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SURVEY

# A Comprehensive Review of Modeling and Optimization Methods for Ship Energy Systems

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**ABSTRACT** This paper presents a comprehensive literature review of the state-of-the art modeling and optimization methods for the power and propulsion systems of ships. Modeling is a tool to investigate the performance of actual systems by running simulations in the virtual world. There are two main approaches in modeling: physics-based and data-driven, which are both covered in detail in this survey paper. The output from the simulations might not be optimal in terms of certain performance criteria such as energy consumption, fuel cost etc. Hence, it is vital to optimize the systems considering the efficient interaction between the components, to yield the optimal performance for the integrated vessel's powertrain. In this paper, the optimization case studies, for the ship energy systems, will be divided in terms of a) optimal design (topology and sizing), b) optimal control and energy management strategies, c) combined optimal design and control. Tables that summarize the literature review outcomes will also be presented at the end of each section. The main outcome is that limited literature is available for optimizations of ship powertrains using data-driven models, especially surrogate models. Surrogate-assisted optimizations for integrated ship energy systems can yield optimal solutions at fast computational speeds, with sufficient accuracy, even for complex, nested, multi-level, multi-objective optimizations.

**INDEX TERMS** Energy systems, modeling, optimizations, ships.

## I. INTRODUCTION

The energy systems of ships are all the components of vessels' powertrains, including the storage, power supply, distribution, and power consumption units [1]. In recent years, there has been a shifting trend to electrification in maritime transportation [2]. The hybrid electric configurations with diesel generators, batteries, fuel cells, solar panels, and other sources for power supply, have attracted increasing interest [3]. Through Alternating Current (AC) or Direct Current (DC) distribution systems, the produced current is delivered to the electric motor that drives the ship's propulsor. Such hybrid electric arrangements tend to replace the conventional diesel mechanical propulsion systems, since they offer reduced emissions, increased energy efficiency, flexibility, and redundancy in case of components' failures, despite their higher cost and complexity [3]. This survey will focus on case studies with hybrid electric ship systems.

Modeling is a tool to investigate the performance of complex power systems by running simulations in a digital environment. In simulations, it is important to find the balance between complexity, time, and accuracy. The most widely used method for components' modeling is the physics-based approach [4]. The models are created based on the laws of physics, and they are represented by mathematical equations with known input-output relationships. However, in complex multi-physics systems, it might become challenging, and time consuming to identify these relationships, and solve the

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problem [5]. A second approach, with a rapid increase in interest, is the data-driven modeling method. With this approach, the components can be modeled without fully understanding the system, its internal parameters, and underlying physics, but instead purely relying on data. However, data-driven approaches may provide physically inconsistent results if they are not properly implemented [6]. In this review paper, both modeling methods are discussed in detail.

Once the components have been modeled, they should be optimized in terms of design and control, considering their integration into the vessel's powertrain, for overall performance improvements. Optimization frameworks include objective function(s), design variables, algorithms, and constraints. This review will focus on multi-objective optimization problems for powertrains of ships, in which a trade-off is required between the different objectives to select the optimal solution from the Pareto Front.

There are a few review papers covering approaches for modeling and optimization of ship energy systems from different perspectives. Trinklein et al. [7] discussed the benefits of using exergy methods for modeling and optimization of ship power systems. Jaurola et al. [8] reviewed the papers that were published until 2017, and they were related to the optimization of design and power management, focusing on diesel mechanical and diesel electric configurations. Xie et al. [9] discussed the rule-based, and optimization-based energy management approaches for ship microgrids, and Banaei et al. [10] focused on optimal control strategies applied only on hydrogen hybrid vessels. To the best of the authors' knowledge, this is the first survey paper, in which the state-of-the-art physics-based and data-driven approaches used in the modeling of innovative ship hybrid energy systems are analyzed. Moreover, it is the first literature review in which novel methodologies for vessel systems' optimization in terms of topology, sizing, control, and energy management are discussed.

The rest of the paper is organized as follows. In Section II, the physics-based and the data-driven approaches for the modeling of ship energy systems are discussed. In Section III, the studies that are relevant to the optimization of ship energy systems in terms of design, control, or a combination of both, are presented. Finally, in Section IV, the conclusions that were drawn from the literature outcomes, and the authors' reflections for potential future directions, based on the research gaps, are presented.

## II. MODELING OF SHIP ENERGY SYSTEMS

### A. PHYSICS-BASED MODELING

In this section, the modeling studies for ship energy systems following physics-based approaches will be discussed. Bagherabadi et al. [11] modeled a marine fuel cell and its auxiliary components using the bond graph method to investigate the system's efficiency and dynamic response for various component sizes and topologies. The model had real time-capabilities, and it could capture the fuel cell dynamics while scaling the power range. Balestra and Schjølberg [12] modeled the powertrain of a hydrogen-fueled ferry, combining real-time operational data and dynamic component models in Simulink, using the ode3 (Bogacki-Shampine) solver. They studied the effects of component sizes on the implemented rule-based Energy Management Strategy (EMS) and vice versa. The developed mathematical model was robust and scalable, so it can be used for powerplants up to 10 MW. Donnarumma et al. [13] modeled a simplified electrical power system, considering the electromechanical behavior of the power-frequency dynamic. The dynamics of the vessel and the electrical system were different, so systems with stiff ordinary differential equations were integrated into the time-domain simulation platform with lower time steps. The model had real time capabilities, and it was used to study the vessel's behavior in harsh operating conditions. The electromechanical dynamics were also considered in [14] for the system-level mathematical modeling of a DC-based distribution shipboard system. For the proposed reduced-order and average-value modeling method, the variable-step ode15s solver was used. The computational efficiency for the simulations was high with sufficient accuracy for both steady-state and transient operations. This approach is flexible for adjustments to other system-level cases. Abrougui et al. [15] used MATLAB/Simulink to solve the ordinary differential equations for the propulsion components of an electric boat. The equations of the electrical machine were simplified, and it was demonstrated fast and accurately that there was no overshooting in ship's forward speed and electric motor's rotational speed. Zhu and Dong [16] used MATLAB/Simulink and SimPowerSystems to solve the governing equations of the dynamic components of an AC distribution system, for a diesel electric ferry. Manufacturer data was used for the parameterization of the components. The reductions in fuel consumption and energy costs were demonstrated by comparisons to the conventional ferry version. Hemdana et al. [17] studied different serial and parallel configurations for the propulsion system of a watercraft with fuel cells, generator, batteries, and solar panels. The overall model was of fourth order, nonlinear, and multivariate. The required power was estimated by solving the differential equations of the propulsion system, and it was verified that all the systems were properly functioning under different topologies. Yang and Zhang [18] presented a backward simulation model in MATLAB/Simulink, including input power demand, ship's dynamic model, management strategy and the power supply components. The simulation model could only reflect the static characteristics of the system. Jaster et al. [19] modeled a hydrogen-based ship system using SimPowerSystems blocks. The propulsion and control modules were simulated following Hardware-in-the-Loop approaches to estimate fast and accurately the loads, energy consumption, and battery State of Charge (SoC).

Most of the physics-based modeling studies are for diesel electric, battery, or hydrogen hybrid vessels. There is a gap in the literature for the modeling of methanol or ammonia fueled energy systems, which have been widely developed in recent years. Simplified mathematical models and ordinary differential equations were mostly used for the modeling of the ship power and propulsion components. MATLAB/Simulink was the most frequently used software tool for the analyses. Power and efficiency estimations, as well as investigation of the dynamic performances were the most common modeling purposes.

A novel physics-based modeling approach, to avoid solving time consuming simulations of complex interconnected power systems, is the co-simulation using Functional Mockup Interface [20]. The models can be solved independently using their own solvers and local time steps, different modeling methods and software tools, but they are simulated together in the same digital environment. This can result in significant reductions of computational time, with ideally similar accuracy. Perabo et al. [21] modeled separately the components of an AC-based diesel electric vessel in MATLAB/Simulink. The simulation of the integrated powertrain was performed in Open Simulation Platform. The solvers used were Euler 1$^{st}$ order for the electric powerplant, and Runge Kutta 4$^{th}$ order for the engines and propellers. The results were obtained after 8 minutes with almost identical accuracy to a monolithic simulation. Ghimire et al. [22] used co-simulation to model a hybrid DC system with batteries, and diesel generators. The components and their controllers were split to different Functional Mockup Units (FMUs) based on the required fidelity. Euler 1$^{st}$ order and Runge Kutta 4$^{th}$ order were the solvers that were used. The results of the dynamic loads were compared to [23], where a monolithic, all-in-one simulation was performed in MATLAB/Simulink for the same system, using a bond graph modeling approach. It was demonstrated that the results were obtained much faster using co-simulation, without sacrificing accuracy. The developed hybrid power system model can be used for real-time virtual testing. Finally, co-simulation was also used in [24] and [25] using Euler and Runge Kutta as integration methods for the different FMUs. The aim in both studies was to investigate the ships' hydrodynamic performances under different conditions.

To the best of the authors' knowledge, there are currently no studies that utilize co-simulation for novel ship power and propulsion systems with alternative fuels, as in most cases diesel mechanical and diesel electric configurations have been analyzed.

The results from the physics-based modeling studies are summarized in Table 1.

### B. DATA-DRIVEN MODELING

In this section, the modeling studies for ship energy systems following data-driven approaches will be discussed. Ghimire et al. [26] developed data-driven polynomial-based dynamic models for each component of the powertrain, to assess the overall efficiency, considering conventional diesel electric and battery hybrid configurations, with AC or DC distribution systems. The computational effectiveness of the method for efficiency estimations of complex power systems was demonstrated. Swider et al. [27] built a statistical model, namely a Generalized Additive Model, which could estimate the ship's required power, and its most influential parameters, for different weather and wave inputs. Such a model was more accurate than a regression-based model since it could incorporate nonlinear effects. Fang et al. [28] proposed a method that utilized an Extreme Learning Machine for characterizing the uncertainties of photovoltaic power generation, and a two-stage framework that covered the worst-case scenario and accommodated these uncertainties during operation. A neural network was trained to predict the power output for various temperature and solar irradiation conditions along the navigation route. This method was proved to be robust as there was flexibility in varying working conditions.

**TABLE 1. Physics-based modeling studies.**

| Ref. | Modeling Methods | Modeling purpose |
|---|---|---|
| [11] | Bond graph method. | Investigation of power efficiency and dynamic response. |
| [12] | Ode3 solver in time domain with fixed time step. | Effects of system sizing on EMS and vice versa. |
| [13] | Ordinary differential equations, model-based techniques. | Ship dynamic performance and operation in harsh conditions. |
| [14] | Variable-step ode15s solver, time-domain. | Dynamic performance, electromechanical dynamics. |
| [15] | Ordinary differential equations – math modeling. | Investigation of overshooting in ship's speed and motor's rotational speeds. |
| [16] | Dynamic mathematical modeling. | Comparison of energy costs with the conventional ferry version. |
| [17] | 4$^{th}$ order nonlinear model, differential equations. | Propulsion power estimation, verification that the components are functional. |
| [18] | Backward simulation modeling. | Investigation of engine's efficiency, power demand, system's stability. |
| [19] | Model-based approach SimPowerSystems blocks. | Estimation of loads, fuel consumption, battery SoC, emissions. |
| [21] | Co-simulation – Euler and Runge Kutta. | Investigation of system's dynamics, power, voltage, and frequency fluctuations. |
| [22] | Co-simulation - Euler and Runge Kutta. | System dynamics, reliability of components. |
| [23] | Bond graph method. | System dynamics, reliability of components. |
| [24] | Co-simulation – Euler and Runge Kutta. | Propulsion system performance under different conditions. |
| [25] | Co-simulation – Euler and Runge Kutta. | Hydrodynamic performance. |

There are a few case studies that focused on the prediction of ship's performance in terms of speed loss and fuel consumption. Karagiannidis and Themelis [29] trained neural networks using data from onboard sensors to estimate the shaft's power and engine's fuel consumption. It was demonstrated that by increasing awareness about hull and propeller conditions, and by delicate data filtering, the model's accuracy could be increased by 1.5%. Coraddu et al. [30] proposed a data-driven digital twin for two tankers to compute the speed loss due to fouling on the ships' hull and propeller. The model was built based on Deep Extreme Learning Machines to detect speed deviations. The method had superior prediction accuracy compared to the standard ISO 19030 approach. An extensive literature review of maritime digital twins is presented in [31], where it was demonstrated that limited information is available in the literature studies for data-driven digital twins of ship energy systems, as in most cases these models are developed based on the laws of physics.

There are a few case studies that used data-driven models for condition monitoring and fault detections in the main machinery ship systems. Lazakis et al. [32] developed a Support Vector Machine, that was trained using noon-report data from normal operating conditions with limited assumptions, to monitor the performance of a marine diesel generator. It was demonstrated that the data-driven model can accurately discern between normal and faulty machinery conditions, and it can be used for different energy systems. Cheliotis et al. [33] developed Regression-based Expected Behavior models that were integrated with Exponentially Moving Weighted Average control charts, without requiring large training datasets. The data-driven models could detect early malfunctions related to exhaust gas temperature and scavenging air pressure of a main engine, to maintain energy-efficient operations.

Surrogate data-driven models have also been used for modeling of complex systems to produce results of sufficient accuracy at fast computational speeds. These models are trained with data from the original physics-based, time-consuming simulations. There are a few case studies from other research fields, for individual energy components, such as fuel cells, batteries, e-motors, power converters and other components, that can comprise parts of modern ship electric powertrains. Surrogate models have been recently used for the performance optimization of fuel cells, which have complex, multi-physics attributes. Ensemble learning models were used in [34] for efficiency improvements, and Support Vector Machines were used in [35] for power density maximization. The data-driven models were trained from the Computational Fluid Dynamics (CFD) results. Surrogate models have also been used for battery modeling and optimizations in electric vehicles, and especially for their thermal management systems. In [36] an Adaptive Kriging High Dimensional model was used, and in [37] a response surface was utilized. In both studies it was aimed to maintain the desired operating temperature range. Surrogate-assisted optimizations have also been performed for electric motors and power converters. In [38] a second order polynomial surrogate model was used for an induction machine, and in [39] a Kriging model for a permanent magnet synchronous motor, to improve their electromagnetic efficiencies. Regarding the power converters, in [40] a neural network was used for efficiency improvements, and in [41] surrogate global optimization was performed for configuration enhancements. Surrogate models have also been used for modeling and optimization of full powertrains of road electric vehicles in [42] and [43], but there is a gap in the literature for maritime drivelines. To the best of the authors' knowledge, the only study that used surrogate models for a ship's powertrain is [44], where a Kriging model was developed at the upper level, and Dynamic Programming was used at the lower level for optimal sizing and control.

Overall, for the data-driven modeling studies of ship energy systems, machine learning models have been mostly utilized for power and efficiency estimations, speed predictions, and condition monitoring of energy systems, under different endogenous and exogenous parameters.

The results from the data-driven modeling studies are summarized in Table 2.

**TABLE 2. Data-driven modeling studies.**

| Ref. | Modeling Methods | Modeling purpose |
|---|---|---|
| [26] | Polynomial-based dynamic model. | Efficiency-modeling of all-electric powertrains. |
| [27] | Generalized additive (statistical) model. | Power estimation for uncertain input conditions. |
| [28] | Extreme learning machine, neural network. | Solar panel power output predictions for uncertain input parameters. |
| [29] | Neural networks. | Prediction of shaft's power and engine's fuel consumption. |
| [30] | Data driven digital twin, Deep Extreme Learning Machines. | Speed loss estimation due to fouling on hull and propeller, to reduce fuel consumption. |
| [32] | Support Vector Machine. | Condition monitoring/fault detection of diesel generators. |
| [33] | Regression-based Expected behavior models. | Detections of malfunction in engine's exhaust and air systems. |
| [34] | Ensemble learning models. | Fuel cell efficiency and power density maximization. |
| [35] | Support Vector Machine. | Fuel cell power density maximization. |
| [36] | Adaptive Kriging High Dimensional model | Hybrid thermal management system of Li-ion batteries. |
| [37] | Response surface. | Thermal performance of air-cooled batteries. |
| [38] | Second order polynomial model. | Electromagnetic efficiency improvement of induction motor. |
| [39] | Kriging surrogate model. | Efficiency improvement of a synchronous motor. |
| [40] | Neural network surrogate model. | Efficiency improvement of a buck power converter. |
| [41] | Surrogate global optimization. | Configuration improvement of power converters. |
| [44] | Kriging surrogate. | System sizing and control. |

## III. OPTIMIZATION OF SHIP ENERGY SYSTEMS

In this section, the studies that are relevant to the optimization of ship energy systems will be discussed. There will be a division in a) optimal design (topology and sizing), b) optimal control, and c) combined optimal design and control studies.

### A. OPTIMAL DESIGN STUDIES

Wu and Bucknall [45] presented a multi-objective optimization for a hydrogen-hybrid ferry. Deterministic Dynamic Programming was used to select the component sizes and yield the optimal performance in terms of operational expenses and emissions, for an averaged operating profile. With the proposed approach and propulsion system, a life-cycle emission reduction of at least 65% could be achieved, compared to the original diesel-based systems. Vieira et al. [46] proposed a configuration optimization for a retrofitted hybrid platform supply vessel, to minimize the carbon emissions and battery degradations. The HOMER software, that implements a proprietary derivative-free approach, was used to optimize the topology of the powertrain, considering uncertainties in power demands. A 10% reduction of carbon dioxide emissions was obtained in the configuration with main and auxiliary generators, a 3 MW battery pack, and a 250-kW fuel cell system.

Zhu et al. [47] presented an optimal design study for a battery hybrid vessel to reduce diesel consumption, lifecycle costs and emissions. The Pareto solutions of the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm were compared in terms of space and quality criteria, and it was demonstrated that the NSGA-II provided more solutions which were less-distributed in space. The same authors in [48] presented a multi-objective design optimization, using the NSGA-II, for an anchor handling tug supply vessel, to minimize diesel consumption and emissions. Hardware-in-the-Loop tests were used for model validations in both studies. The experiments demonstrated that the multi-objective optimization results were closer to the ideal point compared to the single-objective optimizations with focus either on fuel consumption or emissions.

Lan et al. [49] combined the NSGA-II and the MOPSO algorithm to obtain the optimal sizes for solar panels, diesel generators, and batteries of a hybrid tanker, to minimize the capital expenses, fuel costs and onboard emissions. Through a sensitivity analysis, it was demonstrated that the local time and the time zones had the largest effects on the efficiency of the photovoltaic panels. Wang et al. [50] used the NSGA-II to select the optimal component sizes of an unmanned patrol boat with sail-assisted systems, solar panels, and batteries, to reduce the total cost and emissions. The optimal design was compared to a version without photovoltaic arrays. Reduced emissions and lifecycle costs were obtained.

Zhan et al. [51] used the NSGA-II to select the optimal components of a retrofitted diesel electric trailing suction hopper dredger. The fuel consumption and the components' weights were reduced up to 10% compared to the diesel mechanical version. The battery SoC was constrained between 40% and 90%. Zhu and Li [52] used the NSGA-II to select the optimal components for a hybrid electric catamaran, with scalable electrical components, to reduce energy consumption and emissions. About 10% reductions in emissions and energy consumption were observed compared to the conventional diesel mechanical version of the vessel.

Wang et al. [53] proposed a multi-objective design optimization using NSGA-II for a battery hybrid polar cruise ship, to minimize diesel consumption, lifecycle costs, and maximize the battery usage onboard. Compared to the original diesel electric version, the retrofitted system presented a 38% increase of annual time in pure electric mode, with almost the same fuel consumption, but with 8% higher lifecycle costs. Valera-Garcia and Atutxa-Lekue [54] presented a design optimization study using the NSGA-II for a hybrid offshore support vessel, investigating both DC and AC configurations. The total costs including capital and operational expenses were reduced. The spinning reserve power was a safety constraint in the optimization problem, to reduce the system's blackout probability.

Dolatabadi and Mohammadi-Ivatloo [55] presented an optimal sizing study for a hybrid solar-diesel-battery system of an oil tanker, using the Mixed Integer Linear Programming (MILP) algorithm for different operating modes and power requirements. The aim was to reduce fuel and maintenance costs. The uncertain solar radiation was predicted using a Monte-Carlo simulation. To quantify the risks related to the sizing of the energy systems, like variance and expected shortfall, the conditional value-at-risk approach was implemented. Kistner et al. [56] optimized the design of a decentralized AC-based power system, consisting of LNG- fueled Solid Oxide Fuel Cells and batteries, to reduce the capital and fuel costs, and waste power. The ant colony algorithm selected the optimal locations/compartments of the vessel at which the fuel cells were located. Cardenas et al. [57] used parametric sweeping of free design parameters to investigate the compromise of cost/fuel savings, and battery lifetime for a battery hybrid vessel. It was demonstrated that 80% of the maximum cost savings could be achieved when the battery was used only in spinning reserve mode.

The results from the optimal design studies are summarized in Table 3.

### B. OPTIMAL CONTROL STUDIES

There are more studies that analyzed the optimal control strategies onboard vessels, compared to the optimal design cases. Control and EMS are the terms that will be used in this section. An EMS can be rule-based or optimization-based and it is an important part of optimization, as it coordinates the operation of the systems, and it splits the power between the different components, based on the operating profile and other input parameters.

Sun et al. [58] simplified the control problem to a convex formulation, to be solved by the optimizers using the MOSEK with CVX package. The power was optimally split between the batteries and the fuel cells, to reduce the fuel and the degradation costs of the fuel cells. The simulation results demonstrated the effectiveness of the approach for the considered power system. Han et al. [59] proposed an optimal

**TABLE 3.** Optimal design studies.

| Ref. | Optimization Objectives | Methods/Algorithms |
|---|---|---|
| [45] | Operational expenses, emissions. | Deterministic Dynamic Programming. |
| [46] | Carbon emissions, battery degradations. | Derivative-free approach. |
| [47,48] | Diesel consumption, emissions. | NSGA-II. |
| [49] | Capital and fuel costs, onboard emissions. | NSGA-II and MOPSO. |
| [50] | Total cost, emissions. | NSGA-II. |
| [51] | System weight, fuel consumption. | NSGA-II. |
| [52] | Energy consumption, emissions. | NSGA-II. |
| [53] | Diesel consumption, lifecycle costs, battery usage. | NSGA-II |
| [54] | Capital and operational expenses. | NSGA-II. |
| [55] | Fuel and maintenance costs. | MILP. |
| [56] | Capital and fuel costs, waste power. | Ant colony algorithm. |
| [57] | Cost savings, battery lifetime. | Brute-force method |

rule-based EMS, so that the batteries and fuel cells could operate at their optimum levels to maximize the efficiency of the propulsion system. Simplified models and ideal gas equations were considered for reductions of computational complexity. The performance of the power system was validated with real ship data from a small fuel cell-powered boat.

Mitropoulou et al. [60] developed an optimal EMS, using the Nelder Mead algorithm, for a naval ship with hybrid power supply and hybrid propulsion, considering the compromise between fuel and maintenance costs, noise, and infrared signature. Grid losses and battery degradations during charging were not considered. The proposed direct search method provided improved solutions compared to the rule-based start point of the search, and it can be an effective method for multi-objective non-convex problems. Xiang and Yang [61] presented a two-layer multi-objective optimization for a diesel electric fishing boat, considering mode switching to optimize the working points of the diesel engine and electric motor. In the inner layer, the Equivalent Consumption Minimization Strategy (ECMS) was used to reduce the amount of consumed energy, and in the outer layer the ant colony algorithm was utilized to maintain the desired battery SoC. The proposed strategy was compared to optimization and rule based ECMS and demonstrated a reduction of fuel consumption up to 12%.

Dall'Armi et al. [62] used the MILP algorithm and demonstrated that up to 185% longer lifetime for the fuel cells and batteries could be achieved, compared to an optimization that did not consider the progressive aging effects. Zhang et al. [63] proposed a real time EMS, which combined ECMS and a filter-based control strategy. The Sequential Quadratic Programming (SQP) algorithm was implemented to maximize efficiency and minimize the degradations of batteries and fuel cells. The proposed approach provided smoother responses for the batteries and fuel cells, and increased energy efficiency by 5-7% compared to the rule-based and wavelet-based control strategies. Bassam et al. [64] presented a multi-scheme EMS, with coded instructions that were set a-priori. It was aimed to switch between four different strategies during operation, depending on the load profile and the battery SoC, to minimize energy consumption, operating cost, and battery degradations. The results demonstrated that energy savings up to 8% could be achieved compared to the four individual strategies: ECMS, Charge-Depleting-Charge-Sustaining, Classical Proportional Integral and state-based EMS. Voyage planning and scheduling optimizations were presented in [65] using the MINLP, and in [66] using the NSGA-II, to choose the optimal routes and ships' speeds along the voyages, for different uncertain operating conditions. The objectives in both studies were to minimize the operational expenses and the onboard emissions.

In a few cases, data-driven machine learning methods have been used for the optimal control problems. Wu et al. [67] developed a near-optimal EMS using deep reinforcement learning, to control the power of components in uncertain conditions. It was demonstrated that the proposed approach could mitigate the function overestimates in stochastic environments and provide lower cost results by 5.5% and in a shorter time by 93.8%, compared to the Double Q-learning agent in state space, without function approximations, that was presented in [68]. In [69], an optimal ECMS using artificial neural networks, to maximize energy efficiency, was implemented. A Bayesian regularization approach was also utilized to reduce the error between the actual and predicted network's outputs.

Optimal Power Management Strategies (PMS) were presented in [70] and [71] using PSO algorithms to minimize the operational expenses and emissions for hybrid electric vessels. In [71] the implemented fuzzy-based PSO algorithm provided faster convergence to the optimal point than the traditional PSO and Dynamic Programming methods. Mummadi and Vijay [72] presented an optimal control study, under load changes and faulty conditions, for a DC power system of a vessel. Automatic, self-governing, real-time control was achieved, maintaining the power balance and systems' reliability, even after the faults' detections and isolations.

Fuzzy logic EMS were implemented in [73] and [74] for real-time control of hydrogen hybrid powerplants. Reductions of energy consumption up to 14% were observed compared to traditional rule-based EMS. Wang and Li [75] used the NSGA-II to optimize the capacity of a hybrid energy storage system consisting of batteries and supercapacitors, which absorbed the low and high-frequency load fluctuations respectively. The relationship between the investment cost and battery lifetime was presented. The NSGA-II was also used in [76] for the control optimization of a power system consisting of diesel generators, batteries, and supercapacitors to reduce the fuel consumption and emissions. It was demonstrated that the output power of the diesel generators remained almost stable when both energy storage systems were in operation.

The results from the optimal control studies are summarized in Table 4.

**TABLE 4.** **Optimal control studies.**

| Ref. | Optimization Objectives | Methods/Algorithms |
|---|---|---|
| [58] | Fuel and degradation costs of fuel cells. | Convex solvers. |
| [59] | Efficiency of propulsion system. | Rule-based EMS. |
| [60] | Fuel, maintenance costs, noise. | Nelder Mead Algorithm. |
| [61] | Energy consumption, battery SoC range. | ECMS - inner layer, ant colony algorithm - outer layer. |
| [62] | Fuel consumption, battery/fuel cell life. | MILP. |
| [63] | System efficiency, battery/fuel cell life. | ECMS and filter-based strategy, SQP algorithm. |
| [64] | Energy consumption, operating cost, battery degradations. | Multi - scheme EMS – four schemes switched in operation. |
| [65] | Operational expenses, emissions. | MINLP. |
| [66] | Operational expenses, emissions. | NSGA-II. |
| [67,68] | Operational cost and power predictions. | Deep reinforcement learning. |
| [69] | Energy efficiency. | ECMS using artificial neural networks. |
| [70,71] | Operational expenses, emissions. | PMS using PSO algorithms. |
| [72] | Power balance, system stability. | Automatic self-governing fault detection and real-time control. |
| [73,74] | Powertrain efficiency. | Fuzzy logic EMS. |
| [75] | Battery degradations and lifecycle costs. | NSGA-II. |
| [76] | Fuel consumption and emissions. | NSGA-II. |

### C. COMBINED OPTIMAL DESIGN-CONTROL STUDIES

In this section, the studies that analyze combined optimal design and control for ship energy systems will be presented. The design studies are focused on the selection of optimal component sizes and topologies for the various combinations of systems. In the control cases, for a given system design, the energy management strategies are optimized to achieve efficient power splitting between the main power sources. It is important to consider combined optimal design and control for ships' powertrains to avoid performance degradations for the components.

Wang et al. [77] developed a nested plant and control design architecture for a hydrogen-hybrid vessel. In the external optimization layer, the NSGA-II was used to reduce capital expenses, operational costs, and emissions, by varying the sizes of the components. In the inner layer, the MILP algorithm was used to select the optimal control strategy. For an emission-free target, the fuel cells were sized based on load-leveling, the batteries covered the maximum demand and transient load fluctuations, and the diesel generators were used only for emergency purposes. Dall'Armi et al. [78] presented a coupled health-conscious optimization using the MILP algorithm and Monte Carlo analysis, to consider the long-time uncertainties related to fuel cell and battery capital expenses, and hydrogen fuel costs. From the sensitivity analysis it was demonstrated that the hydrogen cost was the most influential parameter in the cost function. The optimal topologies and sizes of components were validated using the approach presented in [79].

Pivetta et al. [79] presented a multi-objective design and operation optimization strategy. The MILP algorithm was used to minimize fuel cell degradation, daily operational costs, and capital expenses. It was demonstrated that the strategy could be adapted to different hydrogen hybrid vessel sizes. In [80] a PSO algorithm was implemented for the component sizing, to reduce the fuel consumption, and a fuzzy logic controller was utilized for optimally splitting the energy between the diesel generators and the batteries. The proposed fuzzy-PSO method reduced the fuel consumption up to 40%, compared to the original conventional boat.

Wu and Bucknall [81] presented an optimal design and control study using a genetic algorithm in the external layer to minimize emissions and fuel costs, and Dynamic Programming in the inner layer for the optimal EMS. It was highlighted that even if hydrogen is produced by steam reforming of natural gas, the well-to-propeller emissions can be reduced by more than 25% for the considered case study. Zhu et al. [82] proposed a bi-level optimization using the MOPSO algorithm for component sizing in the higher layer, and a modified adaptive ECMS for control at the lower level. It was aimed to find the best compromise between emissions, fuel consumption, and Net Present Cost including investment costs, operational expenses, and battery replacement costs. The results were validated experimentally with Hardware-in-the-Loop approaches. It was demonstrated that the bi-level optimization outperformed the two single-level (upper and lower) in terms of convergence to the optimal solutions. The emissions were reduced by 3-7% and the Net Present Cost by 11-14%, with the multi-objective bi-level approach.

Balsamo et al. [83] formulated an optimization problem for a battery-supercapacitor semi-active hybrid system, using the Ritz method. It was demonstrated that the peak current values could be reduced up to 40%. Letafat et al. [84] presented an optimal design and control study for a hydrogen hybrid ferry using the Improved Sine Cosine Algorithm with Harmony Search. The approach yielded a small cost reduction up to 2% compared to a rule-based EMS.

Chen et al. [85] introduced a modified equivalent circuit battery degradation and semi-empirical life prediction model for the optimal design (sizing) and optimal EMS of a hybrid electric propulsion system. Experimental data were used for building the model. An error of 13% was observed in the validation stage. Hofman et al. [86] presented a system-level optimization study, using convex and Mixed Integer solvers, for the simultaneous sizing of the batteries and system control. The simplification of the problem, from non-linear to convex, led to a simulation convergence in around 8 minutes.

There are a few case studies, where data-driven models have been utilized for the combined design and control optimization problems. Chen et al. [87] presented a novel approach, based on Support Vector Machine and frequency control for the joint optimization of the sizing of the battery-supercapacitor hybrid system and the EMS, using the Whale Algorithm. The proposed approach decreased the power fluctuations by 44% compared to the traditional fixed-filter rule-based EMS. Si et al. [88] proposed a configuration optimization combining fuzzy rules and a quantum artificial bee colony algorithm, to reduce the total cost, but also increase the reliability and components' lifetime. An optimal EMS was also developed using the Quantum PSO algorithm to maximize clear energy utilization.

The results from the combined optimal design and control studies are summarized in Table 5.

**TABLE 5. Combined optimal design and control studies.**

| Ref. | Optimization Objectives | Methods/Algorithms |
|---|---|---|
| [77] | Operational and capital costs, emissions. | NSGA-II in the external layer, MILP in the inner layer. |
| [78] | Costs and degradations of components. | MILP algorithm and Monte Carlo analysis. |
| [79] | Operational and capital costs, fuel cell degradations. | MILP algorithm. |
| [80] | Fuel consumption. | PSO algorithm and fuzzy logic controller. |
| [81] | Fuel costs, onboard emissions. | Genetic algorithm - outer layer, Dynamic Programming – inner layer. |
| [82] | Emissions, fuel consumption, net present cost. | MOPSO at higher level, modified adaptive ECMS at lower level. |
| [83] | Battery degradation. | Ritz Method. |
| [84] | Operating costs and capital expenses. | Improved Sine Cosine Algorithm with Harmony Search. |
| [85] | Lifecycle cost, battery lifetime. | Battery degradation and semi-empirical life prediction model. |
| [86] | Capital and operating costs. | Convex and Mixed Integer solvers/algorithms. |
| [87] | Battery degradations, energy efficiency. | Support Vector Machine, Whale algorithm. |
| [88] | Total cost, reliability, and lifetime of components. | Fuzzy rules and a quantum artificial bee colony algorithm, Quantum PSO algorithm. |

Overall, for the optimal design (A), control (B), and combined optimization problems (C), it is worth noting that around 80% of the considered studies used physics-based approaches for the modeling of the components, while only the rest 20% used data-driven methods. The most frequently used optimization algorithms were the NSGA-II, MOPSO and MILP. The most assessed optimization objectives were the capital expenses, operating costs, emissions, and energy consumption. The degradations of components were focused only on fuel cells and batteries. The volumes and weights of ship energy systems were usually considered as constraints in the optimization problems. Moreover, the experimental validations of energy system models were very limited due to the high cost, time, and lab availability. Most case studies validated their approaches with other models and methods from the literature. There are very few studies that considered uncertain conditions in terms of system's performance, costs, or operating profiles. Finally, there is no study covering all the following optimization objectives for a specific case ship or vessel category: lifecycle costs and emissions, energy consumption, degradation of components, safety, and reliability.

## IV. CONCLUSION

This review summarized the state-of-the-art approaches for modeling and optimization of ship energy systems. In this survey paper, the physics-based and data-driven modeling studies were discussed, considering the types of energy systems, modeling methods and purpose for each case. Once the components are modeled, they should be optimized to improve the overall powertrain's performance. The optimization studies in terms of design, control, and a combination of both, were analyzed. The importance of considering simultaneous optimization of sizing and control, to avoid performance degradations of the components and suboptimal solutions, was highlighted. The objectives that needed to be satisfied for each problem, and the methods/algorithms/strategies that were implemented were discussed.

The uniqueness of this paper is twofold. It is the first study that discusses the state-of-the art modeling approaches such as co-simulation, digital twins, and surrogate models for novel ship energy systems. To the best of the authors' knowledge, it is also the only survey paper that approaches optimizations of ship power and propulsion systems from three perspectives i.e., design, control, and a combination of both.

To conclude, ship powertrains are becoming increasingly complex with interconnections of energy systems that can affect the overall performance. The design spaces are multi-dimensional with an increased number of sustainable power and propulsion systems' configurations, and a vast design parameter investigation is required. Hence, the classical modeling and design approaches are highly probable to fail, which makes it challenging to ensure optimality for the integrated powertrain. This indicates that optimization of such complex power systems can be challenging and time consuming, especially for a multi-objective problem. Hence, for future research directions it would be recommended to apply more data-driven approaches, especially surrogate models in the optimizations of ship powertrains, to increase the computational efficiency and be able to test various systems, topologies, and control approaches in a short time interval. Surrogate data-driven models have been widely utilized recently for various energy systems to increase the computational efficiency of optimizations. Despite their increasing applications on energy systems from other research fields, there are almost no studies until now, on surrogate-assisted modeling and optimizations of ship powertrains. By utilizing data-driven surrogate models, the optimal solutions can be obtained at fast computational speeds with sufficient accuracy, even for complex, nested, multi-level, multi-objective optimizations of ship powertrains.

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