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A state-of-the-art review and analysis of battery system technologies for maritime electrification☆,☆☆

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HIGHLIGHTS

- Reviews battery technologies and their suitability for electric and hybrid marine vessels.
- Presents AI strategies and case studies, with their comparison, and considers digital twin applications.
- Covers international standards, guidelines, funded projects, software tools, and industry white papers.
- Describes the relevant UN SDGs in battery systems and marine electrification.
- Identifies key technical challenges and future research directions for safe, scalable electrification.

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ABSTRACT

The maritime industry is among the key players in global trade, transporting the largest portion of the world's goods. It connects economies, supports millions of jobs, and enables the movement of raw materials, energy resources, and manufactured products efficiently across continents. However, this industry is also a major source of greenhouse gas emissions. Considering these emissions, this industry is undergoing a transition to maritime electrification with net-zero emissions. In order to achieve that goal, batteries are the main tool, including the development of fully electric and hybrid vessels. To this end, this paper provides a structured overview of battery systems in marine electrification, covering various aspects of this rapidly evolving field. It presents an analysis of different ship types and the power topologies of electric and hybrid vessels, supported by updated examples of real-world commercialized and produced vessels across different regions. Additionally, the evolution of battery technology is demonstrated by detailing both commercialized and early-stage batteries, with a focus on their power rating, energy density, specific energy, cycle life, and management systems. Furthermore, the applications of Artificial Intelligence (AI) and digital twin technologies in marine electrification are presented with a detailed review of recent developments. The Artificial Intelligence (AI) strategies are classified into several categories, and a case study from a representative strategy of each class in battery and marine electrification is presented. It also includes guidelines and standards issued by official organizations to ensure compliance and safety in the sector. Additionally, it highlights recently completed and ongoing funded projects in marine electrification in the U.S.

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and the EU, as well as the related software tools and industry white papers. Moreover, the correlation between battery systems and marine electrification is provided with the United Nation (UN) Sustainable Development Goals (SDGs) and which SDGs they are effective and aligned. Finally, the updated challenges and future research directions are presented for a forward-looking perspective on the marine electrification sector and its transition to a net-zero industry.

Nomenclature

Abbreviations

AC Alternating Current
ACO Ant Colony Optimization
AI Artificial Intelligence
AK Alaska
ANFIS Adaptive Neuro-Fuzzy Inference System
BESS Battery Energy Storage System
BiLSTM Bidirectional Long Short-Term Memory
BMU Battery Monitoring Unit
BMS Battery Management System
CA California
CAGR Compound Annual Growth Rat
CAN Controller Area Network
CNN Convolutional Neural Network
DC Direct Current
DE Differential Evolution
DL Deep Learning
DNV GL Det Norske Veritas Germanischer Lloyd
DoE Department of Energy
DoT Department of Transportation
DP Dynamic Programming
DRL Deep Reinforcement Learning
ED Economic Dispatch
ECS Energy Conversion System
EMSA European Maritime Safety Agency
EMS Energy Management System
ESS Energy Storage System
FC Fuel Cell
FFNN Feed-Forward Neural Network
FLC Fuzzy Logic Control
FTA Federal Transit Administration
GA Genetic Algorithm
GAI Generative Artificial Intelligence
GANs Generative Adversarial Networks
GPS Global Positioning System
HFC Hydrogen Fuel Cell
HSC High-Speed Craft
HV High-Voltage
HVAC Heating, Ventilation, and Air Conditioning
IEC International Electrotechnical Commission
IMO International Maritime Organization
ISO International Organization for Standardization
KPI Key Performance Indicator
KNN K-Nearest Neighbors
LCA Life Cycle Assessment
LFP Lithium Iron Phosphate
Li-ion Lithium-ion
Li–S Lithium–Sulfur
LiB Lithium-ion Battery
LLM Large Language Model
LP Linear Programming
LSTM Long Short-Term Memory
LTO Lithium Titanate Oxide
MBMS Master Battery Management System
ME Main Engine
Metal-air Li-Air, Zn-Air, Al-Air, Na-Air
MILP Mixed-Integer Linear Programming
ML Machine Learning
MPC Model Predictive Control
NaNiCl Sodium–Nickel Chloride/ZEBRA
NaS Sodium–Sulfur
NiCd Nickel–Cadmium
NiMH Nickel–Metal Hydride
NMC Nickel Manganese Cobalt
NN Neural Network
O.F Objective Function
OEM Original Equipment Manufacturer
OPF Optimal Power Flow
Pb-acid Lead–Acid
PCS Power Conversion System
PMS Power Management System
PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO Particle Swarm Optimization
RBC Rule-Based Control
RL Reinforcement Learning
RNN Recurrent Neural Network
RORO Roll-On/Roll-Off
RS485 Recommended Standard 485
RUL Remaining Useful Life
SA Simulated Annealing
SC Supercapacitor
SDG Sustainable Development Goals
SL Supervised Learning
SoC State of Charge
SoE State of Energy
SoH State of Health
SoP State of Power
SoT State of Temperature
SSB Solid-State Battery
SSL Semi-Supervised Learning
TMS Thermal Management System
TS Tabu Search
UL Unsupervised Learning
UN United Nations
VRB Vanadium Redox Flow
WA Washington
XAI Explainable Artificial Intelligence
ZBR Zinc–Bromine
Zn-ion Zinc-ion

Parameters and Variables

c_{deg} Degradation cost [-]
c_e Electricity price [-]
$\dot{D}$ Aging rate [-]
D_{voy} Required voyage distance [m]
Δt Discrete time interval [s]
E_{bat} Battery capacity [Wh]

E_{ch}	Charged energy [Wh]
EF_{grid}	Grid emission factor [-]
η_{bat}	Battery efficiency [-]
η_{ch}	Charging efficiency [-]
f_{deg}	Battery degradation model [-]
γ_{gen}	Emission factor of onboard generation [-]
γ_{grid}	Emission factor of grid electricity [-]
k	Hull and propeller constant [-]
P_{aux}	Auxiliary load [W]
P_{aux}^{min}	Minimum auxiliary load [W]
P_{bat}	Battery power [W]
P_{bat}^{max}	Battery power limit [W]
P_{bat}^{min}	Minimum battery power limit [W]
P_{ch}	Shore-side charging power [W]
P_{ch}^{max}	Maximum charger power rating [W]
P_{dem}	Demanded power [W]
P_{gen}	Onboard generation power [W]
P_{loss}	Inverter and motor losses [W]
P_{mot}^{max}	Motor power rating [W]
P_{prop}	Propulsion power [W]
dP_{bat}/dt	Power ramp rate [W/s]
r_{bat}	Maximum battery ramp rate [W/s]
SoCend	Minimum final state of charge [-]
SoCmax	Maximum state of charge [-]
SoCmid	Mid-range state of charge [-]
SoCmin	Minimum state of charge [-]
SoCref	Target state of charge [-]
T	EMS horizon [s]
Tbat	Battery temperature [K]
T_{bat}^{max}	Maximum battery temperature [K]
$\mathcal{T}$port	Port charging intervals [-]
v	Vessel speed [m/s]
$v$max	Maximum vessel speed [m/s]
v_{ref}	Reference speed [m/s]
w_{deg}	Weight for battery degradation objective [-]
w_E	Weight for energy consumption objective [-]
w_{em}	Weight for emissions objective [-]

1. Introduction

Maritime transportation is a cornerstone of the global economy, facilitating the transfer of goods across continents and connecting markets worldwide. It handles the largest portion of international trade by volume [1], transporting every type of goods from raw materials, such as oil and coal, to manufactured products, including electronics and automobiles. Its cost-effectiveness and ability to carry large cargo volumes over long distances make it indispensable for industries reliant on global supply chains [2,3]. Following its importance and responsibility for a large portion of global trade, the maritime industry is one of the largest greenhouse gas emitters. In response to global climate concerns, several official programs and targets have been prepared [4]. One of these targets relates to the International Maritime Organization (IMO) (Fig. 1), which has introduced tougher emissions regulations, aiming to reduce emissions from international shipping, targeting 20–30% reductions by 2030 and 70–80% reductions by 2040, both compared to 2008 levels, to achieve net-zero greenhouse gas emissions by 2050 [5,6]. These kinds of regulations necessitate the maritime industry to undergo a transition to a fully renewable and net-zero industry. To achieve this transition, one primary strategy is to change and develop the current vessels to fully electric and hybrid alternatives [7]. In this goal, batteries and Battery Energy Storage System (BESS) are important components in the operation of hybrid and fully electric vessels, enabling the maritime industry to reduce emissions and transition toward sustainable operations [8,9]. In hybrid vessels, BESS integrates with traditional fuel systems to optimize energy use, reduce fuel consumption, and lower greenhouse gas emissions by powering auxiliary systems or enabling emission-free operation in sensitive areas such as ports. For fully electric vessels, high-capacity batteries supply the primary propulsion energy, fully reducing fossil fuel use and enabling zero-emission voyages, particularly for short-sea shipping and ferries. Consequently, most countries are investing considerable amounts in batteries and their applications in the maritime industry. For instance, recent progress in battery technology has been driven by the U.S. Department of Energy (DoE) Battery500 and PROPEL-1 K initiatives, which focus on enhancing battery energy density [6]. In the E.U. several large funding initiatives have been conducted to support maritime electrification [10]. Fig. 2 shows the Energy Storage System (ESS), and BESS global market in the maritime industry, containing the Lithium-ion Battery (LiB), Fuel Cell (FC), and lead acid. Based on the report by Global Marine Battery Market Size [11], the marine battery market is undergoing a transition from traditional lead-acid batteries to advanced LiBs, which dominate with a 44.1% share due to their superior energy density, longer life cycles, and faster charging capabilities. This transition is driving the market's projected growth from US$ 701.2

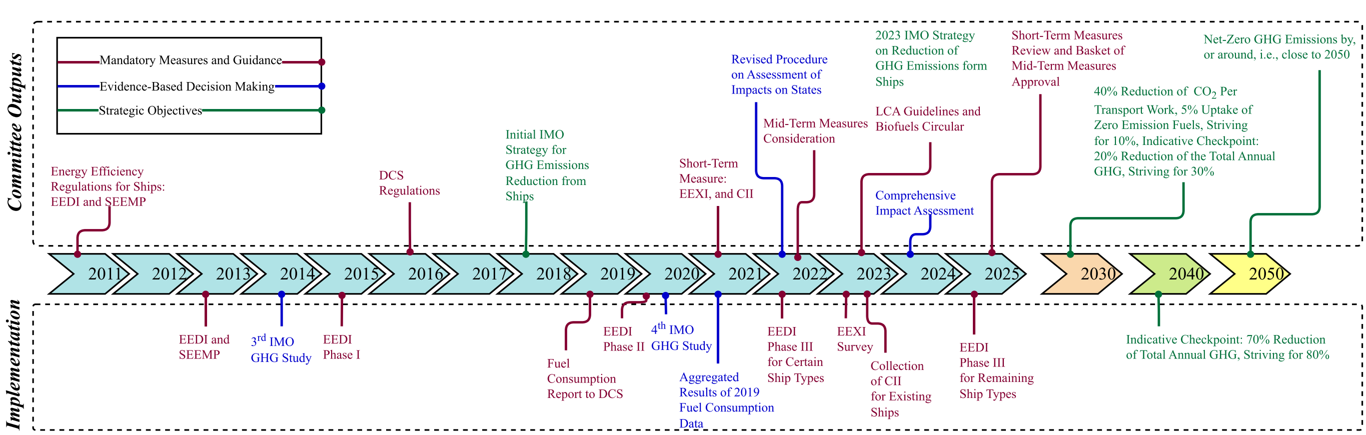

Fig. 1. Updated timeline of the related regulatory actions by IMO, based on the data from [12–14].

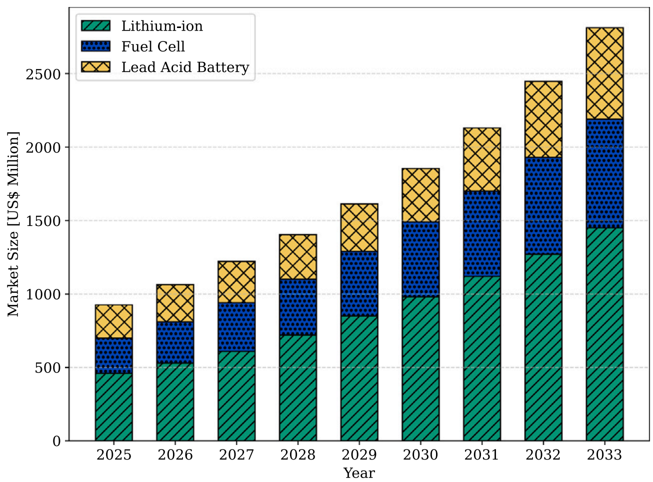

Fig. 2. Energy and battery storage technologies global market in the maritime industry, based on the data from [11].

million in 2023 to US$ 2812.2 million by 2033, at a Compound Annual Growth Rate (CAGR) of 14.9%.

Solid-State Battery (SSB), holding a commanding 63.2% market share, is expected to further develop the industry with its enhanced safety and efficiency, with commercialization anticipated by 2030. The 100–250 Ah capacity segment (48.1% share), 100–500 [Wh/Kg] energy density range (64.3% share), and 150–745 [kW] power output segment (39.1% share) lead their respective categories, while the commercial sector (52.1% share) and Original Equipment Manufacturer (OEM) distribution channel (67.1% share) continue to dominate, manifesting the fact that the market's focus is on advanced technologies and robust supply chains with reduced emissions.

Additionally, the importance of this transition is evident in the conducted research and publications, as the related statistics are shown in Fig. 3, based on the data in Scopus. The results manifest the increasing interest in research on marine electrification and electric ships over the last ten years.

1.1. Literature review

A review is conducted in [15] focusing on decarbonizing cargo ships and offshore oil and gas platforms through two main approaches: 1) transitioning to clean energy sources, and 2) implementing carbon capture technologies. Notable advancements include the use of wind turbines paired with emerging battery technologies for offshore projects, while wave, solar, and tidal energies remain in research phases. CO_2 storage in offshore saline aquifers is highlighted as a cost-effective and environmentally viable option. The review conducted by Wang et al. [16] provides an overview of the progress and challenges in maritime electrification, driven by global decarbonization goals and

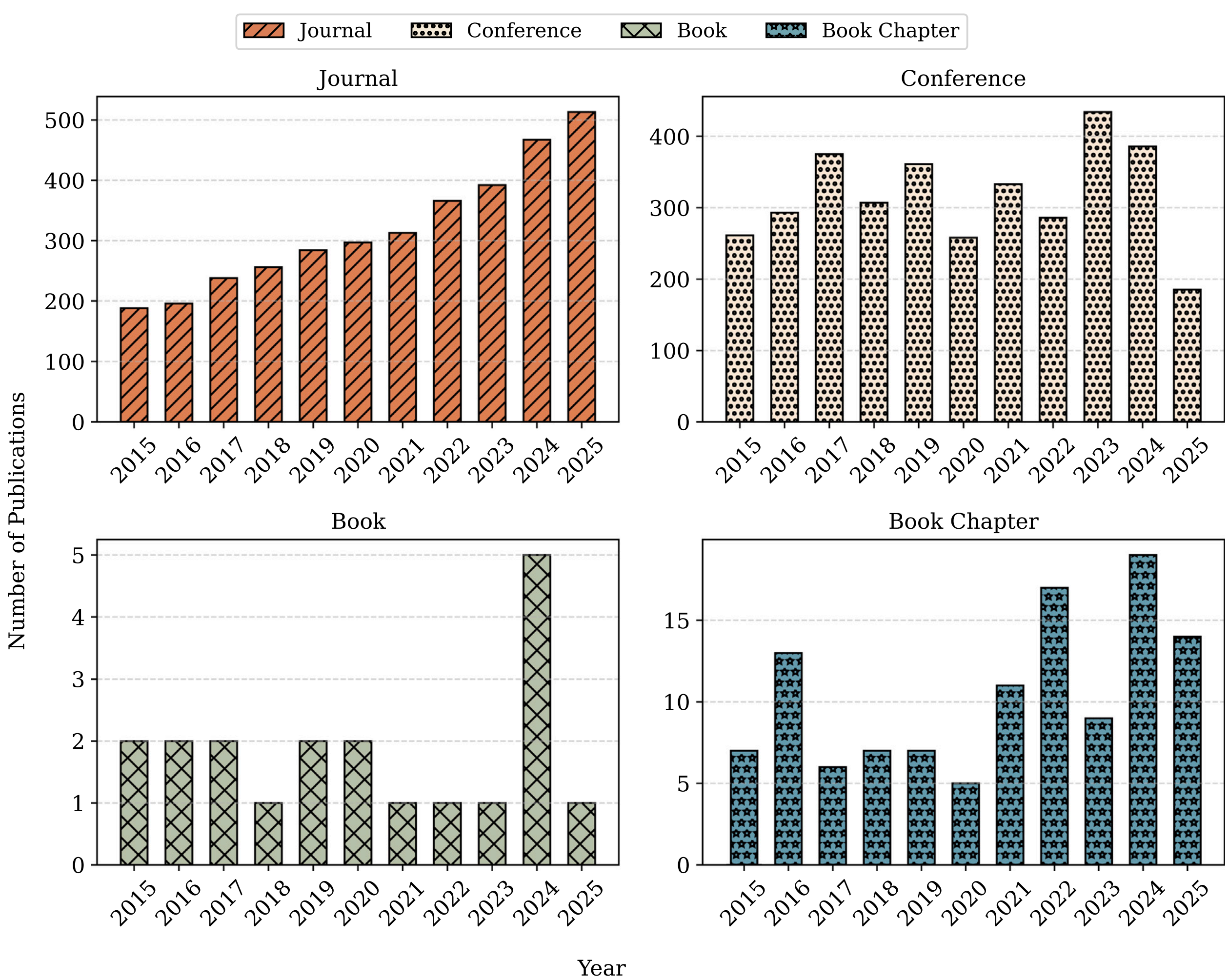

Fig. 3. Publication statistics in maritime electrification: Several publication types including journal, conference, books, and book chapters, are considered, and the related data is gathered from Scopus over the last decade (2015–2025).

stringent IMO regulations. It considered three main ship electrification pathways: (1) battery-electric ships, (2) hybrid-electric ships, and (3) FC electric ones, assessing their technological maturity, economic viability, environmental impact, and regional deployment potential. Additionally, the review [17] discussed the transition toward electrification in transportation, driven by rising greenhouse gas emissions and the depletion of fossil fuels. While land-based transport has seen electrification progress driven by advancements in battery technology and power electronics, attention is now turning to the maritime sector, which accounts for a large portion of global carbon emissions. Consequently, Zahedi and Norum [18] reviewed modeling and simulation techniques for Direct Current (DC) hybrid power systems in low-emission, fuel-efficient vessels. These systems, while advantageous, are complex and require robust analysis tools to optimize their benefits. The review covered modeling of hybrid electric ship components, including mechanical and electrical elements, with power electronic converters modeled using nonlinear averaging methods for system-level studies. Hybrid propulsion technologies are reviewed in [19] as a central solution for reducing emissions and enhancing energy efficiency in the maritime industry. By integrating diesel engines, batteries, and FCs with optimized energy management, hybrid systems lower fossil fuel use and emissions, supporting decarbonization goals and reducing operating costs. Therefore, the role of electric and hybrid marine vessels is reviewed by Aksöz et al. [4], in advancing eco-friendly maritime transport by combining electric and traditional propulsion to enhance efficiency and reduce emissions. This review demonstrated how advancements in charging infrastructure and stringent regulations support sustainable and cost-effective shipping. It also analyzed Energy Management System (EMS), Battery Management System (BMS), and advancements in lithium-based and alternative battery technologies. Commercially available battery technologies are presented in [20], based on their technical and economic characteristics, strengths, and weaknesses, to assess their suitability for marine applications. The review also presented battery technologies already implemented in marine vessels, explored emerging technologies with potential for future marine use, and outlined relevant standards and regulations for battery installation in maritime applications.

The review by Lucà Trombetta et al. [21] provides an overview of the role of large-scale BESS in enabling fully electric and hybrid vessels to meet emission reduction mandates from IMO. Additionally, Kolodziejski and Michalska-Pozoga [22] reviewed recent research on electrification and hybridization, covering various aspects of marine BESS applications, including peak shaving, load leveling, spinning reserve, and load response. Different types of ESS and BMS used in hybrid propulsion vessels are also taken into account. Following this, the challenges of designing zero-emission, battery-driven, high-speed marine vehicles are reviewed by Papanikolaou [23], focusing on maximizing battery capacity and minimizing power requirements to meet high-speed and range demands while keeping structural and lightship weight low. Moreover, the environmental and economic benefits of electrifying marine surface vessels are considered by Chin et al. [24], highlighting reductions in CO_2, NOx, and SOx emissions while lowering fuel and maintenance costs compared to diesel-based propulsion. This has resulted in power systems providing reliable, clean, and dispatchable energy for the marine and offshore industry. Consequently, Mao et al. [8] reviewed all-electric and hybrid systems across ship types such as ferries, container ships, and offshore support vessels, addressing challenges such as battery capacity, economic feasibility, and safety. Innovations in lithium-ion, solid-state, and hybrid battery technologies are described, as well as their integration with renewable energy sources like hydrogen, solar, and wind to reduce carbon emissions. In addition, Haxhiu et al. [25] provide an overview of possible integration schemes for fuel cell- and battery-fed vessels, supported by a comparative assessment and a review of power conditioning stages available in the market. Finally, Karimi et al. [26] reviewed shore-to-ship high-power charging systems for marine vessels, covering recent technologies, control methods, and associated challenges. It presented the battery charging pathway, including key components of power electronics converters, transformers, passive elements, plugs, interconnectors, and the charging EMS. Additionally, Alternating Current (AC), DC, and wireless charging solutions are considered, assessing their applicability. It also introduced recent commercial shore-to-ship interfaces for charging and provided a generic overview of essential control functions for shore-based charging. The summary of the presented literature review, in this paper, is provided in Table 1.

1.2. Literature analytics methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) strategy is used in this overview to collect, filter, and analyze the literature from scientific databases. This review strategy is a structured framework for conducting and reporting systematic literature reviews to enhance transparency, reproducibility, and methodological rigor in research synthesis [27]. The proposed review strategy, as well as the review phases, are shown in Fig. 4.

It starts with keyword selection, the marine electrification keywords, and the AI application in marine electrification are identified, and Boolean operators are used to create an effective search strategy for the review scope/purpose. This is followed by identifying the databases, which involves selecting the related electronic sources,

Table 1
Literature review Summary.

Ref.	Power Topology	Battery Technology	Management Systems	AI Integration	Digital Twin	Guides/ Standards	Funded Projects	Software	Industry White Papers
[15]	✗	✓	✗	✗	✗	✗	~	✗	✗
[16]	✓	✓	✓	✓	✓	✗	✗	✗	✗
[17]	✓	✓	✓	✗	✗	✓	✗	✗	✗
[18]	✓	✗	✗	✗	✗	✗	✗	✗	✗
[19]	✓	✗	✗	~	~	✗	✗	✗	✗
[4]	✓	✓	✗	✓	✗	✗	~	✗	✗
[20]	✗	✓	✗	✗	✗	✓	✗	✗	✗
[21]	✓	✓	✓	✗	✗	✓	✗	✗	✗
[22]	✓	✓	✗	✗	✗	~	✗	✗	✗
[23]	✗	~	✗	✗	✗	✗	✗	✗	✗
[24]	~	✓	✓	✗	✗	✗	✗	✗	✗
[8]	✗	✓	✗	✗	✗	✗	✗	✗	✗
[25]	✓	✗	✓	✗	✗	✗	✗	✗	✗
[26]	✓	✗	✗	✗	✗	✗	✗	✗	✗
Proposed	✓	✓	✓	✓	✓	✓	✓	✓	✓

~: Mentioned a few times, not analyzed in depth.

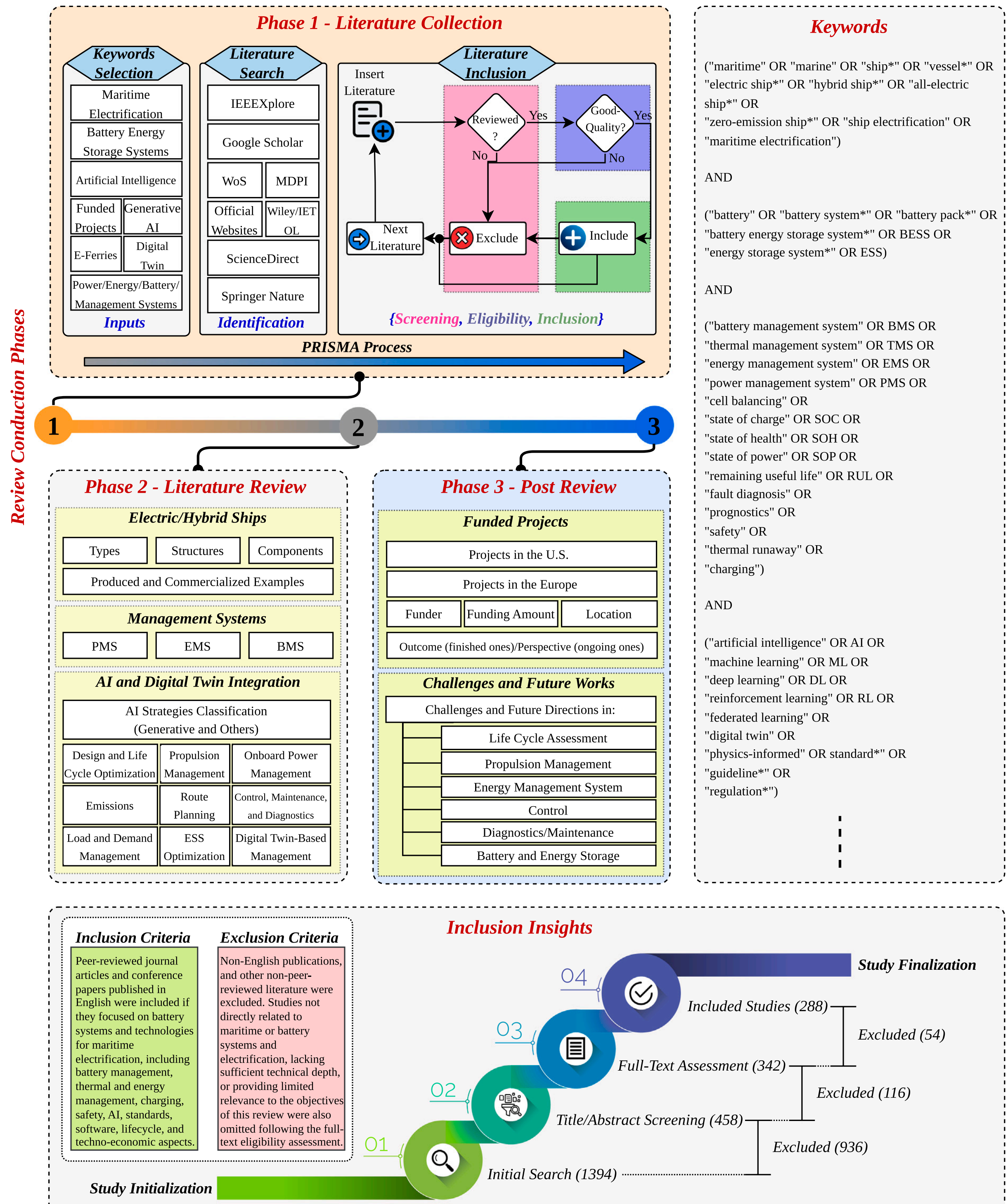

Fig. 4. Literature search and analytics done in this paper: Phase 1 is the literature collection and inclusion by PRISMA. Phases 2 and 3 are the literature review and analytics, followed by post-review insights, respectively.

including IEEEXplore, and ScienceDirect. Collecting the initial references entails executing the searches across these databases to collect the initial works within the scope of the review. The screening stage then reviews titles and abstracts of these records against predefined inclusion and exclusion criteria to exclude the literature with the least correlation. In the next step, the eligibility phase assesses the full-text versions of the remaining literature for detailed compliance with the criteria, excluding those that fail to meet standards and documenting reasons for exclusion. Finally, the inclusion stage incorporates the qualifying studies into the review for data extraction, quality appraisal, and synthesis [28]. Following this strategy, the network map data of the proposed review is shown in Fig. 5.

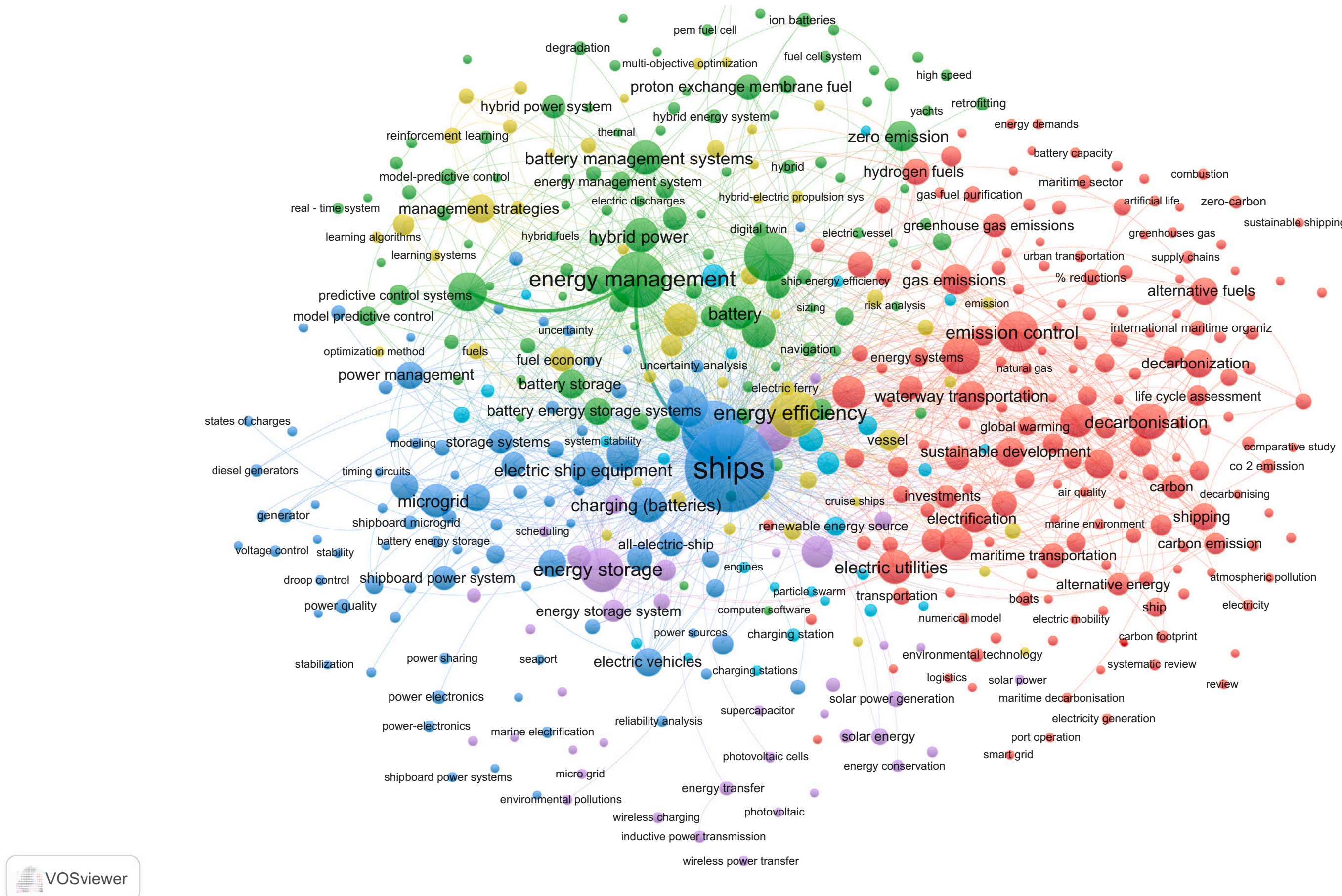

Fig. 5. Network map data of the review, generated by VOSviewer.

1.3. Gaps and contributions

Based on Table 1, although a wide range of reviews have been conducted on marine electrification, none of them have entirely investigated the aspects of marine electrification. It's seen that power topologies and battery technologies are the most covered aspects. Conversely, AI and digital twin integration are the least investigated sections with few works partially describing them. Management systems (Power Management System (PMS), EMS, BMS) are mostly represented. Additionally, guidelines/standards, and funded projects are the least investigated sections which are considerably important to monitor and check the progress being made on maritime electrification. Consequently, there is a gap for a review that considers all these sections in detail and provides the related investigations. To address this, the proposed review aims to fill this gap comprehensively by integrating all seven sections, demonstrating a holistic framework that combines technical innovation, AI/digital twin technology, guidelines/standards, and recently closed/ongoing funded projects, addressing the fragmented focus observed in prior research. The contributions of this review are as follows:

1. Systematically categorizes vessel types and propulsion topologies for electric and hybrid ships, complemented by updated real-world deployment examples across multiple regions,
2. Evaluates the evolution of battery technologies, encompassing both commercial and emerging chemistries, and compares their power density, energy density, specific energy, cycle life, and management requirements in relation to marine operational constraints,
3. Presents recent developments in AI and digital twin integration, highlighting their roles in propulsion management, energy optimization, and predictive maintenance for marine systems,
4. Classifies AI strategies and provides a case study for each representative strategy of those classes in batteries and marine electrification,
5. Reviews and contextualizes relevant international standards and guidelines governing marine battery deployment,
6. Summarizes major completed and ongoing funded initiatives in the U.S. and EU, illustrating current technological priorities and funding trends in maritime electrification,
7. Presents some guidelines, software tools, and industry white papers in marine electrification,
8. Explains and identifies the correlation of battery systems and maritime electrification with United Nation (UN) Sustainable Development Goals (SDGs)
9. Identifies key technical challenges and outlines forward-looking research directions to support scalable and safe maritime electrification.

The paper is structured as follows:

Hybrid/electric ships, their types, structures, and interaction with the seaport microgrid are presented in Section 2. Section 3 describes the battery technologies, their details, and suitability for marine electrification, EMS/PMS, and BMS are considered in Sections 4 and 5. AI, and digital twin integration, guidelines/standards, and recently closed/ongoing funded projects, as well as software tools and industry white papers, are considered in Sections 6 and 7, respectively. Finally, UN

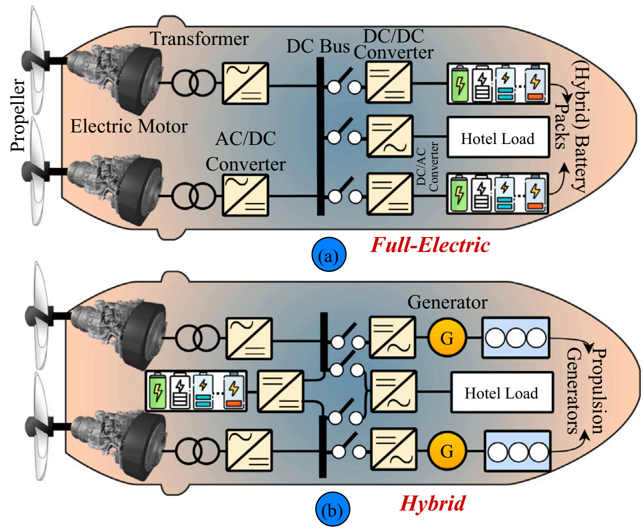

Fig. 6. Power topology of (a) fully electric vessels and (b) hybrid vessels [32].

SDGs, challenges, future research directions, and conclusions are drawn in Sections 8 to 10.

2. Hybrid/Electric ships: structures, types, examples, and seaport interaction

Hybrid and electric ships are a transition in the maritime industry, being developed to reduce environmental impact and enhance system performance [29,30]. These vessels combine traditional combustion engines with electric propulsion systems or rely entirely on Battery/Supercapacitor (SC)/FC-powered electric motors [31]. However, the batteries (especially Lithium-ion Batteries (LiBs)) are the dominant technology that is used in maritime electrification rather than the other ESS alternatives (including SCs, or FCs) [4].

2.1. Structures

The structure and power topology of the fully electric and hybrid ships are shown in Fig. 6.

In the full electric vessel power topology (see Fig. 6 (a)), the system relies entirely on (hybrid) battery packs as the primary energy source. The hybrid battery packs are types of battery packs that include batteries with different technologies. The reason for using hybrid battery packs is that they include different battery technologies that can result in both high-power and high-energy characteristics, which increases the BESS performance, and improves operation [33]. It should be noted that these different battery technologies are thoroughly investigated in the next section (Section 3). Returning to the topology in Fig. 6 (a), power flows from the battery packs through a DC/DC converter to a central DC bus, which is the main distribution point. From the DC bus, electricity is directed to the propulsion system via an AC/DC converter connected to a transformer that steps up or conditions the voltage for the electric motor, which drives the propeller. Additionally, the hotel load, containing non-propulsion electrical needs, such as lighting and Heating, Ventilation, and Air Conditioning (HVAC), is supplied from the DC bus through a DC/AC converter to provide alternating current as required. In the hybrid vessel power topology (Fig. 6 (b)), the system combines multiple generators (G) to supply power for both propulsion and auxiliary needs. For propulsion, the generators, as well as the BESS, are available to supply the system, enabling a combination of mechanical and electrical power delivery to the drive system. As this review focuses on battery-based maritime electrification, the other ESS-based topologies are not considered. For more details about the other ESS-based topologies, they are presented in [25,34–38]. Additionally, based on the vessel purpose and the system efficiency, the converter topologies in hybrid/electric ships can be modified, as different converter topologies are presented in [29,39,40].

2.2. Types and examples

Marine vessels are categorized by their purpose, design, and function, in which each type is designed for specific conditions, cargoes, or missions, with differences in size, propulsion, and technology [21]. Fig. 7 illustrates the overview of various ship types, including High-Speed Craft (HSC) vessels, fishing vessels, tugboats, yachts, cruise ships, offshore supply vessels, DC class offshore vessels, crane vessels, Roll-On/Roll-Off (RORO)/cargo vessels, and shuttle tanker vessels, each with specific power ranges, service applications, and battery system specifications (Nickel Manganese Cobalt (NMC), Lithium Iron Phosphate (LFP), Lithium Titanate Oxide (LTO) technologies with varying power, energy, and cycle ratings). Each vessel type has its operational purpose—such as rapid passenger transport for HSC vessels or heavy lifting for crane vessels—while highlighting power dependencies and technological adaptability. It's comprehended that higher power ranges align with complex offshore tasks, whereas lower ranges are better for specialized, localized functions, manifesting a strategic design alignment with energy demands and operational scope across the maritime industry. Following these different vessels, several commercialized and developed vessels are shown in Fig. 8, considering their power, battery technology, as well as the producer country.

2.3. Interaction with port microgrid

A typical topology of a seaport microgrid is shown in Fig. 9, which is linked to the main power grid and incorporates various renewable energy sources [55,56].

When ships dock, the seaport provides cold-ironing (on-shore power supply) and berth allocation services. The port's central control system manages both energy and logistical operations, sending control signals to each subsystem within the seaport. A seaport microgrid is essentially a seaport that uses microgrid technologies to enhance its operational efficiency. While it shares similarities with land-based microgrids, there are notable distinctions. Seaport microgrids feature comparable components, such as distributed generators, ESS/BESS, and load demand controls, which can operate in both grid-connected and islanded modes. Consequently, their control and operational frameworks may share some commonalities. However, as shown in Fig. 9, the topology of a seaport microgrid is dynamic due to the frequent arrival and departure of ships. Moreover, seaport microgrids include both electrical subsystems and logistical subsystems, including berth allocation, port crane scheduling, and cargo transport. This dual functionality makes seaport microgrids significantly more complex than traditional land-based microgrids. Therefore, specific adaptations are necessary before applying conventional land-based microgrid control and operation strategies to seaport microgrids [57]. Following this importance, seaport microgrids are among the essential factors for marine electrification, as one of their main responsibilities is to charge fully electric/hybrid ships, besides managing logistics. Considering the charging infrastructure, a smart high-power charging network and control system is presented in [58] developed for cold ironing, capable of delivering diverse power types (AC/DC, 50/60 Hz, single/three-phase, 3/4/5-wire configurations, and various voltages). Additionally, the challenges of high-power battery charging are addressed by Guidi et al. [59], for electric ferries, which operate on tight schedules with limited docking times. It highlights inductive wireless power transfer as a solution, enabling safe, fully automated charging and efficient use of docking time. Despite the public transportation systems of buses and trams, marine applications require significantly higher power levels, in the range of 1–2 [MW] per charging unit. The work [59] outlines the technical challenges of designing such

Fig. 7. Different vessel categorizations, including their power range, power service, BESS details, and applications.

high-power inductive charging systems for marine environments and describes a proposed solution. Its concept, integrated into a zero-emission ferry, has been tested in a full-scale laboratory setting and is being implemented for real-world testing on the Norwegian plug-in hybrid ferry MS Folgefonn, used for industrial demonstration projects.

3. Battery technology evolution

Batteries are among the important components in marine electrification, enabling the transition from fossil fuel-powered vessels to cleaner, more sustainable electric alternatives [60]. They power electric

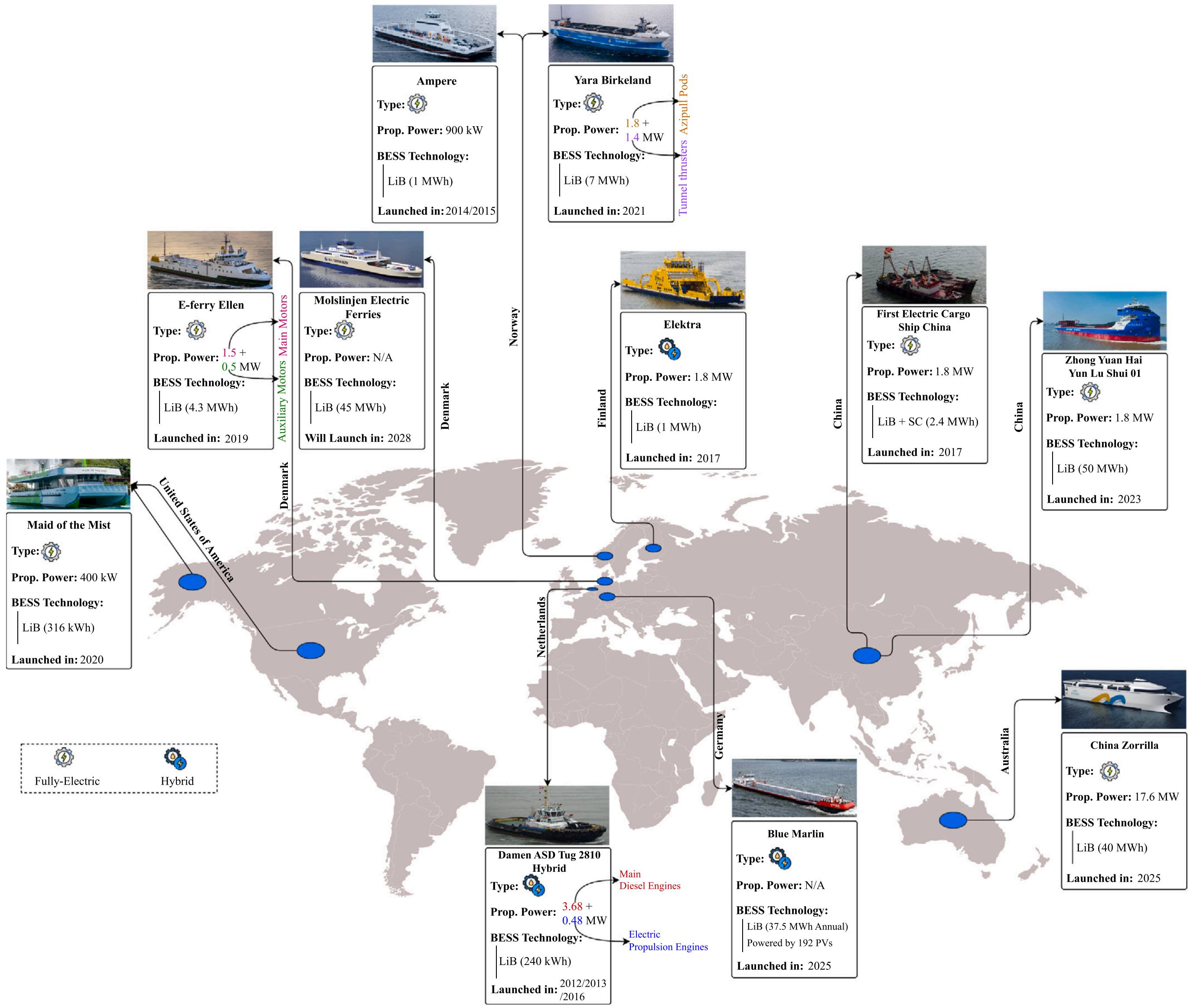

Fig. 8. Examples of commercialized and produced electric/hybrid ships in different countries, including Maid of the Mist (U.S.) [41,42], E-ferry Ellen (Denmark) [43], Molslinjen electric ferries (Denmark) [44,45], Ampere (Norway) [46,47], Yara Birkeland (Norway) [48], Elektra (Finland) [49], the first electric cargo ship in China (China)[50], Zhong Yuan HaiYun Lu Shui 01 (China) [51], China Zorrilla (Australia) [52], Blue Marlin (Germany) [53], and Damen ASD Tug 2810 hybrid (Netherlands) [54].

propulsion systems, reducing greenhouse gas emissions and minimizing environmental impact in marine ecosystems [61,62]. To this end, an outlook is presented on battery technologies and their suitability for marine electrification applications. Fig. 11 illustrates the various batteries (both commercial and emerging) in terms of their power rating, energy density, specific energy, and cycle life [63]. Lead–acid (Pb-acid) batteries, which are traditional rechargeable batteries using lead plates and sulfuric acid electrolyte, have a power rating range of 0 to 20 [MW], specific energy of 20 to 50 Wh/kg, energy density of 50 to 90 [Wh/L], and cycle life of 500 to 1800 cycles. In comparison, Nickel–cadmium (NiCd), robust rechargeable cells with nickel oxide hydroxide and cadmium electrodes, despite environmental concerns over cadmium toxicity, have a broader power rating of 0 to 40 [MW], and lower specific energy at 50 to 75 [Wh/kg] and higher energy density spanning 15 to 150 [Wh/L], with superior cycle life from 2000 to 3500 cycles. Nickel–metal hydride (NiMH), an eco-friendlier alternative to NiCd using a hydrogen-absorbing alloy for the negative electrode, has a lower power rating of 0.01 to 1 [MW], whereas it is higher in energy density at 190 to 490 [Wh/L], with specific energy of 50 to 120 [Wh/kg] and cycle life of 180 to 3000 cycles. Sodium–sulfur (NaS) batteries, high-temperature molten salt systems with sodium and sulfur electrodes separated by a ceramic electrolyte, have power ratings from 0.5 to 10 [MW], specific energy of 200 to 250 [Wh/kg], energy density of 150 to 300 [Wh/L], and cycle life of 2500 to 4500 cycles. Similarly, Sodium–nickel chloride/ZEBRA (NaNiCl) batteries operate at high temperatures with molten sodium and nickel chloride, featuring power ratings of 0 to 1 [MW], specific energy of 100 to 120 [Wh/kg], energy density of 150 to 280 [Wh/L], and a matching cycle life of 2500 to 4500 cycles. LiBs, the most used rechargeable technology with lithium compounds in electrodes and organic electrolytes have a wide power rating of 0.1 to 100 [MW], specific energy of 100 to 265 [Wh/kg], energy density of 200 to 500 [Wh/L], and cycle life from 500 to 14,000 cycles depending on chemistry and usage. Vanadium Redox Flow (VRB) systems, scalable BESSs using vanadium electrolytes in separate tanks for decoupling power and energy

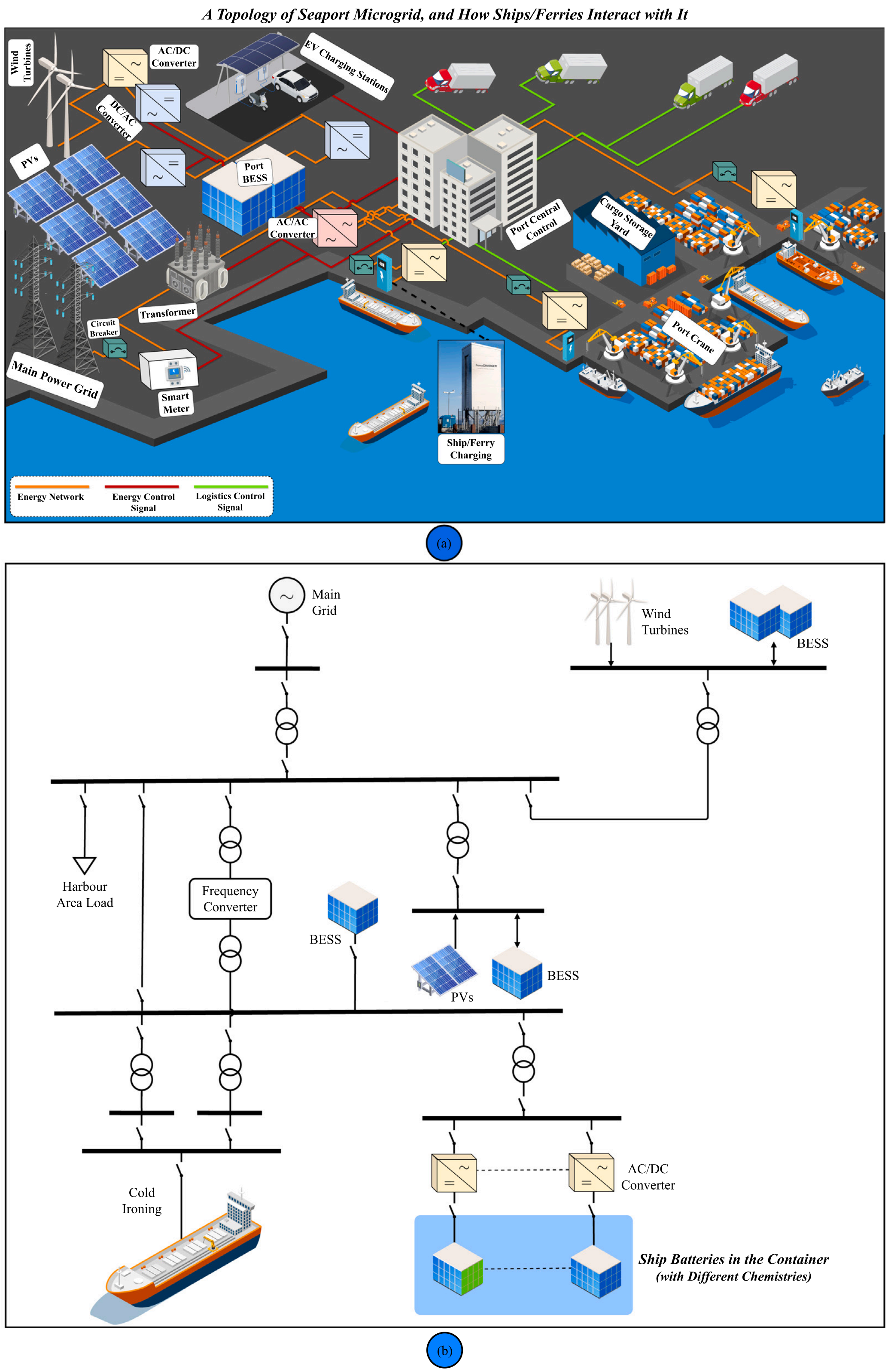

Fig. 9. Topology of a typical seaport microgrid: (a) typical seaport, and (b) example power topology.

capacity, have power ratings of 0.3 to 50 [MW], with lower specific energy at 10 to 50 [Wh/kg] and energy density of 16 to 33 [Wh/L], and a cycle life of 12,000 to 14,000 cycles. Zinc–Bromine (ZBR) batteries, another flow battery type with zinc and bromine in aqueous electrolyte, have power ratings from 0.1 to 10 [MW], specific energy of 30 to 80 [Wh/kg], energy density of 20 to 65 [Wh/L], and cycle life of 1500 to 2000 cycles. SSB systems, emerging next-generation tech replacing liquid electrolytes with solid ones for improved safety and performance,

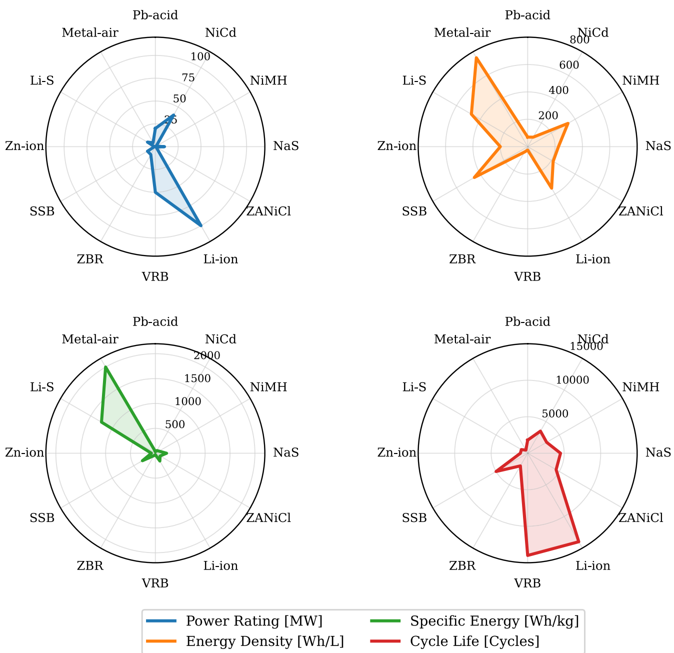

Fig. 10. Comparison of different batteries in terms of power rating, specific energy, energy density, and cycle life; based on the data from Table 2.

boast power ratings of 0.1 to 10 [MW], high specific energy of 200 to 400 [Wh/kg], energy density of 300 to 600 [Wh/L], and cycle life ranging from 1000 to 5000 cycles, which are considered as the complement of LiBs in BESS technologies of marine systems. Zn-ion, aqueous-based rechargeable cells using zinc ions for safer, lower-cost alternatives to lithium, show limited power ratings of 0 to 1 [MW], specific energy of 75 to 85 [Wh/kg], energy density of 150 to 250 [Wh/L], and cycle life up to 1000 cycles. Lithium–Sulfur (Li–S) batteries, high-capacity systems with a lithium anode and sulfur cathode, have power ratings of 0 to 10 [MW], specific energy of up to 2500 [Wh/kg], and an energy density of 350 to 600 [Wh/L], with a shorter cycle life of 0 to 1000 cycles. Finally, Li-Air, Zn-Air, Al-Air, Na-Air (Metal-air) batteries, which generate power through oxidation of metals such as zinc or aluminum with atmospheric oxygen for high-energy applications, have power ratings of 0 to 5 [MW], a high specific energy of 935 to 3463 [Wh/kg], and an energy density of 500 to 1000 [Wh/L], with a limited cycle life of 100 to 500 cycles.

Following these specifications of the presented different batteries, and the typical marine battery systems' energy density (Fig. 12), their suitability for marine applications is presented in Table 2, and Section 10, based on [63,64]. Moreover, since the LiBs are among the most used batteries, three of their most commonly used types in marine electrification are also shown in Fig. 13. NMC, LFP, and LTO batteries suit different maritime applications due to trade-offs in energy density, power, safety, cycle life, and cost: NMC has high energy density and balanced power for longer voyages or space-limited hybrids; however, it requires strong thermal management. LFP is better for safety, longer life, and lower cost for energy-focused or safety-critical operations despite lower density. On the other hand, LTO is better in high-power peaks, fast charging, and extreme durability for frequent short cycles or limited charging, though it is heavier, bulkier, and costlier. Selection depends on several factors, such as voyage length, charging access, power profiles, safety requirements, cycle life, and vessel space/weight limits.

4. Energy and power management systems (EMS/PMS)

In electric ships, the PMS and EMS are interconnected automation systems used for the reliable and resilient operation of the vessel's electrical power plant [65,66]. The PMS primarily handles power control and safety by automatically starting/stopping generators, synchronizing them, balancing loads, preventing blackouts through load shedding, and protecting against faults such as overloads or frequency deviations [67]. In contrast, the EMS operates at a higher strategic level, optimizing overall energy usage, including managing battery charging/discharging, peak shaving, providing spinning reserve, enabling zero-emission modes, and reducing fuel consumption and emissions [68], while integrating with the PMS to maintain ship microgrid stability and resilient operation. Accordingly, the overall EMS/PMS, and their strategies taxonomy are shown in Fig. 14.

The EMS/PMS is the supervisory control layer that coordinates power generation, storage, and consumption across the shipboard microgrid (see Section 14 (a)). Load demand data from the ship microgrid is continuously sent to the EMS/PMS, which performs load management. At the same time, the BMS monitors the battery packs and sends to the EMS/PMS the state information, such as State of Charge (SoC), State of Power (SoP), and State of Temperature (SoT). Using this supervisory data, the EMS/PMS determines (I) how power should be shared between sources and loads, (II) when batteries should charge/discharge, and (III) how to respond to faults or operating constraints. Control commands are then sent back to the microgrid and BESS. Considering the different developed strategies for EMS/PMS, they can be categorized into two classes: (I) global planning (classic, heuristic, and AI-based), and (II) real-time operation (centralized, distributed, and decentralized). Global planning considers extended time horizons and the optimal scheduling of energy resources, using three classes of strategies (classic, heuristic, and AI), or their combination. Classic ones include Rule-Based Control (RBC), Linear Programming (LP), Mixed-Integer Linear Programming (MILP), Economic Dispatch (ED), Optimal Power Flow (OPF), and also Dynamic Programming (DP). The other two classes include heuristic algorithms, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Simulated Annealing (SA), Differential Evolution (DE), and even Tabu Search (TS), as well as AI-driven strategies to enable adaptive and predictive decision-making. Architecturally, EMS/PMS implementations can be (I) centralized, with a single controller handling all decisions, (II) distributed, involving multiple coordinated controllers that exchange information and share responsibilities, or (III) decentralized, featuring autonomous local controllers with limited communication. Additionally, contemporary EMS/PMS developments frequently use AI-based strategies throughout these approaches to enhance robustness and scalability.

All of these strategies and methods require two important components, which are the Objective Function (O.F), and its constraints. For any optimization case, an O.F should be defined [69], considering different aspects of technical (such as full power supply), economic (such as the least system operation cost), and environmental (such as the least carbon emissions). Different O.Fs, and their constraints in battery-powered marine electrification are available in Tables 3 and 4. Mostly, the EMS/PMS minimizes total energy use, operating costs, emissions, or battery degradation, usually formulated as integrals across the entire voyage duration. Optimization occurs under a set of dynamic and algebraic constraints, such as battery power limits, SoC dynamics and boundaries, terminal SoC requirements, and battery power ramp-rate restrictions. At the system level, constraints include real-time power balance among propulsion demands, auxiliary loads, and system losses, while propulsion power is limited by nonlinear speed-power relationships and motor/inverter capacity ratings. Operational practicality is maintained through vessel speed limits and a fixed voyage distance constraint. Further constraints are the battery thermal limits, minimum auxiliary power needs, shore-charging power restrictions, and inter-voyage energy neutrality requirements.

In addition to the presented O.Fs, nowadays mostly multi-objective functions are being used in EMS/PMS to find the optimal solution (like in [90–94]), considering different objectives (technical, economic, and environmental). An overall multi-objective framework is given as follows:

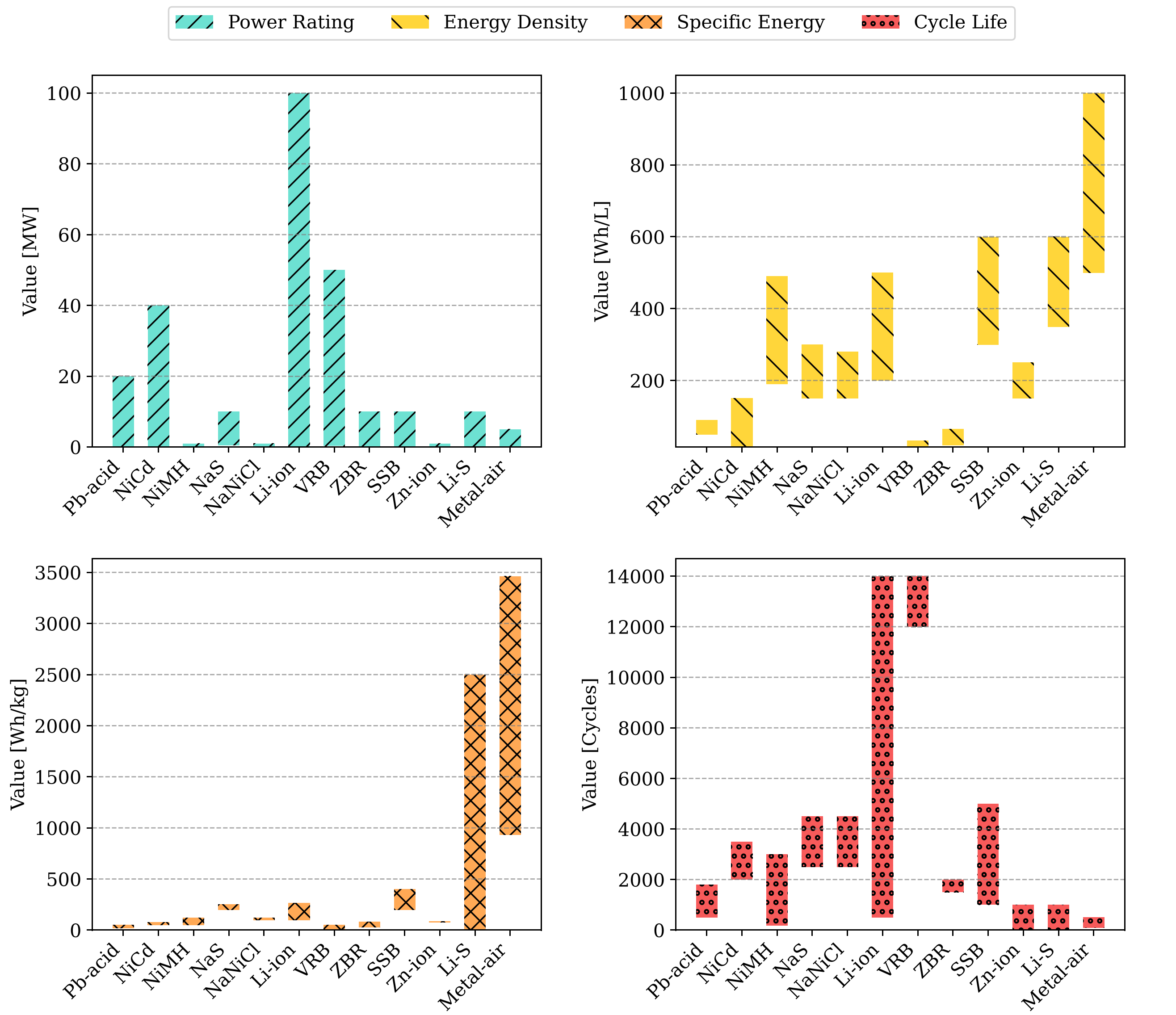

Fig. 11. Comparison of different batteries in terms of their power rating, specific energy, energy density, and cycle life. Power rating is a battery's capacity to deliver power, showing its output capability for various applications. Additionally, specific energy quantifies the energy stored per unit mass. Moreover, energy density measures energy per unit volume, an important indicator for compact designs where space is limited. Furthermore, cycle life is the number of charge/discharge cycles a battery can withstand before its capacity significantly degrades, reflecting its long-term durability and suitability for repeated use [63].

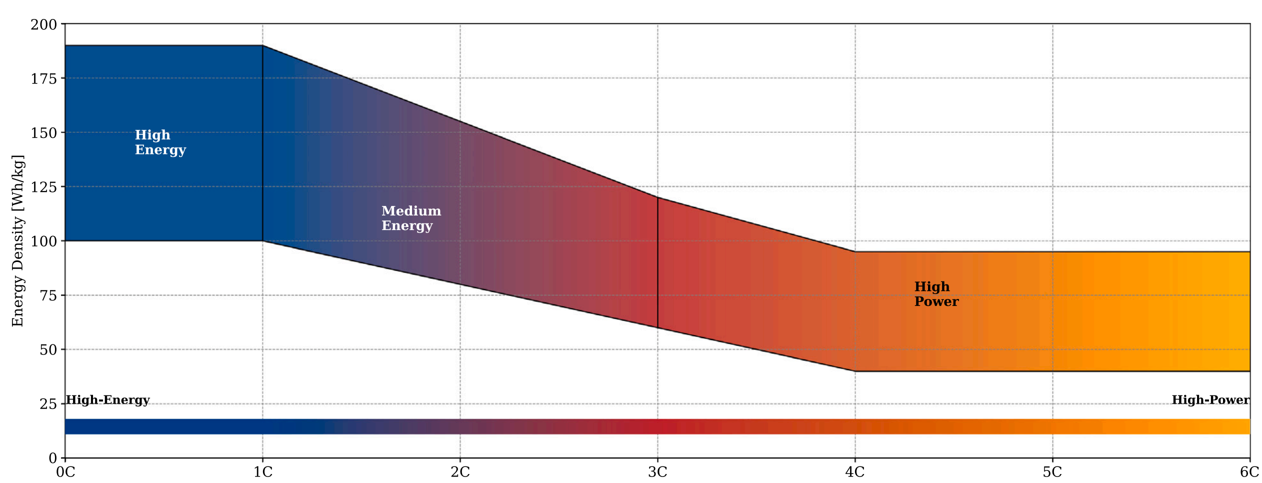

Fig. 12. Typical maritime battery systems energy density, based on the data from [4].

Table 2
Comparison of battery types for maritime applications.

Battery Type	Suitability	Power Rating [MW]	Energy Density [Wh/L]	Specific Energy [Wh/kg]	Cycle Life [Cycles]	Insights
Pb-acid	✗	0–20	50–90	20–50	500–1800	Mature and inexpensive with safe, non-flammable materials; high specific power but low specific energy, and low cycle life due to sulfation; research ongoing on carbon-enhanced plates.
NiCd	✗	0–40	15–150	50–75	2000–3500	Mature, low-cost technology; robust and tolerant to abuse, but with low energy density, hydrogen gas evolution requiring ventilation, memory effect, and toxic Cd leading to environmental issues.
NiMH	✗	0.01–1	190–490	50–120	180–3000	Safe and commercially available; 40% higher specific energy than NiCd, but high self-discharge and hydrogen generation during charge; not competitive for marine applications.
NaS	✗	0.5–10	150–300	200–250	2500–4500	High-temperature molten sodium–sulfur cell; high energy density, high power, and efficiency; however, expensive insulation and safety risks.
NaNiCl	✗	0–1	150–280	100–120	2500–4500	High voltage, tolerant to overcharge, long life and safe; requires heating and thermal management, consuming 10–14% of capacity.
LiB	✓	0.1–100	200–500	100–265	500–14,000	Dominant commercial marine BESS technology; requires advanced BMS and thermal control for safety; widely deployed in hybrid and fully electric vessels.
VRB	✗	0.3–50	16–33	10–50	12,000–14,000	Scalable energy and power; inherently safe with no electroplating risk; but low specific energy and bulky systems make them unsuitable for space-limited vessels.
ZBR	✗	0.1–10	20–65	30–80	1500–2000	Moderate cost and good power output, but low specific energy and limited cycle life.
SSB	✓	0.1–10	300–600	200–400	1000–5000	Emerging solid-electrolyte Li-ion; non-flammable, suppresses dendrite formation; key challenges are ionic conductivity and interface stability; expected to enable marine adoption.
Zn-ion	✓	0–1	150–250	75–85	0–1000	Safe, non-flammable aqueous chemistry using Zn^{2+}; cheap and non-toxic; no dendrite growth and high reversibility; still in early commercialization.
Li–S	✓	0–10	350–600	0–2500	0–1000	High theoretical specific energy and low toxicity (no Ni/Co); challenges include the shuttle effect, low conductivity, and cycle degradation.
Metal-air	✗	0–5	500–1000	935–3463	100–500	Ultra-high theoretical specific energy, but poor rechargeability, electrolyte instability with CO_2/H_2O, and low cycle life; currently early research stage.

A multi-objective optimal control problem is considered over the voyage horizon $t \in [0, T]$. The objective functions jointly minimize total energy consumption, emissions, and battery degradation while satisfying physical and operational constraints. Accordingly, the total energy consumption, emissions, and battery degradation objectives are defined as:

$$J = \begin{cases} J_{\mathrm{E}} = \displaystyle\int_0^T P_{\mathrm{bat}}(t)\, dt \\ J_{\mathrm{em}} = \displaystyle\int_0^T \gamma_{\mathrm{gen}} P_{\mathrm{gen}}(t)\, dt + \sum_k \gamma_{\mathrm{grid}} P_{\mathrm{ch}}(k)\Delta t \\ J_{\mathrm{deg}} = \displaystyle\int_0^T f_{\mathrm{deg}}\big(\mathrm{SoC}(t), P_{\mathrm{bat}}(t), T_{\mathrm{bat}}(t)\big)\ dt \end{cases} \tag{1}$$

where $P_{\mathrm{gen}}(t)$ is the onboard generation power for hybrid vessels and satisfies $P_{\mathrm{gen}}(t) = 0$ for fully electric vessels. The variables $P_{\mathrm{ch}}(k)$, γ_{gen}, and γ_{grid} are the shore-side charging power and the emission factors associated with onboard generation and grid electricity, respectively. Also, $f_{\mathrm{deg}}(\cdot)$ is a battery degradation model dependent on SoC, power throughput, and temperature. The objectives in Eq. (1) are optimized subject to the battery SoC dynamics:

$$\begin{cases} \dot{\mathrm{SoC}}(t) = -\dfrac{\eta_{\mathrm{bat}} P_{\mathrm{bat}}(t)}{E_{\mathrm{bat}}} \\ P_{\mathrm{bat}}^{\min} \le P_{\mathrm{bat}}(t) \le P_{\mathrm{bat}}^{\max} \\ \mathrm{SoC}_{\min} \le \mathrm{SoC}(t) \le \mathrm{SoC}_{\max} \\ \mathrm{SoC}(T) \ge \mathrm{SoC}_{\mathrm{end}} \end{cases} \tag{2}$$

where $\mathrm{SoC}(t)$ is the battery SoC at time t, while $\dot{\mathrm{SoC}}(t)$ represents its time derivative. $P_{\mathrm{bat}}(t)$ is the battery charging/discharging power, with positive values corresponding to power exchange according to the adopted sign convention. η_{bat} is the battery efficiency, and E_{bat} is the nominal energy capacity of the battery. Moreover, $P_{\mathrm{bat}}^{\min}$ and $P_{\mathrm{bat}}^{\max}$ define the minimum/maximum allowable battery power, respectively. The parameters SoCmin and SoCmax specify the permissible lower and upper bounds of the SoC to ensure safe operation and longevity of the battery. Additionally, $\mathrm{SoC}(T)$ represents the SoC at the end of the optimization horizon T, and $\mathrm{SoC}_{\mathrm{end}}$ denotes the minimum required terminal SoC, enforcing a desired energy level at the end of the scheduling period. System-level feasibility is ensured by considering the instantaneous power balance, a nonlinear propulsion power–speed relationship, vessel speed limits, and a voyage distance constraint, respectively:

$$P_{\mathrm{bat}}(t) = P_{\mathrm{prop}}(t) + P_{\mathrm{aux}}(t) + P_{\mathrm{loss}}(t) \tag{3}$$

$$P_{\mathrm{prop}}(t) = k\, v^3(t) \tag{4}$$

$$0 \le v(t) \le v_{\max} \tag{5}$$

$$\int_0^T v(t)\, dt = D_{\mathrm{voy}} \tag{6}$$

Additional operational constraints include minimum auxiliary load requirements, propulsion motor power limits, battery ramp-rate limits, thermal constraints ($T_{\mathrm{bat}}(t) \le T_{\mathrm{bat}}^{\max}$), shore-side charging power limits ($0 \le P_{\mathrm{ch}}(k) \le P_{\mathrm{ch}}^{\max}$), and an inter-voyage energy neutrality condition ensuring sufficient battery replenishment between successive voyages. Regarding the battery SoC, and degradation modeling, there are different strategies for their consideration and modeling, which can be referred to in Refs. [28,95]. The resulting multi-objective optimization problem is formulated as:

$$\min_{\{P_{\mathrm{bat}}(t),\, v(t),\, P_{\mathrm{gen}}(t),\, P_{\mathrm{ch}}(k)\}} \begin{bmatrix} J_{\mathrm{E}} \\ J_{\mathrm{em}} \\ J_{\mathrm{deg}} \end{bmatrix} \tag{7}$$

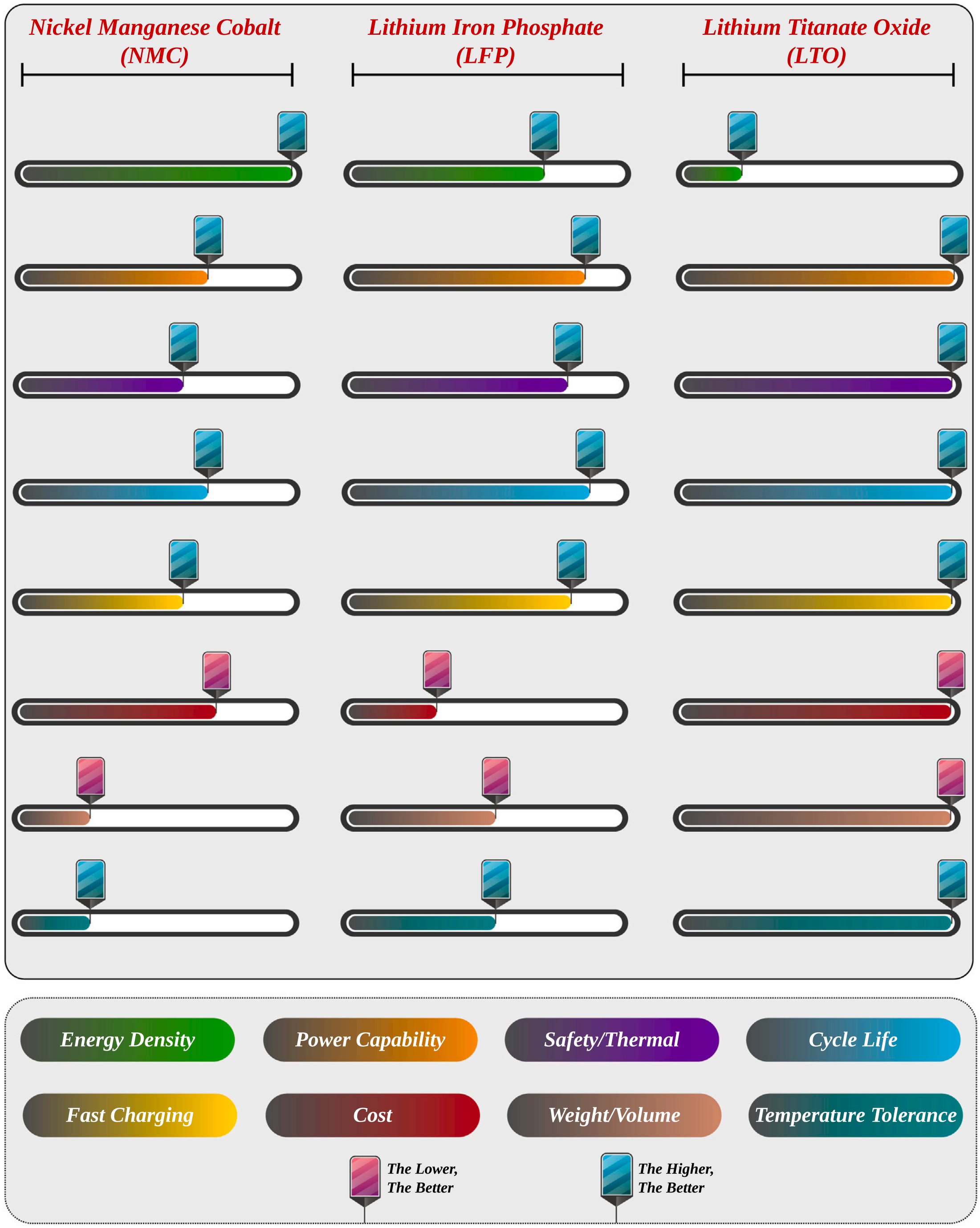

Fig. 13. Comparison of three widely-used LiB types in marine electrification: NMC, LFP, and LTO.

subject to constraints Eqs. (2) to (6). A feasible solution is Pareto optimal if no other feasible solution improves one objective without degrading at least one of the others. The Pareto front is obtained using a weighted-sum ($w_{\mathrm{E}}, w_{\mathrm{em}}, w_{\mathrm{deg}}$) secularization:

$$J_{\mathrm{ws}} = w_{\mathrm{E}} J_{\mathrm{E}} + w_{\mathrm{em}} J_{\mathrm{em}} + w_{\mathrm{deg}} J_{\mathrm{deg}} \quad w_i \geq 0, \ \sum_i w_i = 1, \tag{8}$$

The resulting Pareto-optimal solutions enable systematic trade-off analysis between energy efficiency, emissions (onboard for hybrid vessels and shore—for fully electric vessels), and battery degradation, as shown in Figs. 15 and 16. A review of the presented EMS/PMS taxonomy is available in Table 5.

The Algorithm 1 takes a set of N points (solutions) in an M-dimensional objective space and assigns each point a *Pareto rank*. Rank 1 contains all non-dominated solutions (the best Pareto front). Then, rank 2 consists of the non-dominated solutions of the remaining points after removing rank 1, and so on. The procedure iteratively excludes the current Pareto-optimal layer until no points remain. The algorithm maintains a working set P of indices of yet unranked solutions. In each iteration (each front), it checks every remaining point to determine whether any other remaining point dominates it. If no point in the current P dominates it, then the point belongs to the current front and receives the current rank number. All such non-dominated points are

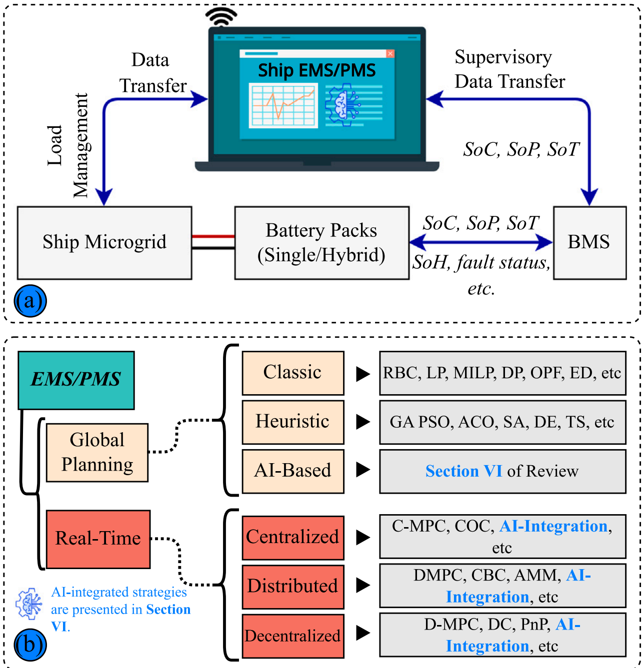

Fig. 14. EMS/PMS in marine electrification: (a) overall structure, and (b) strategy taxonomy.

assigned the rank and removed from consideration for the next fronts. The dominated ones are collected in Q and become the new working set P for the next iteration. The process repeats until P becomes empty.

5. Battery management systems (BMS)

Fig. 17 shows a vessel designed with integrated battery systems for efficient and safe operations.

A vessel battery room is a secure storage area for large battery packs used in propulsion or auxiliary systems. Safety features are prominent, including ventilation to maintain air quality, fire suppression mechanisms to mitigate risks, and a master BMS that continuously monitors charging/discharging and temperature. The room is constructed from non-combustible materials to prevent fire spread, and it incorporates cooling systems along with spill containment measures to handle any potential electrolyte leaks from the batteries [128–130]. Additionally, the command center of the vessel is the operational core, equipped with advanced navigation tools such as radar, Geographical Positioning System (GPS), communication systems, and electronic chart displays for guiding the ship safely. Integrated within it is the PMS, which oversees the coordination of generators, BESS, and propulsion units to optimize power consumption and avoid overloads. Furthermore, a structure of BESS is illustrated in Fig. 18.

In marine applications, individual cells, modules, or packs alone are not able to cover the energy, power, and voltage demands. As a result, these components are linked in series and parallel configurations to create larger battery systems. Typically, beyond electrical connections, marine battery systems incorporate electronic management systems, safety mechanisms, and cooling systems, all enclosed within a waterproof casing [21], as in Fig. 18. A vessel BESS includes several key components that work together to store, manage, and deliver electrical energy efficiently and safely. At the core are the battery cells. Then, battery packs form the next level of organization, consisting of multiple battery cells wired together in series and parallel configurations. This grouping allows the system to achieve the necessary voltage and capacity required for marine applications [33]. By combining cells

Table 3
Objective Functions for EMS in Marine Electrification.

Objective Function	Type	Overall Formulation	Parameters	Insight	Examples
Total Electrical Energy Consumption	Min	$J_E = \int_0^T P_{\text{bat}}(t)\,dt$	P_{bat}: battery power; T: EMS horizon	Minimizes total battery energy usage during the voyage	[70,71]
Propulsion Energy per Distance	Min	$J_{E/D} = \frac{\int_0^T P_{\text{prop}}(t)\,dt}{\int_0^T v(t)\,dt}$	P_{prop}: propulsion power; v: vessel speed	Improves transport efficiency and vessel range	[65,72,73]
Peak Battery Power	Min	$J_{P,\max} = \max_{t\in[0,T]} P_{\text{bat}}(t)$	P_{bat}: battery power	Limits peak discharge to reduce converter stress and oversizing	[74,75]
Battery Power Smoothing	Min	$J_{\Delta P} = \int_0^T \left(\frac{dP_{\text{bat}}}{dt}\right)^2 dt$	dP_{bat}/dt: power ramp rate	Avoids aggressive battery loading and improves system stability	[76]
Electrical Conversion Losses	Min	$J_{\text{loss}} = \int_0^T P_{\text{loss}}(t)\,dt$	P_{loss}: inverter and motor losses	Maximizes electric drivetrain efficiency	[77]
State-of-Charge Regulation	Min	$J_{\text{SoC}} = \int_0^T (\text{SoC}(t) - \text{SoC}_{\text{ref}})^2\,dt$	SoC_{ref}: target SoC	Maintains SoC within safe and efficient operating bounds	[78,79]
Depth-of-Discharge Minimization	Min	$J_{\text{DoD}} = \int_0^T \lvert\text{SoC}(t) - \text{SoC}_{\text{mid}}\rvert\,dt$	SoC_{mid}: mid-range SoC	Reduces deep cycling to extend battery lifetime	[80]
Battery Degradation Penalty	Min	$J_D = \int_0^T c_{\text{deg}}\,\dot{D}(t)\,dt$	c_{deg}: degradation cost; $\dot{D}$: aging rate	Penalizes operating conditions accelerating battery aging	[6,81,82]
Charging Cost (Electric Ship OPEX)	Min	$J_{\text{OPEX}} = \sum_k c_e(k)\,E_{\text{ch}}(k) + \int_0^T c_{\text{deg}}\,\dot{D}(t)\,dt$	c_e: electricity price; E_{ch}: charged energy	Minimizes shore-charging cost and degradation impact	[6]
Charging-Related CO_2 Emissions	Min	$J_{CO_2} = \sum_k EF_{\text{grid}}(k)\,E_{\text{ch}}(k)$	EF_{grid}: grid emission factor	Accounts for upstream emissions of battery charging	[6]
Reserve Power Margin (Penalty)	Max	$J_{\text{res}} = \min_t \left(P_{\text{bat}}^{\max} - P_{\text{bat}}(t)\right)$	$P_{\text{bat}}^{\max}$: battery power limit	Maintains operational safety margin against overloads	[4]
Blackout Risk Penalty	Min	$J_{\text{risk}} = \int_0^T \max\left(0, P_{\text{dem}}(t) - P_{\text{bat}}^{\max}\right)^2 dt$	P_{dem}: demanded power	Penalizes infeasible power demand exceeding battery capability	[82–84]
Speed Tracking Support	Min	$J_v = \int_0^T (v(t) - v_{\text{ref}}(t))^2\,dt$	v_{ref}: reference speed	Ensures propulsion power meets navigation requirements	[85]
Port-Area Emissions Accounting	Min	$J_{\text{port}} = \sum_{k\in\mathcal{T}_{\text{port}}} EF_{\text{grid}}(k)\,E_{\text{ch}}(k)$	$\mathcal{T}_{\text{port}}$: port charging intervals	Evaluates emissions associated with port-side charging	[86–89]

Table 4
Operational constraints for EMS in marine Electrification.

Constraint	Formulation	Parameters	Insights
Battery Power Limits	$P_{bat}^{min} \le P_{bat}(t) \le P_{bat}^{max}$	$P_{bat}^{min}, P_{bat}^{max}$: power limits	Prevents battery over-discharge and excessive charging power
Battery Energy/SoC Dynamics	$\dot{SoC}(t) = -\frac{\eta_{bat} P_{bat}(t)}{E_{bat}}$	η_{bat}: efficiency; E_{bat}: capacity	Describes battery state evolution under charging and discharging
State-of-Charge Bounds	$SoC_{min} \le SoC(t) \le SoC_{max}$	SoC_{min}, SoC_{max}: SoC limits	Ensures safe battery operation and longevity
Terminal SoC Requirement	$SoC(T) \ge SoC_{end}$	SoC_{end}: minimum final SoC	Guarantees sufficient energy reserve at voyage end
Battery Ramp-Rate Limits	$\left\lvert \frac{dP_{bat}}{dt} \right\rvert \le r_{bat}$	r_{bat}: maximum ramp rate	Limits fast power transients and protects converters
Power Balance Constraint	$P_{bat}(t) = P_{prop}(t) + P_{aux}(t) + P_{loss}(t)$	P_{aux}: auxiliary load	Ensures instantaneous power balance onboard
Propulsion Power–Speed Relation	$P_{prop}(t) = k\,v^3(t)$	k: hull and propeller constant	Models nonlinear propulsion power demand
Speed Limits	$0 \le v(t) \le v_{max}$	v_{max}: maximum vessel speed	Restricts vessel operation within safe navigation limits
Voyage Distance Constraint	$\int_0^T v(t)\,dt = D_{voy}$	D_{voy}: required distance	Ensures completion of planned voyage
Thermal Constraint (Battery)	$T_{bat}(t) \le T_{bat}^{max}$	T_{bat}^{max}: temperature limit	Prevents thermal runaway and accelerated degradation
Inverter/Motor Power Limits	$P_{prop}(t) \le P_{mot}^{max}$	P_{mot}^{max}: motor rating	Avoids overloading propulsion components
Auxiliary Load Requirement	$P_{aux}(t) \ge P_{aux}^{min}$	P_{aux}^{min}: minimum auxiliary load	Guarantees critical hotel and safety systems operation
Charging Power Limits (Port)	$0 \le P_{ch}(k) \le P_{ch}^{max}$	P_{ch}^{max}: charger rating	Restricts shore-side charging power
Energy Neutrality (Charging)	$SoC_{dep} \le SoC_{arr} + \sum_k \frac{\eta_{ch} P_{ch}(k)\Delta t}{E_{bat}}$	η_{ch}: charging efficiency	Ensures sufficient energy replenishment between voyages

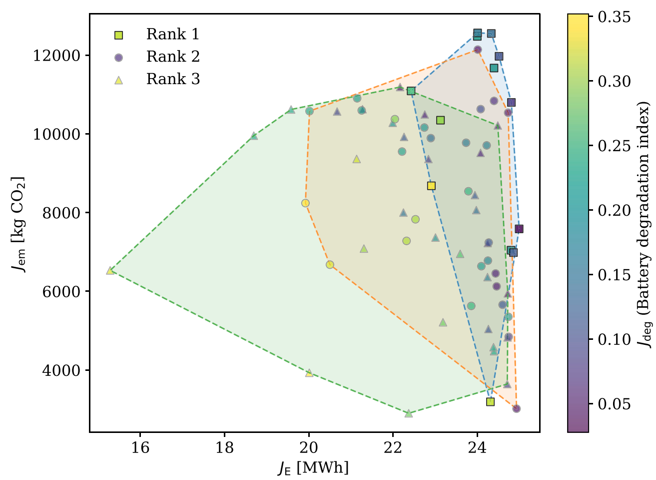

Fig. 15. Pareto front results, considering the top three Pareto ranks using Algorithm 1.

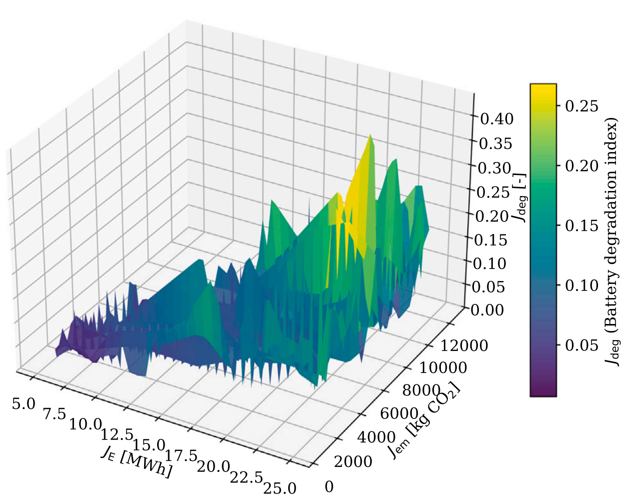

Fig. 16. 3D surface results: The surface illustrates the structure of feasible energy management solutions.

into packs, the BESS can scale up its energy storage capabilities while maintaining modularity for easier maintenance and replacement. To control and monitor the operation of these packs, the system has slave

Table 5
Classification of EMS/PMS Strategies.

Strategy	Variant	Examples
Global Planning	Classic	[96–101]
	Metaheuristic	[29,94,102–110]
	AI-based	Section 6
Real-Time	Centralized	[36,68,111–114]
	Distributed	[79,115–122]
	Decentralized	[123–127]

Algorithm 1 Pareto Front Ranking for Vessels.

Require: $\mathbf{J} \in \mathbb{R}^{N\times 3}$, where $\mathbf{J}_i = \left[J_E^{(i)},\ J_{em}^{(i)},\ J_{deg}^{(i)}\right]$ denotes the objective vector corresponding to the i-th feasible solution
Ensure: rank$[0..N-1]$ {Pareto front index of each solution}
  $front \leftarrow 1$
  $P \leftarrow \{0, 1, \ldots, N-1\}$ {Set of unranked solutions}
  while $P \neq \emptyset$ **do**
    $Q \leftarrow \emptyset$
    for each $i \in P$ **do**
      $dominated \leftarrow$ false
      for each $j \in P$ **do**
        if $j \neq i$ **and** $\mathbf{J}_j$ dominates $\mathbf{J}_i$ **then**
          $dominated \leftarrow$ true
          break
        end if
      end for
      if not dominated **then**
        rank$[i] \leftarrow front$
      else
        $Q \leftarrow Q \cup \{i\}$
      end if
    end for
    $P \leftarrow Q$
    $front \leftarrow front + 1$
  end while

BMS/Thermal Management System (TMS). These slave units monitor and manage individual battery packs, tracking parameters such as voltage, current, temperature, SoC, and State of Health (SoH). Their primary purpose is to ensure safety by preventing issues such as overcharging, deep discharging, or thermal runaway, while optimizing the battery packs' performance, considering their Remaining Useful Life (RUL).

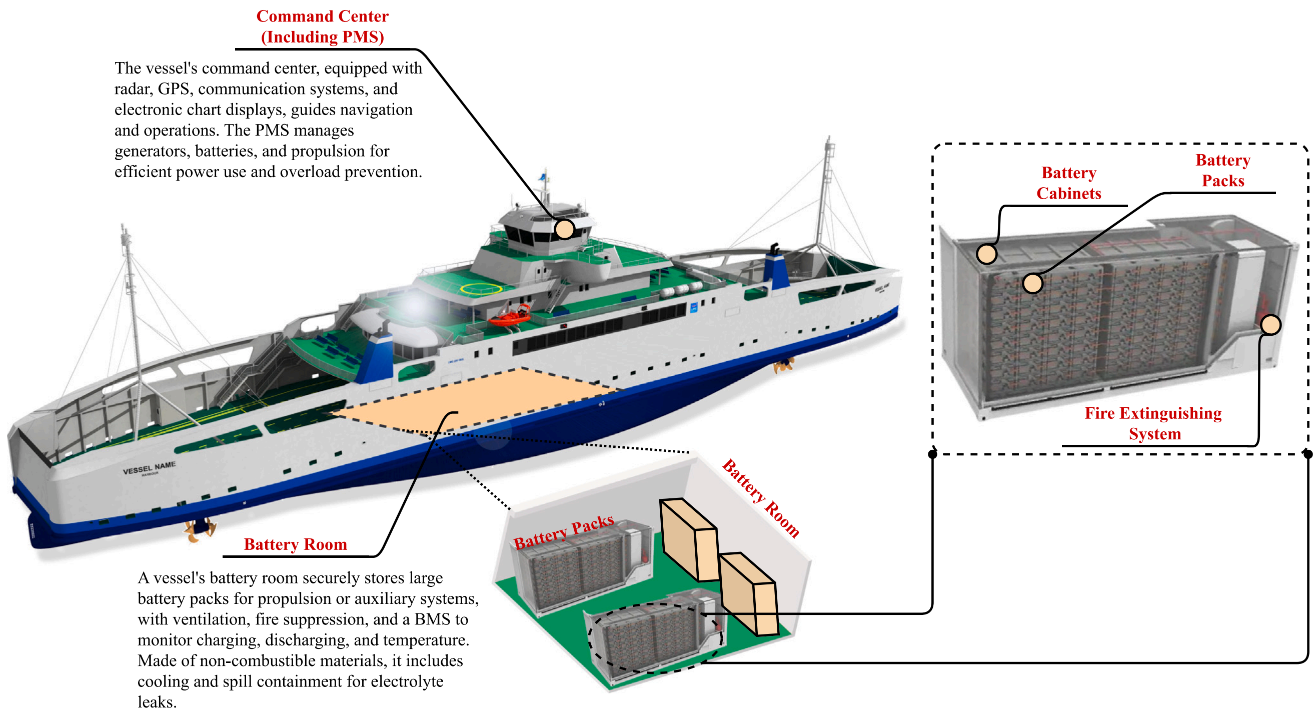

Fig. 17. Battery room normal location inside a vessel.

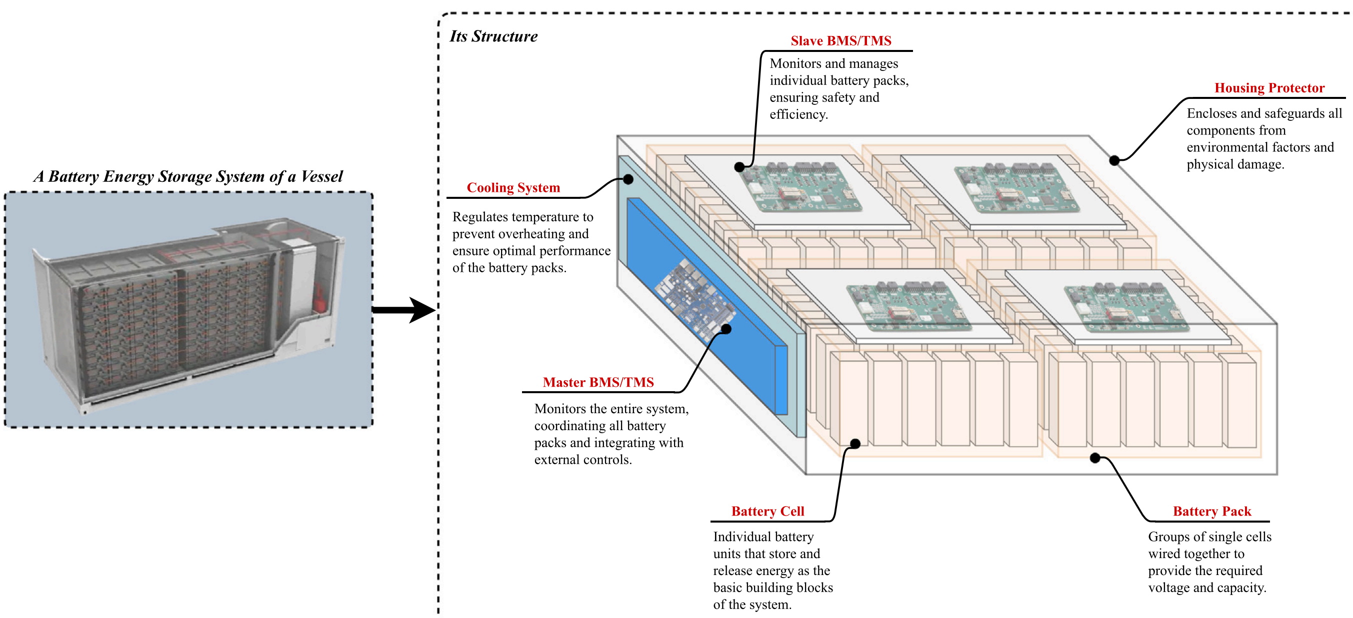

Fig. 18. Structure of a BESS, used in marine battery rooms.

Coordinating the monitoring and control of the entire setup is the master BMS/TMS, which is the BESS main controller. It monitors the overall system, synchronizing the activities of all slave units and battery packs. Additionally, it interfaces with external controls, such as the vessel's PMS [131]. Temperature regulation is handled by the cooling system, which maintains optimal thermal conditions for the battery packs. By preventing overheating through active cooling methods, the BMS ensures consistent performance by commanding the cooling systems to reduce degradation risks, and enhance the system's reliability in varying marine environments. Finally, the housing protector encapsulates all these components (BESS, BMS/TMS units, and HVAC), providing a robust enclosure that shields the components from environmental hazards such as moisture, salt spray, vibrations, and physical impacts common in vessel operations.

Another important factor worth noting in battery systems is the communication protocol used in marine applications. Accordingly, an overall communication structure is shown in Fig. 19 [12].

The communication process in battery systems is proposed to safely monitor, control, and coordinate all components involved in energy storage and delivery. At the center of this process is the BMS. It continuously

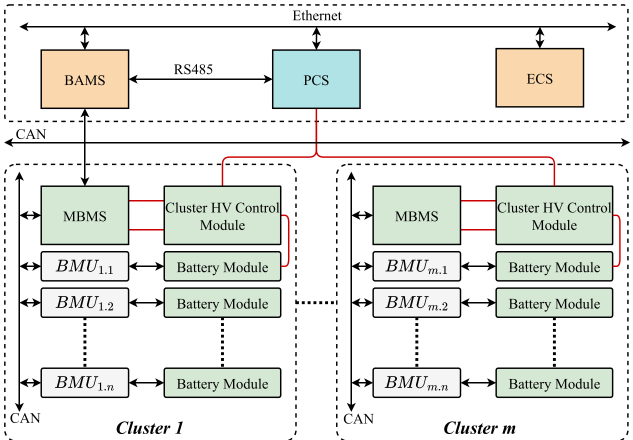

Fig. 19. Overall communication structure of the battery systems in marine applications, based on the data from [12].

gathers data from individual battery cells and modules, such as voltage, current, and temperature, to assess the battery's SoC, SoH, SoT, and overall safety condition. Within a battery pack, communication is typically hierarchical. At the lowest level, cell monitoring units or battery modules measure cell-level parameters and transmit this information to a higher-level controller (Master Battery Management System (MBMS)). This internal communication commonly uses robust, noise-tolerant protocols, such as Controller Area Network (CAN) and Recommended Standard 485 (RS485), which are suitable for electrically harsh environments. These protocols are considered reliable for data transfer even in the presence of High-Voltage (HV) and electromagnetic interference. At a higher level, the MBMS communicates with other system controllers, including the Power Conversion System (PCS), Energy Conversion System (ECS), and Battery Monitoring Unit (BMU). This external communication allows the battery system to coordinate charging, discharging, thermal management, and protection functions with the rest of the system.

Traditional BMS in marine applications face limitations such as reliance on static thresholds, which struggle to adapt to dynamic battery behavior under harsh conditions such as temperature fluctuations and vibrations. These systems often lack real-time predictive capabilities, leading to delayed fault detection, insufficient SoH assessments, and inefficient energy management, which can compromise vessel safety and performance. Following this, transitioning to AI-integrated frameworks addresses these issues by using Machine Learning (ML) for real-time data analysis, enabling predictive maintenance, precise state estimation (SoC, SoH, or SoT), and adaptive control to optimize battery performance in demanding marine environments [132,133]. Additionally, digital twin technology complements AI strategies by creating virtual replicas of battery systems, allowing for real-time simulation, predictive analytics, and cloud-based monitoring. This integration enhances fault detection, optimizes energy usage, and extends battery RUL, for safer and more efficient operations in electric and hybrid marine vessels [134]. Consequently, the applications of AI, and digital twin in the marine environment are presented in the next section (Section 6), considering different marine aspects and components.

6. Artificial intelligence and digital twin integration

6.1. Artificial intelligence (AI)

The same as every other industry, AI has a wide range of applications in the maritime electrification industry. These applications include analyzing different datasets from onboard sensors, weather forecasts, and operational logs to optimize BESS usage, predict energy demands, and manage power distribution on electric and hybrid vessels. ML algorithms enhance route planning by considering currents, wind, and port charging infrastructure, thereby minimizing energy consumption while ensuring timely arrivals. Additionally, AI-driven predictive maintenance identifies potential system failures in various sections of the ship, such as electric propulsion systems, resulting in a considerable reduction in downtime and costs. Consequently, the notable applications of AI in maritime electrification are shown in Fig. 20.

Following these applications, optimizing ship energy system design with ML involves focusing on component choices such as battery sizing or waste-heat recovery systems. This application uses ML strategies to evaluate layouts and perform Pareto trade-offs [135,136], balancing factors such as cost, efficiency, and emissions. By analyzing various design parameters, ML models can simulate and recommend configurations that enhance overall energy performance while minimizing environmental impact and operational expenses [137,138]. AI strategies in propulsion management help decide how to dispatch power among different sources on a ship. The goal is to minimize fuel consumption and emissions while meeting the operational constraints. This includes real-time management of power allocation from engines, batteries, or hybrid systems, to achieve efficient propulsion under varying conditions of speed, load, and sea states [65,139,140].

On the side of the ship's onboard power grid management, it encompasses generators, loads, and ESS, such as BESS, and SC. AI can be used for load shedding, forecasting demand, verifying power supply reliability, and optimizing dispatch. This ensures stable energy distribution, prevents overloads, and improves efficiency by predicting and balancing power needs across the ship [141]. In the AI application within the fuel and emissions optimization, related strategies can predict consumption based on variables such as ship speed, trim, load, sea state, and engine parameters. These predictions guide adjustments to operating conditions, leading to reduced emissions [142,143]. In another application, route planning with AI analyzes real-time data on weather, currents, traffic, or port congestion to select or dynamically adjust paths. This optimization reduces fuel consumption and emissions by avoiding inefficient routes. Advanced algorithms can reroute vessels mid-voyage, incorporating predictive analytics for safer and more economical navigation [144–146]. Control, diagnostics, and maintenance applications use sensor data and AI to monitor engine, auxiliary systems, and hull performance. They detect anomalies early and schedule predictive maintenance, which improves efficiency and reduces downtime. By processing data from onboard sensors, AI identifies potential failures before they occur, extending equipment life and ensuring reliable operations [147–149]. Loads and demand management on ships handle non-propulsion energy uses such as HVAC, lighting, water treatment, and appliances. AI strategies forecast demand patterns to schedule loads effectively, optimizing energy allocation. This strategy prevents wastage, integrates with overall power management, and supports energy conservation by prioritizing essential systems during peak times. For ships with battery or hybrid ESS, AI strategies can estimate various states such as SoC [150], SoH [151], SoP [152], SoT [153], and RUL [154], which are a part of BMS [131]. Additionally, the AI-based strategies conduct balancing actions between cells and packs [28]. This ensures safe, efficient battery operation, prolongs lifespan, and enhances integration with the ship's electrification framework. Fig. 21 manifests an AI-based complete framework, including most of the applications presented in Fig. 20, as well as the different classifications of AI strategies, and their overall training/testing/deploying process.

Based on the developed framework (Fig. 21 (a)), in [155], the onboard database continuously tracks weather conditions, cargo loading, engine performance, and the ship's operational status in real-time. Additionally, it logs fuel consumption data from high-precision mass flow meters for the Main Engine (ME), generators, boiler, and other equipment. The onboard software's user interface displays key monitoring metrics, such as ME speed and power, fuel consumption rates,

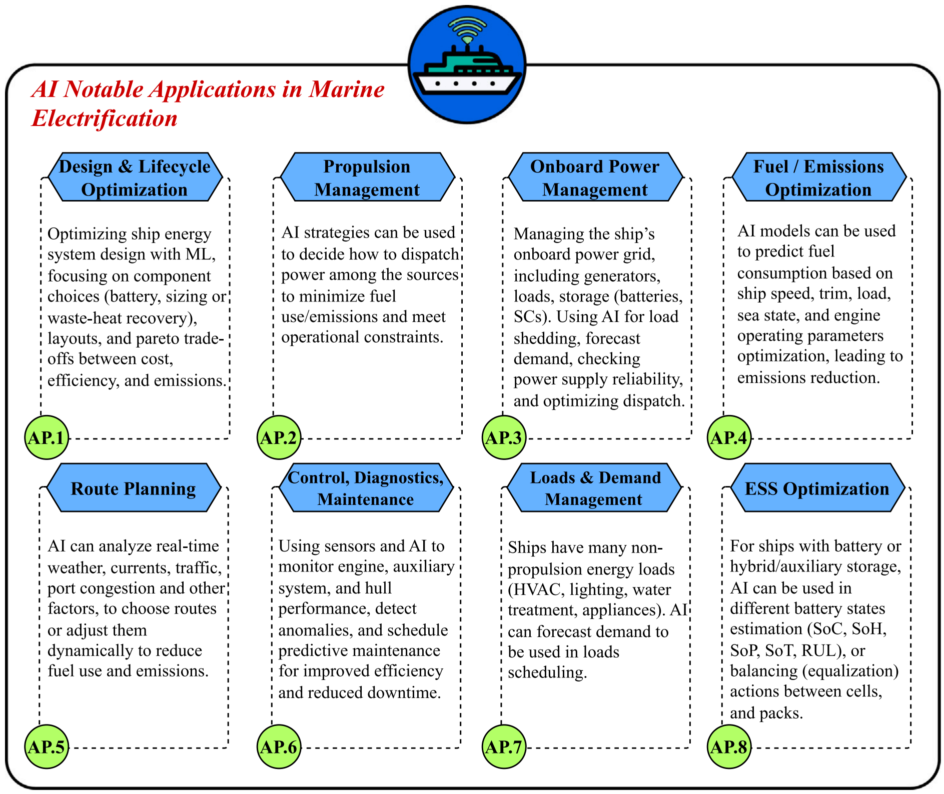

Fig. 20. Notable and well-known applications of AI in maritime electrification. The presented applications are denoted as $(AP_1, \dots, AP_8)$, and are considered in the literature review of AI applications, as shown in Table 7.

ship draft, heel, and trim, alongside energy flow visualizations. Then, it presents graphs showing relationships of ME fuel consumption per nautical mile versus ship speed and ME fuel consumption rate versus shaft speed. Additionally, advanced ML strategies predict real-time shaft power and fuel consumption rates. Ship officers and marine engineers can compare these predictions with actual measurements to identify significant discrepancies, which may indicate inefficient operations or degraded engine performance leading to higher-than-expected fuel use. In this framework, data is transmitted in real-time to an onshore database, enabling ship managers to perform statistical analysis, fuel consumption modeling, data clustering, and physics-based evaluations. They can assess performance variations among sister ships, evaluate ME efficiency, hull fouling, and optimize speed and trim using ML and physics-based strategies.

Overall, to develop an AI-based energy management framework in maritime electrification, three general steps can be taken:

1. The ship's important parameters, inputs, and outputs of the framework should be clarified, such as those in Fig. 21 (a).
2. Then, a suitable ML strategy should be developed, aligned with the scope and aims of the framework. The taxonomy of AI strategies is shown in Fig. 21 (b).
3. Finally, the selected strategy should be trained, tested, and deployed in the framework, as presented in Fig. 21 (c).

These three general steps are the fundamentals to develop an AI-based intelligent management framework for marine electrification applications.

Symbolic AI includes explicit, rule-based systems that use human-interpretable logic and knowledge representation [156,157]. It includes rule-based methods, which rely on predefined *if-then* conditions for decision-making [158,159]; logic-based techniques that use formal logic for inference [160]; knowledge graphs for structuring entities and relationships to enable semantic reasoning [161,162]; case-based reasoning, which adapts solutions from past similar cases [163]; and constraint satisfaction models that define variables and constraints to solve problems by finding valid assignments [164,165].

Data-driven and ML strategies focus on learning patterns from data, subdivided into classic ML and Deep Learning (DL). Classic ML includes Supervised Learning (SL), where models are trained on labeled data for prediction tasks [166]; Semi-Supervised Learning (SSL), which combines labeled and unlabeled data for efficiency [167]; Unsupervised Learning (UL) for recognizing hidden structures or clusters [168]; and Reinforcement Learning (RL), where agents optimize actions through environmental feedback via rewards [169]. DL, on the other hand, involves advanced Neural Networks (NNs), such as Feed-Forward Neural Networks (FFNNs) for unidirectional data processing in pattern recognition [170]; Convolutional Neural Networks (CNNs) used for grid-based data to extract features [171], and Recurrent Neural Networks (RNNs) for handling sequential data with memory of prior inputs [172], including Long Short-Term Memory (LSTM) [173,174], or Bidirectional Long Short-Term Memory (BiLSTM) [175].

Generative AI is also the other AI strategies class that is increasing in the applications of different sectors, including maritime electrification. It's oriented toward creating new data instances that mimic training distributions, useful for simulation or augmentation [176–178]. Generative AI strategies consist of probabilistic generative models that learn underlying probability distributions [179]; variational autoencoders, which encode data into latent spaces for generating variations [180]; and generative adversarial networks, featuring competing generator and discriminator components to produce realistic outputs. In generative adversarial networks, the generator creates synthetic data samples aiming to mimic real data distributions as closely as possible, and the discriminator evaluates both real and synthetic samples, learning to distinguish real data from synthetic ones produced by the generator [181]. Finally, Large Language Models (LLMs) are among the

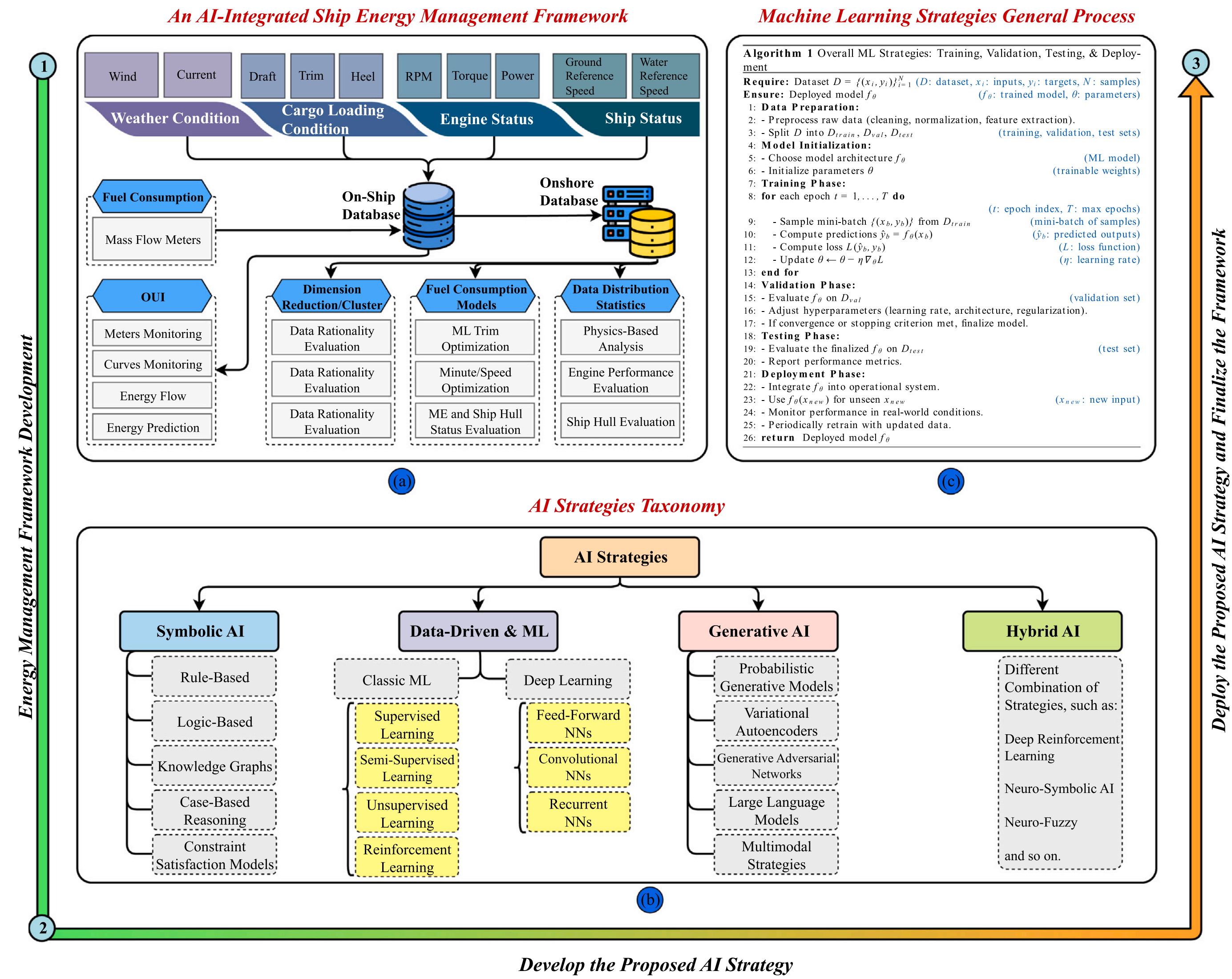

Fig. 21. Artificial Intelligence in maritime electrification: (a) a complete AI energy efficiency framework for ships, conceptualized from [155], (b) different classifications of AI strategies, and (c) their training/testing/deployment process.

other known generative AI strategies trained on extensive resources for human-like performance [33]; and multimodal strategies that integrate multiple data types, such as text and images, for cross-domain creation [182]. For the final classification, **hybrid AI** strategies combine strategies from the other classes to achieve more versatile and robust systems. They feature various integrations, such as Deep Reinforcement Learning (DRL), which integrates deep NNs with RL mechanisms for complex and dynamic decision-making. Therefore, Fig. 22 shows some representative strategies as a case study in battery systems, from each category, alongside their important (hyper) parameters.

In Fig. 22 (a), a double-layer FLC strategy is designed for the parallel hybrid ship which first allocates power between the engine side (diesel engines) and the grid side (shaft generators) using total demand power and battery SoC as inputs [183]. Then, it further distributes power on the grid side between the Liquefied Natural Gas (LNG) generators and the battery (with shaft-generator power and SoC as inputs). It uses Mamdani-type inference with triangular/trapezoidal membership functions, linguistic variables, and centroid defuzzification. The grid-side supply is used at low demand to reduce emissions. An improved version of this FLC further optimizes the membership-function parameters offline using multi-objective particle-swarm optimization (minimizing equivalent fuel consumption and CO_2 emissions) [183]. Considering the RL case study [184], in Fig. 22 (b), a double Q-learning agent is presented to solve the optimal power-split problem for a plug-in hybrid ship as a Markov decision process. The agent's state space comprises discretized fuel cell power level, battery SoC, instantaneous power demand and shore-power availability. Its action is the discrete change in the fuel-cell power set-point at each 15 [Sec] time step. Rewards are defined as a normalized function of the instantaneous voyage cost (hydrogen consumption, fuel cell/battery degradation, and shore electricity), with penalties for constraint violations (SoC or C-rate limits, and fuel cell override). Trained offline on a large set of real stochastic ferry power profiles collected by continuous monitoring, the resulting generic policy is applied online without future-demand knowledge and achieved 96.9 [%] of the cost performance of an equivalent-resolution deterministic dynamic-programming benchmark. As the next case study, NN is considered in Fig. 22 (c), based on [185]. The NN-based EMS generates diverse operational cycles from a representative ship load profile by a Markov chain model based on speed–acceleration frequency distributions. Then, it solves a global optimum for each cycle with dynamic programming to obtain optimal power-split ratios and propulsion modes. Two cascaded NNs are trained on these solutions: the first selects the propulsion mode

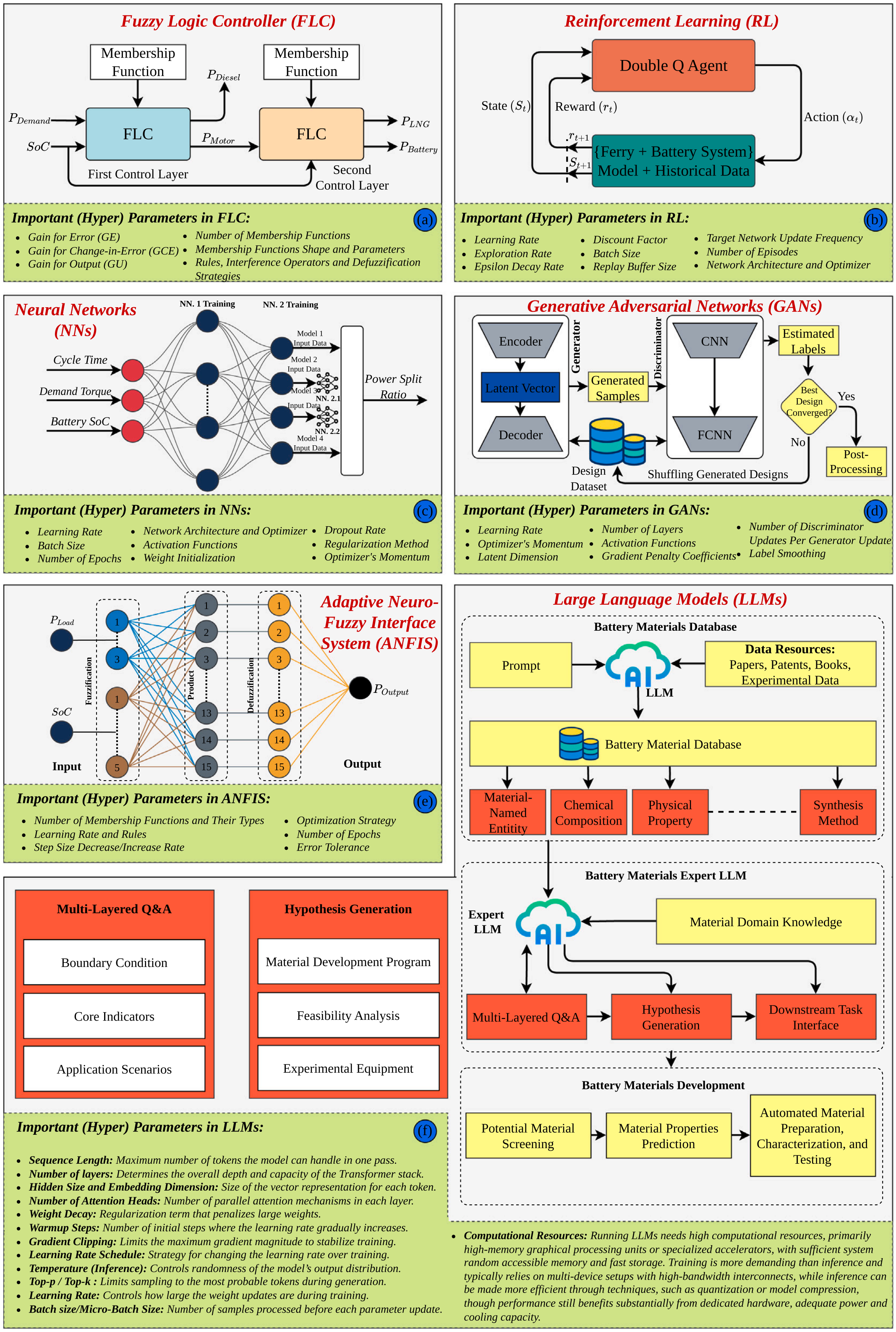

Fig. 22. Representative AI strategies, as case studies, which have been implemented in battery systems: (a) Fuzzy logic control (FLC) [183], (b) RL [184], (c) NN [185], (d) generative adversarial networks (GANs) [186], (e) adaptive Neuro-Fuzzy inference system (ANFIS) [187,188], and (f) LLM [189].

(motor, boost, or charging) while the second outputs the continuous power-split ratio. Once trained, the networks run in real time (0.072 ms per step) and keep engine thermal efficiency near 37 [%] under fluctuating loads.

For the generative AI class, GANs (Fig. 22 (d)), and LLM (Fig. 22f) case studies are presented. The generative design method used a Variational Autoencoder (VAE) as a design generator that treats battery-cell layouts as 2-D images and, together with a CNN performance estimator [186]. It autonomously mined structural features from a training set of 600 randomly sampled layouts whose cooling costs were obtained from high-fidelity COMSOL multiphysics simulations. An iterative loop repeatedly inserted the highest-performing generated candidates back into the training data, progressively biasing the VAE toward low-cost configurations. After a few iterations a final post-processing COMSOL evaluation identified an optimal immersion-cooling layout that reduced pump energy consumption by more than 90 [%] relative to the median of the original designs while keeping all cell temperatures within the target range under 2 [°C] discharge. In the LLM case study [189], the framework for battery materials development uses general, or expert LLMs, guided by prompt engineering and fine-tuning. They are used to extract structured multi-dimensional data—named entities, compositions, microstructures, properties, and synthesis methods—from heterogeneous sources such as papers, patents, and experimental records to construct materials databases. Researchers then interacted with the expert LLM through the multi-layer Question and Answer (Q&A) process to generate research hypotheses on material candidates, feasibility and required equipment. These hypotheses fed a downstream interface that performs screening, property prediction, and synthesis-path optimization, closing the loop with automated preparation, characterization, and testing to accelerate the end-to-end discovery of next-generation battery materials [189]. Lastly, ANFIS is the final representative model, from the hybrid AI category, in Fig. 22 (e). The ANFIS-based EMS is presented in [187], for an all-electric naval ship hybrid system. It takes load demand power and battery SoC as the two inputs and outputs the required fuel-cell power set-point. A hybrid learning algorithm trains the ANFIS on prior knowledge of system behavior so that it continuously balances power flow, maintains a stable DC-bus voltage and keeps the battery within a healthy SoC range.

Following the classification of AI strategies in Fig. 20, and the representative strategies from each class in Fig. 22, they are compared in Table 6, considering several criteria.

In these terms, convergence rates indicate how reliably and quickly an algorithm reaches a stable solution. On the other hand, stability and robustness quantify resilience to noise, disturbances, and model mismatch. Real-time capability measures the ability to produce control actions within the strict sampling periods of power electronics hardware, and cloud-based control suitability reflects amenability to remote, high-latency computation. System dynamics dependency indicates how dependent the model is on the system (plant) dynamics. Moreover, computational complexity assesses the computational resources used by the algorithm, and data requirements gauge the volume and quality of data required as inputs. In addition, interpretability assesses how transparent the decision logic is to human operators, and handling uncertainty refers to the algorithm's ability to cope with incomplete or stochastic information. Thus, adaptability/online learning measures the capacity to refine behavior from streaming experience, and scalability describes performance when the system scale or number of agents grows. Generalization to unseen conditions assesses behavior under operating conditions absent from training. Additionally, safety/constraint satisfaction quantifies the ease of enforcing physical limits. Finally, ease of deployment reflects the effort needed to deploy the algorithm on the proposed system.

Additionally, a literature review of the presented AI applications in Fig. 20 ($AP_1, \ldots, AP_8$) is provided in Table 7.

6.2. Digital twin

Digitalization, alongside electrification, has emerged as an important and early-stage innovation trend in the maritime industry, driven by its ability to enhance performance. New and continually improving tools for design, performance assessment, simulation, and data security are being developed, enabling the creation of more resilient and advanced models [228]. According to the framework presented in [229], for developing digitalization services, the maritime sector can pursue digital transformation through two distinct strategies:

Table 6
Comparison of AI Strategies.

Term	FLC	ANFIS	RL	NNs	GANs	LLMs
Strategy Class	Symbolic AI	Hybrid AI	Data-Driven and ML (Classic ML)	Data-Driven and ML (DL)	Generative AI	Generative AI
Convergence	★★★★★	★★★★☆	★★★☆☆ (Problem-dependent)	★★★★☆	★★★☆☆	★★★☆☆
Stability & Robustness	★★★★★	★★★★★	★★★★☆	★★★★☆	★★★☆☆	★★☆☆☆
Real-Time Capability	★★★★★	★★★★★	★★★☆☆	★★★☆☆	★☆☆☆☆	★★☆☆☆
Cloud-Based Control Suitability	★★☆☆☆	★★☆☆☆	★★★★☆	★★★★☆	★★★★★	★★★★★
System Dynamics Dependency	★★☆☆☆	★★★★☆	★★★★★	★★★★★	★★★★☆	★☆☆☆☆
Computational Complexity	●○○○○	●○○○○	●●●○○	Training: ●●●○○ Inference: ●●○○○	Training: ●●●○○ Inference: ●●○○○	●●●●●
Data Requirements	★☆☆☆☆	★★☆☆☆	★★★★★	★★★★★	★★★★★	★★★★★
Interpretability	★★★★★	★★★★★	★★☆☆☆	★☆☆☆☆	★★☆☆☆	★★★☆☆
Handling Uncertainty	★★★★★	★★★★★	★★★★☆	★★★★☆	★★★★★	★★★★☆
Adaptability/Online Learning	★★☆☆☆	★★★☆☆	★★★★★	★★★☆☆	★★★☆☆	★★★★☆
Scalability	★★☆☆☆	★★★☆☆	★★★★☆	★★★★★	★★★★★	★★★★★
Generalization to Unseen Conditions	★★☆☆☆	★★★☆☆	★★★★☆	★★★★☆	★★★★★	★★★★☆
Safety/Constraint Satisfaction	★★★★★	★★★★☆	★★★☆☆	★★★☆☆	★★☆☆☆	★★☆☆☆
Ease of Deployment	★★★★★	★★★★☆	★★☆☆☆	★★★☆☆	★★☆☆☆	★★★☆☆
Typical EMS Role	Real-time power allocation/mode selection	Real-time power split with learning	Sequential decision-making and long-horizon optimal control	Mode selection and continuous power-split mapping	Offline layout/topology optimization	Knowledge integration, materials discovery, high-level planning
Some of Limitations	Subjective rule design	Needs representative training data	Sample efficiency and real-time safety	Needs large labeled operational data	High cost of fidelity evaluation	Lacks deterministic real-time control guarantees
Example Case Studies	[183]	[187,188]	[184]	[185]	[186]	[189]

Stars (the higher, the better): ★★★★★ Very High, ★★★★☆ High, ★★★☆☆ Medium, ★★☆☆☆ Low, ★☆☆☆☆ Very Low
Circles (the lower, the better): ○○○○○ Very Low, ●○○○○ Low, ●●○○○ Moderate, ●●●○○ High, ●●●●● Very High

Table 7
Overview of AI integration in maritime Electrification.

Ref.	Strategy	AP.1	AP.2	AP.3	AP.4	AP.5	AP.6	AP.7	AP.8	Insights
[190]	K-Means-Cluster Analysis	✓	✗	✗	✓	✗	✗	✗	✗	Uses ML to create new environmental performance indices for ships, using voyage data. Combines clustering and principal component analysis to group ships into four clusters based on design, operation, and environmental efficiency.
[191]	Emotional NN	✓	✓	✗	✓	✗	✗	✗	✗	Presents an emotional NN model to predict ship fuel consumption for bulk carriers and container ships under varying climate conditions.
[192]	ML Classifiers	✓	✗	✗	✗	✗	✓	✗	✗	Addresses integrating uncertain sub-system health estimates and weather forecasts for autonomous crewless vessels, considering various ML models.
[193]	NN	✓	✗	✗	✓	✗	✗	✗	✗	Proposes an ML-driven framework for real-time ship performance management to reduce emissions and enhance efficiency.
[194]	XGBoost	✗	✓	✗	✓	✗	✗	✗	✗	Describes a hybrid physics-based ML system for predicting fuel consumption and CO_2 emissions of a 100 m oil tanker across six scenarios.
[195]	Different ML Strategies	✗	✓	✗	✗	✗	✗	✗	✗	Evaluates ML strategies for predicting propulsion power in two 8400 TEU container ships.
[196]	NN	✗	✓	✗	✗	✗	✗	✗	✗	Considers an NN model to predict propulsion power for polar ship navigation in ice.
[197]	Different SL Strategies	✗	✓	✗	✗	✗	✗	✗	✗	Compares SL strategies for modeling ship speed–power performance using energy-related data.
[198]	DRL	✗	✓	✗	✗	✗	✗	✗	✗	Introduces a DRL-based intelligent energy management framework for hybrid-electric propulsion systems.
[199]	Explainable Artificial Intelligence (XAI)	✗	✓	✗	✗	✗	✗	✗	✗	Uses an IoT-driven approach with XAI models to predict ships' specific fuel consumption.
[200]	Different ML Strategies	✗	✓	✗	✗	✗	✗	✗	✗	Predicts fuel consumption and shaft torque for ship energy efficiency using big data and ML.
[201]	Knowledge Graph	✗	✓	✗	✗	✗	✓	✗	✗	Proposes a knowledge graph method for diagnosing faults in ship diesel engines.
[202]	Adaptive RL	✗	✗	✓	✗	✗	✓	✗	✗	Examines hybrid cyberattacks' impact on a low-emission shipboard microgrid's load frequency control.
[94]	Different ML Strategies	✗	✗	✓	✗	✗	✓	✗	✗	Reviews EMS methodologies for electric ship power systems to enhance fuel efficiency.
[203]	DL	✗	✗	✓	✗	✗	✓	✗	✗	Introduces a DL-driven framework to enhance cybersecurity in DC shipboard microgrids.
[69]	Different ML Strategies	✗	✗	✓	✗	✗	✓	✗	✗	Reviews optimization-based power/energy management systems for electric ships.
[204]	DL	✗	✗	✓	✗	✗	✗	✓	✗	Presents a DL strategy for dynamic positioning load forecasting in marine vessels.
[205]	MPC-RL	✗	✗	✓	✗	✗	✓	✗	✗	Describes an optimized PMS strategy for all-electric ships with DC-grid configurations.
[206]	DL	✗	✗	✓	✗	✗	✓	✗	✗	Proposes a DL-based cybersecurity framework for harbor-integrated shipboard microgrids.
[207]	RL	✗	✗	✗	✗	✓	✗	✗	✗	Proposes a Q-learning-based approach for autonomous navigation of smart cargo ships.
[208]	Different ML Strategies	✗	✗	✗	✗	✓	✗	✗	✗	Describes unsupervised route planning for maritime autonomous surface ships.
[209]	RL	✗	✗	✗	✓	✓	✗	✗	✗	Presents a novel ship route planning method considering weather and emissions.
[210]	DRL	✗	✗	✗	✗	✓	✗	✗	✗	Shows a DRL-based path-planning algorithm for automatic ship berthing.
[211]	RL	✗	✗	✗	✗	✓	✗	✗	✗	Presents a DRL strategy for navigating autonomous surface vehicles in dynamic environments.
[212]	DRL	✗	✗	✗	✗	✓	✗	✗	✗	Represents a DRL-based path planning method for uncrewed surface vehicles.
[213]	DRL	✗	✗	✗	✗	✗	✓	✗	✗	Uses DRL for EMS optimization in all-electric ships with hybrid power sources.
[214]	ML Expected Behavior Strategies	✗	✗	✗	✗	✗	✓	✗	✗	Presents a data-driven fault detection methodology for shipboard systems.
[215]	MI-LightGBM	✗	✗	✓	✗	✗	✓	✗	✗	Considers a fault diagnosis method for shipboard medium-voltage DC power systems.
[216]	DL	✗	✗	✓	✗	✗	✓	✗	✗	Represents an ML-based fault detection method for shipboard power systems.
[217]	Domain Knowledge	✗	✗	✗	✗	✗	✓	✗	✗	Shows a hierarchical fault detection strategy for ship engine management.
[218]	BiLSTM	✗	✓	✗	✗	✗	✓	✗	✗	Describes an intelligent fault diagnosis method for marine shaft generators.
[219]	Feature-Fusion/Multi-Scale 1D Convolution	✗	✗	✓	✗	✗	✓	✗	✗	Manifests a fault diagnosis model for ship integrated power systems.
[220]	ML Regression Strategies	✓	✗	✗	✓	✗	✗	✓	✗	Improves operational efficiency and sustainability of container ports.
[221]	Different ML Strategies	✗	✗	✗	✗	✗	✓	✗	✓	Evaluates data-driven approaches for SoH prediction of LiBs in maritime battery systems.

(*continued on next page*)

Table 7 *(continued)*

Ref.	Strategy	AP.1	AP.2	AP.3	AP.4	AP.5	AP.6	AP.7	AP.8	Insights
[222]	RL	✗	✓	✗	✗	✗	✓	✗	✓	Presents an RL-based EMS for hybrid FC/Battery propulsion systems.
[223]	SSL	✗	✗	✗	✗	✗	✓	✗	✓	Estimates the SoH of LiBs in marine vessels for electrification.
[224]	Battery AI	✗	✗	✗	✓	✗	✓	✗	✓	Applies Battery AI to estimate SoH/SoC of battery systems in hybrid or electric ships.
[225]	K-Nearest Neighbors (KNN)	✗	✓	✗	✓	✗	✓	✗	✓	Optimizes hybrid propulsion and energy systems for vessels on the River Thames.
[226]	Different ML Strategies	✗	✗	✓	✓	✗	✗	✗	✓	Reviews AI and ML applications in maritime power systems and decarbonization.
[227]	DRL	✗	✗	✓	✗	✗	✓	✗	✓	Presents charging control for energy storage systems in shipboard integrated power systems.
[33]	LLM	✓	✗	✓	✓	✗	✓	✓	✓	Uses LLM for optimal hybrid battery sizing in marine electrification to improve efficiency and reduce CO_2 emissions.

1. **Service-based Strategy:** Taking into account the specific operational and decision-making needs of ship owners, the development process involves integrating tailored hardware and software solutions that align with the vessel's requirements. This approach operates within the need-space, prioritizing tactical-level enhancements.
2. **Sensor-based Strategy:** The approach involves utilizing data from existing sensors on a specific ship to create a digitalized framework that enhances its operations. This method functions within the solution space as an entry point for future digital twin-based systems.

Digital twin is a virtual, real-time model of a physical maritime asset, such as a ship, its propulsion system, or BESS, that mirrors its real-world counterpart using data, simulations, and advanced analytics. This technology integrates IoT sensors, AI, and data analytics to create a dynamic, digital representation that is integrated with the physical system, enabling optimization, monitoring, and predictive capabilities in electrified maritime operations [230–232]. A concept of digital twin application in ships is shown in Figs. 23 and 24.

The cloud-based digital twin system is presented in Figs. 23 and 24, designed for managing and optimizing the electrification of ships, with a focus on battery performance and integration with the EMS. At its

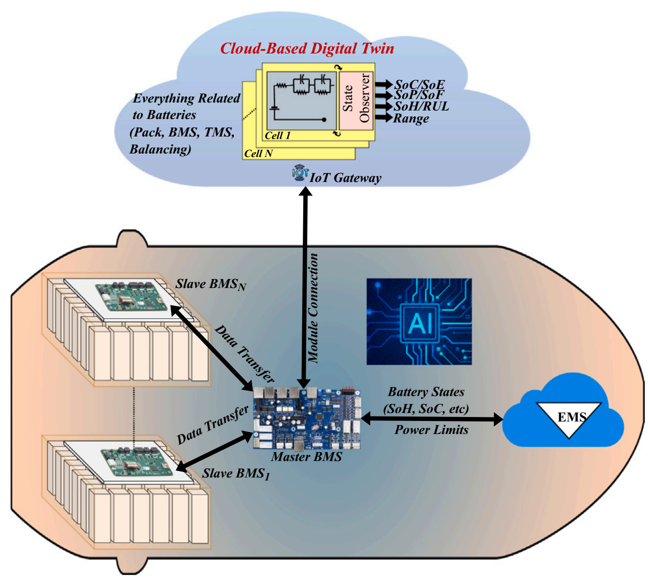

Fig. 24. Concept of digital twin application in ships. Conceptualized from [131].

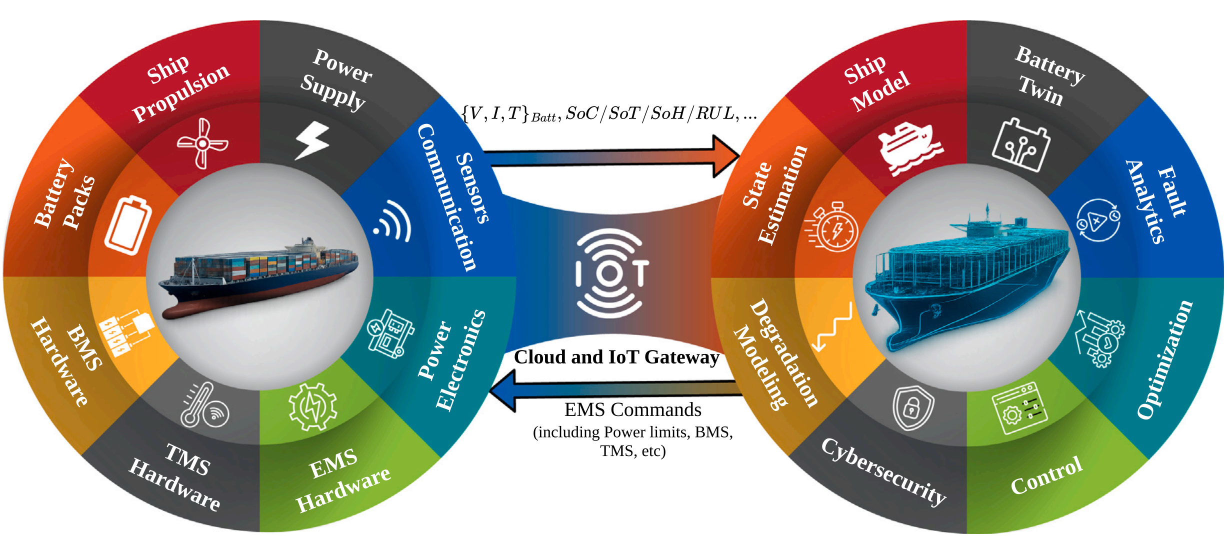

Fig. 23. Overall concept of a digital twin in a battery-powered ship, considering the physical twin, and the digital twin of the ship.

core, the cloud-based digital twin serves as a virtual replica of the ship's battery ecosystem, including the pack, BMS, TMS, and balancing mechanisms. The presented digital twin uses data from individual cells and a state observer to provide real-time battery states such as SoC, State of Energy (SoE), SoP, SoH, and RUL as well as the ship's range. The system is supported by an IoT gateway that facilitates data transfer between the physical battery modules and the cloud-based digital twin. On the ship, the battery setup includes multiple slave BMS units that monitor individual battery modules and transfer data to a central master BMS. The master BMS processes this data to determine battery states and power limits, which are then transmitted to both the digital twin and the EMS. This integration allows for continuous monitoring and adjustment of the electrified propulsion system to ensure optimal performance and safety. The EMS, also cloud-based, syncs with the digital twin to oversee the overall energy management of the ship. It receives battery states and power limits from the master BMS, enabling it to make informed decisions about energy distribution and usage [131]. Finally, the recent research works on digital twin applications in maritime industry are presented in Table 8.

7. Guidelines, standards, software, white papers and funded projects

Due to the importance of battery technologies in marine electrification, several key guidelines and standards have been developed to coordinate global efforts on this. Additionally, a wide range of officially funded projects has also been secured in various regions, including the U.S. and the EU. Some of the proposed key guidelines, standards, and funded projects in the U.S. and EU are presented, alongside the applicable software and white papers, in this section.

7.1. Guidelines, and standards

Some of these guidelines/standards for battery technologies, in maritime electrification, are described in Table 9, including the issuing organizations: U.S. DoE, Department of Transportation (DoT), Det Norske Veritas Germanischer Lloyd (DNV GL), International Electrotechnical Commission (IEC), IMO, International Organization for Standardization (ISO), Maritime Battery Forum, and European Maritime Safety Agency (EMSA).

The guidelines from the U.S. DoE and DoT present for port electrification, utility integration, and maritime decarbonization, focusing on microgrids, shore-side power, and alternative fuels. Standards from DNV GL and the Maritime Battery Forum are about the design, installation, operation, and firefighting strategies for LiB systems in maritime and offshore applications, to ensure safety and performance. The EMSA and IMO guide uniform safety protocols and fire safety regulations for BESS on ships. Additionally, IEC and ISO set safety and testing standards for LiBs in industrial and maritime environments.

7.2. Applicable software and industry white papers

An overview of software tools applicable in marine electrification is shown in Table 10. These software tools cover different applications in marine electrification, including propulsion, EMS, BMS, and PMS. Additionally, recent industry white papers about batteries and marine electrification are presented in Table 11.

These white papers, in Table 11, cover a broad range of important subjects in marine electrification, including battery deployment in deep-sea shipping, maritime electrification technologies, vessel design considerations, charging infrastructure, and regulatory compliance. Several of them focus on evaluating battery chemistries, comparing their energy density, safety performance, lifecycle characteristics, thermal behavior, and suitability for different vessel classes. Environmental and sustainability perspectives are also presented through life-cycle assessments that analyze manufacturing impacts, operational emissions reductions, recycling processes, and overall carbon footprint benefits relative to conventional marine fuels. Furthermore, they provide guidance on battery safety, risk assessment, classification requirements, fire protection measures, and hybrid propulsion system implementation.

Table 8
Digital twin applications in maritime Electrification.

Ref.	Digital Twin Part	Insights
[233]	Ship Operations	A real-time digital twin for ship operations, focusing on predicting ocean waves and hydrodynamic performances of seakeeping and maneuvering to optimize routes and assess risks.
[234]	Ship Itself	A ship digital twin to support full navigation autonomy, monitoring real-time responses to environmental changes, and optimizing controller parameters.
[235]	Ship Itself, and Its Drift	A data-driven digital twin for ships to enhance efficiency and reduce environmental impact by estimating speed loss from marine fouling.
[236]	Shipbuilding	Presenting digital twin technology in creating a virtual replica of ships, aligning with Industry 4.0's Shipyard 4.0 model. By enabling simultaneous product development and optimization of technical solutions, the digital twin enhances shipbuilding efficiency, supports lifecycle management, and improves competitiveness.
[237]	Onboard HVAC Systems	A digital twin framework for optimizing ship HVAC systems, using dynamic simulation to assess transient thermal conditions, energy needs, and system design.
[238]	Ship Propulsion	A data-driven digital twin approach for real-time monitoring of ship propulsion systems, focusing on modeling propeller hydrodynamic torque when physics-based models are limited by intellectual property or data constraints.
[239]	Ship Structure	A structural digital twin for ship structures by addressing inaccuracies in finite element analysis-based surrogate models, particularly due to imprecise boundary constraint descriptions.
[240]	Bulk Carrier Maneuvering	A digital twin task execution model for ship maneuvering in open water, using machine learning on real-world navigational data from a Kamsarmax bulk carrier (Brazil to China, March–May 2023).
[241]	Ship Engine Systems	A six-dimensional digital twin framework for smart engine systems in maritime intelligent transportation, addressing challenges like multidisciplinary knowledge, multi-scale modeling, and real-time complexity. The framework includes physical entity, hardware-in-the-loop, virtual equipment, application service, digital twin data, and connections.
[242]	Ship Engine Systems	An adaptive digital twin framework to predict marine engine performance degradation due to component wear, particularly when using low/zero-carbon fuels.
[243]	Ship Life-Cycle	Review of the application of digital twins in the maritime industry, clarifying the misconception that any virtual ship model constitutes a digital twin. It emphasizes the necessity of mutual data exchange between physical and virtual environments for a true digital twin.
[244]	Ship Itself	Presenting the application of digital twins in ship design, noting their use in specialized problems but highlighting the lack of guidance for broader, interdisciplinary digital twins. It analyzes product data modeling and past ship data standardization efforts to define requirements for effective digital twin data modeling.
[245]	Ship Itself	Review of digital twin applications in the automotive and aviation industries to guide their adoption in the maritime sector, which lags despite its critical role in global trade. Using a systematic PRISMA-based literature review, it categorizes digital twins by single vs. multiple systems, modeling methods (model-driven, data-driven, hybrid), and life-cycle phases (design, manufacturing, operation, maintenance). A five-dimensional digital twin framework is introduced to analyze research objects, subsystem applications, and modeling methods.

Table 9
Some guidelines/standards in batteries including maritime electrification.

Ref.	Guide/Standard	Organization	Insights
[246]	Port Electrification Handbook	U.S. DoE	Framework for ports transitioning to electrification; covers microgrids, shore-side power, and port equipment electrification.
[247]	Maritime Electrification for Utilities Workshop Report	U.S. DoE and DoT	Discusses utility challenges and strategies for supporting maritime electrification; includes grid integration and infrastructure planning.
[248]	Maritime Innovation	U.S. DoE	Highlights maritime decarbonization innovations, including alternative fuels, optimization tools, and efficiency technologies.
[249]	Handbook for Maritime and Offshore Battery Systems	DNV GL	Guidance on specification, design, installation, operation, and maintenance of LiB systems for ships and offshore installations.
[250]	Firefighting Guideline for Maritime Battery Systems	Maritime Battery Forum	Structured approach for developing firefighting strategies for battery systems on hybrid and electric ships; covers fire evaluation and systems.
[251]	Safety of BESS On-board Ships	EMSA	Guidance for uniform safety implementation of on-board BESSs.
[252]	Lithium Battery Guide for Shippers	U.S. DoT	Guidance on safe packaging and transport of LiB.
[253,254]	IEC 62,619	IEC	Safety requirements for secondary LiBs used in industrial applications.
[255]	DNV GL Certification Framework	DNV GL	Covers design approval, type approval, and surveillance for maritime battery systems to ensure safety and performance.
[256]	IMO SOLAS Regulations	IMO	Fire safety, emergency procedures, and crew training requirements specific to battery-powered vessels.
[257,258]	ISO 12,405	ISO	Standardized test methods and requirements for LiBs systems.

Table 10
Some of the technical software applicable in marine electrification.

Software	Application Area	Usage	Creator
Ability OCTOPUS	Electric Propulsion, EMS, PMS	Route optimization, energy efficiency, weather routing	ABB
SISHIP	Electric Propulsion, EMS	Electrical distribution design and ship energy efficiency	Siemens
K-Chief	Electric Propulsion, EMS, PMS	Integrated automation and electrical system control	Kongsberg Maritime
CEON	Electric Propulsion, EMS	Digital monitoring and energy optimization	MAN Energy Solutions
AVEVA Electrical	Electric Propulsion	Marine electrical system design and documentation	AVEVA
MATLAB/Simulink	Electric Propulsion	Modeling and simulation of electric propulsion systems	MathWorks
Orion BMS Software Suite	BMS	Configuration, monitoring, and diagnostics	Ewert Energy Systems
BQStudio	BMS	Battery monitor configuration and debugging	Texas Instruments
CANoe/CANalyzer	BMS	CAN communication testing and BMS validation	Vector Informatik
CRUISE M	Electric Propulsion, BMS, PMS	Battery and hybrid marine system simulation	AVL
Battery Management System Software	BMS	Marine battery monitoring and safety management	Wärtsilä
Corvus Energy BMS Platform	BMS	Ship battery health monitoring and diagnostics	Corvus Energy
MathWorks Battery Toolboxes	BMS	BMS algorithm development and testing	MathWorks
EcoStruxure Power Monitoring Expert	EMS, PMS	Power and energy analytics	Schneider Electric
Delomatic 4 Marine	PMS	Multifunction PMS control system	DEIF
Twin Builder	EMS, BMS, PMS	Digital twin model developer	ANSYS
LabVIEW	EMS, BMS, PMS	Hardware-in-the-loop (HIL) testing and monitoring	National Instruments

Table 11
White papers on maritime battery and electrification technologies.

White Paper	Organization	Insights	Ref.
Environment for the Use of Batteries in Deep-Sea Shipping	CIMAC, Maritime Battery Forum	Guidance on battery deployment in deep-sea vessels, safety considerations, regulatory requirements, crew competency, charging infrastructure, and future battery-powered shipping pathways.	[259]
Maritime Electrification	Bureau Veritas, Maritime Battery Forum	Overview of maritime electrification technologies, battery integration, shore charging, vessel design considerations, operational challenges, and decarbonization opportunities.	[260,261]
Which Battery for Your Ship?	Maritime Battery Forum	Comparison of battery chemistries, energy density, safety characteristics, lifecycle costs, thermal behavior, and application suitability for different vessel types.	[262]
Life Cycle Analysis of Batteries in Maritime Sector	Maritime Battery Forum, Grenland Energy, ABB, DNV GL	Life-cycle assessment of maritime battery systems, including carbon footprint, manufacturing impacts, operational savings, recycling, and environmental benefits compared with conventional marine fuels.	[263]
Battery and Hybrid Ships Technical Resources	DNV	Technical guidance on battery safety, classification rules, hybrid propulsion systems, risk assessment, fire protection, battery-room design, and certification requirements.	[264]
Accelerating the Sea Change	Siemens	Decarbonization pathways for maritime transport, battery-electric ferries, hybrid propulsion architectures, shore charging infrastructure, and vessel electrification economics.	[265]
At the Helm in Shipping – Regulation, Risk and ROI	Wärtsilä	Survey-based industry report covering decarbonization investments, electrification business cases, regulatory drivers, and future maritime technology adoption.	[266]
Is Profitable Decarbonization Possible? A How-To Guide for Ferry Operators	Wärtsilä	Ferry electrification economics, battery-hybrid systems, fuel reduction strategies, and investment planning for operators.	[267]

Table 12
Some marine electrification funded projects in the U.S.

Ref.	Name	Funder (Amount US$)	Insights
[268]	Marine Energy and Offshore Wind Research at Universities	DoE (18 000 000)	**City:** Different Cities **State:** Different States **Outcome/Purpose:** Twenty-seven research and development initiatives are underway to enhance marine energy and offshore wind technologies, aiming to expand the use of renewable energy sources. These efforts, conducted at 17 universities, including five minority-serving institutions, will tackle challenges in the marine and ocean renewable energy sectors while driving innovation and progress.
[269]	Country's First High Speed Zero-Emission Ferry Service	Environmental Protection Agency (55 000 000)	**City:** San Francisco Bay **State:** CA*** **Outcome/Purpose:** The initiative supports the development of a zero-emission network, linking communities served by San Francisco Bay Ferry, such as Oakland, Richmond, Vallejo, and Alameda.
[270]	Ferry System Electrification	Washington State* (1 680 000 000)	**City:** Different Cities **State:** WA*** **Outcome/Purpose:** The plan involves rebuilding and modernizing the fleet, transitioning the country's largest system to hybrid-electric power by 2040.
[271]	Modernize Ferry Services	Federal Transit Administration (FTA) (177 400 000)	**City:** Different Cities **State:** AK*** **Outcome/Purpose:** It will help to enhance the Alaska marine highway system.
[272]	Port's San Diego Clean Cargo Project	Environmental Protection Agency** (86 000 000)	**City:** San Diego **State:** CA **Outcome/Purpose:** The initiative will advance electrification at the Port's two maritime cargo terminals and promote zero-emission freight transport.

* Move Ahead Washington (1 030 000 000) + Climate Commitment Act (599 000 000) + State of Washington Department of Ecology Volkswagen Enforcement Mitigation Action Grant (35 000 000) + Congestion Mitigation and Air Quality Grants (12 500 000) + FTA Passenger Ferry Grant program for Clinton Terminal Electrification (4 900 000) + U.S. DoT Community Directed funding for Seattle Terminal Electrification (2 500 000) + MARAD Marine Highway program for Jumbo Mark II Conversion (1 500 000).
** Environmental Protection Agency (59 000 000) + Port of San Diego, the San Diego Air Pollution Control District, Dole, PASHA, Skycharger, and SSA Marine (28 000 000).
*** CA: California, WA: Washington, AK: Alaska.

Economic and commercialization aspects are also discussed, including return on investment, operational cost savings, decarbonization strategies, and investment planning for ferry operators and shipping companies.

7.3. Funded projects

Following the importance and the growing interest in batteries and maritime electrification, most countries are investing considerable amounts in related projects. Consequently, some of the related finished/ongoing projects, in the U.S. and the EU, are presented in Tables 12 and 13.

Regarding the projects conducted in both regions (U.S. and EU), it's understood that most of the efforts focus on infrastructure upgrades, prototype vessels, and retrofit conversions, with fewer numbers entering commercialization concerning the developing efforts, which is normal, as most of them are in the research and development process.

8. United nation (UN) sustainable development goals (SDG)

The UN SDG are a set of 17 interconnected global objectives adopted by all UN Member States in 2015 as the core of the 2030 Agenda for Sustainable Development [285–287]. Among these SDGs, SDG 7, 9, 13, 14, and 17 are the ones highly correlated to maritime transportation, and electrification, as shown in Fig. 25.

Battery systems in the maritime sector have a high correlation with SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). They enable the use of clean electricity for ship propulsion and onboard power, supporting zero-emission or hybrid vessels on short-sea, ferry, inland, and coastal routes. Therefore, this results in the reduction of dependence on fossil fuels and helps integrate renewable energy sources at ports through shore power and energy storage technologies. At the same time, these systems reduce GHG emissions and air pollutants, directly supporting global climate targets and IMO's pathways toward net-zero shipping. On the other hand, battery systems contribute to SDG 9 (Industry, Innovation and Infrastructure). Advances in maritime battery technology, power electronics, modular energy storage, and the associated charging infrastructure come with industrial innovation and the upgrading of ports and vessels. Additionally, there is relevance to SDG 14 (Life Below Water), as lower emissions, reduced noise, and decreased pollution from electrified ships help protect marine environments and coastal ecosystems. Finally, they come with links to SDG 17 (Partnerships for the Goals).

Maritime electrification is a global challenge that depends on collaboration among international organizations, such as the IMO, national regulators, shipowners, ports, battery manufacturers, technology providers, and industry alliances. These partnerships are important for developing shared standards, safety rules, infrastructure, research, and financing mechanisms that enable the widespread adoption of battery systems in this sector.

9. Discussion

Economic evaluation of battery systems for marine electrification requires a thorough assessment of the financial feasibility, operational returns, and overall long-term cost efficiency of incorporating BESS into ships. Traditional reviews often concentrate only on upfront capital costs. In contrast, contemporary analyses take a total cost of ownership approach that accounts for battery acquisition, installation, vessel modifications, charging facilities, upkeep, capacity fade, replacement, recycling, and disposal at end of life. Following this, operating costs are considerably shaped by savings on fuel, decreased engine servicing, reduced lubricant use, and the removal of mechanical stress that arises when diesel generators run under fluctuating loads. Accordingly, strategies commonly embed battery aging processes, including cycle aging, calendar aging, Depth-of-Discharge (DoD), temperature influences, and charge/discharge rates, to result in realistic forecasts of replacement timing and RUL. Economic results are measured with indicators including net present value, internal rate of return, levelized cost of energy, payback period, return on investment, discounted cash flow, and

Table 13
Some marine electrification funded projects in the EU.

Ref.	Name	Funder (Amount €)	Insights
[273]	E-ferry	European Commission (21 303 800)	**Country:** Denmark **Outcome/Purpose:** Ellen is the first all-electric ferry, launched in 2019 as part of the Horizon 2020 E-Ferry Project, operating between Fynshav and Søby in Denmark.
[274]	GFF	European Commission (12 175 620)	**Country:** Sweden **Outcome/Purpose:** It is the zero-emission, high-speed electric ferry, matching diesel ferry performance with a 30-knot speed, 26 km range in 30 min, and fast charging in under 20 min.
[275]	SEABAT	European Commission (9 588 476)	**Country:** Belgium **Outcome/Purpose:** It developed a fully electric maritime hybrid battery system for waterborne transport, combining two battery types in a standardized, modular design.
[276]	STEESMAT	European Commission (7 752 035)	**Country:** Norway **Outcome/Purpose:** Project seeks to develop advanced onboard DC grid technologies for large vessels, focusing on a plug-and-play power electronic system using solid-state transformer technology. It integrates fuel cells, batteries, and AI-driven smart management systems to enhance energy efficiency.
[277]	HY2FISH	European Commission (2 200 000)	**Country:** Spain, Italy, France, Sweden, Netherlands, Greece, Lithuania, and Germany **Outcome/Purpose:** It focuses on retrofitting a demonstrator fishing vessel off the Spanish coast with innovative, scalable, and cost-effective solutions. It aims to achieve a 40% reduction in fuel consumption and greenhouse gas emissions.
[278]	ALL-DC-SHIPS	European Commission (7 499 448)	**Country:** United Kingdom **Outcome/Purpose:** It develops modular DC/DC power converters, innovative solid-state protection systems, and advanced energy management algorithms to enhance shipboard power efficiency and reliability.
[279]	SYNERGETICS	European Commission (4 184 312)	**Country:** Germany **Outcome/Purpose:** It enhances collaboration among research institutions, the shipbuilding industry, regulatory bodies, ship owners, and technology providers to advance ship hydrodynamics and energy transition solutions.
[280]	Electric Voyage	European Commission (2 313 100)	**Country:** Norway **Outcome/Purpose:** It presented a patented electric propulsion system for boats in the 20-to-40-foot range, delivering high performance. Its accompanying software provides full data digitization and cloud-based remote management of key operational parameters.
[281]	H2-SEAS	European Commission (2 798 772)	**Country:** Latvia **Outcome/Purpose:** It focuses on developing a hydrogen-electric fishing vessel for small-scale fishing fleets, utilizing HFC technology to achieve greater energy efficiency and zero emissions.
[282]	FLEXSHIP	European Commission (7 851 668)	**Country:** Belgium **Outcome/Purpose:** It aims to create a digital green solution for vessel electrification, focusing on designing flexible, modular, and scalable systems to electrify the waterborne sector.
[283]	HARPOONERS	European Commission (7 497 595)	**Country:** Spain **Outcome/Purpose:** It seeks to develop a unique modular AC battery system that integrates essential components into a compact design, removing the need for separate transformers and cooling systems.
[284]	NEMOSHIP	European Commission (7 870 268)	**Country:** France **Outcome/Purpose:** It develops a modular, standardized BESS compatible with various storage units, paired with a cloud-based digital platform for data-driven decision-making to ensure optimal and safe use. The innovations will be demonstrated on a retrofitted hybrid offshore service vessel, a new hybrid cruise vessel, and two fully electric vessels (ferries and short-sea shipping) in a semi-virtual environment.

equivalent annual cost. Other factors are also considered in some conditions, including variable electricity prices, fuel-price swings, carbon taxes, emissions-trading mechanisms, shore-power rates, and income from ancillary services so that investment resilience can be tested under uncertain market conditions. Sensitivity studies, Monte Carlo simulations, and scenario-based optimization are routinely applied to examine how changes in battery prices, electricity costs, service life, and policy incentives affect results. Hybrid configurations that pair batteries with diesel engines, fuel cells, or solar panels are likewise optimized economically through different strategies and AI-driven EMS. The goal is to lower lifetime operating costs while increasing fuel savings and extending battery life.

Considering the Life Cycle Assessment (LCA) of battery systems used in marine electrification, it provides a thorough appraisal of the environmental burdens related to these technologies over their complete circular life cycle, helping stakeholders pinpoint sustainability hotspots and improve resource efficiency. This LCA overall concept is shown in Fig. 26.

Instead of relying on a traditional model, contemporary battery LCAs more often consider a circular-economy framework built around six linked stages [288]: raw materials, battery-grade input materials, battery manufacturing, reuse, re-manufacturing, re-functionalization (second-life uses), and recycling. The process starts with the extraction of raw materials, during which critical minerals such as lithium, nickel, cobalt, manganese, graphite, copper, and aluminum are mined and processed—activities that typically generate substantial GHG emissions, energy use, water consumption, land disturbance, and ecological harm. These resources are then converted into battery-grade input materials, including cathode active materials, anode materials, electrolytes, separators, binders, current collectors, and conductive additives. The purification and chemical synthesis steps involved are among the most energy-demanding parts of battery production. Battery manufacturing itself covers cell production, module assembly, pack integration, installation of the BMS/TMS, quality testing, transport, and installation on vessels. Once in service, batteries deliver major reductions in fuel use, GHG emissions, nitrogen oxides, sulfur oxides, particulate matter, and underwater noise, especially when charged from renewable electricity or shore power. When capacity declines below the level required for propulsion, the reuse stage allows batteries that still hold adequate residual energy to continue operating in less demanding marine roles with lower additional processing. Units that need repair or performance recovery move into the re-manufacturing stage, where defective cells or modules are exchanged, components are refurbished, and packs are rebuilt to restore near-original capability while limiting material demand and embodied carbon. Batteries no longer suitable for ship propulsion yet retaining useful residual capacity can be re-functionalized. This

Fig. 25. United Nations SDG, where the correlated SDG to maritime transportation/electrification are highlighted.

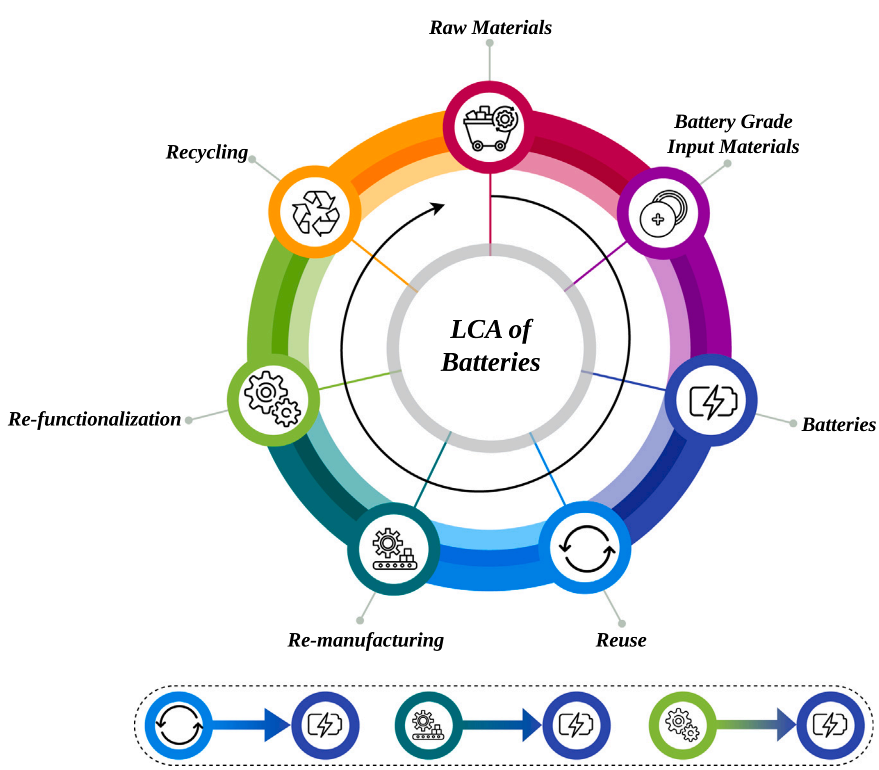

Fig. 26. Life cycle assessment of batteries concept.

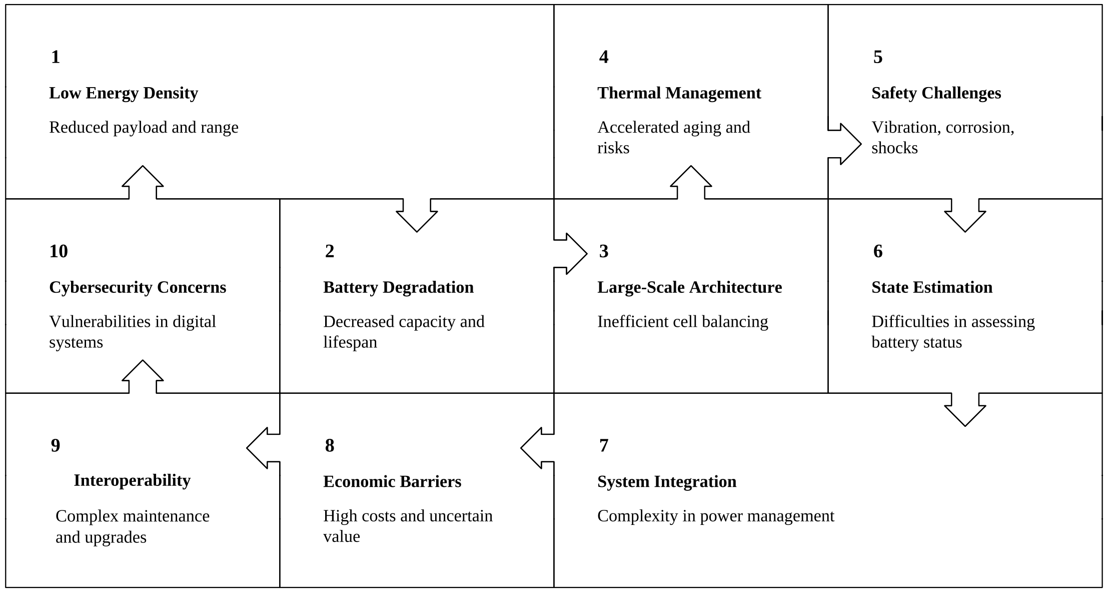

Fig. 27. Challenges associated with marine electrification.

means they can be repurposed for secondary roles, such as stationary storage, RES integration, microgrids, port electrification, peak shaving, or backup power—thereby prolonging their working life and reducing the need for new production. At the end of their useful life, batteries enter the recycling stage, in which valuable constituents (lithium, cobalt, nickel, copper, aluminum, and graphite) are recovered by pyrometallurgical, hydrometallurgical, or emerging direct-recycling methods, cutting reliance on virgin resources and lowering the environmental burden of subsequent battery manufacture.

Although marine electrification has progressed significantly, it still has several challenges that need to be addressed in future research to ensure sustainable and efficient development. These challenges are shown in Fig. 27.

9.1. Challenges

A key challenge is the comparatively low energy density of present-day LiBs relative to traditional marine fuels (such as marine diesel fuel). This leads to higher battery mass and volume, which in turn lowers cargo capacity and limits vessel range, especially on long-haul and deep-sea routes. Capacity fade driven by repeated charge/discharge cycles, high-current operation, temperature swings, and the demanding marine environment further lowers usable energy, raises internal resistance, and shortens operational life, thereby elevating replacement costs. As the energy requirements of large electric and hybrid ships increase, marine battery installations expand accordingly, frequently containing thousands of cells arranged in modules and packs. Such extensive configurations render conventional cell-by-cell balancing progressively less practical, due to the elevated computational demands, communication burdens, longer balancing times, and higher energy losses. Additionally, maintaining voltage and energy consistency across these large packs has therefore become a significant technical challenge, causing the transition from classical cell-level methods toward smarter pack-level balancing techniques better suited to large-scale architectures. As another challenge, thermal control and TMS should be considered. Insufficient heat removal can increase aging, lower efficiency, and heighten the chance of thermal runaway, particularly in tightly packed modules subjected to high power loads. Accordingly, safety risks are intensified by the vibration, humidity, saltwater exposure, and mechanical shocks typical of maritime service, necessitating a robust BMS, advanced fault-diagnosis algorithms, and effective fire-suppression measures. In addition, reliable determination of SoC, SoH, SoP, SoT, and RUL is also challenging regarding the nonlinear electrochemistry of batteries, uncertainties in aging behavior, and continuously varying operating conditions. Combining battery systems with onboard power electronics, propulsion equipment, renewable sources, shore-charging facilities, and hybrid energy setups adds further layers of complexity to EMS and power coordination. Economic obstacles are among the other important challenges. High upfront costs, battery life, recycling costs, and uncertain residual value influence total cost of ownership. Finally, the growing digitalization and connectivity of marine battery systems increase their vulnerability to cyber threats, making secure communication protocols, resilient control structures, and dependable data handling indispensable for safe and reliable vessel operation.

9.2. Future works

Considering the associated challenges, future research can be focused on developing safer, more efficient, intelligent, and sustainable BESS technologies capable of supporting fully autonomous and zero-emission vessels. Significant efforts should be directed toward next-generation battery chemistries, including solid-state, lithium-sulfur, sodium-ion, and metal-air batteries, which possess substantially higher energy densities, improved safety, faster charging capabilities, and reduced dependence on critical raw materials. Artificial Intelligence and physics-informed ML strategies are also a strong focus in battery management by enabling highly accurate prediction of SoC, SoH, SoP, and other states, as well as thermal behavior and fault evolution under diverse operating conditions. As marine battery systems continue to increase in capacity and complexity, future BMS architectures should transition from conventional cell-level balancing to intelligent pack-level balancing frameworks capable of handling large-scale battery packs more efficiently. Therefore, AI-driven adaptive balancing algorithms, decentralized balancing architectures, and digital twin-assisted balancing strategies are expected to significantly reduce balancing time, communication burden, computational complexity, and energy losses while improving battery consistency, reliability, and operational scalability. Furthermore, the development of digital twins, hybrid twins, and cloud-based battery analytics can facilitate real-time monitoring, predictive maintenance, anomaly detection, and lifecycle optimization through continuous synchronization between physical battery systems and their digital counterparts. Advanced TMSs using intelligent control and adaptive thermal optimization can be further investigated to enhance battery safety, efficiency, and service life. From a sustainability perspective, greater emphasis can be placed on circular economy frameworks including battery reuse, re-manufacturing, re-functionalization, and high-efficiency recycling to maximize resource utilization and minimize environmental impacts throughout the battery lifecycle.

10. Conclusion

A comprehensive review of the potential of battery systems to enable fully electric and hybrid vessels is presented in this paper, supported by advancements in battery technologies and real-world applications across diverse ship types. The integration of AI and digital twin technologies further enhances efficiency, safety, and innovation in this sector, while compliance with established guidelines and standards ensures reliable implementation. Ongoing and completed projects in the U.S. and EU demonstrate the global commitment to this transition. Considering the AI strategies, several case studies are presented for each representative strategy (FLC, RL, NN, GANs, ANFIS, and LLM) in battery systems and marine electrification. On the side of the correlation with UN SDGs, battery systems, and marine electrification support SDG 7 and 13 by enabling clean propulsion and cutting emissions toward IMO net-zero goals. They are also effective for SDG 9 through technology and infrastructure innovation, SDG 14 by reducing marine pollution and noise, and SDG 17 through multi-stakeholder partnerships. Despite these advancements, challenges such as battery performance, scalability, and infrastructure development persist, requiring continued research and investment. Future work can be addressed in the development of better battery chemistries for marine electrification, pack-level balancing instead of cell-level balancing, digital twins for predictive maintenance, advanced AI-integrated EMS, BMS, TMS, and circular-economy strategies. The future of marine electrification is promising, with continued innovation and collaboration driving the industry toward a sustainable, net-zero future while balancing economic vitality and environmental responsibility.

CRediT authorship contribution statement

Ashkan Safari: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Hoda Sorouri:** Writing – review & editing, Validation, Investigation, Formal analysis. **Arman Oshnoei:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis. **Frede Blaabjerg:** Writing – review & editing, Validation, Investigation, Formal analysis. **Weihan Li:** Writing – review & editing, Validation, Investigation, Formal analysis. **Changfu Zou:** Writing – review & editing, Validation, Investigation, Formal analysis. **Valdemar Ehlers:** Writing – review & editing, Formal analysis. **Johan Gudbjart:** Writing – review & editing, Formal analysis. **Claus Ebbesen:** Writing – review & editing, Formal analysis. **Pooya Davari:** Writing – review & editing, Investigation, Funding acquisition, Supervision, Project administration, Formal analysis.

Declaration of competing interest

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

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Data availability

No data were used for the research described in the article.

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