IMPROVING SHIP SUSTAINABILITY BY RE-USING ENGINEERING SIMULATORS IN MULTI-OBJECTIVE OPTIMIZATION

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SUMMARY

Modelling and simulation provide a systematic approach for evaluating system design and control concepts with respect to energy efficiency and operability. Adding optimization offers a way to utilize the models more comprehensively. This research deals with simulation-based optimization with the leading principles to use an existing system simulator as black-box in the optimization, and to take advantage of cloud computing. A case of an environmentally sustainable cruise ship design was selected. Alternatives for enhancing the ship's energy efficiency were investigated by introducing different waste heat recovery technologies and battery systems in the machinery. The ship designer's in-house ship energy system simulator was prepared for the optimization framework. Multi-objective optimization scenarios with economic and environmental objectives were conducted using genetic algorithm. Also, the main engines' running hours were of interest. The method was successfully used for finding the best overall solution in this complex ship energy system design task. The results suggest that adding battery capacity alone contributes very moderately to reducing the case ship fuel consumption and, therefore, carbon emissions. A combination of steam turbines and organic Rankine cycle units offered the largest fuel saving potential with the lowest investment cost. The presented optimization approach can bring significant added value for sustainable ship design with minor additional effort on top of the normal modelling activities in the design phase. The research revealed that to streamline the optimization step the simulation input and output management, the resultant validity checking, and the error handling should be anticipated already during the construction of the simulator.

KEY WORDS

Simulation-based optimization, cloud computing, ship design, battery, waste heat recovery

NOMENCLATURE

BMS	battery management system
BPST	back pressure steam turbine
CAPEX	capital expenditure
CST	condensing type steam turbine
FMU	functional mockup unit
EGB	exhaust gas boiler
GA	genetic algorithm
GHG	greenhouse gas
HUE	heat utilization efficiency
HT	high temperature
IMO	International maritime organisation
LT	low temperature
MEPC	Marine Environment Protection Committee
MDO	marine diesel oil
NSGA-II	non-dominated sorting genetic algorithm II
OPEX	operational expenditure
ORC	organic Rankine cycle
PMS	power management system
SFOC	specific fuel oil consumption
ST	steam turbine
STT	steam turbine types

1. INTRODUCTION

Like any modern industrial sectors, the maritime industry must also meet the challenges of environmental sustainability. Marine Environment Protection Committee (MEPC) under IMO (International maritime organisation) recently approved draft of new regulations that would require majority of new and existing ships to combine both technical and operational measures to reduce their carbon intensity (IMO, 2020). The first new regulations regarding this dual approach, including ship energy efficiency design index for operational ships of 400 gross tonnage and above and carbon intensity index for all ships above 5000 gross tonnage are entering into force during 2023. Decarbonisation of a ship can be promoted by operational improvements, technical system optimization, by utilizing low-GHG fuels and through market-based measures (Serra and Fancello, 2020). To achieve the best available environmental sustainability requires a combination of the energy technology chosen onboard and the way it is operated in the given constraints such as route, operating speed, weather, cargo and passengers' comfort. This increased complexity poses challenges for the ship design, which has made modelling and simulation an appreciated method. The pressure on the ship's environmental footprint will increase even more in the future, and this pushes ship designers, shipyards and shipping companies to embrace their sustainability policies and practises. In this, the ability to consider and study different scenarios is important, which emphasizes the role of modelling and simulation.

At its best, simulation aided design covers different aspects holistically, considering the ship construction, synthesis of the system parts, functions and interactions, as well as safety and sustainability over the whole ship life-cycle. Furthermore, to find the best design solution, mathematical optimization methods can be applied using the same model. This ambitious concept has been called a holistic approach to ship design (Boulougouris *et al.*, 2011; Papanikolaou, 2019). Nevertheless, if focusing on the design of efficient energy systems onboard, a typical simulation should cover different energy disciplines and consider variable operational and environmental conditions of the planned shipping. This suggests dynamic or pseudo-dynamic system-wide modelling.

Early modelling studies, such as (Kyrtatos *et al.*, 1999), were focusing on some energy sub-system, most often addressing propulsion. Later studies have broadened the scope of modelling, and also considered the altering conditions during the cruise, to ensure the feasibility of the design, such as in (Zou *et al.*, 2013; Elg *et al.*, 2015; Lepistö *et al.*, 2016; Theotokatos *et al.,* 2017; Zheng and Zhou, 2019). It has been common to use general purpose modelling and simulation platforms, yet also specialized software for ship energy system simulation have been developed, such as DNV COSSMOS (Dimopoulos *et al.*, 2014), and the dynamic simulation tool developed by (Cichowicz *et al.,* 2015). In a typical simulation study, fuel consumption of different design variants is compared. More detailed energy analysis can be found, for example, in waste heat utilization studies, where exergy analysis is combined to energy modelling, such as in (Baldi *et al.*, 2015) and (Marty *et al.*, 2016).

While the energy simulations provide tools for system analysis, such as determining system efficiency or confirming smooth operation in transients, mathematical optimization looks one step further. It searches the best parameter values for minimizing/maximizing a cost function of interest, considering the decision variables and the system constraints. As energy system modelling capabilities have evolved, combining optimization with simulation has emerged. For instance, one study presented a problem of identifying the optimal main design parameters in the early phases of the design process as a multi-objective, combinatorial optimization problem, and suggested different methods for handling the trade-offs between different objectives (Ölçer, 2008). In another study a tool was proposed for optimizing ship main parameters based on a combination of heuristics and statistical analyses of previous ship designs and known modelling approaches for ship propulsion (Boulougouris *et al.,* 2011). The work of (Diez and Peri, 2010) and (Hannapel and Vlahopoulos, 2010) explored robust optimization framework for ship design, emphasizing importance of considering the uncertainty of the input data to the optimization. Ancona and coworkers (Ancona *et al.*, 2018) utilized genetic algorithm (GA) based energy grid software as a starting point for finding a proper load allocation for a defined machinery in a cruise ship. Trivyza et al., (Trivyza, *et al.,* 2018) presented a method for synthesis of both environmental and economic objectives over an expected operational profile. For the optimization, they employed a method, which was as well applied in this study: Non-dominated Sorting Genetic Algorithm II (NSGA-II). In the work of (Marques *et al.,* 2019a) an energy system design optimization approach was developed for liquified gas carriers considering economic, technical and weather aspects, and they presented a related case study in (Marques *et al.,* 2019b). Ritari et al., (Ritari *et al.*, 2020) developed a multi-period mixed-integer linear programming model for deriving a globally optimal power management strategy for the auxiliary engines of a ferry including a battery, with the goal of minimizing the total cost of the battery installation. Huotari et al., applied optimization in a cruise ship case (Huotari *et al.*, 2020), where the ship's local emissions near the coast were minimized with the aid of a fuel cell and battery in addition to a diesel generator set. These studies show that the domain of mathematical modelling and multi-objective optimization involves high computational load and uncertainties in the parameters. Priftis et al., presented a method for a multi-objective, robust, early stage ship design optimization under uncertainty (Priftis *et al.*, 2020). They used surrogate modelling (Kriging) for reducing the otherwise high computational load. Deep learning has also been proposed as a method for improving ship design. Miglianti et al., developed a tool for predicting spectra of cavitating marine propeller generated noise at the design stage (Miglianti *et al.*, 2020).

To introduce mathematical optimization methods into a simulation assisted ship design process is not straightforward in most cases. For example, the available optimization methods may limit the modelling work itself. On the other hand, developing an optimization scheme for each ad-hoc need requires a lot of extra work on top of the very limited time and resources in the concept design stage. Therefore, this article focuses on combining the optimization to existing ship design models and simulation tools. This is seen as a potential path for bringing considerable added value to the simulation aided ship engineering. The approach used in this study incorporates optimization with black-box simulation models, which is known as simulation-based optimization (April *et al.*, 2003; Gosavi, 2015). To deploy this approach, simulation-based optimization framework in the cloud was developed. This research was initiated with the following hypothesis: Today's cloud computing infrastructure enables an easy and flexible framework for taking out-of-a-box marine simulators and solving related optimization problems, as reported in (Lappalainen *et al.*, 2019; Korvola *et al.*, 2020). The optimization framework has been published as open source code in (Korvola and Rummukainen, 2021).

Section 2 introduces the optimization framework. In order to evaluate it in an actual ship design process, a generic energy simulation model of a cruise ship was used. The case ship and the model structure are described in Section 3. The work focused on finding the best solution for enhancing the ship energy efficiency and thus lowering the carbon footprint by introducing a waste heat recovery system, a battery or both. Section 4 reports the main results. Besides the actual optimization results, also experiences gained in the model conversion to be compatible with the optimization framework are given, and insights of using the presented optimization approach in industrial engineering projects. Finally, conclusions and a look at the future steps are given.

2. OPTIMIZATION FRAMEWORK

One of the main goals in this research was to enable optimization for simulation models that were not originally intended for that. Accordingly, gradient-based optimization algorithms are excluded, as simulators do not commonly provide the gradients. The model would have to be transformed into a representation that provides the gradients. This potentially tedious step was to be avoided in this research. Consequently, the focus was on black-box optimization algorithms that only require the ability to set parameters, run simulations and get results. Of these, evolutionary algorithms were chosen as the primary approach, because their calculations parallelise well. Parallel computing is lucrative in the cloud, because the pricing criterion is typically based on number of resources and time. If the algorithm parallelises well, more CPUs can be rented to run it on for a shorter time, obtaining results faster for the same cost.

The general software architecture of the framework, presented in Figure 1, remains essentially as reported previously (Lappalainen *et al.,* 2019). However, the computations were moved from the Microsoft Azure cloud to Rahti, a container cloud provided by CSC – IT Center for Science Ltd. This changed the container orchestration system from Kubernetes to OpenShift. OpenShift is a variant of Kubernetes, thus only minor changes were required in the framework.

The framework aims at providing an efficient service for distributed execution of simulations, as they usually comprise the most significant workload in this type of optimization. The service is implemented in Python using the Flask web service framework (Grinberg, 2018). There is also simple a Socket.IO (Rai, 2013) interface that notifies the client when simulation jobs finish. The Dask library (Dask Development Team, 2016) is used for distributing the simulations. Simulation results are stored in a ZODB database (Fulton, 2000). The client is implemented as an optimization problem module in Opt4J (Lukasiewycz *et al.*, 2011), a Java optimization framework, which provides optimization algorithms, such as the genetic algorithms NSGA-II (Deb *et al.,* 2002) and SPEA2 (Zitzler *et al.*, 2001), particle swarm (Coello *et al.,* 2002) and differential evolution (Price, 2013).

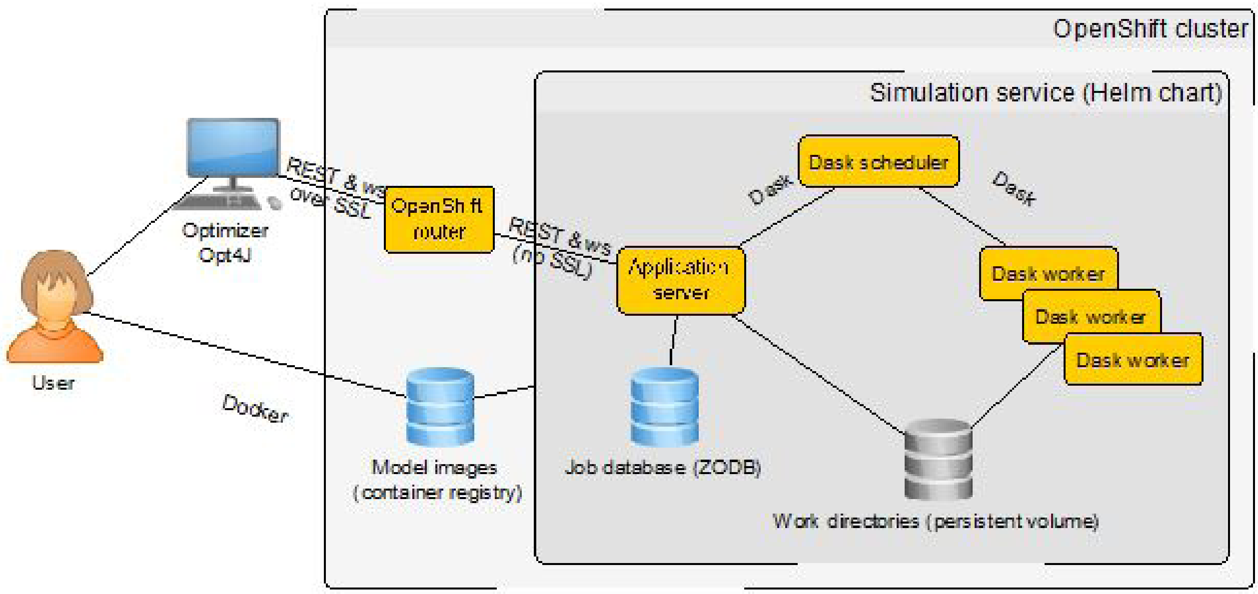

Figure 1. Schematic view of the cloud-based optimization framework.

3. CASE DESCRIPTION

3.1 CASE SHIP

The case vessel is a generic cruise ship which is expected to run on MDO fuel. It represents a typical example of a 4000-passenger cruise ship with diesel electrical propulsion plant. The total installed engine power is 75.6 MW consisting of six medium-speed Wärtsilä 12V46F engines.

The ship main machinery and heat recovery are illustrated in Figure 2. Each engine is equipped with an exhaust gas boiler (EGB). It is assumed in the study that these boilers could produce superheated steam and additional steam can be produced with oil-fired boilers. Also, high temperature (HT) cooling water heat is collected from the engines using a separate waste heat recovery circulation. From this circuit, the waste heat is distributed to all consumers that can utilize the HT water as their heating source. It was assumed that this HT heat could be utilized for air conditioning heating and for evaporators for producing fresh water. The engines' HT heat consists of both high temperature charge air heat and jacket water cooling heat. Generally, also low temperature (LT) heat is produced in the engines, due to lubrication oil cooling and low temperature charge air heat, but this was not utilized in the case vessel.

The operation profile for this study included one year of typical operation regarding vessel propulsion and hotel power in a global operation considering both time in tropical conditions and in Mediterranean and even Northern Europe during summer. The vessel heat consumption was evaluated for the entire year in average conditions with average air temperature being 25 °C. In the current model, the assumption of a constant ambient temperature had impact only for the ship's heat consumption requirements. Figure 3 and Figure 4 illustrate the operation profile with a period of 10 days regarding the most relevant energy flows that were simulated.

3.2 SIMULATION MODEL

Most of the development work for the simulation model had been done years before, and independently of this optimization study. The principles and structure of the model was introduced originally in the 13th COMPIT conference (Elg *et al.*, 2014). The main principles have still applied in the current version of the tool, but the modelling for Deltamarin's energy flow simulation tool was done in the Matlab Simulink environment without Simscape, which was earlier utilized for more accurate modelling of cooling water circuits, for example. Fixed simulation time step of five minutes was used. The ship heat system structure and analysis is described separately in a recent article (Elg, 2022). In the model, the operation profile sets the power demand for the ship. The engine fuel consumption as well as heat production was estimated using the project guide for the Wärtsilä engines. The utilized parameters are included in a separate Appendix. The part-load behaviour was estimated by interpolation between the values provided in the engine guides. The power management system (PMS) logic was assumed to be simplified, including determining the number of operating engines based on a specified load range. These load ranges are also included in the Appendix.

For this study, a possibility to install battery capacity for the ship was included in the model. Without the battery, the ship energy production is calculated at each time step based on the energy conservation principle between the ship power requirements, the available fuel energy content and the engines. Battery brings a dynamic element to the model by either releasing or absorbing all or part of the electricity that the ship systems require. Therefore, battery

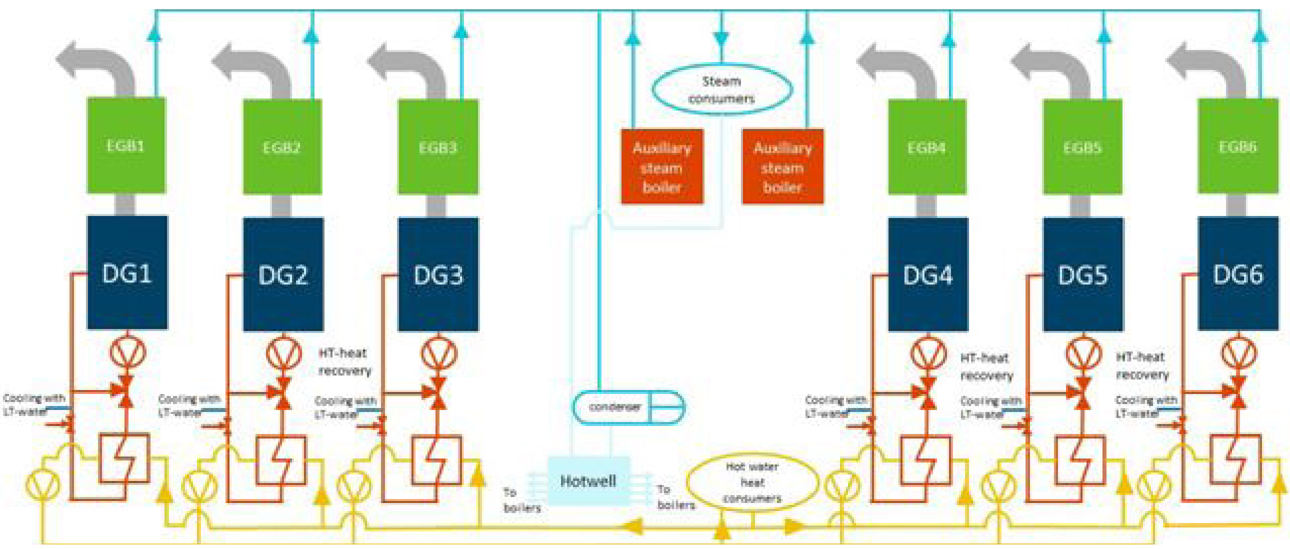

Figure 2. Schematic of the case ship heating and waste heat recovery system.

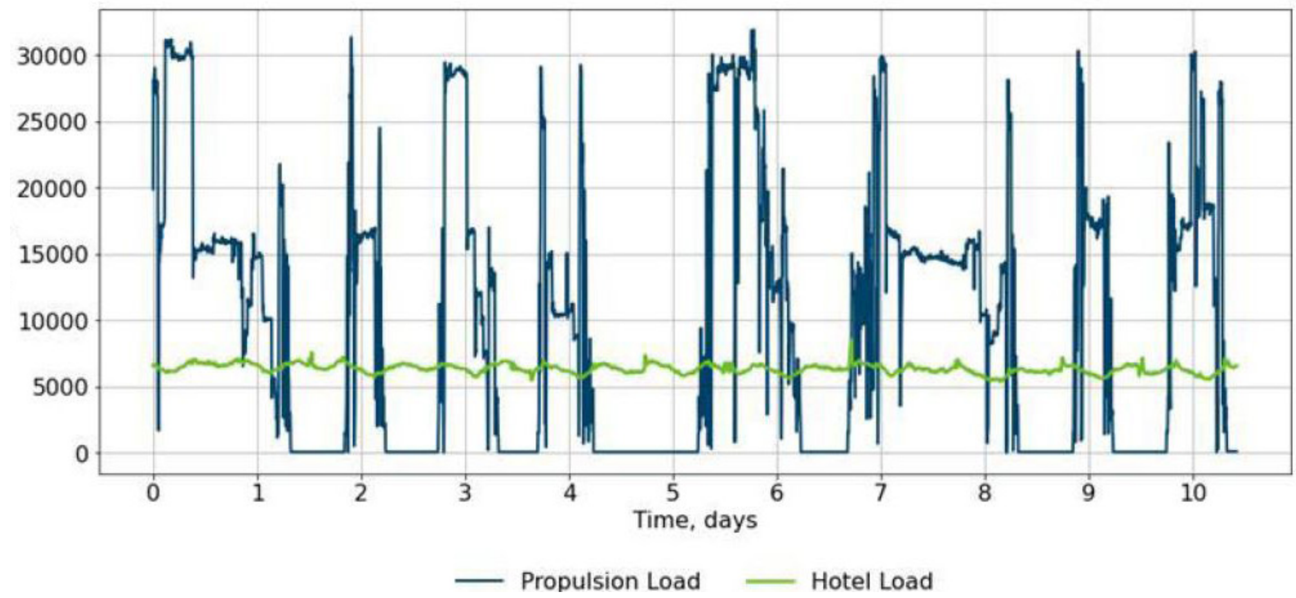

Figure 3. Example of the case ship power profile during 10 operation days.

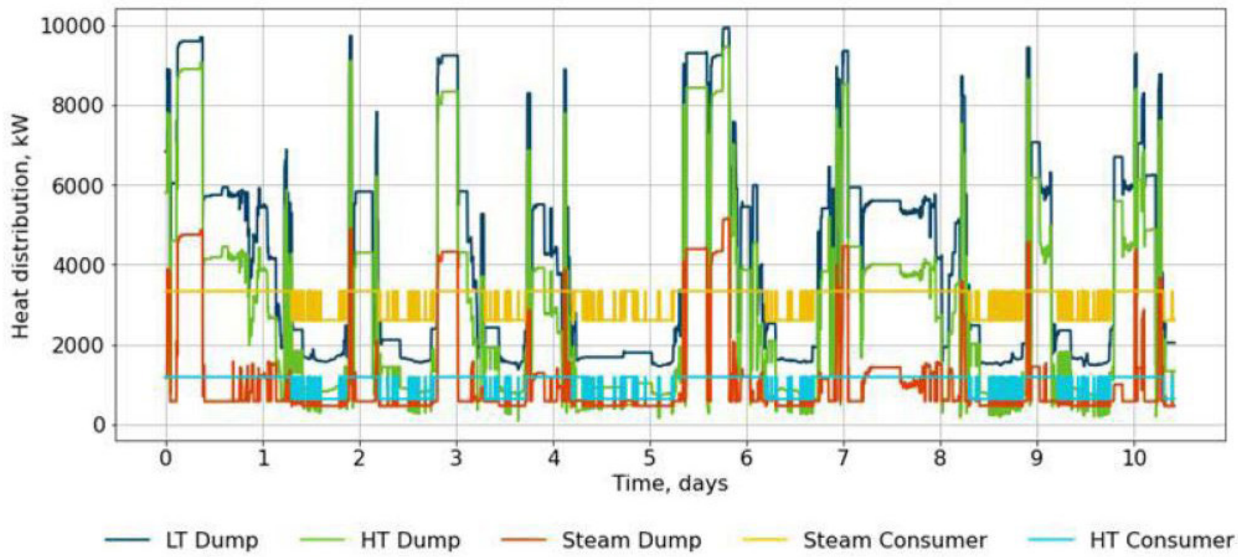

Figure 4. Example simulation of the case ship heat flows during 10 operation days without any waste heat to electricity conversion: LT Dump is the rejected low temperature heat, HT Dump the rejected high temperature waste heat and Steam Dump the non-utilized steam. Steam and HT Consumers illustrate the ship average heat consumption.

either increases or reduces the ship generating sets loading during each time step. The only decision variable used for the optimization regarding the battery was the size of the battery energy storage. In other words, the state of charge range as well as C-rating were fixed and the eventual degradation of the battery over time was not considered.

The battery model logic is based on the principle that the battery management system (BMS) knows the engine loads and specific fuel oil consumption (SFOC) from the previous time step. At the same time BMS predicts the SFOCs of the engines without the battery in the current time step by reviewing the incoming power demands. The battery model compares the two readings. If the SFOCs in new time step are better than in the previous one, the engines may change their loading or even number of the operating engines. In a case when the engine performance is worse in the new time step without the battery, the battery will be utilized. In this case, the battery absorbs the difference by either charging or discharging and keeps the engines running at the same load as in the previous time step. The battery size and the allowed range for the state of charge determine if the battery can be operated to the full extent of the BMS request.

Besides the battery option, the case ship has several options to include waste heat recovery: back pressure steam turbine, condensing type steam turbine and organic Rankine cycles (ORC) at two different temperature levels. These chosen technologies represent existing technology that is available today for the ships.

The condensing type steam turbine partly condenses and lowers the steam pressure down to 0.2 bar in a vacuum condenser and the steam is finally condensed with the low temperature water. The turbine power production is defined as:

$$P = 473.7 \cdot m - 131.6,$$

where P denotes the turbine power production (kW) as a function of steam massflow denoted with m (kg/s).

The back pressure steam turbine power production (kW) is estimated with the following equation:

$$P = 204.01 \cdot m - 33.33,$$

where m is steam mass flow (kg/s). The back pressure steam turbine lowers the steam pressure only down to 1.4 bar, which means that there is still a major part of the recoverable steam enthalpy left after the turbine. Therefore, a steam fired ORC can still be connected in the back pressure turbine exhaust.

While studying optimal dimensioning of the steam turbines, a fixed size for the ORCs was selected. Accordingly, Climeon's 150 kW Heat Power modules, as introduced by (Trota *et al.*, 2019) were utilized in the study for representing the ORCs in two different temperature ranges.

Figure 5 illustrates the simplified system level layout of the studied waste heat recovery alternatives. The ORCs could be operated either as connected to the ship HT circulation loop with the option to boost the circuit temperature with excess steam, or as connected to a separate hot water circulation in somewhat higher temperature. This circuit would be connected to the back pressure steam turbine exhaust. The schematic picture does not visualize all relevant pumps, condensers or coolers, but it illustrates the hierarchy of the modelled processes at a high level. In the model, an assumption was made that the two different turbine types cannot be used simultaneously, but all other combinations of the options were possible.

3.3 OPTIMIZATION PROBLEM

In ship design projects, a typical target is to maximize the ship transport efficiency and environmental sustainability but also to minimize the related costs, both capital and operational expenditures (CAPEX and OPEX). As a modern ship is a highly complex, multi-domain energy system and the input data for any design task may include a large degree of variation, it is often hard to define a single exact target for the optimization. Multi-objective optimization can be used instead, providing the designer a set of optimal solutions to choose from rather than aim for a single answer.

One objective was to reduce the ship's fuel consumption, thus lowering carbon dioxide emissions. However, the investment (CAPEX) should also be kept small. The third objective was to reduce the average number of main engines running hours, leading eventually to lower maintenance costs.

Table 1 presents the heat recovery options and technical variables used in the optimization.

3.4 MODEL CONVERSION FOR THE FRAMEWORK

The simulation model had to be converted from Simulink into a form that allows parallel execution in the cloud, without requiring Matlab installations there. The ideal form for this is a shared library that can be called

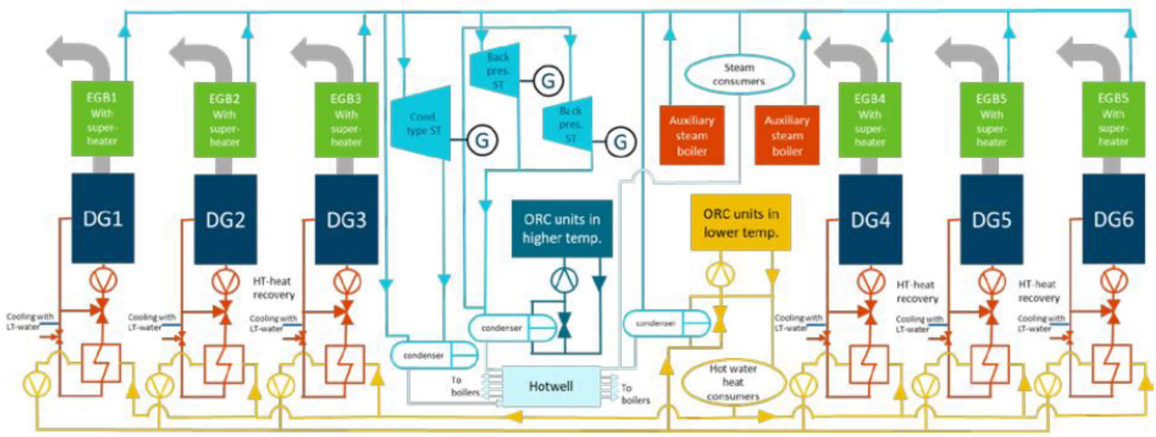

Figure 5. Schematic of the system with the waste heat recovery options: condensing type steam turbine, back pressure steam turbine and organic Rankine cycles in two temperature levels.

Table 1: Options and variables used in the optimization study.

Option name	Description	Variables	Fixed values	Installed size, feasible range	Pieces of equipment	System price	Included in experiments
Battery	Improving the ship engines power plant efficiency by having the possibility to either charge or discharge electricity at each time step	Battery size, kWh	Allowed state of charge is 25–95 % of the battery capacity. The C-rating was set to 3.	0 – 10 000 kWh electricity storage capacity	1	1000 €/kWh	1,2,3
Back pressure steam turbine	Reduces the ship steam pressure from 10 bar (a) to 1.4 bar (a).	Maximum power production, kW. Number of steam turbines.	Min power generation limited to 33% of the max power.	100 – 1000 kW produced electricity	0 – 4	1000 €/kW	1,2
Condensing type steam turbine	Reduces the ship steam pressure from 10 bar (a) to 0.2 bar (a).	Steam turbine unit size as max power production, kW. Number of steam turbines	Min power generation limited to 10% of the max power.	400 – 1000 kW produced electricity	0 – 4	0,1489€/kW + 658900€	3
Organic Rankine cycle	Utilizes as heat source excess steam from ship processes or back-pressure steam turbine outlet steam via intermediate pressurized hot water circulation at the temperature of app. 110 C°.	Number of installed units	Unit size 150 kW. Minimum operation load 50%	150 kW produced electricity	0 – 8	2000 €/kW	2,3
Organic Rankine cycle with hot water	Uses any excess waste heat available from the ship machinery after serving ship heat consumers. Installed in the ship HT water recovery circuit, with inlet of 90–98 C° hot water. If steam ORCs onboard, the excess steam is primarily utilized by them due to higher temperature (higher power plant efficiency).	Number of installed units	Unit size 150 kW, minimum operation load 50%	150kW produced electricity	0 – 8	2000 €/kW	2,3

repeatedly to execute the simulations. The model is simulated with different input parameters received from the optimizer, and the output values are then returned to the optimizer.

Fortunately, a standard packaging and interface for such executable simulation models exists, namely the functional mockup interface (FMI, https://fmi-standard.org/). Model packages conforming to this standard are called functional mockup units (FMU). Simulink Coder was used to translate the Simulink model into C code and an open source tool called Simulix (Wallentin *et al.*, 2018) to package the generated C code as a FMU. The compiled C code runs much faster than the original Simulink model, but some features of Simulink were not supported by the code generation. This caused, unfortunately, some re-engineering for the case model, especially related to its error management. The most relevant cause for the re-engineering was that the model relied on the Matlab assert function, which was ignored by the code generator and had to be replaced with Simulink assertion blocks that could be compiled properly.

3.5 OPTIMIZATION

The optimization algorithm used was NSGA-II, as implemented in Opt4J. The population size (alpha) was 100, the generation size (lambda) was 25, likewise the number of parents (mu). Five rounds of binary tournament were used for selecting parents. Other algorithm parameters were left at their default values. The real type decision variables were encoded in one vector and integers in another, using the composite genotype of Opt4J. Crossover was performed separately for each type.

Simulations were executed on 13 Dask workers with 2 threads each, allowing a whole generation to be evaluated in parallel. The optimization algorithm was executed on a local workstation, allowing progress to be monitored with the Opt4J graphical user interface. Optimization was allowed to run for roughly three hours, then stopped. This was done manually, thus the run times and the number of processed generations varied.[1]

4. RESULTS

4.1 ENERGY SYSTEM OPTIMIZATION

Three experiments with various optimization set ups were conducted, as listed in Table 2. Experiment 1 was performed with only batteries and back pressure steam turbines as the technology options. This scenario represents a typical ship design task with limited technology selection for a specific reason. The potential reasons for limiting the optimization problem are customer's preferences for a specific solution, or technology cost and physical size related issues. Experiment 2 added the ORC units listed in Table 1. Experiment 3 replaced the BPSTs with the condensing steam turbines. Although the results of the second and third experiment are presented together, it is worth noting that optimization did not attempt to decide between BPST and CST. Instead, it tried to find the best BPST solutions and the best CST solutions, which were then just combined into the plots.

Table 2: The optimization experiments.

#	ST type	ORC included	Run time [h:min]	Generations
1	BPST	no	3:32	61
2	BPST	yes	2:47	31
3	CST	yes	3:30	50

The execution times of the experiments vary as discussed in Section 3.5. The progress of multiobjective optimization can be measured with the dominated hypervolume indicator (Zitzler *et al.*, 2003). Even in the shortest experiment, the progress has slowed towards the end, as visualized in Figure 6. The reference point for the hypervolume was obtained by taking for each objective the maximum (worst) value that occurred in the entire experiment.

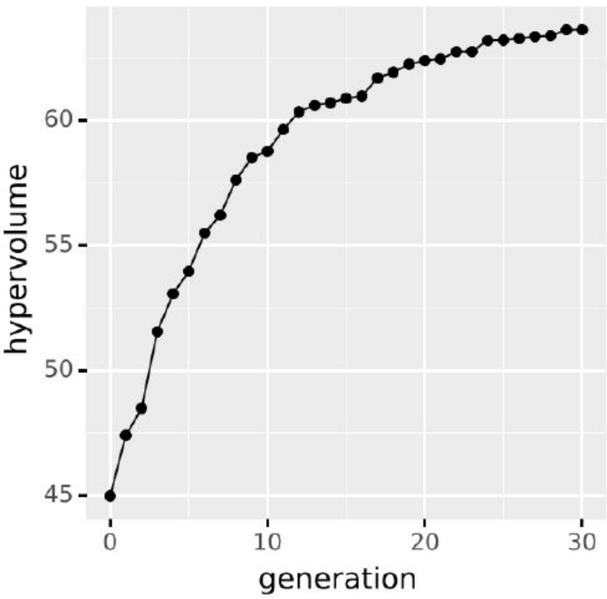

Figure 6. Dominated hypervolume by generation for Experiment 2. As there were three objectives, it is just three-dimensional volume in the units of the objectives [k€ kg/s].

Figures 7–9 and 11–13 illustrate the optimization objectives plotted pairwise against each other. Figures 7–9 show the results for Experiment 1 and Figures 11–13 simultaneously for Experiments 2 and 3. The red highlighted dots represent

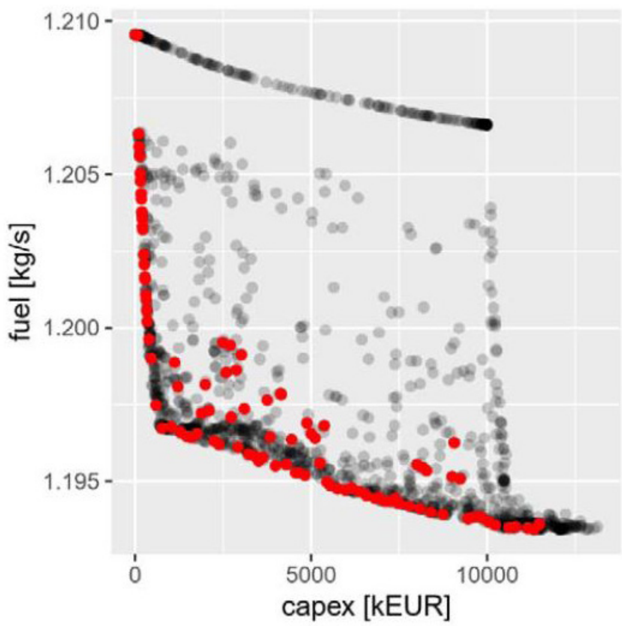

Figure 7. Experiment 1: Ship average fuel consumption and CAPEX with only batteries and back pressure turbine. All simulations shown, non-dominated solutions in red.

1 The generations are always full generations; after commanding to stop, Opt4J still finishes the current generation.

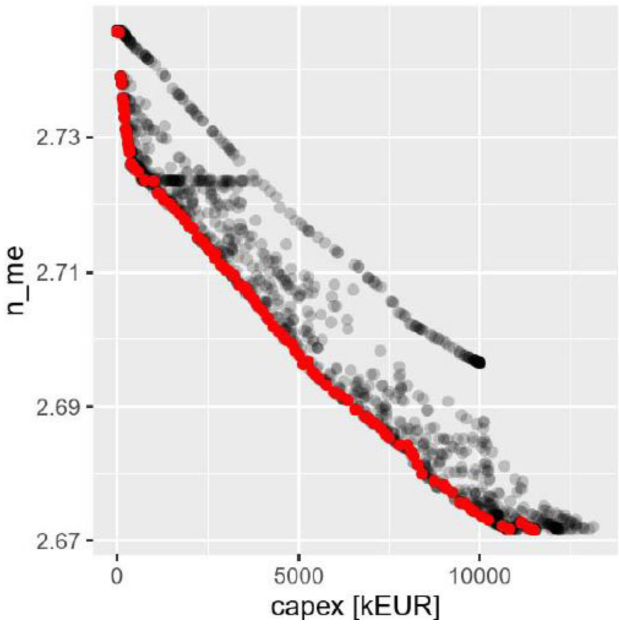

Figure 8. Experiment 1: Average number of main engines in operation and CAPEX with the batteries and back pressure turbine options.

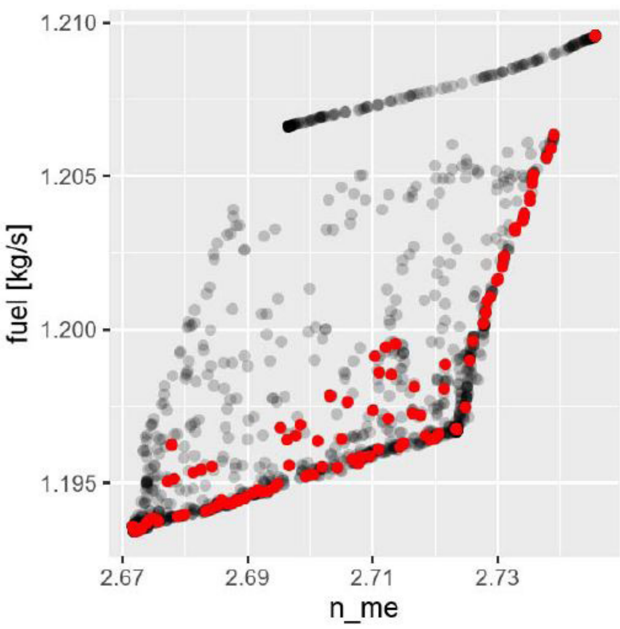

Figure 9. Experiment 1: Ship average fuel consumption and average number of main engines in operation with only batteries and back pressure turbine.

the so-called archive of the genetic algorithm, which approximates the Pareto optimal surface. Figure 7 and Figure 11 illustrate the relationship between ship fuel consumption and the investment costs. Figure 8 and Figure 12 illustrate the average number of engines running. Thus, the smaller the number, the lower amount of engine hours was needed. Figure 9 and Figure 12 plot the ship fuel consumption against engine hours. Unsurprisingly, these objectives are co-aligned; the trade-offs are against CAPEX. The full Experiment 1 results can be examined with Figure 10, where the main decision variables, optimization objectives and some other quantities of interest are plotted together. Figure 14 presents a corresponding summary for Experiments 2 and 3. Table 3 presents the variables that are illustrated in the figures.

4.2 EXPERIMENT 1: ENERGY SYSTEM OPTIMIZATION RESULTS WITH ONLY BATTERY CAPACITY AND BACK PRESSURE STEAM TURBINE AS OPTIMIZATION VARIABLES

As Figure 7 illustrates, the average fuel consumption of the ship varies between 1.193 kg/s and 1.210 kg/s when the optimization was performed with only batteries and back pressure steam turbine capacity as the decision variables. This translates into a fuel saving range from 0 to 1.3% of the ship total fuel consumption in relation to the situation without batteries or waste heat recovery technologies. Interestingly, the most relevant reduction in the fuel consumption can be achieved with a rather modest investment, less than 1 M€.

Figure 8 illustrates the relationship between the average number of main engines running and the investment costs. In this case a rather linear behaviour can been seen in the results.

Figure 9 illustrates the similar trend between fuel consumption and average number of main engine operated than Figure 7; the most significant reduction in fuel consumption is obtained with rather modest changes in the number of running engines. The results indicate that the back-pressure turbine introduction does not significantly influence in the number of engines running, but rather it improves the overall ship machinery power plant efficiency.

Figure 10 suggests that slightly less than 1 MW steam turbine installed power leads to the best results. Battery capacity does not bring much improvement for the fuel consumption in the results. Increasing battery capacity continues to contribute to reduced main engine running hours, while the steam turbine configurations over 1 MW installed power yield only small benefit. Such configurations appear in the results usually after the maximum battery capacity is met, as it would otherwise be more profitable to invest in the battery.

The results, in this case, suggest to favour the steam turbine capacity over the battery capacity, if the retrofit project mainly aims at lowering the fuel consumption and, thus, carbon emissions of the ship. However, the heat utilization efficiency (HUE) indicator in the result matrix (Figure 10) shows rather low values in all cases. This is an in-built indicator in the simulation model of the ship total waste heat

Table 3: Optimization objectives, decision variables and other plotted quantities.

Label	Short name	Unit	Description	Included in experiments
batt_cap	battery capacity	kWh	total battery capacity installed	1,2,3
bpst_n	back pressure turbine number	-	the number of back pressure steam turbines installed	1,2
bpst_P	back pressure turbine power	kW	maximum power of each back pressure steam turbine	1,2
bpst_P_tot	total back pressure turbine installed power	kW	total power of back pressure steam turbines installed	1,2
capex	capital expenditure	1000 €	capital expenditure of the installed new energy solution	1,2,3
fuel	fuel consumption	kg/s	average fuel consumption over the entire operation profile	1,2,3
htorc_n	HT-ORC number	-	number of installed ORC units installed that are connected to the ship high temperature waste heat recovery circuit	2,3
hue	Heat Utilization Efficiency	%	efficiency of utilization of the exergy in ship waste heat flows considering also ship heat consumers. The efficiency is compared to a theoretical situation without any waste heat recovery.	1,2,3
n_me	main engines in operation	-	average number of main engines in operation	1,2,3
P_me_tot	average engine power	kW	time average of total main engine power	1,2,3
P_bpst_act	back pressure turbine actual power	kW	average power actually produced by the back pressure turbines	1,2
sorc_n	steam ORC number	-	number of installed ORC units that are connected to steam turbine exhaust or steam dump condenser via intermediate hot water circulation	2,3
st_P_tot	total steam turbine power	kW	total power of steam turbine capacity installed, either back pressure or condensing type	1,2,3

utilization efficiency, and the expectation is in this type of ship to reach values closer to 20 with the waste heat recovery technology currently available, based on the previous simulation results in the ship design projects. In general, the reason for choosing only this type of waste heat recovery technology for the ship might be the expected very compact size of the technology, compared to the alternatives. The space requirement aspect was, nevertheless, not a parameter in the current optimization study.

4.3 EXPERIMENTS 2 AND 3: ENERGY SYSTEM OPTIMIZATION RESULTS WITH ALL OPTIMIZATION VARIABLES INCLUDED

The optimization Experiments 2 and 3 were performed with various technology options and thus also more decision variables, in order to test more the simulation-based optimization approach and potentially, to identify larger potential for fuel savings. The results are presented together, but separated by marking those, where back pressure steam turbine, denoted with “bpst” is utilized (Experiment 2) and where condensing type steam turbine is utilized (Experiment 3), denoted with “cst”. Thus, the two turbine types were never mixed during the experiments.

Compared to the Experiment 1 results, the optimization runs with all the optimization variables give better results in all aspects of this case study. For instance, the fuel consumption range in Figure 11 covers from the lowest value 1.162 to 1.2095 kg/s at the highest. This translates into maximum fuel savings of 3.9%, even though these results are gained at a very high investment cost. Also, Figure 11 indicates similar pattern with regards to the largest drop in fuel consumption happening with the lower end of the investments. The best combinations both regarding CAPEX and fuel consumption are, primarily, starting with adding condensing type steam turbine capacity and HT-water ORC (htorc) capacity, as this is the more flexible type of ORC being able to consume both HT-heat and leftover steam. Figure 12 and Figure 13 show also that the fastest drop in average engine running hours occurs with the lower investment range.

4.4 DISCUSSION AND FUTURE WORK

This research had two major targets. Firstly, to explore the feasibility of performing cloud-based optimization that is based on existing simulation models which are already an established part of a ship design process. And secondly, to

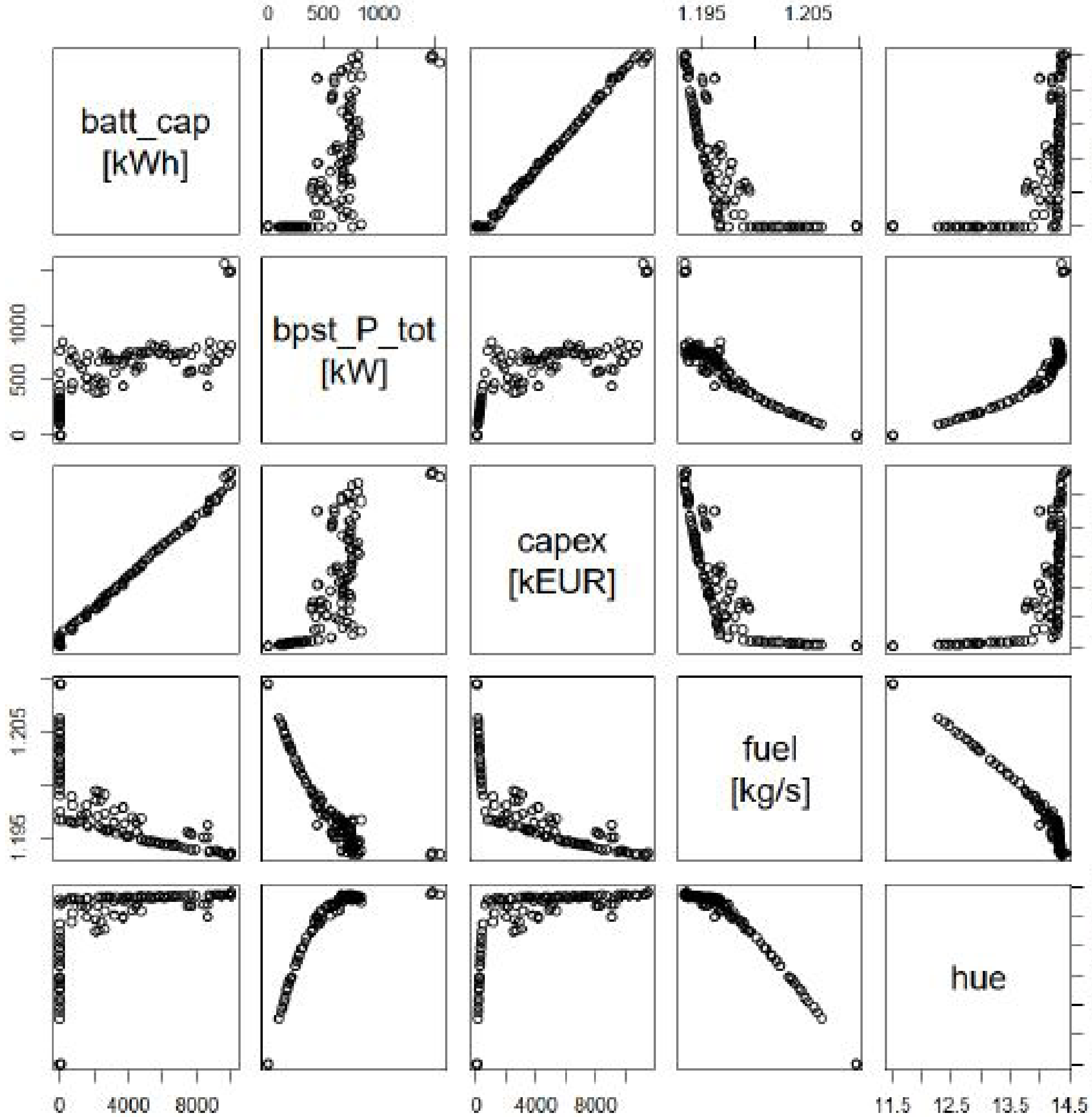

Figure 10. An overview of the results of Experiment 1, optimization with only batteries and back pressure turbines. Quantities are plotted pairwise; plots in the same column share the x axis and those in the same row the y axis, as indicated on the diagonal. Only non-dominated solutions shown.

find relevant design solutions and insights for improved environmental sustainability in the selected case study. These targets were reached, yet not without challenges.

The chosen simulation-based optimization approach was capable to reveal nontrivial patterns in the ship design case and, therefore, it is a very promising way to support the design towards more sustainable shipping. Since an energy simulation model can be developed for a ship at any design stage and nowadays being a rather normal part of the design process, it is important to be able to utilize the existing model as such (or with minimal modifications) for the optimization studies. In the case example, the energy model includes a system level description and analysis of the ship entire energy system. Moreover, it also provides analysis of the profitability of the proposed concepts. After successful optimization experiments, the most promising results can be added to the ship design and the design process may continue without interruptions. The optimization task could be performed at any relevant stage of the design process.

Once the optimization activity is made an integral part of the design process, it is also natural to evaluate the result with the existing conventions and methods, which are already applied in the energy simulation work or

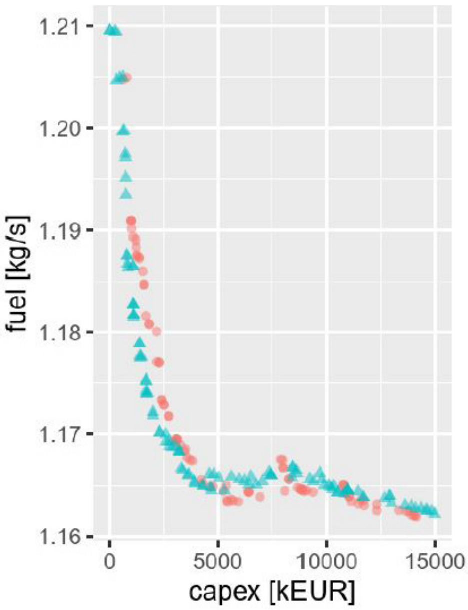

Figure 11. Experiments 2 and 3: Ship average fuel consumption and CAPEX with all optimization variables, including the results with two different steam turbine types (stt). Only non-dominated solutions shown.

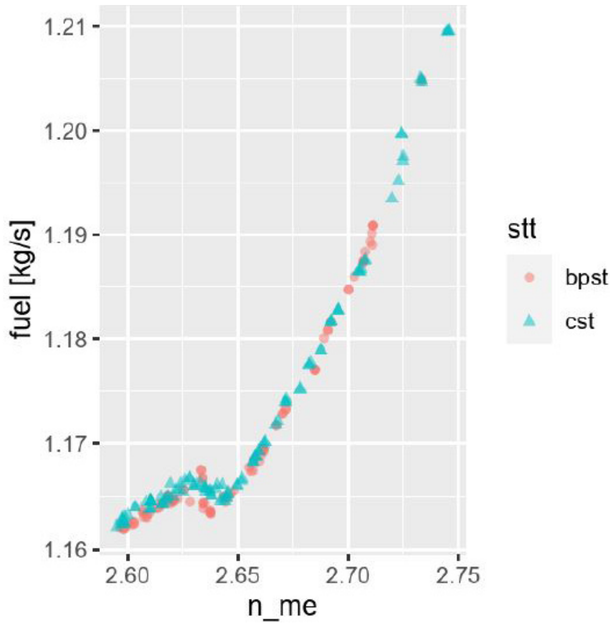

Figure 13. Experiments 2 and 3: Ship fuel consumption and average number of main engines in operation with all optimization variables.

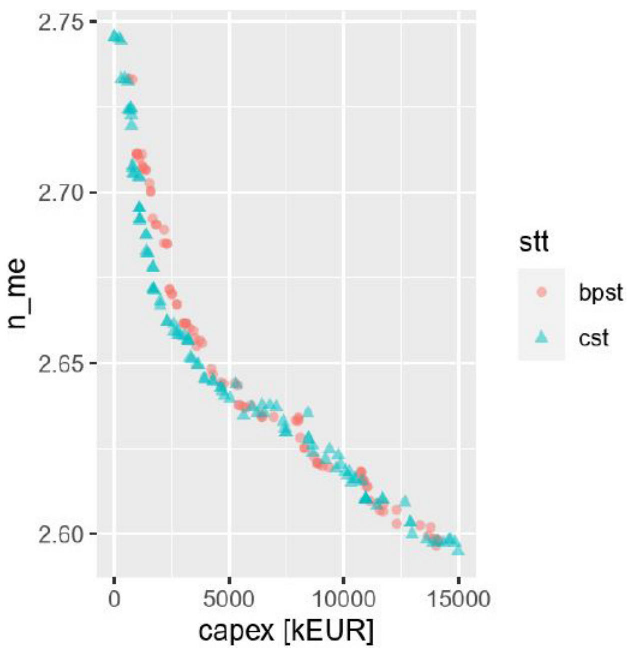

Figure 12. Experiments 2 and 3: Average number of main engines in operation and CAPEX with all optimization variables.

other design disciplines. For instance, the heat utilization efficiency analysis, which was also a part of the results in Figure 10 and Figure 14, reveals that the HUE index shows values between approximately 11 to 20. The analysis is to certain extent case-specific, but the earlier ship design cases with the same modelling framework have shown that this is the expected range for the ship waste heat recovery system performance. Therefore, the first optimization experiment with only back pressure steam turbines did clearly not include the most promising waste heat recovery equipment. The results of the second optimization experiment indicated clear improvement in terms of the HUE analysis and, eventually, in the fuel consumption performance. Depending on the optimization task, various other process efficiency or similar indicators can be utilized to support the evaluation and interpretation of the optimization process results.

An important motivation for this research was to lower the threshold for using optimization in the practice of simulation aided marine engineering. As the ship energy system model already existed in the Matlab Simulink environment, the original assumption was that it could be easily adapted for the optimization. In practice, the task was not that straightforward. The first step in the process was to translate the model into a form that could be executed outside of Matlab. Simulink Coder does that but produces C code with a rather unusual interface. Simulix adapts this interface to FMI. Unfortunately, not all Simulink or Matlab features are supported by these tools. In particular, runtime error checking is lost in the process: the current case model mostly relied on the Matlab “assert” function in error checking, which Simulink Coder essentially ignores, i.e., the calls to assert disappeared in translation. This created additional work for the designer team to improve the original simulation model for being less prone to these errors. Nevertheless, Mathworks has recently introduced a new product, Simulink Compiler, that is able to generate standalone FMUs from Simulink models. This

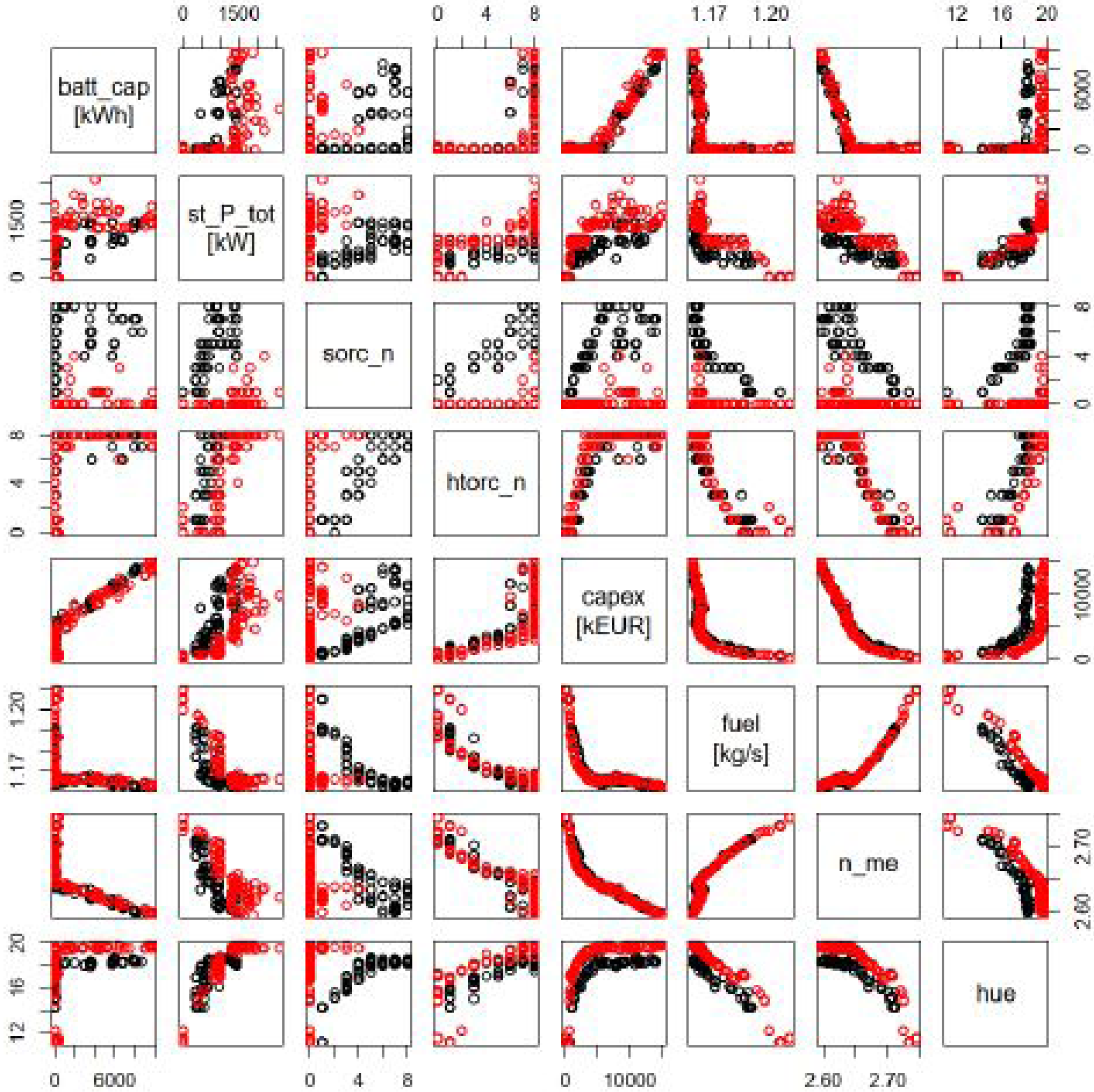

Figure 14. Experiments 2 and 3: Main result matrix of the optimization with all optimization variables included. Black colour indicates the results with the back pressure steam turbine and red indicates results with condensing type steam turbine applied.

tool is adapted now in the ongoing practical design work as a result of this study.

In the study, the translation tools created the FMU interface from the parameters and the top level ports defined in the Simulink model. The existing energy system model originally had none of these. Instead, it reads its inputs from a custom format Excel file into global variables and used the Simulink logging facility to write outputs into a file. Adapting this, particularly the input, took some effort from the research team. It is also fair to assume that this kind of case-specific work for interfacing of inputs and outputs for the translated simulator is a common effort with coming future cases as well. Alternatively, if the calculation time is not of great concern to the ship designer, also the energy simulation model could be called directly with the optimization interface, which reduces the steps in the model treatment. The optimization workflow should, thus, be applied to the specific process of the designer.

Simulation-based optimization requires the simulation model to be rather robust. When formulating the optimization problem, one needs to specify feasible value ranges for all the parameters, and the optimization algorithm executes simulations exploring the whole range of feasible value combinations. If the model has only been used previously with manually picked "reasonable" parameter combinations, simulations may fail surprisingly frequently, when the parameters are picked by a machine with no sense of what is "reasonable". For the Simulink model applied in this study, this problem was initially exacerbated by the loss of runtime error checking on translation to an FMU; instead of halting with an error message, simulations would typically hang, and possibly some may have finished with incorrect results. The error was subsequently resolved. A method was also developed for terminating the simulation in the FMU on error. These first rounds of result generation provided important information about the model configuration that is now considered in supporting the model's later black-box use inside an optimization loop.

Robustness of the optimization solutions is an important area to consider. Firstly, there are numerous variables utilized in the set-up of the case that we present in this study. For instance, the main logic of utilizing ship machinery and the availability of low cost shore power could change the results considerably. Also, the limitations chosen for the current optimization case variables are influencing in the final solutions both in single case simulation and the optimization. Even though this study did not explicitly focus on exploring the robustness of the solutions of this study considering the simulation parameters, certain aspects were, nevertheless, highlighted. In general, one reason for the researchers to suggest and explore the utilization of existing simulation tools for the optimization task was to ensure as reliable basis for the optimization as possible. Typically, the ship simulation model as a part of the ship design project is created to represent as realistically the future operating ship as possible and various calibration and validation steps should be taken already during the creation of the simulation model. The validation typically would include in a ship design projects utilization of model tested hull results for propulsion loads or utilizing measured reference data from processes, such as ship engines as far as possible, considering the stage of the design. The simulation model robustness during optimization is a continuously developing process, but the various indicators such as the earlier mentioned HUE analysis help the designer to evaluate if the results are realistic and would there be reason to search for alternative improvements. The suggested approach of simulation based optimization allows to focus on the robustness of the optimization variables instead of the entire ship energy system model set-up.

The next phase in this research is to study how machine learning approaches could be incorporated in the optimization framework and what benefits it could bring.

5. CONCLUSIONS

A dynamic energy system simulation model of a cruise ship was successfully converted and used in the newly developed and released open-source cloud-based optimization framework. The research showed that to minimise any additional efforts in preparing for and conducting the optimization step, such as simulation input and output management, result validity checking and error handling, these aspects should be anticipated during the modelling (building a simulator) phase. The simulation model should have a reasonably clear interface that allows programmatic setting of the model parameters, execution of simulations and retrieval of reliable results. The case showed that there is an overhead in making the simulation model compatible for the optimization, but the task was worth the effort considering the value of the results, and the fact that the effort was a once-only duty for the in-house simulator used.

Regarding the ship energy system design, the optimization provided two/three main fingings: within the specific ship case and optimization set-up the battery capacity did not contribute much to ship fuel savings, but with a combination of steam turbines and Organic Rankine Cycles considerable fuel savings, up to 3,9% could be made. These savings would translate to ship lower carbon intensity. Another practical result from the study was to visually examine the trends in profitability of the energy saving improvements. In practice, investments above 3 M€ in experiments 2 and 3 did not seem to provide much added fuel savings. The economical comparison and the comparison between the back pressure and fully condensing steam turbines is naturally highly dependent on the optimization variable parameters and the final conclusions would demand studying the sensitivities further.

The results showed that an optimization process that re-used existing models from an ordinary ship design process could bring significant added value with minor additional effort in the actual ship design task. An optimization step can expand the current design space providing increased insight for designers and most of all, support decision making during the project, resulting in a ship that is more efficient in her transport task, and environmentally more friendly. This means benefits for all parties in the design process, both for the customer and for the designer.

This study had two main impacts. Firstly, new insights were gained with the development method for increasing ship sustainability, considering also the related costs and impact to ship main machinery utilization. Secondly, whenever a proper simulator is developed during ship design process, it should be thoroughly exploited. Efficient means for this are crucial for increasing the impact of system simulation. The results gained indicate that the simulation-based optimization in the cloud is a promising direction. This paper helps to raise awareness and provides ideas towards effective simulation-assisted ship design using modern resources such as open source software and cloud computing.

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