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Ship Technology Research
Schiffstechnik

ISSN: 0937-7255 (Print) 2056-7111 (Online) Journal homepage: www.tandfonline.com/journals/ystr20

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To cite this article: Mattis Molinski, Jana Ihrens & Thorsten A. Kern (2026) Unbiased automated optimization of ship energy systems, Ship Technology Research, 73:2, 161-172, DOI: 10.1080/09377255.2026.2690798

To link to this article: https://doi.org/10.1080/09377255.2026.2690798

Published online: 30 Jun 2026.

SHIP TECHNOLOGY RESEARCH (SCHIFFSTECHNIK)
2026, VOL. 73, NO. 2, 161–172
https://doi.org/10.1080/09377255.2026.2690798

Unbiased automated optimization of ship energy systems

Mattis Molinski, Jana Ihrens and Thorsten A. Kern

Institute for Mechatronics in Mechanics, Hamburg University of Technology, Hamburg, Germany

ABSTRACT

Shipping is highly efficient yet a significant greenhouse gas emitter. Achieving the IMO's 2050 carbon-neutrality target demands exceptionally efficient new vessel designs. However, ship design is complex due to the vast number of interacting options – e.g. hybrid electric architectures, renewable integration, sector coupling, and energy storage. Energy system design remains a largely manual, iterative process based on prior experience, often overlooking unconventional concepts. The Maritime Energy System Optimizer (MESO) addresses this gap. MESO is a modular Python platform optimizing the architecture, dimensioning, and operation of sector-coupled ship energy systems via a genetic algorithm. Fitness is evaluated through operational, component, and volume costs, with operation optimization using the open energy modeling framework. Its novelty lies in unbiased architecture optimization over dynamic load profiles, reducing design iterations. MESO is demonstrated in two case studies – a cruise ship's multi-energy system and a container ship's auxiliary electrical system – identifying efficient, unconventional configurations.

ARTICLE HISTORY
Received 15 April 2026
Accepted 14 June 2026

KEYWORDS
Energy system optimization; architecture optimization; coupled energy systems; partial-load operation optimization; green ship design; genetic algorithm; mixed-integer linear programming

1. Introduction

Maritime transport is the backbone of global trade, and one of the most energy-efficient modes of transport. However, due to the massive scale of the industry and a projected continuous increase in shipping volume, it remains a significant contributor to global anthropogenic greenhouse gas (GHG) emissions (IMO 2020). In response to the escalating climate crisis, regulatory bodies have introduced increasingly strict environmental targets. Most notably, the International Maritime Organization (IMO) has revised its strategy, setting a clear trajectory towards net-zero GHG emissions from international shipping by 2050 (IMO 2023).

Meeting these ambitious targets requires immediate and substantial efforts across the maritime sector. Regulatory pressure is increasing not only on a global scale but also at the regional level. For instance, ships calling at European Union ports are now fully integrated into the EU Emissions Trading System (EU-ETS), which directly affects the economic equations of ship operation (Directive EU).

A vast array of measures for direct efficiency improvements is available to ship designers, ranging from alternative carbon-neutral fuels and hybrid electric propulsion concepts to energy storage implementation and extensive sector coupling on board (Balcombe et al. 2019; Bouman et al. 2017). While the integration of these technologies significantly expands the design space and offers immense potential for efficiency gains, it also increases the complexity of the ship design process dramatically. The diverse interactions between electrical, mechanical, and thermal systems create a deeply coupled and interdependent system where isolated component optimization is no longer sufficient (Geertsma et al. 2017).

Conventional ship design processes struggle to keep pace with this expanded design freedom. Traditionally, the design of maritime energy systems has been a slow, iterative, and largely manual process that relies heavily on a shipyard's prior experience and historical baseline data (Papanikolaou 2014). This experience-based approach inherently carries a bias. It often leads to the premature dismissal of highly integrated, unconventional concepts due to their apparent complexity or perceived infeasibility, ultimately yielding robust but sub-optimal energy system architectures. As newly built vessels will have to operate efficiently throughout a 40+ year lifespan bridging the transition to zero-carbon shipping, such design shortcomings will become increasingly costly.

To address this gap and leverage the full potential of modern maritime energy technologies, an unbiased and automated optimization methodology is required. To this end, this paper proposes the Maritime Energy System Optimizer (MESO), a holistic framework designed for the automated optimization of complex

CONTACT Mattis Molinski mattis.molinski@tuhh.de Institute for Mechatronics in Mechanics, Hamburg University of Technology, Eißendorfer Str. 38, Hamburg 21073, Germany

ship energy system architectures. By employing a genetic algorithm that explores the configuration design space without human bias, coupled with a Mixed-Integer Linear Programming (MILP) solver for operational optimization, MESO is a comprehensive method to navigate the multitude of configuration possibilities and identify optimal energy system designs (Molinski et al. 2024).

This paper is structured as follows: Section II outlines the challenges of holistic energy system optimization in the maritime context. Sections 3 and 4 describe the MESO framework, detailing its architecture optimization and operation optimization components. Sections 5 and 6 present two case studies demonstrating MESO's application to a cruise ship and a Very Large Container Ship (VLCS), showcasing its ability to identify efficient and unconventional energy system configurations. Finally, Section 7 concludes the paper.

2. Challenges

Optimizing energy systems for efficiency and sustainability promises significant gains in overall efficiency, especially considering the growing complexity of new innovative technologies (Hartwich et al. 2023; Malpricht et al. 2025). Holistic optimization however – particularly of the supply and storage configuration – is highly challenging, due to the interdependencies between configuration, sizing and operation of the systems (Frangopoulos 2018, 2020).

Dimensioning (sizing of known components) and operational dispatch (power management given a fixed architecture) are comparatively straightforward to optimize in isolation, with a plethora of researchers having successfully applied various methods, including meta-heuristics for sizing (Che et al. 2024; Du et al. 2023; Zhu et al. 2018; Lan et al. 2015) and MILP for dispatch optimization (Wakui et al. 2014; Shao et al. 2017; Bischi et al. 2014). Combining dimensioning of a given configuration with operation optimization is also investigated extensively, using e.g. multi-layer approaches with meta-heuristics (Wang et al. 2021; Wu and Bucknall 2020; Zhu et al. 2020) or higher-order formulations with MILP or non-linear programming (NLP) (Dall'Armi et al. 2022; Pivetta et al. 2021).

Configuration optimization however can quickly become high-dimensional. Determining the optimal architecture, selecting the types of energy sources (e.g. fuel cells vs. internal combustion engines), and integrating them into a unified system creates a dramatically expanded, discrete solution space. This leads to non-deterministic, highly non-convex mixed-integer optimization problems for which no universal, generic solving method exists (Frangopoulos 2020).

This complexity is further increased when attempting to optimally size energy storage systems, such as batteries or thermal accumulators. Determining the exact capacity required to maximize peak-shaving benefits or allow zero-emission port stays heavily depends on the ship's operational profile and the power dispatch strategy. However, the optimal dispatch strategy itself relies entirely on knowing the exact configuration and capacities of the onboard storage and power generation units. This creates a deeply coupled 'chicken-and-egg' problem: the storage cannot be accurately dimensioned without operational data, but the operational data cannot be simulated without a defined configuration.

Studies so far largely resorted to sequentially solving this problem, breaking the holistic approach into isolated steps. For example, an approach is to design the system configuration based on standardized operating conditions first, and only subsequently optimize the energy management parameters, leading to sub-optimal system architectures (Guo et al. 2025). Other researchers optimize the configuration and operation simultaneously, but start with a predefined superstructure of possible configurations, which is then reduced by the optimization process (Wang et al. 2018; Lu et al. 2018). While these approaches can successfully optimize within a given framework, they are constrained by their inability to fundamentally alter the overarching system architecture, again leading to the disregard of potentially superior alternatives.

Additionally, the presented approaches are generally tailored to specific use cases, specific technology sets or specific system types, and thus cannot be easily transferred to other use cases or extended for different applications. Furthermore, the tools used for the optimization are often not open-source, which limits their accessibility and the ability for other researchers to build upon them.

A gap therefore exists for an open-source and flexible framework capable of penetrating the vast solution space of combined synthesis, design and operation optimization of coupled multi-energy systems, without being constrained to rigid assumptions and biases. This study aims to fill that gap with the Maritime Energy System Optimizer (MESO), a holistic optimization framework that specifically aims to be transparent, flexible and extensible.

3. Concept

MESO is an optimization framework that co-optimizes three aspects of coupled energy systems (Molinski et al. 2024) (see Figure 1):

(1) Synthesis: the selection of components and their interconnection (configuration).

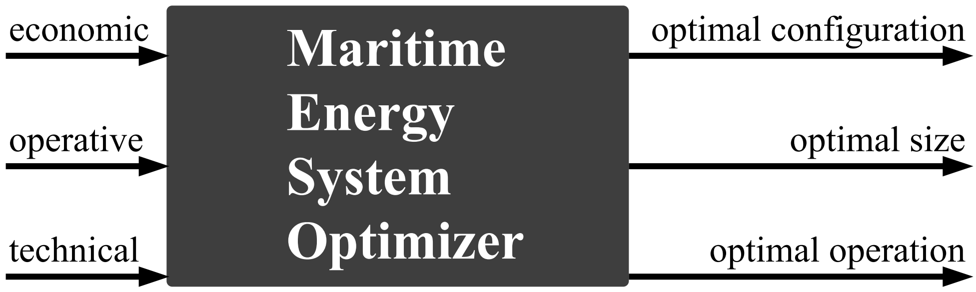

Figure 1. MESO black-box, main inputs are representative load profiles, cost assumptions and component options, while the main output is the optimal system configuration and its optimal operation.

(2) Design: the sizing of the selected components (e.g. the nominal power of a generator or capacity of batteries).
(3) Operation: the scheduling of the components' operation (e.g. the load share between generators and charging/discharging scheduling).

The primary novelty compared to existing approaches is the full configuration optimization combined with optimal sizing and operation optimization, as MESO is accounting for dynamic load profiles. The framework is designed to be freely adaptable to different types of energy systems and optimization problems. The fundamental inputs needed for the optimization are:

- Economic assumptions, e.g. cost parameters for the components and carbon/fuel prices for the fuel cost calculations.
- Operative assumptions, mainly representative demand profiles that the energy system needs to meet.
- Technical assumptions, including the technical characteristics and constraints of the components, as well as any regulatory or physical constraints on the system. Includes the definition of the design space, i.e. the possible configurations and component options that can be considered in the optimization.

4. Genetic algorithm

MESO performs the optimization through a Genetic Algorithm (GA), which is a meta-heuristic inspired by the process of natural selection. GAs are well-suited for optimization problems with vast, discontinuous solution spaces and expensive assessment of the quality of a single combination of optimization variables. The GA iteratively evolves a population of candidate solutions (configurations) towards better solutions based on a defined cost function that quantifies how good a configuration is in terms of the optimization objectives.

The optimization problem can be understood as the minimization of a cost function $f(\mathbf{X})$ (1):

$$\min_{\mathbf{X}} f(\mathbf{X}) \tag{1}$$

with the optimization variable vector $\mathbf{X} = (x_1, x_2, \ldots, x_n)$ and the cost function $f(\mathbf{X})$ that itself includes the operation optimization $\min\,(C_{\mathrm{OPEX}}(\mathbf{X}))$ (2):

$$f(\mathbf{X}) = \min\,(C_{\mathrm{OPEX}}(\mathbf{X})) + C_{\mathrm{FIX}}(\mathbf{X}) + C_{\mathrm{TOPO}}(\mathbf{X}) \tag{2}$$

4.1. Configuration options

Since GAs are based on evolutionary modifiers, it requires a way to abstract the optimization variables X into a so-called gene- or chromosome structure (Kinnebrock 1994). In the case of MESO, three types of optimization variables x_i are implemented:

- Discrete variables, e.g. number of components or subgroups.
- Continuous variables, e.g. nominal power or capacity, with varying discretizations depending on the component.
- Selection variables, e.g. which group or consumer a component is connected to – abstractly also a discrete variable.

The combination of these variables enables the representation of a wide variety of configuration options, ranging from simple gensets (number and power) to selection of different sub-distribution strategies. The chromosomes are implemented in a hierarchical structure, facilitating the extension of optimization variables on system-, component- and attribute-level.

4.2. Fitness

Quantifying the quality of one specific combination of optimization variables $\mathbf{X}$ (= one specific chromosome) requires the evaluation of the fitness function $f(\mathbf{X})$, consisting of three costs:

(1) $\min(C_{OPEX}(\mathbf{X}))$: The operating cost is based on the energy usage over the course of the load profiles, which is determined by the use of an operation optimization. The *Open Energy Modelling Framework* (*oemof*), an open-source framework for modelling an energy system with a graph-based approach is used for this optimization (Hilpert et al. 2018; Krien et al. 2020). Fundamentally, it is using energy flows and transmission efficiencies as a basis, the supplying components' power outputs as optimization variables, the consumer load profiles as constraints and the minimization of energy usage as target. The resulting optimization problem is a MILP-problem solved using an adequate solver. Both open-source (e.g. CBC) and commercial options (e.g. CPLEX) are suitable.
(2) $C_{FIX}(\mathbf{X})$: Fixed cost is made up of all usage-independent costs, notably CAPEX (accounted as depreciation cost based on typical component lifetime) and general operations and maintenance (O&M) – both calculated for the load-profile duration.
(3) $C_{TOPO}(\mathbf{X})$: Topology cost is optionally accounted for to penalize large, widely spread architectures over compact ones with decentral supply strategies. Uses a simplified installation volume for the components and a pathfinding-based approximation of the volume used by piping/networking.

Fundamentally, this fitness function means that the primary objective of the optimization is economic and therefore aiming for a trade-off between the different cost components. Through the inclusion of emission costs, greenhouse gas (GHG) emissions and fuel consumption are indirectly optimized, but the framework can be easily adapted to directly optimize for these or other objectives by changing the cost function. For example, if the optimization is focused on minimizing fuel consumption, the fixed and topology costs can be set to zero, while if the optimization is focused on minimizing CAPEX, the operating cost can be set to zero. The flexibility of the fitness function allows MESO to be applied to a wide range of optimization problems with different objectives and constraints.

4.3. Selection, crossover, mutation

The GA is implemented in python – with elitist selection with random n-point crossover, a fixed mutation rate and a fixed small ratio of insertion (see Figure 2).

The starting population is generated from a reference configuration with high mutation rate (30 %) to ensure a high variability. A population size of 200 with a high elite size of 98 individuals is chosen to ensure fast convergence while still maintaining a high diversity in the population. After sorting, the best 98 individuals are kept as elites, further 98 individuals are generated through crossover and subsequent mutation (15 %) of the elites, and 4 individuals are generated through random mutation of the reference to prevent premature convergence. The algorithm is stopped either after a certain time limit (e.g. 12 h) or after a certain number of generations without improvement of the best solution (e.g. 20 generations of stagnation).

4.4. Verification and validation

Verification on an example application and limited validation of MESO was done in Molinski et al. (2024). Trials showed MESO's usability for different levels of detail and the potential for significant cost savings (> 4.4 % savings for all scenarios) through the evaluation of large numbers of configuration options in a short time. All optima included energy storage, showing the advantage of their ability to shift energy supply and demand, and thus reduce the need for installed generation capacity. The optima also included unconventional configurations, e.g. with fuel cells as the main component, showing the advantage of MESO being able to optimize without bias towards conventional architectures.

GAs are meta-heuristics, meaning convergence against the global optimum is not guaranteed, but rather a good solution is found in a reasonable time. MESO's hyperparameters are tuned to enable fast convergence while maintaining diversity in the population. All runs showed consistent convergence towards high-quality solutions, but the variability in the optima and convergence behavior across multiple runs with different random seeds has not yet been systematically analyzed, meaning results may vary slightly between runs. Future work will include the analysis of the convergence behavior and repeatability of the optimization results, as well as a comparison with other optimization methods to further validate MESO's performance and robustness.

5. Case study 1: cruise ship

The first case study performed to demonstrate the capabilities of MESO is a variation of the verification studies in Molinski et al. (2024). It is based on demand profiles from a >30 MW propulsion power cruise vessel's journey through the Caribbean – with the demand split between 104 consumers and four energy types in 10-minute time resolution (see Figure 3). The configuration options are as follows, with some component parameters changed compared to Molinski et al. (2024):

- LNG-fuelled Diesel Gensets (DGs) with a constant electrical efficiency of 0.5 and an allowed nominal

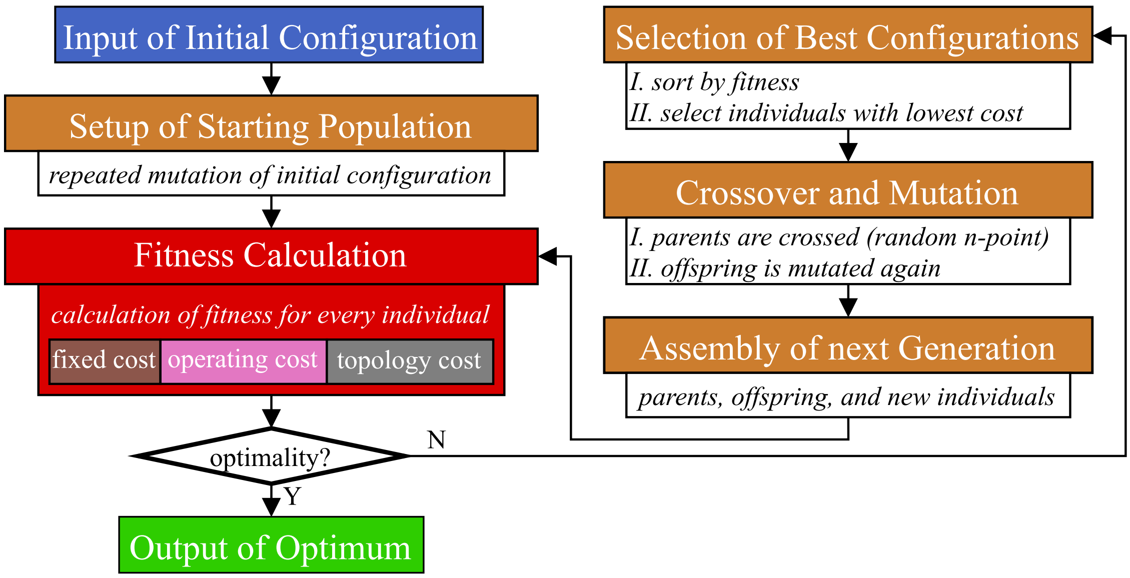

Figure 2. MESO's genetic algorithm process, as described in Molinski et al. (2024).

power range of 5 – 19 MW. Main point of sector coupling with assumed waste heat recovery (WHR) efficiency of 0.2 for high-pressure steam and 0.2 for general heating water.

- Methanol-fuelled High-Temperature Fuel Cells (HT-FCs) with constant electrical efficiency of 0.6 and WHR efficiency of 0.3 for general heating water. Allowed power range of 500 kW – 10 MW.
- LNG-fuelled steam boilers with a fuel-to-steam efficiency of 0.95 and a power range of 2000 to 7000 kW.
- Batteries with per-unit capacity between 100 and 5000 kWh, maximum 2 C charge/discharge rate and a charge/discharge efficiency of 0.95. Degradation is omitted due to the short load profile duration, but a fixed O&M cost is included to partially account for limited cycle life.
- Thermal storages with per-unit capacity between 100 and 10000 kWh., maximum 0.5 C charge/discharge rate, charge/discharge efficiency of 0.95 and 20% self-discharge per hour when not used.

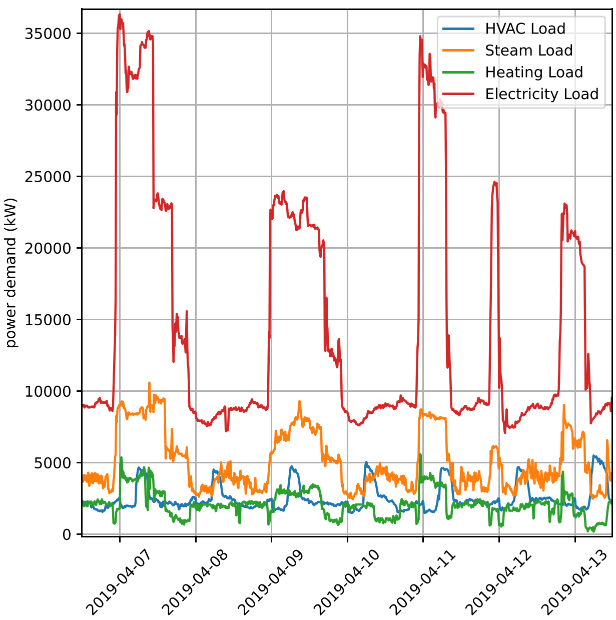

Figure 3. Cruise ship demand profiles, cumulated by type over all consumers, showing how the occurrence of load peaks varies. While electricity demands are highest, thermal demands are still significant and need to be accounted for in a holistic optimization.

The simplification of constant efficiencies is kept from the verification studies, despite partial-load efficiency being considered in the second case study Section 6. This enables a better comparability to the verification studies and better exploration of a design space that is vaster than in the second case study due to more configuration options and sector coupling. Cost parameters are changed compared to the verification studies to match the second case study, and summarized in Tables 1 and 2. The parameters are mainly chosen to demonstrate the flexibility of MESO and are not claiming to perfectly represent real-life cost. Fuel cost estimations include a CO_2 price of 100 €/t, which is in the range of current EU-ETS certificate prices and serves to demonstrate the potential for optimization under current economic conditions. In addition to this baseline

Table 1. Component cost parameters (cruise ship case study). Fixed cost is specific to installed kW, OPEX is specific to kWh (fuel).

	DG	HTFC	Boiler
Fixed cost	**180 €/kW/year**	**16 €/kW/year**	**200 €/kW/year**
Lifetime	20 years	25 years	15 years
CAPEX	1100 €/kW	300 €/kW	2000 €/kW
O&M	800 €/kW	100 €/kW	1000 €/kW
OPEX	**0.0702 €/kWh**	**0.0702 €/kWh**	**0.0949 €/kWh**
Fuel	0.05 €/kWh	0.05 €/kWh	0.07 €/kWh
CO_2	202 g/kWh	202 g/kWh	249 g/kWh

Table 2. Storage cost parameters (cruise ship case study).

	Battery	Thermal Storage
Fixed cost	**100 €/kWh/year**	**2.8 €/kWh/year**
Lifetime	10 years	15 years
CAPEX	800 €/kWh	50 €/kWh
O&M	200 €/kWh	20 €/kWh

configuration, the optimization is done with a fixed-size Photovoltaic (PV) installation. Its power output is calculated based on the ship's route data using the *NASA Langley Research Center (LaRC) POWER Project's All Sky Surface Shortwave Downward Irradiance*-API.

All MESO runs are done on the Hamburg University of Technology (TUHH)'s High Performance Computing (HPC)-cluster using the default MESO settings, with a time limit of 12 h per run.

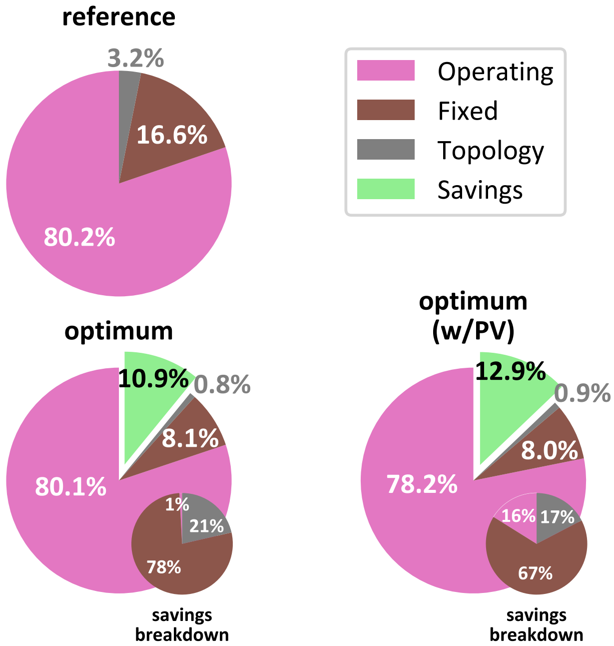

Figure 4. Cost breakdown for the cruise ship case study, showing the cost savings potential of the optimal configurations compared to the reference system and how the cost structure changes with the inclusion of PV.

5.1. Results

Both setups achieve significant cost savings compared to the cruise vessel's real system configuration with four 15.6 MW DGs and two 6 MW steam boilers – at 10.9% savings without and 12.9% savings with PV. The savings with PV are not taking installation costs or general limitations of operating PV systems into account and the results are mainly used as a demonstration of the necessity of integrating different energy systems into one holistic approach. Both optima are generally similar, with optimally sized DGs and large energy storage installations – and both without steam boilers, which shows that the WHR from the DGs is sufficient to meet the thermal demand. Also absent from both optima are HT-FCs, which shows their competitive disadvantage at the chosen cost parameters.

5.1.1. Cost savings

The cost savings potential of the optimal configurations is substantial, at 10.9% without and 12.9% with PV compared to the reference system (see Figure 4 for details). The main driver for this cost decrease is the smaller installed generation capacity enabled by the energy storage and the resulting fixed cost reduction of about 51% in both cases (accounting for 78% and 67% of the savings). The remaining savings are mainly achieved through 75% and 72% lower topology cost (21% and 17% of the total savings respectively), which is achieved through decentral placement of storages, enabling less power to be transmitted across the ship, since short peakloads can be met with local storage instead of needing to be transmitted from the generators. The operational costs, and thereby fuel consumption and GHG emissions, are barely reduced in the baseline case, since a) the overall energy usage is not reduced, b) it is compared to a reference system with optimized operation, and c) no partial-load operation is considered. Higher savings are expected with partial-load efficiency models, as the disadvantage of operating oversized generators at partial-load in the reference configuration would be more pronounced. With PV however, the operational costs are reduced by roughly 2.5%, since the PV is essentially providing free energy, meaning less energy needs to be supplied by the generators (as can be seen in Figure 5). This also explains the higher savings with PV. Cost savings despite not reducing operating costs show the importance of accounting for and optimizing the system's fixed costs, which is only possible through a holistic approach that combines both configuration and operation optimization.

5.1.2. Optimal configurations

The main differences between the two optimal configurations are the installed storage capacities – notably both electric and thermal storage capacities are higher with PV (see Figure 5). While larger batteries are to be expected with essentially free electricity from the PV, larger thermal storages are less intuitive and show the advantage of MESO's holistic approach. The PV reduces the overall energy needed, but can also lead to situations where not enough thermal energy is supplied by the DGs' WHR systems, e.g. during a sunny port stay, when the majority of the electrical demands are met by just the PV. The DGs are then most economically operated at a lower power setting, that would need to be increased to meet the thermal demand, necessitating more thermal energy to be buffered. This effect was more

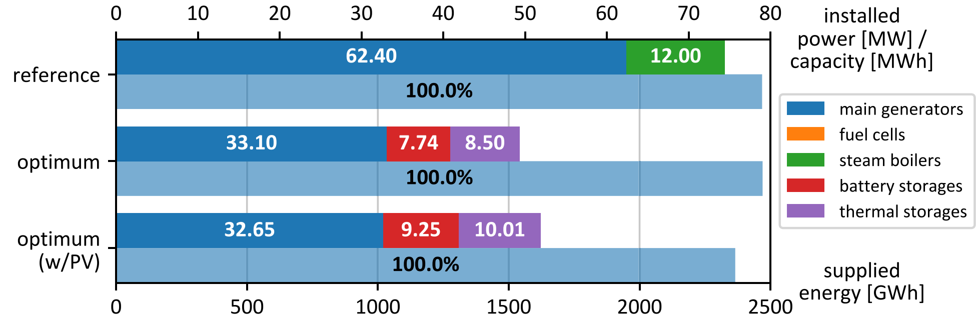

Figure 5. Reference and optimal system configurations for the cruise ship case study and the share of supplied energy by component type, showing the optimal sizing for the use-case and how the inclusion of PV affects the thermal systems.

pronouncedly observed in Molinski et al. (2024), where the optimum included an additional boiler.

5.1.3. Discussion and limitations

In both configurations, the optimal system architecture is significantly different from the conventional reference system, which shows the advantage of MESO being able to explore a vast design space without human bias – and fast – in both cases, more than 35.000 design alternatives were evaluated in the 12 h runs. The results also show how additional information (such as installation of PV) in a later design stage can change the optimal configuration, making it necessary to include MESO throughout the design process.

However, the results fundamentally depend on the chosen cost parameters and the trade-offs they infer. For the given example, the cost parameters were mainly chosen to demonstrate the flexibility of MESO, and the results for the scenario without PV suggest the fixed-cost parameters to have a dominating impact on the optimization, i.e. the CAPEX of the DGs and batteries. The scenario with PV is dominated by the trade-off between operational cost savings through the PV and the fixed cost increase through the larger storage capacities, which is mainly influenced by the fuel cost and the fixed cost parameters of the batteries. A comprehensive sensitivity analysis will further quantify the sensitivity to the most influential parameters.

6. Case study 2: VLCS

The second case study is conducted in collaboration with an industry partner from the cargo sector. The aim is to demonstrate MESO's flexibility and capabilities, and explore unusual configuration options for the auxiliary electrical system conventionally supplied by DGs.

The provided data include one year of measured operational data in 15-minute time resolution for a 368 m VLCS with four auxiliary 3.6 MW DGs. In addition to the cumulated electrical and propulsion demands, the data includes the load share between the individual auxiliary DGs and shaft generator as well as their respective fuel consumptions (an excerpt is shown in Figure 6).

Upon analysis of the operational data, potential for improvement was identified in the operation of the auxiliary DGs – roughly 8% of the time, multiple DGs are active while overall auxiliary demand is lower than a single generator's maximum power capacity. Therefore, the DGs are operated under partial-load conditions, reducing overall fuel efficiency, since Internal Combustion Engines (ICEs) are generally less efficient at lower loads (Heywood 2018). Extended partial-load operation can additionally lead to increased wear and shorter maintenance intervals due to the longer operating hours (Skjong et al. 2017). Prior to the full MESO application, the effect of optimizing the operation of the existing system is therefore quantified.

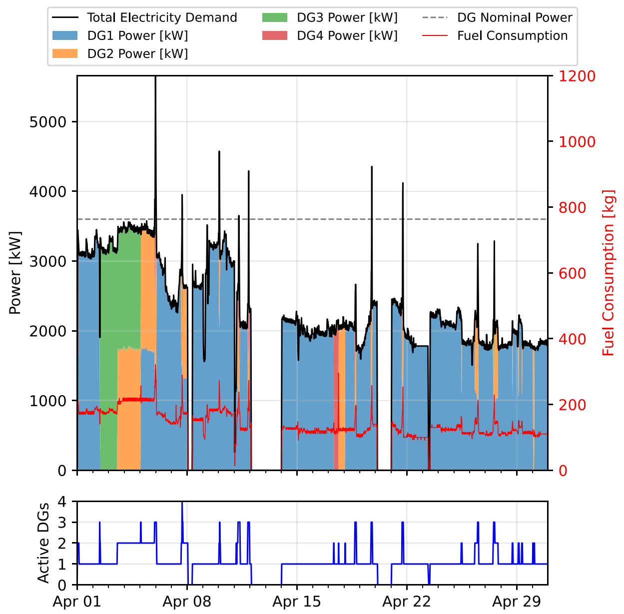

Figure 6. VLCS operational data in 15-minute intervals for April, showing the electrical demand, operation strategy and load share between the DGs (top), and the number of active DGs (bottom). The data show a significant amount of time with more than one DG active, even at low demand, which indicates a potential for optimization.

6.1. Genset modelling

A partial-load efficiency model for the DGs is needed for both full MESO and operation optimization. For the sake of comparability, the model is based on the fuel consumption data, and – since the data only include cumulated fuel consumption for all auxiliary DGs – only using the subset with exactly one auxiliary DG active.

The specific fuel consumption is plotted against relative generator load in Figure 7. Since the data are scattered, piecewise linear regression is used to fit the model.

The scattering has several potential causes, e.g. additional non-linear effects such as ambient conditions (e.g. air temperature, humidity, density), fuel variability (e.g. quality and temperature), load dynamics (e.g. transients and grid frequency stabilization) or the ICE's own auxiliary systems' behavior (Heywood 2018). Since one of the strengths of MESO is the high number of investigated configuration options, enabled by a simplified energy system model, these effects cannot be accounted for in the partial-load efficiency model of the DG. With $R^2 = 99.09\%$ the fit is considered a sufficient approximation of the real load/fuel-consumption relationship.

The data show inconsistencies with usual DG minimal load constraints, as there is a number of datapoints for less than 22% load. In the full MESO application, a load share of less than 22% is omitted, but for the operation optimization, both scenarios – with and without minimal load constraint – are investigated. In order to replicate the auxiliary generators' behavior in *oemof*, the *OffsetConverter*-component is used, which is defined by a minimum and a maximum efficiency and their respective load percentages. For the operation optimization without a minimal load constraint the *OffsetConverter* is coupled to an additional conventional *Converter*-component for < 22% load – with the constraint of only one being allowed to be active at any timestep.

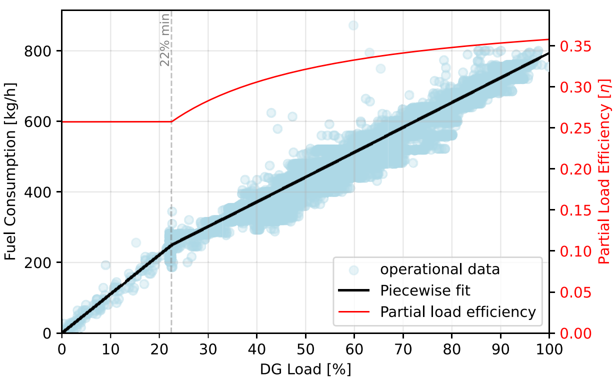

Figure 7. Auxiliary DG partial-load efficiency fit based on operational data. Scattering signals the presence of additional effects. Piecewise linear load/fuel-consumption relationship results in non-linear efficiency curve.

6.2. Operation optimization

Both versions of the operation optimization are conducted based on the full one year operational data. Due to the scattered nature of the real fuel consumption data, a direct comparison with the results of the operation optimization is not meaningful. To get a comparable reference fuel consumption, the partial load efficiency model is applied to the real operation profile – for every time step and every DG the electrical output is divided by the nominal power to get the load share and then evaluated with the fitted curve. The resulting fuel consumption is then directly comparable to the optimized operation profiles.

The difference between the optimal operation profiles is a small number of timesteps with an electrical demand lower than the minimal load constraint, where excess energy is supplied when the minimum power constraint is used (see Figure 8). The excess results in a slightly lower fuel savings potential of ~ 1.79% over one year of operation compared to ~ 2.03% when not constraining the minimum power.

Both optimization setups show fuel savings where the optimizer reduced the number of active DGs compared to the real operation profile, with both optimal operation profiles changing nearly all timesteps where more than one DG is active Figure 8.

While the fuel savings potential through operation optimization is promising, it does not account for other operational reasons that cause more DGs to be active than energetically necessary. Examples include maintaining a spinning reserve to prevent blackouts in the event of sudden load steps or generator failures, ensuring mandatory redundancy during critical operations like maneuvering, and improving transient load capabilities and grid stability when anticipating large load fluctuations (Geertsma et al. 2017).

6.3. MESO setup

The configuration options and thus optimization variables for the full application of MESO include the following:

- DGs, with a partial-load efficiency model based on the operational data (see Section 6.1, efficiency between 0.26 at 22% and 0.36 at 100%), constrained to 550 – 12000 kW nominal power. Assumed fixed WHR efficiency of 0.35.
- Gas Turbine Generator (GTG), partial-load efficiency between 0.26 at 50% and 0.35 at 100%, constrained to 900 – 10000 kW nominal (electrical) power. Recent studies are investigating the implications of augmenting future ship concepts with GTG due to their low emissions and high power density (Mrzljak and Mrakovčić 2016). Fixed 0.45 WHR efficiency.

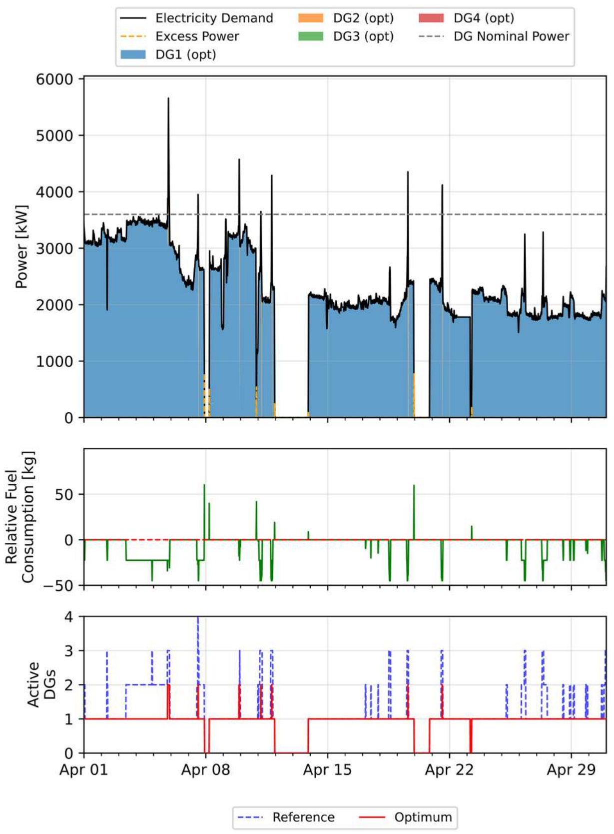

Figure 8. Excerpt of the optimal operation profile with minimal load constraint, showing the excess energy supply at low demand. Shows the fuel savings where the optimizer reduces the number of active DGs, and higher fuel consumption where demand is below the minimum load. Overall fuel savings of $\sim 1.79\%$ over one year of operation compared to $\sim 2.03\%$ when not constraining the minimum power.

- Batteries with a capacity of 10 – 1000 kWh. Charging and discharging efficiency is set to 0.95.

The cost parameters for these components are summarized in Table 3, a CO_2 price of 100 €/t is assumed for the fuel cost calculations. The parameters are based on a combination of literature research and industry feedback, and are chosen to be comparable to the parameters of the cruise ship case study (see Tables 1 and 2) – yet, they are mainly chosen to demonstrate the flexibility of MESO and the potential for optimization, rather than to give an accurate representation of the real system.

The optimization is performed in two variations:

- Baseline with DGs, GTGs and batteries as configuration options.

Table 3. Cost parameters VLCS.

	DG	GTG	Battery
Fixed cost	**90 €/kW/year**	**160 €/kW/year**	**140 €/kWh/year**
Lifetime	20 years	15 years	10 years
CAPEX	900 €/kW	1400 €/kW	1000 €/kWh
O&M	900 €/kW	1000 €/kW	400 €/kWh
Operating cost	**0.098 €/kWh**	**0.0654 €/kWh**	
Fuel	0.071 €/kWh	0.045 €/kWh	
CO_2	270 g/kWh	204 g/kWh	

- Inclusion of one day with 10 MW artificial load – based on the feedback that there can be regulatory requirements to be able to supply a fixed amount of power regardless of the actual demand profile.

To keep the computational and time budgets reasonable for a trial study, the optimization is done based on the operational data from April, which is a well suited excerpt, with a higher share of non-zero load timesteps (89.3% vs. 72.9%), higher than average monthly energy consumption (1525 MWh vs. 1089 MWh) and a higher share of timesteps with more than one DGs active (18.2% vs. 12.1%) compared to the full dataset, making the operation optimization more relevant. The optimization is using the same settings as the cruise ship case study, with a time limit of 12 h per run.

6.4. MESO results

Both optimization runs show significant cost savings potential through a combination of GTGs, DGs and batteries, with higher savings in the baseline scenario than in the scenario with the artificial load. The savings are shown in Figure 9, and the optimal configurations, their share of supplied energy by component type and WHR potential are shown in Figure 10.

6.4.1. Baseline results

The optimal configuration for the baseline scenario includes a 3.73 MW DG, a 2.33 MW GTG and 1.35 MWh of batteries Figure 10(a). The bulk of the demand is supplied by the GTG with the batteries

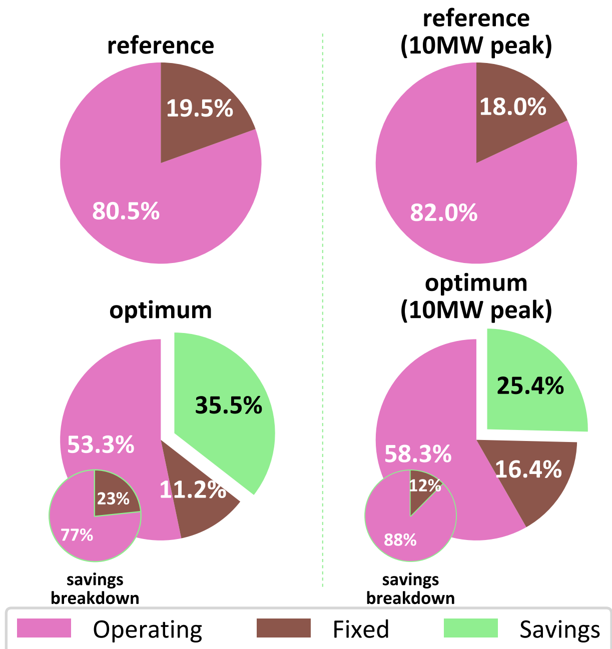

Figure 9. Cost breakdown for the VLCS case study, showing the cost savings potential of the optimal configurations compared to the reference system and how the inclusion of the artificial load reduces the savings potential.

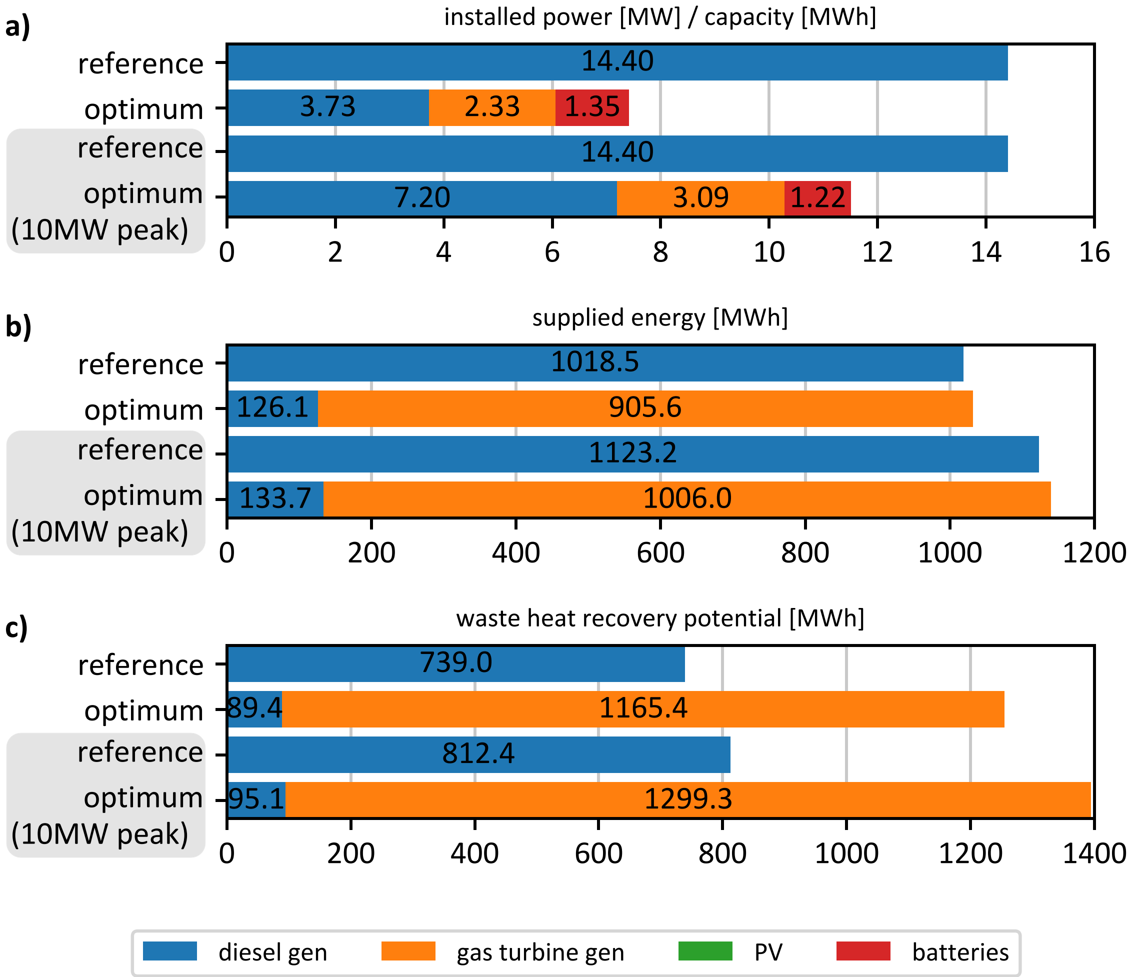

Figure 10. MESO results for VLCS case study: (a) optimal configurations; (b) share of supplied energy by component type; (c) WHR potential. Optimal configurations show how the trade-off between OPEX and CAPEX is different for the components with high usage (GTG) and those with low usage (DGs). WHR potential is higher for the configurations predominantly using the GTG.

buffering peak loads and the DG only in use during peak loads. The cost savings compared to the current configuration are an additional 35.5% on top of the 1.79% fuel savings potential through operation optimization Figure 9. The savings are achieved in two areas:

(1) Reduction of the Operating Cost by 33.8% (77% of savings) through more efficient generation:

1 The GTG has a higher efficiency than the DGs, especially at partial load, and lower specific emissions.
2 The size of the GTG is optimized to the majority of the demand, meaning it can be operated at near-optimal efficiency most of the time. Yet, the optimal size means that some excess energy is generated in low load conditions – about 1.3% Figure 10(b) – but cost savings from the more efficient operation outweigh the cost of excess energy.
3 Batteries allow for peak shaving and load balancing, enabling more operation at optimal efficiency for the GTG and DG.

(2) Reduction of the Fixed Cost by 42.5% (23% of savings) through optimized configuration:

1 The optimized sizing reduces the significant oversizing compared to the actual operation.
2 The optimal sizing includes the trade-off between the higher capital costs of the GTG and the fuel savings, resulting in a more cost-effective overall configuration. For the few times when the demand is higher than the GTG's optimal operating point, the DG's lower capital cost makes it economical, despite its higher operating cost.

Due to the higher WHR potential of the GTG compared to the DGs, the optimal configuration also has a higher WHR potential of 1245.8 MWh compared to 739 MWh in the reference system (68.6% increase – see Figure 10(c)), which would further increase overall efficiency if utilized.

Overall, the results show the potential for cost savings through the application of MESO in the design and operation of the auxiliary power system of a VLCS. Fuel consumption is reduced and the capital investment is optimized by right-sizing the components to better match the demand profile.

6.4.2. Results with artificial load

When including the artificial load, the optimal configuration includes a slightly larger GTG (3.09 MW) and an additional DG (both 3.6 MW) compared to the baseline scenario, while the battery capacity is reduced to 1.22 MWh Figure 10(a). The cost savings compared to the current configuration are reduced to 25.4%. This reduction compared to the baseline scenario mainly results from the increased capital costs of the additional DG needed to meet the regulatory requirement of supplying a fixed amount of power, reducing the fixed cost savings to 8.9%. The operating cost savings are reduced to 28.9% due to the increased fuel consumption of the additional DG and the less optimal operation of the GTG due to the need to meet the artificial load. Similar to the baseline scenario, the WHR potential is higher than the reference system at 1394.4 MWh (71.6% increase – Figure 10(c)). As in the baseline, the cost savings of the optimized sizing outweigh the cost of the excess energy generated in low load conditions, which is about 1.5% in this scenario Figure 10(b).

The potential savings are still significant and show that even with regulatory constraints leading to unrealistic operating conditions, there is a potential for cost savings through the application of MESO. The results also highlight the importance of considering regulatory requirements in the design and optimization of energy systems, as they can have a significant impact on the optimal configuration and the achievable savings.

6.4.3. Discussion and limitations

For both scenarios, roughly 1500 different configurations are calculated in the 12 h optimization runs, which is a notable decrease compared to the cruise ship case study that can be attributed to the added complexity of the operation optimization problems due to the partial-load efficiency models. Still, the number of investigated configurations is higher than what would be possible with a more detailed energy system model, demonstrating MESO's ability to explore a large design space while maintaining computational feasibility. The limitations mentioned in the operation optimization results also apply to the full MESO application, as the optimization does not account for operational reasons that lead to more DGs being active than energetically necessary, but results in a techno-economic optimum under the selected operational assumptions. Class requirements, e.g. for redundancy or reserve margins would affect the optimal architecture with additional generation capacity and could thereby slightly reduce the savings potential and operational efficiency through additional generation capacity. Specific maneuvering modes and spinning reserve requirements can be directly included in the representative load profiles, also leading to more generation capacity and potentially reducing savings potential.

As in the cruise ship case study, the results are highly dependent on the chosen cost parameters and the trade-offs they infer. In contrast to the cruise ship case study, operating costs dominate the cost savings, suggesting the combination of fuel and emission costs and partial-load efficiency parameters for the competing GTGs and DGs to be the most influential assumptions in the optimization. However, the dissimilarity between the cost parameters for the GTGs and DGs suggests a sufficient robustness of the resulting configuration to slight parametrization changes. A comprehensive sensitivity analysis will further quantify the sensitivity to the most influential parameters.

7. Conclusion

This paper presents the Maritime Energy System Optimizer (MESO), a holistic optimization framework for ship energy systems that co-optimizes synthesis, design, and operation. By employing a genetic algorithm for configuration optimization and a MILP solver for operational optimization, MESO enables the exploration of a vast design space without human bias, allowing for the identification of highly efficient and unconventional energy system architectures.

The case studies on a cruise ship's multi-energy system and a VLCS's auxiliary electrical system demonstrated MESO's ability to propose improved, partially unusual configurations compared to traditional configurations while maintaining flexibility in component selection and system design. Both case studies showed more than 10 % cost savings for all scenarios compared to reference systems with optimized operation, showing MESO's effectiveness, ranging from large, coupled energy systems with dimensioning and placement as the main improvement potential, to simpler systems with a focus on more in-depth partial-load operation optimization.

MESO is a powerful tool for energy system design, facilitating the transition towards more sustainable and efficient shipping operations. Its generic implementation and modular design allow for future expansion and facilitate quick adoption of new use cases, even beyond the maritime sector. Ongoing work focuses on further generalization, improved topology representation, algorithmic enhancements, and the investigation of integrating machine learning techniques to enhance optimization performance.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Mattis Molinski http://orcid.org/0000-0003-0750-8133
Jana Ihrens http://orcid.org/0000-0002-1523-9511
Thorsten A. Kern http://orcid.org/0000-0002-3336-4383

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