comparative analysis of these strategies highlights their relative strengths and weaknesses in terms of efficiency, scalability, and implementation costs. We will then detail the challenges and future directions. The chapter identifies major obstacles to the adoption of hybrid PEMFC/ESS systems, including technological, regulatory, and economic challenges. It also explores potential future developments, such as advancements in materials, energy management algorithms, and integration with renewable energy sources, which could address these challenges and improve the viability of these systems in maritime applications. Finally, the conclusion summarizes the findings, emphasizing the critical role of hybrid fuel cell systems in achieving sustainable shipping and the need for ongoing innovation to overcome current limitations in both technology and EMS.

This chapter is structured to provide a thorough analysis of hybrid fuel cell systems in maritime applications. It begins with foundational concepts in the preliminaries in Sect. 2, setting the stage for state-of-the-art analysis and discussions. The document then covers EMS in Sect. 3, breaking them down into RB, OB, and LB approaches. Section 4 tackles the ongoing technical, economic, and regulatory challenges while outlining potential areas for future research. The chapter concludes with a summary of key insights and recommendations in Sect. 5.

2 Preliminaries: Fundamentals of Hybrid Fuel Cell Systems for Ships and Energy Management Strategies

In this section, we first revisit the key concepts surrounding hybrid fuel cell systems and EMS, beginning with a review of fundamental principles. This includes an overview of significant international research projects that have propelled the use of fuel cell technologies within the maritime industry. The discussion explores the architecture of hybrid PEMFC/ESS powertrains, focusing on the specific components of the PEMFC system, including its design, operational mechanisms, and performance factors. Following this, we focus on the role of the ESS, which is integral to balancing power generation and energy demand alongside the PEMFC. The combined benefits of hybrid PEMFC/ESS systems, such as enhanced efficiency and reduced emissions, are contrasted with the challenges they face, such as hydrogen storage, cost, and durability issues. From there, we transition to EMS, which dictates how power is distributed between the PEMFC and ESS. The fundamentals of the three primary approaches (RB, OB, LB) are introduced in this section.

2.1 Overview of International Research Projects for Fuel Cell Systems in Maritime Applications

The application of fuel cell technologies, including PEMFCs, high-temperature PEMFCs, solid oxide fuel cells (SOFCs), and molten carbonate fuel cells (MCFCs), into ship energy systems has experienced a significant increase in recent years. Authors [25, 26] reported an analysis of the developed and ongoing projects and real-world applications for the use of fuel cells in shipping. Table 1 gives an overview of past and ongoing projects from 2000 to date, including the installed fuel cell type and power onboard, the logistic fuel, and the type of application. Figures 1 and 2 present the distribution of fuel cell types and logistic fuel types used in maritime applications, respectively. Figure 1 highlights the dominance of PEMFC technology, which accounts for 75% of the fuel cell types used in the analyzed projects. This prevalence is likely due to PEMFC's high degree of maturity, high efficiency, specific power and power density, and other advantageous technical characteristics that will be further discussed in Sect. 2.5. The remaining portion of the chart is shared between SOFC, which contributes 14.3%, and MCFCs, representing 10.7%. Both SOFC and MCFC offer advantages in terms of fuel flexibility and higher operating temperatures, which can improve thermal efficiency, but their deployment is less frequent due to their lower degree of maturity, lower power density, complex cooling requirements, and high costs.

Figure 2 illustrates the distribution of logistic fuels used in these fuel cell systems, with hydrogen being the predominant fuel, powering 81% of the projects. This indicates the increasing global emphasis on zero-emission technologies and the role hydrogen is expected to play in decarbonizing maritime transportation.

Table 1 Overview of research projects for fuel cell systems in maritime applications [25]

Project name	Time	Country	FC power	FC type	Logistic fuel	Application	Ref.
FCSHIP	2002–2004	EU	–	MCFC	Diesel	RoPax vessel	[34]
FellowSHIP	2003–2018	Norway	320 kW	MCFC	LNG	Offshore supply	[35]
MC-WAP	2005–2010	Italy	150 kW	MCFC	Diesel	RoPax	[36]
ZEMSHIP	2007–2014	Germany	96 kW	PEMFC	H_2	Inland vessel	[37]
Nemo H2	2008–	Netherlands	65 kW	PEMFC	H_2	Passenger boat	[38, 39]
PaXell	2009–2016	Germany	60 kW	PEMFC	MeOH	Cruise ship	[40]
SchIBZ	2009–2018	Germany	100 kW	SOFC	Diesel	General cargo ship	[37, 41]
TESEO	2012–2015	Italy	50 kW	PEMFC	H_2	Yacht	[42, 43]
RiverCell	2015–2022	Germany	90 kW	PEMFC	MeOH	Inland vessel	[44]
Sea Change	2016–2022	USA	360 kW	PEMFC	H_2	Passenger ferry	[45, 46]
ELEKTRA	2017–2019	Germany	300 kW	PEMFC	H_2	Canal tug	[24]
Maranda	2017–2022	EU	165 kW	PEMFC	H_2	Arctic research ship	[47]
HFCMARINE	2018–2020	Denmark	200 kW	PEMFC	H_2	Ferry	[48–52]
HYSEAS III	2018–2022	Scotland	600 kW	PEMFC	H_2	RoPax ferry	[53]
TecBIA	2018–2022	Italy	140 kW	PEMFC	H_2	Research vessel	[54, 55]
H2PORTS	2019–2023	Spain	70 kW	PEMFC	H_2	Reach Stacker	[56]
PaXell 2	2019–2022	Germany	N/A	PEMFC	MeOH	Cruise ship	[57]
Hydrogenia	2019–2021	South Korea	100 kW	PEMFC	H_2	Small boat	[45, 58]
MF Hydra	2020–	Norway	400 kW	PEMFC	H_2	RoPax ferry	[59]
ShipFC	2020–2024	Norway	2 MW	SOFC	NH_3	Offshore vessel	[60]
Nautilus	2020–2024	EU	60 kW	SOFC	LNG	Cruise ship	[61]
HyShip	2021–2024	Norway	3 MW	PEMFC	H_2	RoRo	[62]
HIMET	2021–2022	UK	500 kW	PEMFC	H_2	Ferries	[63]
Helenus	2022–2027	EU	500 kW	SOFC	LNG	Cruise ship	[64]

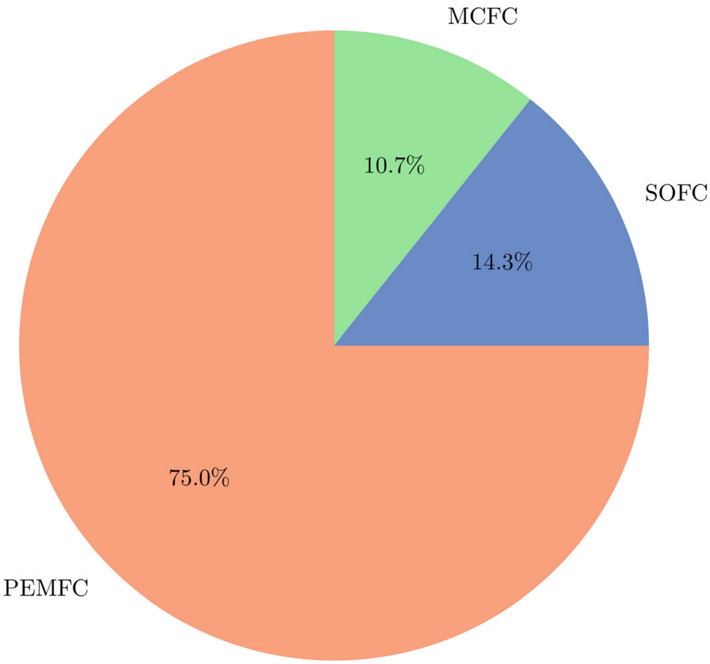

Fig. 1 Distribution of fuel cell types used in maritime applications

Methanol and diesel each account for 9.5%, showcasing their continued relevance in certain applications where hydrogen storage or infrastructure is limited. However, as hydrogen production and distribution infrastructure is expected to improve and higher energy density storage solutions advance, we can anticipate a further shift towards hydrogen as a logistic fuel to power zero-emission fuel cell systems.

As highlighted by the projects' overview, the PEMFC is currently recognized as a technology with a higher potential for decarbonizing the shipping sector, especially in the short and medium-term scenario. The following subsections present the hybrid PEMFC/ESS system architecture, the fundamentals of its main components, and the benefits and challenges related to their applications.

2.2 Hybrid PEMFC/ESS Powertrain Architecture

A hybrid powertrain is generally composed of a main power generator coupled with an ESS. In a hybrid PEMFC/ESS system for all-electric ships, the PEMFC is the main power generator, while the most common ESS are batteries and supercapacitors.

In the current state-of-the-art technology, alternating current (AC) grids with fixed frequencies are usually implemented on all-electric ships [26]. However,

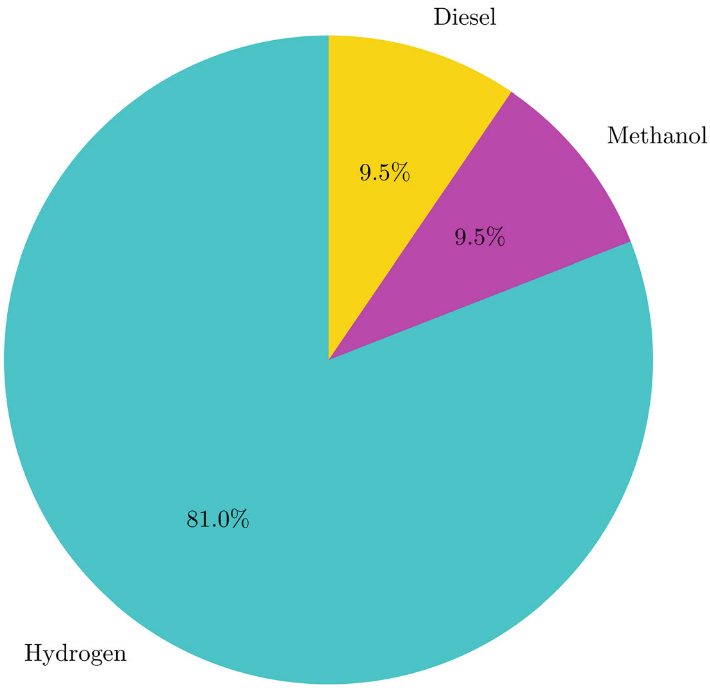

Fig. 2 Breakdown of logistic fuel types used in marine fuel cell systems

when compared to traditional AC distribution systems, the advantages of direct current (DC) distribution have led to its increasing popularity over the past decade [27]. In a DC-distributed system, the voltage from AC generators is first rectified through an AC-to-DC converter before power is transmitted to consumers via a DC bus. Propulsion and thruster loads are then driven by electric motors, which are powered by variable frequency converters (DC to AC). Additionally, other loads, such as hotel services and low-voltage AC distributions, are supplied via fixed-frequency converters and isolation transformers. A key component in this system is the input circuit (IC), a solid-state device used at connection points between different sections of the DC bus. This device isolates faults like short circuits, preventing them from affecting other parts of the DC grid. Power electronic converters are central to the operation of the entire DC-distributed network. DC distribution enables the use of variable-speed generators instead of fixed-speed ones, contributing to significant reductions in fuel consumption and emissions. Furthermore, DC systems offer greater simplicity compared to their AC counterparts, allowing for easier fault prediction and the development of effective protection measures. DC distribution systems present several key benefits, including significant power transmission advantages. For instance, distributing power at 1000 V DC instead of 690 V AC can reduce cable requirements by up to 40%.

Additionally, issues like total harmonic distortion, common in AC systems with frequency converters, are no longer a concern in DC setups. Shore connections are also simplified on the DC side, offering more flexibility in ports as network frequency mismatches are eliminated. Handling peak loads with onboard ESS enhances operational flexibility in ports with low-power feeders. Another significant benefit is the seamless integration of variable-speed shaft generators into the system, which can be managed similarly to other variable-speed generators. The power take-in and power take-off solutions are also streamlined, especially when combined with ESS. Moreover, centralizing all drives in a single lineup reduces the requirements for ambient conditions, such as temperature, humidity, and cleanliness, particularly in critical locations like thruster rooms. This centralization is particularly advantageous during the construction and commissioning phases. The shift to DC distribution has resulted in a notable reduction in both space and weight, with up to a 30% decrease compared to AC systems.

Furthermore, there has been an improvement in electrical efficiency of approximately 0.5–1% due to this transition. Variable-speed motors for auxiliary loads like fans and pumps also achieve enhanced efficiency through flow regulation by adjusting speed rather than relying on throttling.

One of the most significant advantages of a DC distribution system is its ability to seamlessly integrate with ESS-like batteries, supercapacitors, and fuel cells. This integration is essential for smoothing out power fluctuations and enhancing the overall efficiency and reliability of the power system. For instance, the DC distribution system can easily accommodate these energy storage devices to handle load variations and optimize power flow, providing more flexibility in energy management [28]. Additionally, this system minimizes the need for complex synchronization and reactive power issues often encountered in traditional AC distribution systems [29, 30]. These ESS help stabilize load variations from thrusters and other major loads, leading to smoother engine operation [31]. Moreover, installing ESS onboard is expected to generate significant fuel savings [32]. The detailed functionality and integration of ESS will be discussed in the following section [33].

Hybrid powertrains are classified into three main architectures depending on the type of connection between the main power unit and the ESS: series, parallel, and series–parallel [6]. Hybrid PEMFC/ESS systems commonly present series architectures, where all power generators and the corresponding converters are connected to a main electrical grid. The electric power flow generated from both the PEMFC and the ESS is first driven to an electric bus, which flows to the propulsion and the auxiliary power loads of the ship. Hybrid PEMFC-ESS systems usually have a bidirectional electric power flow between the electric bus and the ESS so that the ESS can be charged by the PEMFC when the produced power is higher than the power demand. A schematic example of a hybrid PEMFC/battery powertrain configuration is shown in Fig. 3.

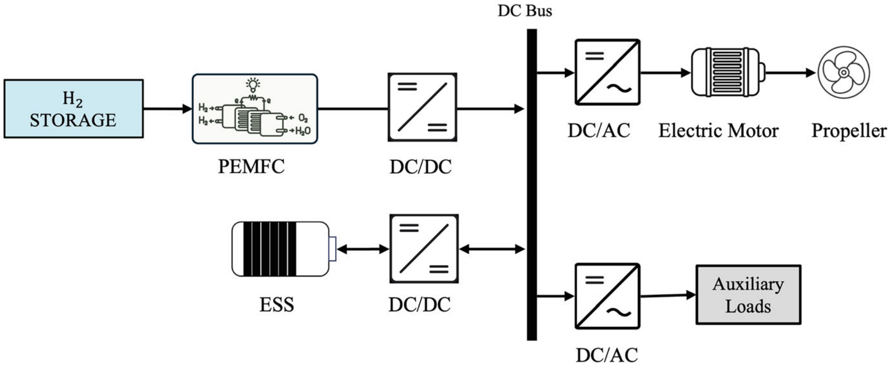

Fig. 3 Schematic of a hybrid PEMFC/ESS powertrain system

2.3 PEMFC System

For hybrid PEMFC/ESS systems, the main power source is represented by the PEMFC. A PEMFC generates electricity through an electrochemical reaction between hydrogen and oxygen, producing water and heat as by-products. The core of the PEMFC consists of a proton-conducting electrolyte membrane sandwiched between two electrodes, the anode and the cathode. At the anode, hydrogen is split into protons (H^+) and electrons (e^-) through the following reaction:

$$H_2 \rightarrow 2H^+ + 2e^- \tag{1}$$

Protons travel through the proton-conducting membrane, while electrons flow through an external circuit, generating electrical power. At the cathode, protons, electrons, and oxygen combine to form water:

$$\frac{1}{2}O_2 + 2H^+ + 2e^- \rightarrow H_2O. \tag{2}$$

The overall cell reaction is

$$H_2 + \frac{1}{2}O_2 \rightarrow H_2O. \tag{3}$$

The electrolyte membrane of a low-temperature (LT) PEMFC typically consists of perfluorsulfonic acid (PFSA), which becomes conductive to protons when hydrated [65]. The need for a hydrated membrane requires the operating temperature to remain below the boiling point of water. LT-PEMFCs typically operate above 65 °C to prevent flooding by condensed product water but below 85 °C to prevent dehydration and subsequent degradation of the polymer membrane [66]. Water management is a critical aspect of LT-PEMFC operations. Dehydration of the membrane leads to a reduction in ionic conductivity, while flooding of the electrode inhibits access of the reactants to the reaction sites. The membrane hydration can be sustained by the water generated in the electrochemical reaction, while excess water must be removed [67].

High-temperature (HT) PEMFCs have been developed based on stable solid polymer membranes that achieve high proton conductivity at temperatures above the dew point of water. A polybenzimidazole (PBI) polymer matrix doped with phosphoric acid (H_3PO_4) is most frequently used as the electrolyte material. This PEMFC type operates at temperatures between 120 °C and 180 °C [68]. Despite potentially offering several advantages, such as higher kinetics of the electrochemical reaction, reduced irreversibilities due to the absence of liquid water, and higher tolerance to fuel impurities, HT-PEMFCs are currently at a less mature state compared to their Low-Temperature counterpart. At the actual state of the art, LT-PEMFCs have been the most applied technology in past and ongoing projects for applications in the maritime sector [26].

PEMFC electrodes are composed of carbon support filled with catalyst nanoparticles (typically platinum-based) in an ionomer matrix. The catalyst layer is critical for speeding up the electrochemical reactions, ensuring efficient electricity generation. The electrolyte membrane, anode, and cathode are sandwiched together to form the membrane electrode assembly (MEA). External to the electrodes, the gas diffusion layer (GDL) ensures uniform distribution of the reactant gases and removal of the excess water produced at the cathode. Finally, like most external components, the bipolar plates play a role in fuel and air distribution, water and heat management, separating air and fuel, and conducting electric current. Bipolar plates for PEMFCs can be made of graphite, (coated) metals, or composites [69].

A single PEMFC generates low voltages, ranging from 0.6 to 0.8 V. The actual power output of a single PEMFC depends on the size of the cell and its current density, typically measured in watts per square centimeter (W/cm^2). Single cells can produce power in the range of 10 to 200 W, but this is insufficient for most real-world applications. To achieve higher power levels, multiple fuel cells are connected in series to form stacks, allowing them to produce higher power outputs, from several up to hundreds of kilowatts. Stacks are subsequently combined in modules to even reach megawatts of total power.

Auxiliary equipment is required to run the cell and allow safe operation and power production of a PEMFC system: the balance of plant (BoP). The BoP of a general PEMFC system can be divided into four subsystems: (i) fuel processing and supply system, (ii) air processing and supply system, (iii) cooling system, and (iv) power conditioning, control, and monitoring systems. The fuel processing system consists of all the components required to ensure that hydrogen entering the PEMFC stack has the proper characteristics. This includes pressure reducers and a humidifier to regulate the pressure and humidity, a condensate collector to remove liquid water, and a hydrogen recirculation pump to reuse unreacted hydrogen. The air supply line includes a blower to deliver atmospheric air to the stack, an air filter to remove contaminants that could poison the PEMFC stack, a humidifier to maintain optimal membrane hydration, and a condensate collector [23]. The cooling system

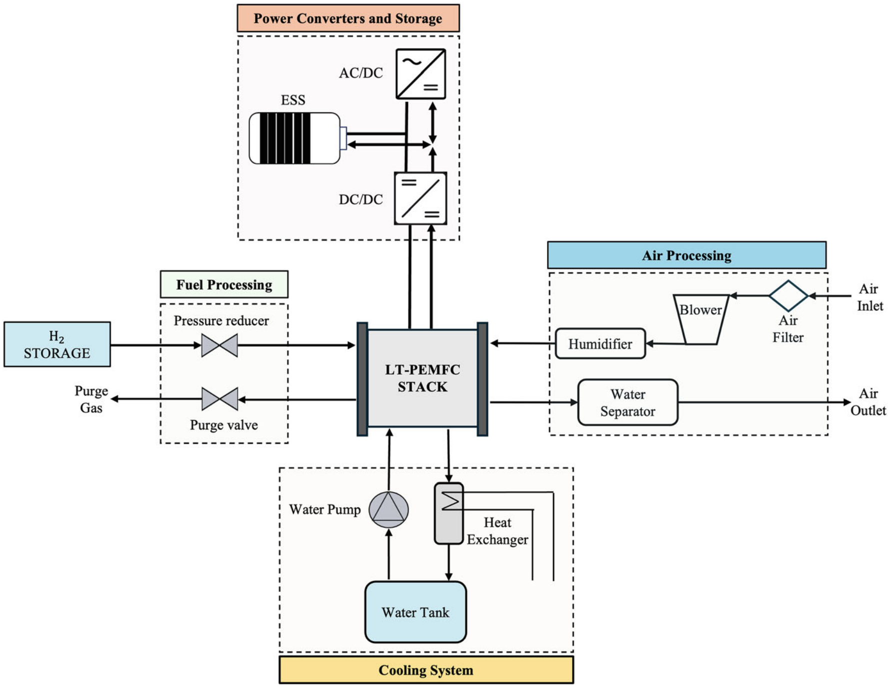

Fig. 4 Schematic example of a PEMFC/ESS system including the BoP: the fuel processing system for the hydrogen flow rate feeding the PEMFC anode and collecting the unreacted fuel, the air processing system to filter and humidify the inlet oxidant air at the cathode and remove the excess water, and a water-based liquid cooling system to control the stack temperature

includes all the components required to remove the excess heat from the PEMFC, maintaining the stack at the selected operating temperature. While several cooling methods exist, liquid cooling is often preferred due to its superior heat transfer capacity and efficiency [70]. The main components of a liquid cooling system include a circulating pump to ensure adequate refrigerant flow, a refrigerant reservoir, a heat exchanger to dissipate heat to the environment or a recovery system, and a deionizer to keep refrigerant conductivity low and avoid short-circuiting. The power conditioning, control, and monitoring system contains all the instrumentation required for system control and data acquisition. This includes safety valves, the control system, and a power inverter/converter. Figure 4 shows a schematic example of a PEMFC system, including the BoP.

2.3.1 PEMFC Performance

The PEMFC load is characterized by the electrochemical nature of its energy conversion process. Differently from traditional engines, fuel cells directly convert the chemical energy of the fuel into electricity, potentially reaching the same ideal efficiency of an ideal heat cycle. The maximum ideal theoretical efficiency (η_{rev}) attained by the cell is determined by the Gibbs free energy (ΔG) and enthalpy (ΔH) of its electrochemical reaction:

$$\eta_{rev} = \frac{\Delta G}{\Delta H}. \tag{4}$$

The maximum attainable voltage from an ideal isothermal PEMFC without losses, also known as Nernst voltage or reversible voltage (E_{rev}), is expressed by the following equations [71]:

$$E_{rev} = E^0 + \frac{RT}{nF} \ln\left(\frac{P_{H_2}\sqrt{P_{O_2}}}{P_{H_2O}}\right), \tag{5}$$

$$E^0 = \frac{-\Delta G^0}{nF}. \tag{6}$$

Where ΔG^0 is the Gibbs free energy of the electrochemical reaction at operation temperature and reference pressure, R is the ideal gas constant, T is the operating temperature (Kelvin), n is the number of electrons transferred in the electrochemical reaction, F is the Faraday constant, and P_x is the partial pressure of the reactant x (bar).

The actual operating voltage declines as the current density increases due to several internal losses:

- Activation losses (V_{act}), originating from the polarization potential needed to drive the electrochemical reaction, dominating the cell performance at low current densities.
- Ohmic losses (V_{ohm}), due to the ionic resistance of the electrolyte and the electronic resistance of the electrodes, dominating the cell performance at intermediate current densities.
- Concentration losses (V_{conc}), caused by mass transport limitation and characteristic of high current densities.

Therefore, the actual operating voltage of the cell is affected by losses as a function of the current density (i) and is described by the following equation:

$$V_{cell}(i) = E_{rev} - V_{act} - V_{ohm} - V_{conc}. \tag{7}$$

Once these losses are accounted for, voltage efficiency may be defined as

$$\eta_{voltage} = \frac{V_{cell}}{V_{rev}}. \tag{8}$$

In addition, the fuel conversion or fuel utilization is usually less than 100% to prevent fuel starvation and purge inert components and contaminants from the anode compartment. The fraction of fuel that is effectively oxidized in a fuel cell is referred

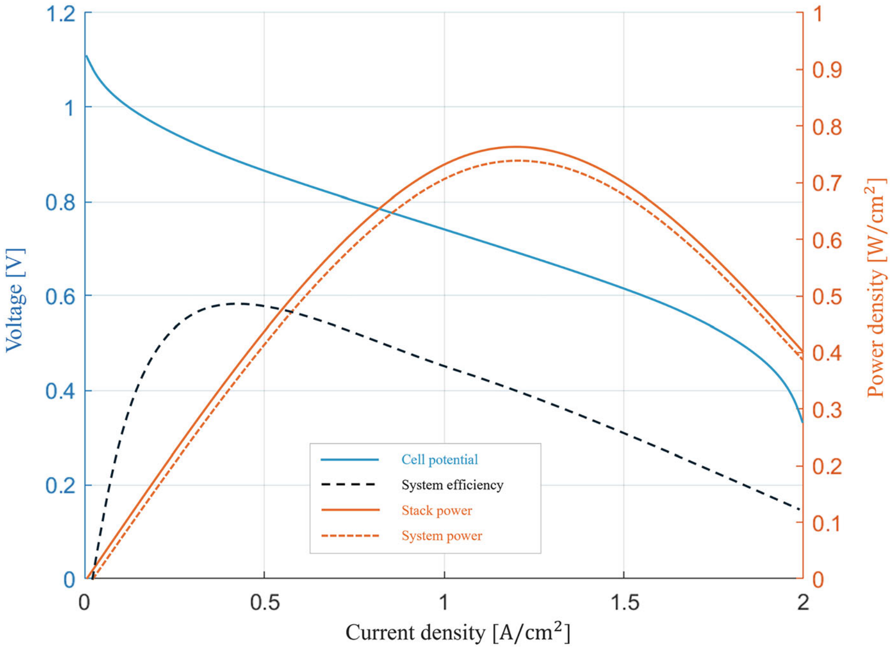

Fig. 5 Simplified example of operational characteristics of a PEMFC system. System efficiency peaks around 50% of the rated power

to as fuel utilization (u_f). The actual PEMFC stack efficiency can be subsequently calculated as

$$\eta_{\text{stack}} = \eta_{\text{rev}} \cdot \eta_{\text{voltage}} \cdot u_f. \tag{9}$$

Finally, the system efficiency is obtained by accounting for the BoP components consumption (P_{BoP}), such as air compressor losses, coolant pumps, blowers, sensors, and control systems. The overall system efficiency, therefore, is

$$\eta_{\text{system}} = \frac{P_{\text{stack}} - P_{\text{BoP}}}{P_{\text{stack}}} \cdot \eta_{\text{stack}}. \tag{10}$$

Figure 5 shows a typical PEMFC system load, power density, and efficiency curves as a function of the current density. PEMFC systems typically have relatively good efficiencies in part load since the electrochemical losses decrease when the operating current reduces. Consequently, the system efficiency usually increases with stack efficiency when the load is reduced. However, the relative contribution of the BoP consumption increases as the load is reduced, eventually nullifying the positive effect of decreasing electrochemical losses. Fuel cell manufacturers often specify minimum load fractions to ensure reliable operation, usually falling in the range from 10% to 30% of rated power [67].

2.4 Energy Storage System

The integration of the ESS is a key point for marine hybrid systems, as it enhances the operational performance of the power systems. ESS functions range from providing backup power and ensuring smooth power delivery to optimizing engine operations for reduced fuel consumption [72]. Table 2 outlines the core functions of the ESS and their specific purposes, highlighting how each function contributes to the overall efficiency of the system.

The choice of the type of ESS is fundamental to ensure the best operating conditions of the hybrid system (Fig. 6). Several ESSs for ship applications are available on the market, with different characteristics in terms of energy and power density, lifetime, cost, efficiency, and safety. Today, batteries are the leading energy storage technology due to their higher energy density, lower cost than other technologies at the same energy level, and already acquired experiences from other

Table 2 Functions and purposes of ESS for marine applications

Name	Description	Purpose
Spinning reserve	The ESS unit stays connected and operational without charging or discharging energy. If generating capacity is lost, it automatically takes over the load for a set period	• Backup power source • Fewer engines needed online • Enhanced efficiency at higher loads • Decreased engine running hours
Enhanced ride through	Like spinning reserve, but localized to a subsystem, such as a thruster or drilling drive	ESS solutions can provide UPS-like functionality for all or specific sections of the power system • New method to achieve higher ERN numbers • Higher power capacity
peak shaving	The unit absorbs load variations, allowing engines to handle only the average system power	• Smooth the power delivered by engines • Offset the necessity to start a new engine • Reduced engine running hours • Enhanced fuel efficiency
Strategic loading	The unit charges and discharges to optimize engine performance, minimizing fuel consumption while accounting for ESS efficiency	• Charging and discharging ESS to optimize the operating point of the diesel generators • Power is assigned at the peak efficiency
Enhanced dynamic performance	The unit smooths abrupt load changes and gradually adjusts engine transitions, automatically incorporating peak shaving when used	• Instant power assistance to support running diesel generators • Enable use of slower power devices, such as LNG/dual fuel engines or fuel cells
Zero-emissions operation	The unit powers the system so that engines can be turned off	• Zero emissions in the harbor • Quiet engine room

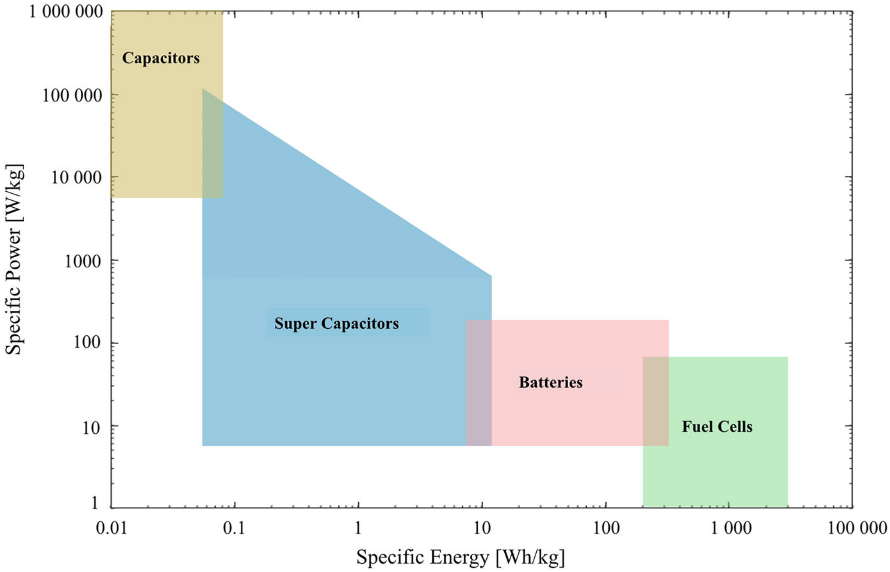

Fig. 6 Functions and purposes of ESS for marine applications

transportation sectors. Structurally, batteries are formed from electrodes, electrolytes, and separators, while the performance depends on the electrode material. LIBs are the most common ESS in shipping applications, thanks to their high energy densities and durability [72]. Furthermore, significant improvements in terms of safety and regulatory aspects of maritime LIBs have been made in recent years, increasing their commercial availability for the sector. The cost of LIBs has also reduced in recent years [72]. The widespread use of LIBs in more recent projects demonstrates these recent advancements and their increase in commercial availability [26].

The operating life of a battery is mainly affected by the depth of discharge (DoD) of its cycles (the percentage of battery capacity that has been discharged, expressed as a percentage of maximum capacity) [73]. Subsequently, their application is more suitable for certain types of ships to increase battery lifetime. In the case of ferries and coastal cruise ships with short voyage times, batteries are suitable ESS because the DoD is relatively low, preventing battery degradation and enhancing its operating lifetime. In the case of tugs and dynamic positioning vessels that require high electric power for a short time, the ESD can be used for a limited time in response to peak operations.

While batteries store energy through electrochemical reactions, capacitors store electricity in the form of electrostatic energy. Ceramic and electrolytic capacitors use a dielectric to store this electrostatic energy, while supercapacitors (or electric double-layer capacitors) are forms of capacitors which utilize a liquid electrolyte to create a Helmholtz layer at the interface of the solid and liquid. In this way, supercapacitors bridge the gap between low-energy, high-power capacitors and high-energy, low-power LIBs, offering higher capacitance, greater power density, and enhanced cycling capability due to their larger electrode surface area and thinner dielectrics [72]. Supercapacitors are particularly suitable for certain applications due to their ability to charge and discharge rapidly. However, their limited energy density is a significant drawback, necessitating the use of additional ESS or power generation solutions for sustained long-term operation. Power density becomes crucial in scenarios where short bursts of power are required, making supercapacitors more effective solutions than batteries [74]. Moreover, supercapacitors generally have longer operating lifetimes than batteries [75]. Supercapacitors are increasingly utilized in maritime applications for peak shaving, a process where they are frequently charged and discharged to manage short bursts of high power demand. This is particularly useful for balancing peak loads, enhancing power system efficiency, and reducing strain on electrical equipment. In maritime settings, supercapacitors are often integrated with hybrid power systems to handle peak load conditions, such as during high-demand operations like dynamic positioning [76]. They provide rapid energy release and help avoid costly grid upgrades by reducing the peak load demand [77]. They can, for example, be used for absorbing loads from the heave compensation of cranes in offshore drilling units [72].

2.5 Benefits and Challenges of Hybrid PEMFC/ESS Systems

In recent years, hybrid PEMFC/ESS systems have gained particular attention as a promising solution for sustainable ship energy systems. Several characteristics make the PEMFC a suitable technology for mobility applications. Firstly, PEMFCs have a quick start-up time, and fast transient response, both in the order of a few seconds [20]. The high degree of maturity already reached in other mobility sectors is a significant advantage for maritime applications, especially in the short-medium term scenario. PEMFCs can achieve high system efficiencies in the range of 40–60%, and specific powers vary from 125 to 750 W/kg, and power density from 50 to 400 W/L at system level [67]. Moreover, PEMFCs offer additional advantages, such as lightweight and more compact sizes when compared to other fuel cell technologies, and they operate at relatively low temperatures, making it easier to contain and reduce thermal losses. In addition, the number of BoP components is low compared to other fuel cell types. Combined with ESS, hydrogen PEMFCs provide a zero-emission solution for ship propulsion plants, that will play a key role in the maritime sector to comply with the stringent upcoming regulatory framework.

On the other side, a series of challenging technical, economic, and safety aspects still hinder the wide spread of marine hybrid PEMFC/ESS systems for a broader range of applications in the sector. First of all, PEMFCs have no fuel flexibility, and hydrogen storage on board is critical for both the intrinsic low energy storage density of the fuel and for its bunkering safety issues. The currently preferred method of hydrogen storage onboard is compressed hydrogen, although liquid hydrogen storage is gaining traction for larger vessels [26]. To complete the same route with hydrogen the required storage will increase by several times compared to conventional fuels, which will reduce cargo space [78]. For this reason, PEMFCs have been mainly considered for small-sized and medium-sized vessels with short or close-to-shore missions [26].

Recently, research interest in alternative hydrogen storage solutions, such as hydrogen carriers and metal hydrides, is growing, and some studies have addressed the possibility of using them for hydrogen-fuelled ships [54, 79]. The research advances on high-density hydrogen storage, and the development of alternative physical and chemical solutions could potentially extend PEMFC use to longer-distance shipping in the future [80]. However, technical, economic, and safety challenging aspects involve not only the onboard storage, but the entire hydrogen supply chain. A global commercially viable green hydrogen supply chain and bunkering infrastructure must be established to allow the widespread use of hydrogen as maritime logistic fuel [78].

Another challenging aspect of hybrid PEMFC/ESS systems is connected to their durability and moderate lifetime. Durability refers to the system performance drop and is associated with the chemical, mechanical, and thermal degradation and aging of its components. The limited durability of PEMFC/ESS systems impacts their reliability, safety, and cost-effectiveness. The degradation of a PEMFC is affected by several internal and external factors: stacks design and assembly, BoP components, operational aspects such as dynamic load demands and controlled operating conditions (e.g., temperature, pressure, humidity), and external factors such as chemical contamination or mechanical stress [81]. PEMFC degradation is a complex and interconnected combination of mechanisms, and a full understanding of the aging process requires a deeper analysis of the application. Currently, most of the knowledge on PEMFC degradation comes from applications in the automotive sector. Maritime applications introduce a novel set of operational and environmental conditions, such as different load demands and operating conditions, influenced by the adopted power control and EMS for the PEMFC/ESS system, new chemical contaminants (e.g., NaCl contamination from marine air), mechanical stresses due to inclinations, ship vibrations, and rough water conditions. The impact of these factors on PEMFC durability remains largely unexplored to date. However, load demand has been identified as one of the most impacting factors on PEMFCs' durability, suggesting that power and EMS could play a crucial role in enhancing the operating lifetime. High load demands, idling, start and stops, and transient loads are recognized as critical operating conditions for PEMFC degradation [82].

Different from PEMFCs, batteries experience degradation both during operations and during resting conditions [83]. Cycle aging occurs when the battery is charged or discharged during operation and depends on battery power/capacity ratio, state of charge (SoC), temperature, number of performed equivalent cycles, and DoD. Calendar aging occurs when no current is flowing in the battery and depends mainly on the battery's SoC and temperature. PEMFC degradation is generally measured in terms of voltage or power loss, while battery degradation results in voltage and power loss, and capacity fade [84]. Similarly to batteries, supercapacitors are also subjected to both cycle and calendar aging, limiting their capacitance and deliverable power [85]. While the power management strategy controls the instantaneous PEMFC/ESS power output to correctly match the power demand of the vessel, the EMS has the additional potential of optimizing the performance and limiting critical operation over time, minimizing degradation, and enhancing the system's lifetime.

2.6 Energy Management Strategies

2.6.1 Intro

As hybrid fuel cell systems are gaining popularity as a zero-emission solution for maritime energy systems, the need to adapt traditional control and EMS to the complex operation of these systems has been raised [86]. Two primary strategies are currently used to manage the complexity of these systems: power management and energy management. While these terms are often used interchangeably, they refer to distinct aspects of system operation. For hybrid fuel cell applications in ships, EMS involves mathematical models to optimize energy allocation between fuel cells, batteries, and other energy sources. Power management refers to the real-time power allocation to meet immediate energy demand. It focuses on distributing power from different sources, such as fuel cells and batteries, at any given moment to meet propulsion and auxiliary loads. Power management ensures that all systems have sufficient power without exceeding operational limits while balancing instantaneous performance and cost. Energy management, on the other hand, involves a more strategic, long-term approach. It is concerned with optimizing the overall energy usage over a period of time, such as an entire voyage. Energy management plans when and how energy should be stored, discharged, or supplied by the fuel cell and auxiliary systems. It aims to minimize total fuel consumption, emissions, and degradation of the power sources, ensuring optimal system performance over time. The key difference lies in the time horizon. Power management operates over short timescales to meet immediate demand, while energy management spans longer periods, focusing on overall efficiency and sustainability. The goal is often to minimize fuel consumption or emissions, subject to operational constraints.

The control hierarchy for vessels using fully electric batteries and fuel cells is structured around three levels: primary, secondary, and tertiary control, each operating at different time granularities and addressing different aspects of the system's operation. These control layers work together to ensure smooth, efficient, and safe operation of the vessel's powertrain. At the heart of the system lies the primary control, which functions at the component level. This layer operates in real-time, reacting within milliseconds to ensure the stability of individual components, such as batteries, fuel cells, inverters, and motors. It is primarily concerned with maintaining the correct voltage, current, and frequency within these systems to ensure that each component performs optimally and safely. For example, it might monitor and adjust the voltage levels within the battery cells or regulate the output of the inverter to keep the electric propulsion running smoothly. The immediacy of primary control makes it the foundation for the vessel's performance, responding in milliseconds (mHz level) to prevent fluctuations that could lead to inefficiencies or component damage.

Building on this is the secondary control, which deals with power management across the entire vessel. This level is responsible for managing the real-time power distribution between the various energy sources—such as batteries and fuel cells—and the electric propulsion system. Power management ensures that the vessel has the right amount of power to meet the propulsion and auxiliary loads at any given time, balancing between energy sources in response to changing operational conditions. Operating on a time scale of seconds to minutes, secondary control is crucial during transitions, such as when the vessel shifts between electric and hybrid modes. By distributing power efficiently, this layer prevents overloads and optimizes the use of available energy, ensuring the vessel runs smoothly even during rapid changes in propulsion demand.

Finally, tertiary control oversees the vessel's EMS. This layer functions over longer timeframes, typically minutes to hours, and optimizes energy use in alignment with the vessel's operational goals. At this level, the focus shifts from moment-to-moment power distribution to a broader, strategic view of energy consumption. The aim here is to make high-level decisions that maximize the overall efficiency of the vessel, considering factors such as fuel economy, battery life, and energy replenishment. For instance, tertiary control might determine when to prioritize using the fuel cells over the batteries to conserve fuel or decide when it's best to charge the batteries when the vessel is docked. The decisions made at this level contribute to long-term sustainability, ensuring that the vessel's energy sources are used in the most efficient manner possible throughout the journey.

Together, these three layers of control create a robust system that balances the immediate demands of component regulation, the dynamic needs of power management, and the long-term energy optimization strategy. The primary, secondary, and tertiary controls, each operating within its own time granularity, ensure that the vessel performs efficiently, safely, and sustainably, regardless of the operational scenario.

A control hierarchy schematic is reported in Fig. 7. At the top, the component-level (primary) control addresses the real-time regulation of individual systems. In the middle, power management (secondary control) deals with power distribution between energy sources and propulsion. At the base of the hierarchy, energy management (tertiary control) focuses on the vessel's long-term operational efficiency. Each level is interconnected, with decisions flowing from fast, momentary adjustments at the component level to slower, strategic decisions about energy use. In the context of EMS for hybrid systems, particularly in fuel cell-battery configurations, there are three main approaches: RB, OB, and LB strategies, as reported in Fig. 8. Each strategy offers unique methods of managing the energy flow within the system, balancing the goals of efficiency, fuel consumption, emissions reduction, and system longevity. In an RB approach, the control of power distribution between components such as fuel cells and batteries is governed by predefined rules that dictate the conditions under which each component operates. These rules often rely on specific thresholds or conditions, such as turning on the battery when power

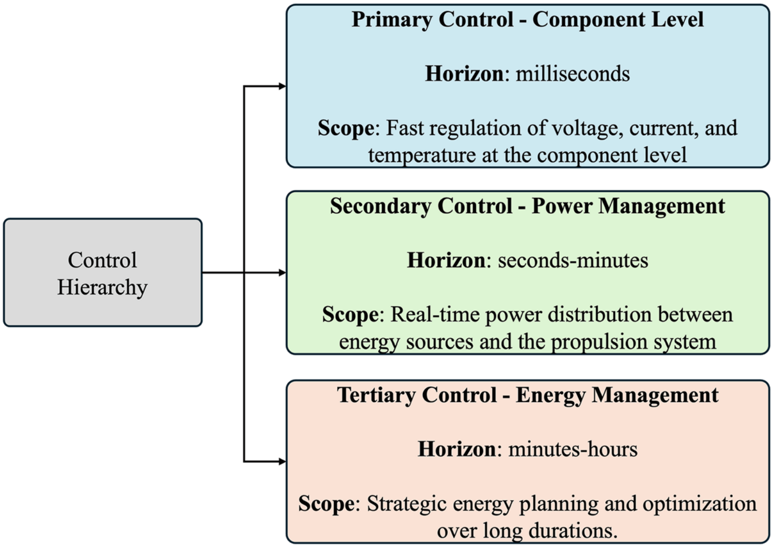

Fig. 7 Control hierarchy for marine energy systems system illustrating the three layers of control: Primary (component-level), secondary (power management), and tertiary (energy management)

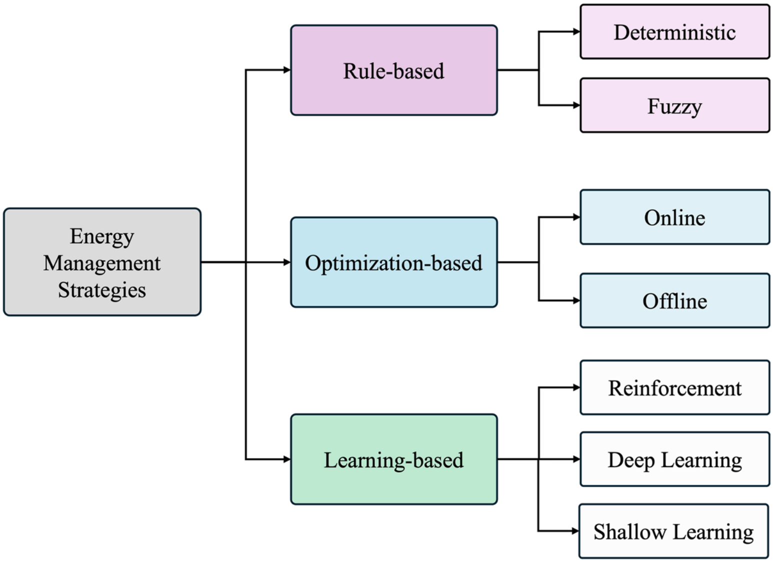

Fig. 8 Overview of EMS categorized into three main approaches: RB (deterministic and fuzzy control), OB (online and offline optimization techniques), and LB (reinforcement, deep learning, and supervised learning methods)

demand exceeds a certain value or activating the fuel cell when the battery's charge drops below a certain level. This kind of approach is relatively straightforward to implement because it follows clear, deterministic logic: if one condition is met, a particular action is triggered. For instance, in a simple system, a rule might state that if power demand goes beyond 100 kW, the battery should kick in to supplement the fuel cell. Or, if the battery's SoC falls below 20%, the fuel cell should become the primary power source. These predefined thresholds create a predictable and reliable system. However, the problem with this deterministic RB approach is its inflexibility. The system operates based on fixed rules, so it cannot adapt dynamically to changing conditions, such as fluctuations in power demand or fuel efficiency. As a result, while easy to understand and implement, it can lead to suboptimal performance because it does not account for real-time changes or optimize energy use effectively over time.

On the other hand, a fuzzy RB approach introduces greater flexibility and adaptability. Unlike deterministic systems, fuzzy logic does not rely on rigid thresholds. Instead, it works with ranges and degrees of truth. For example, rather than having a hard rule that activates the battery only when demand exceeds a specific value, the fuzzy approach might use categories such as low, medium, or high power demand. These categories are not strictly defined by exact numbers but by overlapping ranges. The system then interprets these ranges dynamically, adjusting how much power comes from the fuel cell or battery depending on the situation. In this setup, the battery might gradually start to supplement the fuel cell when power demand is medium, not waiting until it reaches a high, fixed threshold. Fuzzy logic handles this uncertainty and variability much better, allowing smoother transitions between power sources and more efficient management of energy flows. This adaptability is particularly useful in systems where power demand and other factors fluctuate unpredictably. The fuzzy RB approach, therefore, offers better performance by responding in a more nuanced way to the system's real-time needs.

Despite its advantages, the fuzzy RB approach is more complex to design and implement than its deterministic counterpart. The system must evaluate multiple inputs, handle degrees of truth, and continuously adjust decisions based on changing conditions. This requires a more sophisticated control mechanism and a deeper understanding of the system's dynamics. However, the increased flexibility it provides can lead to significant improvements in efficiency, making it a valuable approach for managing energy systems that operate in complex and variable environments.

Although the deterministic RB approach offers simplicity and predictability, it falls short in dynamic settings. With its ability to handle uncertainty and adjust to changing conditions, the fuzzy RB approach can optimize performance much more effectively, though at the cost of increased complexity [87]. The choice between these approaches depends largely on the complexity of the system and the level of adaptability required to meet performance goals.

In contrast to RB strategies, OB energy management techniques approach the control problem with a more sophisticated framework, treating it as a mathematical optimization problem. The goal here is not to rely on predefined rules or thresholds but to dynamically minimize a cost function, including objectives like fuel consumption, emissions, system degradation, or operational costs. By formulating the problem in this way, these techniques can account for various variables and constraints, enabling a more holistic and efficient approach to managing energy flows in complex systems. OB techniques can be implemented in two primary ways: offline and online optimization.

In offline optimization, the control strategy is developed beforehand, using historical data or known conditions to simulate various scenarios and find an optimal solution. This precomputed solution is then implemented during system operation. For instance, before deploying a hybrid power system, the optimization model may be run using expected load profiles, environmental conditions, and system performance data to find the best EMS for a given set of conditions.

Offline optimization has the advantage of being computationally efficient during real-time operation, as the heavy computational work is done in advance. Once the optimal control laws or trajectories are determined, they can be directly applied without requiring intensive calculations. This makes offline optimization particularly suitable for systems where real-time computational power is limited or where conditions are relatively stable and predictable.

However, one major disadvantage is its lack of adaptability. Since offline optimization relies on predefined conditions, it may not perform well if the actual operating conditions deviate significantly from those assumed during the optimization process. In dynamic environments where load demands, fuel costs, or operational constraints can change rapidly, offline optimization may become suboptimal, much like a deterministic RB system. Online optimization, in contrast, involves continuously solving the optimization problem in real-time based on the system's current state and changing conditions. Instead of relying on precomputed solutions, the system dynamically adjusts its control strategy as it operates. This is particularly beneficial in environments where conditions are unpredictable or rapidly changing, as the system can continuously update its strategy to reflect real-time data.

The primary advantage of online optimization is its ability to adapt to real-world fluctuations. For instance, if fuel prices spike, the system can immediately adjust its strategy to prioritize energy sources that minimize costs. Similarly, in a maritime energy system, if the load demand changes unexpectedly or a component experiences degradation, the system can optimize power distribution in real time to maintain performance and efficiency. However, online optimization comes with challenges, most notably computational complexity. Since the optimization problem must be solved continuously, the system requires significant computational resources and must be capable of responding quickly to new inputs. This can be a limiting factor, especially for systems that require fast response times or operate with limited processing power. Additionally, depending on the complexity of the optimization problem and the number of variables involved, solving the problem in real-time can introduce delays, potentially reducing the system's responsiveness. Both offline and online optimization approaches offer clear advantages over traditional RB strategies. While RB methods are straightforward and computationally simple,

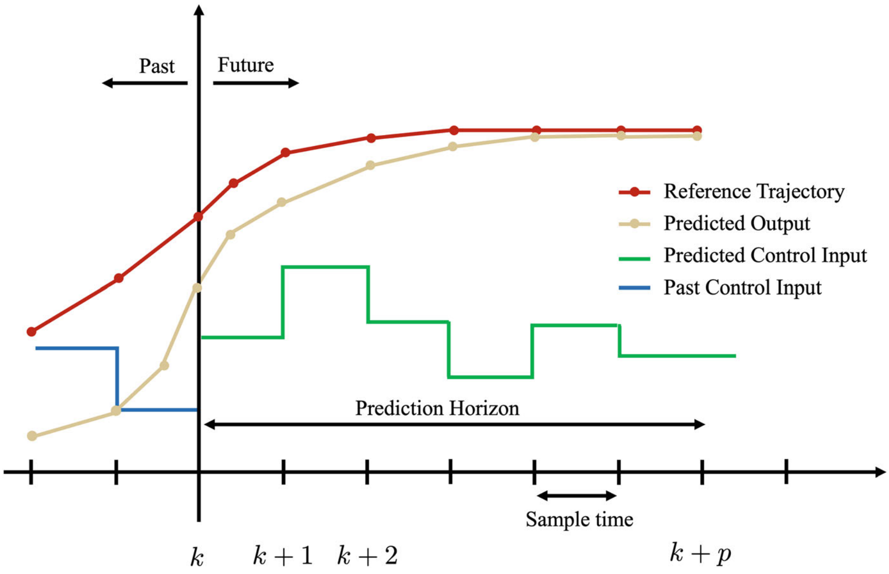

Fig. 9 The reference trajectory (red line) represents the desired system behavior, while the predicted output (tan line) shows the system's future performance based on current control inputs. The predicted control input (green) is optimized over the prediction horizon, balancing power demands and system constraints, with the past control input (blue) indicating previously applied actions. The prediction horizon spans multiple time steps from the current time k to $k + p$ allowing MPC to dynamically adapt to changes in real-time energy demand

they lack the ability to adapt to changing conditions or optimize performance across multiple objectives.

In contrast, OB techniques offer a more flexible and effective way to manage energy flows, especially in complex systems with multiple competing goals, such as reducing emissions, minimizing fuel consumption, and limiting component degradation. One of the most widely adopted methods is model predictive control (MPC), which leverages real-time data and system models to dynamically predict future system behavior and optimize energy and power flow accordingly. At the core of MPC is the concept of optimizing a cost function (as shown in Fig. 9) that typically includes objectives such as minimizing fuel consumption, reducing emissions, and limiting system degradation. In doing so, MPC ensures that operational efficiency is maximized while constraints like power demand, battery SoC, and the longevity of fuel cells and batteries are respected. Figure 9 showcases how MPC uses a reference trajectory (red line) that represents the desired behavior of the system. The predicted output (tan line) shows how the system is expected to behave based on current control inputs. The green line represents the predicted control inputs optimized over a prediction horizon, while the blue line depicts the past control inputs. The core strength of MPC lies in its predictive capability, enabling it to make proactive decisions rather than merely reacting to immediate conditions. For example, if an upcoming surge in power demand is anticipated, the MPC framework can adjust

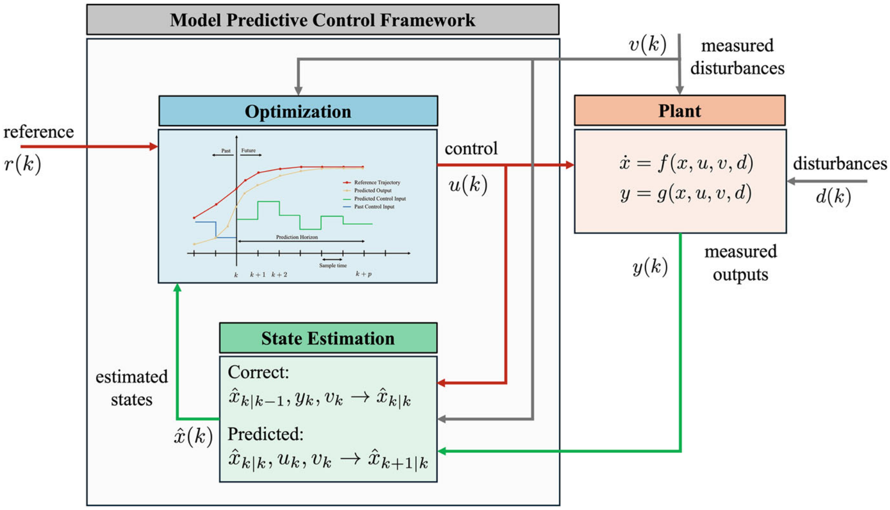

Fig. 10 MPC framework for marine energy systems. The reference input $r(k)$ drives the optimization process, which uses a prediction horizon to balance power distribution and system constraints. The plant model (right) receives the control input $u(k)$, responding to disturbances $d(k)$ and $v(k)$. The state estimation block corrects and predicts future states $\widehat{x}(k)$, ensuring accurate system feedback through real-time measured outputs $y(k)$. The closed-loop system dynamically adjusts control actions to optimize performance and energy efficiency while respecting system constraints and disturbances

power generation or battery charging behavior in advance to meet the load while maintaining system stability.

As illustrated in Fig. 10 the MPC framework consists of three primary components: the optimization block, the plant model, and the state estimation block. The optimization block receives the reference input $r(k)$ and calculates the optimal control actions $u(k)$ based on predicted future states and constraints. The plant model represents the system dynamics, including disturbances $d(k)$ and $v(k)$. At the same time, the state estimation block updates and predicts future states $\widehat{x}(k)$, ensuring that the control actions are continuously refined based on real-time measured outputs $y(k)$.

The core principle of MPC revolves around using a dynamic model of the system—such as those involving fuel cells and batteries—to predict future behavior and make optimal control decisions over a moving time horizon. This allows the controller to not only react to immediate conditions but also to anticipate future changes, leading to more efficient energy management. In practice, MPC solves an optimization problem at each time step. The challenge is that all of these must be achieved while respecting stringent system constraints, such as power demand, battery SoC, and the longevity of system components. To begin, the system model is used to forecast how the system will behave under different control actions. This model considers real-time data inputs, such as current power demand and the SoC of the battery, which ensures the predictions are as accurate as possible.

Based on these predictions, the MPC framework minimizes the cost function by choosing the control inputs that will yield the best performance over the time horizon. For instance, if a surge in power demand is predicted, the MPC can adjust power generation and battery usage in advance to ensure a smooth response. Another key advantage of MPC is its ability to handle constraints naturally. These might include limits on power generation, restrictions on how low the SoC of the battery can fall, or operational boundaries for fuel cells to avoid excessive wear and tear. By considering these constraints directly within the optimization process, MPC can ensure that the system operates within safe limits while still pursuing optimal performance. Once the optimal control strategy is computed, only the first step is implemented in real-time, and the process repeats as new data becomes available. This feedback loop ensures that the system continually adapts to changing conditions, making MPC highly suitable for environments where energy supply and demand can fluctuate unpredictably. MPC's flexibility makes it an ideal choice for multi-objective optimization problems in energy management. It excels at balancing trade-offs, such as minimizing fuel consumption while ensuring the battery remains within its operational limits or optimizing for both short-term efficiency and long-term component health. More advanced optimization techniques, such as Dynamic Programming or Stochastic optimisation optimization [88], can handle more complex systems but often come with increased computational demands. These methods are highly effective for systems requiring real-time adaptability and efficiency.

Finally, LB approaches leverage machine learning algorithms to improve EMSs continuously. Reinforcement Learning, for example, enables the system to learn optimal energy management policies through trial and error by maximizing long-term rewards, making it well-suited for dynamic environments like hybrid power systems. Reinforcement LB models can adaptively control the distribution of energy between components such as batteries and fuel cells, improving operational efficiency over time [89].

Both shallow and deep learning models can be used to predict future power demands or battery states, enabling the system to make more informed decisions [90]. LB methods are particularly powerful in complex, dynamic environments where traditional strategies may fall short, as they adapt based on past performance and new data, offering a robust solution for managing uncertainty [90, 91, 92].

2.6.2 Rule-Based Approaches

A basic strategy is an RB approach in which predefined control rules determine the power distribution between the fuel cell and other energy sources. For example, when the power demand exceeds a certain threshold, the battery might be used to supplement the fuel cell output. While this approach is straightforward to implement, it may not always be optimal.

For example, when focusing on fuel cells, RB strategies can be mathematically formulated using a series of conditional statements

$$P_{fc}(t) = \begin{cases} P_{max,fc} & \text{if } P_{demand}(t) > P_{fc,thresh} \\ P_{demand}(t) & \text{otherwise} \end{cases} \quad (11)$$

where $P_{fc}(t)$ is the power supplied by the fuel cell at a time t, and $P_{demand}(t)$ is the total power demand. The system switches between using full fuel cell power and supplementing with auxiliary sources based on predefined thresholds.

Table 3 provides a structured strategy for energy management in a hybrid fuel cell-battery system for ships, considering both the SoC of the battery and the power demand. The table separates the power demand scenarios into three categories. The fuel cell's primary role is highlighted, particularly for providing base power, while the battery compensates for variable or excess demand. In high-demand situations, the system leverages the combined output of both the fuel cell and the battery to meet total power requirements. The table also reports the system's behavior under three conditions of demand power. When the power demand is equal to zero$P_{demand}(t) = 0$, we are in idle or zero-load conditions. When the battery's SoC is low $SoC(t) < SoC_{min}$, the fuel cell charges the battery until the SoC reaches a safe level. In cases where the battery is sufficiently charged, both the fuel cell and battery are turned off to avoid unnecessary energy consumption. When the battery was previously discharged, but the SoC is still within acceptable limits, the system shuts off to preserve energy. A power demand where $0 < P_{demand}(t) \le P_{opt}$ represents a moderate load where the system can rely primarily on the fuel cell and battery working together. When the SoC is low, the fuel cell works to both meet demand and charge

Table 3 RB EMS for hybrid fuel cell and battery systems

	$P_{demand}(t) = 0$	$0 < P_{demand}(t) \le P_{opt}$	$P_{demand}(t) > P_{opt}$
$SoC(t) < SoC_{min}$	Fuel-cell: ON Battery: Charging (until SoC reaches SoC_{min}) $P_{fc} = -P_{bat} = P_{opt}$	Fuel-cell: ON Battery: Charging (until SoC reaches SoC_{min}) $P_{fc} = P_{opt}$ $P_{bat} = P_{dem} - P_{fc}$	Fuel-cell: ON Battery: OFF $P_{fc} = P_{dem}$
Previous battery mode: Charging $SoC_{min} \le SoC(t) < SoC_{max}$	Fuel-cell: ON Battery: Charging (until SoC reaches SoC_{min}) $P_{fc} = P_{opt}$	Fuel-cell: ON Battery: Charging (until SoC reaches SoC_{min}) $P_{fc} = P_{opt}$ $P_{bat} = P_{dem} - P_{fc}$	Fuel-cell: ON Battery: Discharging $P_{fc} = P_{opt}$ $P_{bat} = P_{dem} - P_{fc}$
Previous battery mode: Discharging $SoC_{min} \le SoC(t) < SoC_{max}$	Fuel-cell: OFF Battery: OFF	Fuel-cell: OFF Battery: Discharging $P_{bat} = P_{dem}$	Fuel-cell: ON Battery: Discharging$P_{fc} = P_{opt}$ $P_{bat} = P_{dem} - P_{fc}$
$SoC(t) \ge SoC_{max}$	Fuel-cell: OFF Battery: OFF	Fuel-cell: OFF Battery: Discharging $P_{bat} = P_{dem}$	Fuel-cell: ON Battery: Discharging $P_{fc} = P_{opt}$ $P_{bat} = P_{dem} - P_{fc}$

the battery. When the battery is in its optimal SoC range, the fuel cell continues to charge the battery if needed or meets the demand and discharges the battery if the SoC is stable. If the battery was discharging in the previous step and the SoC remains within bounds, the battery continues to discharge to meet demand. In high power demand conditions, $P_{\text{demand}}(t) > P_{\text{opt}}$, the fuel cell operates at maximum efficiency, providing P_{opt} while the battery discharges to meet the excess demand. If the SoC is low, the battery is not used, and the fuel cell alone powers the system. For batteries within their operational range, the system effectively balances the power supply by using both the fuel cell and battery, keeping the system running efficiently. Finally, when the battery is full $\text{SoC}(t) \geq \text{SoC}_{\text{max}}$, the battery discharges to meet excess power demand, ensuring that the fuel cell is used optimally without overcharging the battery.

The battery's SoC is critical for determining whether the fuel cell should operate alone or in conjunction with the battery. When the battery's SoC is below a minimum threshold, the system prioritizes recharging the battery to avoid depleting it further. When the SoC is high ($\text{SoC}(t) \geq \text{SoC}_{\text{max}}$), the battery is used for discharging rather than charging, ensuring efficient power use.

This exemplificatory strategy ensures that the fuel cell is optimally used by charging the battery when the power demand is low or moderate, and the battery is used primarily to meet excess demand and discharge more when power requirements exceed the fuel cell's optimal output.

2.6.3 Optimization-Based Energy Management

A more sophisticated approach is OB energy management, where the objective is to minimize a comprehensive cost function that accounts for fuel consumption, emissions, system degradation (including both fuel cells and batteries), and operational efficiency, all while respecting system constraints such as power demand, SoC, and component longevity. The most commonly used optimization technique is MPC, which uses real-time data and system models to forecast future energy demand and dynamically optimize power flow over a moving time horizon. MPC has been widely applied due to its adaptability to real-time conditions and ability to handle system constraints such as power limits and SoC for batteries.

However, there are several other optimization strategies that can be applied depending on the objectives and complexity of the system. Dynamic Programming is another well-known technique that solves problems by breaking them into simpler subproblems. Dynamic Programming can find the globally optimal solution over a defined time horizon, making it suitable for systems with multi-stage decision processes, such as energy management in hybrid systems. However, Dynamic Programming suffers from the curse of dimensionality, making it computationally expensive for large-scale systems [93]. To overcome the computational complexity of Dynamic Programming, Approximate Dynamic Programming uses approximation methods to estimate the cost-to-go function, making it feasible for large-scale energy management problems. Approximate Dynamic Programming is an attractive option for complex systems with high-dimensional state spaces where traditional Dynamic Programming is not computationally feasible [94]. Stochastic optimization techniques explicitly account for uncertainties in the system, such as varying weather conditions or uncertain power demand. These techniques, including stochastic Dynamic Programming and stochastic MPC, optimize energy management by modeling probabilistic scenarios and determining the best strategy under these uncertainties. Stochastic optimization is particularly useful when dealing with unpredictable renewable energy sources [95]. Heuristic and metaheuristic algorithms, such as Genetic Algorithms and Particle Swarm optimization, provide a non-deterministic approach to optimization. These methods can quickly find near-optimal solutions for complex, non-linear problems. Genetic Algorithms evolve potential solutions over generations by mimicking natural selection [96, 97], while Particle Swarm optimization simulates the social behavior of animals to find optimal solutions [98]. These methods are computationally efficient and can be applied to large-scale problems, though they do not guarantee finding the global optimum. Mixed-Integer Linear Programming is an optimization technique used when the problem involves both continuous and discrete variables, such as the on/off states of fuel cells or batteries. Mixed-Integer Linear Programming solves problems where relationships between variables are linear, making it ideal for hybrid systems with discrete switching controls. However, Mixed-Integer Linear Programming is limited to linear problems and may not handle non-linear system behaviors efficiently [99]. In cases where the relationships between system variables are non-linear, Nonlinear Programming can be applied. Nonlinear Programming optimizes the cost function and system constraints for systems where efficiency, degradation, and power output are non-linear, such as in hybrid fuel cell systems. Though more computationally intensive, Nonlinear Programming offers better modeling of real-world systems where non-linearities are prevalent [100]. Bi-level optimization is a hierarchical approach where one optimization problem is nested within another. This is suitable for EMS, where high-level decisions, such as overall power distribution, depend on lower-level decisions, such as device-level operational efficiency. Bi-level optimization is often used in large-scale systems like smart grids [101]. In hybrid energy systems, there are typically competing objectives, such as minimizing fuel consumption, emissions, and system degradation. Multi-Objective optimization allows for the simultaneous optimization of these competing objectives, resulting in a set of Pareto-optimal solutions that offer trade-offs between the different objectives.

Multi-Objective optimization is particularly useful for balancing the conflicting goals of efficiency and environmental sustainability [102, 103]. Receding Horizon Control is similar to MPC but is more flexible in handling real-time changes in system constraints and objectives. Receding Horizon Control continually adjusts the optimization horizon, effectively managing systems where demand and operational constraints frequently change. Receding Horizon Control is particularly suitable for hybrid systems that must adapt to fluctuating power demands [104]. In addition to these standalone methods, hybrid approaches that combine different optimization techniques are often used to leverage the advantages of multiple methods. For example, combining MPC with metaheuristic algorithms like Genetic Algorithm or Particle Swarm optimization can improve performance by speeding up the search for optimal solutions while retaining real-time adaptability [103].

In a hybrid fuel cell system, the energy management problem can be modeled as a multi-objective optimization problem. The goal is to minimize several competing objectives, such as fuel consumption, emissions, and system degradation, and maximize operational efficiency. We seek to minimize the following set of objectives over time $t \in [0, T]$

$$\min_{P_{\mathrm{fc}}(t),\ P_{\mathrm{batt}}(t)} \begin{cases} f_{\mathrm{fuel}}(P_{\mathrm{fc}}(t)), & \text{Fuel consumption} \\ f_{\mathrm{degr,fc}}(P_{\mathrm{fc}}(t)), & \text{Degradation of the fuel cell} \\ f_{\mathrm{degr,batt}}(P_{\mathrm{batt}}(t)), & \text{Degradation of the battery} \\ -f_{\mathrm{eff}}(P_{\mathrm{fc}}(t), P_{\mathrm{batt}}(t)), & \text{System efficiency} \end{cases} \tag{12}$$

where $P_{\mathrm{fc}}(t)$ and $P_{\mathrm{batt}}(t)$ are the power supplied by the fuel cell and battery, respectively, at the time t, $f_{\mathrm{fuel}}(P_{\mathrm{fc}}(t))$ is the fuel consumption cost of the fuel cell, $f_{\mathrm{degr,\ fc}}(P_{\mathrm{fc}}(t))$ is the degradation cost of the fuel cell as a function of its power output over time, $f_{\mathrm{degr,\ batt}}(P_{\mathrm{batt}}(t))$ is the degradation cost of the battery, typically modeled based on charge/discharge cycles or usage patterns, $f_{\mathrm{eff}}(P_{\mathrm{fc}}(t), P_{\mathrm{batt}}(t))$ is a term representing the system's operational efficiency. The optimization is subject to constraints

$$\begin{array}{ll} \mathrm{P_{fc}(t) + P_{batt}(t) = P_{load}(t)} & \text{Power Balance} \\ \mathrm{P_{fc}^{min} \le P_{fc}(t) \le P_{fc}^{max}} & \text{Fuel Cell Power Limits} \\ \mathrm{P_{batt}^{min} \le P_{batt}(t) \le P_{batt}^{max}} & \text{Battery Power Limits} \\ \mathrm{SoC^{min} \le SoC(t) \le SoC^{max}} & \text{Battery SoC Limits} \\ \mathrm{D_{fc}^{min} \le D_{fc}(t) \le D_{fc}^{max}} & \text{Fuel Cell Degradation Limits} \\ \mathrm{D_{batt}^{min} \le D_{batt}(t) \le D_{batt}^{max}} & \text{Battery Degradation Limits} \\ \mathrm{SoH_{fc}(t) \ge SoH_{fc}^{min}} & \text{Fuel Cell SoH Limits} \\ \mathrm{SoH_{batt}(t) \ge SoH_{batt}^{min}} & \text{Battery SoH Limits} \end{array} \tag{13}$$

Where $P_{\mathrm{load}}(t)$ represents the load power requested by the system at a time t, which should be provided by the fuel cell and the battery. $P_{\mathrm{fc}}(t)$ is constrained by minimum $\left(P_{\mathrm{fc}}^{\min}\right)$ and maximum $(P_{\mathrm{fc}}^{\max})$ limits, which could be based on the operating characteristics of the fuel cell to prevent overloading or operating below an inefficient threshold. $P_{\mathrm{batt}}(t)$ is limited by the minimum $(P_{\mathrm{batt}}^{\min})$ and maximum $(P_{\mathrm{batt}}^{\max})$ values to ensure the battery operates within safe limits, considering charge/discharge rates. SoC(t) represents the battery's SoC at a time t, indicating how much charge is left in the battery as a percentage of its total capacity. It is constrained between minimum ($\mathrm{SoC}^{\min}$) and maximum ($\mathrm{SoC}^{\max}$) values to prevent overcharging or deep discharging, which could harm the battery's lifespan. $D_{\mathrm{fc}}(t)$ represents the degradation level of the fuel cell at a time t, capturing the performance loss due to aging, operational stress, or wear. The degradation is kept within limits, D_{fc}^{min} and D_{fc}^{max}, to ensure the fuel cell operates reliably and predictably without excessive wear. $D_{batt}(t)$ refers to the degradation of the battery at a time t, which reflects the reduction in battery performance or capacity due to cycles of charging and discharging. The degradation is constrained between D_{batt}^{min} and D_{batt}^{max}, ensuring the battery remains operational within a desired degradation range. $SoH_{fc}(t)$ is the state of health of the fuel cell and is a measure of the remaining useful life or efficiency of the fuel cell, where 100% (or 1) represents optimal health and 0% represents complete failure. This value is constrained to ensure that the fuel cell does not drop below a minimum acceptable health level (SoH_{fc}^{min}) to maintain functionality. $SoH_{batt}(t)$ indicates the health of the battery, reflecting the remaining capacity relative to its original state. The constraint $SoH_{batt}(t) \geq SoH_{batt}^{min}$ ensures that the battery's state of health remains above a critical level to prevent failure or underperformance.

In order to solve this multi-objective problem, we can combine the objectives into a single scalar function using the weighted sum approach

$$\begin{aligned} \min_{P_{fc}(t), P_{batt}(t)} \int_0^T \Big(& \lambda_1 f_{fuel}(P_{fc}(t)) + \lambda_2 f_{emissions}(P_{fc}(t)) + \lambda_3 f_{degr,\ fc}(P_{fc}(t)) \\ & + \lambda_4 f_{degr,\ batt}(P_{batt}(t)) - \lambda_5 f_{eff}(P_{fc}(t), P_{batt}(t)) \Big) dt \end{aligned} \tag{14}$$

where λ_1, λ_2, λ_3, λ_4, λ_5 are weights representing the relative importance of each objective in the system. This leads to a set of trade-off solutions known as the Pareto front, where improvements in one objective (e.g., minimizing fuel consumption) can only be achieved by worsening another (e.g., increasing degradation).

2.7 Learning-Based Energy Management

LB approaches have emerged as powerful tools to enhance the EMS by enabling accurate prediction of various system states and environmental conditions. These predictions are subsequently used in OB EMS, which plays a key role in minimizing fuel consumption, maximizing efficiency, and reducing emissions. This section discusses how LB methods contribute to energy management in hybrid fuel cell applications and the differences between shallow and deep learning approaches in this domain.

In hybrid fuel cell applications, the role of energy management is to balance the power demands between different energy sources, such as batteries, fuel cells, and auxiliary systems, while ensuring efficient energy use and extending the lifetime of key components. LB methods facilitate this task by accurately predicting power demand, fuel cell behavior, battery SoC, and environmental variables like weather and sea conditions. These predictions feed into the OB EMS, which continuously adjusts energy distribution to meet operational requirements while adhering to performance and sustainability goals.

LB prediction models have proven particularly effective in hybrid fuel cell systems due to their ability to process large amounts of data and recognize complex patterns over time. The models take historical data and system measurements as input and learn to predict future states or energy demand, which are subsequently optimized using mathematical techniques such as linear programming, dynamic programming, or MPC. The success of these predictions directly impacts overall energy efficiency; choosing a learning approach is critical for achieving optimal energy management.

In the context of LB energy management for ships, two main categories of machine learning approaches are widely used for making predictions: shallow and deep learning [105, 106, 107, 108]. Each has its strengths and appropriate application scenarios, depending on the nature of the data and the complexity of the prediction task.

Shallow learning methods [108] include kernel methods (e.g., support vector machines [108]), ensemble methods (e.g., random forests [109], gradient boosting machines [110]), and Gaussian processes [111]. These models are typically characterized by their relatively simple architectures and a limited number of layers. Their primary advantage lies in their ability to handle smaller datasets and structured tabular data effectively, which makes them particularly suitable for certain applications in energy management. Kernel-based methods [108], such as Support Vector Machines, map data into higher-dimensional spaces where linear separations can be applied. They are effective when dealing with non-linear relationships in the data and can produce high-quality predictions with small datasets. Ensemble Methods [109, 110] combine multiple weak learners (such as decision trees) to form a strong predictor. Random Forests and Gradient Boosting Machines are examples of ensemble methods widely used in energy prediction tasks, as they excel at capturing variance and avoiding overfitting, especially in tabular data. Gaussian Processes [111] are a non-parametric approach that provides probabilistic predictions with uncertainty quantification. This characteristic is useful in energy management applications, where uncertainty plays a key role in decision-making under variable environmental conditions. Shallow learning methods are generally well-suited for tabular data, where each input variable is explicitly defined, and relationships between variables can be modeled with relatively simple algorithms. For example, shallow models can efficiently handle historical fuel consumption, power load, or sea state data stored in tabular form due to their ability to deal with structured input.

Deep learning [105, 106, 107], on the other hand, is better suited for more complex and unstructured data types, such as time series data, where sequential dependencies must be captured. Deep learning methods include Long Short-Term Memory networks [112], Temporal Convolutional Networks [113], and Transformers [114], all of which are designed to model long-range dependencies in data and capture dynamic relationships that evolve over time. Long Short-Term Memory Networks [112] are a type of recurrent neural network designed to handle time series data with long-term dependencies. They maintain memory over extended periods, allowing them to predict energy demand or fuel cell behavior based on previous time steps in the data. This makes Long Short-Term Memory Networks particularly useful for managing power flows in hybrid systems, where temporal patterns, such as fuel cell degradation over time, play a crucial role. Temporal Convolutional Networks [113] use convolutional layers to model temporal data, offering a more efficient way to capture dependencies than traditional Recurrent Neural Networks like Long Short-Term Memory Networks. They allow for parallelization during training and are often better at handling longer sequences, making them well-suited for complex, time-dependent energy management tasks in ships, such as forecasting power demands or weather conditions over extended periods. Transformers [114], originally developed for natural language processing, transformers have proven to be highly effective in handling sequential data by using self-attention mechanisms that capture relationships between different time steps without relying on traditional recurrence. Transformers are particularly powerful when dealing with long sequences, where attention to both local and global time steps is critical, such as in predicting fuel consumption over long voyages.

The choice between shallow and deep learning methods depends on the type of data being used for prediction in the EMS. Shallow learning methods typically outperform deep learning approaches when dealing with structured tabular data, as they can efficiently capture relationships between features with relatively low computational cost. For example, predicting short-term energy demands based on current operational conditions (e.g., fuel cell and battery temperature, fuel flow rates, battery SoC) can be effectively handled by ensemble methods or Gaussian processes. However, when the data is more complex and unstructured, such as time series data that includes temporal patterns (e.g., power demand forecasts over time or environmental conditions during voyages), deep learning methods like Long Short-Term Memory networks, Temporal Convolutional Networks, or transformers become more advantageous. These models can learn from past time steps and make predictions that account for long-range dependencies, which is crucial in dynamic systems like ships.

LB energy management for hybrid fuel cell applications in ships benefits from the strengths of both shallow and deep learning methods, with the choice of approach depending on the type and complexity of the data. Shallow learning models are optimal for structured data and straightforward relationships, while deep learning models excel in capturing temporal dependencies and handling unstructured, time-series data in maritime energy management applications.

Both shallow and deep learning approaches have been successfully applied in the context of hybrid fuel cell systems. Tang et al. [115] demonstrated the potential of deep reinforcement learning in optimizing EMS for hybrid fuel cell systems, significantly improving fuel efficiency and reducing emissions in varying operational conditions. On the other hand, shallow models, while simpler, can be used for more basic tasks like short-term power demand forecasting or as components of larger, more complex systems.

Recent advancements in LB EMS also highlight the importance of deep learning in handling real-time optimization and prediction tasks. Hu et al. [116] applied a deep learning framework to predict energy demand and optimize performance in hybrid fuel cell systems, leading to improved system efficiency and lower emissions. Such applications underscore the versatility and power of deep learning in dealing with the complexities of modern energy systems.

Shallow and deep learning offer distinct advantages for EMSs, depending on the complexity of the system and the desired outcomes. Shallow learning models are computationally efficient and suitable for simpler systems or when immediate, straightforward predictions are needed. Deep learning, however, excels in capturing complex interactions and adapting to changing conditions, making it a superior choice for large-scale hybrid fuel cell systems where optimizing energy efficiency, sustainability, and operational reliability is critical. Both shallow and deep learning approaches are essential tools in the evolving landscape of LB energy management, enabling EMS strategies that continuously improve and adapt to meet the challenges of dynamic energy environments.

Reinforcement Learning [117] is a powerful machine learning technique particularly well-suited for EMS due to its ability to learn optimal control strategies through interaction with dynamic environments. In Reinforcement Learning, an agent (in this case, the EMS) makes decisions sequentially, taking actions that influence the system's state, intending to maximize long-term rewards. This approach is highly effective for managing hybrid energy systems, where the optimal strategy may change based on varying operational conditions such as fluctuating energy demands, fuel availability, or battery SoC.

The Reinforcement Learning framework can be mathematically modeled as a Markov Decision Process, where the system is described by a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$, consisting of:

- $\mathcal{S}$: the set of possible *states* the system can be in. For an EMS, states might include the current load demand, SoC of the battery, fuel consumption rate, or energy production capacity.
- $\mathcal{A}$: the set of *actions* the agent can take. Actions in an EMS could include decisions like adjusting the fuel cell output, charging or discharging the battery, or selecting which energy source to use at a given moment.
- $\mathcal{P}$: the *state transition probability* function $\mathcal{P}(s_{t+1}|s_t, a_t)$, which defines the probability of transitioning from one state s_t to the next state s_{t+1} after taking action a_t.
- $\mathcal{R}$: the *reward function* $r(s_t, a_t)$, which gives a numerical reward for the agent's action a_t in state s_t. In EMS, this reward can represent objectives such as minimizing fuel consumption, reducing emissions, or optimizing battery usage.
- γ: the *discount factor* $\gamma \in [0, 1]$, which determines the importance of future rewards compared to immediate rewards.

The objective of the RL agent is to learn an optimal policy π^* that maps states to actions, i.e., $\pi^* : \mathcal{S} \rightarrow \mathcal{A}$, in a way that maximizes the expected cumulative reward over time. This can be formalized as

$$\max_{\pi} \ \mathbb{E}_{\pi}\left[\sum_{t=0}^{T}\gamma^{t}r(s_t,a_t)\right] \tag{15}$$

where $\pi(a|s)$ is the policy that defines the probability of taking action a in state s, and the expectation is taken over the stochastic process governing the state transitions and actions.

In hybrid EMS, the reward function can be designed to capture various system performance metrics, such as minimizing fuel consumption, reducing wear on system components, maintaining an optimal SoC for the battery, or minimizing GHG emissions. This multi-objective nature of the reward function allows the RL framework to balance competing objectives dynamically, enabling the system to operate optimally under varying and uncertain conditions.

A central concept in RL is the exploration-exploitation dilemma. The agent must balance exploration, where it tries new actions to discover potentially better strategies, and exploitation, where it applies the best-known strategy based on past experience to maximize immediate reward.

In the context of an EMS, exploration could involve trying different energy distribution strategies (e.g., prioritizing battery over fuel cell or vice versa) to discover more efficient management policies. However, too much exploration may result in suboptimal decisions in the short term, such as unnecessary battery degradation or excessive fuel consumption. On the other hand, excessive exploitation might cause the agent to miss out on discovering better strategies for energy management in the long run.

To manage this trade-off, RL algorithms typically employ techniques such as ϵ-greedy policies, where the agent selects a random action with probability ϵ (exploration) and the best-known action with probability $1-\epsilon$ (exploitation).

More advanced strategies, such as Upper Confidence Bound [118] or Boltzmann exploration [119], adjust the exploration rate dynamically based on the uncertainty of the agent's knowledge about certain actions.

RL algorithms rely on estimating value functions to guide decision-making:

The *state − value function* $V^{\pi}(s)$ represents the expected cumulative reward starting from the state s and the following policy π

$$V^{\pi}(s) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{T}\gamma^{t}r(s_t,a_t)|s_0 = s\right]. \tag{16}$$

The *action − value function* or Q-learning $Q^{\pi}(s,a)$ gives the expected cumulative reward after taking action a in state s, and then the following policy π

$$Q^{\pi}(s,a) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{T} \gamma^{t} r(s_t, a_t)|s_0 = s, a_0 = a\right]. \tag{17}$$

The agent's goal is to learn the optimal Q-function $Q^{*}(s,a)$ that maximizes the expected cumulative reward. Once the optimal Q-function is learned, the optimal policy π^{*} is simply to choose the action that maximizes the Q-value for any given state

$$\pi^{*}(s) = \arg\max{}_{a} Q^{*}(s,a), \tag{18}$$

Q-learning is one of the most widely used RL algorithms for learning the optimal Q-function through interaction with the environment [120]. It updates the Q-function using the Bellman equation [121].

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r(s_t, a_t) + \gamma \max{}_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)], \tag{19}$$

where α is the learning rate that controls how much new information is incorporated into the Q-value estimate.

Traditional Q-learning methods may struggle with complex systems like hybrid energy management, where the state and action spaces are large or continuous. This is where Deep Reinforcement Learning comes in, which combines RL with deep neural networks to approximate the value function, policy, or both. Deep Reinforcement Learning is particularly effective in energy management, as it can handle large-scale and highly non-linear systems [122].

In Deep Q-Networks, a neural network is used to approximate the Q-function

$$Q(s_t, a_t; \theta) \approx Q^{*}(s_t, a_t), \tag{20}$$

where θ represents the network parameters (weights and biases). The Deep Q-Networks algorithm uses experience replay to store past transitions (s_t, a_t, r_t, s_{t+1}) in a replay buffer and sample mini-batches to update the Q-network, reducing the correlation between consecutive updates and improving the stability of training.

Deep Reinforcement Learning techniques, such as Deep Q-Networks [123] and Policy Gradient methods [124], have been successfully applied to hybrid fuel cell EMS to optimize long-term energy efficiency while balancing multiple objectives, such as fuel consumption, emissions, and system longevity. For instance, in a recent study, Tang et al. [115] used Deep Reinforcement Learning to manage the energy flow in a hybrid fuel cell-battery system, achieving significant improvements in both energy efficiency and emission reduction compared to traditional methods. One of the key advantages of RL, especially in energy management systems, is the ability to learn without a detailed model of the environment. Model-free RL methods, such as Q-learning and Policy Gradient, learn the optimal policy directly from interactions with the environment, bypassing the need for explicit modeling of the system dynamics. This is particularly useful in hybrid fuel cell systems where the dynamics can be highly complex and difficult to model accurately.

3 State-of-the-Art on Energy Management Strategies

This section provides an overview of various EMS (RB, OB, LB) in marine energy systems, highlighting their advantages and disadvantages. EMS play a crucial role in distributing power among the different power-generating components of hybrid marine power plants. This task becomes increasingly complex when the EMS must satisfy multiple, often conflicting objectives, including i) ensuring the vessel can complete its mission, ii) minimizing energy consumption, and iii) reducing component degradation [6].

While this chapter reviews these three EMS strategies, it is important to acknowledge that several comprehensive reviews on energy management systems have been published in the literature. These reviews provide valuable insights into the evolution of EMS methodologies and their specific applications. Readers are encouraged to consult these existing reviews to gain a holistic understanding of EMS strategies in maritime applications.

The growing interest in EMS approaches within the literature reflects a dynamic and evolving landscape for review papers. This development aligns with the themes explored in various book chapters [125, 126, 127]. Initial discussions in these reviews focus on the motivations driving the energy transition and zero-emission goals [23, 125, 128]. They briefly address the economic and environmental imperatives behind the necessity for innovative EMS designs in the maritime sector.

It is also essential to highlight the applicable fuel cell technologies and their configurations in maritime applications. The authors of [23] provide a clear narrative regarding the working principles of various fuel cell types, including PEMFC, SOFCs, and MCFCs. The type of fuel utilized is often influenced by the topology and design of the EMS, with a significant focus on their environmental impacts. PEMFCs are the predominant contributors in this sector; however, HT-PEMFCs, SOFCs, and MCFCs are also gaining attention for their promising capabilities [20, 126].

Additionally, the literature covers other critical system components, such as batteries, DC-DC converters, inverters, and motors [23, 129]. Control approaches are discussed in detail [125, 126, 130, 131] and categorized under RB, OB, and LB methods. RB approaches stand out for their simplicity and ease of implementation, often relying on straightforward engineering operation schemes for decision-making and power allocation [125]. In contrast, OB control strategies are extensively examined, typically divided into online and offline methods. Offline methods are further categorized into classical optimization approaches and heuristic methods. Notable strategies include Dynamic Programming, Linear Programming, Nonlinear Programming, Pontryagin's Minimum Principle, Mixed Integer Linear Programming, and Mixed Integer Nonlinear Programming [125, 126]. Heuristic algorithms, often referred to as intelligent algorithms, include Particle Swarm optimization, Genetic Algorithms, Grey Wolf optimizer, and Ant Colony optimization.

While offline optimization methods can be powerful, they require prior knowledge of load profiles. In contrast, online or real-time optimization strategies focus on smaller segments of the optimization problem, allowing for more efficient computations. Common approaches include the Equivalent Consumption Minimization Strategy (ECMS) and MPC. The selection of the optimization objective function and the application of desired costs in each scenario are crucial components of this approach.

LB strategies, increasingly present in the literature, utilize artificial intelligence methods to explore system dynamics, providing advantages at various stages of control. For instance, regression models can play a significant role in parametric identification within power plant models. The combination of MPC with artificial intelligence forecasting models presents a viable option for enhancing EMS effectiveness [125].

3.1 Rule-Based Energy Management Strategies

RB control systems have long been favored in EMS due to their simplicity, robustness, and real-time performance capabilities [16]. These systems rely on predefined sets of rules to manage the distribution of power between components, allowing for immediate responses to changes in system conditions. However, despite their strengths, RB strategies also present several limitations [132]. Their responses are often suboptimal when compared to more sophisticated OB strategies, as the rules may not align with the broader vehicle design or control objectives [133]. Additionally, these systems tend to have weaker dynamic responses to rapid changes in operating conditions [16], and they require significant expert knowledge during the design phase to ensure the system functions optimally [134]. RB control systems can be categorized into two primary strategies: fuzzy RB and deterministic RB approaches.

Deterministic RB strategies follow predefined rules based on tables or flow charts to determine which power source will be used and to what extent. These deterministic strategies can be further subdivided into several methods. The thermostat control approach is characterized by a simple on/off control method that turns system components on or off based on the current state of the power plant. For example, the system may turn on a diesel generator when the battery's SoC falls below a certain threshold. Xie et al. [135] present a two-layer thermostat-based energy management system where the outer layer controls the activation of the diesel engine based on the SoC and load. However, while thermostat control is common in the automotive industry, it is less suitable for maritime applications, where starting and stopping large engines, such as diesel generators, requires significant energy and increases emissions due to start-up inefficiencies.

The power follower method approach ensures that the power distribution between components follows the highest efficiency levels for each given moment, as identified in pre-established efficiency maps. Trovao et al. [136] applied the power follower method to a hybrid electric vehicle EMS. While this method ensures optimal efficiency at any particular time, it does not guarantee the highest efficiency for the entire operational cycle, making it less effective over extended periods.

Bassam et al. [137] developed an RB PI-control-based EMS for a hybrid fuel cell/ battery passenger vessel, which uses predefined rules to determine the power distribution between the fuel cell and the battery system based on various operational states such as battery SoC, required power, and other operational limits.

Finally, the gliding average control approach, also known as the moving average method, smooths the load demand on power sources by calculating the load's moving average over time. Tritschler et al. [138] applied this method to a fuel cell-based system, finding that it successfully reduced load fluctuations. However, while this method can help extend component lifespan by reducing strain, it can also result in delayed system responses, affecting real-time performance. This trade-off between dynamic response and system longevity is a key consideration for applying gliding average control in hybrid energy systems.

Fuzzy RB strategies utilize fuzzy logic to imitate human reasoning and handle uncertainty in decision-making [134]. Fuzzy logic translates non-binary inputs into outputs that a binary system can process, creating a black-box model that mimics human logic. One of this method's main advantages is its adaptability; the fuzzy rules can be optimized for different drive cycles without requiring deep expertise in the design phase. Studies such as [139] demonstrate fuzzy rule strategies' robustness and anti-disturbance capabilities, showing improved energy efficiency compared to conventional RB approaches. Fuzzy rules' adaptability also allows them to handle a wide range of operating conditions, making them particularly suitable for hybrid energy systems with fluctuating loads.

As research progresses, the limitations of traditional RB strategies are becoming more evident, particularly in the context of complex energy systems [140], particularly in dynamic environments, necessitating continued innovation. Recent trends indicate a shift toward machine LB optimization of RB strategies, reducing dependence on human expertise and allowing for real-time adaptation to changing system conditions [141].

The increasing reliance on machine learning techniques to optimize RB strategies holds promise for the future of energy management in hybrid systems. Several studies that demonstrate improved efficiency and adaptability of RB systems through automated rule optimization [142, 143] highlight this growing integration of machine learning. This approach offers a blend of simplicity, robustness, and adaptability that could redefine the role of RB strategies in complex energy systems.

Machine learning algorithms, such as RL and genetic algorithms, are increasingly being used to optimize rule sets based on large datasets. These approaches enhance the efficiency of EMS by improving adaptability, reducing energy consumption, and increasing system reliability while maintaining the simplicity and responsiveness of RB strategies. Research indicates that RL's ability to optimize EMS in dynamic and

Table 4 Summary of RB EMS in literature

Ref.	Approach	Objective
[16]	RB	Simplicity, real-time performance
[132]	RB	Limitations in dynamic response, suboptimal control
[133]	RB	Suboptimal when compared to OB strategies
[134]	Fuzzy RB	Adaptability, robustness, anti-disturbance capabilities
[135]	Thermostat	SoC-based control, startup inefficiencies
[136]	Power follower	Component efficiency optimization
[137]	RB PI-control	Fuel Consumption optimization
[138]	Gliding average	Load smoothing, reduced strain at delayed response
[139]	Fuzzy RB	Energy efficiency, adaptability for fluctuating loads
[140]	RB	Highlighted limitations in complex systems
[141]	ML-enhanced RB	Real-time adaptation, reduced expert dependence
[142]	RB+GA	Optimization of rule sets for enhanced performance
[143]	RB+GA	Optimization of rule sets for enhanced performance
[144]	RB+RL&GA	Non-convex problems, improved efficiency, and reliability
[145]	RB+RL&GA	Non-convex problems, improved efficiency, and reliability

unpredictable environments, such as grids with renewable energy sources, is highly promising. Meanwhile, genetic algorithms are leveraged for their capacity to handle non-convex optimization problems within EMS frameworks and refine rule sets for better performance in real-world applications [144, 145].

The summary of the referenced works is reported in Table 4.

3.2 Optimization-Based Energy Management Strategies

OB energy management differs inherently from RB energy management. While the decision of RB control systems is, to an extent, predefined by an applied set of rules that aim to describe the system's behavior, OB energy management bases its control decision on the minimization of an objective function. The objective function serves as a mathematical representation of the system's behavior with respect to one or more performance criteria that are deemed significant for the control application. The solution to the resulting optimization problem is contingent upon the selected algorithm. Importantly, the choice of algorithm is not arbitrary; its performance cannot be universally guaranteed to be optimal for all problems, as stated by the no-free-lunch theorem [146]. For energy management, OB strategies can be split up into two different categories: offline methods and online methods, as reported in Fig. 8.

Offline methods solve the problem globally by considering the full operational profile, which allows for an optimization of the complete operation beforehand. However, this includes extensive knowledge of the system and the planned operation, such as route, vessel speed, weather conditions, and power profile. Considering all that information, the optimal control sequence for the operation can be determined using a minimization of the objective function. A variety of different global optimization algorithms can be used, whereby Dynamic Programming [93] is worthy of mentioning in specific. In reality, this method is hard to apply, as much of the required information cannot be accurately determined pre-operation. This limits the applicability of such methods to short time horizons or commonly known load profiles, such as a passenger ferry with a repeating route and power profile. An example of an offline EMS is shown by Xie et al. [147, 148], with a focus on improving fuel efficiency. For this, the EMS is split into two layers, whereby the first is an offline optimization to decide on the power generation plan for the next day, while the second layer allocates the power generation strategy between the fuel cell modules.

Han et al. [149] present a hybrid fuel cell and battery system for a low-power boat, where the EMS aims to optimize system efficiency by managing power flow between the fuel cell and battery. The EMS determines the operating point of each component based on the system's operational states, which maximizes efficiency under various load conditions. The proposed EMS utilizes predefined operating states that consider the battery's SoC, load demands, and fuel cell efficiency. The system dynamically adjusts the power output from the fuel cell and battery based on these states. For example, when the battery's SoC is high, the EMS prioritizes discharging the battery, while at lower SoC levels, it prioritizes recharging the battery using the fuel cell.

Online methods include all approaches to optimize the cost function in real-time. To achieve this, the continuous operation is broken down into singular discrete time steps. With an appropriate sampling rate between the time steps, the system behavior between the time steps can be safely ignored [150]. The operation can be optimized, minimizing the cost function repeatedly for each time step of the operation, and implemented in the system in real-time. The major advantage of those methods compared to the offline methods is the reduced requirements of system and operational knowledge, as well as a reduction of computational time due to the reduction of the problem size to singular time steps rather than a complete operation. On the other hand, online methods are limited by the hardware available on board the vessel, as well as the chosen sampling rate, to ensure the accuracy of the real-time optimization. The latter is of interest as it is a hard limit requirement for the solution time of the chosen algorithm, which generally increases with the system's complexity. However, as energy management is situated on the tertial control layer (see Fig. 7), the time step size is large enough for OB control methods.

The spectrum of online methods can be divided into instantaneous and predictive optimization approaches. Instantaneous optimization approaches address only one of the discrete time steps of the problem and solve the objective function for this respective time step without any knowledge about the future operation. The control problem is set up with an objective function for each time step and solved using an adequate optimization algorithm. The setup of the control problem itself can vary and incorporate various control approaches, such as reference tracking or the introduction of additional Key Performance Indicators to help determine the optimal control sequence. A notable concept for hybrid fuel cell/battery systems is ECMS.

ECMS introduces an equivalent factor to quantify the usage of battery power in comparison to fuel usage from the fuel cell. This approach allows the connection of two inherently different energy sources to the same factor, for example, the financial cost of a kWh, and therefore single out the global minimum for the power split. Further, it is also possible to solve the optimization problem using a variety of algorithms. One example is Particle Swarm optimization. This is demonstrated by Peng et al. [151], who use Particle Swarm optimization to improve the power quality, as well as the battery lifetime.

Predictive optimization approaches combine multiple control steps to solve the control problem. This is also commonly referred to as MPC (see Sect. 2.6.3) or receding horizon control. In this setup of the optimization problem, the optimal control sequence is based on the expected behavior of the system, taking into account a prediction for the future. This allows for the optimization to consider upcoming system changes beforehand, such as upcoming power fluctuations of significant scale. Commonly, only the first step of the optimal control sequence found as a solution to the optimization problem is implemented in the system. Afterward, the control horizon is moved one step forward and optimized again. While this method promises an accurate, optimal control solution because it can adjust to upcoming changes early, it also has some requirements. The first one is a model of the controlled system, which allows for an accurate prediction of the system behavior under the upcoming system conditions. The second one is an accurate forecast of the external conditions, such as the load profile and weather conditions. Both the model of the system and the external prediction model need to fulfill requirements on the accuracy of their forecast, as otherwise, the added uncertainty invalidates the control performance. In addition, predictive OB approaches also increase the size of the control problem as they add multiple steps together, which leads to an increase in computational requirements and solution time. A first example of predictive control of hybrid fuel cell/battery systems is shown by Banaei et al. [152]. The authors propose a stochastic MPC for the control of a fuel cell/battery/cold-ironing vessel for the optimization of operational cost, as well as considering aging factors for the fuel cell to account for component degradation. The summary of the referenced works is reported in Table 5.

Table 5 Summary of OB EMS

Ref.	Approach	Objective
[93]	Dynamic programming—Offline	Global optimization
[147]	Two layer—Offline	Fuel efficiency
[148]	Two layer—Offline	Fuel efficiency
[149]	PSO—Offline	Power quality, battery lifetime
[150]	Two layer—Offline	Fuel efficiency, power quality, system efficiency
[151]	MPC—Online	Real-time optimization
[152]	Stochastic MPC—Online	Cost, aging

3.3 Learning-Based Energy Management Strategies

LB EMS are becoming increasingly essential for optimizing energy distribution and minimizing operational costs in hybrid fuel cell and battery systems within maritime applications. These strategies leverage operational data from the ship's energy systems to inform control decisions, dynamically adapting to real-time conditions. Compared to traditional RB methods, LB approaches often outperform by learning from data and utilizing predictive capabilities that are not restricted by predefined rules [153]. Furthermore, they avoid the extensive computational demands and modeling complexities associated with offline OB strategies.

In the context of hybrid fuel cell systems for ships, operational data such as power demand, load profiles, fuel consumption, and battery states can be harnessed to train machine learning models that predict energy requirements over short time horizons. This predictive capability enables LB strategies to effectively manage the dynamic and variable nature of ship energy management. However, challenges persist regarding data availability, as hybrid fuel cell/ESS systems are not yet widely adopted in the maritime industry, which limits access to large, high-quality datasets.

LB EMS is becoming increasingly critical for optimizing energy distribution and reducing operational costs in hybrid fuel cell and battery systems used in maritime applications. These strategies leverage real-time operational data from the ship's energy systems to inform dynamic control decisions, adapting continuously to changing conditions. Compared to traditional RB methods, LB approaches often demonstrate superior performance by learning from historical data and utilizing predictive capabilities, which are not limited by predefined rules [153]. Additionally, they avoid the significant computational demands and modeling complexities inherent in offline OB strategies. In the context of hybrid fuel cell systems for ships, operational data—including power demand, load profiles, fuel consumption, and battery states—can be used to train machine learning models that predict energy requirements over short timeframes. This predictive capability enables LB strategies to manage the dynamic and variable nature of shipboard energy systems more effectively. However, challenges remain, particularly in terms of data availability, as hybrid fuel cell/ESS systems are not yet widely deployed in the maritime industry, limiting access to large, high-quality datasets.

Among the promising approaches within LB energy management is reinforcement RL, which has demonstrated the ability to optimize energy consumption, reduce fuel usage, and enhance overall system efficiency. RL frameworks, particularly deep RL, have shown success in real-time decision-making for hybrid fuel cell systems. For example, Jung and Chang [154] applied Deep RL to manage the energy flow in a hybrid fuel cell/battery-powered ship, achieving significant reductions in fuel consumption and operational expenditures.

In another noteworthy application, Jung et al. [154] propose a Deep RL-based EMS tailored for hybrid electric ship propulsion systems powered by liquid hydrogen. This system integrates PEMFCs, a fuel gas supply system, and lithium-ion battery systems. The Deep RL EMS was evaluated against benchmark algorithms such as dynamic programming and sequential quadratic programming, demonstrating superior real-time optimization capabilities across various operational scenarios.

Moreover, Wu et al. [155] present a Double Q-learning-based RL EMS for plug-in PEMFC and battery-powered ships. Their method optimizes cost-effectiveness in operating these hybrid ships without requiring prior knowledge of future power demands. The study focuses on a coastal ferry, utilizing continuous monitoring data from real-world voyages to train and validate the RL agent. The energy management system is designed to efficiently allocate power among the fuel cell, battery, and shore power, taking into account factors like fuel cell degradation and battery charging/discharging dynamics.

Gan et al. [156] provide a comprehensive examination of machine learning algorithms to approximate MPC for real-time energy management in hybrid energy ships. Their research introduces an approximate MPC strategy aimed at minimizing operating costs and deviations from the reference SoC of a ship's battery. Various machine learning algorithms, including Random Forest, Gradient Boosting Decision Trees, and Support Vector Machines, were evaluated for their performance in real-time energy management tasks on a ferry equipped with photovoltaic systems. The results indicate that the Random Forest algorithm strikes the best balance between training accuracy and computational efficiency, making it well-suited for real-time applications in hybrid energy ship systems.

Neural networks are also a powerful tool in LB EMS due to their capability to model complex, nonlinear relationships within data, making them particularly suitable for the intricate dynamics of hybrid fuel cell/battery systems. Geng et al. [157] demonstrate an accurate method for estimating the SoC of batteries for all-electric ships, employing a Long Short Term Memory recurrent neural network. This approach improves estimation accuracy by considering nonlinear dependencies in input variables like voltage, current, and battery temperature, achieving a maximum absolute SoC estimation error of 2.0%.

Walker et al. [92] explore the application of shallow and deep machine learning models for power demand forecasting in a hybrid marine energy system. The study focuses on predicting the total power demand of a vessel that operates using electric motors, batteries, and diesel engines, which is increasingly relevant in optimizing energy efficiency and reducing emissions in maritime transport. By comparing shallow learning models (such as kernel methods and ensemble techniques) with a deep learning model (Temporal Convolutional Network), the paper highlights both the potential and challenges of applying machine learning techniques in energy and power management systems.

In addition, Zhou et al. [158] introduce a Soft Actor-Critic RL framework aimed at optimal energy management in electric vehicles equipped with hybrid ESS, including batteries and supercapacitors. The proposed energy management system overcomes the limitations faced by traditional RB and OB control strategies, improving energy efficiency, battery longevity, and overall performance by dynamically allocating power between the battery and supercapacitor during peak power demands. This approach has been validated through extensive experiments, demonstrating superior performance compared to other control strategies, including deep deterministic policy gradient and RB methods.

Kernel methods, such as Support Vector Machines and Kernel Ridge Regression, are increasingly applied in maritime energy management tasks due to their effectiveness in modeling nonlinear relationships, even with small datasets. This characteristic is particularly beneficial in the maritime domain, where operational data for hybrid fuel cell systems may often be sparse. Kernel methods can predict energy usage and optimize system control by transforming the input space into a higher-dimensional feature space using the kernel trick, thus enabling the algorithm to manage complex relationships among operational parameters without requiring extensive data or computational resources [91].

For example, Valchev et al. [91] employed kernel-based learning methods to optimize energy flow in hybrid propulsion systems, finding that Kernel Ridge Regression effectively predicted power demand for controlling and allocating energy between fuel cells and batteries. This demonstrates the potential of kernel methods in scenarios with limited data, which are common during the early stages of hybrid fuel cell technology deployment in maritime applications.

Ensemble methods, such as Random Forests and Gradient Boosting Machines, are also powerful in maritime energy management because they combine multiple models to enhance predictive accuracy and robustness. These ensemble methods have been utilized to predict energy consumption, optimize fuel usage, and manage power distribution in hybrid fuel cell systems. For instance, Wen et al. [159] implemented a hybrid ensemble model designed for interval prediction of solar power output in shipboard power systems. Their model integrates various machine learning techniques—including neural networks, Radial Basis Function Neural Networks, Extreme Learning Machines, and Elman Neural Networks—with Particle Swarm optimization to address the stochastic nature of solar power generation on moving ships. This hybrid approach was validated using real-world data from a large oil tanker operating along a route from China to Yemen, demonstrating improved prediction accuracy compared to conventional methods.

LB EMS present significant potential to enhance energy efficiency and reduce operational costs in hybrid fuel cell/battery systems for maritime applications. Approaches such as reinforcement learning, neural networks, and ensemble methods are particularly well-suited for managing maritime energy systems' dynamic and complex nature. Nevertheless, the success of these methods hinges on the availability of quality operational data, careful model tuning, and effective management of computational constraints aboard ships. As the adoption of hybrid fuel cell systems in maritime applications continues to grow, the integration of advanced LB methods will likely play a pivotal role in optimizing EMS. Despite their advantages, machine LB methods face challenges related to the quantity and quality of training data required and the substantial computational power needed to train these models effectively. The summary of the referenced works is reported in Table 6.

Table 6 Summary of research on LB EMS

Ref.	Approach	Application
[154]	DRL	Hybrid fuel cell/battery-powered ships
[154]	DRL	Hybrid electric propulsion systems powered by liquid hydrogen
[155]	Double Q-learning	EMS for PEMFC and battery-powered ships
[156]	Approximate MPC	Real-time energy management in hybrid energy ships
[157]	LSTM	SoC estimation for all-electric ships
[92]	TCN	Power demand forecasting in hybrid marine energy systems
[158]	SAC-RL	EMS in electric vehicles with hybrid ESS
[91]	KRR	Energy flow optimization in hybrid propulsion systems
[159]	Hybrid	Solar power output prediction in shipboard power systems

3.4 *Comparative Analysis of Energy Management Strategies*

In their comparative study, the authors of [153] between Dynamic Programming and ECMS indicate that both the Partially Observable Markov Decision Process and Dynamic Programming deliver equivalent optimal solutions. This study underscores the critical relationship between the performance of ECMS and the Partially Observable Markov Decision Process, highlighting their dependence on the precise definitions of co-states used in their calculations.

A key distinction exists between EMS in the automotive and maritime sectors, particularly regarding the utilization of regenerative braking and the steady load demands of marine power plants. As observed by [160], the energy savings realized through ECMS in shipping are less significant than those documented in the automotive industry, largely due to the limitations of ship propellers in capturing energy via regenerative braking. The literature indicates that RB systems often incur higher costs compared to OB strategies [160, 161, 162]. Historically reliant on the expertise of engineers, there is a discernible shift toward offline-optimized RB strategies in recent research [161]. Notably, the Partially Observable Markov Decision Process strategy consistently yields optimal solutions while maintaining lower computational complexity compared to other methods [163]. Furthermore, the cost differential between RB and OB strategies tends to vary with the load profile; more variable loads typically benefit more from non-RB strategies than constant loads. While OB strategies often provide superior fuel efficiency relative to RB methods, they frequently present complexities that hinder real-time application or are overly reliant on precise tuning of co-states in online methods. Literature commonly notes that strategies such as ECMS and Partially Observable Markov Decision Process are optimized for specific drive cycles but are rarely tested under unpredictable, random cycles, which is a crucial factor for both shipping and automotive applications. This observation raises questions regarding their effectiveness in random operational scenarios and whether certain shipping operations—such as ferry routes along the Norwegian coast, as studied by [164] might experience more consistent load cycles. Additionally, while numerous studies acknowledge that hybrid propulsion systems could contribute to addressing global GHG challenges, most tend to concentrate primarily on optimizing fuel consumption. Surprisingly, only a limited number of studies explicitly integrate GHG considerations into their findings, indicating a gap in the comprehensive evaluation of EMS effectiveness in relation to environmental impacts.

4 Challenges and Future Directions

The integration of state-of-the-art EMS for hybrid PEMFC/ESS applications in ships faces a variety of technical, economic, and regulatory challenges. Technical challenges include the complexity of optimizing power flow in real-time, especially with fluctuating energy demands and the integration of renewable energy sources like solar. Critical obstacles remain to achieve seamless transitions between energy sources and maintain system stability while respecting operational constraints such as fuel cell efficiency, battery SoC, and thermal management.

The performance degradation of PEMFC over time, as well as the ESS aging, adds to the complexity of designing predictive models that accurately capture the system dynamics. Currently, most of the existing health-conscious EMS set upper or lower boundaries to the fuel cell and ESS operating ranges, or battery' SoC. Developing models able to quantify the degradation or the lifetime of these energy sources and integrating them into EMS remains an open challenge.

On the economic front, the high capital cost of fuel cell technologies and advanced EMS is a significant barrier to widespread adoption. Regulatory challenges also hinder adoption, as international maritime regulations are still evolving to include standards for the safe and efficient operation of hydrogen-based systems. Compliance with environmental regulations, such as the IMO's goals for carbon reduction, requires further harmonization of policies and incentives to facilitate green shipping technologies.

Looking ahead, future research directions should focus on improving the longevity and efficiency of fuel cells through advances in material science. Developing practical models to estimate fuel cells and batteries degradation, and their interaction and combined effect on the hybrid systems' lifetime is crucial for the integration of health-conscious approaches into EMS. Enhanced optimization algorithms, such as machine learning-driven predictive control, could offer more robust energy management solutions that can adapt to the variability in marine operational profiles. Furthermore, research into integrated systems that combine hydrogen fuel cells with renewable energy sources will be key to reducing dependency on fossil fuels. Addressing economic challenges will require continued efforts to scale up hydrogen production and infrastructure and improve energy storage density through alternative storage solutions, as well as innovations in reducing the cost of fuel cells. On the regulatory side, establishing clear, global guidelines for hydrogen safety, handling, and emissions reporting will be critical to accelerating the adoption of hybrid fuel cell systems in the maritime sector.

5 Conclusion

The adoption of state-of-the-art EMS for hybrid PEMFC/ESS applications in ships represents a critical step toward reducing emissions and enhancing energy efficiency in the maritime sector. Among these strategies, RB, OB, and LB approaches each offer unique benefits and face specific limitations. RB methods, while straightforward and reliable, lack the flexibility needed for dynamic marine environments where operational conditions fluctuate. In contrast, OB techniques, particularly MPC, provide advanced real-time adaptability, making them well-suited for optimizing energy distribution in complex scenarios. While LB strategies that leverage machine learning hold the promise of continuous system improvement through adaptation to new data, they require further development to be widely adopted in practical marine applications. Despite the clear advantages of these approaches, several challenges impede widespread adoption. Technical challenges persist, including modeling the degradation of fuel cells and batteries over time, the complexity of real-time optimization, and the need for more accurate predictive models capable of handling diverse operational conditions. Additionally, the high capital costs associated with hybrid PEMFC/ESS systems and the evolving nature of regulatory frameworks in the maritime industry present substantial economic and regulatory hurdles. These challenges must be addressed to utilize and exploit the full potential of these technologies.

Looking to the future, research must prioritize efforts to improve the durability and performance of fuel cells and batteries and focus on their degradation modeling. The development of more computationally efficient optimization algorithms will also be essential, particularly as MPC, though powerful, remains computationally intensive for practical real-time applications in the marine sector. Exploring more scalable algorithms, especially those driven by machine learning, could offer more effective solutions for managing multiple competing objectives, such as balancing power demand and preserving system longevity.

Another crucial area for future development is the integration of renewable energy sources, such as wind-assisted propulsion and solar power, into hybrid fuel cell systems. This will reduce reliance on hydrogen and improve the sustainability of marine energy systems. Hybrid configurations that blend renewable energy with hydrogen-based systems will be vital for optimizing fuel efficiency, thus aligning with the broader goals of maritime decarbonization. However, the integration of other renewable sources into marine hybrid systems will increase the complexity of their operation, control, and EMS.

Addressing the economic challenges will require targeted financial strategies to lower the barriers to adoption. Governments and industry stakeholders should collaborate to create economic incentives that support the transition to hybrid systems. Subsidies for hydrogen production, grants for infrastructure development, and tax incentives for retrofitting ships with hybrid systems can help mitigate the high upfront costs. Additionally, scaling up production and standardizing fuel cell components will be key to driving down costs and making hybrid systems more financially viable. With the potential to optimize operational efficiency, minimize fuel consumption, and increase components' operational lifetime, EMS can significantly contribute to enhancing the cost-effectiveness of marine hybrid fuel cell systems.

From a regulatory perspective, the maritime industry will need clear, consistent guidelines to facilitate the adoption of hybrid fuel cell technologies. Regulatory bodies should continue to lead the effort in establishing global standards for hydrogen-based systems, addressing critical issues such as safety protocols, emissions reporting, and operational guidelines. A harmonized regulatory framework will reduce uncertainty for shipping companies and incentivize investment in clean technologies.

Finally, to support the successful deployment of these advanced systems, specialized training programs are essential. These programs should equip ship operators and engineers with the necessary skills to safely operate and maintain hybrid fuel cell systems, as well as provide training on the use of advanced energy management tools. As these technologies become more complex, building a skilled workforce will be critical to ensuring their effective use and long-term success.

References

1. I. M. O. (2020). Fourth IMO GHG Study 2020 Full Report: Tech. Rep. [Online]. Available: https://www.imo.org/en/OurWork/Environment/Pages/Fourth-IMO-Greenhouse-Gas-Study-2020.aspx
2. H. Council. (2021). Hydrogen for net zero-a critical cost-competitive energy vector.
3. Whitehead, J., Newman, P., Whitehead, J., & Lim, K. L. (2023). Striking the right balance: Understanding the strategic applications of hydrogen in transitioning to a net zero emissions economy. *Sustainable Earth Reviews, 6*(1), 1.
4. Yrjänäinen, A., Johnsen, T., Dæhlen, J. S., Kramer, H., & Monden, R. (2018). Requirements and operational profiles. In *A holistic approach to ship design: Volume 1: Optimisation of ship design and operation for life cycle* (p. 75).
5. Sorensen, A. J., et al. (2017). Toward safer, smarter, and greener ships: Using hybrid marine power plants. *IEEE Electrification Magazine, 5*(3), 68–73.
6. Geertsma, R. D., Negenborn, R. R., Visser, K., & Hopman, J. J. (2017). Design and control of hybrid power and propulsion systems for smart ships: A review of developments. *Applied Energy, 194*, 30–54.
7. Sürer, M. G., & Arat, H. T. (2022). Advancements and current technologies on hydrogen fuel cell applications for marine vehicles. *International Journal of Hydrogen Energy, 47*(45), 19865–19875.
8. Gianni, M., Pietra, A., Coraddu, A., & Taccani, R. (2022). Impact of SOFC power generation plant on carbon intensity index (CII) calculation for cruise ships. *Journal of Marine Science and Engineering, 10*(10), 1478.
9. Baldi, F., Coraddu, A., & Mondejar, M. E. (2022). *Sustainable energy systems on ships: Novel technologies for low carbon shipping*. Elsevier.
10. Baldi, F., & Coraddu, A. (2022). Towards halving shipping GHG emissions by 2050: The IMO introduces the CII and the EEXI. In *Sustainable energy systems on ships* (pp. 513–517). Elsevier.

11. Vasilikis, N., Geertsma, R., & Coraddu, A. (2023). A digital twin approach for maritime carbon intensity evaluation accounting for operational and environmental uncertainty. *Ocean Engineering, 288*, 115927.
12. Soares, C. G., & Santos, T. A. R. (2022). *Trends in maritime technology and engineering*. CRC Press Taylor & Francis Group.
13. Kopka, T., Mylonopoulos, F., Coraddu, A., & Polinder, H. (2023). Decentralized power sharing with frequency decoupling for a Fuel Cell-Battery DC Shipboard Power System. *Modelling and Optimisation of Ship Energy Systems 2023*. https://doi.org/10.59490/moses.2023.670
14. Kopka, T., Löffler, C., Coraddu, A., & Polinder, H. (2023). Hierarchical control strategy for fuel cell-battery shipboard power system utilizing a modular control architecture. *IEEE*, 1–8.
15. Nguyen, H. P., et al. (2021). The electric propulsion system as a green solution for management strategy of CO2 emission in ocean shipping: A comprehensive review. *International Transactions on Electrical Energy Systems, 31*(11).
16. Inal, O. B., Charpentier, J. F., & Deniz, C. (2022). Hybrid power and propulsion systems for ships: Current status and future challenges. *Renewable and Sustainable Energy Reviews, 156*, 111965.
17. Yang, Z., Huang, H., & Lin, F. (2022). Sustainable electric vehicle batteries for a sustainable world: Perspectives on battery cathodes, environment, supply chain, manufacturing, life cycle, and policy. *Advanced Energy Materials, 12*(26), 2200383.
18. Editorial. (2021). Lithium ion batteries need to be greener and more ethical. *Nature, 595*, 7.
19. Peters, J. F., Baumann, M., Zimmermann, B., Braun, J., & Weil, M. (2017). The environmental impact of Li-Ion batteries and the role of key parameters – A review. *Renewable and Sustainable Energy Reviews, 67*, 491–506.
20. van Biert, L., Godjevac, M., Visser, K., & Aravind, P. V. (2016). A review of fuel cell systems for maritime applications. *Journal of Power Sources, 327*, 345–364.
21. Kandidayeni, M., Trovão, J. P., Soleymani, M., & Boulon, L. (2022). Towards health-aware energy management strategies in fuel cell hybrid electric vehicles: A review. *International Journal of Hydrogen Energy, 47*(17), 10021–10043.
22. Mallouppas, G., & Yfantis, E. A. (2021). Decarbonization in shipping industry: A review of research, technology development, and innovation proposals. *Journal of Marine Science and Engineering, 9*(4), 415.
23. Xing, H., Stuart, C., Spence, S., & Chen, H. (2021). Fuel cell power systems for maritime applications: Progress and perspectives. *Sustainability, 13*(3), 1213.
24. Tronstad, T., Åstrand, H. H., Haugom, G.-P., & Langfeldt, L. (2017). *Study on the use of fuel cells in shipping*. European Maritime Safety Agency.
25. Elkafas, A. G., Rivarolo, M., Gadducci, E., Magistri, L., & Massardo, A. F. (2022). Fuel cell systems for maritime: A review of research development, commercial products, applications, and perspectives. *PRO, 11*(1), 97.
26. Dall'Armi, C., Pivetta, D., & Taccani, R. (2023). Hybrid PEM fuel cell power plants fuelled by hydrogen for improving sustainability in shipping: State of the art and review on active projects. *Energies (Basel), 16*(4), 2022.
27. Chen, W., et al. (2021). DC-distributed power system modeling and hardware-in-the-loop (HIL) evaluation of fuel cell-powered marine vessel. *IEEE Journal of Emerging and Selected Topics in Industrial Electronics, 3*(3), 797–808.
28. Maurya, R., Prakash, S., & Singh, A. K. (2023). Challenges, configuration, control, and scope of DC microgrid systems: A review. *Journal of Electrical Engineering & Technology, 18*(3), 1655–1674.
29. Chen, D., & Xu, L. (2017). AC and DC microgrid with distributed energy resources. In *Technologies and applications for smart charging of electric and plug-in hybrid vehicles* (pp. 39–64). Springer Nature.
30. Pires, V. F., Pires, A., & Cordeiro, A. (2023). DC microgrids: Benefits, architectures, perspectives and challenges. *Energies (Basel), 16*(3), 1217.

31. Aghmadi, A., & Mohammed, O. A. (2024). Energy storage systems: Technologies and high-power applications. *Batteries, 10*(4), 141.
32. Abo-Khalil, A. G., & Alobaid, M. (2023). A guide to the integration and utilization of energy storage systems with a focus on demand resource management and power quality enhancement. *Sustainability, 15*(20), 14680.
33. Oliveira, D. Q., et al. (2021). A critical review of energy storage technologies for microgrids. *Energy Systems*, 1–30.
34. Alkaner, S., & Zhou, P. (2006). A comparative study on life cycle analysis of molten carbon fuel cells and diesel engines for marine application. *Journal of Power Sources, 158*(1), 188–199.
35. Trondstad, T., & Endresen, Ø. (2005). FellowSHIP-Fuel cells for low emission ships. In *Risoe International Energy Conference* (pp. 141–149). Risoe National Laboratory, Systems Analysis Dept. https://doi.org/10.11581/20623166
36. Bensaid, S., Specchia, S., Federici, F., Saracco, G., & Specchia, V. (2009). MCFC-based marine APU: Comparison between conventional ATR and cracking coupled with SR integrated inside the stack pressurized vessel. *International Journal of Hydrogen Energy, 34*(4), 2026–2042.
37. Nehter, P., Wildrath, B., Bauschulte, A., & Leites, K. (2017). Diesel based SOFC demonstrator for maritime applications. *ECS Transactions, 78*(1), 171.
38. McConnell, V. P. (2010). Now, voyager? The increasing marine use of fuel cells. *Fuel Cells Bulletin, 2010*(5), 12–17.
39. Chakraborty, S., Dzielendziak, A. S., Koroglu, T., & Yang, K. (2013). Evaluation of smart eco-friendly public transport options in coastal cities: Towards a green future for the city of Southampton (Vol. 2). In: R. A. Shenoi, P. A. Wilson, S. S. Bennett (eds.) University of Southampton. https://eprints.soton.ac.uk/359323/
40. German e4ships project reports on fuel cell maritime demos. *Fuel Cells Bulletin, 2016*(10), 5 (2016). https://doi.org/10.1016/S1464-2859(16)30271-1.
41. Huerta, G. V., Jordán, J. Á., Dragon, M., Leites, K., & Kabelac, S. (2018). Exergy analysis of the diesel pre-reforming solid oxide fuel cell system with anode off-gas recycling in the SchIBZ project. Part I: Modeling and validation. *International Journal of Hydrogen Energy, 43*(34), 16684–16693.
42. Borgogna, G., et al. (2019). Design and development of a laboratory for the study of PEMFC system for marine applications. *EDP Sciences*, 02020.
43. Rupo, D., Perano, M., Centorrino, G., & Sanchez, A. V. (2018). A framework based on sustainability, open innovation, and value cocreation paradigms—A case in an Italian maritime cluster. *Sustainability, 10*(3), 729.
44. A. Energy. (2024). RIVERCELL: SERENE to Maritime. [Online]. Available: https://serene.advent.energy/cases/rivercell-serene-to-maritime/
45. E. R. M. (2021). The Fuel Cell Industry Review 2021. [Online]. Available: https://www.erm.com/globalassets/documents/fuel-cell-industry-review/thefuelcellindustryreview2021.pdf
46. S. Maritime. (2024). SeaChange Project. [Online]. Available: https://www.switchmaritime.com/projects
47. M. Project. (2024). *Marine application of a new fuel cell powertrain validated in demanding Arctic conditions*. MARANDA.
48. Vafamand, N., Boudjadar, J., & Khooban, M. H. (2020). Model predictive energy management in hybrid ferry grids. *Energy Reports, 6*, 550–557.
49. Igder, M. A., Rafiei, M., Boudjadar, J., & Khooban, M.-H. (2020). Reliability and safety improvement of emission-free ships: Systemic reliability-centered maintenance. *IEEE Transactions on Transportation Electrification, 7*(1), 256–266.
50. Rafiei, M., Boudjadar, J., & Khooban, M.-H. (2020). Energy management of a zero-emission ferry boat with a fuel-cell-based hybrid energy system: Feasibility assessment. *IEEE Transactions on Industrial Electronics, 68*(2), 1739–1748.

51. Khooban, M. H., Gheisarnejad, M., Farsizadeh, H., Masoudian, A., & Boudjadar, J. (2019). A new intelligent hybrid control approach for DC–DC converters in zero-emission ferry ships. *IEEE Transactions on Power Electronics, 35*(6), 5832–5841.
52. Banaei, M., Boudjadar, J., & Khooban, M.-H. (2021). *Optimal energy resources scheduling of hybrid diesel/battery ships in shallow waters* (pp. 369–378). Springer.
53. Trillos, J. C. G., Wilken, D., Brand, U., & Vogt, T. (2021). Life cycle assessment of a hydrogen and fuel cell ropax ferry prototype. *Progress in Life Cycle Assessment, 2019*, 5–23.
54. Cavo, M., Gadducci, E., Rattazzi, D., Rivarolo, M., & Magistri, L. (2021). Dynamic analysis of PEM fuel cells and metal hydrides on a zero-emission ship: A model-based approach. *International Journal of Hydrogen Energy, 46*(64), 32630–32644.
55. Cavo, M., et al. (2022). Thermal integration of PEM Fuel Cells and metal hydrides storage system for Zero Emission Ultimate Ship (ZEUS). *EDP Sciences*, 04004.
56. Di Ilio, G., Di Giorgio, P., Tribioli, L., Cigolotti, V., Bella, G., & Jannelli, E. (2021). *Assessment of a hydrogen-fueled heavy-duty yard truck for roll-on and roll-off port operations*. SAE Technical Paper.
57. e4ships. (2024). PA-X-ELL 2: Entwicklung und Erprobung eines emissionsfreien und nachhaltigen Energieversorgungssystems für Seeschiffe. [Online]. Available: https://www.e4ships.de/deutsch/seeschifffahrt/pa-x-ell-2/
58. Danfoss. (2024). Hydrogenia Vessel Case Story. [Online]. Available: https://www.danfoss.com/en/service-and-support/case-stories/dps/hydrogenia-vessel-case-story/
59. Meca, V. L., Villalba-Herreros, A., d'Amore-Domenech, R., & Leo, T. J. (2022). Zero emissions wellboat powered by hydrogen fuel cells hybridised with batteries. *Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, 236*(2), 525–536.
60. Trivyza, N. L., Cheliotis, M., Boulougouris, E., & Theotokatos, G. (2021). Safety and reliability analysis of an ammonia-powered fuel-cell system. *Safety, 7*(4), 80.
61. CORDIS. (2024). *Nautical integrated hybrid energy system for long-haul cruise ships*. CORDIS.
62. H. Project. (2024). HyShip Project. [Online]. Available: https://hyship.eu/
63. E. M. E. C. (EMEC). (2024). HIMET: Hydrogen in an Integrated Maritime Energy Transition. [Online]. Available: https://www.emec.org.uk/projects/hydrogen-projects/himet/
64. CORDIS. (2024). *High efficiency Low emission nautical solid oxide fuel cell*. CORDIS.
65. Wang, Y., Diaz, D. F. R., Chen, K. S., Wang, Z., & Adroher, X. C. (2020). Materials, technological status, and fundamentals of PEM fuel cells–a review. *Materials Today, 32*, 178–203.
66. Kandlikar, S. G., Garofalo, M. L., & Lu, Z. (2011). Water management in a pemfc: Water transport mechanism and material degradation in gas diffusion layers. *Fuel Cells, 11*(6), 814–823.
67. van Biert, L., & Visser, K. (2022). Fuel cells systems for sustainable ships. In *Sustainable energy systems on ships* (pp. 81–121). Elsevier.
68. Rosli, R. E., et al. (2017). A review of high-temperature proton exchange membrane fuel cell (HT-PEMFC) system. *International Journal of Hydrogen Energy, 42*(14), 9293–9314.
69. Wang, H., & Turner, J. A. (2010). Reviewing metallic PEMFC bipolar plates. *Fuel Cells, 10*(4), 510–519.
70. Pietra, A., Gianni, M., Zuliani, N., Malabotti, S., & Taccani, R. (2022). Experimental characterization of a PEM fuel cell for marine power generation. *EDP Sciences*, 05002.
71. Larminie, J., Dicks, A., & McDonald, M. S. (2003). *Fuel cell systems explained* (Vol. 2). J. Wiley.
72. E. M. S. Agency. (2020). Study on Electrical Energy Storage for Ships. [Online]. Available: https://www.emsa.europa.eu/publications/item/3895-study-on-electrical-energy-storage-for-ships.html
73. Reusser, C. A., & Pérez Osses, J. R. (2021). Challenges for zero-emissions ship. *Journal of Marine Science and Engineering, 9*(10), 1042.

74. Zhou, Z., Benbouzid, M., Charpentier, J. F., Scuiller, F., & Tang, T. (2013). A review of energy storage technologies for marine current energy systems. *Renewable and Sustainable Energy Reviews, 18*, 390–400.
75. Ongaro, F., Saggini, S., & Mattavelli, P. (2012). Li-ion battery-supercapacitor hybrid storage system for a long lifetime, photovoltaic-based wireless sensor network. *IEEE Transactions on Power Electronics, 27*(9), 3944–3952.
76. Chen, W., Ådnanses, A. K., Hansen, J. F., Lindtjørn, J. O., & Tang, T. (2010). Super-capacitors based hybrid converter in marine electric propulsion system. *IEEE*, 1–6.
77. Kopka, R., & Tarczyński, W. (2017). A fractional model of supercapacitors for use in energy storage systems of next-generation shipboard electrical networks. *Journal of Marine Engineering & Technology, 16*(4), 200–208.
78. Stark, C., Xu, Y., Zhang, M., Yuan, Z., Tao, L., & Shi, W. (2022). Study on applicability of energy-saving devices to hydrogen fuel cell-powered ships. *Journal of Marine Science and Engineering, 10*(3), 388.
79. Lázár, M., et al. (2023). A newly proposed method for hydrogen storage in a metal hydride storage tank intended for maritime and inland shipping. *Journal of Marine Science and Engineering, 11*(9), 1643.
80. Taccani, R., Malabotti, S., Dall'Armi, C., & Micheli, D. (2020). High energy density storage of gaseous marine fuels: An innovative concept and its application to a hydrogen powered ferry. *International Shipbuilding Progress, 67*, 29–52.
81. Wu, J., et al. (2008). A review of PEM fuel cell durability: Degradation mechanisms and mitigation strategies. *Journal of Power Sources, 184*(1), 104–119.
82. Pei, P., & Chen, H. (2014). Main factors affecting the lifetime of Proton Exchange Membrane fuel cells in vehicle applications: A review. *Applied Energy, 125*, 60–75.
83. Redondo-Iglesias, E., Venet, P., & Pelissier, S. (2018). Calendar and cycling ageing combination of batteries in electric vehicles. *Microelectronics Reliability, 88*, 1212–1215.
84. Lorenzo, C., Bouquain, D., Hibon, S., & Hissel, D. (2021). Synthesis of degradation mechanisms and of their impacts on degradation rates on proton-exchange membrane fuel cells and lithium-ion nickel–manganese–cobalt batteries in hybrid transport applications. *Reliability Engineering and System Safety, 212*, 107369.
85. Naseri, F., Karimi, S., Farjah, E., & Schaltz, E. (2022). Supercapacitor management system: A comprehensive review of modeling, estimation, balancing, and protection techniques. *Renewable and Sustainable Energy Reviews, 155*, 111913.
86. Shekhawat, M., & Bansal, H. O. (2023). An extensive review on hybrid electric vehicles powered by fuel cell-enabled hybrid energy storage system. *Environmental Science and Pollution Research, 30*(57), 119750–119771.
87. Ragab, A., Marei, M. I., & Mokhtar, M. (2023). Comprehensive study of fuel cell hybrid electric vehicles: Classification, topologies, and control system comparisons. *Applied Sciences, 13*(24), 13057.
88. Wang, B., Najjar, L., Xiong, N. N., & Chen, R. C. (2013). *Stochastic optimization: Theory and applications*. *Hindawi Publishing Corporation*.
89. Tang, X., et al. (2024). Reinforcement learning-based energy management for hybrid power systems: State-of-the-art survey, review, and perspectives. *Chinese Journal of Mechanical Engineering, 37*(1), 43.
90. Walker, J. M., Coraddu, A., Savio, S., & Oneto, L. (2023). Shallow and deep learning models for vessel motions forecasting during adverse weather conditions. *Modelling and Optimisation of Ship Energy Systems, 2023*.
91. Valchev, I., Coraddu, A., Oneto, L., Kalikatzarakis, M., Tiddens, W., & Geertsma, R. D. (2022). 'Artificial Intelligence-based short-term forecasting of vessel performance parameters', Institute of Marine Engineering. *Science and Technology*, 31.
92. Walker, J. M., Coraddu, A., & Oneto, L. (2024). *Power demand forecasting for a hybrid marine energy system with shallow and deep learning* (pp. 1–8). IEEE.

93. Bellman, R., & Kalaba, R. (1957). Dynamic programming and statistical communication theory. *Proceedings of the National Academy of Sciences, 43*(8), 749–751.
94. Powell, W. B. (2007). *Approximate dynamic programming: Solving the curses of dimensionality* (Vol. 703). John Wiley & Sons.
95. Birge, J. R., & Louveaux, F. (2011). *Introduction to stochastic programming*. Springer Science & Business Media.
96. Holland, J. H. (1992). Genetic algorithms. *Scientific American, 267*(1), 66–73.
97. Goldberg, D. E. (1994). Genetic and evolutionary algorithms come of age. *Communications of the ACM, 37*(3), 113–120.
98. Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. *IEEE*, 1942–1948.
99. Wolsey, L. A. (2020). *Integer programming*. John Wiley & Sons.
100. Bertsekas, D. P., Hager, W., & Mangasarian, O. (1999). *Nonlinear programming*. Athena Scientific.
101. Colson, B., Marcotte, P., & Savard, G. (2005). Bilevel programming: A survey. *4or, 3*, 87–107.
102. Deb, K. (2001). Nonlinear goal programming using multi-objective genetic algorithms. *Journal of the Operational Research Society, 52*(3), 291–302.
103. Zhang, T., Li, W., & Wang, R. (2023). Surrogated-assisted multimodal multi-objective optimization for hybrid renewable energy system. *Complex & Intelligent Systems, 9*(4), 4075–4087.
104. Hartley, E. N., & Maciejowski, J. M. (2014). Reconfigurable predictive control for redundantly actuated systems with parameterised input constraints. *Systems and Control Letters, 66*, 8–15.
105. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
106. Aggarwal, C. C. (2018). *Neural networks and deep learning*. Springer.
107. Bishop, C. M., & Bishop, H. (2023). *Deep learning: Foundations and concepts*. Springer Nature.
108. Shalev-Shwartz, S., & Ben-David, S. (2014). *Understanding machine learning: From theory to algorithms*. Cambridge University Press.
109. Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5–32.
110. Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 785–794).
111. Rasmussen, C. E. (2003). *Gaussian processes in machine learning*. Springer.
112. Van Houdt, G., Mosquera, C., & Nápoles, G. (2020). A review on the long short-term memory model. *Artificial Intelligence Review, 53*(8), 5929–5955.
113. Bai, S., Kolter, J. Z., & Koltun, V. (2018). An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. *arXiv preprint arXiv:1803.01271*.
114. Vaswani, A. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*.
115. Tang, X., Zhou, H., Wang, F., Wang, W., & Lin, X. (2022). Longevity-conscious energy management strategy of fuel cell hybrid electric vehicle based on deep reinforcement learning. *Energy, 238*, 121593.
116. Hu, H., Yuan, W.-W., Su, M., & Ou, K. (2023). Optimizing fuel economy and durability of hybrid fuel cell electric vehicles using deep reinforcement learning-based energy management systems. *Energy Conversion and Management, 291*, 117288.
117. Ris-Ala, R. (2023). *Fundamentals of reinforcement learning*. Springer.
118. Wen, Y., Su, Q., Shen, M., & Xiao, N. (2022). Improving the exploration efficiency of DQNs via the confidence bound methods. *Applied Intelligence, 52*(13), 15447–15461.
119. Tokic, M., & Palm, G. (2011). *Value-difference based exploration: Adaptive control between epsilon-greedy and softmax* (pp. 335–346). Springer.
120. Jang, B., Kim, M., Harerimana, G., & Kim, J. W. (2019). Q-learning algorithms: A comprehensive classification and applications. *IEEE Access, 7*, 133653–133667.

121. Kim, J., & Yang, I. (2020). Hamilton-Jacobi-Bellman equations for Q-learning in continuous time. *PMLR*, 739–748.
122. Jha, A. V., Appasani, B., Gupta, D. K., Ramavath, S., & Khan, M. S. (2023). Machine learning and deep learning approaches for energy management in Smart Grid 3.0. In *Smart Grid 3.0: Computational and communication technologies* (pp. 121–151). Springer.
123. Zheng, C., Li, W., Li, W., Xu, K., Peng, L., & Cha, S. W. (2022). A deep reinforcement learning-based energy management strategy for fuel cell hybrid buses. *International Journal of Precision Engineering and Manufacturing-Green Technology, 9*(3), 885–897.
124. Zhang, D., et al. (2024). An improved soft actor-critic-based energy management strategy of fuel cell hybrid vehicles with a nonlinear fuel cell degradation model. *International Journal of Precision Engineering and Manufacturing-Green Technology, 11*(1), 183–202.
125. Guo, X., et al. (2024). Energy management system for hybrid ship: Status and perspectives. *Ocean Engineering, 310*, 118638.
126. Xie, P., et al. (2021). Optimization-based power and energy management system in shipboard microgrid: A review. *IEEE Systems Journal, 16*(1), 578–590.
127. Jaurola, M., Hedin, A., Tikkanen, S., & Huhtala, K. (2019). Optimising design and power management in energy-efficient marine vessel power systems: A literature review. *Journal of Marine Engineering & Technology, 18*(2), 92–101.
128. Ge, Y., Zhang, J., Zhou, K., Zhu, J., & Wang, Y. (2023). Research on energy management for ship hybrid power system based on adaptive equivalent consumption minimization strategy. *Journal of Marine Science and Engineering, 11*(7), 1271.
129. Truong, H. V. A., Do, T. C., & Dang, T. D. (2024). Enhancing efficiency in hybrid marine vessels through a multi-layer optimization energy management system. *Journal of Marine Science and Engineering, 12*(8), 1295.
130. Balsamo, F., Capasso, C., Lauria, D., & Veneri, O. (2020). Optimal design and energy management of hybrid storage systems for marine propulsion applications. *Applied Energy, 278*, 115629.
131. Feng, X., Zainudin, E. B., Tseng, K. J., & Low, K. C. A. (2022). *On maritime electrification–electrification technologies, charging infrastructure and energy management strategies* (p. 012034). IOP Publishing.
132. Hofman, T., Steinbuch, M., Van Druten, R., & Serrarens, A. (2007). Rule-based energy management strategies for hybrid vehicles. *International Journal of Electric and Hybrid Vehicles, 1*(1), 71–94.
133. Hu, X., Zou, C., Tang, X., Liu, T., & Hu, L. (2020). Cost-optimal energy management of hybrid electric vehicles using fuel cell/battery health-aware predictive control. *IEEE Transactions on Power Electronics, 35*(1), 382–392.
134. Lü, X., et al. (2020). Energy management of hybrid electric vehicles: A review of energy optimization of fuel cell hybrid power system based on genetic algorithm. *Energy Conversion and Management, 205*, 112474.
135. Xie, P., Tan, S., Bazmohammadi, N., Guerrero, J. M., & Vasquez, J. C. (2022). A real-time power management strategy for hybrid electrical ships under highly fluctuated propulsion loads. *IEEE Systems Journal, 17*(1).
136. Trovão, J. P. F., & Pereirinha, P. J. G. (2015). Control scheme for hybridised electric vehicles with an online power follower management strategy. *IET Electrical Systems in Transportation, 5*(1), 12–23.
137. Bassam, A. M., Phillips, A. B., Turnock, S. R., & Wilson, P. A. (2016). An improved energy management strategy for a hybrid fuel cell/battery passenger vessel. *International Journal of Hydrogen Energy, 41*(47), 22453–22464. https://doi.org/10.1016/j.ijhydene.2016.08.049
138. Tritschler, P. J., Bacha, S., Rullière, E., & Husson, G. (2010). Energy management strategies for an embedded fuel cell system on agricultural vehicles. In *19th International Conference on Electrical Machines, ICEM 2010*. IEEE.

139. Yang, J., Zhang, T., Hong, J., Zhang, H., Zhao, Q., & Meng, Z. (2021). Research on driving control strategy and Fuzzy logic optimization of a novel mechatronics-electro-hydraulic power coupling electric vehicle. *Energy, 233*, 121221.
140. Sorrentino, M., Rizzo, G., & Arsie, I. (2011). Analysis of a rule-based control strategy for on-board energy management of series hybrid vehicles. *Control Engineering Practice, 19*(12), 1433–1441.
141. Liu, H., Gegov, A., & Cocea, M. (2016). Rule-based systems: A granular computing perspective. *Granular Computing, 1*.
142. Liu, Y., Liu, J., Zhang, Y., Wu, Y., Chen, Z., & Ye, M. (2020). Rule learning based energy management strategy of fuel cell hybrid vehicles considering multi-objective optimization. *Energy, 207*, 118212.
143. Akbulut, O., Cavus, M., Cengiz, M., Allahham, A., Giaouris, D., & Forshaw, M. (2024). Hybrid intelligent control system for adaptive microgrid optimization: Integration of rule-based control and deep learning techniques. *Energies (Basel), 17*(10), 2260.
144. Fayyazi, M., et al. (2023). Artificial intelligence/machine learning in energy management systems, control, and optimization of hydrogen fuel cell vehicles. *Sustainability, 15*(6), 5249.
145. Lee, S., Seon, J., Hwang, B., Kim, S., Sun, Y., & Kim, J. (2024). Recent trends and issues of energy management systems using machine learning. *Energies (Basel), 17*(3), 624.
146. Wolpert, D. H., & Macready, W. G. (1997). No free lunch theorems for optimization. *IEEE Transactions on Evolutionary Computation, 1*(1), 67–82. https://doi.org/10.1109/4235.585893
147. Xie, P., Asgharian, H., Vasquez, J. C., Guerrero, J., Araya, S. S., & Liso, V. (2023). Day-ahead energy management for hybrid electric vessel with different PEM fuel cell modular configurations. In *2022 the 3rd international conference on power, energy and electrical engineering* (Vol. 9, pp. 99–106). https://doi.org/10.1016/j.egyr.2022.12.091
148. Xie, P., Asgharian, H., Guerrero, J. M., Vasquez, J. C., Araya, S. S., & Liso, V. (2024). A two-layer energy management system for a hybrid electrical passenger ship with multi-PEM fuel cell stack. *International Journal of Hydrogen Energy, 50*, 1005–1019. https://doi.org/10.1016/j.ijhydene.2023.09.297
149. Han, J., Charpentier, J.-F., & Tang, T. (2014). An energy management system of a fuel cell/battery hybrid boat. *Energies (Basel), 7*(5), 2799–2820.
150. Rawlings, J. B., Mayne, D. Q., & Diehl, M. (2017). *Model predictive control: Theory, computation, and design* (2nd ed.). Nob Hill Publishing.
151. Peng, X., Chen, H., & Guan, C. (2023). Energy management optimization of fuel cell hybrid ship based on particle swarm optimization algorithm. *Energies (Basel), 16*(3), 1373.
152. Banaei, M., Boudjadar, J., & Khooban, M.-H. (2021). Stochastic model predictive energy management in hybrid emission-free modern maritime vessels. *IEEE Transactions on Industrial Informatics, 17*(8), 5430–5440. https://doi.org/10.1109/TII.2020.3027808
153. Serrao, L., Onori, S., & Rizzoni, G. (2011). A comparative analysis of energy management strategies for hybrid electric vehicles. *Journal of Dynamic Systems, Measurement and Control, Transactions of the ASME, 133*(3).
154. Jung, W., & Chang, D. (2023). Deep reinforcement learning-based energy Management for Liquid Hydrogen-Fueled Hybrid Electric Ship Propulsion System. *Journal of Marine Science and Engineering, 11*(10), 2007. https://doi.org/10.3390/jmse11102007
155. Wu, P., Partridge, J., & Bucknall, R. (2020). Cost-effective reinforcement learning energy management for plug-in hybrid fuel cell and battery ships. *Applied Energy, 275*, 115258.
156. Gan, M., Hou, H., Wu, X., Liu, B., Yang, Y., & Xie, C. (2022). Machine learning algorithm selection for real-time energy management of hybrid energy ship. *Energy Reports, 8*, 1096–1102.
157. Geng, P., Xu, X., & Tarasiuk, T. (2020). State of charge estimation method for Lithium-ion batteries in all-electric ships based on LSTM neural network. *Polish Maritime Research, 27*(3), 100–108. https://doi.org/10.2478/pomr-2020-0051

158. Mazzi, Y., Ben Sassi, H., Errahimi, F., & Es-Sbai, N. (2024). A soft actor-critic reinforcement learning framework for optimal energy management in electric vehicles with hybrid storage. *Journal of Energy Storage, 99*, 113344.
159. Wen, S., Zhang, C., Lan, H., Xu, Y., Tang, Y., & Huang, Y. (2019). A hybrid ensemble model for interval prediction of solar power output in ship onboard power systems. *IEEE Trans Sustain Energy, 12*(1), 14–24.
160. Kalikatzarakis, M., Geertsma, R. D., Boonen, E. J., Visser, K., & Negenborn, R. R. (2018). Ship energy management for hybrid propulsion and power supply with shore charging. *Control Engineering Practice, 76*, 133–154.
161. Zhu, D., Pritchard, E., Dadam, S. R., Kumar, V., & Xu, Y. (2022). Optimization of rule-based energy management strategies for hybrid vehicles using dynamic programming. *Combustion Engines, 184*(1), 3–10.
162. Fares, D., Chedid, R., Panik, F., Karaki, S., & Jabr, R. (2015). Dynamic programming technique for optimizing fuel cell hybrid vehicles. *International Journal of Hydrogen Energy, 40*(24), 7777–7790.
163. Song, K., Wang, X., Li, F., Sorrentino, M., & Zheng, B. (2020). Pontryagin's minimum principle-based real-time energy management strategy for fuel cell hybrid electric vehicle considering both fuel economy and power source durability. *Energy, 205*, 118064.
164. Jafarzadeh, S., & Schjølberg, I. (2018). Operational profiles of ships in Norwegian waters: An activity-based approach to assess the benefits of hybrid and electric propulsion. *Transp Res D Transp Environ, 65*, 500–523.