

PAPER • OPEN ACCESS

Piecewise-linear MILP optimization for energy system design onboard hybrid ships

To cite this article: Andriy Vasylyev *et al* 2024 *J. Phys.: Conf. Ser.* **2893** 012040

View the [article online](#) for updates and enhancements.

You may also like

- [Real-time inverse high-dose-rate brachytherapy planning with catheter optimization by compressed sensing-inspired optimization strategies](#)
C V Guthier, K P Aschenbrenner, R Müller et al.
- [Conversion of dose-volume constraints to dose limits](#)
Jianrong Dai and Yunping Zhu
- [Toward semi-automatic biologically effective dose treatment plan optimisation for Gamma Knife radiosurgery](#)
Thomas Klinge, Hugues Talbot, Ian Paddick et al.



ECS The Electrochemical Society
Advancing solid state & electrochemical science & technology

247th ECS Meeting
Montréal, Canada
May 18-22, 2025
Palais des Congrès de Montréal

Showcase your science!

Abstract submission deadline extended: December 20

ECS UNITED

Piecewise-linear MILP optimization for energy system design onboard hybrid ships

Andriy Vasylyev^{1*}, Matteo Passalacqua¹, Luca Mantelli¹, Massimo Rivarolo¹ and Alessandro Sorce¹

¹ TPG - DIME, Università di Genova, Genova, Italy

*E-mail: andriy.vasylyev@edu.unige.it

Abstract. In recent decades the share of GHG (Green House Gases) such as carbon dioxide (CO₂), and local pollutants as carbon monoxide (CO), nitrogen oxides (NO_x), and sulphur oxides (SO_x) produced by shipping has significantly increased. In the case of CO₂, the IMO (International Maritime Organization) has estimated that emissions will increase by a range of 90-130% in 2050 as compared to 2008. In this scope, penetration of new technologies such as Battery Energy Storage Systems (BES) can reduce the share of emissions, giving more flexibility to the ship's system. In this work, an optimization algorithm based on Mixed-Integer-Linear-Programming (MILP) approach has been developed to define the best environmentally sustainable technology mix to be installed on board. The model is based on Demand-Driven optimization, where the main goal is to satisfy electrical and thermal energy demand, which is achieved by using linear constraints. The objective function is defined to minimize on-board energy production costs considering the CAPEX and OPEX of each technology, choosing the best technology mix and giving the schedule of working conditions for each installed technology. The non linearity of the components' characteristic curves is tackled through piecewise-linearization approach. In this way, the algorithm can optimize the real operating conditions for technologies with higher accuracy of partial load conditions. The case study is based on real energy demand profiles of a cruise ship sailing between Stockholm and the island of Åland, in the Baltic Sea.

1. Introduction

As CO₂ emissions continue to rise rapidly, reaching a record 36.8 Gtons in 2022 [1], it has become crucial to limit their increase in the most impactful sectors. In the mobility sector, maritime transport plays a significant role, with CO₂ emissions increasing from 962 to 1056 Mtons (+9.6%) between 2012 and 2018 [2]. Currently, nearly 98% of maritime vessels use Internal Combustion Engine (ICE) technology for propulsion, the vast majority being powered by diesel oil [2], which has a substantial environmental impact, especially for large ships like cruise ships and tankers.

The International Maritime Organization (IMO) has implemented various regulations to reduce emissions, establishing several Emission Control Areas to limit sulfur and nitrogen oxides, particularly in coastal regions. In 2023, the IMO set an updated long-term strategy aiming to reduce CO₂ emissions per transport work by 30% by 2030, with efforts to achieve a 70% reduction by 2040 compared to 2008 levels [3].



In this context, introducing low-carbon fuels and innovative technologies is essential. Researchers are exploring the replacement of heavy fuel oil (HFO) with more sustainable alternatives such as natural gas, ammonia, and methanol, which can be used in ICEs alone or in combination with other fuels [4], [5]. Additionally, Proton-exchange membrane fuel cells (PEMFC) are promising for onboard use due to their high efficiency, zero greenhouse gases (GHG) or pollutant emissions, low noise and vibrations. Both ICEs and PEMFCs can also be integrated with Battery Energy Systems (BES) [6], [7], [8] to create either a hybrid-electric (HE) power generation system or a completely zero-emission hybrid FC-electric (HFCE) architecture. Alongside alternative fuels, thermal HE power generation systems are widely considered in the maritime context as drop-in solution for carbon emission reduction [9], [10], while HFCE systems strongly depend on the maturity of marine-ready fuel cell technology.

Given the ongoing development of various low-carbon innovative technologies, it is crucial to compare all potential solutions to identify the most promising ones. It is also paramount to account for the specific characteristics and constraints of naval applications as well as the costs associated with onboard energy production, as highlighted in [11]. Moreover, an effective onboard electrical and thermal power management is considered paramount to increase conversion efficiency and achieve decrease in carbon emission in maritime sector [12], [13].

Mixed-Integer Linear Programming (MILP) models have been extensively used to optimize the installation and operation of distributed energy systems [14], including renewables and energy storages [15]. The use of the MILP approach is was deeply analysed by Vasylyev A. et. al. comparing different optimizing algorithm implemented in MatLab [16]. However, only a few applications of MILP models for the optimization of the energy generation on ships can be found in literature [17], [18]. Furthermore, MILP models have also been implemented to investigate innovative technologies for maritime application [19].

In previous work, the authors developed an optimization model to manage energy demand, using a simplified model for handling the off-design conditions of the technologies considered [20]. The novelty of this work is utilizing the Piecewise linearization (PWL) which is a powerful yet simple method to be used in combination with MIP problems [21]. This method is particularly useful in optimization and control problems when dealing with nonlinearities can be complex and computationally intensive. By breaking down a nonlinear function into linear segments, the problem becomes more manageable and can be solved using linear programming techniques which are well-developed and efficient [22]. Different methods of piecewise linearization can be employed to this scope [22], [23].

In this paper, the optimal strategy of energy allocation is evaluated for a reference hybrid ICE-BES cruise ship via a piecewise-linearized Mixed-Integer Linear Programming (MILP) approach, supporting both the preliminary design phase through the selection of the best set of energy systems installed on a ship and its optimal operating strategy based on the installed power converters.

2. MILP Model description

The model developed for this study was designed as capable of supporting the preliminary design phase of the energy systems installed on a ship and its optimal operating strategy based on the installed power converters. The optimization is performed by comparing different technologies for onboard electric and thermal power generation. The optimization model was evaluated considering an objective functions which considers overall costs (including CAPEX and OPEX as per Eqs. (6), (7) and (8)) and CO₂ cost by means of the carbon tax. The optimization model was

developed in MATLAB, while the mathematical optimization procedure relies on the built-in Yalmip toolbox, and for solving the problem, the Gurobi solver for linear problems was used. [24]. To find the optimal solution, the optimizer considers the following technologies:

- Internal Combustion Engines (ICE) or Diesel generators (DG)
- Heat Recovery Heat Exchanger (HRHE)
- Fired Boilers (FB)
- Battery Energy Storage (BES) (electrochemical Lithium-ion batteries)

ICEs contribute to both propulsion and electrical power, while HRHEs and FBs cover the thermal demand by recovering waste heat from DG exhaust gases and producing heat via direct combustion, respectively. BESs are charged via ICE DGs and discharged on the ship's electrical bus as optimally needed. Considering an electric motor driving the propeller assembly installed on the ship, the propulsive power is included into the electricity balance. To account for the overall energy transformation efficiency of 95%, the propulsive demand is adjusted accordingly.

The solution found by the MILP model is limited by different types of constraints that are implemented on the algorithm. Specific operative constraints ensure that the variables under consideration stay within physical limits, while constraints related to power, efficiency, current, and fuel consumption ensure that the physics of each component is complied with.

Table 1 reports the main characteristics of the power system components that have been devised for this study and are chosen by the optimizer as the best applicable solutions.

Table 1. Characteristics of the power system components considered in the simulation

Component	ID of item	Max Power [kW] or Rated Capacity [kWh] ^a	Efficiency [-]	Reference	No. of items installed (Selected by the optimizer)
ICE DG	A	7500	Variable with load (PWL)	[25]	2
	B	11930	Variable with load (PWL)	[25]	1
HRHE	A	1000	0.85	[26]	1
	B	1500	0.9	[26]	1
FB	A	1500	0.9	[27]	1
	B	970	0.9	[28]	1
BES	A	990 ^a	0.95	[29]	1
	B	3725 ^a	0.95	[30]	1
	C	1970 ^a	0.94	[31]	1
	D	960 ^a	0.93	[32]	0

^a For BES components, the energy capacity in kWh is reported.

2.1 Piecewise linearization approach

The characteristic curves of power systems are often described by non-linear functions. This is due to the dependency of their relevant parameters (such as efficiency, volume and weight) upon different physical quantities. Thus, piecewise linearization of such curves allows for simpler and faster computation. The process involves dividing the domain of the nonlinear function into several intervals and then approximating the function within each interval using a linear equation. This piecewise linear model provides a close approximation to the original nonlinear function while maintaining the simplicity of linear relationships.

As a general example for the piecewise linearization approach, the ICE DG system will be considered. The fuel consumption of the energy system is strongly dependent on the power output of the ICE DG. In this way, the optimized power variable and the cost associated with operating the system can be linked through linearized fuel consumption. To define a proper linearized function it must be introduced the auxiliary variable called “on-off DG” defined as a three-dimensional matrix with index i for a specific component, j for the linearized piece, and k for the optimized hour.

$$P_{min}(i, j) \cdot onoff_{DG}(i, j, k) \leq P_{DG}(i, j, k) \leq P_{max}(i, j) \cdot onoff_{DG}(i, j, k) \quad (1)$$

$$\alpha(i, j) = \frac{\dot{m}_{fuel,max}(i, j) - \dot{m}_{fuel,min}(i, j)}{P_{max}(i, j) - P_{min}(i, j)} \quad (2)$$

$$\beta(i, j) = \dot{m}_{fuel,max}(i, j) - \alpha(i, j) \cdot P_{max}(i, j) \quad (3)$$

$$\dot{m}_{fuel}(i, j, k) = \alpha(i, j) \cdot P_{DG}(i, j) + \beta(i, j) \cdot onoff_{DG}(i, j, k) \quad (4)$$

$$\eta(i, j) = \frac{P_{DG}(i, j)}{\dot{m}_{fuel}(i, j) \cdot LHV} = \frac{P_{DG}(i, j)}{(\alpha(i, j) \cdot P_{DG}(i, j) + \beta(i, j)) \cdot LHV} \quad (5)$$

Equations 1 to 5 comprehensively describe how the linearised function optimization problem has been implemented. Eq. (1) defines the bounds for the optimized function P_{DG} according to the linear range in which the system is subject to operate. Eqs. (2) and (3) are used to define the coefficient for the piecewise linearization of the fuel consumption of the DG considering the operating conditions. It is important to note that α and β have just two dimensions considering the specific diesel generator and a specific linearized piece, while for the P_{DG} third dimension is also used to describe the variability through optimized hours. Eq (4) highlights the link between fuel consumption and the operating conditions of the DG, this variable is used to evaluate the fuel cost, Ω_{HFO} , in Eq. (8) and CO2 cost, Ω_{CO2} , in Eq. (7) in the total objective function. Finally, Eq. (5) can be used to calculate the efficiency of the DG. This variable is not used as an input to the objective function, as this would make the model non-linear making it impossible to use MILP. On the other hand, this variable is very useful to compare the real operating curve with the approximate one used to optimise the objective function.

2.2 Case study description

Demand data refer to the thermal and electric consumptions of a real cruise ship sailing between Stockholm and the island of Åland, in the Baltic Sea. The ship was built in 2004 and has a capacity of 1800 passengers, a design speed of 21 knots, a length of 176.9 m, a beam of 28.6 m and a draught of 6.5 m [18].

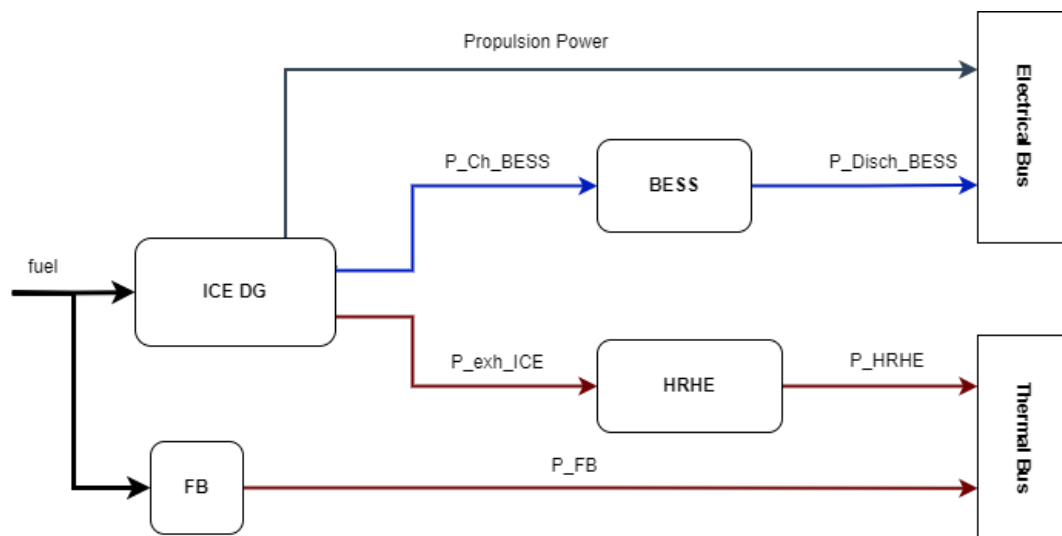


Figure 1. Power flow diagram for the case study HE cruise ship.

Thanks to a comprehensive data analysis and energy demand clustering, five typical days were identified. These days are considered in this work as representative of the electricity and heat demands for a ship with a similar size. The ship's mission profile was considered. The propulsive energy demand is included into the electrical load, having considered fully electric propulsion. The complete powertrain arrangement scheme is depicted in Figure 1.

Figure 2 represents the electrical and thermal loads for each typical day. Typical days are repeated throughout the year with the amounts reported in Table 2. The optimizer identifies the energy mix capable of satisfying these loads while minimizing the objective function (overall costs, including CAPEX, OPEX and CO₂ cost).

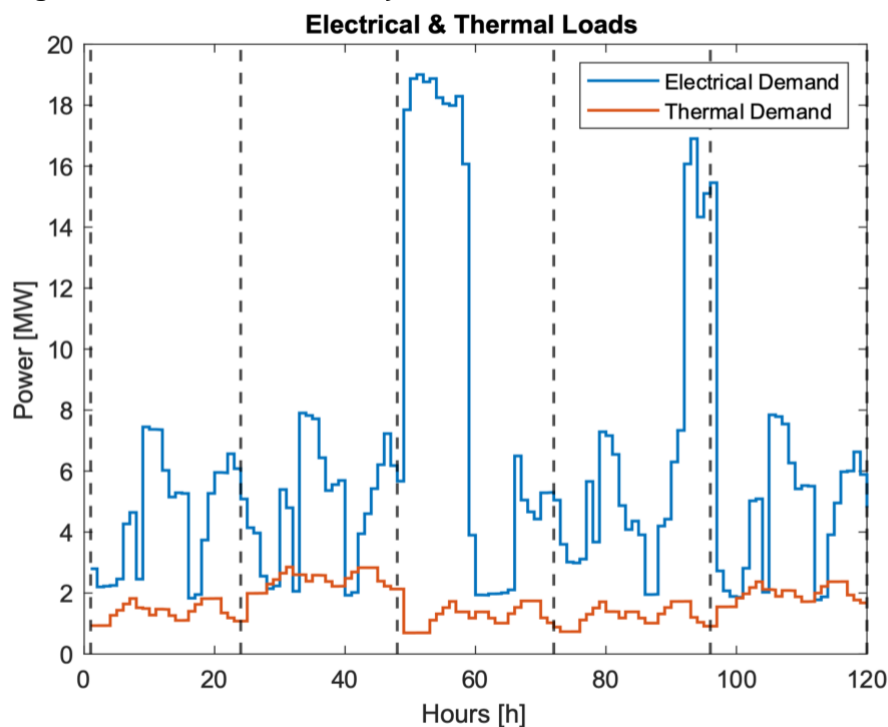


Figure 2. Electrical and thermal loads for the case study ship. Each typical day is represented by the columns laying between each pair of dashed lines.

2.3 Objective function

Both costs functions are calculated considering the typical days presented in Section 2.2.

The objective cost function Ω to be minimized is reported as sum of Ω_{TCE} (6), Ω_{CO2} (7) and Ω_{HFO} (8):

$$\Omega_{TCE} = \sum_{i=1}^S (CAPEX_i N_i) \quad (6)$$

$$\Omega_{CO2} = (\dot{m}_{HFO}^{tot} \Delta t C_{CO2}) EF_{HFO} * 1000 \quad (7)$$

$$\Omega_{HFO} = \dot{m}_{HFO}^{tot} \Delta t C_{HFO} \quad (8)$$

The costs in Ω_{TCE} (Total Cost of Equipment) include the capital cost to purchase each i -th energy system (CAPEX) and the cost of fuel consumed by it C_{HFO} over the year. HFO cost is considered to be 0.53 €/kg [33], and it is assumed to be constant over the year.

The cost of CO₂ emissions in Ω_{CO2} are computed considering an emission factor (EF_{HFO}), that is the average mass of carbon dioxide produced by the combustion per kg of HFO consumed, multiplied by the fuel consumption $\dot{m}_{HFO}$ and the value of the carbon tax C_{CO2} . The EF for HFO is assumed to be 3.15 kg_{CO2}/kg_{HFO} [34], while the carbon tax is assumed to be 100 €/ton_{CO2}.

3. Results

In this chapter, the results of the MILP optimization model are presented. The simulation leads to a stable solution with a residue whose value is lower than 0.3% after around 140s.

Figure 3 shows the optimal schedule that covers the ship's electrical demand. It appears clear that most of the onboard power is produced by ICE generators and only a limited amount originates from the BES. The maximum power discharge from the batteries occurs at the 10th hour of the typical day 2 and is equal to 2.97 MW, which makes up for 38% of the maximum electrical demand for the typical day 2 (7.9 MW), which also occurs at the same hour. The maximum battery power charge occurs at the 16th hour of the typical day 2 and equals 2.93 MW, which is 152% of the electricity demand of the same hour.

Figure 4 highlights the optimal schedule for the thermal demand of the case study ship. Thanks to the large availability of exhaust gases from the ICE DGs, the vast majority of the thermal demand is covered by the HRHE and the simulation model is able to maximize operation in this optimal condition.

Table 2. Electrical and thermal demand characteristics

	Max Electrical Demand [MW]	Max Thermal Demand [MW]	Number of days
Typical day 1	7.5	1.8	57
Typical day 2	7.9	2.9	19
Typical day 3	19	1.7	25
Typical day 4	17	1.7	148
Typical day 5	7.8	2.4	116

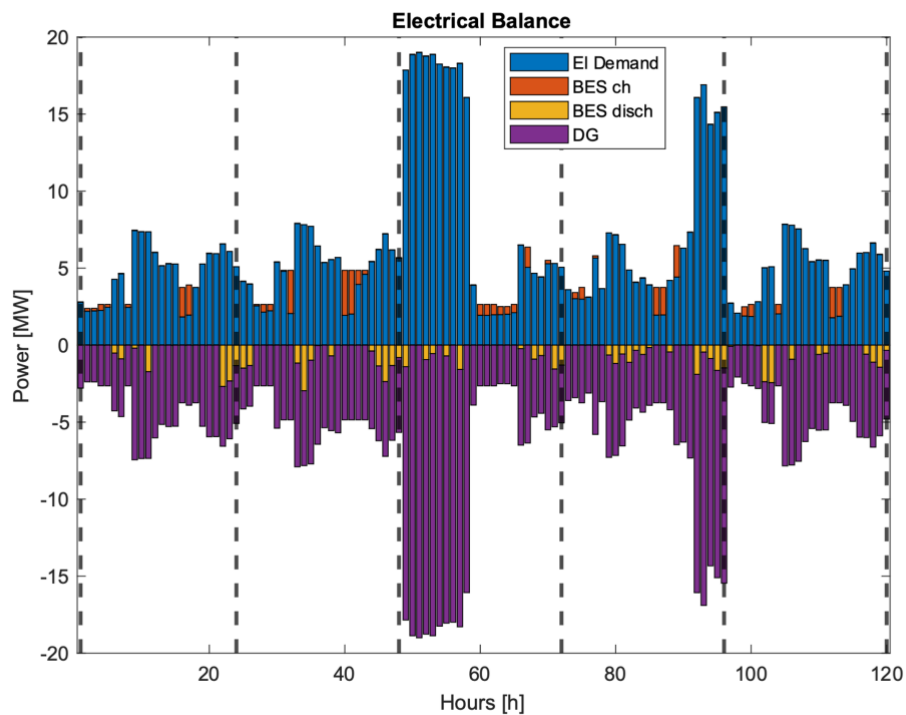


Figure 3. Electrical demand and optimal overall electrical energy balance

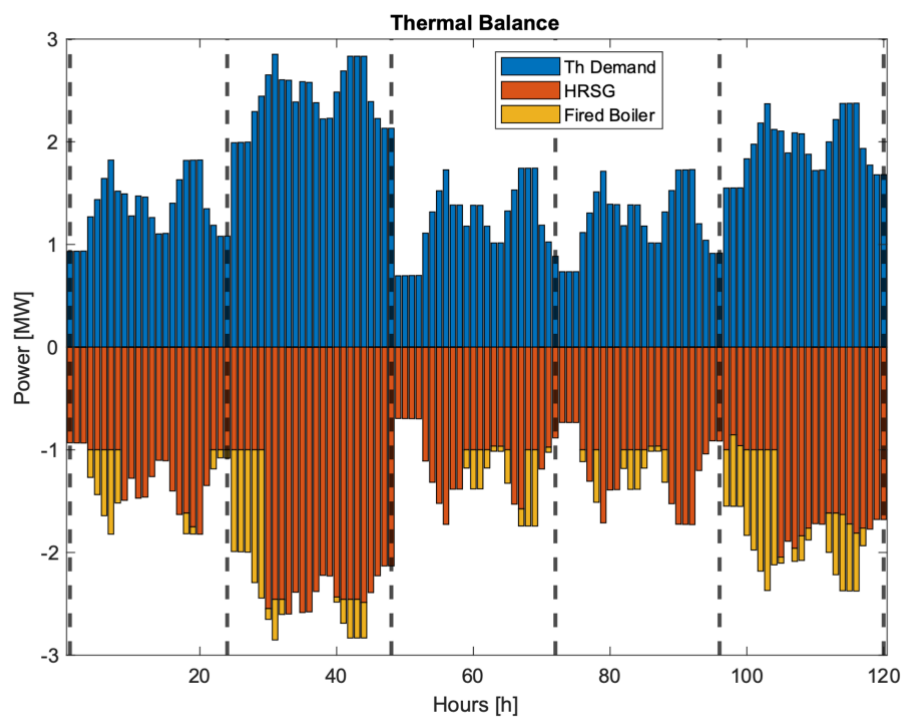


Figure 4. Thermal demand and optimal overall thermal energy balance

The maximum thermal power provided by the auxiliary FB is equal to 1.44 MW and is registered at the 5th hour of typical day 2, contributing 59% to the overall thermal demand in that hour. It should be observed that the high share of FB thermal power in the first hours of that day is due to the limited power production of the DGs (Figure 3), which guarantees less exhaust mass flow and in turn, a lower thermal recovery potential.

Figure 5 depicts the optimized operation strategy for the BES, both in terms of power (Figure 5 top) and state of charge (SoC, Figure 5 bottom), further splitting up the contributes from each battery pack. When high charging or discharging powers are required, the largest battery pack (BES 2, 3.73 MWh capacity) operates most of the time and with narrower ranges of charge and discharge, while smaller BESs are working either to cover the power spikes or when lower overall battery power is required, typically with higher ramp-ups.

In Figure 6, the sharing of thermal power provided from HRHE and FB is represented. HRHE A often works at full load (Table 1), while HRHE B operates at hours of large demand. Moreover, the same trend as Figure 4 is visible: the fired boilers operate when ICE DGs are at part load and cannot provide sufficient heat to the WHR unit (early hours of typical days 2 and 5). This confirms again the optimizer's tendency to always favour heat recovery instead of its production via FBs and operate them only when strictly bounded by the heat demand.

Finally, Figure 7 shows the reduction in CO₂ emissions thanks to the installation of the BES system. The reduction is registered to be more than 20 tons over the five typical days mission, which consist of roughly 5% reduction for the considered HE layout with respect to the full-ICE powered ship and translates into a saving of approximately 1450 tons CO₂ on a yearly basis.

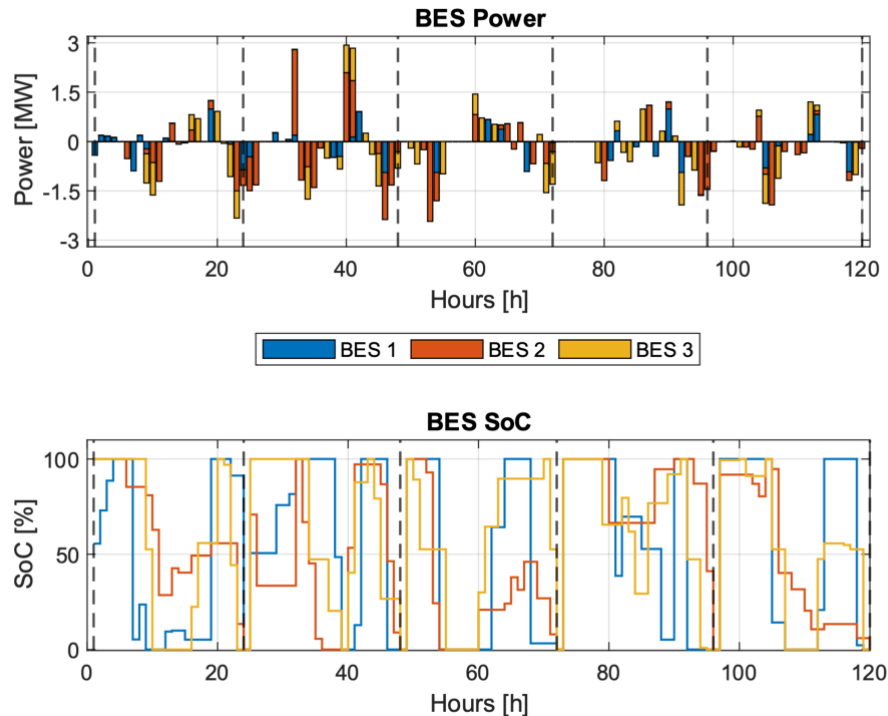


Figure 5. BES optimal power allocation and SoC.

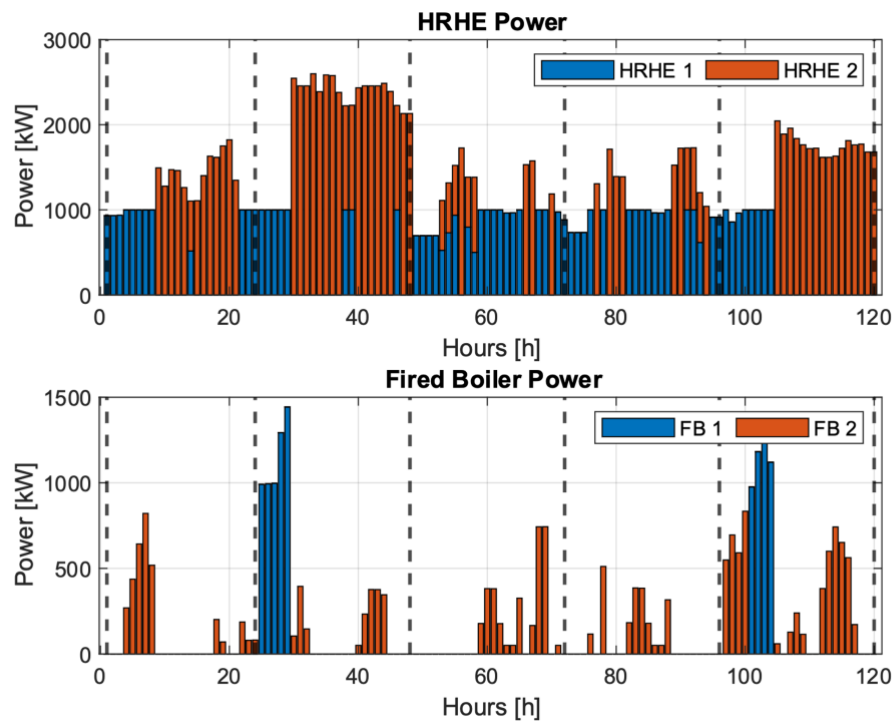


Figure 6. HRHE and FB optimal thermal power allocation

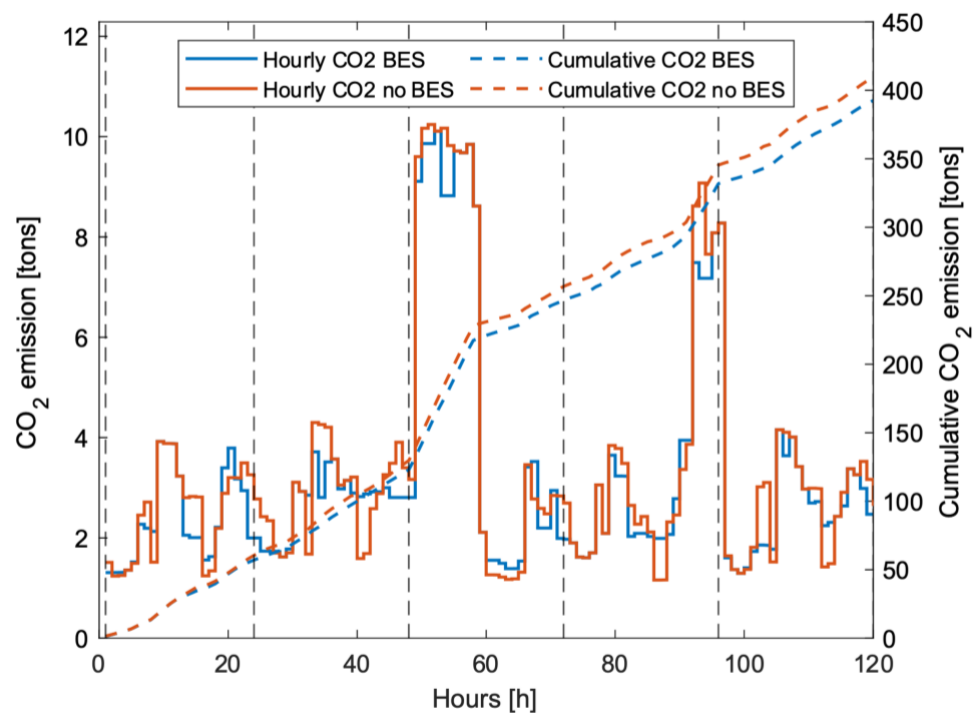


Figure 7. Trend of hourly CO₂ emission and cumulative savings over the whole mission

Table 3. Objective function values in the optimized case

	Fuel Cost DG	Fuel Cost FB	Fuel Cost TOT	CO ₂ Cost DG	CO ₂ Cost FB	CO ₂ Cost TOT	BES SoC _i Cost	CAPEX	Total Obj Value
With BESS [M€]	4.84	0.13	4.97	2.79	0.07	2.86	0.03	0.66	8.52
No BESS [M€]	4.88	0.13	5.01	2.81	0.08	2.89	0.00	0.68	8.58
Variation	-0.76%	-3.73%	-0.84%	-0.76%	-3.73%	-0.84%	100%	-3.22%	-0.66%

4. Conclusions

This article presented a MILP model to determine the best power generation mix of a HE ship. The model was developed in MATLAB environment, relying on the Yalmip toolbox for the optimization procedure. The model compares different power generation technologies to find the layout that minimizes a certain objective function. The main system constraints were implemented to take into account constitutive equations and energy balances (electrical and thermal) of each energy system. Then, the model was applied to a case study of a cruise ship for five electrical and thermal load profiles, each one representative of a typical navigation day within an entire year. Such load profiles are based on experimental data available from literature.

An objective function aimed at cost minimization is implemented. The optimal plant layout requires the installation of three ICE (2x ICE DG A and 1x ICE DG B), three BES systems (one per type, BES A, BES B and BES C), and two HRHE (one per type, HRHE A and HRHE B). The optimal electric and thermal power generation mix have been optimized on a hourly base and results show that heat recovery from the ICE DG exhaust is maximized depending on the electrical demand, while electrical power is provided mostly from engines and only for 38% maximum from BES. The CO₂ saving is registered to be 5% over 120 hours mission, for a yearly reduction of roughly 1450 tons.

In conclusion, it is possible to state that the developed optimizer is stable and flexible. The use of a MILP approach in the formulation of the problem guarantees rapid convergence of the solution, with a residue always lower than 0.3% after 140s, and PWL of the systems' characteristic curves guarantees better adherence to the actual off-design behaviour of the components.

Future improvements will include the expansion of the database with a larger set of technologies, both consolidated and innovative such as PEM fuel cells, hydrogen and heat pumps, allowing for a wider range of possible layout simulations. Moreover, a sensitivity analysis onto relevant parameters will be carried out to identify the marginal cost of innovative technologies.

Acknowledgements

The Authors acknowledge the Project funded under the National Recovery and Resilience Plan (PNRR), Mission 4 Component 2 Investment 1.3 - Call for tender No. 1561 of 11.10.2022 of University and Research Ministry (MUR); funded by the European Union – NextGenerationEU, PE0000021, Network 4 Energy Sustainable Transition – NEST.

References

- [1] IEA, “World Energy Outlook 2023,” 2023. [Online]. Available: www.iea.org/terms
- [2] DNV, “MARITIME FORECAST TO 2050,” 2022.
- [3] IMO, “INITIAL IMO STRATEGY ON REDUCTION OF GHG EMISSIONS FROM SHIPS,” 2018. [Online]. Available: <http://www.imo.org>
- [4] A. Armellini, S. Daniotti, P. Pinamonti, and M. Reini, “Evaluation of gas turbines as alternative energy production systems for a large cruise ship to meet new maritime regulations,” *Appl Energy*, vol. 211, pp. 306–317, Feb. 2018, doi: 10.1016/j.apenergy.2017.11.057.
- [5] P. Balcombe *et al.*, “How to decarbonise international shipping: options for fuels, technologies and policies,” 2019.
- [6] A. Bouakkaz, A. J. G. Mena, S. Haddad, and M. L. Ferrari, “Efficient energy scheduling considering cost reduction and energy saving in hybrid energy system with energy storage,” *J Energy Storage*, vol. 33, Jan. 2021, doi: 10.1016/j.est.2020.101887.
- [7] O. B. Inal and C. Deniz, “Assessment of fuel cell types for ships: Based on multi-criteria decision analysis,” *J Clean Prod*, vol. 265, Aug. 2020, doi: 10.1016/j.jclepro.2020.121734.
- [8] M. Rivarolo, D. Rattazzi, and L. Magistri, “Best operative strategy for energy management of a cruise ship employing different distributed generation technologies,” *Int J Hydrogen Energy*, vol. 43, no. 52, pp. 23500–23510, Dec. 2018, doi: 10.1016/j.ijhydene.2018.10.217.
- [9] S. E. Damian *et al.*, “Review on the challenges of hybrid propulsion system in marine transport system,” Dec. 10, 2022, *Elsevier Ltd*. doi: 10.1016/j.est.2022.105983.
- [10] A. Dotto and F. Satta, “Techno-economic optimization of hybrid-electric power plants onboard cruise ships,” *Energy Conversion and Management: X*, vol. 20, Oct. 2023, doi: 10.1016/j.ecmx.2023.100436.
- [11] M. Rivarolo, D. Rattazzi, L. Magistri, and A. F. Massardo, “Multi-criteria comparison of power generation and fuel storage solutions for maritime application,” *Energy Convers Manag*, vol. 244, Sep. 2021, doi: 10.1016/j.enconman.2021.114506.
- [12] Y. Yan *et al.*, “Multi-objective design optimization of combined cooling, heating and power system for cruise ship application,” *J Clean Prod*, vol. 233, pp. 264–279, Oct. 2019, doi: 10.1016/j.jclepro.2019.06.047.
- [13] F. Baldi, F. Ahlgren, F. Melino, C. Gabriellii, and K. Andersson, “Optimal load allocation of complex ship power plants,” *Energy Convers Manag*, vol. 124, pp. 344–356, Sep. 2016, doi: 10.1016/j.enconman.2016.07.009.
- [14] H. Ren and W. Gao, “A MILP model for integrated plan and evaluation of distributed energy systems,” *Appl Energy*, vol. 87, no. 3, pp. 1001–1014, 2010, doi: 10.1016/j.apenergy.2009.09.023.

- [15] C. Wouters, E. S. Fraga, and A. M. James, “An energy integrated, multi-microgrid, MILP (mixed-integer linear programming) approach for residential distributed energy system planning - A South Australian case-study,” *Energy*, vol. 85, pp. 30–44, Jun. 2015, doi: 10.1016/j.energy.2015.03.051.
- [16] A. Vasylyev, A. Vannoni, and A. Sorce, “Best Practices for Electricity Generators and Energy Storage Optimal Dispatch Problems,” *Journal of Gas Turbine and Power*, vol. 146, no. 3, 2023, doi: <https://doi.org/10.1115/1.4063529>.
- [17] D. Steen, M. Stadler, G. Cardoso, M. Groissböck, N. DeForest, and C. Marnay, “Modeling of thermal storage systems in MILP distributed energy resource models,” *Appl Energy*, vol. 137, pp. 782–792, Jan. 2015, doi: 10.1016/j.apenergy.2014.07.036.
- [18] F. Baldi, F. Ahlgren, T. Van Nguyen, M. Thern, and K. Andersson, “Energy and exergy analysis of a cruise ship,” *Energies (Basel)*, vol. 11, no. 10, Oct. 2018, doi: 10.3390/en11102508.
- [19] W. Zhang *et al.*, “Assessment of cruise ship decarbonization potential with alternative fuels based on MILP model and cabin space limitation,” *J Clean Prod*, vol. 425, Nov. 2023, doi: 10.1016/j.jclepro.2023.138667.
- [20] M. Cavo, L. Mantelli, M. Rivarolo, and A. Vasylyev, “A MILP approach for hybrid energy systems design for sustainable maritime mobility,” in *36th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, ECOS 2023*, 2023. doi: 10.52202/069564-0131.
- [21] M. Bernreuther, “Solving Mixed-Integer Programming Problems Using Piecewise Linearization Methods,” 2017. [Online]. Available: <http://nbn-resolving.de/urn:nbn:de:bsz:352-2-1gxw6ja5feelr3>
- [22] M. H. Lin, J. G. Carlsson, D. Ge, J. Shi, and J. F. Tsai, “A review of piecewise linearization methods,” 2013. doi: 10.1155/2013/101376.
- [23] E. Camponogara and L. F. Nazari, “Models and Algorithms for Optimal Piecewise-Linear Function Approximation,” *Math Probl Eng*, vol. 2015, 2015, doi: 10.1155/2015/876862.
- [24] J. Efborg, “YALMIP : A toolbox for modeling and optimization in MATLAB,” 2004.
- [25] “WinGD General Technical Data (GTD).”
- [26] “Heating systems - Steam boilers and Waste Heat Boilers,” 2023.
- [27] “Alfa Laval Aalborg - Micro Waste heat recovery boiler,” 2023. [Online]. Available: www.alfalaval.com
- [28] “Alfa Laval Aalborg-xs-tc7a,” 2023.
- [29] “Energy Storage Systems - Corvus Orca,” 2023.
- [30] “Energy Storage Systems 12 Corvus Energy • Corvus Blue Whale,” 2023.

- [31] “Energy Storage Systems 14 Corvus Energy Corvus Energy Safety Innovations Passive Single-cell-level Thermal Runaway (TR) Isolation Corvus Dolphin Energy NxtGen,” 2023.
- [32] “Nidec Marine Battery,” 2023. [Online]. Available: www.nidec-industrial.com
- [33] “EMEA Bunker Prices.” Accessed: Jun. 10, 2024. [Online]. Available: <https://shipandbunker.com/prices/emea>
- [34] Marine Benchmark, “Maritime CO2 Emissions,” 2020. Accessed: Jun. 10, 2024. [Online]. Available: https://safety4sea.com/wp-content/uploads/2020/11/Marine-Benchmark-Maritime-CO2-Emissions-2020_11.pdf