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Review Article

Advanced control in energy systems and review of future developments in marine energy system control

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ABSTRACT

The trend of electrification of propulsion systems also introduced all-electric drive in the maritime sector. Maritime all-electric drive systems operate using an energy system containing a variety of components, such as batteries, internal combustion engines, or fuel cells. The introduction of new components in the energy system increases both the flexibility as well as the complexity of the system operation. The most commonly used rule-based control is no longer sufficient to solve the control problem. Consequently, the usage of advanced control strategies in maritime has become a topic of research in recent years. In the operation of a maritime energy system, several objectives are of interest as targets of the optimisation, including cost, emission, or an enlargement of component lifetime. Depending on the choice of objective, the control strategy can differ. By integrating multiple objectives in control, the operation is optimised to find the best working point to fulfil the different interests. This article first reviews the commonly used advanced control structures in the maritime, automotive, and building control sectors. A comparison is used to identify further potential for advanced control usage in marine applications. In addition, the implementation of advanced control is reviewed in architecture and optimisation algorithms. Secondly, the control objectives used in the literature are presented and analysed in terms of their usage and potential of the combination. Thirdly, the currently used validation strategies and published results are reviewed and interpreted in terms of potential and required future work. Lastly, open gaps in the state of research are identified and potential for future work is outlined.

Contents

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A list of acronyms used throughout the paper is provided in Table 1.

1. Introduction

Reducing shipping sector emissions is urgently required to meet the goals of the Paris Agreement in facing the dangers of global warming and climate change (ipc, 2021; IEA, 2021). Annual CO_2 produced by the shipping sector represents nearly 3 % of global emissions and is still growing even with the current International Maritime Organisation (IMO) measures already in place (Eyring, Köhler, van Aardenne,& Lauer, 2005; IMO Uk, 2020; IMO Uk et al., 2015). Additionally, ships contribute to the acidification of the ocean and coastal regions, global sulphur loading, and increased ozone perturbation in the summer months (Dalsøren et al., 2009; Endresen et al., 2003; Eyring et al., 2010). The net CO_2 emissions and sulphur emissions of shipping relate mainly to the selected fuel and fuel consumption of a vessel (IMO Uk et al., 2015). Other hazardous emissions such as NOx, Particulate Matter (PM), and methane slip also strongly depend on the operating point of the combustion engines and the combustion process at their operating points. Modern alternative power and propulsion plant concepts allow the integration of alternative fuels such as hydrogen, methanol, and ammonia, novel power sources such as fuel cells, and energy storage (ES) technologies. These novel power systems concepts and components can effectively reduce the fuel consumption of fossil fuels and allow optimising power source operation and reducing hazardous emissions (Eyring, Köhler, Lauer, & Lemper, 2005). Therefore, novel power and propulsion systems and their control can reduce the vessel's emission output during operation (Hansen & Wendt, 2015; Nuchturee et al., 2020) (see Table 1).

In electric and hybrid propulsion plants, the mechanical propulsion system of a vessel is replaced completely or partly with an electric system driving the propellers and thrusters while also providing the energy for other loads, such as mission loads, hotel loads, and auxiliary loads (Geertsma et al., 2017). This electric power plant consists of a variety of components that can be arranged in different AC or DC configurations, including power sources Internal Combustion Engines (ICE), Fuel Cells (FC), PhotoVoltaic systems (PV), ES systems (batteries and supercapacitors) and power conversion components (electric motors, generators, transformers and frequency converters) (Nuchturee et al., 2020). A transport solution that is already commonly used in the automotive and is also under investigation for the maritime is battery-electric ship propulsion (Korberg et al., 2021). Battery-electric propulsion offers a zero-emission solution and is therefore an attractive choice, especially for road vehicles used on short distances; for example in cities. However, their application in the maritime is currently limited to short travel distances and not a solution for most types of vessels and operations (Perčić et al., 2020). This is due to their relatively low energy density and the limitations in weight and size for shipping, which leads to short autonomous travel distances. While the voyage range still limits their application for most purposes, batteries have been shown to significantly reduce emissions during port operation and at berth (Barone et al., 2024).

The optimal power and propulsion system configuration varies between types of vessels and heavily depends on the required autonomous travel distance, the operating profile and the propulsion, mission system, climate system, and auxiliary loads to be supplied (Korberg et al., 2021; Perčić et al., 2020). However, the change to electric and hybrid propulsion and the wide variety in power and ES sources and conversion technologies increases the system complexity in comparison to both a mechanical and full electrical propulsion system with a single power source (Nuchturee et al., 2020).

This increased system complexity also complicates the power and energy management problem of scheduling the required power to match the load demand while minimising fuel consumption, hazardous emissions, and maintenance (Nema et al., 2009). Thus, the commonly used rule-based control is not sufficient to control the energy system operation anymore (Jaurola et al., 2019; Nema et al., 2009), and advanced control strategies must be used to manage electric vessels' power generation and distribution. These advanced control strategies can also include multiple control objectives to establish the best trade-off between conflicting objectives in the control strategy (Nuchturee et al., 2020). Prominent objectives of interest for operating the vessel are operational cost, greenhouse gas and hazardous emission output, and degradation of energy system components.

However, vessels have a large diversity in system design and operational profiles. They can be divided into categories significantly

Table 1
Acronyms.

Acronym	Description
AC	Alternating current
AE	All-electric
AES	Automotive energy systems
AHU	Air handling unit
B	Battery
BES	Building energy systems
CI	Cold ironing
CL	Component lifetime
CR	Cost reduction
DC	Direct current
DE	Diesel engine
DG	Diesel generator
DDMPC	Data-driven model predictive control
DSM	Demand side management
DR	Demand response
DP	Dynamic programming
E	Endurance
ECMS	Equivalent consumption minimisation strategy
EMS	Energy management system
ER	Emission reduction
ES	Energy storage
ESS	Energy storage system
EV	Electric vehicle
FC	Fuel cell
FE	Fuel efficiency
FS	Fuel saving
GHG	Greenhouse gas
GT	Gas turbines
HES	Hybrid energy systems
HEV	Hybrid electric vehicles
HRES	Hybrid renewable energy systems
HVAC	Heating, ventilation, and air-conditioning
ICE	Internal combustion engine
MAC	Multi-agent control
MES	Marine energy systems
MPC	Model predictive control
MOO	Multi-objective optimisation
NN	Neural network
UC	Ultra-capacitor
PEM-FC	Proton-exchange membrane fuel cell
PM	Particulate matter
PMP	Pontryagin's minimum principle
PV	Photovoltaic systems
PSO	Particle swarm optimisation
RL	Reinforcement learning
SOC	State of charge

influencing the opportunities to improve energy performance through advanced control. First, vessels with a large amount of crew or passengers, such as cruise ships or large naval vessels consist of large climate systems with a high amount of heating, ventilation, and air-conditioning (HVAC). The large thermal loads and passenger-comfort requirements of these vessels are inherently different from the operation of most other vessel types. However, the operation of the climate system on these ships is comparable to the operation of large building complexes that also experience high thermal loads. A second category is vessels with a transport or continued service purpose, for which the load profile is plannable and repetitive. The supply of these loads can be optimised with predictive control strategies, as the load profile structure allows for the development of accurate time-series forecasting strategies. While these strategies start to be of interest for the maritime sector, both the development of predictive control, as well as the corresponding forecasting methods, have been under investigation in the sectors of building systems, power systems, or micro-grids for years. Examples of ships in this category are cargo vessels, ferries, and survey boats. Third, vessels with dynamic positioning and irregular tasking have an unpredictable and fluctuating load. This amount of uncertainty in the load profile presents a challenge for the energy management and requires strategies that can adapt to fast-changing conditions. This resembles load profiles and energy system operation in the field of individual transport automotive. Optimising energy management under changing environment conditions has been of high interest for cars and the strategies can inspire innovation in the maritime. These vessel types include small offshore vessels, tug boats or small water taxis. The last category is vessels with high peak power loads, which present a different challenge for the electrical system's operation and are comparable to large microgrid operations. These operations require the control to maintain the system stability at all times while ensuring that the peak load demand is met accordingly. Prominent examples are working vessels for the offshore industry, such as crane vessels for installing wind turbines and naval vessels with laser weapons. Concluding, the very different load profiles of various ship types have parallels to different energy system sectors, which can provide insights and inspiration. Extending the view onto the work done in those fields provides more input to drive the innovation in the maritime. Therefore, an analysis of marine energy system control benefits from considering heterogeneous sectors of energy system research.

Many novel contributions have reviewed recent developments in advanced control in energy systems. The research can be divided into research on operation and control in the maritime sector and studies focusing on the operation of energy or power systems in related sectors. In an assessment of the current and future state of hybrid energy systems (HES) for microgrids, Nema et al. (2009) stated in 2009 that HES cannot compete with fossil-fuelled systems yet. The authors further point out that systems of such complexity require advanced control for system optimisation. Ammari et al. (2021) presented an extensive review on sizing, optimisation, control, and energy management of hybrid renewable energy systems (HRES) for microgrids in 2021. In 2015, Arul et al. (2015) investigated optimal control strategies for terrestrial HRES, focusing on the supply of air conditioning loads. In a review from Bharatee et al. (2022), intelligent power management strategies for microgrids are analysed and compared to using a normal grid. These microgrid reviews are relevant to maritime energy systems, representing a microgrid without any main grid connection.

A variety of reviews targeted the usage of advanced control for power and energy management in applications such as **buildings** (Dounis & Caraiscos, 2009; Drgoňa et al., 2020; Shaikh et al., 2014), **automotive** (Zhou & Du, 2021) or **residential (micro-) grids** (Rev, 2019; Al-Ismail, 2021; Bihari et al., 2021; Elmouatamid et al., 2021; Haider et al., 2016; Molderink et al., 2010; Olivares et al., 2014; Rajesh et al., 2017; Roslan et al., 2019; Sen & Kumar, 2018; Touma et al., 2021). Microgrid integration, control, and operation have been important topics in recent years. Guerrero et al. (2013) reviewed the advanced control of intelligent microgrids in 2013. The power and energy management of microgrids incorporating energy storage systems (ESS) was studied by Liu et al. (2022). In addition to architectures and management schemes, the authors also evaluate the situation of ESS usage for the maritime sector, which shows that it is an important factor for strategic loading, spinning reserve, and the extension of the generator capacity. This is further detailed by the review of Nuchturee et al. (2020), who analyse the effects of increasing the energy efficiency of marine power and energy systems. Several researchers investigated different advanced control approaches in maritime power and energy management problems in the past years (Gao et al., 2018; Hein et al., 2020; Kanellos, 2014; Kanellos et al., 2017a; Tang et al., 2020). Those control approaches differ in terms of the choice of control strategy and problem definition.

However, among all these reviews, only three focus on maritime systems. In 2022, Xie et al. (2022) reviewed marine power and energy management and analysed objectives, control approaches, and solution strategies. The main focus is set on the objectives of fuel consumption, CO_2 emissions, sizing optimisation, operational cost, and availability. Control strategies and solution approaches are reviewed from the marine sector's perspective without considering the developments of other sectors or potential lessons. Moreover, the authors do not address the objectives of extension of the component lifetime, hazardous emissions other than CO_2, or noise generation. Furthermore, the aspect of

Table 2
Distribution of papers included in the literature review.

Topic	Review papers	Methodological papers	Total	Percentage
Building	13	42	55	22.4 %
Microgrids	20	39	59	24.1 %
Automotive	5	30	35	14.3 %
Maritime	3	61	64	26.1 %
Supplementary	10	22	32	13.1 %
Total	**51**	**194**	**245**	100.0 %

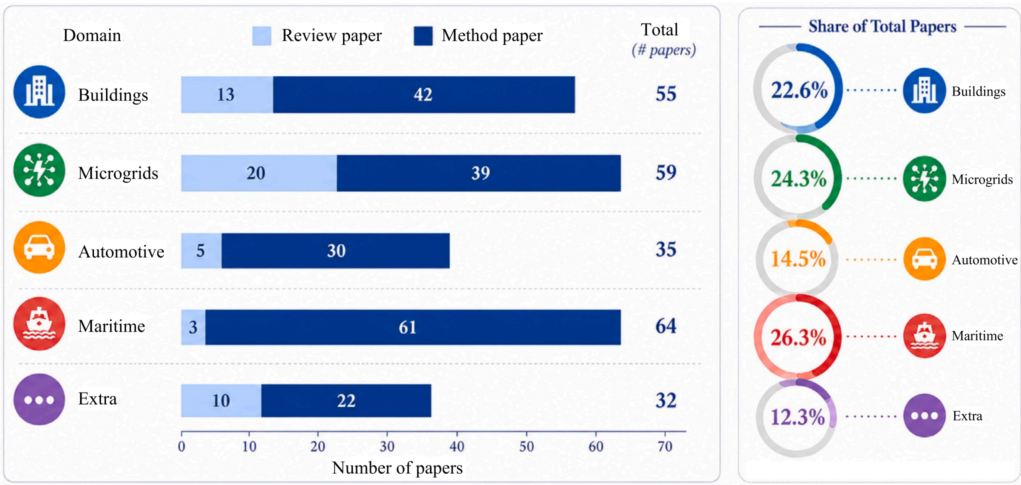

Fig. 1. Distribution of the reviewed literature across the selected application domains, distinguishing between review papers and methodological papers.

data-driven methodologies has not yet been addressed. Xu et al. (2022) focus on the operation of shipboard DC microgrids, with some focus on control architectures and flow management on a primary control level. In 2019, Jaurola et al. (2019) reviewed the optimisation of the design of a hybrid vessel and the corresponding EMS using rule-based control strategies. Even though studies have already used several control strategies to optimise different objectives in vessel energy management, the literature lacks a clear qualitative and quantitative overview. This leaves open questions about potential objectives, how to achieve them, and selection criteria for control strategies based on the power system architecture and its control objectives.

This review paper aims to build on previous works by providing an overview of control strategies and control objectives utilised for energy systems in building energy systems, smart microgrids, electric and hybrid vehicle systems, and maritime energy systems. We especially aim to analyse its potential to reduce Greenhouse Gas (GHG) and hazardous emissions, component maintenance, and ship reliability and dynamic operation. Lastly, we want to provide selection criteria for energy system control for ships inspired by the work done across the fields based on vessel types and operational profiles. Thus, our review provides the following contributions:

- A structured overview of advanced control strategies across multiple domains.
- Analysis of data-driven approaches in energy system control across these domains.
- Analysis of the potential of advanced control to improve hazardous emissions and maintenance objectives, besides fuel consumption, CO_2, and cost.
- Development of selection criteria regarding the choice of control strategy and objective based on ship application types, and an overview of previously achieved improvements on these objectives.

2. Literature search and selection criteria

The literature search was conducted in two main stages. First, the maritime literature was examined to identify studies addressing power and energy management in combination with advanced control strategies. Second, related work from the automotive, building, and electric-grid energy sectors was reviewed to identify advanced control approaches that may be transferable or relevant to maritime energy systems. Within the electric-grid domain, the search focused specifically on microgrids, as these systems share several characteristics with shipboard power systems, including distributed generation, storage integration, load balancing, and supervisory energy-management requirements.

The surveyed literature was classified into two categories: review papers and methodological papers. Review papers were included to capture the state of the art, dominant research trends, and open challenges within each sector. Methodological papers were selected to analyse specific control formulations, optimisation strategies, modelling assumptions, and implementation approaches. During the screening process, studies relying exclusively on conventionally tuned rule-based controllers were excluded, since the focus of this review is on advanced control and optimisation-based energy-management strategies.

The final selection is summarised in Table 2 and visualised in Fig. 1. In total, 245 papers were analysed, comprising 51 review papers and 194 methodological papers. This corresponds to approximately 21% review papers and 79% methodological papers. The distribution of review papers differs across sectors, reflecting the relative maturity and breadth of the corresponding research fields. The largest number of review papers was found in the microgrid literature, whereas the maritime sector contained comparatively fewer review studies focused specifically on advanced energy-management control.

For each primary sector, at least 30 methodological papers were selected for detailed analysis. The review was further supplemented by 32 additional papers from related areas, including general energy systems, sustainability-oriented energy management, and ship energy-system design. The resulting body of literature provides the basis for the comparative analysis presented in the following sections.

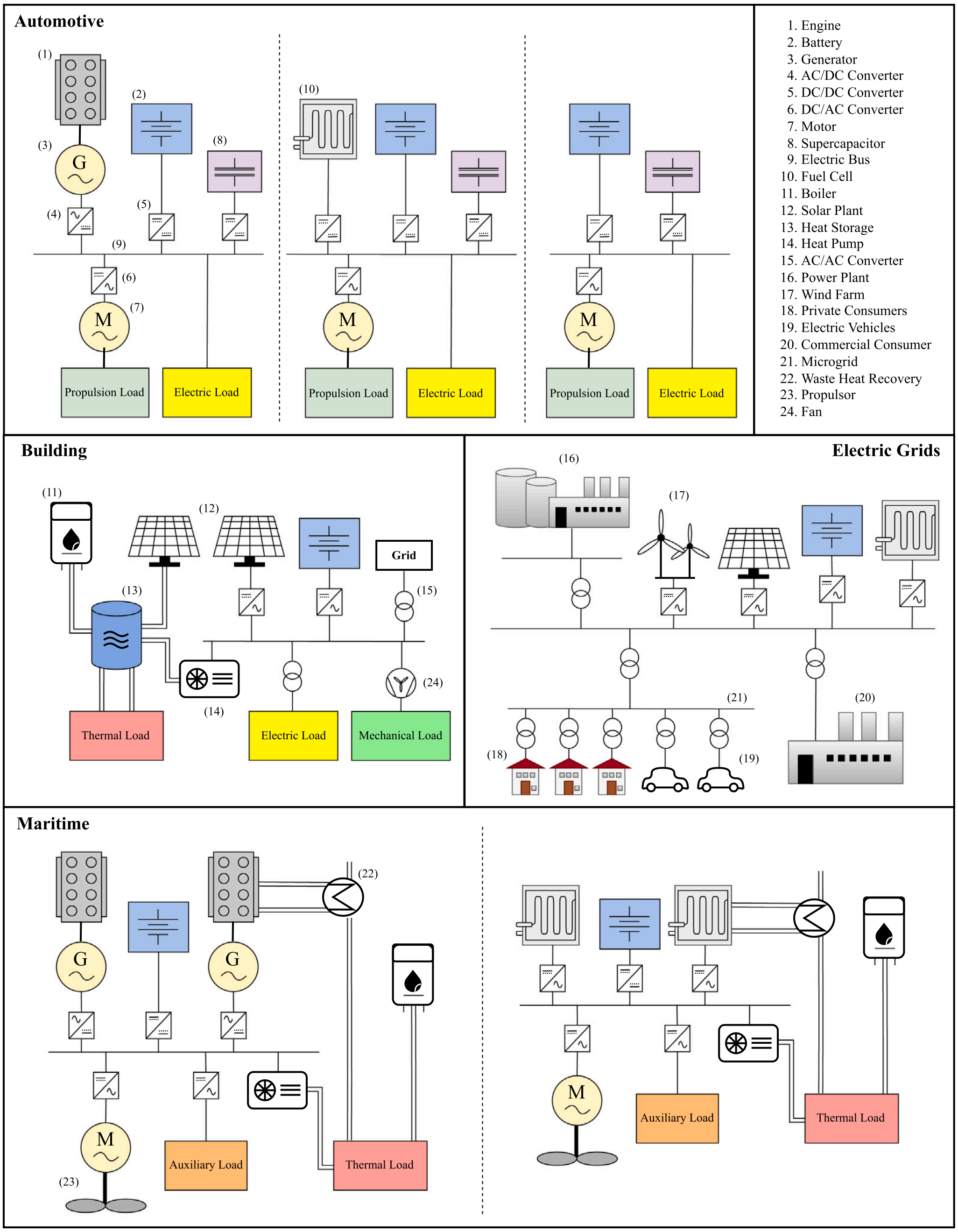

Fig. 2. Example layouts of the energy systems used in the four investigated sectors: residential, smart microgrids, automotive and marine energy systems.

3. Energy systems

HES that combine power sources, such as combustion engines, fuel cells, wind and solar power generation, and integrate them with ES technologies are increasingly being adopted across various sectors (Ammari et al., 2021; Nema et al., 2009). Their respective task is to provide different forms of energy to loads required by consumers. Those loads can be thermal, electrical, mechanical or hydraulic. While the components used in the HES are often similar, the configuration, size, and characteristics of the power plant differ depending on the application. These HES all use power and energy management to optimise load sharing. Considering similarities and differences, research on power and energy management across various fields can be compared and utilised to identify promising directions for further investigation. Fig. 2 shows a first overview of the power plant layouts in the four sectors: buildings, smart microgrids, automotive and marine. Those energy systems will be further analysed in terms of energy demand, system layout, and operational profile to identify similarities between them.

3.1. Building energy systems

Building energy systems (BES) fulfil the task of managing a building's indoor air quality, the inhabitants' comfort and power supply to a variety of electrical loads. A large portion of the building energy requirement is the thermal load for heating and cooling. This is also represented in the dynamic characteristics of the energy system, as buildings are large thermal masses, which leads to prolonged reaction times and slow changes in the room temperature. The thermal load of buildings varies based on the time of year, the corresponding outside temperature, the weather, and the presence of inhabitants, which is

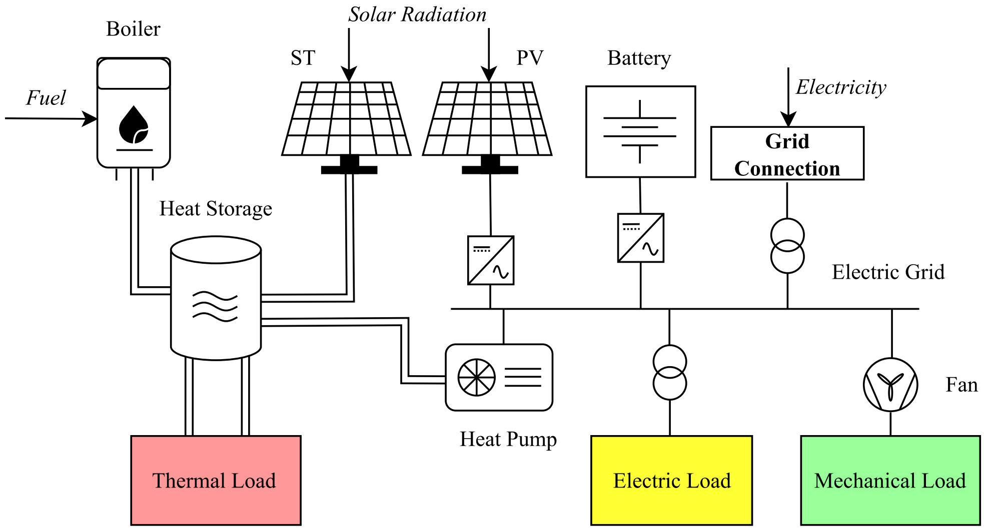

Fig. 3. Exemplary layout of a building energy system.

typically related to the time of day. Recently, the thermal load has been increasingly provided by electrically supplied heat pumps, as opposed to the previous use of boilers for heating. For large buildings, these heat pumps are part of the heating, ventilation, and air conditioning (HVAC) system. In this case, ventilation refers not only to refreshing air from the outside to the inside but also to heating and cooling a space and maintaining indoor quality by removing pollutants and allergens. The remaining electric load includes the lighting and a variety of electric devices. While conventional BES used to contain one or more boilers for heat generation and a connection to the terrestrial grid for electricity, modern BES integrate heat generation and auxiliary loads and utilise local power sources, such as PV panels and wind turbines, in interconnected systems.

While a conventional BES used to contain only a boiler for heat generation and a connection to the terrestrial grid for electricity, modern BES integrate a variety of different components into interconnected systems. An exemplary layout is shown in Fig. 3. Different energy sources can be utilised to provide the required load. Thermal energy can be generated by the conversion of chemical energy to heat in a boiler, for example, gas (Freund & Schmitz, 2021). Other ways to create thermal energy are converting solar energy into heat and using electricity in heat pumps (Cupeiro Figueroa et al., 2020). The integration of combined heat and power units (CHP) allows for more flexibility in the BES. The thermal system often incorporates a heat storage from which the heat is distributed to the consumers (Freund & Schmitz, 2021). For cooling demands, chillers and corresponding heat exchange circles can be integrated as air conditioning in the thermal energy system (Brandi et al., 2022; Cai et al., 2016; Marinakis et al., 2013). The main components of the thermal energy systems are pumps, which allow circulation of the heated or cooled liquid through the system (Brandi et al., 2022; Cupeiro Figueroa et al., 2020). Those systems are also referred to as air-handling units (AHU) (Li et al., 2021). In a similar way, electricity can be provided in several ways. Common BES incorporate an electrical grid to distribute the requested electric load to the consumers and integrate potential generation components (Jin et al., 2017). Solar energy can be transformed into electricity by the use of photovoltaic (PV) panels and integrated into the electric grid of the BES (Brandi et al., 2022). Further electrical energy can be provided by electric grids connected to residential buildings (Marinakis et al., 2013). The system can be combined with battery storage (Brandi et al., 2022), which is not yet as common as the use of heat storage. When a PV plant or a battery system is integrated into the BES, a conversion between the produced direct current and the commonly used alternating current (AC) grids needs to be considered (Brandi et al., 2022). The last aspect of HVAC systems is the ventilation of air through the rooms, which is especially important in large building complexes, such as commercial ones. The air needs to be circulated using mechanical energy (Marinakis et al., 2013). This conversion is mostly done by converting electrical energy to mechanical energy.

The operational profile of BES depends on the type of building and is mainly oriented around times of habitation. An important factor is also the global region in which the system is positioned, as a building in a cold region will mostly require heating (Freund & Schmitz, 2021) and hotter regions demand air-conditioning (Marinakis et al., 2013). While commercial buildings have their main load during the day, a residential building may have load spikes in the evening when everyone uses electric devices at home. A building's internal energy dynamics are highly non-linear and expensive to model, as they need to incorporate location-specific and building-specific data, such as angle of sunlight for windows or insulation parameters, to accurately resemble the BES. The load demand can be predicted with accuracy using a suitable approach, time step and forecast horizon (Hilliard et al., 2016).

Key BES characteristics relevant to advanced EMS/PMS control design are summarised in Table 3.

3.2. Smart microgrids

Electrical energy systems are the main electrical energy providers and have been connected worldwide. Therefore, the electric grid is built up at different levels, including national or international high-voltage grids, smaller regional grids, and even local microgrids, which might or might not be connected to regional grids. This interconnects various forms of energy producers with different types of energy consumers. Therefore, the control research focuses on different aspects, based on the various levels of energy transmission grids. However, due to the scope of this work, this paper will focus on microgrids. Microgrids often focus on managing large electric plants and coordinating several parallel energy generation components and consumers. Those microgrids exist in two forms: connected to higher levels of the electric grid or autonomous. Microgrids are applied in various forms, such as a residential district, a wind power park, or a full-electric vessel. Interestingly, literature uses different forms of microgrids, as a classical and a modern form, which is often referred to as a smart microgrid. Classic microgrids most often focus on the management and stability of the electric power system itself, while smart microgrids often focus on coordinated and optimised control aspects.

This difference leads to a different research focus for both categories. For classical microgrids, an important part of grid operation is stabilising the frequency by ensuring power balance and sharing. Matching the power request with generation involves fast action and

Table 3
Characteristics of Building Energy Systems relevant to advanced EMS/PMS control design.

Characteristic	Description
Energy demand types	Primarily thermal (heating & cooling via HVAC); secondary electric (lighting, appliances, PV integration) (Brandi et al., 2022; Freund & Schmitz, 2021; Marinakis et al., 2013)
System dynamics	Slow; buildings are large thermal masses with prolonged reaction times and gradual temperature changes (Drgoňa et al., 2020; Shaikh et al., 2014)
Load profile predictability	High; load is mainly driven by occupancy schedule, time of day, season, and outdoor weather — all of which can be forecast (Hilliard et al., 2016; Oldewurtel et al., 2012)
Key disturbances	Outdoor temperature, solar irradiation, occupancy, relative humidity, wind intensity, variable electricity prices (Brandi et al., 2022; Freund & Schmitz, 2021; Široký et al., 2011; Sturzenegger et al., 2016)
Control objectives	Thermal comfort (indoor temperature within bounds), visual comfort (lighting/blinds), indoor air quality (CO_2, humidity), energy/cost minimisation, demand response (DR) (Karlsson & Hagentoft, 2011; Maasoumy et al., 2014; Oldewurtel et al., 2010)
Recommended control strategy	MPC (physics-based or data-driven/DDMPC); MAC for large multi-zone buildings; adaptive MPC for robustness under uncertainty (Cai et al., 2016; Drgoňa et al., 2020; Kathirgamanathan et al., 2021; Stoffel et al., 2023)
Recommended architecture	Hierarchical (top-level EMS + zone-level HVAC controllers); distributed/MAC for large commercial complexes (Lefort et al., 2013; Wang et al., 2012)
Analogue vessel type	Cruise ships and large naval vessels with high thermal & hotel loads, slow climate-system dynamics, and occupancy-driven profiles (Gianni et al., 2022)
Key limitations	Non-linear, location- and building-specific dynamics are costly to model; data-driven models require sufficient operational data and pre-processing (Mugnini et al., 2020; Prívara et al., 2013; Sturzenegger et al., 2016)

a strong focus on fault protection, as failure of such a large system can be critical in many applications. Therefore, the main research focuses are managing a stable operation, as well as isolation and fault protection. Modern smart Microgrids have a slightly shifted focus, as they often target the top-level management of several consumers or producers, such as a residential neighbourhood incorporating multiple HVAC systems, rooftop PV, smaller fuel-based systems, for example FC, or a wind farm with multiple power sources. For this, coordinating all the components in parallel becomes a challenge. While system stability is still quite an important aspect, additional objectives, such as economic or pollution aspects, gain importance for control research. Therefore, research focuses a lot on distributed control or on demand side management (Malik et al., 2019).

Micrograds can accommodate various components that produce, transform or consume electric energy. An exemplary layout is shown in Fig. 4. Common energy producers in microgrids are, for example, generators, fuel cells, wind turbines or solar panels. In grid-connected microgrids, electric energy can also be provided by a main power grid. Storage systems, such as batteries, flywheels, or pump hydro storage, are important, especially for integrating renewable and volatile energy producers. Electric energy consumers can be of various natures, including the electricity supply for a building, electric motors, or battery systems. Microgrids can exist on both AC and DC electric grids. A general requirement for an electric grid is to maintain the stability of the system voltage, for which the power balance is highly important.

The operational profile of microgrids includes power fluctuation at high frequencies and with steep ramp rates. If the power balance is not adjusted accordingly, this fluctuation can result in changes in the grid voltage, which can damage the components and lead to partial or total electrical failure. Therefore, scheduling power generation and storage components to match the power balance is of high importance. The overall trend of the load profiles depends on the consumers of the microgrid. If the grid also includes the thermal management of the consumers, for example, by integrating the exhaust gas of a large commercial power plant, the much slower dynamics of the thermal load need to be incorporated as well. A microgrid managing residential quarters has an overall different load profile than a microgrid in an electric vessel. Not managing the fluctuations correctly, especially with large changes in the power demand, can result in blackouts or system damage.

3.3. Automotive energy systems

Automotive energy systems (AES) provide mechanical and electrical energy to a vehicle for propulsion of the vehicle and a variety of small electrical loads. Thermal loads comprise a small part of the total load and are typically fed with an electrical load for cooling and local heating.

Heating can also be provided by excess heat from the combustion engine, if an ICE is used in the propulsion system. Automotive electrification has developed from conventional mechanical drivetrains toward battery-electric, hybrid-electric, and fuel-cell-electric powertrains. The common system layout for electric vehicles (EVs) and hybrid electric vehicles (HEVs) includes combinations of ICEs, batteries, electric machines, fuel cells, and, in some cases, supercapacitors (M. Sabri et al., 2016; Panday & Bansal, 2014; Tie & Tan, 2013; Zhang, Wang, et al., 2020). For FC applications, proton-exchange membrane fuel cells (PEM-FCs) are most commonly considered in automotive systems because of their relatively low operating temperature and dynamic response.

Three simplified exemplary layouts are shown in Fig. 5, featuring ICE–battery, FC–battery, and battery-only systems. These layouts are intended to illustrate technology-integration opportunities and should not be interpreted as an exhaustive taxonomy of electrified powertrain

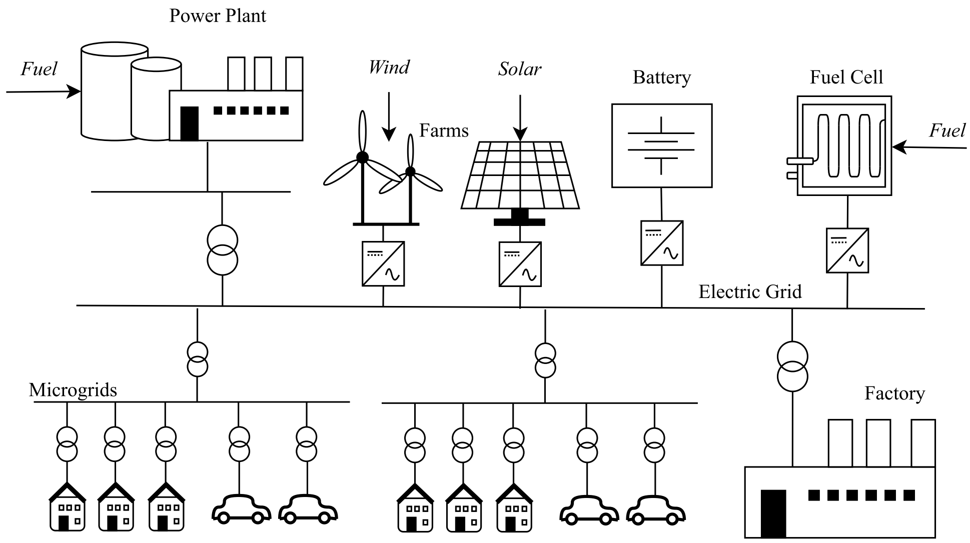

Fig. 4. Exemplary layout of a smart microgrid system.

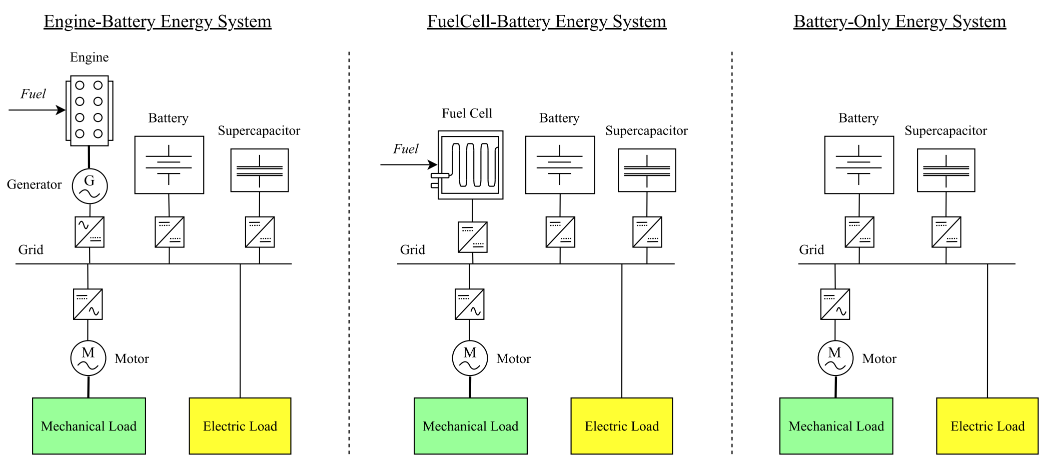

Fig. 5. Three simplified exemplary layouts of automotive energy systems.

architectures. In practice, HEV and FC-HEV systems can be arranged as series, parallel, or series–parallel configurations. Series architectures mainly require generator or fuel-cell scheduling, battery state-of-charge management, and electrical-bus power balancing. Parallel and series–parallel architectures introduce additional control degrees of freedom because mechanical and electrical propulsion paths can both contribute to the demanded wheel or shaft power. Consequently, the EMS must determine the optimal power split, engine operating point, electric-machine contribution, mode selection, and, where applicable, clutch or gear engagement. This explains why ECMS, PMP, MPC, DP, and learning-based strategies have been widely investigated for advanced automotive EMS, especially for parallel and series–parallel HEV configurations (Nüesch et al., 2014; Xie et al., 2019; Zhou & Du, 2021). Battery-only systems are a common choice for individual urban transport, while ICE–battery and FC–battery combinations remain widely discussed for larger vehicles, public transport, and applications requiring longer range or higher power flexibility.

The main hybrid powertrain architectures and their EMS/PMS implications are summarised in Table 4.

The operational profile of an AES depends on the driver's choice. However, there are standardised load profiles on which AES control strategies can be tested. Those include acceleration periods and normal city traffic. Based on the user's preference, the operational profile is very uncertain. Common load profiles for city traffic do not exceed certain durations, which allows for preplanning of battery use and charging potential.

3.4. Marine energy systems

Marine energy systems (MES) provide various energy forms to a vessel, including mechanical, electrical and thermal energy. The propulsion configuration can be categorised in mechanical, electrical and hybrid propulsion and the power supply in combustion, electrochemical, stored and hybrid power supply (Geertsma et al., 2017). Two exemplary layouts of a state-of-the-art MES with full electric propulsion, direct current hybrid power supply and waste heat recovery are shown in Fig. 6. The left side of the diagram displays an ICE-based energy system, while the right side shows a topology based on FC. The energy demands vary drastically between different types of ships. For cargo vessels, the main load is the requested mechanical energy for propulsion. Alternatively, service vessels, such as offshore installation vessels and cruise ships, often have equally large mission loads or thermal loads, respectively. For example, a cruise ship can be transiting at transit speed while most passengers are asleep, and it can be sailing slowly with all thermal and entertainment systems working at maximum capacity. Similarly, an offshore installation vessel will first transit to its operation place and then install wind turbines with its crane while maintaining its position with dynamic positioning. In this case, the energy demand of the transit may be significantly lower than the high loads from the crane operation combined with dynamic positioning. Electrical loads not used to generate mechanical energy for the propulsion can be divided into mission loads, hotel services loads

Table 4
Hybrid powertrain architectures and their EMS/PMS implications.

Architecture	Dominant energy path	Main EMS/PMS control challenge	Typical control methods
Series hybrid	ICE/FC → generator or DC bus → electric motor	Scheduling of engine, generator, fuel cell, and battery power; SOC management; electrical-bus power balancing; limited mechanical power-split freedom.	MPC, DP, ECMS, rule-based supervisory EMS
Parallel hybrid	ICE mechanically coupled to the drivetrain or shaft, with an electric machine providing assist or generation	Torque split between mechanical and electrical paths; engine operating-point optimisation; regenerative operation; clutch or gear coordination where applicable.	ECMS, PMP, MPC, DP, adaptive EMS
Series–parallel hybrid	Combined mechanical and electrical power paths with mode-dependent energy flow	Power-split optimisation, mode selection, engine/load-point control, battery SOC management, and coordination of multiple propulsion paths.	ECMS, PMP, MPC, DP, RL-based EMS

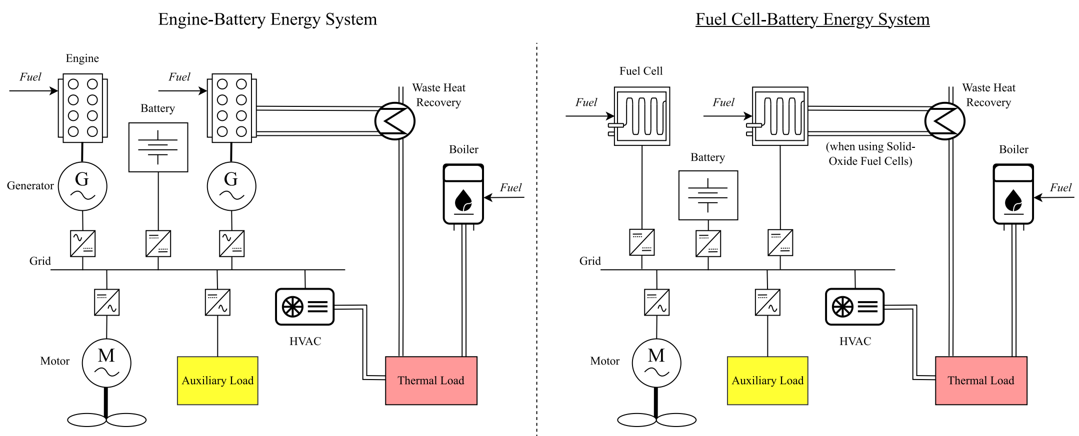

Fig. 6. Two exemplary layouts of a marine energy system.

and auxiliary loads and are mainly provided by the electrical power system infrastructure.

To accommodate those diverse energy demands, different power generation components can be integrated into the MES. The use of ICE or Gas Turbines (GT) is highly common for producing mechanical energy to drive the propeller in mechanical propulsion or generators, which transform mechanical energy into electrical energy for the electric grid in electrical propulsion (Delft & for Climate Action , European Commission). ICE and GT are also considered for the integration of alternative fuels in the maritime sector, either through newly designed engines or retrofitted versions of existing engines. Commonly discussed options include liquefied natural gas (LNG), methanol, ammonia, and hydrogen (Korberg et al., 2021).

The maturity of these fuels differs substantially. LNG is already commercially deployed as a marine fuel, methanol is entering wider application through newbuild and retrofit pathways, whereas ammonia- and hydrogen-fuelled ICE applications remain more strongly associated with demonstration, early adoption, and ongoing technology development (DNV, 2025, 2026).

Consequently, the EMS/PMS literature does not yet cover these fuel options with equal depth, especially when fuel-flexible operation, transient emissions, combustion stability, safety constraints, and hybridisation with batteries or fuel cells are considered.

Current open research fields for alternative-fuel ICE-based hybrid marine propulsion include fuel-flexible dispatch, transient emission control, combustion-stability constraints, thermal management, and the logistics of fuel infrastructure in ports and refuelling stations. From a control perspective, LNG dual-fuel operation introduces methane-slip and load-dependent emission trade-offs; methanol operation introduces fuel-flexibility and efficiency/emission trade-offs; ammonia combustion introduces challenges related to combustion stability, NOx formation, and possible N_2O emissions; and hydrogen ICE operation introduces storage, safety, and abnormal-combustion constraints. These issues create a strong need for advanced EMS/PMS approaches that coordinate engines, batteries, fuel cells, converters, storage systems, and thermal subsystems while considering efficiency, emissions, degradation, and operational constraints.

Research also introduced FC for marine power generation in the past years (Nuchturee et al., 2020). This includes both the use of PEM-FC, as well as Solid-Oxide Fuel Cells (SOFC). While the latter are mainly used for systems with low thermal loads, the high temperature SOFCs are suitable for high-thermal-load systems, such as cruise ships, due to their high waste heat production. FC also present a step towards alternative fuels in the maritime. For PEM-FC, hydrogen is the relevant fuel (Broer et al., 2025), while the high-temperature SOFC can accommodate a variety of different alternative fuels (van Biert et al., 2018; Gianni et al., 2022). Furthermore, energy storage technologies, such as batteries, can be integrated to buffer for slow dynamics of power generation components or load transits (Georgescu et al., 2018; Hemmati & Saboori, 2016; Nuchturee et al., 2020). Notably, for short-distance vessels, such as ferries, battery-only MES are an efficient solution, similar to AES (Perčić et al., 2020). Common full-electric ship layouts operate on AC, while with the increasing integration of components such as batteries and fuel cells, DC distribution architectures become more relevant (Xu et al., 2022). Zahedi et al. (2014) showed that the use of DC grids can improve the overall efficiency of full-electric vessel power systems by running the diesel generators at variable speeds. The power system also incorporates various components for transformation, fault protection, and distribution, such as transformers, rectifiers, switches, and converters. The heat demand of the vessel can be supplied using boilers. However, the use of waste heat recovery systems that utilise the exhaust gas of FC, GT or ICE to provide thermal energy via a heat exchanger is increasing in interest.

3.5. Analysis and comparison

The preceding sector-specific review shows that Marine Energy Systems cannot be interpreted as a direct extension of a single terrestrial energy domain. Instead, MES combine features that are separately observed in Building Energy Systems, smart microgrids, and Automotive Energy Systems. Table 5 summarises this cross-sector comparison in terms of energy demand, dominant dynamics, load-profile characteristics, and control challenges. The comparison highlights that the closest terrestrial analogue depends strongly on the vessel type and mission profile. Therefore, the similarities should not be interpreted as universal mappings, but rather as useful reference cases for identifying transferable control concepts, modelling assumptions, and energy-management objectives.

A first category consists of vessels with large crew or passenger capacity, such as cruise ships and large naval vessels. These vessels may have substantial propulsion demand, but they are also characterised by significant hotel and thermal loads. In this respect, they share important features with BES. The thermal subsystem has large inertia, slow dynamics, and strong dependence on external weather conditions, occupancy, ventilation demand, and comfort constraints. Consequently, the energy-management problem is not limited to propulsion-power allocation, but also includes the coordinated operation of HVAC units, thermal comfort regulation, and indoor-air-quality management. The analogy with BES is therefore particularly useful for transferring methods such as model predictive control, demand-side management, thermal-load forecasting, and comfort-constrained optimisation.

A second category includes vessels with high auxiliary or mission-related electric loads. Examples include offshore work vessels operating cranes or dynamic-positioning equipment, dredgers, tugboats, and naval vessels with high-power electrical mission systems. In these cases, the shipboard power system exhibits similarities with smart microgrids. The dominant challenge is the reliable coordination of multiple generators, energy-storage systems, converters, and large time-varying loads. The control problem is strongly affected by fast power fluctuations, steep ramp rates, voltage-stability constraints, fault protection, and real-time power-balancing requirements. The smart-microgrid analogy is therefore relevant for studying hierarchical control, distributed energy management, storage dispatch, voltage regulation, and resilience-oriented control.

A third category comprises vessels whose main function is transport. Within this group, it is useful to distinguish between unscheduled and scheduled operation. Small vessels operating without a fixed mission profile, such as water taxis, yachts, or small offshore support vessels, resemble individual EV/HEV operation. Their load demand is largely user- or mission-dependent, and therefore uncertain. The energy-management task focuses on powertrain operation under fluctuating loads, battery state-of-charge management, range estimation, charging-window prediction, and component degradation. In contrast, vessels operating on known routes and schedules, such as ferries, cargo vessels, and survey vessels, are more closely related to scheduled automotive transport such as buses and trucks. Their load profiles are more predictable, which enables route-aware optimisation, planned charging, economic dispatch, and storage-lifetime management. Comparable to the automotive sector, FC systems and hybrid powertrain structures are becoming increasingly relevant for selected marine applications. For vessels with highly dynamic propulsion or mission-load profiles, parallel and series–parallel architectures can reduce part of the repeated energy-conversion losses associated with purely series energy-flow paths. This benefit is most relevant when mechanical and electrical propulsion paths can be coordinated so that engines, electric machines, batteries, and fuel cells operate closer to favourable efficiency or ageing regions. However, these architectures also increase EMS/PMS complexity. The control problem is no longer limited to scheduling power sources on an electrical bus, but also includes power-split optimisation, mode selection, torque or thrust-path coordination, and prediction of future load demand. Therefore, automotive EMS methods developed for parallel and series–parallel HEVs, including ECMS, PMP, MPC, DP, and adaptive or learning-based approaches, provide relevant methodological reference points for marine hybrid propulsion control.

Overall, the comparison shows that MES represent a multi-domain control problem. Depending on the vessel type, the dominant control challenge may be thermal-load management, electric-network stability, uncertain propulsion demand, or optimal operation over a known mission profile. Table 6 condenses these observations into a vessel-type-oriented synthesis. This interpretation supports the selection of suitable modelling and control approaches by linking vessel characteristics to the most relevant terrestrial energy-system analogue.

4. Control strategies

In the following, we will discuss the control of the four featured energy system sectors. This will include a discussion of the objectives of the respective control strategies and the setup of the control problem and its constraints. Based on this, the current trends in research for control approaches are discussed.

4.1. Control of building energy systems

To analyse the current research in control of BES, we analyse the set up of BES control problems in a first step. Four main aspects of the control problem are of interest: (i) control objectives, (ii) constraints, (iii) the used variable space, which consists of state and control variables, and (iv) disturbances. With this, an analysis of the application of advanced control strategies for BES control is conducted. The lessons learnt from this sector can subsequently be considered for control strategies of vessels with a large amount of crew or passengers.

4.1.1. Control objectives

The most important objective in controlling BES is to maintain the comfort inside the building (Castilla et al., 2014; Merz et al., 2018). Three comfort factors can be defined for this: Thermal Comfort, Visual Comfort and Air Quality (Shaikh et al., 2013). Those three factors are influenced by different aspects of the energy system, described in Section 3.1. Thermal comfort is ensured by keeping the indoor temperature inside a predefined range, which provides the individual's well-being and contributes to happiness and working efficiency (Arroyo et al., 2022; Cai et al., 2016; Drgoňa et al., 2018; Hagras et al., 2003; Karlsson & Hagentoft, 2011; Khosravi et al., 2019; Oldewurtel et al., 2010; Wang et al., 2019; Yuan & Perez, 2006). Electric lighting and the possibility of opening or closing blindings on the windows ensure visual comfort. Indoor Air quality targets exchanging fresh air into a room to maintain healthy CO_2 levels, filtering of recirculated air to prevent emission pollution of the air and heating and air-conditioning to maintain the temperature and moisture level (Huang, 2011; Li et al., 2021; Maasoumy et al., 2014). Conflicting with those three objectives is another important objective: minimising the energy consumption of the BES (Bünning et al., 2020; Dahl Knudsen & Petersen, 2016; Freund & Schmitz, 2021; Li & Wang, 2020; Ma et al., 2012; Oldewurtel et al., 2012; Široký et al., 2011; Stoffel et al., 2023; Sturzenegger et al., 2016; Wang et al., 2012; Yu et al., 2015). Previous work has shown that advanced control strategies can provide 13 to 28% energy savings (Analysis of Energy Savings Potentials for Integrated Room Automation, 2010; Castilla et al., 2014; Drgoňa et al., 2020). A similar objective is the minimisation of cost (Alrumayh & Bhattacharya, 2015; Brandi et al., 2022; Zhao et al., 2013).

Table 5
Comparison of energy system characteristics across sectors and corresponding vessel types.

Sector	Energy demand	System dynamics	Load profile	Key control challenges	Analogue vessel type	References
Building Energy Systems	Thermal demand for HVAC, heating and cooling; electric demand for lighting and appliances.	Slow dynamics due to large thermal inertia and prolonged reaction times.	Predictable; mainly driven by occupancy, weather, and time of day.	Thermal-comfort regulation; nonlinear behaviour; computationally expensive prediction models.	Cruise ships; large naval vessels with significant HVAC and hotel loads.	Brandi et al. (2022), Drgoňa et al. (2020), Freund and Schmitz (2021), Hilliard et al. (2016)
Smart Microgrids	Electric demand from multiple generators, ESS, and renewable sources.	Fast dynamics; high-frequency power fluctuations and steep ramp rates.	Variable; dependent on consumer mix; peak loads are critical.	Power balance; voltage stability; fault protection; peak-load management; real-time optimisation; source-storage coordination; reserve management.	Offshore work vessels; crane ships; naval vessels with high auxiliary loads.	Ammari et al. (2021), Guerrero et al. (2013), Liu et al. (2022), Nema et al. (2009)
Automotive — individual transport, EV/HEV	Mechanical propulsion demand with limited electric and thermal auxiliary loads.	Medium-speed dynamics; fast transients during acceleration and braking.	Highly uncertain; driver-dependent and generally not route-predefined.	Load uncertainty; real-time control; SOC management; battery-ageing mitigation.	Water taxis; small offshore support vessels; tugboats.	M. Sabri et al. (2016), Tie and Tan (2013), Zhou and Du (2021)
Automotive — scheduled transport, bus/truck	Mechanical propulsion demand with limited electric and thermal auxiliary loads.	Medium-speed dynamics; repetitive drive cycles and plannable charging windows.	Known route and schedule; low-to-medium uncertainty; repetitive operation.	Energy-storage management over known missions; economic optimisation; battery-lifetime preservation.	Ferries; cargo vessels; survey vessels.	Perčić et al. (2020), Vuelvas et al. (2021), Zhou and Du (2021)
Marine Energy Systems	Mechanical propulsion demand; electrical mission, hotel, and auxiliary loads; thermal demand including HVAC and WHR.	Multi-timescale behaviour: slow thermal, medium propulsion, and fast power-system dynamics.	Vessel-dependent; ranges from scheduled operation to uncertain mission profiles.	Multi-source operation; competing objectives involving cost, emissions, and degradation; nonlinear dynamics; real-time constraints; fuel-flexible EMS/PMS for alternative-fuel ICE, FC, and battery-hybrid operation; thermal management; component lifetime.	Reference sector.	Geertsma et al. (2017), Nuchturee et al. (2020), Xie et al. (2022), Xu et al. (2022)

Table 6
Vessel-type synthesis of cross-sector energy-system similarities.

Vessel category	Dominant energy-system characteristics	Closest terrestrial analogue
Passenger-intensive vessels, e.g., cruise ships and large naval vessels	Large hotel and HVAC loads; high thermal inertia; slow thermal dynamics; comfort and indoor-air-quality constraints; weather- and occupancy-dependent demand.	Building Energy Systems
High-auxiliary-load vessels, e.g., offshore work vessels, dredgers, tugboats, crane vessels, and naval vessels	Large and variable electric loads; fast power fluctuations; steep ramp rates; need for voltage stability, fault protection, storage coordination, and real-time power balancing.	Smart microgrids
Unscheduled small transport vessels, e.g., water taxis, yachts, and small offshore support vessels	User- or mission-dependent propulsion demand; uncertain load profile; limited onboard energy capacity; battery SOC management; range and charging-window estimation.	Individual EV/HEV transport
Scheduled transport vessels, e.g., ferries, cargo vessels, and survey vessels	Known route and timetable; repetitive load profile; predictable charging or bunkering opportunities; route-aware energy management and economic operation.	Scheduled automotive transport, e.g., buses and trucks

While the lighting leads to an instantaneous electric load, both thermal comfort and air quality can be characterised by slow dynamics. Due to these slow dynamics, potential heat storage, and the allowed variance in the system parameters, the load of the heating, cooling, and ventilation can be scheduled, allowing the management of load demand with available supply or cost of supply. This enables optimising operational costs by taking into account variable electricity prices and future loads based on the scheduling of heating, cooling, and ventilation. This optimisation can also be combined with Demand Side Management and Demand Response behaviour, particularly if the BES includes local power generation and local energy storage (Rotger-Griful & Jacobsen, 2015). Thus, an important objective for BES is to minimise operational costs by considering variable electricity prices, energy storage, and varying the system operating parameters with operating conditions and space attendance. An overview of the objectives used in the literature is shown in Table 8.

4.1.2. Constraints

BES control problems consist of hard and soft constraints on the system operating parameters. The hard constraints ensure system operational limitations and power system stability. The soft constraints often include minimum and maximum values for the comfort objectives thermal comfort, visual comfort and air quality. The bandwidth determined by the slack variables allows a state to vary within a defined bandwidth. This is especially useful for thermal comfort, as the heating and cooling load can be planned in time to increase energy efficiency or reduce cost.

4.1.3. Variable space

We analysed the control problems of a selection of relevant papers from the BES control field to identify common variables for the problem setup. An overview is presented in Table 7. The table consolidates the detailed component-level extraction from the literature with a role-oriented classification of the variables used in BES control problems.

In this table, we identified three main classes of variables. The first class consists of state variables, which describe the present condition of the system. These variables are determined by the physical behaviour of the building and its energy-system components, and they are directly related to the control objectives included in the problem formulation. State variables can describe the building itself, such as indoor temperature (Dahl Knudsen & Petersen, 2016; Drgoňa et al., 2018; Široký et al., 2011), indoor air quality (Široký et al., 2011; Sturzenegger et al., 2016; Wang et al., 2012), or indoor illumination (Oldewurtel et al., 2012; Široký et al., 2011; Wang et al., 2012). They can also describe energy-system components, such as the supply temperature of the heating or cooling unit (Brandi et al., 2022; Cai et al., 2016; Freund & Schmitz, 2021; Široký et al., 2011), the state of charge of a battery, or the current produced by a photovoltaic unit (Brandi et al., 2022; Wang et al., 2012). In feedback control, the state variables are commonly compared with reference values or admissible comfort bands to evaluate the deviation between the actual system state and the desired state.

The second class consists of control variables, which can be actively changed to influence the state variables. For a BES control problem, several control opportunities exist, including the regulation of heating, cooling, ventilation, storage operation, and local electrical power flows. Control variables can therefore be divided into variables associated with the building environment and variables associated with energy-system components. As is common in energy-management problems, these variables are mainly setpoints for load sharing, power flows, temperatures, air flows, or actuator positions. Their implementation and the protection of local stability are often handled by lower-level primary controllers, such as PID feedback controllers.

Control variables may include the air-temperature setpoint (Cai et al., 2016; Karlsson & Hagentoft, 2011; Zhang et al., 2022), the supply airflow (Huang, 2011; Oldewurtel et al., 2012; Sturzenegger et al., 2016; Zhang et al., 2022), or the fresh-air ratio of the ventilation system (Li et al., 2021). The temperature or flow rate of water in a heating or cooling circuit can also be adapted to influence the thermal dynamics of a building (Dahl Knudsen & Petersen, 2016; Drgoňa et al., 2018; Freund & Schmitz, 2021; Široký et al., 2011; Sturzenegger et al., 2016). From the electrical side of BES control, most components are controlled through power, current, or flow setpoints (Brandi et al., 2022; Sturzenegger et al., 2016; Wang et al., 2012). These include the connection to the terrestrial grid, battery systems, photovoltaic panels, and heating or cooling units. Air exchange can be influenced by adapting fan speed, while fresh-air ratio control is commonly implemented through dampers. When indoor illumination is not controlled only by electric lighting, blind-position control can be used to regulate daylight and solar gains (Oldewurtel et al., 2012).

The third class consists of quantities that cross the system boundary and influence the system behaviour. These are classified as inputs or disturbances. Common BES disturbances include outside temperature (Brandi et al., 2022; Dahl Knudsen & Petersen, 2016; Freund & Schmitz, 2021; Oldewurtel et al., 2012; Pippia et al., 2021; Široký et al., 2011; Sturzenegger et al., 2016), solar irradiation (Brandi et al., 2022; Oldewurtel et al., 2012; Wang et al., 2012), and occupancy (Freund & Schmitz, 2021; Pippia et al., 2021; Široký et al., 2011; Sturzenegger et al., 2016). Other studies also consider variable electricity prices (Brandi et al., 2022; Široký et al., 2011; Sturzenegger et al., 2016), relative humidity (Brandi et al., 2022), or wind intensity (Wang et al., 2012). Disturbances affect the system states and cannot be directly manipulated by the controller, but their influence is essential for predictive control and demand-response operation.

4.1.4. Strategies

Various advanced control strategies are investigated in the literature to control intelligent buildings. The strategies can be grouped into the ones using a hierarchical approach and the distributed ones. Hierarchical approaches aim to control the system via a centralised approach, which groups different levels of control in hierarchical order. Distributed control uses a decentralised approach, where zonal controllers decide independently about the upcoming control steps. Some strategies also integrate a forecast of the system behaviour, such as model predictive control (MPC), or operational data, such as data-driven strategies. A consolidated overview of the strategies, objectives, system applications, model representations and study-level evidence is provided in Table 8.

MPC is a control strategy that uses an internal system model to predict future behaviour over a predefined time horizon (Rawlings et al., 2017). This knowledge is then used to optimise the control problem also taking into account the future time horizon. MPC has been utilised in the control of intelligent buildings already since 2006 (Yuan & Perez, 2006). A wide variety of studies (Huang, 2011; Ma et al., 2012; Oldewurtel et al., 2012, 2010; Široký et al., 2011) showed the successful implementation of the control strategy. MPC is especially promising for energy savings and to exploit opportunities for demand side management. The effects can be quantified in terms of cost, such as about 15 % (Oldewurtel et al., 2010) of energy saving (Dahl Knudsen & Petersen, 2016; Oldewurtel et al., 2012). The main objective for a building is to ensure the thermal comfort of inhabitants at all times (Karlsson & Hagentoft, 2011). Thermal comfort defines an interval of indoor air temperature in which humans feel satisfied. Those lower and upper boundaries can vary between day and night in a fixed schedule, which makes the problem suitable for predictive control. Buildings are also suitable for MPC due to their low uncertainty in the load profile, which is often determined by the outside weather and the occupancy of the inhabitants.

However, the robustness of the control is an important factor since the system's dynamics incorporate a high amount of non-linearity. A stochastic scenario-based MPC was introduced by Pippia et al. (2021) in 2021 and demonstrated to perform better than MPC controllers from literature in varying scenarios, showing the robustness of the approach. MPC was studied in many different forms, such as stochastic or adaptive MPC, and validated in large case studies. The research on MPC is continued in the form of large experimental validation studies on actual buildings to compare the results of field test and simulation (Afram & Janabi-Sharifi, 2017; Freund & Schmitz, 2021; Sturzenegger et al., 2016).

One main factor limiting the application of MPC for building control is the time-consuming and costly development of physical high-fidelity prediction models (Prívara et al., 2013; Sturzenegger et al., 2016). As a possible solution to this, the current focus of MPC research for building control has shifted towards integrating data and machine learning methodologies in the predictive control strategy. This allows for replacing the physics-based prediction model with a data-driven model based on operational data. The control is called data-driven model predictive control (DDMPC).

DDMPC can be considered as a further development of MPC. In this control, the prediction of future system behaviour is not done using a physics-based model but by using data and machine learning methods to train a data-driven prediction model. This requires data from the system, mainly in the form of sensor data about temperature, humidity and CO_2 levels, as well as the corresponding weather data. Recently, a high amount of research in this field became visible with the focus on both advanced control (Kathirgamanathan et al., 2021; Maddalena et al., 2020; Stoffel et al., 2023) and prediction model development (Li & Wen, 2014). Machine learning prediction models achieved nearly the same accuracy as white-box models, or even outperformed them depending on the application and fidelity of the white-box model (Afram

Table 7
Building EMS variable space.

Variable class	Variable	Component/domain	Role in BES control problem	References
State variables	Indoor temperature	Building	Primary comfort state used to enforce thermal comfort bands, often with different day/night or occupancy-dependent limits.	Brandi et al. (2022), Cai et al. (2016), Karlsson and Hagentoft (2011), Li et al. (2021)
	Indoor CO_2 concentration	Building/ventilation	Indoor-air-quality state; CO_2 concentration is commonly used as a proxy for ventilation demand and air-quality constraints.	Li et al. (2021), Široký et al. (2011), Sturzenegger et al. (2016), Wang et al. (2012)
	Indoor illumination	Building/lighting	Visual-comfort state associated with daylight availability, artificial lighting demand, and shading conditions.	Oldewurtel et al. (2012), Široký et al. (2011), Wang et al. (2012)
	Supply temperature	Heating unit/cooling unit/storage tank	Thermal-distribution state describing the temperature supplied by heating, cooling, or storage components.	Brandi et al. (2022), Cai et al. (2016), Freund and Schmitz (2021), Široký et al. (2011)
	Supply duct pressure	Fan/air-handling unit	Air-distribution state relevant for ventilation control and fan operation.	Cai et al. (2016)
	State of charge	Battery	Energy-storage state used to schedule charge/discharge operation and maintain storage availability.	Brandi et al. (2022)
	PV current	PV panel	Electrical-generation state associated with photovoltaic production.	Brandi et al. (2022), Wang et al. (2012)
	Wind-turbine current	Wind turbine	Electrical-generation state associated with local wind-energy production.	Wang et al. (2012)
Control variables	Air-temperature setpoint	Building/HVAC	Main HVAC control input for regulating zone-level thermal comfort.	Cai et al. (2016), Karlsson and Hagentoft (2011), Zhang et al. (2022)
	Supply airflow	Air-handling unit/ventilation	Ventilation control input used to regulate air exchange, air quality, and ventilation energy consumption.	Huang (2011), Oldewurtel et al. (2012), Sturzenegger et al. (2016), Zhang et al. (2022)
	Fresh-air ratio	Building/ventilation damper	Damper-related control input defining the proportion of fresh and recirculated air in the ventilation system.	Li et al. (2021)
	Heating/cooling flow	Building/thermal circuit	Thermal-flow control variable influencing room-temperature dynamics and heating or cooling power delivery.	Dahl Knudsen and Petersen (2016), Drgoňa et al. (2018), Freund and Schmitz (2021), Široký et al. (2011)
	Blind position	Building/shading	Shading-control variable affecting daylight availability, solar gains, and visual comfort.	Oldewurtel et al. (2012)
	Water flow	Storage tank/thermal circuit	Thermal-storage or hydronic-circuit control variable used to influence heat exchange and storage operation.	Brandi et al. (2022)
	Fan speed	Fan/air-handling unit	Actuator-level ventilation control variable affecting air circulation, duct pressure, and ventilation power.	Cai et al. (2016)
	Battery current	Battery	Electrical storage control variable used to regulate charge/discharge power.	Brandi et al. (2022), Wang et al. (2012)
	Grid current	Grid connection	Electrical power-flow control variable used to regulate exchange with the external grid.	Brandi et al. (2022), Sturzenegger et al. (2016), Wang et al. (2012), Zhang et al. (2022)
	Ventilator speed	Ventilation system	Ventilation actuator variable affecting air exchange and indoor air quality.	Wang et al. (2012)
	Heater current	Heating unit	Electrical actuator variable controlling heat supply from electric heating components.	Wang et al. (2012)
	Cooling flow	Cooling unit	Cooling-system control variable used to regulate cooling delivery and indoor temperature.	Wang et al. (2012)
Inputs/disturbances	Wind speed	Wind turbine/weather	Input to local wind-generation models and disturbance affecting building ventilation and thermal losses.	Wang et al. (2012)
	Solar irradiation	PV panel/building envelope	Input for PV generation and external disturbance affecting solar heat gains, daylight availability, and cooling demand.	Brandi et al. (2022), Karlsson and Hagentoft (2011), Oldewurtel et al. (2012), Wang et al. (2012)
	Outside temperature	Building envelope/weather	Dominant thermal disturbance affecting heating and cooling demand.	Brandi et al. (2022), Dahl Knudsen and Petersen (2016), Freund and Schmitz (2021), Široký et al. (2011)
	Occupancy	Building/internal gains	Internal disturbance influencing heat gains, ventilation demand, lighting demand, and comfort requirements.	Freund and Schmitz (2021), Pippia et al. (2021), Široký et al. (2011), Sturzenegger et al. (2016)

(continued on next page)

Table 7 (*continued*).

Variable class	Variable	Component/domain	Role in BES control problem	References
	Electricity prices	Grid/market	Exogenous economic signal affecting cost-optimal scheduling, Demand Response, and storage operation.	Brandi et al. (2022), Široký et al. (2011), Sturzenegger et al. (2016)
	Relative humidity	Building/weather	Comfort-related disturbance affecting perceived comfort, latent loads, and condensation risk.	Brandi et al. (2022)

& Janabi-Sharifi, 2015; Arendt et al., 2018). However, high prediction accuracy can only be realised with proper data availability, data preprocessing, model selection and training (Mugnini et al., 2020). One advantage of creating prediction models from operation data is the saving in time and cost compared to the development of dynamic white-box models for complex systems (Sturzenegger et al., 2016).

Data-driven and physically based approaches can also be combined in hybrid models, which use machine learning methods as well as physical relations. The idea behind this method is to improve the accuracy of the data-driven model by incorporating equations for well-known relations while still benefiting from the ability to learn the non-linearity of the system behaviour introduced by machine learning (Stoffel et al., 2022). According to the 'no free lunch theorem for optimisation' (Wolpert & Macready, 1997), no algorithm can be determined to outperform all the others. Therefore, many machine learning methods can be used for prediction modelling. Research for prediction modelling and DDMPC was carried out with Gaussian Processes (van der Meer et al., 2018), Neural Networks (Afram & Janabi-Sharifi, 2015; Bünning et al., 2020; Coccia et al., 2020; Drgoňa et al., 2018), Linear Regression (Khosravi et al., 2019), as well as Regression Trees and Random Forests (Jain et al., 2018).

Various research studies on DDMPC in the building control sector have been published in recent years. The incentive is to replace the time- and cost-consuming physical models with models based on operational data, which can be easily measured from real-life buildings. In addition, buildings possess several non-linear dynamics such as the temperature, humidity or CO_2 level spread over a room, as well as the losses through walls or other surfaces, which are computationally expensive to model but can be learned by proper machine learning models. Several studies applied DDMPC to reduce energy consumption while maintaining thermal comfort at the same time (Bünning et al., 2020; Coccia et al., 2020; Jain et al., 2018). Learning from data can also be utilised in online learning models, which improve their performance further while already in operation. Methods utilised were neural networks (Bünning et al., 2020; Coccia et al., 2020; Drgoňa et al., 2018), regression trees (Drgoňa et al., 2018) or gaussian processes (Jain et al., 2018). Furthermore, a comparative analysis of the use of MPC, DDMPC and Reinforcement learning (RL) strategies is carried out for the application of building control, showing a high potential for energy savings in the application of black-box MPC controllers (Stoffel et al., 2023).

RL is a control strategy that has gained interest in recent years for energy management. RL approaches can be implemented in two ways: model-based and model-free. A model-based RL approach can also be combined with techniques such as transfer learning to pre-train models to reduce the required data for a sufficient model (Yu et al., 2021). Over the past three years, a variety of studies was carried out implementing an RL control approach for building control (Brandi et al., 2022; Deng et al., 2022; Zhang et al., 2022). Based on this, many researchers reviewed and commented on the developments of RL based control for buildings (Maddalena et al., 2020; Wang & Hong, 2020; Yu et al., 2021). This evaluation helped to identify the challenges of this control approach. While the research interest in the topic is very high and advantages can be found in the potential to benefit from the rapid and recent developments of the machine learning sectors, the RL control is still in the research phase (Wang & Hong, 2020). Major challenges could be identified in the low data efficiency, implementation of multiple timescales and multiple objectives, problems in the generalisation and robustness (Yu et al., 2021). In addition, the training process was found to be data-demanding and time-consuming (Wang & Hong, 2020). An interesting combination of RL and MPC was presented by Arroyo et al. (2022) to develop a control benefitting from the high performance of MPC and the ability of continuous learning and to deal with uncertain environments of RL.

Another prominent approach for BES is the use of a distributed control strategy, for example multi-agent control (MAC). Distributed control is an approach to decentralise the control structure, by using independent controllers that communicate amongst each other rather than according to a predefined hierarchy (Antonelli, 2013). This is in general realised by defining independent zones containing their own, independent controllers, also called agents. Information and interface data is handed over between the controllers, but no control directions. Every agent contains its own objective and constraint system and interacts with the agents of neighbouring zones through communication links. This way every zone is controlled by a separate agent, while not being separate from the complete system. Summing up the objective functions of all agents, the objective function of the complete system can be described. MAC allows for real-time optimisation of large systems and, due to its distributed nature, is effective at preventing errors against failing components, subsystems and communication links. Another advantage is that the agents only require knowledge about their specific zone, which breaks down the problem into smaller pieces (Li & Wang, 2020). Prominent applications can be found in the control of microgrids and large buildings. Several researchers investigated the use of zonal agent based control in the past years (Cai et al., 2016; Li & Wang, 2020; Wang et al., 2012; Zhang et al., 2022; Zhao et al., 2013). The main advantage of using an agent based approach is the possibility to increase the flexibility of a large system by using a distributed architecture than the commonly used central control architecture (Li & Wang, 2020). The main focus for MAC in building control is the reduction of energy consumption while ensuring indoor temperature and air quality. Another focus of MAC for buildings is the realisation of real-time control in the application (Li et al., 2021).

4.2. Control of smart microgrids

In the following, the research on control of electric microgrids is analysed. We present common objectives, alongside constraints and variable spaces. Subsequently, we analyse common strategies. Control strategies focused on microgrids directly apply to ship electrical grids, as these can be seen as autonomous microgrids with the ship hull as a clear system boundary.

4.2.1. Control objectives

When analysing research on microgrid control, a variety of objectives used can be identified. An overview of objectives found in literature is presented in Table 9. An important objective for microgrid control is Demand Side Management. The idea of DSM is to shape the load profile in terms of changes in the time pattern and the magnitude of the load (Gellings, 1985). This is done using the utility tools planning, implementation and monitoring of the customer electricity usage. Implementing this objective for microgrid control helps the integration of renewable energy technologies into the market by flattening out peaks and filling gaps in the energy demand Hussain et al. (2018), which can be more volatile or less energy dense than common fossil

Table 8
Building EMS control strategies.

Strategy	Representative source / implementation	Objective	Application	Architecture and model representation	Validation, contribution, or maturity
MPC	MPC (Yuan & Perez, 2006)	Temperature	Multi-zone building	Hierarchical or centralised predictive control using an internal building model.	Early application of MPC to multi-zone building temperature control.
	MPC (Oldewurtel et al., 2010)	Temperature/cost	Office building	Centralised MPC with prediction of thermal behaviour and electricity-price effects.	Shows peak-electricity and cost-reduction potential; approximately 15 % cost saving reported in the literature.
	Stochastic MPC (Oldewurtel et al., 2012)	Energy efficiency	HVAC unit	Predictive control with uncertainty treatment for weather, occupancy, and demand.	Demonstrated energy-saving and demand-response potential under uncertainty.
	MPC (Ma et al., 2012)	Energy efficiency	Multi-zone building	Physics-based predictive model for coordinated demand reduction.	Shows applicability of MPC for building demand reduction and thermal-load scheduling.
	MPC (Dahl Knudsen & Petersen, 2016)	Energy efficiency/emissions	Space heating	Predictive control for thermal-load scheduling and demand-response participation.	Demonstrated potential for energy and emission reductions through predictive space-heating control.
	MPC (Široký et al., 2011)	Energy efficiency	Real building	Model-based predictive controller applied to a real building.	Experimental validation; shows feasibility of MPC beyond simulation.
	Robust MPC (Maasoumy et al., 2014)	Air quality	HVAC unit	Robust predictive control addressing modelling uncertainty.	Addresses robustness limitations of standard MPC in uncertain HVAC operation.
	MPC (Sturzenegger et al., 2016)	Energy efficiency	Office building	Predictive climate control with building and HVAC models.	Field-test validation and comparison between simulation and real-building performance.
	Robust MPC (Huang, 2011)	Air quality	VAV unit	Robust MPC for ventilation and air-quality control.	Demonstrates MPC applicability to air-quality and ventilation-system control.
	MPC (Freund & Schmitz, 2021)	Energy efficiency	Real building	Physics-based MPC with practical implementation focus.	Experimental implementation in a real building; supports transition from simulation to field deployment.
	RL–MPC (Arroyo et al., 2022)	Temperature	Multi-zone building	Hybrid control combining MPC performance with reinforcement-learning adaptation.	Demonstrates a combined approach to exploit MPC structure and RL learning capability.
	MPC (Alrumayh & Bhattacharya, 2015)	Cost minimisation	Smart building	Predictive optimisation using cost-related objectives.	Shows applicability of MPC to economically motivated building control.
	MPC (Karlsson & Hagentoft, 2011)	Temperature	Heater	Model-based predictive control for thermal-comfort regulation.	Demonstrates temperature-control benefits in heating applications.
	Supervisory MPC (Afram & Janabi-Sharifi, 2017)	Demand Side Management	HVAC unit	Hierarchical supervisory MPC for HVAC scheduling and demand management.	Demonstrates DSM-oriented building control using MPC.
	Robust stochastic MPC (Pippia et al., 2021)	Temperature	Building	Scenario-based nonlinear MPC addressing uncertainty and nonlinear dynamics.	Reported improved robustness compared with MPC controllers from the literature.
DDMPC and ML-based MPC	Discrete MPC with ANN (Ferreira et al., 2012)	Energy efficiency	Real building	MPC supported by neural-network prediction models.	Demonstrates early integration of neural networks into building predictive control.
	MPC/ML-MPC (Drgoňa et al., 2018)	Temperature	Multi-zone building	Data-driven or approximate predictive models for thermal dynamics.	Shows the use of machine learning models to reduce modelling burden in MPC.
	DDMPC with ANN (Stoffel et al., 2022)	Energy efficiency	Building	Hybrid data-driven and physics-based predictive model.	Demonstrates integration of physical relations and neural-network learning for improved prediction.
	DDMPC with regression trees (Jain et al., 2018)	Demand Side Management	Testbench	Data-driven MPC using regression-tree prediction models.	Demonstrates DDMPC for DSM and benchmarked predictive control.
	DDMPC with ANN (Bünning et al., 2020)	Energy efficiency	Real building	Neural-network-based predictive model embedded in MPC.	Demonstrates energy-efficient control while maintaining thermal comfort.
	DDMPC (Wang et al., 2019)	Temperature	Building	Data-driven predictive control using operational building data.	Demonstrates data-driven thermal-comfort control without full white-box model development.
	DDMPC with linear regression (Khosravi et al., 2019)	Temperature	Building	Linear-regression prediction model for MPC.	Shows that simpler data-driven models can be used when appropriate data are available.

(*continued on next page*)

Table 8 (*continued*).

Strategy	Representative source / implementation	Objective	Application	Architecture and model representation	Validation, contribution, or maturity
	Comparative MPC/DDMPC/RL study (Stoffel et al., 2023)	Energy efficiency	Building	Comparative assessment of advanced controllers, including white-box MPC, black-box MPC, and RL.	Shows strong potential for energy savings with black-box MPC and provides comparison across advanced control families.
	Data-driven control review (Kathirgamanathan et al., 2021)	Energy efficiency/comfort	Building control	Review of data-driven predictive-control methods for building applications.	Summarises the shift from white-box modelling toward operational-data-based prediction models.
	Data-driven methods review (Maddalena et al., 2020)	Energy efficiency/comfort	Building control	Review of data-driven control, MPC, and learning-based methods.	Identifies opportunities and limitations of data-driven control for buildings.
RL and learning-based control	Adaptive RL (Brandi et al., 2022)	Operational cost	BES	Learning-based adaptive control using operational data and system interaction.	Demonstrates cost-oriented adaptive learning control for BES operation.
	Multi-agent RL (Zhang et al., 2022)	Grid stability	HVAC unit	Distributed or multi-agent deep reinforcement learning.	Applies learning-based distributed control to HVAC and grid-stability-related objectives.
	Deep Q Network (Deng et al., 2022)	Energy efficiency	HVAC unit	Model-free deep reinforcement learning for HVAC control.	Demonstrates RL-based energy-efficient HVAC operation in simulation.
	RL and deep RL review (Yu et al., 2021)	Energy efficiency/comfort	Building control	Model-free and model-based RL; includes transfer learning and deep RL methods.	Identifies key challenges: data efficiency, multiple timescales, multi-objective control, generalisation, and robustness.
	RL review (Wang & Hong, 2020)	Energy efficiency/comfort	Building control	Review of reinforcement-learning approaches for building control.	Highlights that RL remains largely research-oriented due to data-demanding and time-consuming training.
MAC and distributed control	MAC (Wang et al., 2012)	Energy efficiency	Multi-zone building	Distributed agent-based control with zone-level agents and communication links.	Demonstrates distributed energy-efficient control for multi-zone buildings.
	MAC (Cai et al., 2016)	Temperature	Multi-zone building	Multi-agent coordination of zone-level thermal-control objectives.	Demonstrates zonal temperature control with distributed coordination.
	MAC (Li & Wang, 2020)	Energy efficiency	Multi-zone ventilation	Distributed multi-agent control for ventilation systems.	Shows improved flexibility compared with centralised control and reduced problem complexity through local agents.
	MAC (Li et al., 2021)	Air quality	Multi-zone building	Real-time multi-agent optimal control for indoor air quality.	Demonstrates real-time capability of distributed air-quality control.
	MAC (Zhao et al., 2013)	Operational cost	BES	Agent-based energy-management system.	Shows applicability of distributed control to cost-oriented BES operation.
Adaptive and fuzzy control	Adaptive control/adaptive RL (Brandi et al., 2022)	Operational cost	BES	Adaptive parameter or policy update using operational data.	Improves robustness under changing operating conditions and uncertain dynamics.
	Robust/adaptive MPC (Maasoumy et al., 2014)	Air quality	HVAC unit	Robust control treatment of model uncertainty.	Addresses uncertainty and robustness in building HVAC control.
	Fuzzy MAC (Hagras et al., 2003)	Temperature	Multi-zone building	Rule-based fuzzy and hierarchical genetic-fuzzy multi-agent control.	Proof-of-concept for fuzzy distributed control of thermal comfort.

fuel energy generation. The utility in the marketplace for energy is used to alter the consumer demand Gellings (1985). This can also be used to integrate alternative fuel production and use into the electricity grid, for example hydrogen-based systems (Abdelghany, Bakr and Mariani, Liuzza & Glielmo, 2024).

Another objective found in literature is Demand Response. DR describes changes to the electricity consumption pattern of end-users based on the electricity price of the marketplace (Albadi & El-Saadany, 2007). The idea is to consume energy when the marketplace is low, while trying to avoid electricity use at times of high prices. The objective includes all intentional modulations to end user consumption patterns (Haider et al., 2016).

A third commonly used objective in literature is the economic minimisation of the operational cost (Banfield et al., 2020; Sanjari et al., 2017). This is also often combined with a DR approach taking into account the variability in electricity prices over the day (Banfield et al., 2021; Mirakhorli & Dong, 2018). Other studies focus mainly on stabilising the voltage of the grid, as a task to incorporate a large variety of different and uncertain generation plants, such as rooftop PV (Banfield et al., 2021; Kabir et al., 2014; Sun et al., 2017). This can also be combined with the aim of optimal operation of an ESS system, in the table referred to as energy storage system management (ESS-M) (Huang & Liu, 2013; Kabir et al., 2014). Use of objectives, such as reduction of fuel consumption (Heymann et al., 2018) remains an exception.

Table 9 consolidates the objective definitions with the publication-level objective mapping. In this way, the table captures both the conceptual role of each objective and the way these objectives are combined in the reviewed microgrid-control literature.

Table 9
Smart microgrid EMS objectives.

Objective	Category	Description and EMS role	Publications and objective combinations
Demand Side Management (DSM)	Economic/load	Load-profile shaping in time and magnitude to reduce peaks, fill demand valleys, and improve the integration of renewable generation into electricity markets. DSM acts at the demand-planning level and is used to coordinate consumption with available generation, storage capacity, or alternative-fuel production.	Conceptual basis: Gellings (1985). DSM-focused and related studies: Hussain et al. (2018), Rahim et al. (2016), Sonnenschein et al. (2015), Worthmann et al. (2015). Combined DSM and cost optimisation: Hussain et al. (2018). Extension toward hydrogen-based or alternative-fuel-integrated systems: Abdelghany, Bakr and Mariani, Liuzza and Glielmo (2024).
Demand Response	Economic/load	Modulation of end-user electricity consumption according to time-varying market prices. The objective is to shift consumption toward low-price periods and reduce demand during high-price peaks. DR is often coupled with cost minimisation and predictive scheduling.	Conceptual basis: Albadi and El-Saadany (2007), Haider et al. (2016). DR and price-responsive control: Cole et al. (2014), Tan et al. (2014), Wang and Tang (2017), Zhang et al. (2015). Combined DR, cost optimisation and voltage-related objectives: Mirakhorli and Dong (2018). Combined DR and cost optimisation: Cole et al. (2014), Tan et al. (2014), Zhang et al. (2015).
Operational cost minimisation	Economic	Minimisation of total operating cost, including energy procurement, local generation scheduling, storage operation, and time-varying electricity prices. This objective is frequently combined with DR, DSM, voltage management, or alternative-fuel operation.	Cost-focused studies: Banfield et al. (2020), Cai et al. (2021), Elkazaz et al. (2020), Sanjari et al. (2017), Zhang, Fu, et al. (2020). Cost with DR: Cole et al. (2014), Mirakhorli and Dong (2018), Tan et al. (2014), Zhang et al. (2015). Cost with voltage-stability considerations: Banfield et al. (2021), Mirakhorli and Dong (2018). Cost with DSM: Hussain et al. (2018). Cost with hydrogen or alternative-fuel operation: Abdelghany, Bakr and Mariani, Liuzza and Glielmo (2024), Abdelghany, Mariani, Liuzza, and Natale (2024), Abdelghany et al. (2021, 2022).
Voltage stability	Stability/grid	Maintenance of grid-voltage stability through coordinated balancing of generation, storage, and demand. This objective is especially relevant when volatile renewable sources, such as rooftop PV, are integrated into the microgrid.	Voltage-stability motivation and grid-support objective: Kabir et al. (2014), Sun et al. (2017). Voltage-focused control studies: Duan et al. (2020), Li et al. (2022, 2014), Wang et al. (2020), Zhang et al. (2014). Voltage combined with cost or DR: Banfield et al. (2021), Mirakhorli and Dong (2018). Voltage combined with ESS management: Kabir et al. (2014).
Energy Storage System Management (ESS-M)	Storage/grid	Optimisation of charging and discharging of energy storage systems, including batteries and flywheels. ESS-M supports voltage stability, peak shaving, renewable-energy integration, and energy arbitrage.	ESS-focused studies: Huang and Liu (2013), Kabir et al. (2014). ESS management in microgrid EMS reviews and optimisation studies: Liu et al. (2022). ESS combined with voltage stability: Kabir et al. (2014).
Fuel consumption reduction and alternative-fuel operation	Efficiency/fuel	Reduction of fuel consumption from generator-based sources. This objective is less common in grid-connected residential microgrids, but becomes relevant for autonomous, islanded, hybrid, or hydrogen-based microgrids.	Fuel-consumption reduction in autonomous or generator-based microgrids: Heymann et al. (2018). Fuel and cost objectives in hydrogen-based systems: Abdelghany, Bakr and Mariani, Liuzza and Glielmo (2024), Abdelghany, Mariani, Liuzza, and Natale (2024), Abdelghany et al. (2021, 2022).

4.2.2. Constraints

Microgrid control problems are limited by sets of equality and inequality constraints. The most prominent equality constraint is the power balance between energy consumption and production. This constraint is essential for the stability of the microgrid and enforces the balance between electricity generation, storage exchange, and load demand. Additional sets of constraints are introduced as upper and lower boundaries for the components incorporated in the microgrid. These inequality constraints are important to keep the operation of each component within its allowed operational envelope. With these constraints, the solution space of the control problem is limited to physically viable solutions.

4.2.3. Variable space

Observing the variable space of microgrid control problems, we can identify the system voltage as a very common state variable. Besides this, the ESS SOC and generated PV current are also frequent states in residential grid management. These are often controlled via setpoints for the current or power of the components. Common disturbances can be changes in wind and solar energy generation, unexpected consumer behaviour, or failures in the electric grid or transmission system. The effects of these disturbances lead to uncertainties in the requested load profile, which need to be compensated immediately by the controller to protect the stability of the electrical system.

4.2.4. Strategies

Several review papers analysed the control of microgrids in recent years (Olivares et al., 2014; Sen & Kumar, 2018). This includes the detailed analysis of the integration of renewable energy sources (Bihari et al., 2021), control of AC microgrids (Rajesh et al., 2017), control of DC microgrids (Rev, 2019; Al-Ismail, 2021), and energy management (Elmouatamid et al., 2021; Roslan et al., 2019; Touma et al., 2021). Further research also analyses the development and control of residential smart grids (Haider et al., 2016; Molderink et al., 2010).

Focusing on the control strategies themselves, a large research interest is found in MPC. Several researchers investigate the optimisation potential when including a future prediction (Abdelghany, Bakr and Mariani, Liuzza & Glielmo, 2024; Abdelghany, Mariani, Liuzza, & Natale, 2024; Abdelghany et al., 2021; Banfield et al., 2020; Elkazaz et al., 2020; Parisio et al., 2015). In 2015, Banfield et al. (2021) present a distributed MPC approach for the control of residential energy storage, taking into account three objectives. Microgrid control systems using MPC are also shown to be widely effective in grids incorporating over 15000 residential buildings (Mirakhorli & Dong, 2018) in the reduction of peak loads, while saving energy alongside. Use of MPC can also enable the control of a residential grid to be more robust, while integrating a variety of energy sources (Zhang et al., 2015). Cole et al. (2014) implement a coordinated MPC control to achieve a DR peak shifting in a community. Worthmann et al. (2015) compared the performance of both a centralised and a distributed MPC approach, stating that the best performance is achieved with the centralised layout, whereby the distributed approach is more feasible for large systems. Xing et al. (2019) implement a distributed MPC for collaborative energy management. The operation of a grid incorporating large amounts of renewable energies and ESS technologies can be cost-efficiently optimised using MPC as well (Zhang, Fu, et al., 2020). Abdelghany, Bakr and Mariani, Liuzza and Glielmo (2024), Abdelghany, Mariani, Liuzza, and Natale (2024), Abdelghany et al. (2021) propose an MPC-based energy management for a microgrid to manage wind turbines, ESS and a hydrogen production and usage facility. The authors show the potential to successfully use surplus electricity from the wind turbines for hydrogen production, which can later be used to fill gaps. This work was also further extended to integrating the demand of hydrogen-based vehicles into the control scheme (Abdelghany et al., 2022).

In recent years, the interest in data-driven microgrid control methodologies has also increased. Li et al. (2014) trained a NN for the control of a rectifier/inverter for a microgrid application to improve applicability to dynamic systems. In contrast, Sun et al. (2017) used a NN to maximise the output of a PV power plant. Both researchers used the DP solution to train the NN. Another study trained a NN to manage the battery inside a residential grid (Huang & Liu, 2013). The results of the ongoing research indicate that NN could be a valid option for replacing complex controllers for single components or interfaces. In addition to the research on NN, RL is also investigated for its capabilities. In 2020, Duan et al. (2020) implemented deep RL for the voltage control of a microgrid. Similarly, Li et al. (2022) use RL to optimise load shedding and voltage control. RL is also studied in combination with MPC (Cai et al., 2021) or MAC (Wang et al., 2020).

A control approach, more related to the power management of the electrical grids, is coordinated control. This approach allows for integrating various low-level producers, such as rooftop PV. Using a coordinated control, Kabir et al. (2014) show that the operation of the battery alongside the PV production helps with peak shaving and stabilising the voltage of the grid. With a focus on the coordination of several consumers, Wang and Tang (2017) present a supply-based feedback control using adaptive utility functions for the control of residential HVAC units alongside a grid. This also includes the residential comfort in the problem in combination with the requirement of DR. Distributed control is also studied for microgrids (Kohn et al., 2015). Significant work on distributed control of microgrids was presented by Dörfler et al. (2016). In this study, the authors show that the adoption of lower layer droop control in combination with distributed control approaches can achieve economic optimisation. This allows leaving the simple selection of droop coefficients and the rules of power sharing for the top-layer energy management system. However, this opens a new aspect of high-level energy management to design fairness in energy trading (Behrunani et al., 2023) and developing systems towards a more communicating and coordination-centred control.

This also leads to a high research interest in agent-based control strategies (Kamboj et al., 2026; Kantamneni et al., 2015; Khan & Wang, 2017; Mahela et al., 2022). Sonnenschein et al. (2015) develop an agent-based control to achieve demand side management by aligning the EV charging problem with PV production. A similar approach also uses MAC to incorporate wind power and PV production into a residential grid (Ricalde et al., 2011). MAC is also studied for the application in microgrids by various researchers (Logenthiran et al., 2011; Wang et al., 2020; Zheng & Cai, 2010). In 2014, Zhang et al. (2014) present MAC for the voltage stability of a microgrid. Wang et al. (2020) present a framework to combine MAC with RL strategies. A similar approach is investigated by Chen et al. (2022) for a power grid. MAC control is also tested for DC technologies, as shown by Shehata et al. (2019) in 2019. Current studies show that distributed control approaches can be beneficial in controlling large, multi-component systems (Banfield et al., 2021; Worthmann et al., 2015).

Table 10 consolidates the strategy-level synthesis and the publication-level mapping. It therefore replaces both the compact study-extraction table and the broader strategy-overview table.

4.3. Control of automotive energy systems

This subchapter analyses the construction of AES control problems and the approaches used in common literature. We analyse common control objectives, constraints, variable space, control strategies, and solution algorithms.

4.3.1. Control objectives

An overview of the objectives found in the literature is shown in Table 11. A commonly used objective is a reduction of the fuel consumption of the vehicle (Hu et al., 2022; Li et al., 2018, 2019; Torreglosa et al., 2011; Valenti et al., 2021; Wang et al., 2018). Reducing the amount of fuel consumed reduces operational costs and expands the autonomous distance the vehicle can travel without refuelling. Corresponding to this, another objective is the minimisation of EV battery discharge (Hung & Wu, 2012; Moreno et al., 2006; Reddy et al., 2019), which also expands the travel distance without recharging. The third prominent objective is the reduction of ageing effects on the components both for battery and fuel cells (Rodriguez et al., 2022; Tang et al., 2021; Valenti et al., 2021). The objectives are also sometimes combined in multi-objective control approaches. Table 11 consolidates the objective definitions with the publication-level objective mapping, including fuel-consumption reduction, battery-discharge minimisation, component-ageing reduction, range extension, operational-cost minimisation, and emission reduction.

4.3.2. Constraints

A very important constraint for AES control is the power balance. This constraint ensures that the power generated by the power sources matches the operation's required power demand. In addition, component constraints are used to restrict the operation of each system component to their respective limits. Examples are the minimum and maximum battery state of charge (SOC), current limitation of power sources and power converters and the operating envelope of the ICE, expressed as a torque–speed relationship. Together, these constraints ensure the power system and its components operate in a safe operating region.

4.3.3. Variable space

An analysis of the literature from the automotive sector shows the most common variables used for an AES control problem. An overview is shown in Table 12. Common state variables include the current from or to the battery and the voltage of the electric bus. Further, the SOC of the battery and supercapacitor can be used as a state. A common state for power generation components, such as fuel cells or engines, is the provided current. In the case of FCs, the FC current and FC voltage and the hydrogen and oxygen flows can also be considered as states. Three types of control variables were observed. The first one controls the engine by selecting a value for the torque or the speed. Components such as FCs and UCs can be controlled by a chosen current set point. Finally, converters, such as DC/DC converters, can be controlled as current or voltage sources by controlling the duty factor of power electronic switches. The propulsive load required is either used as input to the system or as a disturbance.

Table 12 consolidates the detailed component-level extraction with the role-oriented interpretation of each variable in the AES energy-management problem.

4.3.4. Strategies

Road transport presents an inherently fast control problem for energy management, as the dynamic conditions in traffic need to be met in real-time. Therefore, the approaches can be divided into instantaneous optimisation, which optimises every time step without considering future or past knowledge, and predictive control strategies. Several researchers reviewed the energy management in the automotive sector in recent years (Panday & Bansal, 2014; Zhang, Wang, et al.,

Table 10
Smart microgrid EMS control strategies.

Strategy family	Representative source/implementation	Objectives	System/application	Architecture, prediction, or model representation	Validation, contribution, or maturity
Review and taxonomy studies	Microgrid-control reviews (Olivares et al., 2014; Sen & Kumar, 2018)	Control architecture/EMS classification	Microgrids	Review of hierarchical, centralised, distributed, and decentralised microgrid-control structures.	Establishes the main control layers and motivates the use of advanced EMS strategies.
	Renewable-integration review (Bihari et al., 2021)	Renewable integration	Renewable microgrids	Review of control and integration approaches for renewable energy sources.	Highlights the additional uncertainty and variability introduced by high renewable penetration.
	AC and DC microgrid reviews (Rev, 2019; Rajesh et al., 2017)	Voltage stability/grid control	AC and DC microgrids	Review of AC/DC-specific control, planning, and stability challenges.	Relevant to shipboard AC and DC power systems, which can be interpreted as bounded autonomous microgrids.
	EMS reviews (Roslan et al., 2019; Touma et al., 2021)	EMS coordination	Microgrid EMS	Review of energy-management methods for coordinated generation, storage, and load operation.	Summarises the EMS layer as the decision-making level coordinating lower-level electrical control.
	Residential smart-grid reviews (Haider et al., 2016; Molderink et al., 2010)	DSM/DR	Residential smart grids	Review of residential control, demand-side management, and demand-response strategies.	Provides the link between smart-grid EMS and consumer-side flexibility.
MPC-based EMS	MPC (Elkazaz et al., 2020)	Cost	Local microgrid	Centralised MPC for cost-oriented energy management.	Demonstrates operational-cost reduction in a local microgrid.
	Stochastic MPC (Parisio et al., 2015)	Cost	Multiple microgrids	Stochastic MPC with uncertainty-aware prediction.	Demonstrates MPC-based economic management for interconnected or multiple microgrids.
	MPC (Banfield et al., 2020)	Cost	Residential grid	Economic MPC for residential-grid energy management.	Compares economic control formulations for cost reduction.
	Distributed MPC (Banfield et al., 2021)	Cost, DSM, stability	Residential energy storage	Distributed MPC for coordinated residential storage operation.	Considers multiple objectives and supports distributed feasibility for larger residential systems.
	Distributed MPC (Worthmann et al., 2015)	DSM	Residential grid	Comparison of centralised and distributed MPC.	Reports better performance for centralised control, while distributed control is more feasible for large systems.
	MPC (Mirakhorli & Dong, 2018)	Cost, DSM, stability	Residential grid	MPC with load and price prediction for large-scale residential energy management.	Shows in grids incorporating more than 15000 residential buildings, with peak-load reduction and energy savings.
	Coordinated MPC (Cole et al., 2014)	DR	Residential grid	Coordinated MPC for community-scale residential air-conditioning loads.	Demonstrates demand-response peak shifting at community scale.
	Distributed MPC (Xing et al., 2019)	Efficiency	Microgrid	Cooperative distributed MPC for collaborative energy management.	Demonstrates collaborative optimisation across microgrid components or agents.
	MPC (Zhang, Fu, et al., 2020)	Cost	Microgrid	MPC for cost-efficient operation with renewable energy and ESS technologies.	Demonstrates cost optimisation in renewable-rich microgrid operation.
	MPC with RL (Cai et al., 2021)	Cost	Residential grid	Hybrid learning and predictive-control approach for peak and cost management.	Shows potential for combining MPC structure with RL adaptability.
	Robust MPC (Zhang et al., 2015)	Cost	Residential grid	Robust MPC for smart-grid operation under uncertainty.	Improves robustness while integrating multiple energy sources.
	MPC for hydrogen-based microgrids (Abdelghany, Bakr and Mariani, Liuzza & Glielmo, 2024; Abdelghany, Mariani, Liuzza, & Natale, 2024)	Cost, DSM	Microgrid with wind, ESS, hydrogen production and usage	Hierarchical or unified MPC-based EMS coordinating wind turbines, ESS, and hydrogen production/use.	Shows the use of surplus renewable electricity for hydrogen production and later use to fill energy gaps.
	Two-stage MPC (Abdelghany et al., 2022)	Cost, DSM	Microgrid with hydrogen-based vehicle demand	Two-stage MPC integrating hydrogen-based vehicle demand into the microgrid control scheme.	Extends hydrogen-based microgrid EMS to include transport-related hydrogen demand.
Data-driven and NN-based control	NN-based battery management (Huang & Liu, 2013)	Battery/ESS management	Microgrid with ESS	Self-learning neural-network controller for battery operation.	Demonstrates learning-based ESS management in residential microgrids.
	NN for PV output maximisation (Sun et al., 2017)	PV output/voltage support	PV plant with grid connection	Neural network trained using dynamic-programming solutions.	Shows NN-based control potential for PV-grid applications.
	NN for converter control (Li et al., 2014)	Fault protection/interface control	Microgrid rectifier/inverter	Neural network used for rectifier/inverter control in dynamic microgrid applications.	Indicates that NN controllers can replace complex component-level controllers or interfaces.
RL and learning-based control	Deep RL (Duan et al., 2020)	Voltage stability	Microgrid	Model-free deep RL for autonomous voltage control.	Demonstrates deep-RL-based voltage regulation in simulation.
	RL load-shedding control (Li et al., 2022)	Voltage stability/load shedding	Microgrid	RL-based optimisation of load shedding and voltage control.	Shows RL applicability to emergency or corrective microgrid-control actions.
	MPC with RL (Cai et al., 2021)	Cost/peak reduction	Residential grid	Hybrid control combining prediction-based optimisation with learning.	Shows the potential of RL to support predictive peak-management strategies.
	MAC with RL (Wang et al., 2020)	Voltage stability	Microgrid	Multi-agent and reinforcement-learning framework.	Shows how RL can be embedded in distributed microgrid-control architectures.
	Multi-agent deep RL (Chen et al., 2022)	Efficiency	Power grid/microgrid	Deep RL combined with multi-agent coordination.	Extends learning-based multi-agent control concepts to power-grid applications.

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Table 10 (*continued*).

Strategy family	Representative source/implementation	Objectives	System/application	Architecture, prediction, or model representation	Validation, contribution, or maturity
Coordinated and distributed control	Coordinated PV-battery control (Kabir et al., 2014)	Voltage stability/peak shaving/ESS management	Grid-connected PV and battery system	Coordinated control of PV production and battery operation.	Shows that coordinated battery and PV operation supports peak shaving and grid-voltage stabilisation.
	Supply-based feedback control (Wang & Tang, 2017)	DR	Residential HVAC with grid interaction	Adaptive utility functions and supply-based feedback for coordinating consumers.	Includes residential comfort together with demand-response requirements.
	Distributed intelligent control (Kohn et al., 2015)	Cost	Microgrid	Distributed intelligent microgrid control.	Demonstrates distributed decision-making for microgrid energy management.
	Distributed control with droop layer (Dörfler et al., 2016)	Economic optimisation	Microgrid/power grid	Distributed optimisation combined with lower-layer droop control.	Shows that distributed control can achieve economic optimisation while leaving droop power-sharing rules to lower layers.
	Fairness-oriented autonomous control (Behrunani et al., 2023)	Energy trading/fairness	Autonomous microgrid	Coordination-centred high-level energy management.	Highlights fairness as a design objective in distributed energy-trading systems.
MAC and agent-based control	Agent-based DSM (Sonnenschein et al., 2015)	DSM	Residential grid	Decentralised agent-based control aligning EV charging with PV production.	Demonstrates DSM through agent-based coordination of flexible demand and local generation.
	Smart-grid MAC (Ricalde et al., 2011)	Efficiency	Wind power and PV	Multi-agent coordination for renewable integration.	Incorporates wind and PV production into residential-grid control.
	MAC with RL (Wang et al., 2020)	Voltage stability	Microgrid	Data-driven multi-agent autonomous control with RL components.	Combines distributed control and learning for voltage-stability objectives.
	MAC (Logenthiran et al., 2011)	Efficiency	Microgrid	Multi-agent energy-management system.	Demonstrates agent-based EMS for microgrid efficiency improvement.
	MAC (Zheng & Cai, 2010)	Efficiency	Microgrid	Distributed multi-agent control.	Supports distributed coordination across microgrid components.
	MAC (Zhang et al., 2014)	Voltage stability	Microgrid	Distributed multiple-agent control.	Demonstrates MAC for voltage-stability control.
	MAC for DC technologies (Shehata et al., 2019)	Efficiency	Microgrid/DC technology	Agent-based EMS implementation for DC-oriented microgrid technology.	Shows applicability of MAC to DC microgrid technologies.
	MAC for EV integration (Kamboj et al., 2026)	Efficiency	EVs/power grid	Multi-agent coordination for grid-integrated electric vehicles.	Shows the relevance of agent-based strategies for EV-grid interaction.
	MAC reviews (Kantamneni et al., 2015; Mahela et al., 2022)	Coordination/resilience/scalability	Power grids and microgrids	Review of multi-agent systems for grid and microgrid applications.	Establishes MAC as a scalable strategy for large multi-component energy systems.

2020). This includes a focus on control of FC-based vehicles (Sulaiman et al., 2015), as well as a focus on energy management strategies for ICE–battery HEV (M. Sabri et al., 2016). For the discussion of advanced control approaches, mainly studies on HEV are considered as the battery-only EV often employ more straightforward control strategies.

Equivalent Consumption Minimisation Strategy (ECMS) is a control strategy for instantaneous optimisation in which equivalent cost factors for each objective are determined. With the equivalent cost factors, different types of power sources or objectives can be used for the same objective function. One common application is the consumption minimisation between an engine or fuel cell and the usage of a battery. The main objective is in general fuel consumption reduction (García et al., 2012; Lei et al., 2020; Li et al., 2018, 2019; Zhang et al., 2017), which can be combined with component health (H. Li et al., 2019) or CO_2 emission output (Nüesch et al., 2014) as secondary objectives.

ECMS has been a topic of high interest in the automotive control sector for the past ten years. One big advantage of ECMS is that it does not require a high-fidelity prediction model or operational data since it does not predict the future behaviour of the states. This is very suitable for the load profiles in transport applications that involve a high amount of uncertainty due to non-predetermined routes and operating profiles. Several studies showed the successful implementation of ECMS. Prominent use cases are the optimisation between a hydrogen fuel cell and a battery system (H. Li et al., 2019; Torreglosa et al., 2011; Zhang et al., 2017) and between an ICE and a battery (Gao et al., 2009; Lei et al., 2020; Nüesch et al., 2014). The control strategy showed promising results for reducing fuel usage, which helps to extend the vehicle's autonomous travel distance. Furthermore, H. Li et al. (2019) also showed a possible extension of the normal ECMS with adaptive equivalent factors and online state estimation. ECMS is shown to be a valid choice for EMS and PMS in hybrid vehicles and to achieve promising results in reducing fuel consumption.

With a focus on predictive control, MPC is also of high research interest for the automotive sector (Zhou & Du, 2021) with the major objective of reducing fuel consumption (Borhan et al., 2012; Cairano et al., 2014; Hu et al., 2022; X. Li et al., 2019; Uebel et al., 2019; Valenti et al., 2021; Wang et al., 2018; Xie et al., 2019; Zhang et al., 2021). This can also be combined with a second objective to reduce the ageing of the energy system components, most prominently batteries (Valenti et al., 2021). A small amount of studies focuses on the minimisation of cost, which can also be related to fuel consumption (Hu et al., 2022; Pozzato et al., 2020). A major point in evaluating MPC for application in the automotive sector is computational efficiency due to the small time step widths of the control. Various researchers aimed to implement a control in real-time (X. Li et al., 2019; Xie et al., 2019; Zhang et al., 2021). Xie et al. (2019) showed in 2019 that their stochastic MPC solved with Pontryagin's Minimum Principle (PMP) was less computationally expensive than the commonly used dynamic programming (DP). Other researchers use quadratic programming (X. Li et al., 2019) or a combination of MPC with an instantaneous optimisation (Zhang et al., 2021). A last application is the bridge to another sector, residential grid control, in which the role of electric vehicles changes again to temporary energy storage. MPC was also used to investigate this combination of smart grids with electric vehicles (Kennel et al., 2013).

The use of data-driven methods for MPC was also studied in the automotive sector. Besides operational data, information used for prediction modelling are real driving cycles, speed profiles and traffic information. Already in 2006, the first study tested NN to minimise the battery discharge in hybrid electric vehicles (Moreno et al., 2006). NN were also studied in other applications when Chen et al. (2021) used long short-term memory networks in a cost-optimisation strategy for an energy system with battery and ultracapacitor. Other machine learning approaches investigated include Q-learning (Z. Chen et al., 2022) and extreme learning machines (Tang et al., 2021). Tang et al. (2021) used the latter to model the vehicle speed prediction. With this, the authors proposed a control strategy that focuses on energy savings and battery aging prevention, taking into account temperature.

The usage of RL also started to gain interest in the automotive sector. One large advantage over a predictive control strategy is the

Table 11
Automotive EMS control objectives.

Objective	Category	Description and EMS role	Representative publications and objective combinations
Fuel-consumption reduction	Economic / efficiency	Reduction of fuel or hydrogen consumption during the operation of hybrid, plug-in hybrid, and fuel-cell vehicles. This objective reduces operating cost and extends the autonomous travel distance without refuelling. It is the most common objective in AES control and can refer either to internal-combustion-engine fuel use or fuel-cell hydrogen consumption.	Engine-fuel minimisation: Hu et al. (2022), Wang et al. (2018). Fuel-cell hydrogen-consumption minimisation: Li et al. (2018), Rodriguez et al. (2022). Fuel reduction combined with cost: Hu et al. (2022), Tang et al. (2021). Fuel reduction combined with battery ageing: Tang et al. (2021), Valenti et al. (2021). Fuel-cell consumption combined with battery and fuel-cell lifetime: H. Li et al. (2019), Rodriguez et al. (2022).
Battery-discharge minimisation and range extension	Storage / range	Minimisation of battery discharge to extend electric driving range and reduce the need for recharging. This objective is especially relevant for battery-electric vehicles and hybrid vehicles where battery energy must be preserved over a mission or driving cycle.	Range-extension and battery-discharge minimisation: Moreno et al. (2006), Reddy et al. (2019). Range and cost combined: Hung and Wu (2012). Battery-discharge minimisation is often implicitly connected to SOC management, charging-window planning, and power-split optimisation in hybrid AES control.
Component-ageing reduction	Lifetime / maintenance	Reduction of degradation in batteries and fuel-cell stacks caused by high current, frequent cycling, high power demand, rapid load changes, and unfavourable operating points. This objective extends component lifetime and reduces maintenance or replacement cost.	Battery-ageing-aware control: Tang et al. (2021), Valenti et al. (2021). Battery and fuel-cell ageing reduction: H. Li et al. (2019), Rodriguez et al. (2022). Fuel-cell lifetime management: Pereira et al. (2021). Ageing reduction combined with fuel-consumption minimisation: Tang et al. (2021), Valenti et al. (2021). Ageing reduction combined with fuel-cell hydrogen-consumption minimisation: H. Li et al. (2019), Rodriguez et al. (2022).
Operational-cost minimisation	Economic	Minimisation of the total operational cost, including fuel consumption, electricity use, charging decisions, and potentially component degradation. Cost is less often used as a standalone objective than fuel consumption, but it appears in multi-objective formulations and economic MPC formulations.	Standalone or explicit cost minimisation: Chen et al. (2021), Pozzato et al. (2020). Cost combined with range extension: Hung and Wu (2012). Cost combined with fuel-consumption reduction: Hu et al. (2022), Tang et al. (2021). Economic control formulations can incorporate fuel price, electricity price, battery degradation cost, and charging strategy.
Emission reduction	Emission / environmental	Reduction of pollutant emissions or greenhouse-gas-related outputs. In the extracted AES literature, emission reduction appears less frequently than fuel consumption, range, and lifetime objectives. It is usually treated as a secondary objective coupled to fuel-consumption minimisation and engine operating-point selection.	Emission-aware ECMS formulation, including NOx: Nüesch et al. (2014). Emission objectives are closely linked to the fuel-consumption objective because emissions depend on the fuel type, engine operating point, and transient power-split behaviour.
Multi-objective AES control	Integrated EMS	Combination of several objectives in a single energy-management problem, typically involving fuel consumption, cost, battery SOC, component ageing, range, or emissions. Multi-objective formulations are important because AES operation involves trade-offs between short-term efficiency and long-term component health.	Fuel and battery ageing: Tang et al. (2021), Valenti et al. (2021). Fuel-cell consumption with battery and fuel-cell lifetime: H. Li et al. (2019), Rodriguez et al. (2022). Fuel and cost: Hu et al. (2022). Range and cost: Hung and Wu (2012). Fuel and emissions: Nüesch et al. (2014). Fuel-cell consumption and fuel-cell lifetime: Pereira et al. (2021).

ability to implement real-time control. Zhou et al. (2019) showed an application for a multi-step RL approach with an expanded prediction horizon length compared to MPC. Another study showed that RL approaches could nearly reach the fuel efficiency of a dynamic programming solution while being more time efficient (Lee et al., 2020).

Table 13 consolidates the strategy-level synthesis and the publication-level mapping. It therefore replaces both the compact study-extraction table and the broader strategy-overview table.

4.4. Control of marine energy systems

Finally, we analyse the control design for MES. Our analysis first includes the definition and comparison of different objectives used in literature and their potential combination for multi-objective control approaches. Subsequently, we analyse the constraints and the variable space. Finally, we investigate the research on control strategies and solution algorithms.

4.4.1. Control objectives

The operation of MES introduces a variety of objectives into the control problem. The first distinction is between objectives for stable system operation and those for optimisation of the operation over the complete or part of the operating cycle. Stable operation is achieved in the primary control layer with speed control for propulsion engines and diesel generators; speed, torque and power control for electric drives; and voltage control for generators (Geertsma et al., 2017). Dynamic load sharing is mostly regulated by droop control (Guerrero

Table 12
Automotive EMS variable space.

Variable class	Variable	Component / domain	Role in AES control problem	References
State variables	Battery power	Battery	Battery power is used as an energy-storage state or monitored quantity in predictive EMS formulations. It is directly related to battery loading, power-split decisions, and battery energy depletion.	Borhan et al. (2012), Pereira et al. (2021)
	Battery current	Battery	Current flowing from or to the traction battery. It is relevant for battery-power tracking, converter control, thermal loading, and ageing-aware energy management.	H. Li et al. (2019), Valenti et al. (2021)
	Battery SOC	Battery	State of charge of the battery. This is one of the central energy states in AES control because it determines available electric range, admissible charge/discharge operation, and long-term energy balance.	Borhan et al. (2012), Li et al. (2018)
	Supercapacitor SOC	Supercapacitor	State of charge of the supercapacitor. It is used to manage short-term high-power buffering and to coordinate the power split between battery, fuel cell, engine, and supercapacitor.	Lei et al. (2020), Li et al. (2018)
	Supercapacitor current	Supercapacitor	Current flowing through the supercapacitor. It describes the instantaneous charge/discharge contribution of the supercapacitor and is relevant for transient power support.	H. Li et al. (2019)
	Fuel-cell hydrogen and oxygen flow	Fuel cell	Hydrogen and oxygen flow rates into the fuel-cell stack. These states are relevant for reactant-management constraints, fuel-cell efficiency, and safe operation of fuel-cell/battery systems.	Li et al. (2018), Zhang et al. (2017)
	Fuel-cell voltage	Fuel cell	Output voltage of the fuel-cell stack. It is used to describe fuel-cell electrical behaviour and power-delivery capability.	Pereira et al. (2021), Zhang et al. (2017)
	Fuel-cell current	Fuel cell	Output current of the fuel-cell stack. It is a key state for fuel-cell power delivery, hydrogen consumption, efficiency, and transient operating constraints.	H. Li et al. (2019), Zhang et al. (2017)
	Bus voltage	DC or AC electric bus	Voltage of the electric bus. It is used to monitor power balance, converter operating limits, and electrical stability of the AES power network.	X. Li et al. (2019), Li et al. (2018)
	FC/ICE output power	Fuel cell/internal combustion engine	Instantaneous output power of the fuel cell or internal combustion engine. It determines source loading, fuel consumption, emissions, and power-split behaviour.	Li et al. (2018, 2019)
Control variables	Engine torque	Internal combustion engine	Torque setpoint of the engine. This control variable directly determines the engine operating point and therefore influences fuel consumption, emissions, and driveline power delivery.	Borhan et al. (2012), Lei et al. (2020)
	Engine speed	Internal combustion engine	Rotational-speed setpoint of the engine. Together with torque, it defines the engine operating point and can be used to optimise fuel efficiency or emissions.	Borhan et al. (2012), Lei et al. (2020)
	Fuel-cell current setpoint	Fuel cell	Current setpoint for the fuel cell. It determines the instantaneous fuel-cell power contribution and therefore affects hydrogen consumption, transient stress, and power sharing.	Li et al. (2018), Pereira et al. (2021)
	Supercapacitor/ultra-capacitor current setpoint	Supercapacitor/ultra-capacitor	Current setpoint for the supercapacitor or ultracapacitor. It determines the short-term power-buffering contribution and supports transient load sharing.	Li et al. (2018), Zhang et al. (2017)
	DC/DC converter current	Power converter	Converter-current control variable used to regulate power exchange between storage, sources, and the electric bus.	H. Li et al. (2019)

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Table 12 (*continued*).

Variable class	Variable	Component / domain	Role in AES control problem	References
	DC/DC converter duty cycle	Power converter	Duty factor of the power-electronic switches. It regulates the converter as an effective current or voltage source and controls power flow between components.	Borhan et al. (2012), X. Li et al. (2019)
Inputs/disturbances	Propulsion load	Vehicle/drivetrain	Requested propulsive power or traction load. It can be treated as an input when the driving cycle is known, or as a disturbance in predictive EMS formulations when future demand is uncertain.	Li et al. (2018), H. Li et al. (2019)
	Vehicle speed/driving cycle	Vehicle/mission profile	Standardised or measured speed profile used for prediction modelling, driving-cycle characterisation, and load forecasting. It is commonly used to derive future traction-power demand.	Moreno et al. (2006), Tang et al. (2021)

et al., 2011), although alternative approaches for DC architectures utilising different timescales with fast switching power electronics have been proposed (Amgai & Abdelwahed, 2014; Seenumani et al., 2012). When batteries are included, they can also be used to improve stable operation as proposed in Zahedi et al. (2014). Together with secondary, automatic, often rule-based control such as automatic starting and stopping, load shedding and voltage and frequency setpoint adjustment, this is referred to as power management (Geertsma et al., 2017).

When utilising power sources with differences in quasi-static behaviour, which takes place on slower timescales than power management, load sharing needs to be optimised over the operating profile. This is similar to load sharing between a battery and combustion engine in AES, but more and different types of power sources are often used in MES. This optimisation of load sharing over the operating profile is called energy management. While the original objective of energy management has been to minimise energy use, the principal optimisation approach can also include other objectives. Taking into account energy minimisation and other objectives, energy management determines the optimal power split between the power generating components, either through instantaneous optimisation or by utilising a prediction of future system operation to optimise over a future time horizon, and subsequently updates the power split setpoints to the power management layer. It is also possible to incorporate more than one objective in an energy management strategy, which results in a compromise between all considered objectives. The relation between objectives can range from supporting over indifferent to opposing each other. An overview of the commonly used objectives for MES is presented in Table 14.

Table 14 consolidates the publication-level objective mapping with the objective taxonomy used for tertiary marine EMS and secondary PMS objectives. It therefore combines the detailed literature extraction with the interpretation of objective category, sub-objective, objective interaction, and relevant control time horizon.

The most common objective in marine energy management is to minimise the fuel consumption of a single fuel, most prominently diesel, which can be translated into the financial aspect of operational cost. In general, the reduction in fuel consumption equals an increase in fuel efficiency. Research showed that fuel consumption can already be reduced by using advanced control without implementing an additional ESS (Lai & Illindala, 2018; Wang et al., 2021). For example, Kanellos et al. (2014) implement demand side management with the objective of cost reduction for an all-electric (AE) cruise ferry. However, the fuel efficiency increases further by using an ESS system to buffer for energy transitions and to operate engines or fuel cells at their optimum. The reduction of fuel consumption in a system using an ESS was studied by a variety of researchers (Fang et al., 2019, 2020; Jiang et al., 2025; Kalikatzarakis et al., 2018; Kanellos, 2014; Xie et al., 2024). This objective is common for systems that include ICE (Kalikatzarakis et al., 2018), as well as FC-based systems (Jiang et al., 2025). The cost of shore power is another factor that is frequently considered in a cost reduction objective. Shore power, also called cold-ironing (CI), can be used to save fuel under operation further. Researchers who include CI in their studies often use a cost reduction objective (Banaei et al., 2021; Kanellos et al., 2017a; Tang et al., 2020; Tang, Li, & Lai, 2018; Tang, Wu, & Li, 2018; Xie et al., 2024). The last two factors of a cost reduction objective are the cost of emission output (Hein et al., 2020) and the maintenance cost of the vessel, which is caused by the degradation of vessel components.

Another frequently used objective in marine power and energy management studies is the reduction of emission output, most importantly CO_2 (Fang et al., 2019; Gao et al., 2018; Kanellos et al., 2017a, 2014; Papalambrou et al., 2017; Skjong et al., 2017; Tang, Wu, & Li, 2018). Commonly, this is combined with a reduction of the operational costs (Fang et al., 2019; Gao et al., 2018; Kanellos et al., 2017a, 2014; Papalambrou et al., 2017; Skjong et al., 2017; Tang, Wu, & Li, 2018). The emission reduction can also be combined with a reduction of hazardous emissions such as NOx (Kanellos et al., 2017a; Skjong et al., 2017) and SOx (Kanellos et al., 2017a). Some studies also investigate noise generation as an emission-related objective (Kanellos et al., 2017a; Skjong et al., 2017).

A third objective group is the extension of the component lifetime by reducing the ageing rate of the vessel components. Battery ageing is most commonly found in studies that incorporate battery energy storage (Banaei et al., 2021; Fang et al., 2019, 2020; Hein et al., 2020). Battery ageing can be reduced by limiting the depth of discharge, the current rates and by keeping the battery temperature in a certain range. Other common components are the ICE and FC (Jiang et al., 2025). Reducing the wear of those components through optimal operation will lead to fewer and less frequent replacements and avoid unplanned faults. The reduction of generator wear is a common objective in MES studies (Gao et al., 2018; Hein et al., 2020; Kanellos et al., 2017b, 2014; Skjong et al., 2017; Tang, Li, & Lai, 2018).

A last objective, which is available only if an EMS system is included in the power plant, is the availability of the ship system. Availability is defined as the probability that a system will perform its required function during the course of a mission or period of time (Kalikatzarakis et al., 2018). Objectives focusing on system availability aim at keeping the system reliability high to prevent failure and keep the ship functional. This objective is found in a smaller amount of papers (Kalikatzarakis et al., 2018; Kanellos et al., 2017b; Skjong et al., 2017).

4.4.2. Constraints

As the MES is an electric power system, an important constraint is the power balance (Geertsma et al., 2017). This constraint ensures the balance between generated power and load demand at all times. In addition to the power balance, component constraints are used to restrict the operation of each power system component to their respective limits. Examples are the minimum and maximum SOC of

Table 13
Automotive EMS control strategies.

Strategy family	Representative source / implementation	Objective	System/application	Architecture, prediction, or model representation	Validation, contribution, or maturity
Review/taxonomy	Automotive EMS reviews (Panday & Bansal, 2014; Zhang, Wang, et al., 2020)	Strategy classification	Road vehicles	Reviews of advanced EMS approaches.	Classifies instantaneous, predictive, optimisation, and learning strategies.
	FC-vehicle EMS review (Sulaiman et al., 2015)	FC EMS	Fuel-cell vehicles	Review of FC energy-management methods.	Informs FC–battery and FC-supercap hybrid design.
	ICE–battery HEV EMS review (M. Sabri et al., 2016)	HEV EMS	ICE–battery HEV	Review of HEV energy-management strategies.	Highlights complexity beyond battery-only EV EMS.
ECMS and instantaneous optimisation	ECMS (Li et al., 2018)	Fuel consumption	FC HEV	Instantaneous ECMS power-split optimisation.	Shows fuel savings in FC hybrid vehicles.
	ECMS (Li et al., 2019)	Fuel consumption	FC HEV	ECMS for FC–battery operation.	Shows fuel savings in FC HEVs.
	Adaptive ECMS (Lei et al., 2020)	Fuel consumption	ICE HEV	Adaptive factor tuning for ICE–battery split.	Shows ECMS extension for ICE HEVs.
	ECMS (Nüesch et al., 2014)	Fuel, NOx	ICE HEV	Emission-aware ECMS for ICE HEVs.	Extends ECMS toward emission control.
	ECMS (Torreglosa et al., 2011)	Fuel consumption	FC HEV	ECMS for FC–battery/supercap power sharing.	Validates ECMS in FC hybrids.
	Adaptive ECMS (H. Li et al., 2019)	Fuel, degradation	FC HEV	Adaptive ECMS with online estimation.	Adds degradation-aware adaptation.
	ECMS (Zhang et al., 2017)	Fuel consumption	FC HEV	ECMS for hydrogen FC–battery split.	Shows hydrogen savings in FC HEVs.
	ECMS (García et al., 2012)	Fuel consumption	FC HEV	ECMS for FC–battery–supercap hybrids.	Evaluates FC-supercap hybrid viability.
	ECMS (Gao et al., 2009)	Fuel consumption	ICE HEV	ECMS for ICE–battery hybrids.	Validates ECMS for ICE HEV fuel saving.
MPC and predictive optimisation	Nonlinear MPC (Borhan et al., 2012)	Fuel consumption	ICE HEV	Nonlinear predictive control for hybrid powertrains.	Shows MPC fuel savings in ICE HEVs.
	Multi-horizon MPC (Hu et al., 2022)	Fuel, cost	ICE HEV	Multi-horizon predictive control.	Combines fuel and cost objectives.
	Nonlinear MPC (Wang et al., 2018)	Fuel consumption	NG HEV	Nonlinear MPC with drivetrain/load prediction.	Shows fuel savings in NG HEVs.
	Nonlinear MPC with RNN (Pereira et al., 2021)	Fuel, degradation	FC HEV	RNN-supported MPC prediction.	Adds degradation-aware predictive control.
	Adaptive MPC (Jinquan et al., 2019)	Fuel consumption	ICE HEV	Adaptive MPC for changing driving conditions.	Shows adaptive fuel savings.
	Two-level MPC (Uebel et al., 2019)	Fuel consumption	ICE HEV	Layered MPC structure.	Targets real-time predictive EMS.
	MPC with ELM (He et al., 2021)	Fuel consumption	ICE HEV	ELM-supported MPC prediction.	Shows data-driven predictive EMS.
	Economic MPC (Pozzato et al., 2020)	Cost	ICE HEV	Online economic MPC.	Shows cost-oriented HEV control.
	Stochastic MPC (Xie et al., 2019)	Fuel consumption	ICE HEV	Stochastic MPC with Pontryagin.	Lower computation vs. DP.
	MPC (Rodriguez et al., 2022)	Cost, degradation	FC HEV	Predictive control combined with fuzzy-logic or degradation-aware modelling.	Addresses cost and degradation objectives in FC HEV energy management.
	Real-time MPC (X. Li et al., 2019)	Fuel consumption	ICE HEV	Predictive energy management solved with computationally efficient optimisation, including quadratic programming.	Demonstrates real-time optimal energy management capability.
	ECMS–MPC (Zhang et al., 2021)	Fuel consumption	ICE HEV	Combination of MPC with instantaneous optimisation.	Reduces computational burden while retaining predictive information.
	Stochastic MPC with Markov chain Cairano et al. (2014)	Efficient operation	ICE HEV	Stochastic prediction using Markov-chain-based driving behaviour or load modelling.	Demonstrates stochastic predictive control for efficient HEV operation.

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Table 13 (*continued*).

Strategy family	Representative source / implementation	Objective	System/application	Architecture, prediction, or model representation	Validation, contribution, or maturity
	MPC for EV-grid interaction (Kennel et al., 2013)	Grid-connected EV energy management	Smart grid/EV	MPC applied to the coupling between smart grids and electric vehicles.	Shows the bridge between automotive EMS and residential-grid control when EVs act as temporary storage.
Data-driven MPC and machine-learning-supported control	NN-based EMS (Moreno et al., 2006)	Distance/battery	HEV	NN-based hybrid EMS.	Early NN work for battery discharge reduction.
	MPC with LSTM (Chen et al., 2021)	Cost	EV + ultracapacitor	LSTM-based prediction for MPC.	Shows LSTM-supported predictive EMS.
	Deep Q-learning MPC (Z. Chen et al., 2022)	Fuel consumption	ICE HEV	Deep Q-learning-supported predictive EMS.	Applies RL tools inside MPC.
	MPC with ELM (Tang et al., 2021)	Fuel, degradation	ICE HEV	ELM-based speed prediction.	Proposes fuel and aging-aware control.
Reinforcement learning	RL (Reddy et al., 2019)	Battery management	FC HEV	Learning-based EMS for FC hybrids.	Shows RL potential for battery EMS.
	Multi-step RL (Zhou et al., 2019)	Efficient operation	HEV	Multi-step RL with extended horizon.	Shows advanced RL with look-ahead.
	RL (Lee et al., 2020)	Fuel consumption	ICE HEV	RL EMS benchmarked against DP.	Nearly matches DP fuel efficiency.

a battery (Banaei et al., 2021; Gao et al., 2018; Hein et al., 2020), minimum and maximum power output bounds of generators or fuel cells (Gao et al., 2018; Hein et al., 2020; Kanellos, 2014), and maximum current or slew-rate limitations on components (Haseltalab et al., 2016; Papalambrou et al., 2017). The current ramp-rate limitations are important, especially for slower fuel-cell dynamics. In addition, operational constraints can also express operational requirements, such as the minimum spinning reserve (Kalikatzarakis et al., 2018; Kanellos, 2014). Together, these constraints ensure the power system and its components operate in a safe and feasible way.

4.4.3. Variable space

An overview of common variables in MES control problems is presented in Table 15. Common state variables include the battery SOC (Banaei et al., 2021; Fang et al., 2019; Gao et al., 2018; Hein et al., 2020) and the grid voltage or frequency (Geertsma et al., 2017; Haseltalab & Negenborn, 2017; Haseltalab et al., 2016). Further common states are the current or power output of power-generation components such as engines, fuel cells or PV panels (Banaei et al., 2021; Vu et al., 2017). Propulsive load, requested power or wind speed are typical disturbances. The control variables are generally either the power or current setpoints for various components. This includes the power split between several generators or the commanded current to a battery.

4.4.4. Strategies

In the maritime sector, a wide variety of control approaches was used for the energy management and power management of electric and hybrid vessels. Several researchers reviewed the energy management in the maritime sector in recent years (Maloberti & Zaccone, 2025; Oo & Kong, 2023; Planakis et al., 2022b; Xie et al., 2022).

The first prominent control approach for MES is the Equivalent Consumption Minimisation Strategy (ECMS). Originally proposed for automotive HEV, ECMS was also found to be effective for MES. The major objective is the reduction of fuel consumption by optimising the power split between an ICE and a battery (Li et al., 2018, 2019). L"offler et al. (2025) present a multi-objective ECMS for hybrid and fully electric vessels, which includes fuel consumption, CO_2, NOx and battery ageing. The study compares several multi-objective formulations across a variety of operating profiles and vessel types, demonstrating that the ECMS can be applied across vessel types.

Several control approaches for MES are related to the idea of hierarchical control architectures. A hierarchical control architecture implements a hierarchy between the controllers of the system. Information is passed between the different levels of control, whereby in general control inputs are passed down top to bottom. A hierarchical structure provides the advantage of combining different degrees of complexity or time step widths in separate levels of one control. This is shown by Kanellos (2014), who implement a 3-stage optimisation using dynamic programming and particle swarm optimisation. Other publications incorporate droop control (Alam et al., 2022; Jin et al., 2018), MPC (Haseltalab et al., 2016; Vu et al., 2017) or other multi-level approaches (Fang & Xu, 2020; Hein et al., 2020) in a hierarchical framework. Hierarchical control shows good results for the application in the control of ESS in the EMS/PMS (Fang et al., 2019; Jin et al., 2018; Kanellos, 2014), incorporation of predictive control (Haseltalab et al., 2016; Hein et al., 2020; Vu et al., 2017), and the optimisation of power sharing between components (Alam et al., 2022). Hierarchical control is a suitable choice for use cases focusing on the optimal integration of ESS and system state prediction.

Distributed control is an approach to decentralise the control structure, by using independent controllers that communicate amongst each other rather than a predefined hierarchy (Antonelli, 2013). This is generally realised by defining independent zones supervised by own controllers. Information and interface data is handed over between the controllers, but no control directions. A common approach for distributed control is the usage of control agents to optimise the operation of dynamic systems. Applications for distributed agent control are shown for shipboard microgrids (Feng et al., 2012; Vu et al., 2015; Wang et al., 2021). The studies showed that the resilience and flexibility of the system control were improved. Besides the use of agents, distributed control can also be implemented in other frameworks, as shown by Lai and Illindala (2018) using the ADMM algorithm or Edrington et al. (2020) optimising with Algebraic Consensus. One common objective for the application in the control of shipboard microgrids is real-time control, where distributed control frameworks were shown to achieve good results. Besides the ability to operate in real-time, one advantage of distributed architectures is their applicability for survivable control. Distributed control strategies were shown to be able to sufficiently shed loads in less important zones of a shipboard power grid to ensure operability and maintain critical loads under all circumstances (Feng et al., 2018; Lai & Illindala, 2018).

Table 14
Marine EMS/PMS objectives.

Category	Sub-objective	Description/role	Relation/horizon	Key references/combinations
Cost reduction and energy efficiency	Fuel consumption / cost	Fuel/cost reduction, the most common MES objective across diesel, hybrid, and FC vessels.	Often aligned with CO_2, but may conflict with degradation under aggressive battery/generator use.	Representative studies on fuel/cost, emissions, degradation, and noise-aware EMS: Banaei et al. (2021), Fang et al. (2019), Kanellos et al. (2017a), Lai and Illindala (2018), Tsoumpris and Theotokatos (2019), Xie et al. (2024).
Cost reduction and energy efficiency	Shore power / cold ironing	Shore-power cost during port/at-berth operation and electricity-price-driven dispatch.	Often beneficial with fuel cost; emissions depend on grid mix.	Key studies on shore power and cost-aware EMS: Banaei et al. (2021), Kanellos et al. (2017a), Tang, Wu, and Li (2018).
Cost reduction and energy efficiency	Emission cost	Monetary penalty for emissions, combining economic and environmental objectives.	Generally aligns with emissions; often complements fuel cost objectives.	Emission-aware economic EMS studies: Hein et al. (2020), Kanellos et al. (2017a).
Cost reduction and energy efficiency	Maintenance cost	Degradation-related cost linking short-term dispatch to long-term replacement.	Often adversarial with aggressive operation; supports degradation reduction.	Degradation-aware EMS studies: Banaei et al. (2021), Hein et al. (2020), Tsoumpris and Theotokatos (2019).
Emission reduction	CO_2 reduction	Greenhouse-gas reduction; often tied to fuel consumption in single-fuel systems.	Generally aligns with fuel cost; may conflict with degradation if extra cycling is required.	Representative CO_2-aware EMS studies: Fang et al. (2019), Hein et al. (2020), Kanellos et al. (2017a).
Emission reduction	NOx/hazardous emissions	Reduction of combustion-related hazardous emissions, which depend on engine operating point and transient behaviour.	Partly independent from CO_2; critical in ECAs, ports, and nearshore.	Hazardous-emission-aware EMS studies: Löffler, Geertsma, Polinder, and Coraddu (2024), Nüesch et al. (2014), Planakis et al. (2022a).
Emission reduction	CH_4/methane slip	Methane-slip reduction for gas or dual-fuel engines.	Often differs from fuel-efficiency objectives; important for LNG/dual-fuel vessels.	Not yet widely covered in the extracted MES objective matrix.
Component degradation reduction	Battery lifetime extension	Minimise battery ageing from cycling, C-rate, and temperature.	Often adversarial with fuel cost and fast transients; relevant long-term.	Battery-degradation EMS studies: Banaei et al. (2021), Hein et al. (2020), Tsoumpris and Theotokatos (2019).
Component degradation reduction	Fuel-cell/ICE lifetime extension	Reduce FC/ICE/generator wear by limiting ramps and cycling.	Can conflict with cost; supports stable load sharing.	Degradation-aware EMS studies: Banaei et al. (2021), Edrington et al. (2020), Hein et al. (2020), Park et al. (2015).
Component degradation reduction	Power ramp mitigation	Limit power ramps to reduce stress on machines and converters.	Good for lifetime and stability; may conflict with fast load following.	Ramp-mitigation EMS studies: Edrington et al. (2020), Park et al. (2015), Seenumani et al. (2012).
Noise and vibration reduction	Noise reduction	Reduce engine/generator noise for port, passenger, and tactical operation.	Often adversarial with fuel cost; indirectly linked to CO_2.	Noise-aware EMS study: Mitropoulou et al. (2020).
Noise and vibration reduction	Vibration reduction	Reduce vibration for comfort, acoustic signature, or mechanical stress.	May conflict with fuel cost; relevant for passenger and tactical vessels.	Relevant extension for passenger and naval MES.
Secondary control objectives	Power-system stability	Maintain frequency and voltage for safe shipboard operation.	Prerequisite for EMS; relevant in real time.	PMS stability and droop/DC studies: Geertsma et al. (2017), Guerrero et al. (2011), Zahedi et al. (2014).

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Table 14 (*continued*).

Category	Sub-objective	Description/role	Relation/horizon	Key references/combinations
Secondary control objectives	Load sharing	Power split between parallel components, including diesel generators, fuel cells, batteries, electric drives, and shore-power interfaces. At PMS level, this implements or stabilises the setpoints provided by the EMS layer.	Supports tertiary objectives because it determines how EMS decisions are physically realised. Relevant in real time and over fast dynamic timescales.	Load-sharing and PMS formulation: Geertsma et al. (2017). Real-time power management: Seenumani et al. (2012). Distributed power management: Wang et al. (2021).
Secondary control objectives	Real-time optimisation	Fast solution time is required because shipboard electrical systems can experience rapid load changes due to propulsion, thrusters, hotel loads, mission loads, and auxiliary systems.	Acts as a constraint on the choice of control strategy, prediction horizon, and solver. Relevant in real time.	Real-time PMS and multi-level predictive control: Haseltalab and Negenborn (2019), Haseltalab et al. (2016), Seenumani et al. (2012).

Table 15
Variable space of Marine Energy System control problems.

Variable class	Variable	Role in MES control problem	References
State variables	Battery/ESS State of Charge	Energy-storage state used to monitor available stored energy, enforce admissible SOC limits, and schedule charge/discharge operation.	Banaei et al. (2021), Fang et al. (2019), Gao et al. (2018), Hein et al. (2020)
	Grid voltage/frequency	Electrical-network state associated with power-system stability, power balance, and PMS-level voltage/frequency regulation.	Geertsma et al. (2017), Haseltalab and Negenborn (2017), Haseltalab et al. (2016)
	Power output of engines/generators	Source-loading state used to evaluate fuel consumption, generator operating point, load sharing, and power-generation constraints.	Banaei et al. (2021), Vu et al. (2017)
	Fuel-cell current/voltage	Fuel-cell operating state related to stack power, hydrogen consumption, transient limits, and fuel-cell health.	Banaei et al. (2021)
	PV panel current	Renewable-generation state used for PV-equipped vessels and solar-power contribution estimation.	Tang, Wu, and Li (2018)
Control variables	Battery charge/discharge power setpoint	Storage-control input used to command battery charging or discharging and to buffer load transients.	Banaei et al. (2021), Gao et al. (2018), Hein et al. (2020)
	Engine/generator power setpoint	Source-control input used to allocate power among engines or generators and determine their operating points.	Gao et al. (2018), Hein et al. (2020), Kanellos (2014)
	Fuel-cell power setpoint/current setpoint	Fuel-cell control input used to define the fuel-cell contribution to the power split and regulate fuel-cell loading.	Banaei et al. (2021), Vu et al. (2017)
	Converter signals, current/voltage/duty factor	Power-electronic control variables used to regulate current, voltage, and power flow between sources, storage, converters, and the shipboard grid.	Haseltalab et al. (2016), Papalambrou et al. (2017)
Disturbances/inputs	Required propulsive load/load torque	Exogenous load demand imposed by the vessel mission, propulsion system, manoeuvring condition, and environmental resistance.	Banaei et al. (2021), Fang et al. (2019), Gao et al. (2018), Haseltalab et al. (2016)
	Solar irradiation	Weather-dependent input for PV-equipped vessels; determines available solar generation and affects renewable-power forecasting.	Tang, Wu, and Li (2018)
	Wind speed	Environmental disturbance influencing vessel resistance, propulsion load, and renewable generation when wind-energy systems are present.	Fang et al. (2019)

For marine application, MPC was introduced as a control strategy around 2015 and the research interest increased drastically afterwards. MPC was shown to be successfully implemented for both tertiary (Banaei et al., 2021; Hou et al., 2018; Papalambrou et al., 2017; Tang, Wu, & Li, 2018) and secondary (Haseltalab & Negenborn, 2017; Haseltalab et al., 2016; Park et al., 2015) control. Several forms of MPC were used, such as adaptive MPC (Hou et al., 2018) or stochastic MPC (Banaei et al., 2021). Other research combined MPC with distributed energy and power dispatch architectures (Edrington et al., 2020). MPC for maritime EMS is applied for a variety of objectives. A common one is the realisation of demand side management and power generation scheduling (Edrington et al., 2020; Park et al., 2015; Stone et al., 2015; Vu et al., 2017). Other studies showed promising results for achieving savings in cost and emissions (Tang, Wu, & Li, 2018) and component aging prevention (Banaei et al., 2021). Another important objective for marine PMS and EMS is the ability to solve the problem in real-time (Haseltalab et al., 2016). In more recent work, MPC was also studied for fuel-cell-based vessels (Jiang et al., 2025; Xie et al., 2024).

The current state of literature shows that MPC is a suitable control strategy for certain marine power and energy systems. Considering the load profiles of vessels in the maritime sector, the main application of the strategy are vessels with low uncertainty in operation, for example with a fixed route and time-scheduled operating profile. Observing the usage of objectives, it can be stated that the current status of MPC application is still on a basic level. Many studies carried out proof of concept for power scheduling and did not implement complex objectives. A challenging factor is the prediction models required, since marine energy systems display non-linear behaviour. Potential for improvements can be identified by observing the building control sector, which incorporates MPC for highly non-linear systems as well. The computational efficiency can be improved by taking into account the developments of the automotive sector. In addition, by looking at the progress of other sectors, open gaps can be identified in improving robustness and real-life validation.

The use of data-driven methods for MES control has also gained interest. Planakis et al. (2022a) present an approach using machine learning models trained on marine loading cycles for energy management validation. Several researchers showed that RL strategies can provide promising results for MES control (Maloberti & Zaccone, 2025; Oo & Kong, 2023). Oo and Kong (2023) present a real-time energy management approach for marine applications using a Markov approximation-based RL strategy. The advantage over existing approaches is the real-time applicability without requiring any prior knowledge of the load profile.

Table 16 consolidates the strategy-level synthesis and the publication-level mapping. It therefore replaces the compact study-extraction table and the broader strategy-overview table, while preserving the distinction between ECMS, hierarchical control, distributed control, MPC, data-driven approaches, reinforcement learning, demand-side management, and heuristic or fuzzy strategies.

4.5. Generic approach to energy system control model development

After analysing the control of all four energy systems, general rules for the set-up of an energy system control can be derived. The energy system can be represented inside the controller as a mathematical system model S. For control application, continuous time models are discretised. Under the condition that the sampling rate is chosen accordingly a discrete time model is mathematically proven to accurately resemble the system behaviour (Rawlings et al., 2017). The system model S entains a set of functions to describe the system behaviour and is represented by:

$$S = (X, U, Y, \{f\}_{i=1}^{n}, F, h), \tag{1}$$

where X is state space, U is the input space, and, Y is the output space. In this formulation, $\{f\}_i^n$ contains all functions of potential subsystems, h maps the output to the space Y, while F describes the system evolution of a point x as follows:

$$x_{k+1} = F(f_1(x_k, u_k), \dots, f_n(x_k, u_k), u_k). \tag{2}$$

In addition, the output space is connected to the state and input space using

$$y_k = h(x_k, u_k). \tag{3}$$

This general representation of a control model in discrete time needs to be tailored for the specific energy system. The chosen state variables x and control variables u depend on the exact system to be controlled and are chosen dependent on its exact properties. The set of functions then derives from the chosen variables and the components entained in the system. To further shape the energy system controller, an objective function, as well as a set of equality and inequality constraints needs to be added. These aspects are going to be detailed in the following to illustrate the build-up of a generic energy system model.

Objective function design. The objective function can be build up from several aspects and adjusted to the intended application of the controller. These aspects can be divided into parts that maintain the system operation and additional objectives that aim to optimise the operation.

For maintaining the system operation, two formulations are commonly used in the objective function of most problems. The first one is a term to bind the state variables x_k to desired reference points r_k:

$$\|y_k - r_k\|_{Q_k}^2, \tag{4}$$

using an error matrix Q_k to penalise deviation from the reference. The second is a term to penalise excessive control actions. This can be done in two formulations. Either the values of the control variables are penalised in the form of

$$\|u_k\|_{R_k}^2, \tag{5}$$

using an error matrix R_k, or the fluctuation of the control variables is penalised as follows:

$$\|\Delta u_k\|_{R_k}^2. \tag{6}$$

The change of control values is defined as:

$$\Delta u_k = u_k - u_{k-1}, \tag{7}$$

where u_{k-1} is the control action of the previous step. Commonly, if control actions deviate from a zero in the steady-state, the first formulation is chosen, while the second is employed when the system receives a continuous stream of control actions. In this case, the change of control values needs to be punished to limit fluctuation.

In addition to the formulations for the maintenance of system operation, optimisation objectives can be added to achieve a desired operation of the system. The common optimisation objectives discussed in this paper are:

- Fuel consumption: $\sum_{k=0}^{N-1} \dot{m}_{f,k}(x_k, u_k) \cdot \Delta t$
- Emission output: $\sum_{k=0}^{N-1} \dot{m}_{e,k}(x_k, u_k) \cdot \Delta t$
- Component degradation: $\sum_{k=0}^{N-1} \Phi_k(x_k, u_k)$
- Operational cost: $\sum_{k=0}^{N-1} c_k \cdot P_k(x_k, u_k) \cdot \Delta t$

where $\dot{m}_{f,k}$ is the fuel mass flow rate, $\dot{m}_{e,k}$ is the emission mass flow rate, Φ_k is the degradation rate of a component, c_k is the energy price, and P_k is the power consumed or generated, all evaluated at time step k. For multi-objective control, a weighted sum of these terms is typically used:

$$J = \sum_{k=0}^{N-1} \left[\|y_k - r_k\|_{Q_k}^2 + \|\Delta u_k\|_{R_k}^2 + \sum_j w_j \cdot \ell_j(x_k, u_k) \right], \tag{8}$$

where w_j are scalar weighting factors and ℓ_j are the individual optimisation objective terms.

Table 16
Marine EMS control strategies.

Strategy family	Representative source / implementation	Objective(s)	System/application	Architecture, prediction, or model representation	Validation, contribution, or maturity
Review and taxonomy studies	Maritime EMS reviews (Planakis et al., 2022b; Xie et al., 2022)	EMS/PMS classification; optimisation-based control; real-time EMS; environmental sustainability	Hybrid and electric vessels	Review and taxonomy of optimisation-based, real-time, learning-based, and environmentally oriented marine energy-management strategies.	Establishes the main research trends and motivates the comparison between maritime EMS/PMS and terrestrial energy-system control.
ECMS and instantaneous optimisation	ECMS transfer from automotive HEV concepts (Li et al., 2018, 2019)	Fuel consumption; ICE–battery or FC–battery power split	Hybrid powertrains	Instantaneous optimisation using equivalent consumption factors, originally developed for automotive HEV and transferred conceptually to marine hybrid systems.	Suitable for uncertain load profiles because it does not require a prediction model or a known future mission profile.
	Marine ECMS (Kalikatzarakis et al., 2018)	Fuel consumption	Hybrid marine power plant	ECMS-based marine energy management for power-split optimisation.	Early marine application showing potential for fuel-consumption reduction.
	Health-aware ECMS (Tsoumpris & Theotokatos, 2019)	Fuel consumption; battery health	Hybrid marine power plant	ECMS extended with health-aware terms for energy-storage degradation.	Shows the possibility of combining instantaneous fuel minimisation with component-health considerations.
	Emission-aware and multi-objective ECMS (Löffler, Geertsma, Mitropoulou, et al., 2024; Löffler et al., 2023)	Fuel consumption; CO_2; NOx; battery ageing	Hybrid and fully electric vessels	Multi-objective ECMS formulations including fuel use, emissions, and battery-ageing penalties.	Shows applicability across operating profiles and vessel types; extends ECMS from single-objective fuel minimisation to multi-objective marine EMS.
Hierarchical control	Three-stage optimisation (Kanellos, 2014)	ESS integration; power sharing; optimal power management	All-electric ship/shipboard power system	Hierarchical optimisation combining dynamic programming and particle swarm optimisation.	Shows the value of separating optimisation layers in marine power-management problems.
	Hierarchical droop-based control (Alam et al., 2022; Jin et al., 2018)	Power sharing; voltage/frequency regulation; robustness	Shipboard microgrids	Hierarchical control including lower-level droop or robust droop-based power-sharing layers.	Suitable for integrating PMS-level stability requirements with higher-level EMS decisions.
	Hierarchical predictive control (Haseltalab et al., 2016; Vu et al., 2017)	Predictive scheduling; real-time PMS/EMS; power sharing	Shipboard power systems	Multi-level architecture combining prediction-based optimisation with lower-level power-management control.	Demonstrates how different time scales can be handled within one layered architecture.
	Multi-level and robust scheduling (Fang & Xu, 2020; Hein et al., 2020)	Cost; emissions; degradation; ESS scheduling	Hybrid and electric vessels	Hierarchical or multi-step optimisation with robust or multi-objective formulations.	Shows suitability of hierarchical control for ESS coordination, multi-objective scheduling, and uncertain operation.
Distributed and multi-agent control	Multi-agent shipboard microgrid control (Feng et al., 2012; Wang et al., 2021)	Real-time power dispatch; flexibility; resilience	Shipboard microgrids	Distributed control using agents that communicate local information and coordinate without a single central hierarchy.	Demonstrates improved resilience and flexibility for shipboard microgrid operation.
	Distributed energy management using ADMM (Lai & Illindala, 2018)	Fuel consumption; survivable control; load shedding	Shipboard power grid	Distributed optimisation using the alternating direction method of multipliers.	Demonstrates real-time distributed energy management and the ability to preserve critical loads.
	Algebraic-consensus-based distributed EMS (Edrington et al., 2020)	Generator degradation; distributed dispatch	Shipboard power system	Distributed optimisation using algebraic consensus.	Demonstrates distributed power dispatch and coordination without relying on a fully centralised controller.
	Survivable load control (Feng et al., 2018)	Load shedding; critical-load preservation	Shipboard power grid	Distributed survivable control for prioritising loads under constrained or faulted operation.	Shows that distributed approaches can shed non-critical loads while maintaining essential ship functions.

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Table 16 (*continued*).

Strategy family	Representative source / implementation	Objective(s)	System/application	Architecture, prediction, or model representation	Validation, contribution, or maturity
MPC and predictive control	MPC for tertiary EMS (Hou et al., 2018; Tang, Wu, & Li, 2018)	Cost; emissions; battery ageing; scheduling	Hybrid vessels; PV-equipped vessels; shipboard EMS	Predictive optimisation using future load, generation, weather, or operational information.	Demonstrates MPC applicability to tertiary EMS objectives such as cost, emissions, and ageing prevention.
	MPC for secondary PMS (Haseltalab & Negenborn, 2017; Park et al., 2015)	Real-time power management; generator stress reduction; stability	Shipboard power systems	Predictive PMS operating at faster time scales than tertiary EMS.	Demonstrates MPC applicability to real-time power management and generator-load coordination.
	MPC for DSM and scheduling (Edrington et al., 2020; Vu et al., 2017)	Demand-side management; power-generation scheduling	Shipboard power systems	Predictive control for load scheduling, power-generation allocation, and power-management coordination.	Shows MPC potential for DSM and power-generation scheduling in marine electrical systems.
	Stochastic MPC (Banaei et al., 2021)	Cost; battery ageing; fuel-cell ageing; scheduling	Hybrid marine power system	Stochastic predictive control accounting for uncertain disturbances or future operating conditions.	Suitable for systems with uncertain load profiles and degradation-sensitive components.
	Adaptive MPC (Hou et al., 2018; Papalambrou et al., 2017)	Fuel consumption; robustness; emissions	Hybrid vessels/marine power systems	Adaptive or robust predictive formulation addressing model uncertainty and changing operating conditions.	Improves robustness under uncertainty and supports application to nonlinear marine systems.
	Two-layer and real-time MPC for FC-based vessels (Jiang et al., 2025; Xie et al., 2024)	Fuel consumption; real-time EMS; FC operation	Fuel-cell-based marine systems	Two-layer or real-time predictive EMS for coordinating FC, ESS, and load demand.	Recent extension of MPC-based marine EMS toward FC-based vessel architectures.
Data-driven and learning-supported control	Data-driven fuel-consumption modelling (Coraddu et al., 2017)	Fuel-consumption modelling; performance prediction	Marine vessels	Data-driven model development for vessel fuel-consumption estimation.	Provides a modelling basis for later data-driven EMS and validation frameworks.
	ML-based EMS validation (Planakis et al., 2022a)	Energy-management validation; loading-cycle modelling	Marine vessels	Machine-learning models trained on marine loading cycles.	Shows the use of data-driven models for validating energy-management strategies.
Reinforcement learning	Markov-approximation-based RL (Oo & Kong, 2023)	Real-time EMS; fuel consumption	Marine applications	Model-free learning strategy using Markov approximation; no prior knowledge of the load profile required.	Shows real-time applicability and suitability for uncertain load profiles.
	Environmentally sustainable RL-oriented EMS (Maloberti & Zaccone, 2025)	Fuel consumption; environmental impact	Marine energy systems	Learning-based or environmentally oriented EMS formulation.	Indicates increasing interest in RL and data-driven control for sustainable marine energy management.
Demand-side management and rule-based coordination	Demand-side management (Kanellos et al., 2014)	Cost; emissions; load scheduling	All-electric cruise ferry	Centralised optimisation and demand-side management for shipboard loads.	Demonstrates DSM as a marine EMS strategy, especially for large all-electric vessels.
	Data-driven robust coordination (Fang et al., 2020)	Fuel consumption; robust coordination	Hybrid marine power system	Robust coordination of energy sources using data-driven or uncertainty-aware information.	Used as a coordination strategy and benchmark for advanced EMS designs.
Fuzzy logic and case-specific optimisation	Fuzzy logic EMS (Yuan et al., 2018)	Fuel consumption	Hybrid marine power system	Rule-based fuzzy logic controller for energy-management decisions.	Useful for case-specific control where interpretability and simple implementation are prioritised.
	Case-specific optimal EMS (Tang, Li, & Lai, 2018)	Fuel consumption; electricity cost; PV integration	Hybrid vessel with PV and ESS	Optimisation-based strategy tailored to a specific hybrid-PV vessel configuration.	Demonstrates scenario-specific optimisation but with lower generality than model-based or learning-based strategies.

Equality constraints. Equality constraints express relationships that must always be exactly satisfied. The most fundamental equality constraint in energy system control is the power balance:

$$\sum_i P_{gen,i,k} - \sum_j P_{load,j,k} = 0 \quad \forall k, \tag{9}$$

where $P_{gen,i,k}$ is the generated power by source i and $P_{load,j,k}$ is the consumed power by load j at time step k. Equality constraints can also express the dynamics of the system model in the form $x_{k+1} = F(\cdot)$ as introduced above.

Inequality constraints. Inequality constraints express operational limits on state and control variables. Component operating limits can be written in a general form as:

$$x_{min} \leq x_k \leq x_{max} \quad \forall k, \tag{10}$$

$$u_{min} \leq u_k \leq u_{max} \quad \forall k. \tag{11}$$

In addition, ramp rate constraints on control variables can be expressed as:

$$\Delta u_{min} \leq \Delta u_k \leq \Delta u_{max} \quad \forall k. \tag{12}$$

These constraints cover physical limits, such as minimum and maximum SOC of a battery, maximum current of a fuel cell, torque–speed envelopes of engines, and maximum slew rates of power generation components. Soft constraints can also be introduced by adding slack variables $\varepsilon_k \geq 0$ to relax the bounds at the cost of a penalty term in the objective function:

$$x_{min} - \varepsilon_k \leq x_k \leq x_{max} + \varepsilon_k, \tag{13}$$

$$J \mathrel{+}= \rho \|\varepsilon_k\|^2, \tag{14}$$

where ρ is a large penalty weight. This formulation is commonly used for comfort constraints in BES and reserve constraints in MES, where strict hard bounds would render the problem infeasible under disturbances.

5. Optimisation algorithms

After reviewing the control strategies and architectures, we will now focus on the optimisation algorithms used to solve the control problems. A variety of algorithms is used in the literature for solving energy management problems, ranging from exact methods to metaheuristic approaches.

5.1. Exact methods

Exact methods solve optimisation problems to global optimality or certify infeasibility. Dynamic Programming (DP) is one of the most widely used exact methods for energy management optimisation. DP decomposes the problem into overlapping subproblems and solves them recursively (Bellman, 1957). For a finite horizon problem with N steps, the optimal cost-to-go function $V_k(x_k)$ is computed backward from the terminal condition:

$$V_k(x_k) = \min_{u_k} \left[\ell(x_k, u_k) + V_{k+1}(F(x_k, u_k)) \right], \tag{15}$$

with $V_N(x_N) = \ell_f(x_N)$. DP guarantees global optimality but suffers from the curse of dimensionality, which limits its applicability to low-dimensional state spaces. DP is widely used as a benchmark for other control strategies in the maritime (Kanellos, 2014), automotive (Nüesch et al., 2014), and building sectors.

Linear Programming (LP) and Mixed Integer Linear Programming (MILP) are used when the problem can be expressed or linearised as a linear program. In the maritime and microgrid sectors, MILP is used for unit commitment problems, where discrete decisions such as on/off states of generators are involved (Hein et al., 2020).

5.2. Metaheuristic methods

Metaheuristic methods are used when the problem is too complex or non-linear for exact methods. Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO) are among the most used approaches in the maritime sector (Gao et al., 2018; Kanellos, 2014). Those approaches perform stochastic search in the solution space and converge to near-optimal solutions without requiring gradient information. Their main disadvantage is the computational cost and the lack of convergence guarantees.

Table 17 summarises the main numerical approaches and solvers used for EMS/PMS optimisation problems. The table includes exact, metaheuristic, analytical, distributed, data-driven, and nonlinear-programming approaches, and compares them in terms of non-linear problem suitability and real-time applicability.

6. Multi-objective control

Multiple objectives can be combined into one control problem to find the best trade-off solution between conflicting objectives. Several methods exist to combine objectives. The most common is the weighted-sum approach, in which each objective is multiplied by a scalar weight and all terms are summed to form one scalar objective function. Adjusting the weights allows moving along the Pareto front of optimal trade-off solutions. Another approach is the ε-constraint method, in which one objective is minimised while all others are kept below predefined thresholds. Lexicographic optimisation prioritises objectives by rank, minimising secondary objectives only when the primary objective is satisfied.

In the literature, the combination of fuel consumption and component lifetime extension is the most commonly studied multi-objective pair in maritime EMS (Banaei et al., 2021; Fang et al., 2019; Hein et al., 2020). Cost and emission reduction are also frequently combined (Kanellos et al., 2017a; Tang, Wu, & Li, 2018). The combination of hazardous emission reduction and lifetime extension is a topic with high potential and limited research so far. Addressing this combination could provide insights into the feasibility of simultaneously achieving environmental and maintenance benefits in maritime energy management.

Table 18 summarises the pairwise relationships between the main tertiary MES control objectives. The table should be read as a qualitative synthesis of the reviewed literature rather than as a strict mathematical classification. In the table, beneficial relationships indicate that the objectives generally support each other or have aligned operating points; indifferent/unknown relationships indicate weak coupling, unclear interaction, or insufficient evidence; and adversarial relationships indicate that the objectives compete and require an explicit trade-off. Grey cells indicate the diagonal of the matrix, where an objective is compared with itself.

The combination of *fuel cost reduction and CO_2 reduction* is the most investigated relationship, with five studies, because the two objectives are generally aligned for single-fuel systems (Fang et al., 2019; Gao et al., 2018; Kanellos et al., 2017a, 2014; Tang, Wu, & Li, 2018). The combination of *fuel cost reduction and component degradation reduction* is the most studied adversarial pairing, with four studies (Banaei et al., 2021; Hein et al., 2021, 2020; Hou et al., 2018). The combination of *emission reduction and degradation reduction* is addressed in three studies (Fang et al., 2019; Gao et al., 2018; Tsoumpris & Theotokatos, 2019). Noise reduction has only limited coverage and is explicitly considered in one multi-objective study (Mitropoulou et al., 2020). Shore-power cost is linked to fuel-cost reduction through cold-ironing and at-berth operation (Banaei et al., 2021; Kanellos et al., 2017a; Tang et al., 2020; Tang, Li, & Lai, 2018; Tang, Wu, & Li, 2018; Xie et al., 2024).

The literature also reveals several research gaps. Major open gaps include the simultaneous integration of fuel cost, emissions, and degradation in one control formulation; hazardous emissions beyond CO_2,

Table 17
Overview of numerical approaches and solvers used for marine EMS/PMS optimisation problems.

Algorithm	Type	NL/RT	Role in EMS/PMS optimisation	Key references
Dynamic Programming	Exact/global	✓/×	Global benchmark for finite-horizon EMS problems; guarantees optimality but is limited by the curse of dimensionality.	Bellman (1957), Kanellos (2014), Lee et al. (2020), X. Li et al. (2019)
Particle Swarm Optimisation	Metaheuristic/global	✓/×	Population-based search for nonlinear and non-convex EMS problems; mainly suitable for offline or supervisory optimisation.	Kanellos (2014), Tang, Li, and Lai (2018)
Genetic Algorithm (GA)	Metaheuristic/global	✓/×	Evolutionary search for multi-objective or non-convex scheduling problems when gradients or convexity are unavailable.	Hein et al. (2020), Mitropoulou et al. (2020)
Quadratic Programming (QP)	Exact/local	(✓)/✓	Efficient solver for convex quadratic or locally approximated MPC formulations; suitable for real-time implementation.	X. Li et al. (2019), Park et al. (2015)
Pontryagin's Minimum Principle	Analytical	✓/✓	Analytical optimal-control method used to derive computationally efficient EMS laws and ECMS-type benchmarks.	Kalikatzarakis et al. (2018), Xie et al. (2019)
MILP/MINLP	Exact/mixed-integer	✓/×	Used for unit commitment, generator on/off scheduling, and mixed continuous–discrete EMS decisions.	Banaei et al. (2021), Fang et al. (2019), Hein et al. (2020)
ADMM	Distributed / iterative	(✓)/✓	Decomposes large EMS/PMS problems into coupled subproblems solved by local controllers or agents.	Lai and Illindala (2018)
Algebraic Consensus	Distributed	(✓)/✓	Consensus-based real-time power dispatch and power sharing between generators, zones, or distributed controllers.	Edrington et al. (2020)
Neural Network / Reinforcement Learning	Data-driven	✓/✓	Approximates control policies or value functions; useful for real-time EMS when sufficient training data or simulation models exist.	Feng et al. (2012), Oo and Kong (2023), Wang et al. (2021)
NLP/Interior Point	Exact/local	✓/(✓)	Local solver for nonlinear EMS formulations; real-time suitability depends on size, convexity, initialisation, and implementation.	Gao et al. (2018), Skjong et al. (2017), Tang et al. (2020)

Notes: NL = nonlinear problem suitability; RT = real-time applicability. ✓= applicable or demonstrated; (✓) = partially applicable or problem-dependent; ×= generally not suitable for real-time EMS/PMS use in the reviewed literature.

Table 18
Pairwise relationships between maritime EMS tertiary control objectives.

Objective A / Objective B	**Fuel cost reduction**	**CO_2 reduction**	**Hazardous emissions, NOx/PM**	**Battery lifetime extension**	**ICE/FC lifetime extension**	**Noise reduction**	**Shore-power cost**
Fuel cost reduction	—	Beneficial	Indifferent	Adversarial	Adversarial	Adversarial	Beneficial
CO_2 reduction	Beneficial	—	Indifferent	Adversarial	Adversarial	Adversarial	Beneficial
Hazardous emissions, NOx/PM	Indifferent	Indifferent	—	Unknown	Unknown	Unknown	Unknown
Battery lifetime extension	Adversarial	Adversarial	Unknown	—	Beneficial	Indifferent	Indifferent
ICE/FC lifetime extension	Adversarial	Adversarial	Unknown	Beneficial	—	Indifferent	Indifferent
Noise reduction	Adversarial	Adversarial	Unknown	Indifferent	Indifferent	—	Indifferent
Shore-power cost	Beneficial	Beneficial	Unknown	Indifferent	Indifferent	Indifferent	—

including NOx, PM, and CH_4; engine and fuel-cell lifetime as standalone objectives; maintenance cost as an explicit economic term; and noise and vibration reduction objectives for passenger, nearshore, port, and naval operation.

7. Validation and results

After analysing the control objectives, architectures, strategies, and optimisation algorithms, the validation methods and published results are reviewed in this section. Validation is a critical aspect of advanced energy-management research because reported savings depend strongly on the baseline controller, the assumed operating profile, the vessel or system configuration, and the fidelity of the model used for assessment. Validation strategies differ significantly between sectors due to the availability of real systems, hardware, operational data, and standardised benchmark cycles.

7.1. Validation strategies

In the building control sector, a large number of studies have been validated in actual buildings (Afram & Janabi-Sharifi, 2017; Freund & Schmitz, 2021; Sturzenegger et al., 2016). This level of experimental validation is not yet common in the maritime sector, where most studies rely on simulation-based validation. In the automotive sector, standardised driving cycles provide a reproducible benchmark for comparing control strategies (Lei et al., 2020; Nüesch et al., 2014). In the maritime sector, representative load profiles for specific vessel types and operational profiles are less standardised, which complicates the comparison of results across studies.

Recently, the use of machine learning models trained on maritime loading cycles has been proposed as a data-driven approach to bridge the gap between simulation and real-world validation (Planakis et al., 2022a). In addition, hardware-in-the-loop and scaled demonstrator setups are increasingly used to validate maritime energy management strategies in a more realistic environment (Jiang et al., 2025; Xie et al., 2024).

The resulting validation landscape is therefore heterogeneous. Some studies compare an advanced controller against a rule-based baseline, others compare variants of the same optimisation framework, and only a limited number include experimental, hardware-in-the-loop, or real-time validation. For this reason, the results reported in the literature should be interpreted as evidence of potential rather than as directly comparable performance indicators across all vessel types.

7.2. Published results

The results published in the literature vary significantly in scope and comparability. Fuel consumption savings between 5 and 30% are reported across a range of vessel types and operating profiles, depending on the control strategy, the baseline, and the power-system configuration (Fang et al., 2019; Hein et al., 2020; Kalikatzarakis et al., 2018). Emission reductions broadly follow fuel consumption improvements for CO_2, but may differ substantially for hazardous emissions such as NOx, where the engine operating point plays a critical additional role (Kanellos et al., 2017a; Skjong et al., 2017). The potential for battery lifetime extension through advanced control has been demonstrated in several studies, with reductions in degradation rates of up to 20% reported (Banaei et al., 2021; Fang et al., 2020). The current state of research does not allow us to conclude more than indications about the potential of advanced control usage in MES operation. For more concrete validation, further research will be required.

Table 19 summarises representative comparative results from marine EMS/PMS studies. The table highlights the diversity of validation approaches, including rule-based comparisons, variants of the same strategy, standard droop-control benchmarks, and simulation-based comparisons. It also shows that most reported improvements concern fuel consumption, operating cost, emissions, degradation, or real-time feasibility, while direct comparability remains limited by the absence of standard maritime benchmark cycles.

8. Reflection and future work

Based on the analysis of the four sectors and their control strategies, objectives, and validation approaches, this section reflects on the potential for knowledge transfer to marine energy system control and identifies open gaps for future research.

8.1. Cross-sector transfer to maritime control

The analysis of the four sectors reveals several concrete opportunities for knowledge transfer to maritime energy system control. These opportunities are best understood by relating vessel types to the sectors whose control challenges they most closely resemble.

Vessels with large crew or passenger complements, such as cruise ships and large naval vessels, share the dominant control challenge of building energy systems: managing large thermal masses with slow dynamics, comfort constraints, and forecastable occupancy-driven load profiles. The thermal inertia of cabin and accommodation areas, the HVAC load structure, and the potential for thermal storage all make predictive control strategies developed in the building sector — including MPC, DDMPC, and demand-side management — directly transferable to the hotel energy management of such vessels. Waste heat from engines or fuel cells can furthermore be integrated in a manner comparable to CHP in buildings.

Vessels with regular, predictable transport duties, such as ferries, ro–ro vessels, and survey vessels, share the control challenge of transport-oriented microgrids and predictive building systems. Their repetitive load profiles allow the development of accurate forecast models and enable schedule-based predictive control. MPC strategies validated in buildings and smart microgrids are applicable to these vessel types, provided that suitable prediction models for the marine load profile are available. The development and validation of such models is therefore an important area of future work.

Vessels with dynamic positioning, irregular tasking, or highly uncertain loads, such as offshore support vessels, tugs, and water taxis, share the control challenge of the automotive sector: fast-changing conditions, uncertain load demand, and the need for real-time energy management decisions under computational constraints. ECMS and real-time RL strategies developed for HEV and EV applications are therefore directly relevant for these vessel classes. Key open challenges include adapting the equivalent factor tuning approaches from automotive ECMS to the larger and more heterogeneous power systems of such vessels.

Vessels with high peak power demands, such as crane vessels, cable layers, and naval vessels with directed-energy systems, share the control challenge of islanded microgrids: multi-source coordination, power balance under fast transients, reserve management, and fault tolerance. Control architectures and stability-oriented strategies from the microgrid sector are therefore relevant for these vessels.

The introduction of fuel cells and alternative fuels in the maritime sector introduces additional control challenges that span all vessel types. These include managing the slow dynamic response of high-temperature SOFC, integrating hydrogen storage management into the EMS, coordinating multi-fuel operation under emission and efficiency objectives, and extending component lifetime objectives to include fuel-cell degradation. These challenges require adapting strategies from both the automotive FC-vehicle literature and the microgrid hydrogen-storage literature.

8.2. Open gaps and future research directions

Based on the review, several open gaps can be identified.

The first gap concerns the validation of advanced control strategies in real maritime applications. Most studies rely on simulation-based validation using simplified load profiles. Future work should target hardware-in-the-loop validation, scaled demonstrators, and ultimately field trials on actual vessels, following the approach already adopted in the building control sector.

The second gap concerns the treatment of hazardous emissions as a primary control objective. While CO_2 and fuel consumption are widely addressed, NOx, SOx, particulate matter, and methane slip are only treated in a small number of studies. Future work should address these objectives explicitly, particularly for vessels operating in emission control areas.

A third gap concerns multi-objective control combining lifetime extension and emission reduction. These two objectives are both of high practical relevance but have rarely been addressed together. Future work should investigate whether simultaneous improvement in both objectives is achievable and under what conditions trade-offs arise.

A fourth gap concerns the use of data-driven methods for maritime load forecasting and DDMPC. While data-driven approaches are mature in the building and automotive sectors, they are only beginning to be explored in the maritime sector. The development of representative marine load datasets and validated prediction models is a prerequisite for this development.

Table 19
Overview of comparative results from marine EMS/PMS studies.

Reference	Strategy	Objective(s)	Vessel/system	Benchmark	Reported result/saving
Kanellos et al. (2014)	DSM/rule-based	Cost reduction	AE cruise ferry	Variant	Cost savings; emission trade-off.
Kanellos et al. (2017a)	Multi-objective	Cost + CO_2	Vessel with ESS	Rule-based	Higher savings with ESS.
Kalikatzarakis et al. (2018)	ECMS	Fuel + emission	Tugboat hybrid	Rule-based	Fuel savings; configuration-dependent.
Yuan et al. (2016)	ECMS	Fuel	Hybrid vessel	Rule-based	Fuel savings; example-specific.
Wang et al. (2021)	Multi-agent + droop	Fuel	Shipboard microgrid	Droop control	10% fuel saving vs. droop.
Fang et al. (2019)	Two-step MO	Cost + lifetime	Hybrid vessel	Variant	Lifetime benefits; cost trade-off.
Banaei et al. (2021)	Stochastic MPC	Cost + ageing	FC–battery vessel	Rule-based MPC	Extended FC life; cost may rise.
Tang, Wu, and Li (2018)	MPC	Cost + CO_2	PV-diesel-battery	Rule-based	Simulated cost and CO_2 savings.
Skjong et al. (2017)	NLP EMS	Fuel cost	Offshore vessel	Rule-based	Improved fuel economy.
Mitropoulou et al. (2020)	MO GA	Cost + noise	Diesel-electric vessel	Single-objective	Noise objective added; needs validation.
Tsoumpris and Theotokatos (2019)	Health-aware ECMS	Emission + health	Hybrid vessel	Standard ECMS	Degradation and emission reduction.
Löffler, Geertsma, Polinder, and Coraddu (2024)	MO ECMS	Fuel + NOx	Diesel-hydrogen vessel	Rule-based	Fuel and NOx reduction.
Xie et al. (2024)	Two-layer MPC	Fuel + cost + CO_2	Hybrid ship	Rule-based MPC	Fuel/emission gains in simulation.
Jiang et al. (2025)	Two-level MPC	Cost + fuel	FC–battery vessel	Rule-based	Real-time capable; fuel/cost savings.

A fifth gap concerns the integration of alternative-fuel ICE-based and fuel-cell-based systems into maritime EMS/PMS frameworks. This includes LNG, methanol, ammonia, hydrogen, and fuel-cell-compatible energy carriers. The corresponding control challenges go beyond conventional fuel-consumption minimisation. They include fuel-flexible dispatch, mixed-integer fuel and operating-mode decisions, transient emission control, combustion-stability constraints, methane-slip mitigation for LNG and dual-fuel operation, NOx and possible N_2O control for ammonia combustion, hydrogen-storage and safety constraints, thermal-management integration, and degradation-aware operation of batteries and fuel cells. Future work should therefore develop EMS/PMS formulations that coordinate engines, batteries, fuel cells, converters, and thermal subsystems under fuel-specific efficiency, emission, safety, and lifetime constraints.

8.3. Selection criteria for maritime energy management

Based on the cross-sector analysis and the review of maritime control literature, selection criteria for the choice of control strategy and objective can be derived for different vessel types and operational profiles. An overview of these criteria is presented in Table 20. The table maps vessel categories to the most relevant control sector analogies, the most appropriate control strategies, and the primary and secondary objectives of interest. These criteria are intended as guidance and not as strict prescriptions, as the specific power system configuration, the operational profile, and the availability of data and computational resources must always be taken into account in the final design choice.

9. Conclusion

This paper reviewed advanced control strategies for power and energy management across four sectors: Building Energy Systems, smart microgrids, Automotive Energy Systems, and Marine Energy Systems. The review covered control objectives, constraints, variable spaces, architectures, control strategies, optimisation algorithms, and validation approaches, with the aim of identifying transferable knowledge for maritime power and energy management.

A total of 245 papers were analysed, including 51 review papers and 194 method papers across the four sectors and additional supporting literature. The comparison shows that MES should not be treated as a single homogeneous control problem. Instead, different vessel types exhibit control characteristics that resemble different terrestrial sectors. Passenger-intensive vessels share similarities with BES because of their large HVAC and hotel loads. Vessels with high auxiliary or mission loads resemble islanded smart microgrids because their main challenge is the coordination of multiple sources, storage devices, converters, and large dynamic loads. Scheduled transport vessels benefit from predictive strategies developed for repetitive transport and microgrid operation, while vessels with uncertain or highly dynamic missions share features with automotive energy management.

A central contribution of the review is the introduction of a generic mathematical framework for energy-system control model development. This framework provides a common formulation for states, controls, disturbances, constraints, objectives, and prediction models. It therefore creates a consistent basis for comparing control problems across sectors and for designing maritime EMS/PMS strategies in a more systematic way.

The review shows that the most mature transferable methods are not the same for all vessel types. MPC and DDMPC are particularly relevant for vessels with predictable routes, schedules, or thermal loads, where forecasts can be exploited effectively. ECMS and real-time learning-based strategies are better suited to vessels with uncertain, fast-changing, or weakly predictable load profiles. Distributed, multi-agent, and coordinated microgrid-control strategies are especially relevant for vessels with high peak loads, islanded electrical networks,

Table 20
Selection criteria for EMS/PMS strategies by vessel type.

Vessel category	Analogy	Load features	Strategy & objectives	References
Passenger-intensive vessels, e.g., cruise ships and large naval vessels	Building Energy Systems	Large hotel/HVAC loads; slow thermal dynamics; occupancy/weather variability.	MPC, DDMPC, hierarchical control, zonal MAC; comfort, HVAC, CO2, cost, lifetime.	Brandi et al. (2022), Drgoňa et al. (2020), Gianni et al. (2022), Mondejar et al. (2017)
High-auxiliary-load vessels, e.g., offshore vessels, crane ships, cable layers, naval vessels	Smart microgrids	Fast transients; peak loads; reserves; fault tolerance.	Distributed/MAC/hierarchical real-time control; stability, voltage, load sharing, reserve.	Edrington et al. (2020), Feng et al. (2012, 2018), Lai and Illindala (2018)
Unscheduled small transport and manoeuvring vessels, e.g., water taxis, tugs, small offshore support vessels	Automotive individual transport	Uncertain route; variable propulsion; rapid transients.	ECMS/adaptive/real-time learning; power-split and mode-selection control for parallel or series–parallel hybrid layouts; fuel, emissions, SOC, health.	Kalikatzarakis et al. (2018), Löffler, Geertsma, Mitropoulou, et al. (2024), Löffler, Geertsma, Polinder, and Coraddu (2024), Löffler et al. (2023), Tsoumpris and Theotokatos (2019)
Scheduled transport vessels, e.g., ferries, cargo vessels, ro–ro vessels, survey vessels	Scheduled transport	Known routes; fixed timetables; repetitive loads.	MPC/DDMPC/hierarchical EMS; route-aware power-split and charging/bunkering optimisation; fuel, cost, CO_2, hazardous emissions, SOC, battery life, shore-power.	Banaei et al. (2021), Hou et al. (2018), Jiang et al. (2025), Löffler et al. (2024), Tang, Wu, and Li (2018), Xie et al. (2024)
Short-distance battery-electric ferries	Automotive EVs	Known range; repetitive missions; planned charging.	SOC/MPC/ECMS-style control; SOC, charging, efficiency, battery life.	Barone et al. (2024), Perčić et al. (2020)

reserve requirements, and fault-tolerance constraints. This suggests that future maritime EMS/PMS design should be vessel-specific rather than based on a single universal control architecture.

The review also shows that maritime EMS research remains dominated by fuel-consumption and cost-reduction objectives. Although these objectives are essential, they are no longer sufficient for future hybrid, electric, and alternative-fuel vessels. Hazardous emissions, component degradation, maintenance cost, noise, vibration, availability, and safety-related objectives remain underrepresented. In particular, the joint optimisation of fuel cost, hazardous emissions, and component lifetime is still insufficiently explored, despite its direct relevance for vessels operating under emission regulations, high energy prices, and increasing reliability requirements.

Validation remains the weakest element of the maritime control literature. Most studies are still simulation-based, and the lack of standard maritime load profiles makes it difficult to compare reported savings across papers. In contrast, the building and automotive sectors benefit from real-building demonstrations, standardised driving cycles, and increasingly mature data-driven benchmarks. Future maritime research should therefore prioritise benchmark operating profiles, hardware-in-the-loop testing, scaled demonstrators, and field validation on actual vessels.

Overall, the review demonstrates that the maritime sector can benefit substantially from control methods developed in adjacent sectors, but direct transfer is not sufficient. Successful adoption requires vessel-specific modelling, realistic operating profiles, explicit treatment of power-system and safety constraints, and stronger validation under representative maritime conditions. The next step for maritime EMS/PMS research is therefore not only to develop more advanced algorithms, but to connect algorithms, objectives, constraints, and validation into control frameworks that are robust, explainable, and operationally credible for real vessels.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript. All sources of funding and institutional support relevant to the work have been disclosed in the manuscript.

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