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Optimization-based Power and Energy Management System in Shipboard Microgrid: A Review

Peilin Xie, Josep M. Guerrero, Sen Tan, Najmeh Bazmohammadi, Juan C. Vasquez, Mojtaba Mehrzadi, Yusuf Al-Turki

***Abstract*—The increasing demands for reducing greenhouse emissions and improving fuel efficiency of marine transportation have presented opportunities for electric ships. Due to the complexity of multiple power resources coordination, varied propulsion loads, changeable economical and environmental requirements, power/energy management system (PMS/EMS) becomes essential in both designing and operational processes. The existing literature on PMS/EMS can be categorized into rule-based and optimization-based approaches. Compared to the rule-based PMS/EMS, which relies heavily on human expertise, as well as predefined strategies and priorities, the optimization-based approaches can offer more efficient solutions and are more widely used nowadays. This paper provides a comprehensive review of the marine optimization-based power/energy management system and discusses the future trends of PMS/EMS in ship power systems.**

***Index Terms*—energy management, optimization, power management, review, shipboard power system.**

I. Introduction

TRANSPORTATION industry is currently the foundation of the national economy. Marine transportation takes 80% of the world's trade. Currently, diesel generators are still the major power source for all maritime applications. Due to the widespread use of fossil fuels, marine fleet becomes a large contributor to greenhouse gasses (GHGs) and other emissions. As a result, there is a growing interest towards improving fuel efficiency and reducing the environmental footprint of the marine vessels [1]. The use of highly fuel-efficiency power sources such as fuel cells, and renewable energy sources (RESs) such as wind, and solar energy would be opportunities to solve that problem. However, the presence of pulse loads, such as radars, sonars, and electromagnetic (EM) weapons may exceed the ship's rated generation capacity, leading to unstable operation. The use of energy storage system (ESS) can increase the flexibility in power allocation among the hybrid power sources, offering the potential to improve efficiency and reduce emission during ship operations [2], [3]. Therefore, future ship power systems have a tendency to hybrid power ships, which include traditional gensets and various new equipment, such as, alternative energy sources, fuel cell, gas capture system, ESSs, and so on. However, issues arise when different types of energy sources work together. The complex power flow condition, the requirement of coordination between multiple energy resources, and the potential in improving fuel efficiency and reducing total costs make the PMS a necessity. PMS refers to a group of functions, scheduling algorithms, and control methods. It determines the distribution of the power demanded between different energy sources to promise continuous power supply for complex load conditions and to ensure a cost-effective, environmentally friendly, and reliable integrated energy system with high efficiency. Furthermore, motivated by the need for achieving a flexible shipboard arrangement and meeting the future on-board power demand, future ships will trend towards all-electric ships (AES). The electrification of ships, especially for the propulsion electrification, has enlarged the total capacity of the hybrid shipboard power system (SPS) and thus provides a foundation for PMS to determine the ship economic and environmental behaviors, which further complicate PMS but also facilitate the study of it.

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P. Xie, J. M. Guerrero, S. Tan, N. Bazmohammadi, J. C. Vasquez and M. Mehrzadi are with the center for research on Microgrids, Department of Energy, Aalborg University, Denmark.

Yusuf Al-Turki is with the center of Research Excellence in Renewable Energy and Power Systems, Department of Electrical and Computer Engineering, Faculty of Engineering, King Abdulaziz University, Jeddah, Saudi Arabia

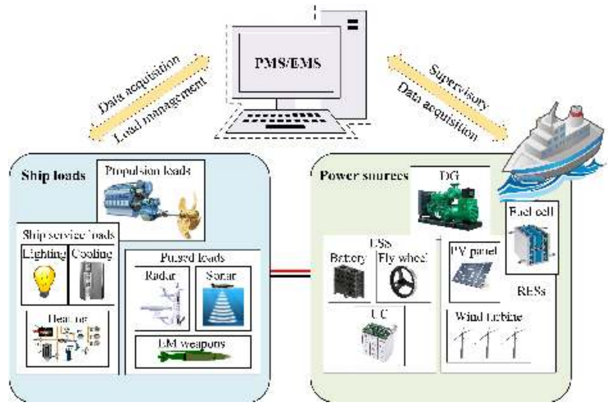

Fig. 1. Overall structure of PMS/EMS integrated SPS

Fig. 1 gives the overall structure of the SPS integrated with a PMS/EMS. An SPS is typically powered by hybrid power sources, which consist of traditional gensets (diesel generators), RESs (PV panel, wind turbine, sea wave energy), fuel cells, and ESSs (batteries, fly wheels, UCs). And the electrical loads of it have the characteristics of high dynamics, periodicity, uncertainty, and high dependence on the marine environment, which consists of propulsion load, ship service load, and pulsed load. The PMS/EMS acts as a coordinator between the ship loads and power sources. Besides, An SPS also includes electronic converters, transmission network, communication lines, and so on.

An SPS can be considered as a typical mobile microgrid that usually operates in islanded mode when the ship is at sea and in grid-connected mode when it arrives to the seaport. Therefore, ship microgrids show some resemblances to terrestrial microgrids such as the network architecture and increased use of power electronic converters. Strategies developed for terrestrial microgrids can be extended for maritime microgrids as well [4], such as droop control, virtual synchronous generators [5], or other controller developed for electrical converters [6]–[9]. However, specific characteristics and challenges exist for SPSs, such as the presence of high dynamic loads (planned or unexpected pulse loads, large share of propulsion loads, fluctuated loads from the sea), the requirement of economical and environmental power sharing between the onboard gensets and ESSs, the various operating scenarios (regular cruising, full-speed sailing, docking, loading/unloading, and anchoring, etc.), and limited ship space for energy facilities installation. All these require further studies of PMS/EMS for maritime microgrids.

Although a large number of reviews on SPSs can be found in the literature, the existing articles mostly emphasize on hybrid renewable energy systems [10], electric propulsion systems [2], SPS architectures [4], [11], [12], SPS stability and power quality [12], [13], control technologies [4], [13], as well as the coordination between SPS and seaport microgrids [14]. Rare of them focuses on a detailed overview of the PMS strategies [4], [11]–[13]. It is worth mentioning that, apart from PMS, many research works focus on energy management system (EMS). The main difference between a PMS and an EMS is that a PMS deals with the instantaneous power flow, while an EMS focuses on the utilization and planning of energy sources during a certain time period and is always integrated with the future predictions and estimations systems. The targets of PMS are mainly about the enhancement of electrical reliability or availability, and EMS is more related to cost-saving and energy efficiency. However, usually there is not a clear line between PMS and EMS. In some cases, different terminologies are used for the same control system. Therefore, this review does not make a detailed distinction between EMS and PMS.

The existing PMS strategies of SPSs can be generally classified into optimization-based [15]–[18] and rule-based [19]–[24] methods. The rule-based strategies rely on human expertise, predefined strategies, and priorities [25], which are easier for implementation, and do not require high computation efforts. However, it may not achieve an optimal solution. Furthermore, they may require significant tuning efforts and may change significantly for each topology [26]–[28]. On the contrary, the optimization-based strategies rely on analytical or numerical optimization algorithms which can give optimal or sub-optimal solution [29], and have drawn much attention from researchers. Currently, a lot of research works on optimization-based PMS/EMS have appeared. In this paper, we provide an extensive review of PMS/EMS in SPSs, focusing on optimization-based strategies especially.

The paper is organized as follows: In section II, the overall targets and constraints used in the shipboard power management strategies are summarized. In section III and section IV, we discuss the global planning based and real-time optimization based PMS approaches respectively and several significant methods are briefly studied. Conclusion and future trends are presented in section V.

II. Optimization-based PMS Approaches

An optimization problem refers to finding the minimum of a cost function with consideration of several constraints. Hence, it requires computational resources and data gathered from the whole power system to have a global view of the entire process. In this section, the optimization problem formulation will be discussed by introducing its two essential parts: objectives and constraints.

A. Objectives

For any optimization methods, an objective function must be defined, which usually takes into account environmental, technical, and economic aspects. The existing literature for the PMS/EMS problem of SPSs are mainly focused on the optimal design of power plants and optimal power/energy scheduling and can be classified into the following problems:

o1. Fuel consumption minimization: Due to the widespread use of fossil fuels, the efficiency of diesel marine vessels has been one of the major concerns. In ship power generation, the fuel consumption typically includes two parts, for generation (FC_{dg}) and for start-up (FC_{st}) [30],

$$FC = FC_{dg} + FC_{st} \tag{1}$$

Start-up cost is generally considered as a constant value and only dependent on the on/off status of the generator, and sometimes ignored in some literature. While generation cost is affected by a number of factors [31], [32],

$$FC_{dg} = \sum_{j=0}^{T}\sum_{i=1}^{N_{dg}}(st_{ij} \cdot SFOC(P_{ij}, n_{ij}) \cdot P_{ij} \cdot \Delta T_j) \tag{2}$$

where T is the generator operating time; N_{dg} is the number of diesel generators; st_{ij} is the switching status of the generator, using two-bit representation, 0 (switch-off) and 1 (switch-on); $SFOC$ is the specific fuel consumption ($grFuel/MWh$), decided by engine output power P_{ij}, and for variable-speed diesel generator, it is also affected by engine speed n_{ij}.

From Eq. 2, it can be learned that for the purpose of minimizing the fuel consumption, diesel generators are encouraged to work at their optimal fuel efficiency point, which can be achieved by an appropriate adjustment of generator output power, engine speed, and switching status. Besides, due to the utilization of ESSs, it provides more opportunities, and challenges as well, for the flexible operation and optimal control of diesel generators in improving fuel efficiency.

It is also worth to be noted that, the fuel cell is another fuel consumer, attracting growing interests because of its advantages in high efficiency, small in size, and low environmental impact [33] and is usually used in hybrid with ESSs. To enhance the fuel cell efficiency, optimal power split between the hybrid power sources is the key point and has been studied a lot in vehicle area but few on marine applications [33], [34].

o2. Environmental footprint reduction: Reducing environmental footprint generally refers to reduce GHG emission [31], which is commonly assumed to be proportional to the fuel consumption and usually measured in grams of CO_2 per kWh of the consumed electricity. The conversion factor between fuel consumption and CO_2 emission can be found in the guidebook given by International Maritime Organization (IMO) [35]. And according to the IMO policy, energy efficiency design indicator (EEDI) and energy efficiency operation indicator (EEOI) are two key indicators that are commonly used to define ship GHG emissions during its lifetime operation. It should be noted that, due to the drawback of considering only one operation point, EEDI can not accurately account the GHG emissions during ship lifetime, which makes EEOI more widely applied in ship PMS/EMS designing.

EEOI is the ratio of CO_2 mass emitted per unit of transport work, representing ship operational efficiency indirectly. And it is defined as :

$$EEOI = \frac{\sum_k (FC_k \cdot C_{F_k})}{m_{cargo} \cdot D} \tag{3}$$

where k is the fuel type; FC_k is the mass of consumed fuel; C_{F_k} is the conversion factor transferring fuel mass to CO_2 mass; m_{cargo} is cargo tonnes and D is the distance in nautical miles.

Eq. 3 maintains a good balance between ship operational efficiency and GHG emission. To improve the ship operational efficiency, several factors can be optimized, for example, ship routing and scheduling, vessel speed, generator operation time, and the trade-off between carbon emission and investment cost.

o3. Economic investment minimization: It refers to the financial expenditures associated with the management of energy, which mainly includes operation costs and investment costs. Ship operation costs are the expenses for running gensets, ESSs, or other assets, consisting of fuel cost, maintenance cost, start-up/shut-down cost, etc.. Generally, it is estimated as functions of the produced power (electrical, thermal or cooling), running time, on-line gensets numbers, and capacity. Ship investment costs are composed of the installation and replacement of the ESS, typically decided by economic specific values, installed size, capacity, and life-span of gensets.

For the purpose of evaluating the system cost, most literature simply uses net present cost which is the total sum of the capital cost including all the operation and investment costs. Such method can effectively evaluate the economic cost during a certain period of time in a simple way. However, we remark that in a long time horizon, the annualized cost of the system (representing the summation of the system capital cost per annum) and life cycle cost (representing the summation of all one-time and recurring costs during the useful lifespan) are necessary [36]. And considering different types of ESS technologies, it is particularly important to assess the cost of the storage subsystem per unit energy stored over the lifetime of the storage. In this way, it provides a fair comparison for the different capital costs and lifetimes of various ESS technologies [37].

o4. Ship equipment weight and size optimization: The optimal equipment (ESS, DGs, engines, carbon capture system, etc.) sizes help to reduce footprint and improve SPS's survivability, and quality of service with a possible minimum investment cost. The problem of finding the optimal size of an energy equipment requires optimal scheduling and dispatch for the whole power generation system and is always formulated as a cost minimization problem. It involves a large number of variables, parameters, and specific information, for example, the energy supplied, the on/off time period of gensets, the number of charging and discharging cycles, the SOC status of ESS, the ship efficiency factor $EEOI$, the foot space, the fuel oil consumption costs, as well as the input information such as load information, ship operating conditions, ship cruising and voyage times.

It should be mentioned that, typically, ship sizing problem is formulated in conjunction with other objectives, such as minimization of GHG emission, total cost or footprints, etc. Due to the inherent conflict between them, the trade-off between the multi-objective has to be addressed carefully with respect to ship load conditions, electrical and mechanical constraints [38].

o5. Maximization of the endurance of navigation: It refers to increase the cruising capacity of the ship, which mainly depends on the battery state of charge and the remaining fuel volume of the diesel engines [39]. However, not much literature has been found in solving this problem.

It is worth to be noted that, instead of considering only one objective, multi-objective optimization has been drawing much attention by considering many conflicting objectives while taking into account their priorities. For example, o2 and o3, o3 and o4, o1 and o5 are commonly considered as conflicting and have been investigated in many studies.

B. Constraints

In many practical problems, design variables must satisfy certain specified electrical or physical requirements and so may not take arbitrary values. These restrictions are referred to as design constraints and are key to ensure system stability and safety. The most common constraints are listed below.

c1. Power and energy balance: Generally, ship electric loads comprise of propulsion loads L_{prop}, service loads $L_{service}$, auxiliary load L_{auxi}, and pulse loads L_{pulse} from high power mission. The total output power of ship power resources (DGs, ESS, fuel cell, RESs, etc.) should meet the electrical loads at any time interval. So it is formulated as an equality constraint:

$$\sum_{i=1}^{N_{dg}} st_{ij} \cdot P_{ij} + P_{ESS,j} = L_{service} + L_{prop} + L_{pulse} + L_{auxi} \tag{4}$$

c2. Restraints for power quality: It refers to the maintenance of the voltage and frequency stability of the electrical power system. To ensure stable operation, voltage and frequency variations should be limited. Commonly, the voltage variation is limited under ±5% and the frequency variation is no higher than ±3%.

c3. Restraints of power plants: To avoid unsafety and mechanical damages, restraints on generators must be addressed, such as generator loading constraints, generator ramp rate constraint, generator operation and out of operation time constraints. To avoid system blackout, the maximum allowable continuous loading of the generators should be defined. Similar constraints also hold for other types of power resources (RESs, fuel cell, etc.). In addition, to compensate for power shortages or frequency drops within a given period of time, one necessary way is to keep active spinning reserves capacity at a certain level, mainly by maintaining the total unused capacities of DGs and the ESS.

c4. Restraints of ESS: It mainly refers to the limits of ESS energy capacity, charging and discharging power, current state of charge (SOC), and the maximum depth of discharge (DoD_{max}), formulated as inequality constraints.

c5. Environmental constraints: GHG emissions should be monitored on-line and kept below a certain upper limit. According to IMO, EEDI and EEOI require a minimum energy efficiency level (CO_2 emissions) for different ship type, size segments, voyage, and transport mode. Specific data can be found in [40].

c6. Ship voyage constraints: Including ship speed constraint, which should be bounded in a specific region; limits of total traveled distance, which should be almost equal to the total route distance at the end of optimization process and is always represented by the deviation of the actual traveled distance from the scheduled one; limits on the quantity carried by the ships and so on.

c7. Constraints for the auxiliary system: For example, heat balance, limitation of heat losses and temperature.

After searching the relevant literature on shipboard optimization-based PMS/EMS since 2016, the ratios of these constraints and research objectives are summarized in Fig. 2 and Tab. I, respectively. Concluded from Fig. 2 that, the power balance constraint is the most important one with the highest priority regardless of the optimization objectives, followed by restraints for onboard gensets and ESSs. These ensure the stable operation of the whole power system. Although there is no mandatory policy requirement for the GHG emissions, we can see that a large number of papers voluntarily take into account the constraint of ship efficiency factors in the context of maintaining normal marine navigation. These aforementioned constraints broadly cover several aspects of the study and provide a general direction to guide future research. The specific constraints used in each study depend on the researchers' goals and working conditions.

This section reviewed the general optimization objectives and constraints used in the previous studies. To solve the power/energy management problem, optimization techniques are reviewed in the next two sections. The general classification principle in this paper is whether the method requires entire system information, has the ability to acquire the optimal solution, and can be applied in real-time or not. From this perspective, the optimization-basde PMS/EMS are categorized into global planning methods and real-time methods.

III. Global Planning

Global planning strategies minimize the cost functions using the knowledge of future and past information while considering the aforementioned objectives. Tab. I gives a summary of recent studies categorized by PMS/EMS objective functions while Tab. II presents an overview of the commonly used optimization methods. Nowadays, there exist many optimization methodologies falling into this category. They can be generally classified into the classical optimization methods and heuristic algorithms based methods.

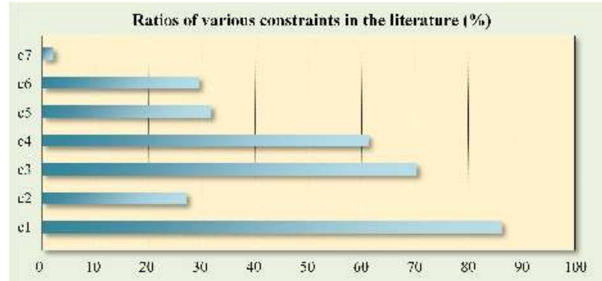

Fig. 2. Ratios of various constraints

TABLE I
Objectives considered in shipboard PMS/EMS literature.

Objectives	References
o1	[30], [32], [33], [39], [41]–[53]
o2	[15], [30], [32], [39], [41], [46], [51]–[64]
o3	[15], [32], [44], [50], [54]–[59], [61], [63]–[78]
o4	[16], [45], [47], [60], [62], [67], [68], [71]–[73], [79]–[85]
o5	[39]

A. Classical optimization methods

Classical optimization methods take advantage of the analytical properties of the problem to generate a sequence of points that converge to a global optimal solution. Dynamic programming, linear programming, and mixed-integer programming fall into this category.

a) Dynamic Programming: Dynamic Programming (DP) is one of the most efficient mathematical techniques, capable of solving multiple optimization problems, and can always generate the most fuel-efficient results while dealing with other energy management problems. It systematically evaluates a large number of possible decisions in a multi-step problem, and make a wise decision in each step, minimizing the total cost for all decisions made. DP requires a mathematical model where decision variables, parameters, and constraints are clearly defined, and the whole power demand is known as a prior. With the assumption that the ship load forecasting is available, [30] uses DP to solve the optimization problem in its demand-side optimal power management system. By doing that, reduction in the operation cost and GHG emission can be achieved. However, ESSs and investment capital are not considered. Considering the computing complexity induced by energy storage and propulsion power adjustment means, [41] separates the optimization problem into three stages and uses DP to deal with the first two stages. The same assumption about the ship load is made in [41]. It should be noted that although DP can handle these complicated problems in some cases, it may cost huge computation efforts and may

TABLE II
SUMMARY OF GLOBAL PLANNING BASED PMS/EMS REFERENCES IN SPSS

Global Planning		References
Classical Optimization Methods	Dynamic programming	[16], [30], [41], [54], [79]
	Linear programming	[80]
	Nonlinear programming	[32]
	Mixed integer linear programming	[55], [64]
	Mixed integer nonlinear programming	[32], [42], [52], [53], [56], [65]–[69], [78], [81], [82]
	Interval optimization method	[70]
	Augmented yita-constraint method	[71]
	Adaptive-multi-clustering algorithm	[57]
Heuristic Methods	Genetic algorithm	[43], [44], [72], [83]
	NSGA-II	[15], [39], [45]–[47], [58]–[60], [73]
	Particle swarm optimization	[48]–[50], [61]–[63], [74], [84], [85]
	Improved Sine Cosine Algorithm (ISCA)	[75]
	Whale Optimization Algorithm	[76]
	Salp swarm algorithm	[33]
	Differential evolution	[77]
	Grey wolf optimization	[51]

fail to deal with the situation when there are time coupling constraints, such as the coupling startup state and running state of devices [86]. It also requires prior knowledge of the ship power demand which is not always possible in real applications. Thus, it is not normally suitable for real-time control but can be used as a benchmark for improving other strategies [87].

b) Linear and Nonlinear Programming: linear programming (LP) is the most simple form of classical optimization methods which captures the first-order effects of various system parameters that should be optimized. LP has been widely used in various engineering disciplines, such as flow control, power management, and so on [88], [89]. However, due to the complexity of the SPS and the nonlinear inherent of it, LP is rarely used in the marine field and most of the works are based on its derivative methods or nonlinear programming (NLP) approaches.

To solve a nonlinear programming problem, one efficient way is using linearization to transform it into a series of linear problems [90]. For example in [32], a two-step multi-objective optimization method for hybrid ESS management is established with the aim of minimizing battery life cycle degradation. And by applying the piecewise linearization, the NLP problem is solved by Gurobi Optimizer. However, linearization might result in increasing computational complexity or failure in capturing dynamic responses, especially when the NLP problems are sequential, parallel, or multi-objective. Due to the quadratic relationships between system states, for example, the fuel consumption of diesel generators can be approximately represented by a quadratic function of produced power [78], [91], and the quadratic cost functions in multi-objective optimization, quadratic programming (QP), a particular and one of the simple types of NLP, is the most commonly used algorithm in real-application optimization problems. In addition, as a particular case of convex optimization, algorithms such as the alternating direction method of multipliers (ADMM) can solve the QP problem with contradicting objectives [92].

c) Mixed Integer Programming: It is worth mentioning that, in real-world applications, some or all of the variables are constrained to be binaries or integers. Such problems are called integer programming problems that can be categorized into mixed-integer linear programming (MILP) [65]–[67], [81] and mixed-integer nonlinear programming (MINLP) [56], [66], [78].

The main reasons that result in a mix-integer problem are the quantities that can only be integers, e.g. number of DGs, and batteries [93], or the quantities that represent decisions, e.g. switching status of the diesel generators, charging and discharging of ESSs, or ship speed [66], [67], [69], [81], [82], [84]. The objective function can be generally classified into a single objective of minimizing the fuel cost [69], [93], overall operation cost [66], [68], or finding the optimal selection, sizing, and management of the ESS [67], [81], [82], [84], and the multi-objective of optimizing the ship operating cost and gas emissions simultaneously [32], [53], [55], [56], [64].

The most common ways to solve the NLP and MINLP problems are either converting the problem into an LP problem by using linearization methods or incorporating nonlinear solvers such as GUROBI, CPLEX, and normal boundary intersection method as used in [53].

d) Other methodologies: Apart from the aforementioned optimization methods, there are many other methods that can be used in the power management system of SPSs, such as interval optimization methodology (IOM) [70]. The classical algorithms can obtain the optimal solution within the desired tolerance [94]. However, owing to the inherent complexity, they may result in large computational efforts and is considered to be NP-Hard in nature, especially for large-scale systems. As a result, researchers have to seek alternative algorithms to make a satisfactory compromise between the optimality of the solution and the computational burden. In [68], for example, a meta-heuristics method is utilized to solve the MINLP problem.

B. Heuristic Algorithm

The complexity of some optimization problems that cannot be tackled by exact mathematical methods has suggested using heuristic algorithms to explore more quickly the solution space, even finding a sub-optimal solution. In heuristic optimization strategies, logical rules determine the operating mode of the plant and the setting for the battery charging and discharging system. However, it has to be noted that the probability of finding the global solution decreases when the problem size increase.

a) Genetic Algorithm: Genetic algorithm (GA) is a search algorithm based on the mechanism of natural selection and natural genetics, which dates back to earlier than 1975. GA comprises three processes: selection, crossover, and mutation. During these processes, parents with higher fitness values are more likely to be chosen and the offsprings are more likely to be similar to these parents. Hence, GA tends to converge to sub-optimal solutions and cannot produce all potential solutions. However, due to the advantages in solving complex nonlinear optimization problems and promising more accurate exploration of the solution space than other gradient-based heuristic algorithms, GA has been widely used in SPSs. Some examples are optimal sizing of generation system [83], power demand prediction and allocation [43], [44], [72].

In other examples to solve multi-objective PMS problems, Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been utilized because of its ability to maintain a good spread of solutions and converge near the true Pareto-optimal set [95]. As in [15], [47], [58], [59], conflicting objectives of reducing GHG emission and overall operational cost are considered. Some additional objectives which are included in the cost function are optimizing ESS size, minimization of fuel consumption [39], [45], [46], and minimization of the overall mechanical losses [96]. In addition, to enhance the performance of the local optimization of NSGA-II in the population diversity preservation, an improved NSGA-II algorithm was adopted in [39] by replacing the polynomial variation with difference mutation operators.

b) Particle Swarm Optimization Algorithm: Particle swarm optimization (PSO) algorithm's precursor was a simulator of social behavior, that was used to visualize the movement of a birds' flock, first introduced in 1995. Since then, several variants of PSO have been developed while incorporating concepts such as nearest-neighbor velocity matching and acceleration by distance. Comparing to other heuristic algorithms, PSO has the benefits of fast convergence, good computational efficiency, and relatively robust operation in locating global optima, while it can solve highly nonlinear and complex problems.

Traditional PSO has been widely used to solve the optimization problem in SPS. A PSO-based EMS is developed in [48] to reduce fuel consumption by optimizing ship voyage based on real operation profile. The performance of PSO is affected by a set of parameters described as inertia weight and acceleration factors. For the purpose of achieving a higher optimization performance, researchers have suggested to develop a self-adaptive mechanism to tune these parameters along with the algorithm iterations. For example in [61], a fuzzy-based PSO is proposed to improve the computational efficiency of the algorithm and tackle with antagonistic optimization objectives. The proposed method can significantly reduce the operation cost and footprint while satisfying the technical and operational constraints of the ship. However, in some cases, PSO suffers from immature convergence or entrapment to a local solution. To deal with this issue, an advanced version of PSO named particle swarm optimization of composite particle (PSO-CP) was developed initially in [97] and used in [50], [68]. Although PSO and its variants have been proven to be effective and computationally efficient in many applications. These methods might not be very efficient when applied to a dynamic system. Thus, adaptive PSO which allows randomizing particles and dynamically changing parameters has been introduced to compensate for this issue. In [74], an adaptive multi-context cooperative co-evolving PSO is employed to dispatch power flows with great electricity cost savings. PSO can also be used to deal with the multi-objective optimization problems along with sorting technique based on NSGA-II [15], [47]. Optimal results can be picked up depending on the user's preferences.

c) Other methodologies: Apart from the above mentioned most commonly used algorithms, other methods relying on heuristic algorithms have been used to solve the power management optimization problems such as evolutionary algorithm [98], differential evolution algorithm [77], Pareto Concavity Elimination Transformation (PaCcET) [99], and Grey wolf optimization [51].

C. Discussion

In general, classical optimization methods are suitable for problems with small numbers of variables. The results obtained can guarantee to be optimal and can be used as a benchmark for other methods. Compared to classic optimization methods, heuristic algorithms are most often employed when approximate solutions are sufficient and exact solutions are computationally expensive [100]. Generally, to ensure the optimum and computational efficiency at the same time, heuristic algorithms are usually supplemented with classic algorithms.

IV. Real-time Optimization

Although global planning strategies are capable of sorting global optimum solutions, they may cost too much computational effort and require prior knowledge of entire ship routine information, which makes it capable of designing, sizing, voyage scheduling, and energy dispatch in early-stage management, but unsuitable for real-time power management. Real-time optimization (RTO) refers to the techniques which allow the continuous evaluation and manipulation of the process operating conditions considering the most recent information to minimize the desired cost function. The direct benefit of RTO is providing the system with real-time optimized commands to reach the desired operation following the currently available information.

RTO strategies consist of equivalent consumption minimization strategy (ECMS), model predictive control (MPC), sequential function method (SFM), and so on. Tab. III gives a summary of the literature on real-time PMS/EMS optimization methodologies.

A. Equivalent Consumption Minimization Strategy

ECMS is the most well-known technique for instantaneous optimization, which has been widely researched for land-based vehicles and has proven to be effective in improving fuel economy. Motivated by that, ECMS is investigated for electrical ships recently. ECMS formulates a cost function as a sum of the real fuel consumption and equivalent fuel consumption related to the energy storage SOC variation. The instantaneous minimization problem will be solved at each instant only using arguments based on actual energy flow.

$$\min C = C_f(t) + C_{ess}(t) \tag{5}$$

$$C_{ess}(t) = ef(t) \cdot \frac{P_{ess}(t)}{Q_{LHV}} \tag{6}$$

where $C_f(t)$ represents the real fuel consumption. Q_{LHV} is the fuel lower hearing value (energy content per unit of mass) and considered as a constant. From Eq. 6, the equivalent fuel consumption of ESS, $C_{ess}(t)$, depends on its output power, P_{ess}, and equivalence factor, ef. ef converts electrical power consumption into fuel consumption and needs to be chosen carefully.

In conventional ECMS, ef is assumed to be constant [87], [101], [102]. Although this assumption will ease the real-time implementation, it might fail to capture the real transformation relationship and result in unsatisfactory performance. Adaptive ECMS (A-ECMS) has been recently proposed to automatically tune the ef according to the current or predictive information, which in particular can be categorized into two groups including adaptation based on driving cycle prediction [17], [103] and adaptation based on driving pattern recognition. The former predicts the future information to calculate the most appropriate ef, while the latter assumes that ef are similar for cycles with similar statistical properties and selects the most suitable ef from the predefined set after defining the driving pattern. For ships with fixed-cycle operational modes and on a fixed sailing course, the latter will largely simplify the optimization process and thus require less computational space. However, most literature on driving pattern recognition remaining concentrate on electric vehicles, relevant works on SPS has yet to be published.

It should be noted that more accurate prior knowledge of the marine load profile can guarantee better final results. Given the full ship routine, ECMS has been shown effective in achieving a good fuel efficiency that is close to the global optimal solution from dynamic programming [104]. However, in cases that the load profile is not a priori known, an accurate load prediction system will be required to be integrated with ECMS to achieve better results. Hence, there would be a trade-off between the computational effort and the optimality of the final solution, which makes ECMS a method that deserves further research.

B. Model Predictive Control

Model predictive control (MPC) is a promising optimal control, which has been proven to be efficient and robust for dynamic systems. It enables the PMS to look ahead as far as the established prediction horizon and generate a future sequence of control inputs $(u(k), u(k+1), u(k+2), \cdots, u(k+N_c))$, which optimizes a predefined cost function $\mathcal{L}$, while meeting all the electrical and physical constraints. Basic MPC scheme takes the following procedure,

1) Measure the state $x(k)$ of the system.
2) Solve the optimization problem

$$\min\ J(u(\cdot)) = \sum_{k=1}^{N_p} \mathcal{L}(x(k), u(k)) \tag{7}$$

with respect to

$$u(\cdot) \in \mathbb{U}^N, \tag{8}$$

$$x(k+N_p) = f(x(k), u(k), u(k+1), \cdots, u(k+N_c)) \tag{9}$$

subject to

$$\begin{aligned} h(\mathbf{x}(k)) &= 0 \\ g(\mathbf{x}(k)) &\geq 0 \end{aligned} \tag{10}$$

where N_p is the prediction horizon and N_c is the control horizon.

3) Compute the control input value in the next sampling period. MPC takes the form of receding horizon control procedure, which means although the optimal trajectory of the future control signal is completely described within the moving horizon window, only the first sample of the control inputs are utilized while neglecting the rest of the samples.

The main advantage of MPC is that it optimizes the current timeslot while taking future timeslots into account, which makes it adapt well to the high dynamic system. To solve the optimization problem at each control step, it is essential to choose a proper method that balances the needs for fast convergence and optimality of the results. Efficient numerical algorithms have been proposed to address challenges in the real-time implementation of MPC, such as NLP [105], and LP [106]. Heuristic algorithms mentioned in section III can be also used to solve optimization problems in MPC, such as PSO [107], [108]. Since most optimization problems of MPC are in quadratic form, quadratic programming becomes the most commonly used method [18], [109]–[113]. Typically, sequential quadratic programming (SQP), an iterative procedure, is the most well known gradient-based method that has been found wide applications in MPC. SQP solves the QP sub-problems and uses the solution to construct a new iterate for every iteration [114]. To improve computational efficiency, integrated perturbation analysis and SQP (IPA-SQP) approach has been utilized in [115]–[118]. IPA-SQP achieves optimal solutions for each MPC sampling instant by combining perturbation analysis (i.e., providing closed-form solutions when some of the parameters are changed) together with SPQ (i.e., achieving local optimality).

Apart from the traditional MPC method, advanced methodologies can be integrated with MPC for more precise load prediction. To efficiently handle the uncertain pulse-power load condition, integration of MPC with the auto regressive integrated moving average (ARIMA) model is one of the effective methods for uncertain pulse load forecasting, which largely improves the system overall performance under high power pulsed load condition [119]. In order to estimate the propulsion-load torque, [120] integrates adaptive parameter identification approach with MPC to formulate an AMPC and uses linear prediction for future load information prediction, which achieves much better performance in terms of improved system efficiency, enhanced reliability, improved thrust production, and reduced mechanical wear and tear. Besides, to improve the system stability in case of fault occurrence, fault scenario-based MPC is developed in [121] to predict the system states for fault-free operation.

It is worth to be noticed that, while MPC is suitable for real-time control, a key drawback is the difficulty in making a satisfactory balance between real-time computing efficiency and ensuring long-term optimality. This motivates to seek for alternative approaches, such as hierarchical control strategy [122], [123], multi-agent system (MAS), artificial intelligence algorithm [76], [124], sensitivity function method [125], recursive searching algorithm [98], deploying improved solver, and multi-core hardware [116].

C. Distributed Real-time PMS for Large-scale SPS

The aforementioned PMS strategy is in the centralized arrangement. Thanks to the knowledge of the entire system, it can converge to the global optimum solutions. However, for large-scale ship power management, the centralized PMS might impose a high computational burden and suffer from single point failures, which allows the distributed PMS to be further studied in large SPSs. In a distributed control scheme, each energy source sends signals to the local controller. Local controllers communicate with each other to make appropriate decisions for global optimizing. In that case, it can significantly reduce the computational burden on each local controller without any risk of single point failure.

Although there has been a lot of researches in both energy management and distributed control, the union of these two ideas hasn't reached too much fruition so far. The prior-art in the distributed ship PMS mainly focuses on MAS, distributed MPC (DMPC), and ADMM.

MAS is inspired by the biological phenomena, which aims to achieve system objectives cooperatively that are difficult to reach by a single agent or a centralized controller. By dividing a single optimization problem into several sub-problems (i.e., being solved individually by every single agent), MAS technologies have great potential for real-time power management in large-scale systems. In [91], a distributed MAS-based PMS is proposed for the optimal power-sharing with minimum distribution losses and economic dispatch of resources. Multiple agents take part in the process of solving the MIQP problem by solving a subset of the resulting search tree. In [126], the optimization problem is solved by using a real-time distributed PSO methodology for achieving the optimal distributed power controllers' parameters. In [127], a real-time heterogeneous MAS-based load management strategy is proposed to achieve dynamic generation and load balancing for DC zonal SPSs. Artificial potential function is integrated into the MAS framework to coordinate various electrical elements to achieve group goals and improve the dynamic behavior of the system.

TABLE III

SUMMARY OF REAL-TIME OPTIMIZATION-BASED PMS/EMS REFERENCES IN SPS

Real-time		References
Centralized	ECMS	[17], [87], [101]–[103], [132]
	MPC	[18], [61], [105]–[120], [133]–[140]
	Hierarchical control	[122], [123]
	SFM	[125]
	AI	[76], [124]
Distributed	MAS	[91], [126], [127]
	ADMM	[128]
	DMPC	[129], [130]

Apart from the MAS, ADMM has been widely used in other power system applications as it can break convex optimization problems into smaller pieces, each of which is easier to be handled. In the SPS, [128] develops a modified nested EMS based on the ADMM to obtain the solution strategy with contradicting objectives. [129] and [130] combine the ADMM with MPC to formulate a DMPC for real-time power management. DMPC can not only inherit the advantage of explicit accommodating of constraints and good optimization performance but also has the advantages of a distributed framework, namely flexibility and error tolerance, which can support plug-and-play operation.

Although there has been a small amount of research working on the distributed PMS for the SPSs, especially for ships on zonal electrical distribution (ZED), most studies remain focused on centralized power management strategies. Current studies on distributed ship PMS mainly concentrate on the maximum load supplement with limited energy capacity [127], [130], [131], maintaining a high SOC of ESSs [129] and reducing the system operational cost [91], [92], [130]. Little of them considers the factors that have been studied a lot in the centralized SPS, such as the GHG emission, the uncertainties brought by sensor failure or environmental variation, and the negative effects from pulsed loads and fluctuated loads. However, with the emerging of ZED systems, ZED-based SPSs are drawing more interest because of their advantages in lower acquisition costs, lower weight, and better operational flexibility. This will motivate further research and application of distributed PMSs.

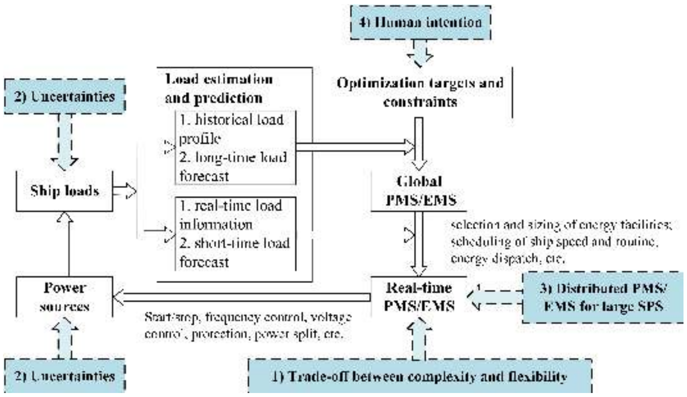

Fig. 3. Recommendations to future PMS/EMS

V. Conclusions and Future Trends

A. Conclusion

The increasing of global environmental concerns has boosted the development of the electrical ships. In that case, there is an urgent to improve the power/energy management system performance in terms of energy-saving, environmentally-friendly, safe, and economic operation.

In this paper, methods employed in the literature for optimization-based shipboard power/energy management have been reviewed. The main strategies of global planning based PMS and real-time optimization based PMS for SPSs have been discussed. It is clear that the former requires full knowledge of the system information or accurate load prediction to achieve the global optimum solution. It is more suitable for early-stage designing, ship routine scheduling and energy dispatch problems with considerations of designer's control targets and constraints. While the latter uses the instantaneous measured data or short-term load forecasting results and provides real-time guidance for enhancing system performance. Thus, it is capable of dealing with uncertainty, pulsed loads, and long-term disturbances, and mainly used for real-time power splitting, generator start/stop controlling. protection, and etc.. Apart from centralized PMS, distributed PMS is gaining more interest because of the safety and computational efficiency requirements for large-scale SPSs.

B. Potential Research Trends

In the future, works recommended to improve the performance of PMS/EMS in SPSs are listed in the following. The suggested studies are exhibited in Fig. 3 to build a future EMS/PMS structure:

1) Given the limited computational capacities and the requirement of real-time scheduling for the shipboard PMS/EMS, it is recommended that the measures of complexity and flexibility should be included in the PMS/EMS. Thus, it can provide a fair comparison of the trade-off between optimal scheduling and computational considerations.
2) The uncertainties imposed by RESs, propulsion loads, variable sea conditions and communication failures might result in large deviation of the forecast data and increase complexity of the energy management systems. As a result, a robust energy management method combining the real-time control strategy with the forecasting method is necessary to provide good performance even when the forecast data deviates significantly from the real values [141].
3) Only a few studies have been conducted on the shipboard distributed PMS in previous literature. Most studies focus on the centralized arrangement. Therefore, many challenges should be resolved, such as system uncertainties, communication delays, and the trade-off between computational efficiency and system complexity.
4) Future EMS/PMS should have the capability of tackling not only the ship operational issues but also offering comfortable service to customers. Human intention feedforward control is recommended to be integrated into the PMS [142], so that on-demand monitoring and customers commands could be allowed to more actively interact with power/energy management.

References

[1] P. Nema, R. Nema, and S. Rangnekar, "A current and future state of art development of hybrid energy system using wind and pv-solar: A review," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 8, pp. 2096–2103, 2009.

[2] R. Geertsma, R. Negenborn, K. Visser, and J. Hopman, "Design and control of hybrid power and propulsion systems for smart ships: A review of developments," *Applied Energy*, vol. 194, pp. 30–54, 2017.

[3] S. Tan, Y. Wu, P. Xie, J. M. Guerrero, J. C. Vasquez, and A. Abusorrah, "New challenges in the design of microgrid systems: Communication networks, cyberattacks, and resilience," *IEEE Electrification Magazine*, vol. 8, no. 4, pp. 98–106, 2020.

[4] M. Al-Falahi, T. Tarasiuk, S. Jayasinghe, Z. Jin, H. Enshaei, and J. Guerrero, "Ac ship microgrids: Control and power management optimization," *Energies*, vol. 11, no. 6, p. 1458, Jun 2018.

[5] P. Xie, C. Yuan, Y. Guan, S. Tan, M. Li, J. C. Vasquez, and J. M. Guerrero, "Stability analysis considering dual physical constraints of parallel-connected virtual synchronous generators forming microgrids," in *2019 IEEE Energy Conversion Congress and Exposition (ECCE)*, 2019, pp. 2092–2098.

[6] B. Wei, A. Marzàbal, J. Perez, R. Pinyol, J. M. Guerrero, and J. C. Vásquez, "Overload and short-circuit protection strategy for voltage source inverter-based ups," *IEEE Transactions on Power Electronics*, vol. 34, no. 11, pp. 11 371–11 382, 2019.

[7] B. Wei, Y. Gui, S. Trujillo, J. M. Guerrero, J. C. Vásquez, and A. Marzàbal, "Distributed average integral secondary control for modular ups systems-based microgrids," *IEEE Transactions on Power Electronics*, vol. 34, no. 7, pp. 6922–6936, 2019.

[8] B. Wei, A. Marzàbal, R. Ruiz, J. M. Guerrero, and J. C. Vasquez, "Davic: A new distributed adaptive virtual impedance control for parallel-connected voltage source inverters in modular ups system," *IEEE Transactions on Power Electronics*, vol. 34, no. 6, pp. 5953–5968, 2019.

[9] B. Wei, J. M. Guerrero, J. C. Vásquez, and X. Guo, "A circulating-current suppression method for parallel-connected voltage-source inverters with common dc and ac buses," *IEEE Transactions on Industry Applications*, vol. 53, no. 4, pp. 3758–3769, 2017.

[10] P. Nema, R. Nema, and S. Rangnekar, "A current and future state of art development of hybrid energy system using wind and pv-solar: A review," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 8, pp. 2096–2103, 2009.

[11] J. Thongam, M. Tarbouchi, A. Okou, D. Bouchard, and R. Beguenane, "All-electric ships—a review of the present state of the art," in *2013 Eighth International Conference and Exhibition on Ecological Vehicles and Renewable Energies (EVER)*. IEEE, 2013, pp. 1–8.

[12] S. G. Jayasinghe, L. Meegahapola, N. Fernando, Z. Jin, and J. M. Guerrero, "Review of ship microgrids: System architectures, storage technologies and power quality aspects," *inventions*, vol. 2, no. 1, p. 4, 2017.
[13] K. Ni, Y. Hu, and X. Li, "An overview of design, control, power management, system stability and reliability in electric ships," *Power Electronics and Drives*, vol. 2, no. 2, pp. 5–29, 2017.
[14] S. Fang, Y. Wang, B. Gou, and Y. Xu, "Toward future green maritime transportation: An overview of seaport microgrids and all-electric ships," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 1, pp. 207–219, 2019.
[15] Y. Huang, H. Lan, Y.-Y. Hong, S. Wen, and S. Fang, "Joint voyage scheduling and economic dispatch for all-electric ships with virtual energy storage systems," *Energy*, vol. 190, p. 116268, 2020.
[16] R. Derollepot and E. Vinot, "Sizing of a combined series-parallel hybrid architecture for river ship application using genetic algorithm and optimal energy management," *Mathematics and Computers in Simulation*, vol. 158, pp. 248–263, 2019.
[17] M. Kalikatzarakis, R. Geertsma, E. Boonen, K. Visser, and R. Negenborn, "Ship energy management for hybrid propulsion and power supply with shore charging," *Control Engineering Practice*, vol. 76, pp. 133–154, 2018.
[18] T. Van Vu, D. Gonsoulin, F. Diaz, C. S. Edrington, and T. El-Mezyani, "Predictive control for energy management in ship power systems under high-power ramp rate loads," *IEEE Transactions on Energy Conversion*, vol. 32, no. 2, pp. 788–797, 2017.
[19] Y. Guo, M. Khan, M. Faruque, and K. Sun, "Fuzzy logic based energy storage supervision and control strategy for mvdc power system of all electric ship," in *2016 IEEE Power and Energy Society General Meeting (PESGM)*. IEEE, 2016, pp. 1–5.
[20] M. M. S. Khan, M. O. Faruque, and A. Newaz, "Fuzzy logic based energy storage management system for mvdc power system of all electric ship," *IEEE Transactions on Energy Conversion*, vol. 32, no. 2, pp. 798–809, 2017.
[21] Y. Yuan, T. Zhang, B. Shen, X. Yan, and T. Long, "A fuzzy logic energy management strategy for a photovoltaic/diesel/battery hybrid ship based on experimental database," *Energies*, vol. 11, no. 9, p. 2211, 2018.
[22] S. Faddel, A. A. Saad, M. El Hariri, and O. A. Mohammed, "Coordination of hybrid energy storage for ship power systems with pulsed loads," *IEEE Transactions on Industry Applications*, vol. 56, no. 2, pp. 1136–1145, 2019.
[23] E. B. Beşikçi, T. Kececi, O. Arslan, and O. Turan, "An application of fuzzy-ahp to ship operational energy efficiency measures," *Ocean Engineering*, vol. 121, pp. 392–402, 2016.
[24] N. Karim, R. Lisner, H. Kazemi, and F. Annaz, "Rule-based power management for the all-electric ship," in *Proceedings of the Australian University power engineering conference*. Citeseer, 2002.
[25] S. F. Tie and C. W. Tan, "A review of energy sources and energy management system in electric vehicles," *Renewable and sustainable energy reviews*, vol. 20, pp. 82–102, 2013.
[26] E. Silvas, T. Hofman, N. Murgovski, L. P. Etman, and M. Steinbuch, "Review of optimization strategies for system-level design in hybrid electric vehicles," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 1, pp. 57–70, 2016.
[27] S. F. Tie and C. W. Tan, "A review of energy sources and energy management system in electric vehicles," *Renewable and sustainable energy reviews*, vol. 20, pp. 82–102, 2013.
[28] N. Sulaiman, M. Hannan, A. Mohamed, E. Majlan, and W. W. Daud, "A review on energy management system for fuel cell hybrid electric vehicle: Issues and challenges," *Renewable and Sustainable Energy Reviews*, vol. 52, pp. 802–814, 2015.
[29] Y. Huang, H. Wang, A. Khajepour, H. He, and J. Ji, "Model predictive control power management strategies for hevs: A review," *Journal of Power Sources*, vol. 341, pp. 91–106, 2017.
[30] F. D. Kanellos, G. J. Tsekouras, and N. D. Hatziargyriou, "Optimal demand-side management and power generation scheduling in an all-electric ship," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 4, pp. 1166–1175, 2014.
[31] F. Kanellos, "Optimal power management with ghg emissions limitation in all-electric ship power systems comprising energy storage systems," *IEEE Transactions on power systems*, vol. 29, no. 1, pp. 330–339, 2013.
[32] S. Fang, Y. Xu, Z. Li, T. Zhao, and H. Wang, "Two-step multi-objective management of hybrid energy storage system in all-electric ship microgrids," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3361–3373, 2019.
[33] A. Fathy, H. Rezk, and A. M. Nassef, "Robust hydrogen-consumption-minimization strategy based salp swarm algorithm for energy management of fuel cell/supercapacitor/batteries in highly fluctuated load condition," *Renewable energy*, vol. 139, pp. 147–160, 2019.
[34] A. M. Bassam, A. B. Phillips, S. R. Turnock, and P. A. Wilson, "An improved energy management strategy for a hybrid fuel cell/battery passenger vessel," *International journal of hydrogen energy*, vol. 41, no. 47, pp. 22 453–22 464, 2016.
[35] M. E. P. Committee *et al.*, "Guideline for voluntary use of the ship energy efficiency operational indicator (eeoi)[r]," *London: International Maritime Organization*, 2009.
[36] A. L. Bukar and C. W. Tan, "A review on stand-alone photovoltaic-wind energy system with fuel cell: System optimization and energy management strategy," *Journal of cleaner production*, vol. 221, pp. 73–88, 2019.
[37] E. Eriksson and E. M. Gray, "Optimization and integration of hybrid renewable energy hydrogen fuel cell energy systems–a critical review," *Applied energy*, vol. 202, pp. 348–364, 2017.
[38] C. Yan, G. K. Venayagamoorthy, and K. A. Corzine, "Optimal location and sizing of energy storage modules for a smart electric ship power system," in *2011 IEEE Symposium on Computational Intelligence Applications In Smart Grid (CIASG)*. IEEE, 2011, pp. 1–8.
[39] D. Gao, X. Wang, T. Wang, Y. Wang, and X. Xu, "An energy optimization strategy for hybrid power ships under load uncertainty based on load power prediction and improved nsga-ii algorithm," *Energies*, vol. 11, no. 7, p. 1699, 2018.
[40] C. S. Index, "Clean shipping index methodology and reporting guidelines," *Gothenburg: Clean Shipping index*, 2018.
[41] F. Kanellos, "Optimal power management with ghg emissions limitation in all-electric ship power systems comprising energy storage systems," *IEEE Transactions on power systems*, vol. 29, no. 1, pp. 330–339, 2013.
[42] F. Baldi, F. Ahlgren, F. Melino, C. Gabrielii, and K. Andersson, "Optimal load allocation of complex ship power plants," *Energy Conversion and Management*, vol. 124, pp. 344–356, 2016.
[43] H.-M. Chin, C.-L. Su, and C.-H. Liao, "Estimating power pump loads and sizing generators for ship electrical load analysis," *IEEE Transactions on Industry Applications*, vol. 52, no. 6, pp. 4619–4627, 2016.
[44] M. A. Ancona, F. Baldi, M. Bianchi, L. Branchini, F. Melino, A. Peretto, and J. Rosati, "Efficiency improvement on a cruise ship: Load allocation optimization," *Energy conversion and management*, vol. 164, pp. 42–58, 2018.
[45] J. J. Valera-García and I. Atutxa-Lekue, "On the optimal design of hybrid-electric power systems for offshore vessels," *IEEE Transactions on Transportation Electrification*, vol. 5, no. 1, pp. 324–334, 2018.
[46] C. Zhang and B.-z. JIA, "The research of power allocation in diesel-electric hybrid propulsion system," in *2019 Chinese Automation Congress (CAC)*. IEEE, 2019, pp. 3664–3668.
[47] R. Tjandra, S. Wen, D. Zhou, and Y. Tang, "Optimal sizing of bess for hybrid electric ship using multi-objective particle swarm optimization," in *2019 10th International Conference on Power Electronics and ECCE Asia (ICPE 2019-ECCE Asia)*. IEEE, 2019, pp. 1460–1466.
[48] E. A. Sciberras, B. Zahawi, D. J. Atkinson, A. Breijs, and J. H. van Vugt, "Managing shipboard energy: A stochastic approach special issue on marine systems electrification," *IEEE Transactions on Transportation Electrification*, vol. 2, no. 4, pp. 538–546, 2016.
[49] F. D. Kanellos, A. Anvari-Moghaddam, and J. M. Guerrero, "Smart shipboard power system operation and management," *Inventions*, vol. 1, no. 4, p. 22, 2016.
[50] A. De, S. K. Kumar, A. Gunasekaran, and M. K. Tiwari, "Sustainable maritime inventory routing problem with time window constraints," *Engineering Applications of Artificial Intelligence*, vol. 61, pp. 77–95, 2017.
[51] M. D. Al-Falahi, K. S. Nimma, S. D. Jayasinghe, H. Enshaei, and J. M. Guerrero, "Power management optimization of hybrid power systems in electric ferries," *Energy Conversion and Management*, vol. 172, pp. 50–66, 2018.
[52] S. Fang, Y. Xu, and Z. Li, "Joint generation and demand-side management for shipboard carbon capture and storage system," in *2019 IEEE/IAS 55th Industrial and Commercial Power Systems Technical Conference (I&CPS)*. IEEE, 2019, pp. 1–8.
[53] S. Fang and Y. Xu, "Multi-objective robust energy management for all-electric shipboard microgrid under uncertain wind and wave," *International Journal of Electrical Power & Energy Systems*, vol. 117, p. 105600, 2020.

[54] P. Michalopoulos, F. D. Kanellos, G. J. Tsekouras, and J. M. Prousalidis, "A method for optimal operation of complex ship power systems employing shaft electric machines," *IEEE Transactions on Transportation Electrification*, vol. 2, no. 4, pp. 547–557, 2016.

[55] Z. Li, Y. Xu, S. Fang, Y. Wang, and X. Zheng, "Multi-objective coordinated energy dispatch and voyage scheduling for a multi-energy ship microgrid," *IEEE Transactions on Industry Applications*, 2019.

[56] A. De, A. Choudhary, and M. K. Tiwari, "Multiobjective approach for sustainable ship routing and scheduling with draft restrictions," *IEEE Transactions on Engineering Management*, vol. 66, no. 1, pp. 35–51, 2017.

[57] C. Yao, M. Chen, and Y.-Y. Hong, "Novel adaptive multi-clustering algorithm-based optimal ess sizing in ship power system considering uncertainty," *IEEE transactions on power systems*, vol. 33, no. 1, pp. 307–316, 2017.

[58] C. Shang, D. Srinivasan, and T. Reindl, "Economic and environmental generation and voyage scheduling of all-electric ships," *IEEE transactions on power systems*, vol. 31, no. 5, pp. 4087–4096, 2015.

[59] V. Bolbot, N. L. Trivyza, G. Theotokatos, E. Boulougouris, A. Rentizelas, and D. Vassalos, "Cruise ships power plant optimisation and comparative analysis," *Energy*, vol. 196, p. 117061, 2020.

[60] Z. Jianyun, C. Li, X. Lijuan, and W. Bin, "Bi-objective optimal design of plug-in hybrid electric propulsion system for ships," *Energy*, vol. 177, pp. 247–261, 2019.

[61] F. D. Kanellos, A. Anvari-Moghaddam, and J. M. Guerrero, "A cost-effective and emission-aware power management system for ships with integrated full electric propulsion," *Electric Power Systems Research*, vol. 150, pp. 63–75, 2017.

[62] R. Kumar, M. Fozdar *et al.*, "Optimal sizing of hybrid ship power system using variants of particle swarm optimization," in *2017 Recent Developments in Control, Automation & Power Engineering (RDCAPE)*. IEEE, 2017, pp. 527–532.

[63] F. D. Kanellos, A. Anvari-Moghaddam, and J. M. Guerrero, "Smart shipboard power system operation and management," *Inventions*, vol. 1, no. 4, p. 22, 2016.

[64] Z. Li, Y. Xu, S. Fang, Y. Wang, and X. Zheng, "Multiobjective coordinated energy dispatch and voyage scheduling for a multienergy ship microgrid," *IEEE Transactions on Industry Applications*, vol. 56, no. 2, pp. 989–999, 2019.

[65] E. Skjong, T. A. Johansen, M. Molinas, and A. J. Sørensen, "Approaches to economic energy management in diesel–electric marine vessels," *IEEE Transactions on Transportation Electrification*, vol. 3, no. 1, pp. 22–35, 2017.

[66] Z. Li, Y. Xu, S. Fang, X. Zheng, and X. Feng, "Robust coordination of a hybrid ac/dc multi-energy ship microgrid with flexible voyage and thermal loads," *IEEE Transactions on Smart Grid*, 2020.

[67] A. Ritari, J. Huotari, J. Halme, and K. Tammi, "Hybrid electric topology for short sea ships with high auxiliary power availability requirement," *Energy*, vol. 190, p. 116359, 2020.

[68] A. De, V. K. R. Mamanduru, A. Gunasekaran, N. Subramanian, and M. K. Tiwari, "Composite particle algorithm for sustainable integrated dynamic ship routing and scheduling optimization," *Computers & Industrial Engineering*, vol. 96, pp. 201–215, 2016.

[69] H.-M. Chin, C.-L. Su, and C.-H. Liao, "Estimating power pump loads and sizing generators for ship electrical load analysis," *IEEE Transactions on Industry Applications*, vol. 52, no. 6, pp. 4619–4627, 2016.

[70] S. Wen, H. Lan, Y.-Y. Hong, C. Y. David, L. Zhang, and P. Cheng, "Allocation of ess by interval optimization method considering impact of ship swinging on hybrid pv/diesel ship power system," *Applied Energy*, vol. 175, pp. 158–167, 2016.

[71] Y. Yan, H. Zhang, Y. Long, Y. Wang, Y. Liang, X. Song, and J. James, "Multi-objective design optimization of combined cooling, heating and power system for cruise ship application," *Journal of cleaner production*, vol. 233, pp. 264–279, 2019.

[72] A. Boveri, P. Gualeni, D. Neroni, and F. Silvestro, "Stochastic approach for power generation optimal design and scheduling on ships," in *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*. IEEE, 2017, pp. 1–6.

[73] S. Mashayekh and K. L. Butler-Purry, "An integrated security-constrained model-based dynamic power management approach for isolated microgrids in all-electric ships," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp. 2934–2945, 2015.

[74] R. Tang, X. Li, and J. Lai, "A novel optimal energy-management strategy for a maritime hybrid energy system based on large-scale global optimization," *Applied energy*, vol. 228, pp. 254–264, 2018.

[75] A. Letafat, M. Rafiei, M. Sheikh, M. Afshari-Igder, M. Banaei, J. Boudjadar, and M. H. Khooban, "Simultaneous energy management and optimal components sizing of a zero-emission ferry boat," *Journal of Energy Storage*, vol. 28, p. 101215, 2020.

[76] H. Chen, Z. Zhang, C. Guan, and H. Gao, "Optimization of sizing and frequency control in battery/supercapacitor hybrid energy storage system for fuel cell ship," *Energy*, p. 117285, 2020.

[77] B. Manasa and K. Vaisakh, "Optimal shipboard power management by classical and differential evolution methods," *International Research Journal of Engineering and Technology (IRJET)*, vol. 06, pp. 269–279, 2019.

[78] Q. Xu, B. Yang, Q. Han, Y. Yuan, C. Chen, and X. Guan, "Optimal power management for failure mode of mvdc microgrids in all-electric ships," *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 1054–1067, 2018.

[79] G. La Tona, M. Luna, M. di Piazza, and A. Pietra, "Energy management system for efficiency increase in cruise ship microgrids," in *IECON 2019-45th Annual Conference of the IEEE Industrial Electronics Society*, vol. 1. IEEE, 2019, pp. 4056–4062.

[80] S. Fang, Y. Xu, Z. Li, Z. Ding, L. Liu, and H. Wang, "Optimal sizing of shipboard carbon capture system for maritime greenhouse emission control," *IEEE Transactions on Industry Applications*, vol. 55, no. 6, pp. 5543–5553, 2019.

[81] A. Anvari-Moghaddam, T. Dragicevic, L. Meng, B. Sun, and J. M. Guerrero, "Optimal planning and operation management of a ship electrical power system with energy storage system," in *IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2016, pp. 2095–2099.

[82] A. Dolatabadi, R. Ebadi, and B. Mohammadi-Ivatloo, "A two-stage stochastic programming model for the optimal sizing of hybrid pv/diesel/battery in hybrid electric ship system," *Journal of Operation and Automation in Power Engineering*, vol. 7, no. 1, pp. 16–26, 2019.

[83] A. Boveri, F. Silvestro, and P. Gualeni, "Ship electrical load analysis and power generation optimisation to reduce operational costs," in *2016 International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC)*. IEEE, 2016, pp. 1–6.

[84] A. Boveri, F. Silvestro, M. Molinas, and E. Skjong, "Optimal sizing of energy storage systems for shipboard applications," *IEEE Transactions on Energy Conversion*, vol. 34, no. 2, pp. 801–811, 2018.

[85] S. Wen, H. Lan, D. C. Yu, Q. Fu, Y.-Y. Hong, L. Yu, and R. Yang, "Optimal sizing of hybrid energy storage sub-systems in pv/diesel ship power system using frequency analysis," *Energy*, vol. 140, pp. 198–208, 2017.

[86] S. Cao, Z. Yang, H. Cheng, Y. Zheng, and J. Geng, "Time coupling constraints modeling and analysis in unit commitment," in *Proceedings of the 2016 International Conference on Electrical, Mechanical and Industrial Engineering*. Atlantis Press, 2016/04, pp. 176–180. [Online]. Available: https://doi.org/10.2991/icemie-16.2016.44

[87] M. Jaurola, A. Hedin, S. Tikkanen, and K. Huhtala, "Topti: a flexible framework for optimising energy management for various ship machinery topologies," *Journal of Marine Science and Technology*, vol. 24, no. 4, pp. 1183–1196, 2019.

[88] C. Wang, K. Ren, and J. Wang, "Secure optimization computation outsourcing in cloud computing: A case study of linear programming," *IEEE transactions on computers*, vol. 65, no. 1, pp. 216–229, 2015.

[89] D. G. Luenberger, Y. Ye *et al.*, *Linear and nonlinear programming*. Springer, 1984, vol. 2.

[90] M. Carrión and J. M. Arroyo, "A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem," *IEEE Transactions on power systems*, vol. 21, no. 3, pp. 1371–1378, 2006.

[91] M. R. Hossain and H. L. Ginn, "Real-time distributed coordination of power electronic converters in a dc shipboard distribution system," *IEEE Transactions on Energy Conversion*, vol. 32, no. 2, pp. 770–778, 2017.

[92] K. Lai and M. S. Illindala, "A distributed energy management strategy for resilient shipboard power system," *Applied energy*, vol. 228, pp. 821–832, 2018.

[93] F. Baldi, F. Ahlgren, F. Melino, C. Gabrielii, and K. Andersson, "Optimal load allocation of complex ship power plants," *Energy Conversion and Management*, vol. 124, pp. 344–356, 2016.

[94] A. Miró, C. Pozo, G. Guillén-Gosálbez, J. A. Egea, and L. Jiménez, "Deterministic global optimization algorithm based on outer approximation for the parameter estimation of nonlinear dynamic biological systems," *BMC bioinformatics*, vol. 13, no. 1, p. 90, 2012.

[95] M. Basu, "Dynamic economic emission dispatch using nondominated sorting genetic algorithm-ii," *International Journal of Electrical Power & Energy Systems*, vol. 30, no. 2, pp. 140–149, 2008.

[96] D. Gao, X. Wang, T. Wang, Y. Wang, and X. Xu, "Optimal thrust allocation strategy of electric propulsion ship based on improved non-dominated sorting genetic algorithm ii," *IEEE Access*, vol. 7, pp. 135 247–135 255, 2019.

[97] L. Liu, S. Yang, and D. Wang, "Particle swarm optimization with composite particles in dynamic environments," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 40, no. 6, pp. 1634–1648, 2010.

[98] A. Armellini, S. Daniotti, P. Pinamonti, and M. Reini, "Evaluation of gas turbines as alternative energy production systems for a large cruise ship to meet new maritime regulations," *Applied energy*, vol. 211, pp. 306–317, 2018.

[99] V. Sarfi and H. Livani, "A novel multi-objective security-constrained power management for isolated microgrids in all-electric ships," in *2017 IEEE Electric Ship Technologies Symposium (ESTS)*. IEEE, 2017, pp. 148–155.

[100] S. A. Cook, "An overview of computational complexity," *Communications of the ACM*, vol. 26, no. 6, pp. 400–408, 1983.

[101] L. C. W. Yuan, T. Tjahjowidodo, G. S. G. Lee, R. Chan, and A. K. Ådnanes, "Equivalent consumption minimization strategy for hybrid all-electric tugboats to optimize fuel savings," in *2016 American Control Conference (ACC)*. IEEE, 2016, pp. 6803–6808.

[102] L. W. Chua, T. Tjahjowidodo, G. G. Seet, and R. Chan, "Implementation of optimization-based power management for all-electric hybrid vessels," *IEEE Access*, vol. 6, pp. 74 339–74 354, 2018.

[103] J. Zhu, L. Chen, X. Wang, and L. Yu, "Bi-level optimal sizing and energy management of hybrid electric propulsion systems," *Applied Energy*, vol. 260, p. 114134, 2020.

[104] C.-C. Lin, H. Peng, J. W. Grizzle, and J.-M. Kang, "Power management strategy for a parallel hybrid electric truck," *IEEE transactions on control systems technology*, vol. 11, no. 6, pp. 839–849, 2003.

[105] F. Balsamo, C. Capasso, G. Miccione, and O. Veneri, "Hybrid storage system control strategy for all-electric powered ships," *Energy Procedia*, vol. 126, pp. 1083–1090, 2017.

[106] R. Tang, Z. Wu, and X. Li, "Optimal operation of photovoltaic/battery/diesel/cold-ironing hybrid energy system for maritime application," *Energy*, vol. 162, pp. 697–714, 2018.

[107] S. Paran, T. Vu, T. El Mezyani, and C. Edrington, "Mpc-based power management in the shipboard power system," in *2015 IEEE Electric Ship Technologies Symposium (ESTS)*. IEEE, 2015, pp. 14–18.

[108] K. Wang, X. Yan, Y. Yuan, X. Jiang, X. Lin, and R. R. Negenborn, "Dynamic optimization of ship energy efficiency considering time-varying environmental factors," *Transportation Research Part D: Transport and Environment*, vol. 62, pp. 685–698, 2018.

[109] L. C. W. Yuan, T. Tjahjowidodo, G. S. G. Lee, and R. Chan, "Optimizing fuel savings and power system reliability for all-electric hybrid vessels using model predictive control," in *2017 IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*. IEEE, 2017, pp. 1532–1537.

[110] G. Papalambrou, S. Samokhin, S. Topaloglou, N. Planakis, N. Kyrtatos, and K. Zenger, "Model predictive control for hybrid diesel-electric marine propulsion," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 11 064–11 069, 2017.

[111] D. E. Gonsoulin, T. V. Vu, F. Diaz, H. Vahedi, D. Perkins, and C. S. Edrington, "Coordinating multiple energy storages using mpc for ship power systems," in *2017 IEEE Electric Ship Technologies Symposium (ESTS)*. IEEE, 2017, pp. 551–556.

[112] Z. Wu and X. Xia, "Tariff-driven demand side management of green ship," *Solar Energy*, vol. 170, pp. 991–1000, 2018.

[113] A. Haseltalab and R. R. Negenborn, "Model predictive maneuvering control and energy management for all-electric autonomous ships," *Applied Energy*, vol. 251, p. 113308, 2019.

[114] J. Hou, J. Sun, and H. F. Hofmann, "Mitigating power fluctuations in electric ship propulsion with hybrid energy storage system: Design and analysis," *IEEE Journal of Oceanic Engineering*, vol. 43, no. 1, pp. 93–107, 2017.

[115] H. Park, J. Sun, S. Pekarek, P. Stone, D. Opila, R. Meyer, I. Kolmanovsky, and R. DeCarlo, "Real-time model predictive control for shipboard power management using the ipa-sqp approach," *IEEE Transactions on Control Systems Technology*, vol. 23, no. 6, pp. 2129–2143, 2015.

[116] J. Hou, Z. Song, H. Park, H. Hofmann, and J. Sun, "Implementation and evaluation of real-time model predictive control for load fluctuations mitigation in all-electric ship propulsion systems," *Applied energy*, vol. 230, pp. 62–77, 2018.

[117] J. Hou, Z. Song, H. Hofmann, and J. Sun, "Adaptive model predictive control for hybrid energy storage energy management in all-electric ship microgrids," *Energy Conversion and Management*, vol. 198, p. 111929, 2019.

[118] T. V. KISHOR, J. HPawar, and S. MODUGU, "An analysis: Hybrid res fuzzy based predictive control for shipboard using the ipa-sqp," *International Journal of Scientific Engineering and Technology Research*, vol. 5, pp. 7492–7499, 2016.

[119] N. Zohrabi, H. Zakeri, and S. Abdelwahed, "Efficient load management in electric ships: A model predictive control approach," in *2019 IEEE Applied Power Electronics Conference and Exposition (APEC)*. IEEE, 2019, pp. 3000–3006.

[120] J. Hou, J. Sun, and H. Hofmann, "Adaptive model predictive control with propulsion load estimation and prediction for all-electric ship energy management," *Energy*, vol. 150, pp. 877–889, 2018.

[121] T. I. Bø and T. A. Johansen, "Dynamic safety constraints by scenario-based economic model predictive control of marine electric power plants," *IEEE Transactions on Transportation Electrification*, vol. 3, no. 1, pp. 13–21, 2016.

[122] G. Seenumani, H. Peng, and J. Sun, "A reference governor-based hierarchical control for failure mode power management of hybrid power systems for all-electric ships," *Journal of power sources*, vol. 196, no. 3, pp. 1599–1607, 2011.

[123] G. Seenumani, J. Sun, and H. Peng, "A hierarchical optimal control strategy for power management of hybrid power systems in all electric ships applications," in *49th IEEE Conference on Decision and Control (CDC)*. IEEE, 2010, pp. 3972–3977.

[124] S. Hasanvand, M. Rafiei, M. Gheisarnejad, and M.-H. Khooban, "Reliable power scheduling of an emission-free ship: Multi-objective deep reinforcement learning," *IEEE Transactions on Transportation Electrification*, 2020.

[125] G. Seenumani, J. Sun, and H. Peng, "Real-time power management of integrated power systems in all electric ships leveraging multi time scale property," *IEEE Transactions on Control Systems Technology*, vol. 20, no. 1, pp. 232–240, 2011.

[126] T. Vu, S. Paran, T. El Mezyani, and C. Edrington, "Real-time distributed power optimization in the dc microgrids of shipboard power systems," in *2015 IEEE Electric Ship Technologies Symposium (ESTS)*. IEEE, 2015, pp. 118–122.

[127] X. Feng, K. L. Butler-Purry, and T. Zourntos, "Real-time electric load management for dc zonal all-electric ship power systems," *Electric Power Systems Research*, vol. 154, pp. 503–514, 2018.

[128] K. Lai and M. S. Illindala, "A distributed energy management strategy for resilient shipboard power system," *Applied energy*, vol. 228, pp. 821–832, 2018.

[129] C. S. Edrington, G. Ozkan, B. Papari, D. E. Gonsoulin, D. Perkins, T. V. Vu, and H. Vahedi, "Distributed energy management for ship power systems with distributed energy storage," *Journal of Marine Engineering & Technology*, vol. 19, no. sup1, pp. 31–44, 2020.

[130] T. V. Vu, D. Perkins, D. Gonsoulin, C. S. Edrington, B. Papari, K. Schoder, M. Stanovich, and M. Steurer, "Large-scale distributed control for mvdc ship power systems," in *IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2018, pp. 3431–3436.

[131] X. Feng, K. L. Butler-Purry, and T. Zourntos, "Multi-agent system-based real-time load management for all-electric ship power systems in dc zone level," *IEEE Transactions on Power Systems*, vol. 27, no. 4, pp. 1719–1728, 2012.

[132] Z. Hong, Q. Li, Y. Han, W. Shang, Y. Zhu, and W. Chen, "An energy management strategy based on dynamic power factor for fuel cell/battery hybrid locomotive," *International Journal of Hydrogen Energy*, vol. 43, no. 6, pp. 3261–3272, 2018.

[133] D. Gonsoulin, T. Vu, F. Diaz, H. Vahedi, D. Perkins, and C. Edrington, "Centralized mpc for multiple energy storages in ship power systems," in *IECON 2017-43rd Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2017, pp. 6777–6782.

[134] A. R. Dahl, L. Thorat, and R. Skjetne, "Model predictive control of marine vessel power system by use of structure preserving model," *IFAC-PapersOnLine*, vol. 51, no. 29, pp. 335–340, 2018.

[135] P. Stone, D. F. Opila, H. Park, J. Sun, S. Pekarek, R. DeCarlo, E. Westervelt, J. Brooks, and G. Seenumani, "Shipboard power management using constrained nonlinear model predictive control," in *2015 IEEE Electric Ship Technologies Symposium (ESTS)*. IEEE, 2015, pp. 1–7.

[136] T. I. Bø and T. A. Johansen, "Battery power smoothing control in a marine electric power plant using nonlinear model predictive control,"

IEEE Transactions on Control Systems Technology, vol. 25, no. 4, pp. 1449–1456, 2016.

[137] T. V. Vu, D. Gonsoulin, D. Perkins, F. Diaz, H. Vahedi, and C. S. Edrington, “Predictive energy management for mvdc all-electric ships,” in *2017 IEEE Electric Ship Technologies Symposium (ESTS)*. IEEE, 2017, pp. 327–331.

[138] J. Hou, J. Sun, and H. Hofmann, “Integrated control of power generation, electric motor and hybrid energy storage for all-electric ships,” in *2016 American Control Conference (ACC)*. IEEE, 2016, pp. 6797–6802.

[139] A. Haseltalab and R. R. Negenborn, “Predictive on-board power management for all-electric ships with dc distribution architecture,” in *OCEANS 2017-Aberdeen*. IEEE, 2017, pp. 1–8.

[140] A. Haseltalab, R. R. Negenborn, and G. Lodewijks, “Multi-level predictive control for energy management of hybrid ships in the presence of uncertainty and environmental disturbances,” *IFAC-PapersOnLine*, vol. 49, no. 3, pp. 90–95, 2016.

[141] S. Tan, J. M. Guerrero, P. Xie, R. Han, and J. C. Vasquez, “Brief survey on attack detection methods for cyber-physical systems,” *IEEE Systems Journal*, 2020.

[142] D. Lee and C.-C. Cheng, “Energy savings by energy management systems: A review,” *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 760–777, 2016.

Peilin Xie (S’19) received the B.S. degree in Electrical Engineering from Beijing Jiaotong University, Beijing, China in 2015, and the M.S. degree in Electrical Engineering and Automation from North China Electric Power University, Beijing, China, in 2018. She is currently working toward her Ph.D. degree with the Department of Energy Technology, Aalborg University, Aalborg, Denmark.

Her research mainly include virtual synchronous generator technology, the power management control for shipboard microgrids, and distributed PMS for large-scale shipboard microgrids.

Josep M. Guerrero (S’01-M’04-SM’08-FM’15) received the B.S. degree in telecommunications engineering, the M.S. degree in electronics engineering, and the Ph.D. degree in power electronics from the Technical University of Catalonia, Barcelona, in 1997, 2000 and 2003, respectively. Since 2011, he has been a Full Professor with the Department of Energy Technology, Aalborg University, Denmark, where he is responsible for the Microgrid Research Program. From 2014 he is chair Professor in Shandong University; from 2015 he is a distinguished guest Professor in Hunan University; and from 2016 he is a visiting professor fellow at Aston University, UK, and a guest Professor at the Nanjing University of Posts and Telecommunications. From 2019, he became a Villum Investigator by The Villum Fonden, which supports the Center for Research on Microgrids (CROM) at Aalborg University, being Prof. Guerrero the founder and Director of the same centre (www.crom.et.aau.dk).

His research interests is oriented to different microgrid aspects, including power electronics, distributed energy-storage systems, hierarchical and cooperative control, energy management systems, smart metering and the internet of things for AC/DC microgrid clusters and islanded minigrids. Specially focused on microgrid technologies applied to offshore wind, maritime microgrids for electrical ships, vessels, ferries and seaports, and space microgrids applied to nanosatellites and spacecrafts. Prof. Guerrero is an Associate Editor for a number of IEEE TRANSACTIONS. He has published more than 500 journal papers in the fields of microgrids and renewable energy systems, which are cited more than 50,000 times. He received the best paper award of the IEEE Transactions on Energy Conversion for the period 2014-2015, and the best paper prize of IEEE-PES in 2015. As well, he received the best paper award of the Journal of Power Electronics in 2016. During six consecutive years, from 2014 to 2019, he was awarded by Clarivate Analytics (former Thomson Reuters) as Highly Cited Researcher. In 2015 he was elevated as IEEE Fellow for his contributions on “distributed power systems and microgrids.”

Sen Tan (S’20) received the B.S. degree in Automation, the M.S. degree in Control Engineering both from Northeastern University, Liaoning, China, in 2014 and 2017 respectively. He is currently pursuing the Ph.D. degree with the Department of Energy Technology, Aalborg University, Denmark.

His research interests include distributed control and power management strategy design for microgrid, fault detection and motor drive technologies.

Najmeh Bazmohammadi received the bachelor’s degree in electrical engineering and the master’s degree in electrical engineering-Control from the Ferdowsi University of Mashhad, Iran in 2009 and 2012, respectively and the Ph.D. degree in electrical engineering-Control from the K. N. Toosi University of Technology, Tehran, Iran in 2019. She is currently a postdoctoral research fellow with the Center for Research on Microgrids (CROM), Department of Energy Technology, Aalborg University, Denmark.

Her current research interests include modeling and control of dynamic systems, decision-making under uncertainty, model predictive control and its application in energy management of hybrid and renewable-based power systems and life support systems.

Juan C. Vasquez (M'12-SM'14) received the B.S. degree in electronics engineering from the Autonomous University of Manizales, Manizales, Colombia, and the Ph.D. degree in automatic control, robotics, and computer vision from BarcelonaTech-UPC, Spain, in 2004 and 2009, respectively. In 2011, He was Assistant Professor and in 2014, Associate Professor at the Department of Energy Technology, Aalborg University, Denmark. In 2019, He became Professor in Energy Internet and Microgrids and currently He is the Co-Director of the Villum Center for Research on Microgrids (see crom.et.aau.dk). He was a Visiting Scholar at the Center of Power Electronics Systems (CPES) at Virginia Tech, USA and a visiting professor at Ritsumeikan University, Japan. His current research interests include operation, advanced hierarchical and cooperative control, optimization and energy management applied to distributed generation in AC/DC Microgrids, maritime microgrids, advanced metering infrastructures and the integration of Internet of Things and Energy Internet into the SmartGrid. Prof.Vasquez is an Associate Editor of IET POWER ELECTRONICS and a Guest Editor of the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS Special Issue on Energy Internet. Prof. Vasquez was awarded as Highly Cited Researcher by Thomson Reuters from 2017 to 2019 and He was the recipient of the Young Investigator Award 2019. He has published more than 450 journal papers in the field of Microgrids, which in total are cited more than 19000 times. Dr. Vasquez is currently a member of the IEC System Evaluation Group SEG4 on LVDC Distribution and Safety for use in Developed and Developing Economies, the Renewable Energy Systems Technical Committee TC-RES in IEEE Industrial Electronics, PELS, IAS, and PES Societies.

Mojtaba Mehrzadi received the B.Sc. degree in Electrical Engineering from Islamic Azad University (IAU) of Iran, at the Department of Engineering and Technology, in 2007, and the MSc Degree in Control Theory & Control Engineering from IAU, Iran in 2012, respectively. He is currently working towards a Ph.D. degree at the Department of Energy Technology, Aalborg University, Denmark. His research interests include the power management system in the hybrid maritime microgrid.

Yusuf Al-Turki (M'90-SM'17) received the Ph.D. degree in power systems from the University of Manchester, UK , in 1985. Since 1999, he is a Professor with the Department of Electrical and Computer Engineering, King Abdulaziz University, Saudi Arabia. Currently, he is Vice President for Graduate Studies and Scientific Research at the same university. His research interests include: system modeling, power system dynamics, renewable energy and microgrids.