

Review

Energy Management Strategies and Capacity Sizing for Hybrid Ship Systems

Tino Vidović ¹, Gojmir Radica ^{1,*}, Nikolina Pivac ² and Branko Lalić ²

¹ Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, University of Split, 21000 Split, Croatia; tino.vidovic.00@fesb.hr

² Faculty of Maritime Studies, University of Split, 21000 Split, Croatia; npivac@pfst.hr (N.P.); blalic@pfst.hr (B.L.)

* Correspondence: goradica@fesb.hr

Abstract

This comprehensive review investigates hybrid propulsion technologies as a pathway to decarbonization and improved energy efficiency in the maritime sector. Through a review of the recent literature, this study synthesizes current knowledge on energy management strategies and capacity sizing approaches for hybrid ship propulsion systems. Reported results indicate that optimized energy management can reduce fuel consumption and greenhouse gas emissions while minimizing total operational costs. Among real-time strategies, the Equivalent Consumption Minimization Strategy emerges as particularly suitable for maritime use due to its low computational demand and independence from full voyage profile knowledge, yet its maritime application remains far less developed than in the automotive domain. Capacity sizing and energy management are usually treated as separate optimization problems, limiting the achievability of truly optimal solutions. Only a few studies adopt integrated co-optimization frameworks, and these are typically built around simplified or fixed operational profiles. Moreover, the coupling between energy management parameters, such as the ECMS equivalence factor, and hardware sizing remains insufficiently explored. To address this, the review contributes a ship-specific classification of energy management strategies, a consolidated treatment of battery sizing methods with explicit attention to degradation, and a generalized two-loop framework that couples component sizing with ECMS-based energy management. The findings suggest that future research should prioritize adaptive energy management formulations calibrated for stochastic maritime duty cycles, the incorporation of battery degradation models into co-optimization, and validation against stochastic, real-world operating conditions.

Keywords: hybrid ship propulsion; energy management strategy; equivalent consumption minimization strategy; capacity sizing; co-optimization



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1. Introduction

Since ships account for about 3% of global anthropogenic greenhouse gas (GHG) emissions [1], the maritime sector is mainly pursuing three routes to mitigation: deploying new technologies, switching to alternative fuels, and electrifying propulsion systems in combination with multiple energy sources for propulsion [2].

For many years, direct technological measures for emission reduction have already been applied and have delivered substantial cuts in emissions, including Exhaust Gas Recirculation (EGR), scrubbers, dual-fuel concepts, Fuel–Water Emulsions (FWEs), Waste Heat Recovery (WHR) systems, and Selective Catalytic Reduction (SCR) [3–5].

Nevertheless, although these technologies are effective in lowering GHG emissions, they also drive up both capital and operating expenditures because of the additional installation and maintenance requirements [6].

Alternative fuels such as methanol, biodiesel, ammonia, biogas, hydrogen, and Liquefied Petroleum Gas (LPG) are also being explored as promising options because of their emission-reduction potential [7,8]. Methanol use in internal combustion engines is being studied as a means to lower CO₂ emissions, since its carbon content is only 37.5% compared with 85.7% in marine gas oil, which corresponds to a lower CO₂ emission factor of 1.375 and, hence, lower specific CO₂ emissions, despite higher specific fuel consumption [9]. In contrast, hydrogen and ammonia, owing to their carbon-free structures, are regarded as particularly attractive alternative fuels for the maritime sector, while biodiesel is considered the most mature biofuel in terms of production technology and supply chain [10]; via esterification, oils and fats are converted to fatty acid methyl esters, yielding a fuel with diesel-like properties but reduced SO_x emissions. Alternative fuels offer the potential to simultaneously reduce CO₂, NO_x, SO_x, and particulate matter emissions across the entire well-to-wake lifecycle when produced from renewable sources [9]. However, there is the need for significant investment in ship engine modifications in order to ensure safe and reliable operation with low-flashpoint and chemically aggressive fuels such as methanol and ammonia, which require compatible materials, revised safety protocols, and adequate bunkering infrastructure [11].

Hybrid-electric propulsion, employed on ships to cut harmful gas emissions by lowering fuel consumption, constitutes the third main approach. When such systems are used not only for propulsion but also to supply electrical power to auxiliary onboard systems, they can deliver multiple benefits, extending beyond the reduction of CO₂, NO_x, and other pollutant emissions [12–14]. In the maritime sector, batteries, supercapacitors, and even flywheels as energy storage devices are included in hybridization technologies, which are combined with internal combustion engines and fuel cells [15–17], with batteries being the most widely adopted option.

Experimental tests on inland navigation vessels have demonstrated that operating hybrid propulsion in “zero-emission” mode can yield up to a fourfold increase in energy efficiency compared with conventional propulsion while also substantially reducing emissions and noise [18]. Data-driven investigations of fully electric ship powertrain efficiency further indicate that hybridizing ship energy systems enhances overall efficiency and operational flexibility, with hybrid DC architectures providing additional gains owing to variable-speed engine operation [19]. Depending on the applied management strategy, hybrid diesel–electric configurations can deliver fuel savings in the range of 6.9–8.8%, with cruising vessels such as yachts and cruise ships exhibiting the highest savings potential [20], whereas fuel-cell-based hybrid systems can raise overall energy efficiency by about 22.5% when integrated into a cogeneration plant [21].

Previous studies have focused on various approaches for reducing emissions in the maritime industry, including direct technological innovations such as EGR, SCR, and WHR systems as well as the use of alternative fuels. However, few studies have comprehensively reviewed hybrid propulsion technologies in conjunction with energy management strategies for hybrid ship systems. Since the system capacity sizing and energy management strategies are usually addressed as independent optimization problems, potential for achieving globally optimal solutions is limited. Existing review articles have addressed hybrid ship power and propulsion architectures and multi-energy system configurations [13,14], but they generally treat energy management and component sizing as separate topics and do not examine the coupling between them. In contrast, the present review brings these two strands together and focuses specifically on the interaction between real-time energy

management—in particular ECMS—and battery sizing through co-optimization, which, to the best of our knowledge, has not been the focus of previous maritime reviews. This paper provides a comprehensive review of energy management strategies and optimal sizing approaches for hybrid ship systems. Hence, integrated co-optimization frameworks are examined as a promising pathway toward globally optimal hybrid ship system design.

The main contributions of this review are (1) a classification of energy management strategies—rule-based, global optimization, and real-time optimization—framed specifically for hybrid ship propulsion (Figure 1); (2) a structured synthesis of battery energy storage sizing methods, both analytical and metaheuristic, with explicit treatment of battery degradation and cost–benefit trade-offs; (3) a critical review of co-optimization frameworks that jointly address sizing and energy management, identifying the coupling between the ECMS equivalence factor and battery sizing as an underexplored problem; and (4) a generalized two-loop co-optimization framework (Figure 2) together with prioritized research directions for realistic, stochastic maritime duty cycles.

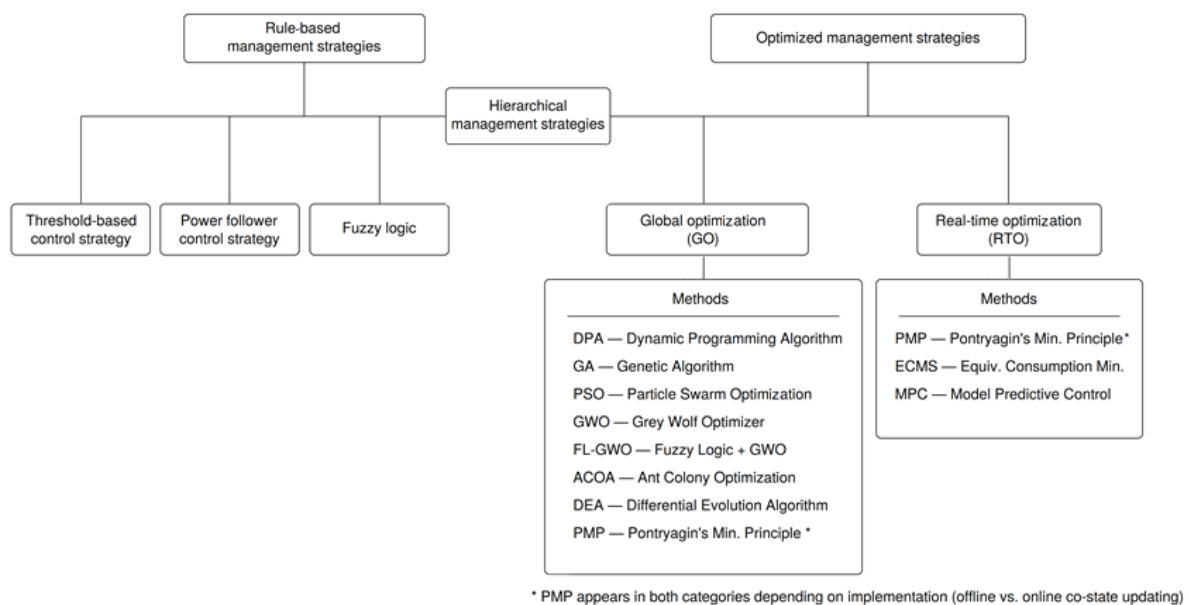


Figure 1. Classification of management strategies.

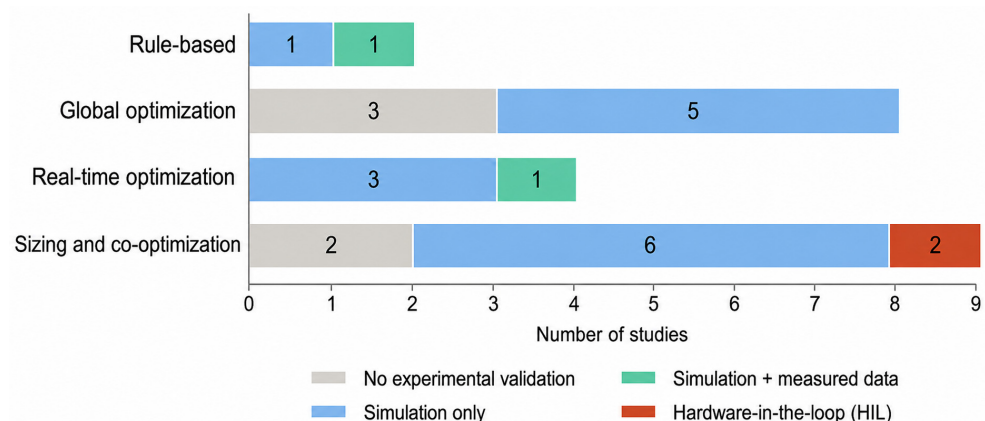


Figure 2. Reviewed studies' validation by category.

This work was conducted as a structured narrative review. The relevant literature was identified through searches of Scopus, Web of Science, IEEE Xplore, ScienceDirect, Google Scholar, and the MDPI open-access library, using combinations of the keywords “hybrid ship”, “maritime/marine”, “energy management strategy”, “ECMS”, “battery

sizing”, “capacity sizing”, “co-optimization”, and “battery degradation”. The search covered publications from 2012 to 2025, with an emphasis on the most recent work; seminal earlier studies, such as the original ECMS formulation, were included where needed for context. Studies were included if they addressed energy management and/or component sizing for hybrid marine power and propulsion systems or presented transferable methods from closely related domains such as road vehicles and microgrids. Works dealing only with conventional propulsion, with alternative fuels in isolation, or with non-propulsion applications were excluded.

2. Energy Management Strategies

This section reviews energy management strategies for hybrid ships, classifying the main approaches and assessing their suitability for real-time maritime operation; a comparative summary is given in Table 1. The implementation of a smart real-time energy management strategy is of critical importance for vessels with hybrid propulsion to ensure greater system and component efficiency and reliable, safe, and economical operation. Given that hybrid energy systems comprise multiple energy sources and a range of loads, they can exhibit different dynamic behaviors under varying operating conditions. Consequently, the Energy Management System (EMS) must be carefully structured and implemented so that it responds appropriately to changing dynamic demands while maintaining a safe power supply for both auxiliary and propulsion systems. A well-designed EMS can enhance overall energy efficiency and lower fuel consumption by coordinating each energy source to operate under near-optimal conditions. Broadly, two EMS approaches are employed on ships: rule-based strategies and optimization-based management strategies [22], as shown in Figure 1.

2.1. Rule-Based Strategies

A rule-based energy management strategy is a static control approach that exhibits good robustness and low computational demand, enabling real-time implementation through practical control rules derived from prior operational experience and expert knowledge [23]. Various management strategies using the same approach have been proposed for hybrid systems with multiple energy sources [24].

The most rudimentary formulation within this category is the on-off (threshold-based) control, which is conceptually analogous to the thermostat control strategy historically deployed in the automotive domain [25]. In a marine hybrid configuration, this strategy activates or deactivates specific power sources based on rigid, predefined thresholds, such as the battery state of charge (SOC) limits or total grid load demands. The key benefits of this strategy are shorter battery charging and discharging times and higher average engine efficiency. In the context of hybrid ship power systems, this strategy is straightforward to implement and provides reliable real-time control, making it suitable for vessels with relatively stable load profiles, but it is limited in its ability to handle the dynamic and unpredictable nature of maritime operations.

Another rule-based strategy often used is the power follower control strategy [23], known in the maritime literature as the load-following or load-leveling strategy, which adjusts generator output to directly track the instantaneous load demand, with the battery compensating for transient fluctuations. In hybrid ship applications, the load-following strategy is closely related to the peak shaving approach, in which the battery compensates for transient load peaks while generators operate at or near their optimal specific fuel oil consumption (SFOC) point. The deployment of backup systems to follow the load in load-following mode results in the engine operating outside its rated conditions, consuming more fuel and leading to higher emissions and increased operating costs.

In contrast, because a rule-based management strategy relies heavily on the designer's experience, identifying truly optimal operating points becomes challenging for more complex and highly dynamic systems. Since maritime operating conditions are inherently unpredictable and influenced by external factors such as waves and wind, more advanced management strategies gain importance when dealing with dynamic, time-varying non-linear problems. Fuzzy logic control is one such approach, as it does not require an exact mathematical model while still maintaining acceptable accuracy.

Yuan et al. [26] developed a fuzzy logic-based management method for energy management of a photovoltaic system, battery, and diesel hybrid ship designed to carry wheeled cargo (RORO). As a result of the study, fuel consumption and emissions were reduced by enhancing the ship's overall performance, validated through comparison of measured operating data with simulation results. A separate investigation compared a fuzzy-logic-based EMS with a proportional–integral (PI)-based EMS for medium-voltage DC all-electric ship power systems [27]. Although both approaches were able to supply the ship under varying power demands, fuzzy logic achieved better battery SOC management by adaptively adjusting charge and discharge rates. However, designing effective fuzzy rules calls for substantial expertise in system operation and behavior prediction, and the inherently dynamic nature of ships makes them difficult to represent with a fixed linear mathematical model.

A more advanced form of rule-based strategy that bridges the gap between rule-based and optimization-based approaches is the hierarchical management strategy. It addresses the limitation of achieving both economic goals and local dynamic stability of the system simultaneously [28]. Instead of one control layer, this management strategy organizes management in two or more levels that operate on different time scales and have different goals. The upper layer is in charge of generator control, managing power distribution between generators and batteries in order to achieve optimal fuel consumption and long-term economic efficiency. It operates at a slower pace, based on generation cost, with a lower update frequency. The lower layer executes real-time cascade control, including DC bus voltage regulation, load balancing between components, and ensuring overall system stability. It handles short-term, local decisions and operates in real time, responding to instantaneous fluctuations. Moreover, the upper layer can also incorporate optimization-based approaches [29,30]. In the literature, hierarchical strategies are therefore often considered as a separate category, positioned between purely rule-based and optimization-based strategies, as they may combine elements of both.

2.2. Optimized Management Strategies

Optimization-based energy management strategies can be broadly categorized into two paradigms—Offline Global Optimization (GO) and Online Real-Time Optimization (RTO)—which primarily differ in their planning time frame and the information available in the moment of optimization. While GO optimizes energy distribution over the entire voyage assuming a known or predicted mission profile, RTO relies on real-time system state feedback and operates over a short, receding time horizon to respond to instantaneous load demands and disturbances.

GO uses all system models and conditions with a theoretical basis and precise mathematical equations to perform a comprehensive optimization within a given period. GO can include the Dynamic Programming Algorithm (DPA) [31], Genetic Algorithm (GA) [32], Particle Swarm Optimization (PSO) [33], Grey Wolf Optimizer (GWO) algorithm [34] Ant Colony Optimization Algorithm (ACOA) [35], the simulated annealing algorithm [36], and the Differential Evolution Algorithm (DEA) [37] or other advanced optimization algorithms.

The DPA requires all information about the optimization problem in advance. In research on optimizing energy production scheduling for a fully electric ship using the

DPA, with respect to operational constraints such as greenhouse gas emissions or travel schedules and assuming that ship load changes can be predicted, it is possible to achieve a reduction in operational costs and greenhouse gas emissions [31].

The GA exhibits high versatility and broad applicability while maintaining relatively low algorithmic complexity. For instance, Ancona et al. [32] applied GA-based optimization to reduce fuel consumption by optimizing load sharing among different energy source configurations on a cruise ship. Their results showed that hybrid configurations delivered the best performance across the considered criteria, including both economic and environmental indicators.

In a study for a tanker, Kumar and Fozdar [33] used two different PSO variants to determine optimal power of diesel generator set, capacity of solar panels and energy storage systems (ESSs), concluding that without ESSs, the solar–diesel hybrid system configuration is not economically feasible.

In order to ensure the efficiency and safety of ship operation with photovoltaic/battery/diesel systems and a “cold ironing” system, a three-stage optimal energy management framework and control strategy based on adaptive multi-context operation cooperative evolving PSO was developed by Tang et al. [38]. Although the proposed strategy lowers the ship’s electricity costs and increases solar energy utilization, its extensive optimization procedure demands a very large dataset, which raises the computational burden and lengthens the time needed to obtain the results.

Al-Falahi et al. [34] implemented two management strategies (GWO algorithm and a rule-based approach), using fuel consumption and emission reduction as the performance metrics. Compared to the traditional rule-based method, which depends on predefined conditions, the GWO achieves superior performance in reducing emissions and fuel consumption. The study concluded that the GWO can address multi-objective optimization problems subject to numerous operational constraints, while traditional methods use predetermined conditions. The management strategy obtained by the GWO serves to minimize fuel consumption and power distribution for a ferry with diesel generators, a battery energy storage system, and a ferry load profile.

The algorithm proposed by Al-Falahi et al. in a separate study combines fuzzy logic optimization with the FL-GWO to lower the operating costs of a hybrid-electric ferry, and the results indicate that the FL-GWO surpasses the standard GWO in fuel savings, achieving improvements of 3.14% under normal and 1.81% under high load conditions. Neither paper [34,39] conducted comparisons with other types of metaheuristic optimization algorithms to further confirm the effectiveness of the proposed management algorithm.

The application of the ACOA with the RTO method called Equivalent Consumption Minimization Strategy (ECMS) on a diesel–electric hybrid ship, with the aim of reducing fuel consumption and battery state-of-charge fluctuations, was given by Xiang and Yang [35]. The ACOA-based EMS nearly doubled the efficiency compared to the rule-based strategy, reducing fuel consumption by 6.9% to 12.1%.

Zhao and Wang [40] proposed an energy management strategy for a ship power system using the DEA to simultaneously optimize ship speed, generator on/off scheduling, and power distribution among generator sets and diesel engines. The goal was to minimize total operating costs while satisfying greenhouse gas emission constraints. The strategy was validated through simulation using navigation data from a passenger/Ro-Ro ship with three generators and two diesel engines. The authors highlighted that the algorithm was fully parameterized and applicable to any ship type, as its primary input was the fuel consumption curve of the engine and generator. However, the reported cost reduction of approximately 3% is relatively modest. Also, the study did not compare the DEA

against other GO methods. Thus, the comparative advantage of the DEA over alternative approaches remains unclear.

The second primary paradigm within optimization-based power management is RTO. RTO architectures focus exclusively on instantaneous or short-horizon energy demands by formulating causal, real-time cost-minimization functions. Pontryagin's Minimum Principle (PMP) and previously mentioned ECMS represent two of the most widely adopted mathematical frameworks in this category. PMP minimizes global, time-dependent optimization problems by decomposing them into instantaneous local sub-problems through the minimization of the Hamiltonian function at each time step, significantly reducing the computational burden relative to global search algorithms.

PMP has been widely studied in road hybrid vehicle applications [41], where real-time minimization of fuel consumption under unpredictable driving cycles has demonstrated superior performance compared to rule-based management. Although PMP is mainly used for Plug-in Hybrid-Electric Vehicles (PHEVs), it can be applied in shipping as well.

The model predictive control (MPC) method was used by Shagar, V. et al. [42] to avoid frequency transients caused by the propeller in the ship's energy system. The mitigation device was a battery energy storage system, directly connected to a DC frequency converter. Simulation results demonstrate that when combined with the battery system, the proposed MPC-based solution keeps transient frequency deviations in the ship's power system within the limits specified by the relevant quality standards.

Chen et al. [43] proposed a hybrid ship propulsion energy management strategy that integrates MPC with PMP to overcome the robustness shortcomings of conventional PMP-based approaches. The method uses proportional state feedback to dynamically correct boundary conditions at each control interval, preserving solution optimality while compensating for real-world disturbances. Beyond providing closed-loop correction to the PMP framework, the MPC prediction horizon effectively reduces the scope of energy management from the full voyage to a shorter rolling window, enabling more practical real-time implementation.

Zahedi et al. [44] proposed an optimization algorithm for determining optimal loading conditions for a hybrid ship propulsion system with the lowest fuel consumption. The studied system included diesel engines, a synchronous generator, rectifier units, and a Li-ion battery as the energy storage. The resulting fuel consumption in the simulation was compared with that of a conventional AC system and a DC power system without energy storage. The results showed that while the DC system without energy storage provides noticeable fuel savings compared to the conventional AC system (15% fuel savings), optimal utilization of energy storage in the DC system can result in an additional 7% savings compared to the DC system without energy storage.

Wu et al. [45] developed an EMS based on a Double Q-learning model. Although reinforcement learning methods are sometimes classified as a distinct data-driven category in the literature, Double Q-learning is treated here within the RTO framework due to its ability to make real-time decisions based on current system states without requiring prior knowledge of the voyage profile. The Double Q model was trained using stochastic power profiles collected by continuously monitoring a passenger ferry, using a plug-in hybrid model composed of fuel cells and a battery propulsion system. Energy management strategies generated by the model were validated using a second test dataset collected during another measurement period. The limitation of this method is the need for a large amount of data due to the method's validation requirements. Furthermore, as the Q model includes maximization biases, system performance may produce unsatisfactory results. Investment and operational costs were also not considered, which may affect the economic viability of the method.

The ECMS aims to calculate optimal power management reference points and optimal management formulations to minimize engine fuel consumption [46]. In a demonstration of the ECMS on a hybrid ferry, a 10% reduction in fuel consumption was achieved by optimizing the power balance between energy sources [47]. Furthermore, the ECMS is particularly well suited for marine applications due to its real-time optimization capability and low computational demand, without requiring complete prior knowledge of the voyage profile [48]. For this reason, the ECMS is investigated in greater depth.

Equivalent Consumption Minimization Strategy

The ECMS is a well-known real-time energy management optimization strategy, originally introduced by Paganelli et al. [49]. Its core concept is to transform the global optimization task into a sequence of local optimization problems by minimizing an equivalent fuel consumption. In this framework, equivalent fuel consumption is defined as the sum of the actual fuel used by the internal combustion engine and the fuel equivalent of the energy drawn from storage (typically batteries). Building on Pontryagin's Minimum Principle (PMP), an equivalence factor is introduced to convert electrical energy into an equivalent amount of fuel energy [50].

Physically, the equivalence factor expresses the cost of using stored electrical energy in the same currency as fuel. It represents the average efficiency of the energy conversion path between fuel and electricity and thereby encodes the expected future fuel cost of either depleting or replenishing the battery. A discharge event is penalized because the energy removed from the battery will eventually have to be regenerated by burning fuel, while a charging event is credited because it stores energy that displaces future fuel use. The equivalence factor therefore acts as the link that reformulates the global optimization problem by minimizing fuel consumption over an entire mission into a local, instantaneous minimization that can be solved in real time. Because it carries this predictive cost information, the choice of the equivalence factor is of the key importance for the ECMS. An inappropriate value leads either to premature battery depletion or to underutilization of the storage system, in both cases sacrificing fuel economy.

Various approaches have been used to determine the equivalence factor. However, the majority of research on equivalence factor determination has been conducted in the context of road hybrid vehicles. While the underlying mathematical framework is transferable, the specific methods require significant adaptation before they can be applied to maritime systems.

The first approach is to set the equivalence factor as a constant during the entire optimization process. This is the simplest approach, but the selection of the constant value is crucial, as it directly affects algorithm performance. Therefore, many works have used different methods to optimize this value, such as bibliometric analysis [51], driving pattern recognition-based adaptation [52], static optimization with system constraints [53], dynamic programming combined with the ECMS [54], and equivalence factor tuning for different hybrid configurations [55]. Such offline calibration is conceptually simple and computationally light during operation, but it requires complete knowledge of the operating cycle in advance and must be recalibrated for every individual cycle, which limits the general applicability of the strategy when the mission profile changes.

Table 1. Comparison of energy management strategies for hybrid ship systems.

EMS Method	Paradigm	Computational Demand	Real-Time Capability	Requires Prior Voyage Knowledge	Optimality	Implementation Complexity	Applicable Vessel Types	Maritime Maturity/Adoption
Threshold/on–off control [47]	Rule based	Low	Yes	No	Heuristic (suboptimal)	Low	Tugs, ferries, and hybrid vessels with distinct operating modes	Established
Power follower/load following [23]	Rule based	Low	Yes	No	Heuristic (suboptimal)	Low	General hybrid vessels	Established
Fuzzy logic control [26,27]	Rule based	Low–Medium	Yes	No	Heuristic	Medium (expert rules)	RORO, PV hybrid, and all electric	Moderate
Hierarchical multi-layer [30]	Rule based/hybrid	Medium	Yes	Partial	Heuristic + local	High	FC/battery hybrid ships (inland waterway vessels)	Rare
Dynamic programming (DP) [31]	Global optimization	High	No	Yes	Global optimum	Medium	All-electric ships	Rare (benchmark)
Metaheuristics (GA, PSO, GWO, ACO, and DE) [32,34,35,40]	Global optimization	High	No	Yes	Near global/Pareto	Medium–High	Cruise ships, ferries, and tankers	Moderate
Pontryagin’s minimum principle (PMP) [43]	Real-time optimization	Medium	Yes	Partial	Local (instantaneous)	Medium	Mainly road; limited marine	Rare
Model predictive control (MPC) [42]	Real-time optimization	Medium–High	Yes	Partial (horizon)	Local (horizon)	High	Frequency-sensitive ship grids	Rare
Equivalent consumption minimization (ECMS) [46,47,50]	Real-time optimization	Low	Yes	No	Near optimal (instantaneous)	Medium	Tugboats and ferries	Rare (promising)
Reinforcement learning (Double Q-learning) [45]	Real time/data driven	High (training)	Yes	No	Heuristic (learned)	High	Passenger ferries (plug-in FC/battery)	Experimental

The second approach starts from a constant equivalence factor and corrects it online using feedback on the battery state of charge relative to a reference value, without requiring prior knowledge of the operating cycle. This has been implemented through proportional–integral correction of the equivalence factor based on the SOC deviation [56] and through reformulations that remove the SOC deviation from the cost function altogether and instead treat the SOC limits as optimization constraints that bound the search space [57]. The main weakness of these methods is the residual sensitivity of the equivalence factor function to the operating cycle, so that fuel economy degrades when the actual profile deviates from the one assumed during the offline tuning of the baseline factor.

The third approach does not require complete knowledge of the driving cycle but exploits information about it, either by recognizing the current cycle type and switching to correspondingly pre-optimized factors [58] or by predicting the upcoming power trajectory from route and navigation data and updating the equivalence factor accordingly [59]. It can therefore be applied in a real-time management system using past, current, and future information from 3D maps in the vehicle [60], GPS-based navigation systems [61–63], and telemetry systems [64]. An ECMS based on this estimation method is also called an Adaptive ECMS (A-ECMS) or Telemetric ECMS (T-ECMS). In road transport, the weakness of this approach is that driving cycle information prediction methods usually suffer from prediction errors and high computational costs. In the maritime domain, by contrast, voyages typically follow planned routes with comparatively stable and repetitive load profiles, so navigation path information such as route, speed schedule, and expected environmental conditions could, in principle, be exploited to estimate the equivalence factor far more dependably than is possible on the road. Beyond its role in fuel economy, the equivalence factor also determines how intensively the battery is charged and discharged and thus directly influences the cycling stress imposed on the storage system. This connects the choice of equivalence factor to the sizing [65] and the expected lifetime of the battery [66], since the way energy is managed during operation and the capacity installed on board jointly govern both the achievable fuel savings and the rate of battery degradation.

Although originally developed for automotive applications, a hybrid management technique combining the ECMS with a rule-based strategy, including an SOC controller and engine start–stop logic, was described by Škugor et al. [67]. In a marine context, Vu et al. [68] introduced a new optimization-based method with a load-prediction scheme that requires only information about the general operating characteristics of the ship, predicting load requirements at a given moment from historical data. Simulation results show that the optimal operating cost of a hybrid tugboat is 9.31% lower compared to the rule-based energy management strategy. In the case of load uncertainty, the algorithm yields a cost 8.90% lower compared to the rule-based energy management strategy. Kalikatzarakis et al. [50] applied both an ECMS and A-ECMS to a hybrid tugboat with the aim of reducing fuel consumption, comparing the strategies against a rule-based controller and the global optimum obtained via dynamic programming. The results showed fuel savings of 5–10% for typical operating profiles with the ECMS, within 1–2% of the global optimum. However, the A-ECMS does not consistently outperform the conventional ECMS, as the adaptive algorithm is limited by its short prediction horizon and the unpredictability of load demand distribution. Optimization-based strategies have also demonstrated marked gains over rule-based control. An ECMS combined with ant colony optimization for a parallel diesel–electric hybrid ship nearly doubled the efficiency relative to a rule-based strategy, reducing fuel consumption by 6.9% to 12.1% [35], while metaheuristic power management optimization for electric ferries has likewise been shown to outperform conventional rule-based approaches [34].

Hybrid propulsion is relatively new in the maritime sector compared with the automotive industry, and standardized operating cycles for ships are generally not available [69]. As a result, marine studies often rely on vessel-specific load profiles, which limits the generalization of results and makes cross-comparison between strategies more difficult. These differences indicate that the maritime sector is, in several respects, particularly well suited to optimization-based energy management strategies. The comparatively stable and repetitive operating profile of ships reduces the uncertainty that most undermines such strategies in road transport, while the high-power levels, the coexistence of propulsion and auxiliary loads, and the presence of significant environmental disturbances mean that even modest improvements in energy allocation translate into substantial fuel and emission savings.

2.3. Comparative Assessment of Energy Management Strategies

To consolidate the strategies discussed in the preceding sections and enable a direct comparison across paradigms, Table 1 evaluates the principal energy management methods along eight dimensions: paradigm, computational demand, real-time capability, dependence on prior voyage knowledge, optimality, implementation complexity, applicable vessel types, and maritime maturity. The ratings represent a qualitative synthesis of the reviewed literature and are intended as relative comparisons rather than absolute measures.

“Paradigm” follows the rule-based/global optimization/real-time optimization classification used throughout this review. “Applicable vessel types” lists the vessel categories in which each method has been reported or is best suited, and “maritime maturity” denotes the relative level of demonstration and adoption in marine applications. Metaheuristic methods are grouped, as they share comparable characteristics across these dimensions.

Several patterns emerge from this comparison. Rule-based strategies, such as threshold and load-following control, are computationally light, operate in real time without prior knowledge of the voyage, and are the most mature in marine practice, but they achieve only heuristic, generally suboptimal performance and cope poorly with the dynamic and unpredictable nature of maritime operation. Global optimization methods, including dynamic programming and metaheuristic algorithms, deliver globally optimal or Pareto-optimal solutions and handle multiple objectives and constraints, but they require full prior knowledge of the mission profile and impose a high computational burden, which restricts them to offline use or to benchmarking. Real-time optimization methods sit between these extremes, seeking near-optimal performance while remaining computationally tractable for online implementation.

It is worth emphasizing that much of the methodological maturity in optimization-based energy management, particularly the ECMS and its adaptive variants, originates from the automotive sector, where drive cycles are short and well characterized. Maritime duty cycles differ substantially: voyages are longer, load is dominated by propulsion and strongly influenced by sea state and weather, and standardized operational cycles are largely absent. Consequently, threshold-based and load-following rule-based strategies remain the most directly deployable on ships today, while the ECMS is the most promising real-time optimization approach for maritime adoption, provided its equivalence factor is calibrated against representative ship load profiles rather than transferred from automotive practice. Methods requiring full a priori cycle knowledge, such as dynamic programming, are useful mainly as offline benchmarks.

3. Optimal Capacity Sizing Methods

This section reviews battery energy storage sizing methods, with the aim of identifying how operational profile, battery degradation, and cost–benefit constraints are handled. The

performance and economic viability of a hybrid ship energy system depend not only on how energy is managed during operation but also on how its components are dimensioned at the design stage. This review focuses on battery energy storage system (BESS) sizing as the most widely adopted energy storage technology in maritime hybrid systems. While supercapacitors and flywheels have been mentioned in the literature as alternative storage options, their sizing methodologies remain largely underdeveloped in the maritime context and are therefore outside the scope of this review. Thus, determining the optimal capacity of the BESS is one of the greatest challenges in hybrid ship system design [70], as it directly affects investment costs, fuel savings, and the estimated lifetime of the energy storage system [71].

Sizing decisions are made prior to vessel operation and have long-term consequences that are difficult to reverse. The best sizing options depend on the vessel's performance characteristics and safety constraints in different operating modes. The storage systems are often used, but there are limitations on their dimensions [72]. An undersized BESS may fail to deliver the expected fuel savings or operational flexibility, while an oversized system leads to unnecessary capital expenditure, accelerated battery degradation, and a suboptimal cost–benefit ratio [73]. The sizing problem is therefore a constrained optimization challenge because the vessel's operational profile, battery aging characteristics, regulatory requirements, and economic constraints must be considered.

Most of the sizing studies reviewed here were carried out directly on marine cases such as ferries, tugboats, and tankers, so their conclusions on fuel savings and cost–benefit trade-offs constitute direct marine evidence. The underlying optimization algorithms (PSO, GA, NSGA-II, and HHO) and, in particular, the battery degradation and aging models they rely on, are largely transferred from general battery science, electric vehicle, and stationary microgrid research; their marine validity therefore depends on whether marine-specific operating temperatures, C-rates, and duty cycles are represented. This distinction is highlighted where relevant so that transferred assumptions are not mistaken for marine-validated results.

3.1. Conventional Optimization Methods for Capacity Sizing

The conventional approach determines the optimal BESS capacity by deriving and evaluating a series of mathematical equations [74]. Throughout the selection process, the objective functions and predefined system constraints are repeatedly assessed for multiple parameter combinations, and the set yielding the best performance—including the BESS capacity—is chosen as the optimal solution. Barrera-Cardenas et al. [65] developed a methodology for sizing BESSs for hybrid maritime energy systems and applied it to cases with two operational profiles: the first, in which a BESS is used as a power reserve, or the second, which strategically loads the engine to keep it in the optimal operating range. This methodology proposes a range of different system capacities using expected battery lifetime, annual fuel savings, and the Cost–Benefit Index (CBI) as three key performance indices. Battery lifetime is crucial for the economic sustainability of BESSs and primarily depends on battery cell aging, which decreases capacity and increases internal resistance over time. For lithium-ion batteries, capacity degradation is a more reliable end-of-life criterion than increased internal resistance [66]. The study defined two modes of battery aging. Calendar degradation occurs during rest periods and depends on temperature and SOC, while cycling degradation occurs during active use. Total degradation in a given period is calculated based on cycling degradation and calendar degradation. The study concluded that BESS use for strategic loading should be limited. However, the cost analysis presented in this work is subject to substantial limitations, as key variables—such as operation and maintenance costs and the BESS lifetime—are difficult to estimate accurately.

This finding is corroborated by [75], where cost–benefit analysis similarly concluded that BESS use for strategic loading is economically irrelevant, with high-capacity installations leading to decreased CBI and accelerated battery degradation.

Kim et al. [76] proposed an approach for determining battery capacity where the optimal BESS capacity was determined based on the most demanding power supply condition and was calculated according to IEEE Standard Std. 485-2010 [77]. Given that the standard has been superseded, the proposed calculation method is no longer suitable for use in the current system.

3.2. Metaheuristic Optimization Methods for Capacity Sizing

Modern optimization techniques are becoming increasingly widespread, giving rise to a new class of methods commonly referred to as metaheuristic optimization. Most metaheuristic algorithms are nature inspired, simple, and easy to implement, relying on a strong theoretical foundation rather than empirical techniques to quickly identify the best solution [78]. Nature-inspired metaheuristic optimization methods can be grouped into four main categories [79], and some algorithms have already been mentioned in previous chapters.

The first category of nature-inspired algorithms comprises evolutionary algorithms, which employ operators such as selection, crossover, mutation, and reproduction to search for the best solutions [80]. The previously discussed GA and DEA are representative members of this category.

The second category consists of algorithms inspired by physical laws, which serve as the basis for these optimization techniques [80], with well-known algorithms such as simulated annealing and the Multi-Verse Optimizer (MVO).

The third category consists of algorithms based on human behavior, which are inspired by various circumstances often associated with human behavior and perception [80]. The most recognized algorithms in this category are Human Group Formation (HGF) and Harmony Search (HS).

The last category encompasses swarm intelligence optimization techniques, which are inspired by the collective behavior of groups such as animal herds, insect colonies, and bird flocks [81]. PSO is the most commonly used algorithm in this category, while others include the GWO and Harris Hawks Optimization (HHO).

Metaheuristic optimization was demonstrated by Sciberras and Norman [82], where the GA was used to find the optimal BESS capacity. The amount of fuel savings achieved by the proposed method depended on system capacity and weight as well as costs, but a comparison with a baseline system without a BESS was not conducted. Thus, the absolute benefit of BESS integration cannot be established, limiting the practical applicability of the reported results.

Optimal BESS sizing was used in a multi-objective optimization approach in the work of Zhu et al. [83] from 2018. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) applied in this article gives results in all three objective functions, reducing fuel consumption by 14.99%, greenhouse gas emissions by 14.12%, and lifecycle costs by 12.11%. The proposed strategy was validated using a hardware-in-the-loop setup; however, employing a rule-based EMS with fixed parameters constrains the achievable optimal performance.

Damian et al. [84] performed BESS capacity optimization in two steps using the HHO algorithm, where the optimal BESS capacity was defined after finding the proper operating point, but the BESS state of charge during operation was not considered. This is a significant methodological limitation, as SOC directly determines the usable capacity of the battery at any given moment and constrains both charging and discharging behavior. Neglecting

SOC dynamics in a sizing study risks overestimating the effective capacity of the selected BESS, potentially leading to undersized systems in real operational conditions.

Wen et al. [85] performed a cost analysis using the PSO algorithm to optimize the capacities of three storage technologies—lead-acid batteries, Li-ion batteries, and supercapacitors—for a tanker equipped with a hybrid diesel generator and PV system. The simulation results indicate that employing an ESS is more economical than conventional storage; however, battery maintenance and lifetime were not considered, leading to suboptimal outcomes.

Optimal BESS sizing was investigated by Tjandra et al. [86] using MOPSO and NSGA-II to minimize fuel consumption and installed BESS capacity, with battery lifetime treated as a constraint. The results show that fuel savings in the hybrid-electric ferry depend strongly on the selected BESS capacity. A drawback of this approach is that the designer must trade off one objective against the other to gain additional benefits: achieving lower fuel consumption requires installing a large BESS and periodically replacing it to satisfy lifetime constraints, which, in turn, leads to high investment costs.

Lan et al. [87] investigated the challenge of optimal sizing of a hybrid ship energy system composed of a PV/diesel system and energy storage system by using different PSO variants. Triangular PSO (TRIPSO) and PSO with a Time-Varying Inertia Weight (TVIW-PSO) achieve notable gains in cost savings and emission reduction. The results indicate that applying TVIW to PSO and TRIPSO enhances optimization performance, but at the expense of higher computational complexity. However, as the problem becomes more complex and its dimensionality increases, these algorithms struggle to reach an optimal solution within a reasonable time, which limits their practicality in real applications. [79].

4. Co-Optimization of System Sizing and Energy Management

This section reviews integrated co-optimization frameworks, establishing how component sizing and energy management can be jointly optimized and where current approaches fall short. Treating system sizing and energy management as independent optimization problems inherently limits the achievability of globally optimal solutions. An increasing number of studies address this limitation through integrated co-optimization frameworks that simultaneously optimize component sizing and energy management strategy. However, co-optimization architectures reported in the literature differ in how tightly the sizing and energy management problems are coupled [69,88]. In a sequential approach, component sizing is resolved first, and the energy management strategy is subsequently optimized for the fixed design because the design decisions are made without knowledge of the eventual control policy. This decoupling is prone to suboptimal outcomes. An iterative approach alternates between the two problems, exchanging results across successive passes until the solution stabilizes, which mitigates but does not eliminate the decoupling. In a nested (two-layer) approach, an outer layer proposes candidate designs, and, for each candidate, an inner layer solves the full energy management problem and returns its performance, so that every design is evaluated together with its own optimal control strategy. In a simultaneous approach, sizing and control variables are placed in a single combined optimization problem that offers the most complete coupling but entails the largest search space and the highest computational cost.

For the iterative, nested, and simultaneous formulations, which are typically solved with metaheuristic optimizers, the reported optimality should be understood in terms of convergence and, in multi-objective settings, Pareto-optimality rather than a proven global optimum. Convergence denotes that the optimizer's solution stabilizes such that further iterations yield no meaningful improvement, while Pareto-optimality denotes that no objective can be improved without degrading another [89]. This contrasts with the

sequential approach, whose principal weakness is not convergence but the decoupling itself, and with exact methods such as dynamic programming, which can guarantee a global optimum but only under full prior knowledge of the mission profile.

Zhang et al. [90] introduced an early concept of co-optimization back in 2012. They developed an improved PSO algorithm that more efficiently finds optimal solutions for complex engineering problems. They added mechanisms that prevent poor solutions and integrated it with a simulation tool that automatically adapts data formats. The approach was tested on an electric ship power system design example, and they concluded that the improved PSO achieved up to 52% reduction in fuel consumption compared to proportional power distribution and outperformed a validated hybrid PSO-GA method by up to 2.4% in solution accuracy and 32% in reliability. The study established that equipment selection, system configuration, and operational control strategy must be addressed collectively rather than sequentially to achieve truly optimal system performance.

In 2020, Zhu et al. [69] proposed a two-stage multi-objective optimization that uses PSO for component sizing at the higher level and a Modified Adaptive Equivalent Consumption Minimization Strategy for energy management at the lower level. The optimization encompassed three objectives: fuel consumption, GHG emissions, and total lifecycle costs. In the absence of a standardized operational cycle for ships, a generic tugboat route with two standard cruising styles was analyzed. A single voyage profile lasted 4800 s, and the tugboat operates six trips per day, 200 days per year. Experiments on a HIL platform show that the two-stage optimization reduces fuel consumption by 3.37%, GHG emissions by 6.70%, and costs by 13.95% compared to single-stage optimization. This method is particularly important for HEPS design and can be applied to various types of vessels. This is one of the rare works that simultaneously addressed sizing and management strategy of components, but it only worked on a load profile for a tugboat and used an ECMS method that did not take into account the vessel's route.

Cha et al. [91] introduced a co-optimization framework for a fuel cell and battery hybrid-electric ferry, integrating MOGAQPSO-based component sizing with deterministic dynamic programming for energy management in a nested two-layer architecture. While the outer layer focuses on optimizing fuel cell stack configuration and battery capacity through cost minimization and efficiency maximization, the inner layer resolves the optimal power distribution over the voyage cycle. When applied to a short-haul ferry route, the framework revealed that fuel cell degradation costs constitute a dominant share of total operational expenses, reaching up to 58%. The authors further categorize co-optimization strategies into sequential, iterative, nested, and simultaneous approaches, noting that sequential methods are prone to suboptimal outcomes due to the decoupling of sizing and control decisions.

Furthermore, Feng et al. [88] highlighted the distinctions between sequential, nested, and simultaneous optimization approaches and introduced a simultaneous optimization method for jointly optimizing propulsion system components and the energy management strategy of an LNG-fueled hybrid-electric ship. The proposed method achieved a reduction in carbon dioxide equivalent emissions by 40% and a decrease in fuel costs by 76% compared to conventional diesel-mechanical propulsion.

Pang et al. [92] proposed an integrated approach that simultaneously optimizes propulsion system sizing and energy management for an LNG-fueled hybrid-electric ferry. They used dynamic programming to determine the optimal sizing of the engine and battery energy storage system alongside a baseline energy management strategy, while an extended Kalman filter-based model predictive control scheme was subsequently introduced for real-time optimal power control. The results demonstrated a reduction in CO₂ equivalent emissions by 12.28%, a decrease in battery capacity loss by 12%, and a reduction in ferry

operating costs by \$305,286 over ten years of operation. A key distinguishing feature of this study is the explicit inclusion of battery degradation costs within the integrated optimization framework, enabling a more comprehensive assessment of lifecycle performance.

Maloberti and Zaccone [89] proposed a nested optimization framework for hybrid marine propulsion systems that simultaneously addresses component sizing and energy management through a two-layer structure. The outer layer employs NSGA-II to optimize battery capacity and generator sizing, while the inner layer minimizes equivalent CO₂ emissions through optimal power management for each candidate design. Applied to a small ferry case study, the integrated framework demonstrated reductions of up to 27% in greenhouse gas emissions at the same investment cost compared to the industry-standard requirement-based design approach. Alternatively, the framework showed 6% reduction in investment cost at equivalent emission levels. The study showed that optimizing power management in isolation is insufficient, as a static requirement-based sizing procedure still produces a dominated solution. This confirms that sizing and energy management must be addressed jointly in order to achieve Pareto-optimal performance.

Ke et al. [93] explicitly addressed the coupling between system sizing and energy management as a key optimization challenge. Using model predictive control for energy management and the Harris Hawks Optimization algorithm for capacity sizing, the two problems were treated as an integrated optimization framework. The proposed co-optimization method reduced the average power fluctuation rate of the generator by 73.24%, decreased the HESS investment cost by 27.01% compared to single-layer optimization, and lowered the battery degradation cost by 77% relative to the single-layer approach.

One of the few studies to directly address the co-optimization of hardware configuration and energy management parameters was presented by Guo et al. [94]. They developed a co-optimization approach for the hardware configuration and energy management parameters of a diesel–electric hybrid ship, using an ECMS-based energy management strategy combined with a hybrid Ivy-SA optimization algorithm. The optimization simultaneously addressed engine parameters, battery capacity, and ECMS equivalence factors as interdependent variables, explicitly recognizing that optimizing hardware configuration and energy management parameters in isolation cannot guarantee optimal system performance. Applied to a series-parallel hybrid Ro-Pax vessel under real operating conditions, the Ivy-SA algorithm achieved a 14.49% reduction in lifecycle costs compared to the baseline configuration, outperforming PSO, the GWO, and other algorithms. The study further confirmed that the charge and discharge equivalence factors of the ECMS are strongly coupled with battery sizing, reinforcing the need for integrated optimization approaches that jointly address system design and energy management.

The stacked horizontal bar chart in Figure 2 shows how the reviewed studies are distributed across four method categories (rule based, global optimization, real-time optimization, and sizing and co-optimization) and, within each category, how the studies break down by the level of validation they report.

In detail, Figure 2 summarizes the subset of references that constitute the primary maritime case studies on energy management or system sizing. It shows the specific control strategies or sizing methods applied to ship power and propulsion systems and how their performance was evaluated.

The following categories of references were excluded: background and contextual sources (emissions, regulations, fuels, battery chemistry, and propulsion architecture reviews), methodological or theoretical sources cited to explain a concept rather than to present a marine application, and sources supporting adjacent topics such as battery degradation modeling or standards. Applying these criteria, 24 maritime energy

management and sizing studies are taken in consideration, which form the basis of the validation analysis.

The rule-based category includes a total of two studies. One study was validated through simulation only, while the other combined simulation with measured data. No studies in this category reported experimental validation without simulation, and none employed HIL testing.

The global optimization category comprises eight studies in total. Three studies reported no experimental validation, whereas five studies were validated through simulation only. No studies in this category used measured data or HIL testing, indicating that validation was limited exclusively to simulation-based approaches.

The real-time optimization category contains four studies. Three studies were validated through simulation only, while one study combined simulation with measured data. No studies reported experimental validation without simulation, and none used HIL testing. Consequently, validation in this category remained largely simulation based, with only limited use of real-world measurements.

The sizing and co-optimization category has a total length of nine studies. Two reported no experimental validation, six were validated through simulation only, and two used hardware-in-the-loop testing. Notably, the only two HIL studies in the entire review fall in this category, while none of the rule-based or real-time optimization studies were validated experimentally beyond the use of measured data.

Joint optimization of system sizing and energy management under realistic maritime operating conditions remains an underexplored area, representing a key direction for future research. Based on the principles identified in the reviewed co-optimization studies, a generalized two-loop framework is synthesized (Figure 3), illustrating how component sizing and the ECMS can be coupled within a single optimization process.

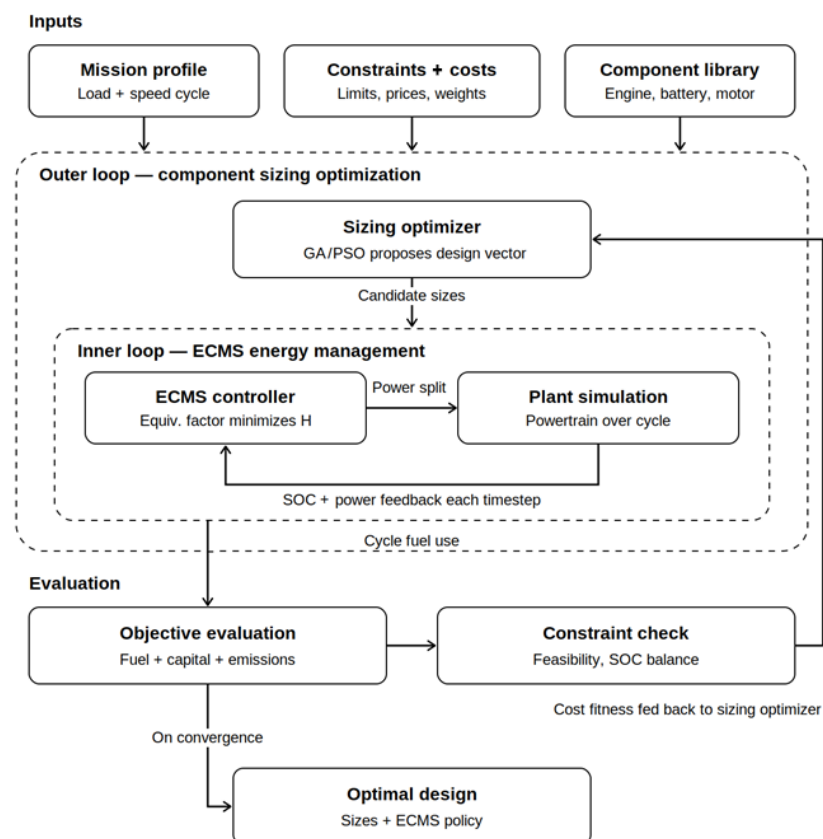


Figure 3. Example block diagram of the co-optimization framework.

The logic is a two-loop co-optimization of sizing (outer loop) and the ECMS (inner loop).

An optimizer in the outer loop (e.g., GA or PSO) proposes the design vector: engine size, battery capacity, and electric motor power. For each candidate, it calls the inner loop. In the inner loop, for the given component sizes, the ECMS controller splits power between the engine and the battery by minimizing total equivalent fuel consumption, where an equivalence factor converts battery power into an equivalent fuel rate. The powertrain simulation runs through the entire mission profile, and SOC and power are fed back at every time step.

The two loops also operate on fundamentally different time scales, which is the main reason they cannot be merged trivially. The outer loop acts at the design, or lifecycle, scale, where the sizing decision is made once, before the vessel enters service, and its consequences persist over years of operation. The inner loop acts at the operational scale, allocating power across the entire mission profile at each time step. As a result, a single design proposed by the outer loop implies a complete operational simulation in the inner loop, which is why each candidate evaluation is computationally demanding and why the two problems must be treated as coupled rather than solved in isolation.

For the evaluation, a combined objective function (fuel + capital cost + emissions) and a constraint check (feasibility, SOC balance at the end of the cycle) produce a “fitness” value that is returned to the outer optimizer. Upon convergence, the optimal component sizes together with the corresponding ECMS policy can be obtained.

The key idea is that sizing and the ECMS are not separated and every evaluation of a component size includes the full optimal ECMS, so the optimum is not local but genuinely coupled.

5. Concluding Remarks and Perspectives

This review investigated hybrid propulsion technologies and energy management strategies for hybrid ship systems, aiming to map the current state of the art and identify the key research gaps that prevent the realization of truly optimal solutions. An analysis of rule-based, global optimization, and real-time optimization strategies highlighted the ECMS as especially promising for maritime applications, given its modest computational demands and its ability to function without full voyage profile knowledge. Despite this potential, its application to maritime systems, and in particular the determination of the equivalence factor under realistic ship load conditions, has received far less attention than comparable work in the road vehicle domain. As for the sizing approaches, both analytical and metaheuristic methods reveal recurring trade-offs between fuel savings and cost–benefit performance, while battery degradation has emerged as a significant yet frequently neglected consideration.

The primary finding of this review is that system sizing and energy management continue to be treated as independent optimization problems throughout the existing literature. Integrated co-optimization frameworks that explicitly account for this coupling consistently surpass sequential approaches, delivering measurable gains in lifecycle costs, emissions, and battery degradation across a variety of vessel types and operational scenarios. Even so, the majority of these frameworks are built around simplified or fixed operational profiles, and the relationship between ECMS equivalence factors and hardware sizing parameters, while confirmed in recent studies, has yet to receive adequate attention in the wider literature. To this end, this review also synthesizes a generalized two-loop co-optimization framework (Figure 3) that can serve as a conceptual starting point for jointly optimizing sizing and the ECMS under realistic maritime profiles.

Three directions should be prioritized in future research. The first should involve developing adaptive ECMS formulations calibrated specifically for maritime load profiles. The second direction should involve the integration of battery degradation models into co-optimization frameworks to enable decisions that account for the full system lifecycle. The third direction should be focused on validating integrated optimization methods against stochastic, real-world maritime operating conditions rather than idealized voyage assumptions. The difficulty lies in the absence of standardized operating cycles for ships, which forces reliance on vessel-specific profiles and limits generalization. A viable approach is to build representative duty cycles from measured operational data, similar to the standardized driving cycles used in the automotive sector, which would give a common basis for testing and comparing integrated sizing and energy management methods. Progress in these areas would make a substantial advancement toward hybrid ship systems that are comprehensively optimized for environmental performance, economic viability, and operational reliability.

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