Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Engineering
Department of Marine Technology

Øyvind Stokke

Economic Control Design for Hybrid Electric Ships

Master's thesis in Marine Technology
Supervisor: Mehdi Zadeh
June 2020

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Abstract

One of the large global challenges we are facing today is the environmental issues, with increasing temperatures and more extreme weather conditions. The maritime industry is a large contributor to the world's emissions with around 3% of both the annual global CO_2 emissions and the annual global greenhouse gas emissions. In order to reach the climate goals the world has agreed upon, the need for innovations and more efficient solutions are clear.

One of the emerging means to reduce emissions and fuel consumption is hybrid power systems, where the use of energy storage systems (ESS) allows for reduced use of fossil fuels. In this thesis, hybrid power systems are investigated and an energy management system (EMS) algorithm is proposed for a battery/genset hybrid ship. A literature study on hybrid power systems has been conducted, where several aspects of hybrid power systems are investigated: Different power system topologies are discussed, a few ESS technologies are investigated and compared, and the typical control structure and its components are examined.

The energy management algorithm proposed is based on Mixed-Integer Quadratic Programming (MIQP). It minimizes the total costs of operation through calculating optimal power set points for the battery and the different gensets. The set points are calculated based on a minimization of fuel consumption, battery degrading, state of charge variations, genset load transients and the weighted sum of active gensets. The total costs are evaluated based on the fuel cost, the cost for CO_2 taxes, the maintenance cost and the battery degrading cost.

The algorithm is tested on load profiles extracted from vessel operation for two vessel types, a platform supply vessel (PSV) and a ferry. The performance is compared with results extracted from vessel data, and four cases are tested for the two load profiles: optimal control without battery and optimal control with battery for three different battery sizes. Results showed the lowest total cost for optimal control without battery for both load profiles. The reduction was larger for the PSV with a 3.2% reduction compared to only 0.8% for the ferry. Optimal control with battery for the PSV showed the lowest fuel consumption and maintenance cost, but relatively high battery degrading costs. This resulted in a slightly higher total cost compared to vessel operation, with the smallest battery giving a 0.5% increase. For the ferry case, optimal control with battery showed small reductions in fuel cost and significant reductions in maintenance cost. But due to very high battery degrading cost, the total cost was increased by between 23.3% and 27.2%.

Samandrag

Ei av dei store globale utfordringane vi står overfor er miljøendringar, med aukande temperaturar og meir ekstremvêr. Den maritime industrien er ein stor bidragsytar til verdas utslepp, med omkring 3% av både dei årlege globale CO_2 utsleppa og dei årlege globale drivhusgassutsleppa. For å klare å nå klimamåla som verda har vorte einige om, er behovet for innovasjonar og effektive løysingar tydeleg.

Ei framvoksande metode for å redusere utslepp og drivstofforbruk er hybride kraftsystem, der energilagringssystem (ESS) kan brukast for å redusere bruken av fossile brennstoff. I denne avhandlinga er hybride kraftsystem sett nærmare på, og ei algoritme for eit energistyringssystem for eit batteri/generatorsett (gensett) hybridskip er foreslått. Eit litteraturstudie på hybride kraftsystem er gjennomført, der fleire aspekt er undersøkt: Forskjellige topologiar for kraftsystem er diskutert, nokre teknologiar for ESS er undersøkt og samanlikna, og den typiske styringsstrukturen for hybride kraftsystemet og dei tilhøyrande komponentane er sett nærmare på.

Energistyringsalgoritma som er foreslått baserer seg på Blanda Heiltal Kvadratisk Programmering (MIQP). Den minimerar dei totale operasjonskostnadane gjennom å kalkulere optimale effektsettpunkt for batteri og gensett. Settpunkta er kalkulert ut ifrå ei minimering av drivstofforbruk, batterielding, variasjonar i ladetilstand, variasjonar i lasttilstand for gensetta og den vekta summen av aktive gensett. Dei totale kostnadane er evaluert basert på drivstoffkostnad, CO_2 avgift, vedlikehaldskostnad og kostnad for batterielding.

Algoritma er testa på lastprofil henta ut frå to typer fartøy i operasjon, eit forsyningsfartøy (PSV) og ei ferge. Oppførselen er samanlikna med resultat henta ut frå fartøysdata, og fire casar er testa for kvart fartøy: optimal styring utan batteri og optimal styring med batteri for tre forskjellige batteristørrelsar. Resultata viste den lågaste totale operasjonskostnaden for optimal styring utan batteri for begge lastprofilane. Reduksjonen i kostnad var større for PSV'en enn ferga, med 3.2% mot 0.8% reduksjon. Optimal styring med batteri for PSV'en viste det lågaste drivstofforbruket og vedlikehaldskostnaden, men relativt høg kostnad for batterielding. Dette resulterte i litt høgare totalkostnad samanlikna med fartøysdataen, med 0.5% auke for tilfellet med det minste batteriet. For fergecasane med batteri, viste resultata små reduksjonar i drivstofforbruk og betydelige reduksjonar i vedlikehaldskostnad. På grunn av veldig høge batterieldingskostnadar vart totalkostnadane likevel auka voldsomt med mellom 23.3% og 27.2%

Preface

This master thesis has been carried out at the Department of Marine Technology at the Norwegian University of Science and Technology (NTNU). It marks the final part of my Master of Science degree and corresponds to a workload of 30 credits. The thesis has been written in collaboration with Ulstein Design & Solutions AS and Blue Ctrl AS. Associate Prof. Mehdi Zadeh has been the supervisor.

I did not have any prior knowledge on energy management systems or the use of batteries. It has been challenging to go into a new field of study, but also exciting to work on problems that are driving the maritime industry forward.

I would like to thank Mehdi Zadeh and Daeseong Park for their guidance and invaluable help throughout the process. They have both been flexible and available digitally in a different and difficult time during the COVID-19 outbreak.

At last I want to thank Espen Skjong at Blue Ctrl and Egil Rødskar at Ulstein Design & Solutions for providing information and the data used in the case study.

Øyvind Stokke

Øyvind Stokke, Trondheim, June 10th 2020

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Acronyms and Abbreviations

AC	=	Alternating current
AIS	=	Automatic Identification System
AVR	=	Automatic Voltage Regulator
BMS	=	Battery Management System
CAPEX	=	Capital expenditures
CDC	=	Cyclic degradation curve
CH_4	=	Methane
CMU	=	Cell Monitoring Unit
CO_2	=	Carbon dioxide
DC	=	Direct current
DNV GL	=	Det Norske Veritas and Germanischer Lloyd
DP	=	Dynamic positioning
EASAC	=	European Academies' Science Advisory Council
EMS	=	Energy Management System
EOL	=	End of Life
EIS	=	Electrochemical Impedance Spectroscopy
ESS	=	Energy Storage System
Genset	=	Generator set
GHG	=	Greenhouse gas
Li-ion	=	Lithium-ion
MEA	=	More-Electric Aircraft
MG	=	Micro grid
MGC	=	Micro grid community
MMU	=	Module Monitoring Unit
MILP	=	Mixed-Integer Linear Programming
MINLP	=	Mixed-Integer Nonlinear Programming
MIQP	=	Mixed-Integer Quadratic Programming
MPC	=	Model Predictive Control
NO_x	=	Nitrogen oxides
N_2O	=	Nitrous oxide
OCV	=	Open Circuit Voltage
OPEX	=	Operational Expenditures
PI	=	Proportional-Integral
PMU	=	Pack Monitoring Unit
PSV	=	Platform Supply Vessel
PWM	=	Pulse-width modulation
SEI	=	Solid Electrolyte Interphase
SFOC	=	Specific Fuel Oil Consumptions
SLD	=	Single Line Diagram
SOC	=	State of Charge
SOH	=	State of Health
SO_x	=	Sulphur oxides

Chapter 1

Introduction

The section 1.1 include parts taken from my project thesis [4].

1.1 Background

The need and demand for more environmentally friendly ships is increasing. Climate changes, with its extreme weather conditions, has lead to an increased awareness among both the general public and the experts on the need for change in our way of living. This is manifested by the Paris Agreement [5], which was negotiated by representatives of 196 state parties and adopted by consensus on December 12th, 2015. The agreement states that the increase in global average temperature should be kept well below two degrees celsius above pre-industrial levels. The goal can be reached by peaking emissions as soon as possible. European Academies' Science Advisory Council's (EASAC) report on extreme weather events in Europe [6], states that the number of floods and extreme rainfalls worldwide has increased by more than four times from 1980 to 2016. Similarly has the number of extreme temperatures, droughts and storms more than doubled. Prof. Michael Norton, EASAC's environmental programme director, said that greenhouse gas emissions by people were "*fundamentally responsible for driving these changes*" [7]. According to Greenhouse Gas Studies (GHG) [8], the total shipping emissions for the year 2012 were approximately 938 million tonnes CO_2 and 961 million tonnes CO_2-equivalents for GHGs combining CO_2, CH_4 and N_2O. For the period 2007-2012, on average, shipping accounted for approximately 3.1% of annual global CO_2 emissions and approximately 2.8% of annual GHGs on a CO_2-equivalent basis.

Since the shipping industry is such a big contributor to the world's emissions, all measures to reduce this are welcomed in the pursuit to reach the two degree target of the Paris agreement [5]. Traditionally the marine power systems have consisted of diesel engines and generators, but in the recent years, other technologies and energy sources have emerged as possible options. The most relevant being batteries, fuel cells and supercapacitors. Especially battery technology has seen a big improvement. This is helped by other industries such as the automotive industry also pursuing zero-emission alternatives. This improvement in battery technology have made electric cars approach the convenience of the fossil-fuel driven cars. And with the Norwegian tax politics favouring electric cars, the share of new cars using an all-electric driveline exceeded 40% in Norway for 2019 [9]. The maritime industry has different challenges in the electrification process compared to the automotive industry and the extent of electric solutions have not reached the same levels. In applications where the time between each visit at quay is short, like ferries or short range transport, the use of only electricity is possible. There are examples in operation like MV *Ampere*, the world's first all-battery driven car ferry, operating between Lavik and Oppedal in Norway [10]. And projects under development like *Yara Birkeland*, the world's first autonomous and zero-emission container vessel, set to launch in 2020 at the earliest [11]. For many marine operations the long distance and time between each charging possibility makes the use of only electricity impossible with today's technology. In these cases hybrid solutions are a way to still take advantage of alternative energy sources. An example is the MS *Color Hybrid*, the world's largest plug-in hybrid ship using batteries [12], launched in 2019.

A study done by DNV GL shows that in order to reduce the CO_2 emissions in 2040 below 2015 levels it will require the use of zero-emission options like electricity and biofuels. Further it concludes that hybrid solutions will also contribute to emission reductions, and that battery hybrids is highly cost-effective [13]. How environmentally friendly hybrid solutions really are in a lifetime perspective is often questioned, considering production and recycling of batteries. Compared to electric cars the hybrid ships are designed for many more daily hours of use, thus, the savings in reduced fuel consumption for a marine hybrid system is huge compared to the energy use and emissions related to production and recycling of batteries [13]. In the case of all-electric battery ferries that are charged from the grid the environmental calculation is very dependent on the type of electricity production used in the area. In Norway for instance, where most energy is from 100% renewable hydroelectric power, battery is highly favourable. The potential reduction in exhaust gas emissions of a load leveling strategy using a battery-genset hybrid system is assessed in [14]. The investigation are based on operational data from a shipping fleet consisting of all types of bulk carriers. Results showed a maximum potential reduction in NO_x, SO_x and CO_2 emissions for the dry bulk sector of 14%. In [15] the pros and cons of installing batteries on offshore support vessels are assessed. The pros include large reductions of global warming potential, 40-45% in the Arctic areas and around 20% in the North Sea. In terms of reduction of local pollution, hybrid solutions was found to give reductions around 25-30%. Hence, the environmental advantage is large. The economic advantages was found to be is less prominent, at least for retrofitting, with a payback time of 10-15 years. However, for new-builds the possibility to replace gensets with batteries result in a reduces investment cost and a payback time of around 5 years. Since the economics of the hybrid solutions are very dependant on the fuel and battery costs, the profitability in the future is uncertain. A reduction in battery cost is expected and even retrofits may become economically favourable in the future.

1.2 Research Question and objectives

The research question investigated in this thesis is ”How can a battery/genset hybrid ship be operated to reduce total costs of operation?”.

This thesis is partly an extension on the work from the specialization project conducted autumn 2019. The objective was then to investigate hybrid power systems with regards to operation and design. The objectives for the master thesis are:

- Investigate and create an overview of hybrid ship power systems
- Investigate state of the art approaches to energy management systems
- Develop an energy management algorithm
- Use load profiles extracted from ship data to assess the developed algorithm. Compare the results with results extracted from the ship data. The algorithm should be tested with and without the use of batteries and the results should be evaluated.
- Test the algorithm for various battery sizes and assess the results

1.3 Main contribution

The main contribution to the field from this master thesis is the development of an Energy Management System, minimizing the operational costs for a ship hybrid power system using Lithium-ion batteries as energy storage. The EMS considers fuel consumption, battery degrading, maintenance cost through running hours as well as dynamics of the diesel generators when deciding on the optimal operation.

1.4 Thesis Outline

The remaining part of the thesis is structured as follows:

Chapter 2 - Overview of energy and emission control for hybrid ships:

Includes a literature review on different aspects of hybrid power systems. Different topologies and energy storage technologies are dicussed. The control layers of hybrid ship power systems are discussed in detail and at last, state of the art approaches to energy management are investigated.

Chapter 3 - Conclusion and further work:

A conclusion on the work conducted in the master thesis and proposals for further work

Appendix - Paper: Economic Control Design for Hybrid Electric Ships.

The main part of the master thesis is the paper. Hybrid power systems and control are discussed and an energy management algorithm is proposed. A case study is conducted in order to assess the algorithm.

Chapter 2

Overview of energy and emission control for hybrid ships

As this master thesis is a continuation of the project thesis previously conducted by me, relevant parts from the project thesis is included in this chapter [4].

The conventional topologies of marine power systems include mechanical propulsion and diesel-electric power systems. With a mechanical topology the power is produced by diesel engines, which is connected to the propulsion through shafts and a gear-box. The electricity demand from hotel- and auxiliary loads are distributed through a separate micro-grid and produced by smaller diesel generators (gensets). Mechanical propulsion have a few advantages including low complexity, low investment cost and low conversion losses due to few components in the drive train. However, as diesel engines operate most efficiently at loads between 80-100% of rated power, mechanical propulsion systems has limited flexibility in the produced power, making it most suitable for operations with a stable load demand [16].

With a diesel-electric topology the power is produced by gensets which distributes the power through a high voltage electrical bus. The bus then feeds variable speed motors for propulsion, hotel loads and auxiliary loads. The diesel-electric approach offer increased flexibility compared to mechanical propulsion. The power generation is typically done by several small gensets rather than a few big, this allows for better efficiency for various load levels by varying the number of active gensets. With the power being distributed with cables rather than shafts, the flexibility of the engine room layout is also increased. Disadvantages to diesel-electric propulsion includes increased investment cost and larger conversion losses due to more conversion stages [16].

Hybrid power systems are a means to reduce the fuel consumption and emissions, by introducing zero-emission energy sources and allowing for better fuel efficiency for the traditional energy sources. The introduction of additional energy sources increase the complexity of the power system, with new challenges emerging. More energy sources means more ways to distribute the load generation between the different sources, which again means that the task of operating the power system efficiently increases in complexity. In addition to controlling the hybrid power system, the task of dimensioning the different energy sources are important, the power system should have the required performance at the lowest cost possible. Hence, when considering a hybrid power system, there are two main challenges: the optimal control problem, which should minimize the operational expenditures (OPEX) and the optimal design problem, which should minimize the capital expenditures (CAPEX). An illustration of possible influential parameters for the two problems, for a battery/genset hybrid power system can be seen in Figure 2.1 .

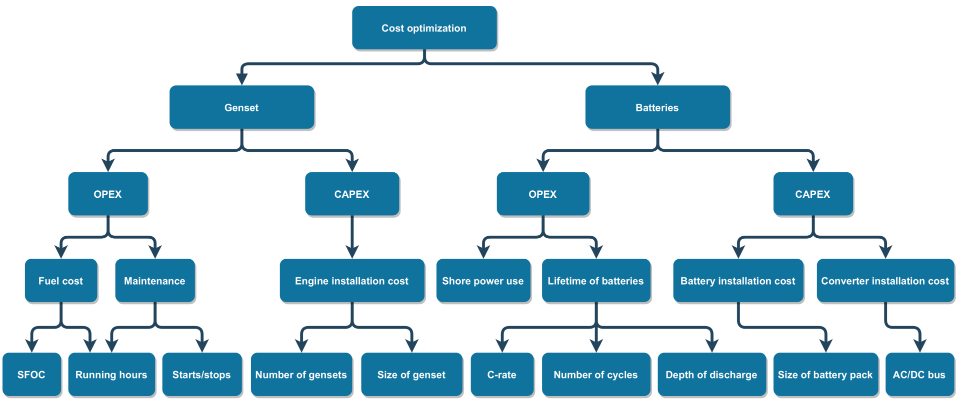
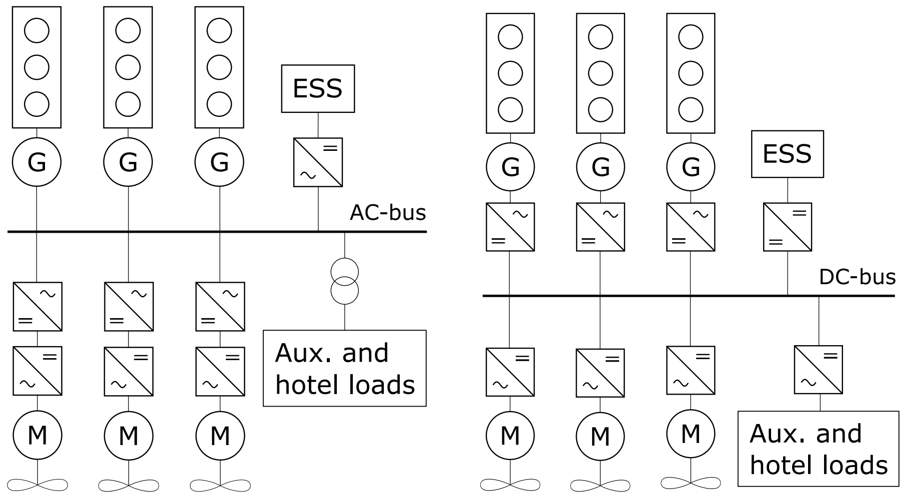


Figure 2.1: Parameters to consider when designing and operating a battery/genset hybrid power system.

2.0.1 Hybrid power system topologies

There are two main topologies of genset based hybrid power systems, AC distribution grid and DC distribution grid. Figures illustrating these two topologies can be seen in Figure 2.2a and Figure 2.2b. The limitiations for DC-grids in terms of transferring electric power over long distances caused the AC-grids to become standard for land-based electric grids, with its transformers and possibilities to transfer high voltages easily [17]. This induced the development of transformers and AC-motors, which made AC-grids the unquestioned standard also for marine applications. However, with the emerging of alternative DC-based energy storage systems and the development of power electronics the use of DC-grids has become more relevant. There are several important differences between AC and DC systems [18]. Since there is no need for frequency control in the DC system, the prime mover are free to operate in their optimal speed without concerns regarding synchronization. The response time of the power generation is faster for DC system, as there is no need for paralleled power sources to be phase matched. AC systems has an advantage in terms of security. Due to the reactive currents causing higher cable impedance compared to DC systems, the short-circuit current is automatically limited. However, the higher cable impedance also results in increased losses for AC compared to DC. In addition to the limited short-circuit current, the zero crossing of the AC systems allows for simple and reliable circuit breaking compared to the DC system, which is favourable for the safety of the power electronics. The fact that DC systems only need two conductors compared to the three needed for AC systems, results in a weight advantage for the DC system. Another difference is that the DC system does not have an significant acoustic signature like the AC system. However, the DC system creates a constant magnetic field that could cause problem due to interference with mines and sensors/equipment.

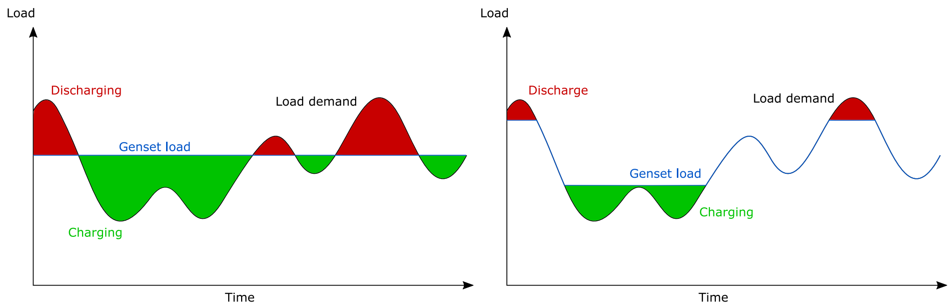


(a) AC-grid. **(b)** DC-grid.

Figure 2.2: Typical hybrid power system topologies.

2.0.2 Energy Storage Systems

A wide range of energy storage technologies exists, e.g batteries, supercapacitors, compressed air storage and pumped hydro storage [2]. Some of the technologies like pumped hydro storage requires large spaces and is not convenient for shipboard applications. A few of the technologies that are more suitable are discussed later on. Introducing energy storage to the power system has several advantages. The energy storage can be used as back up power during critical operations like dynamic positioning (DP), functioning as spinning reserve instead of a genset running on low efficiency during the operation. For heavy lifting cranes and cranes with heave compensation, the energy storage can be used to store regenerative power from the crane operation in order to reduce fuel consumption [19]. The energy storage can operate in load sharing, possibly allowing for gensets running on low efficiency to be shut off, reducing fuel consumption, emissions in addition to noise and vibrations for the comfort of the crew [20]. Other operating modes for hybrid power



(a) Load leveling operation.

(b) Peak shaving operation

Figure 2.3: Operational modes for hybrid power systems.

systems include load leveling, peak shaving and load smoothing, which will be discussed further below.

Load leveling

In load leveling operation the energy storage handles any load fluctuation around a constant load. Discharging in periods of higher load demands, and charging in periods of low load demand. Hence, allowing the genset(s) to operate at a constant load. By scheduling the active gensets with an optimal loading condition, the fuel economy and emissions of the operation can be improved compared to without energy storage. An illustration of the load leveling strategy is showed in Figure 2.3a

Peak shaving

During peak shaving operation the energy storage handles the peak loads. This can reduce cost by reducing the demand for installed genset power. The strategy can also increase efficiency by allowing gensets that otherwise would be needed to handle the peak loads to be shut off. These gensets would typically be running inefficiently in the low load periods, and since energy storage has no emission during down times they are favourable to use for handling the peak loads. During high demand peak loads the energy storage will discharge to provide the demanded power, while in low demand troughs the energy storage will be charged. This results in the gensets operating closer to the optimal loading condition than it otherwise would be doing. An illustration of the peak shaving strategy can be seen in Figure 2.3b.

Load smoothing

Since energy storage typically handles high frequency load fluctuations better than gensets, a load smoothing strategy can also be beneficial. By letting the energy storage handle the high frequency fluctuations and assigning a low-pass filtered load demand to the gensets, one can reduce the wear and tear on the gensets. An illustration of the strategy can be seen in Figure 2.4

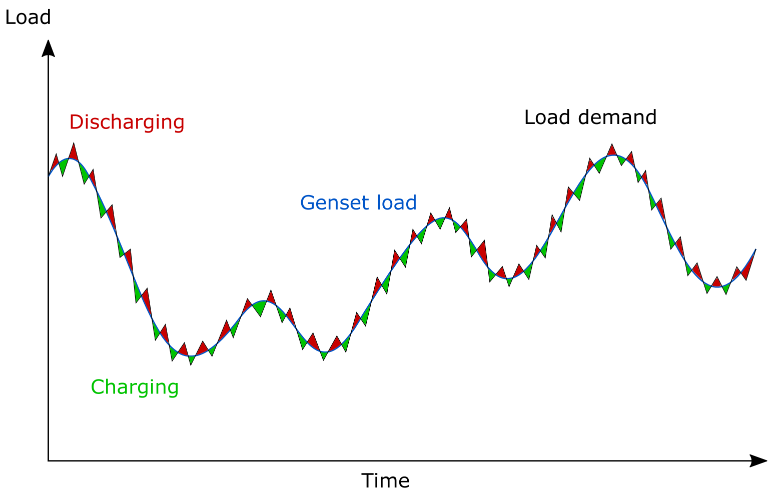


Figure 2.4: Hybrid power system in load smoothing operation.

2.0.3 Flywheel as energy storage

A flywheel is a mechanical energy storing device. The system typically consists of a flywheel connected to a motor/generator. The flywheel is supported by bearings and often encapsulated in a vacuum to minimize air friction. Energy is stored in the flywheel as rotational energy when the motor accelerates the flywheel, the energy can then be extracted at a different time by the flywheel running the generator to produce electricity [21]. The energy stored in the flywheel is proportional to the square of the rotational speed and the mass of the flywheel [22]. Advantages of flywheels include low maintenance cost, capability of handling a high number of cycles without performance loss, easy and accurate measurement of available energy and environmentally friendly construction materials. The largest disadvantages are low energy density and little flexibility in physical footprint of the device. Since the flywheel must stand upright to operate efficiently, the feasibility of flywheels for shipboard applications may be limited [13].

2.0.4 Supercapacitor as energy storage

A supercapacitor is a capacitor with very high capacitance and low voltage limits. It consists of two metal plates coated in a high surface area carbon. As the capacitance is proportional to the area of the plates, this allows the supercapacitor to hold large charges [2]. The electrodes in the supercapacitor does not degrade chemically over time, thus the supercapacitor has a long charge-discharge cycle liftime, losing very little performance over time. This combined with fast charge-discharge speeds, make supercapacitors ideal for applications that require many rapid charge/discharge cycles and high power for short time periods [23]. In ship applications this is for instance the case in heavy lift operations with heave compensations. Disadvantages of supercapacitors include low energy density, high self-discharge rate and high cost per watt [24].

2.0.5 Battery as energy storage

There are many battery technologies, or chemistries, available, the ones that are most interesting for use in energy storage in shipboard applications are variants of Lithium-ion batteries. This is because they offer great versatility with the highest energy density and the highest power density compared to other battery chemistries. However, the performance comes with a cost, as Li-ion batteries also are the most expensive batteries. Li-ion battery packs can be structured to best fit the performance demands, with either focusing on high energy or high power. For shipboard applications it is often a combination that is required, and in these cases an energy optimized system is often sufficient due to the charging currents being relatively low compared to the size of the battery pack [13].

Ageing effects are an important subject when considering battery as energy storage. Ageing effects include both calendar ageing and cyclic ageing. Calendar ageing is time dependent ageing, where the battery see both an increase in iternal resistance and a decrease in capacity when stored. The dominant reason for the calendar ageing effect is the formation of a solid electrolyte interphase(SEI), which is built up of decomposition products of the electrolyte. The SEI consumes lithium when formed and increase the internal resistance with an increasing layer thickness. The increase in internal resistance and decrease in capacity is higher when the battery is stored at a higher State of Charge (SOC) and thereby voltage [25]. The cyclic ageing does also increase internal resistance and decrease capacity. The cyclic ageing is a result of degradation of active materials reversibility [26]. During intercalation and de-intercalation when the battery are charging and discharging, the material is experiencing volume change. This volume change is a stress factor and can result in cracks in the SEI, the SEI will then repair the cracks and consume lithium in the process, hence, increasing the internal resistance and decrease capacity [25].

In order to describe the behaviour of the battery mathematically, an equivalent circuit of the battery is typically used. Basic elements like voltage sources, resistors and capacitors are combined in order to approximate the electrochemical process and the dynamics of the battery [27]. A widely used equivalent circuit for batteries is the Thevenin equivalent circuit model, which can be seen in Figure 2.5. It consists of an internal resistor, R_s, the resistor-capacitor parallel network, R_p(equivalent polarization resitance) and C_p(equivalent polarization capacitance), and the open circuit voltage (OCV), $v_{oc}(h(t)$, which is a nonlinear function of the SOC. The model takes the current, $i_b(t)$, as input and the terminal voltage, $v_b(t)$, as output. The accuracy of the model can be improved by adding more $R_p|C_p$ circuits, at the cost of increased complexity [28]

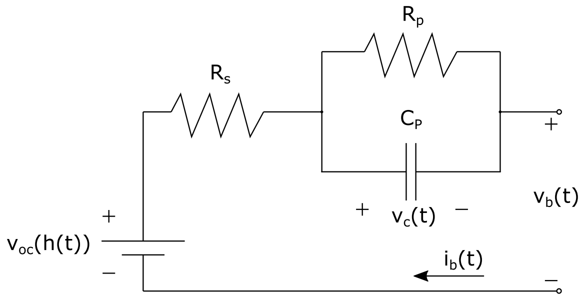


Figure 2.5: Thevenin equivalent circuit of a Lithium-ion battery.

The values for the resistors and capacitor, i.e R_s, R_p and C_p, are dependent on the temperature, the SOC, and also the degrading of the battery. And thus these values must be updated when the model is used in real-time. However, the variations of the temperature and SOC are quite small and can thus be assumed to be quasi-stationary, meaning they are constant over a small time window. Online identification can capture the parameters faster than the variations in temperature and SOC [27].

2.0.6 Comparison of energy storage technologies

There are a few key properties to consider when choosing an energy storage system. In Figure 2.6 an overview and comparison of battery, supercapacitor and flywheel energy storage is summarized.

2.0.7 Control levels in hybrid power systems

A hybrid power system consists of more than one energy source, and in order to operate the power system efficiently and reliably a system to control the power production and delivery is needed. This control system can be divided into layers. These layers typically include the operator on top giving the mission requirements, an energy management system (EMS), a power management system (PMS), the low-level control and for the case of battery energy storage also a battery management system (BMS). An overview of the control layers and the signals between them can be seen in Figure 2.7 and are discussed further below.

	Battery(Li-io)	Supercapacitor	Flywheel
Power density	Medium 500-2000 kW/kg	Very high 30 kW/kg	High 2.5-30 kW/kg
Energy density	Medium 90-190 Wh/kg	Very low 5 Wh/kg	Low 5-100 Wh/kg
Charge-/discharge dynamics	Medium min-hours	Very fast sec-min	Fast sec-min
Self discharge	Medium 1-3% per month	High ~5% per day	Very high ~20% per hour
Cyclic lifetime	Medium ~3000 cycles	Very high > 500 000 cycles	High > 100 000 cycles
Efficiency	High > 90%	Very high 95%	High 80-90%

Figure 2.6: Comparison of the properties of a few energy storage technologies, data extracted from [1],[2] and [3].

Energy Management System

The EMS is a supervisory system and its main task is related to operating the power system as efficient as possible. The EMS monitors the status of the different energy sources and the load demand, based on this information and mission requirements it assigns loads to the different sources. There are several objectives that are related to efficient operation, e.g. Minimizing fuel consumption, emissions, power loss in components and extending the lifetime of components [29].

There are three main categories of EMS: rule based, optimization based and learning based. Rule based methods are most common in practice, due to their more intuitive nature and ease of implementation. However, the more advanced methods have a larger potential. The optimization methods can be divided into two categories, offline and online optimization. For offline optimization a prediction of the load conditions are needed. Predicting load conditions is very hard due to the uncertain nature of weather conditions at sea, e.g waves, wind and currents. Thus, offline optimization is more useful for optimal design of the power system. Based on likely load conditions or collected data, different designs can be tested and evaluated. The online optimization methods are usually based on numerical optimization methods and an instantaneous cost function [29]. Methods used to solve these numerical optmization problems include model predictive control(MPC), linear-, quadratic- or nonlinear programming, depending on the formulation of the prob-

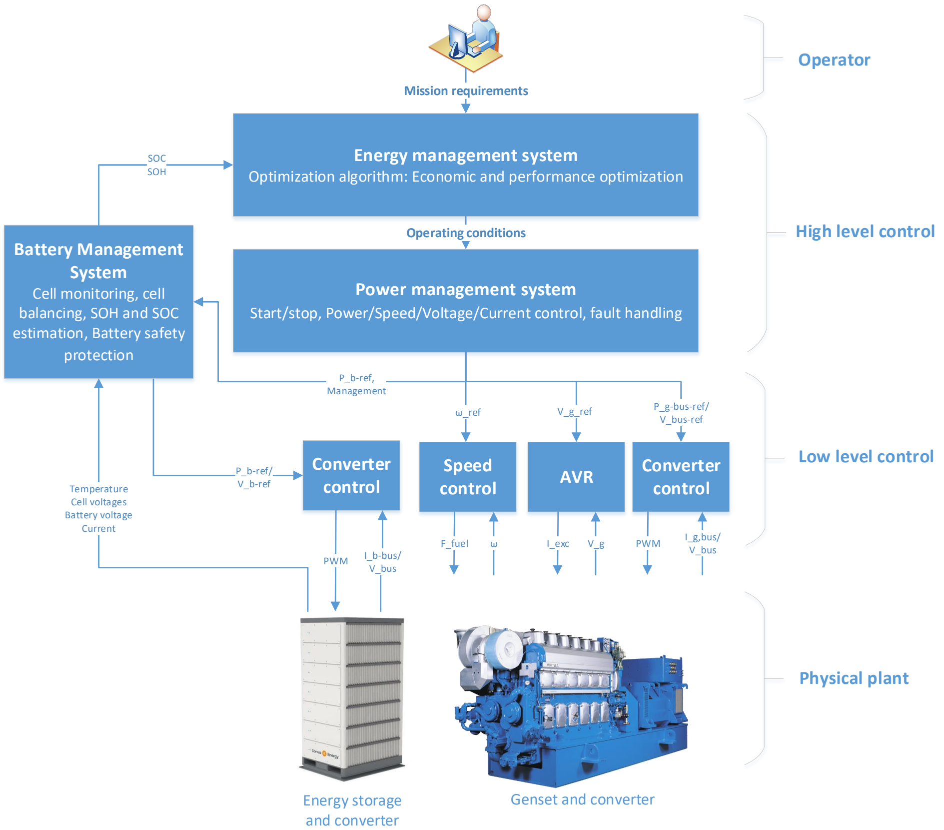


Figure 2.7: Overview of the control layers in hybrid power systems.

lem. As the rule- and optimization based methods can be lacking in their ability to adapt to random conditions, learning based strategies are being investigated. The learning based methods can be divided into three types: supervised-, unsupervised- and reinforcement learning. Both supervised- and unsupervised use data sets to learn favourable behaviours. In supervised learning the data set has labeled examples provided by a supervisor that has extensive knowledge of the data, while in unsupervised learning the data set used is unlabeled, and unknown or hidden structures in the data can be discovered. In reinforcement learning an agent is learning in real time, taking actions based on a goal where different actions give different rewards. Based on previous actions and rewards the agent learns what actions that are favourable [30].

Power Management System

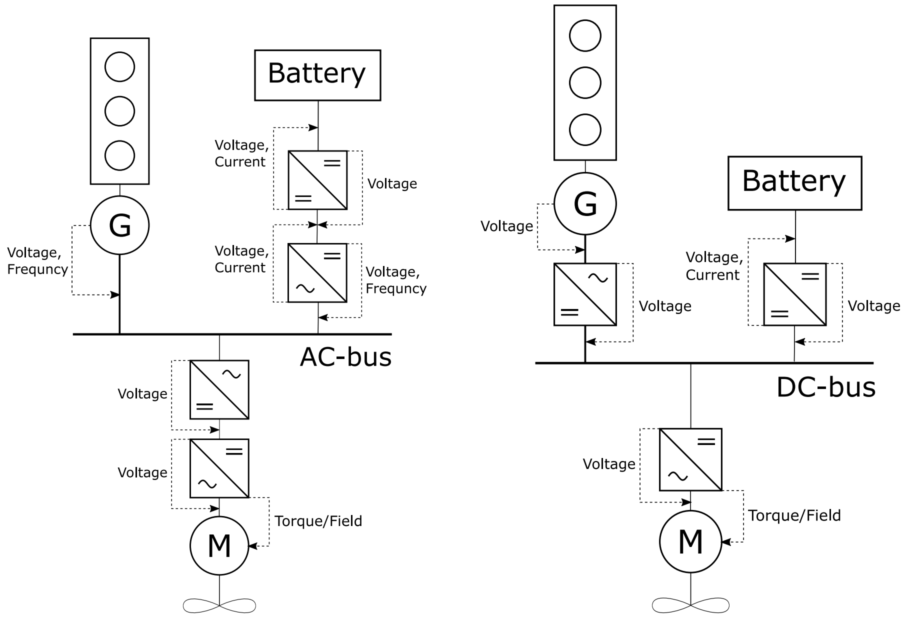
The Power Management System (PMS) is responsible for the instantaneous power availability of the power system. It should ensure that sufficient power is available at all times and that the vessel is prepared for a fault situation [31]. The PMS should maximize the blackout capabilities, minimize the fuel consumption and serve to decrease maintenance cost through protecting the equipment against fault and malfunctions [32]. While the EMS is more related to the efficiency of the operation, the PMS is related to the safety and reliability of the operation and hence there are several functionalities that are required by class authorities [33]. These include, among others:

- Load dependent starting of additional generators
- A failure in a power management system shall not cause alteration to the power generation, and shall initiate and alarm at the main navigation workstation
- Overload, caused by the stopping of one or more generators, shall not create a blackout

Low level control

To maintain a stable and correct power flow according to the higher levels of control, a low level control system is needed. The different parts of the power system operate on different voltages, some components use DC, while others use AC. In order to control the voltages and the power flow, power electronic converters are used. Power electronic converters include DC-DC converters, inverters and rectifiers. The different components have different control objectives, which are illustrated for both and AC system and a DC system in Figure 2.8a and Figure 2.8b.

In the AC case the generators objectives are the voltage and the frequency. The voltage is then controlled by an automatic voltage regulator (AVR), while the frequency is dependent on the rotational speed of the prime mover [34]. Thus, the rotational speed should be kept as constant as possible. In the DC case the objective of the generator is only to control AC voltage and then DC through a rectifier, as the DC bus is not frequency dependant. This enables the prime mover to run at varying rotational speeds, allowing for better fuel economy and less emissions. In the AC system the battery is connected to the bus through two converters, a DC-DC converter and an inverter. The control objective are dual since the battery can both be charged and discharged. While discharging the DC-DC converter should maintain the voltage, and the inverter should maintain voltage and frequency according to the AC bus requirements. While charging both the DC-DC converter and the inverter should maintain the voltage and current to the battery. With a DC bus the inverter stage is not needed and the objective for the DC-DC converter becomes to maintain the DC bus voltage while discharging and maintaining the voltage and the current to the battery while charging.



(a) AC power system.

(b) DC power system.

Figure 2.8: Illustration of control objective for converters.

The voltage and current controllers can be proportional-integral (PI) controllers. Different control loops can be designed with a pulse-width modulation (PWM) block. The PWM block use selected values for amplitude- and frequency-modulation ratios for the control wave and carrier wave to decide the output magnitude and frequency. Thus, selection of these values are importants. Current-mode control is mostly used for servo drives and has benefits like fast response, but has drawbacks in terms of bad voltage regulation through possible noise in the control loop [34]. The voltage-mode control loop has benefits like stable modulation and simpler circuits, but with drawbacks in slow response and variable loop gain. A cascaded voltage-current PI controller is also a well used method for converter control. The controller consist of an outer loop voltage PI controller that produce the current reference for an inner loop current PI controller, which then produce the signal to the PWM block that generates the switching signal to the converter in order to produce the desired output. In this cascaded setup it is very important that the bandwidth of the inner loop current controller is higher than the bandwidth of the outer loop voltage controller in order to ensure the dynamic performance of the controller. An overview of a cascaded voltage-current PI controller can be seen in Figure 2.9.

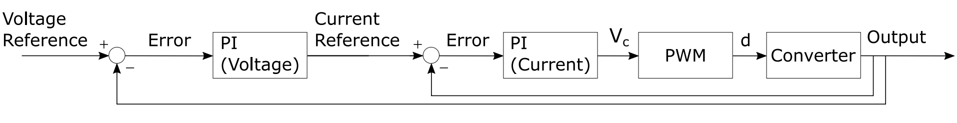


Figure 2.9: Cascaded voltage-current PI controller used for converter control.

Other control strategies for converter control include model predictive control (MPC) for ouput voltage control, and hybrid control that combines behaviours of continous- and discrete time dynamical systems to produce desired output voltage [34].

Challenges for the low level control include converter efficiency, voltage and frequency stability, harmonic distortion in ac power systems and short-circuits in dc power systems [34]. Converter efficiency is dependent on the power output compared with the power rating of the converter, as well as input voltage. Lower normalized power output is connected with a decrease in efficiency.

2.0.8 Battery Management System

In order to implement a battery pack in a hybrid power system an integral part is the battery management system (BMS). The quality of the battery pack is said to be only as good as its BMS [35]. For large scale battery systems the battery pack can be divided into three main layers, the individual cells, modules consisiting of several series connected cells and the entire battery pack consisting of a series of modules. Thus, the BMS can also be divided into a similar hierarchy, with cell monitoring units (CMUs) for each cell, module monitoring units (MMUs) for each module and a pack management unit (PMU) on the top. Such a hierarichal structure is beneficial in terms of flexibility and scalability, and allowing for redundancy in an easy way by duplicating the system. There are also BMSs that only have the two upper layers of MMUs and PMU, as the cost of having CMUs on each cell can be expensive. However, without measurements from each individual cell, the BMSs capabilities on the cell level, e.g tracking cell history like lifetime, number of cycles, storing of serial number, becomes reduced.

The BMS should have several features that ensure the safety, reliability and efficiency of the battery pack. These features include cell monitoring, battery safety and protection, state of charge estimation, state of health estimation, cell balancing, thermal management and charge control [36].

Cell monitoring

The BMS should aquire information about the status of each battery cell, in terms of voltage, current and temperature. The relation between open-circuit voltage (OCV) and the SOC is different for various battery chemistry. Thus, the required accuracy of the voltage measurement is dependent on the battery chemistry. Some battery chemistries like Li-$FePO_4$ have a flat OCV-SOC curve, requiring very high accuracy in the voltage measurement, while other chemistries like Li-Po have a steeper OCV-SOC curve requiring less accuracy. The current is also used in SOC calculation algorithms, and thus a high measurement accuracy for current is also needed, a typical method is to integrate current over time to estimate the stored charge. This integration requires the current sensor to be offset free over the working temperature range and time [36].

Battery safety and protection

The BMS should prevent any hazardous working conditions for the battery pack. These conditions are mostly related to operating the battery outside of the limitations of the battery chemistry. This can be deep charging of the battery, i.e operating the battery below a certain SOC level, overcharging a fully charged battery, going beyond the cutoff voltage of the battery or charging/discharging at a charging rate (C-rate) that is outside the safety limitations of the battery chemistry. Keeping the operating temperature within the limits of the battery is essential for the safety of the operation and should be monitored by the BMS.

State of charge estimation

The state of charge (SOC) is important information to ensure safe operation, preventing over-discharge and over-charge. In addition to that the SOC is essential to the energy management system in order to optimize the use of the battery pack. The SOC is not directly measurable, and thus the BMS needs an algorithm to estimate the SOC of the battery pack. Conventional methods to estimate the SOC include estimations based on the OCV-SOC curve and integration of the current over time or the two combined. Other methods are electrochemical impedance spectroscopy (EIS) [37], and online model-based methods where the battery is modeled as a nonlinear system. The challenge with the online model-based methods are the parameters for the battery model that are changing with varying SOC values.

State of health estimation

The state of health (SOH) describes the ageing of the battery, i.e number of cycles the battery has left before it reaches end of life (EOL). This is essential information for the energy management system in order to operate the power system in a way that prolongs the lifetime of the battery pack.

Cell balancing

Battery packs for shipboard applications consists of a number of battery cells connected in parallel and series in such a a way that it delivers the desired voltage and capacity. If these cells have large differences in voltage and capacity the efficiency of the entire battery pack is compromised. For instance if the cutoff voltage in discharge is reached for one cell before the others, the discharge will stop and the remaining capacity in the other cells will not be used. Thus, the BMS must have the capability to rebalance the cells to keep them at an even voltage and capacity level.

Thermal management

The efficiency and safety when using batteries are highly dependent on the temperature. And the BMS should have capabilities to monitor and control the temperature of the battery pack. This is done through sensors and cooling systems that can be either air- or liquid-based.

Charge control

The battery chemistry determines the capabilities of the battery pack in terms of C-rate during charge and discharge. As keeping the C-rates within the limitations of the battery is crucial for the batteries efficiency and lifetime. Even though the assigned battery power is chosen by the energy management system, the BMS should be able to protect the battery pack from charging in a way that damages the battery.

2.1 State of the art hybrid electric power systems

As mentioned earlier implementing hybrid solutions efficiently is . Both the optimal management reducing the operational costs and the sizing problem for various hybrid systems and applications have been investigated in literature.

In [38] operational data from three different vessel types, a ferry, a platform supply vessel (PSV) and a seismic survey vessel, were analyzed. The three cases were tested with two different types of EMS and three different power system configurations. The EMSs included: a Mixed-Integer Linear Programming (MILP) optimization algorithm and a simpler logic-based algorithm. The power system configurations included: four fixed-speed gensets, three fixed-speed gensets and one variable-speed genset, four fixed-speed gensets and an energy storage system (ESS). The objective function in the MILP included a term to minimize the generated power, a term to even out the number of running hours over the gensets, and one term to even out the number of starts and stops over the gensets. The results were compared based on three key values: total fuel consumption, running hours for all gensets and the number of starts/stops for all gensets. Results showed that both the number of running hours and the fuel economy was improved by implementing an ESS and using the MILP EMS for the ferry and the PSV. While the seismic survey ship showed the largest improvement on fuel consumption with implementing a variable speed genset. For further work, optimizing the lifetime of the battery pack and implementing genset dynamics in the EMS algorithm is suggested.

A hybrid power system consisting of fuel cells, Lithium-ion batteries and supercapacitors are investigated in both [39] and [40]. In [40] a three-part controller is proposed. A feedback PI-controller is used to keep a steady DC bus voltage by feeding a DC bus current reference to a Model Predictive Controller (MPC), the MPC is then used to calculate current references for each of the energy sources, and a hysteresis controller is used to create pulse-width modulation signals (PWM) for the converters to produce the desired currents. The target is to keep the DC bus voltage steady and the fuel cell and battery current slopes according to certain references, in order to lengthen the time span of the energy storage system. The controller scheme was tested using the MATLAB/Simulink environment and a physical test bench. Results showed that the controller scheme successfully limited the battery and fuel cell current slopes and kept the DC bus voltage stable within 6.23% overshoot and voltage ripple of 4.25%. In [39] a comparative study of different EMS strategies for a more-electric aircraft (MEA) is conducted. The strategies investigated are: state machine control, rule-based fuzzy logic, PI-controller, frequency decoupling and fuzzy logic, equivalent consumption minimization strategy. Each are analyzed and compared based on the following criteria: hydrogen consumption, state of charge (SOC) of the supercapacitor and battery, the overall system efficiency and the stresses on each of the energy sources. Results showed that the PI-controller gave the lowest fuel consumption, but with high use of battery. The state machine control gave the highest overall efficiency and low stress on the battery and supercapacitor. The frequency decoupled fuzzy logic gave the lowest fuel cell stress and lowest use of battery, but with higher fuel consumption and lower overall efficiency. Conclusion is that EMS for a MEA should be a multi-scheme and the scheme to be used should be chosen based on a specific criteria.

In [41] an EMS with an economic control strategy is proposed for a microgrid community (MGC). The MGC consist of more than one microgrid (MG) and the EMS has a two-level hierarchial structure. The lower level focuses on minimizing the operational cost for each MG, while the upper level focuses on minimizing the operational cost of the entire MGC. The objective function on the upper level include the cost of producing power based on fuel cost, the maintenance cost based on the output power, startup cost and the exchanged power. The exchanged power is positive if the upper level delivers power to the underlaying MGs. The objective function for the lower levels is similar, except the sign of the exchanged power is opposite of the upper level. Hence, the power are exchanged between the different MGs in order to minimize the operational costs.

In [42] a methodology for finding the optimal size of a battery based ESS is proposed. The study is on shipboard applications and the problem is divided into the two problems, the optimal size problem and the optimal EMS problem. In the sizing problem the total cost is minimized. The total cost consists of the investment cost and replacement cost of the battery pack and power electronics and the fuel cost from using the gensets. The number of replacements of the battery pack that is needed is calculated based on the energy exchanged and average depth of discharge found when solving the optimal EMS problem. Solving the optimal EMS also returns the fuel cost needed for the optimal sizing problem. The objective function of the EMS has four terms, that each have an associated weight. The first term minimizes the power generated by the generators, while the second term minimizes the number of start-ups. The third term is a penalty function that penalizes the generators operating outside of the optimal loading conditions, the penalty function is a piecewise linear function related to the specific fuel oil consumption (SFOC) curve for the gensets. The last term considers the average SOC of the ESS, added with a negative sign in the objective function. Case studies was conducted based on ship data from a PSV and a ferry. Conclusions showed large lifetime net savings for both cases, especially high for the PSV.

In [43] a drillship power system is analyzed in terms of optimal sizing of an ESS and economic dispatch. The EMS is formulated as a Mixed-Integer Non-Linear Program (MINLP). The formulation include a second or third order polynomial for the fuel cost function and an exponential term for the cost of start-up/shut down. In addition to the terms related to operational cost, there is also included a term for the investment cost of the ESS including power electronics.

In [44] an assessment of the benefit from electric and hybrid propulsion for different vessel types is conducted, based on an analysis of their respective operational profiles. The study used data from Automatic Identification System (AIS) and vessel types included: Tankers, Bulk carriers, General cargo ship, container ships, Ro-Ro ships, Reefers, Offshore vessels and Passenger ships. Results showed that offshore vessels and passenger ships proved the largest potential for hybridisation with their dynamic operational profiles and large share of operational time under lower, more inefficient loading conditions. Suggested further work was a case study on offshore vessels and passenger ships, investigating the improvements to energy efficiency by implementing a hybrid power system.

Chapter 3

Conclusion and further work

3.1 Conclusion

In this thesis, different ways of operating hybrid ship power systems efficiently have been explored. A literature study on aspects of hybrid power system has been conducted. Different topologies have been discussed. A few energy storage system technologies have been investigated and compared, and different operating modes for hybrid power systems that can improve performance have been discussed. The typical control structure for hybrid ships and its components have been explored and state of the art approaches to energy management have been reviewed.

A paper has been written, where an energy management algorithm for a battery/genset hybrid ship is proposed. The algorithm is based on Mixed-Integer Quadratic Programming and the objective is to minimize total costs of operation. This is done through minimizing fuel consumption, cyclic battery degrading, SOC variations, genset load variations and the weighted sum of active gensets. The algorithm was assessed on two different load profiles extracted from vessels in operation, one from a PSV and one from a ferry. Four different cases was tested for each load profile: optimal control without battery and optimal control with battery for three different battery sizes. The performance was compared to results extracted from the vessel operation. Results were assessed based on the total cost of operation, which includes: fuel cost, CO_2 tax cost, battery degrading cost and maintenance cost.

Results for the PSV load profile showed that optimal control without battery gave the lowest total cost. However, by introducing batteries the fuel consumption and maintenance cost was reduced the most, but due to relatively high battery degrading costs, the total cost was slightly increased. The cost increase is not massive, and it can be argued that if second hand value of the battery is considered, the battery option would be favourable. Results for the ferry load profile showed a slight reduction in total cost by using optimal control without battery. However, the algorithm did not give desirable results when introducing batteries for the ferry load profile, as a large degradation of the battery was seen due to aggressive battery usage, resulting in large increases in total cost.

3.2 Further work

The algorithm proposed uses certain simplifications, and thus there are several points where further work should be considered. Suggested points include:

- In order to more accurately assess the fuel consumption, the exact SFOC curves for the gensets in consideration should be used.
- The influence starting and stopping of the genset have on maintenance needs investigating.
- The effects different loading percentages for the gensets have on maintenance needs investigating.
- The battery degrading calculations does not consider calendar effects, and the cyclic degrading is assumed to be similar throughout the battery's lifetime, which is inaccurate. Therefore further development of the battery model should be considered, accounting for calendar effects and more accurate estimations of cyclic degrading.
- The investment cost of the power system should be considered. The battery installation cost and the possible reduction in installed genset power would need assessing to truly evaluate the options.
- Second hand value for batteries should be investigated, as it could lead to battery use becoming favourable.
- Physical footprint and weight for the battery pack should be considered.
- The algorithm performed much better for the PSV load profile, compared to the ferry load profile. And should therefore be improved to better handle various load profiles.
- Further tuning of the weights to improve performance should be considered.
- The algorithm should be tested on a simulation model in order to verify the results.

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Appendix

Paper:

Economic Control Design for Hybrid Electric Ships

Øyvind Stokke

Economic Control Design for Hybrid Electric Ships

Øyvind Stokke
dept. of Marine Technology
Norwegian University of Science and Technology
Trondheim, Norway
oyvind.sto@hotmail.com

***Abstract*—The maritime industry is a large contributor to the world's emissions with around 3% of both annual global CO_2 emissions and annual global greenhouse gas emissions. In order to reduce both these emissions and the costs of operation, the efficiency of the marine power systems must be improved. A way of reducing emissions and fuel consumption is to introduce energy storage systems. In this paper an energy management algorithm for battery/genset hybrid ships based on Mixed-Integer Quadratic Programming (MIQP) is proposed. The algorithm minimizes the fuel consumption and maintenance cost, as well as the cyclic degrading of batteries. The algorithm is tested on load profiles extracted from vessel data for two different vessel types, a Platform Supply Vessel (PSV) and a ferry. The performance of the algorithm is compared to the data extracted from vessel operation and assessed based on fuel cost, CO_2 tax cost, maintenance cost and the cost of battery degrading. Four cases of optimal control is tested for both the PSV and the ferry, one without use of battery and three cases with batteries of different sizes. Results indicate that optimal control without battery has the lowest total costs. By using batteries the fuel consumption and emissions can be further reduced, but due to relatively high battery degrading costs, the total costs are slightly increased. The algorithm performs significantly better for the load profiles extracted from PSV operation compared to ferry operation**

***Index Terms*—Hybrid power system, energy management, battery energy storage, optimization**

I. INTRODUCTION

The increasing awareness of the climate challenges we are facing, calls for new solutions and innovations in order to reduce the global emissions. In the Paris agreement [1] the world has agreed upon a limit target for the increase in global average temperature, saying the increase should be kept below two degrees celsius above pre-industrial levels. This is a bold target, and requires climate friendly measures in all industries. The shipping industry is responsible for large emissions, with approximately 3% of both the annual global CO_2 emissions and the annual global greenhouse gas emissions [2]. Thus, reducing the emissions from shipping are a significant contribution to the global environment.

Marine power systems typically consists of diesel engines with mechanical propulsion, or diesel-electric topologies with diesel-generators (gensets) and electric propulsion. In order to reduce emissions one can either improve the efficiency of the traditional fossil fuel based energy sources, or introduce alternative zero-emission energy sources e.g. batteries. As emissions are closely related to the fuel consumption, which is a large expense for ship owners, improving the efficiency of the operation has large economic motivations.

The fuel consumption is highly dependent on the loading conditions of the gensets. Gensets typically have an optimal loading condition between 70-90% of rated power [3]. This range is where the specific fuel oil consumption (SFOC) is at its lowest, and moving out of this optimal range, especially to lower load conditions, results in the efficiency dropping dramatically. Today the genset scheduling is mostly done manually, this reliability on human judgement often results in suboptimal unit commitment. It is a common practice for operators to have more gensets active then strictly needed, hence, having gensets running in inefficient loading conditions. This practice is the result of a distrust in the power management system (PMS) and its ability to provide the vital power and fault handling [4]. The mission requirements may also demand redundancy (spinning reserve) on the available power for critical operations, e.g. in Dynamic Positioning (DP), to ensure that no hazardous situations occur in the case of a component failure. Thus, using a more advanced energy management systems (EMS) instead of relying on human interaction to assign the different loads to the different energy sources, can be beneficial to increase the efficiency of the power system.

Introducing a hybrid power system with energy storage systems (ESS) is one way of reducing the fuel consumption and emissions that have emerged in recent years. There are several advantages to introducing an energy storage system (ESS). It can allow for emission-free operations at low loads, and it allows for more optimal loading conditions of the gensets through operating modes like peak shaving, load levelling and load smoothing [5]. When additional energy sources are introduced the complexity of the EMS increases and several approaches to the task can be found in literature. In [4] an Mixed-Integer Linear Programming (MILP) approach is proposed, considering generated power, running hours and No. starts and stops. In [6] an Model Predictive Control (MPC) is combined with a Proportional-Integral (PI) controller and a hysteresis controller, for a hybrid solution consisting of fuel-cell, battery and a supercapacitor. In [7] a comparative study of EMS strategies for a more-electric aircraft (MEA) is conducted. Strategies compared include: state machine control, rule-based fuzzy logic, PI, frequency decoupling and fuzzy logic and equivalent consumption minimization. In [8] both the investment cost and the operational cost are assessed for a drillship power system, the EMS is based on Mixed-Integer Nonlinear Programming (MINLP) and includes a polynomial fuel cost function and an exponential cost function for the start-up/shut-down.

The main contribution of this paper is the development of an energy management algorithm for a battery/genset hybrid based on Mixed-Integer Quadratic Programming (MIQP). The algorithm minimizes the fuel consumption, the battery degrading related to cyclic loss, the variations in SOC of the battery and load variations for the gensets. The performance of the algorithm is assessed on load profiles extracted from vessel data and compared with the genset scheduling extracted from the vessel data as well as for different battery sizes.

II. Hybrid electric power system for ship using battery pack

A hybrid electric power system has various energy sources, and thus the task of distributing the loads to the different energy sources becomes more complex compared to conventional power systems. The control system of hybrid power systems is typically divided into layers with the operator on the top, followed by EMS, PMS, Battery Management System (BMS) and the low-level control, an illustration of the control layers can be seen in fig. 1.

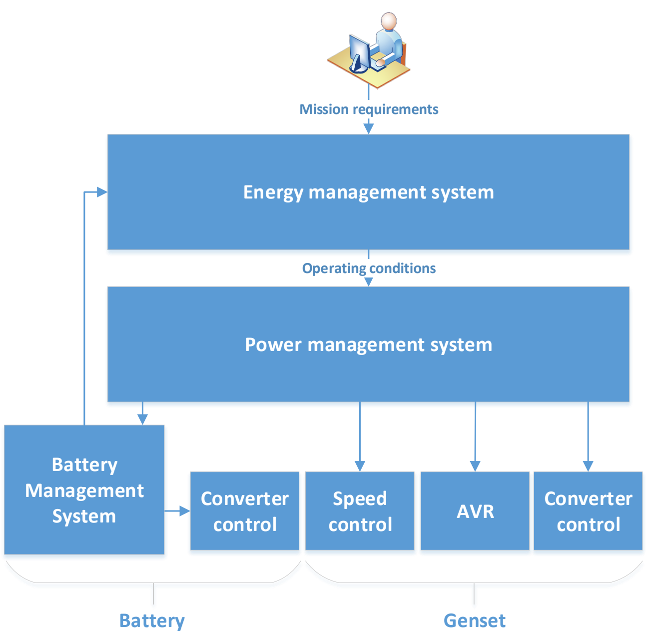

Fig. 1: Control layers for hybrid power system.

The EMS is a supervisory control system that is responsible for unit commitment, distributing the load demand to the different energy sources. The EMS has a few objectives including: minimizing fuel consumption, minimizing emissions, minimizing power loss in components and extending the lifetime of components [9]. The PMS is responsible for the instantaneous power availability and fault handling, protecting the equipment and maximize the blackout capabilities of the power system [10],[11]. The BMS handles the control and monitoring of the battery pack, ensuring the battery pack is not operated outside of its limitation. Important features of the BMS include: cell monitoring, state of charge (SOC) estimation, state of health (SOH) estimation, cell balancing, thermal management and charge control [12]. At the bottom there is the low-level control, e.g converter control, speed control and automatic voltage regulators (AVR). The low-level control should maintain a stable and correct power flow according to the higher levels of control [13].

In this paper an EMS algorithm is proposed. A flowchart describing the manner of operation of the algorithm can be seen in fig. 2. As seen in the figure the output produced by the EMS is the power set points for the battery pack and the different gensets. This output is produced based on a load demand for the time step in consideration, (k), and a minimization of the five different terms illustrated by blocks. The arrows on top of each block represent the input parameters used for the calculation of each term, and the arrows on top of the entire EMS block represents external inputs that is needed. The SOC variation term takes in a SOC reference, the battery power and feedback on the previous SOC value in order to minimize the deviation from the SOC reference. The battery degrading calculation uses the battery size and a cyclic degrading curve, which describes the relation between cyclic degradation and C-rate, in combination with the battery power in order to minimize the degradation of the battery. The fuel consumption is minimized based on SFOC curves, the power set point and the rated power for each genset. The maintenance term uses the rated power of each genset in order to minimize the weighted sum of active gensets, as larger engines are more expensive to run in terms of maintenance. The load variation term uses feedback on the previous loading conditions of the gensets, and the current power set point in order to minimize the transients of the genset loading.

In the case study two ship types were investigated, a platform supply vessel (PSV) and a ferry. A single line diagram (SLD) of the power system of the PSV can be seen in fig. 3, it is based on a real ship with the addition of a battery. As seen in the figure it includes four gensets, two large and two small. The propulsion system includes two large main propellers and three smaller, two bow thrusters and a retractable thruster. In reality the configuration is a two split bus, where each side has one large and one small genset as well as one bow thruster and one main propeller connected. The retractable can be connected to both buses. However, for the EMS algorithm it is assumed that the ship always operates with a closed bus tie, as illustrated in the SLD, allowing for free distribution of the power generation between the different energy sources.

III. Methodology - The EMS algorithm

The EMS proposed is based on Mixed-Integer Quadratic Programming (MIQP). The configuration of the power system is as seen in fig. 3. A MIQP formulation includes quadratic terms in the objective function, with linear constraints. The decision variables are both continous and integer, hence, mixed-integer. The objective function contains four terms, a term

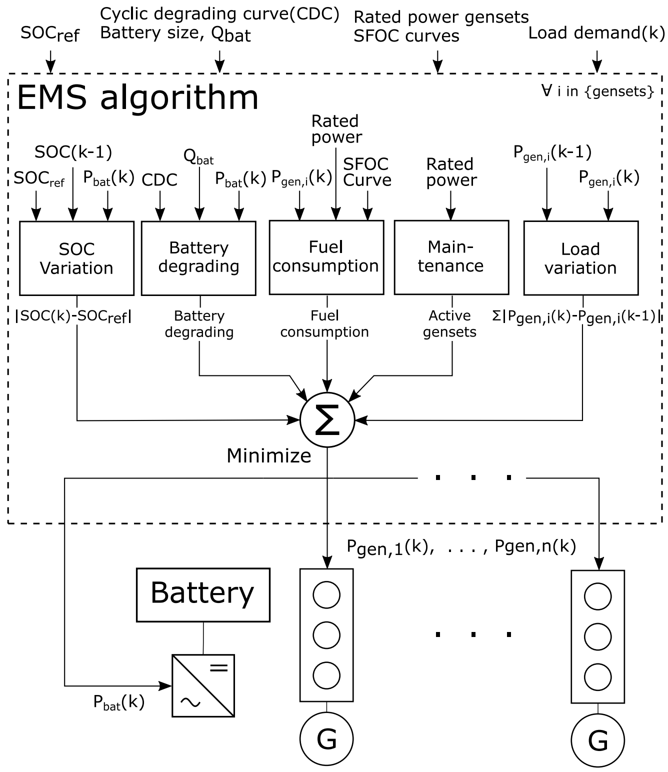

Fig. 2: Flowchart of the EMS algorithm.

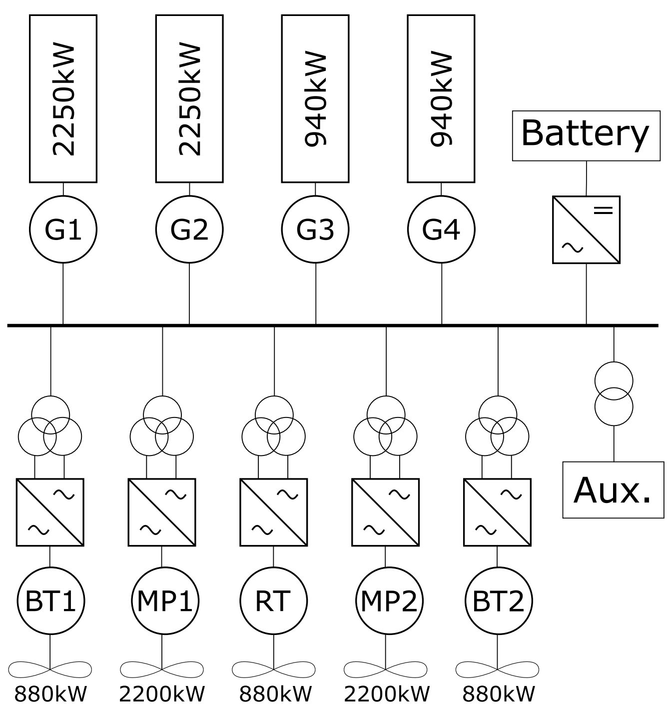

Fig. 3: SLD of the PSV power system configuration.

that minimizes the fuel consumption, a term that minimizes the cyclic degrading of the battery, a load variation term that penalizes large transients in the power output from the gensets and a term that penalize SOC variations from a reference value. The objective function is seen in eq. (1). For comparison a configuration without battery is also tested. In that case only the fuel consumption, active gensets and the ramp term are included, leaving a Mixed-Integer Linear Programming (MILP) problem.

A. *Fuel consumption term*

The term related to the fuel consumption in the objective function is the first term in eq. (1), and the parameters are described in table I. The fuel consumption of the gensets is dependent on the specific fuel oil consumption (SFOC) curve. Thus, to operate as efficiently as possible the SFOC curve for the genset must be know and accounted for in the optimization. However, the SFOC curve is a nonlinear curve, which results in a difficult and time demanding optimization problem. Thus, a piecewise-linear approximation is used for the SFOC curve, moreover a convex combination formulation is used. For simplification purposes it is assumed that all four gensets have the same SFOC curve. The SFOC curve used was extracted from [14], and is based on data from the ”46” engine family by Wärtsilä, ranging from 5850 kW to 18 480 kW. The SFOC curve is not exactly right for the genset considered in this paper, but the SFOC curve is assumed to follow the same trends and have similar optimal loading conditions. The piecewise-linear SFOC curve used can be seen in fig. 4.

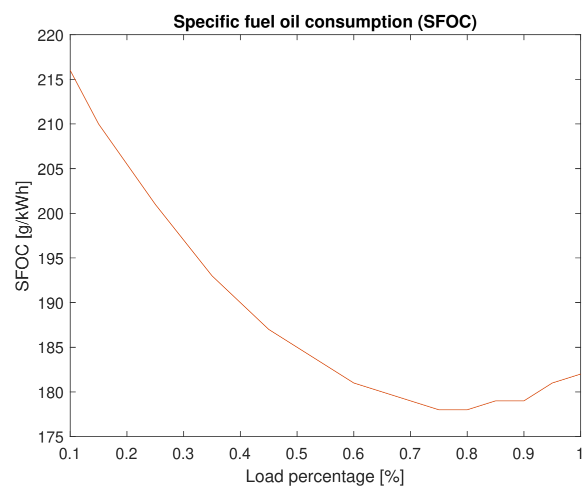

Fig. 4: Piecewise-linear specific fuel oil consumption, extracted from [14].

The SFOC curve describes the relation between the loading condition in percentage of rated power for the genset and the SFOC in $\frac{g}{kWh}$. To calculate the fuel consumption the SFOC must be multiplied with the power delivered by the genset and the time step considered. For the EMS algorithm it is desirable to have a relation between load in kW and fuel consumption in $\frac{kg}{h}$. This relation was found for the different engine sizes based on the SFOC curve.

A convex combination is a linear combination of points, where all coefficients are non-negative and sums up to 1 [15]. For one-dimensional functions, as is the case for the fuel consumption curve, a convex combination of two points can describe any point on the line between the two points. Hence, by knowing points for a nonlinear function, convex combinations can be used to express the function piecewise linearly.

In a convex combination formulation of an optimization problem, the coefficients are decision variables, e.g for genset i and point n it is $\lambda_{gen,i,n}$. The $\lambda_{gen,i,n}$ variables describes where on the line between two data points you are, e.g if $\lambda_{gen,1,2}$ has the value 1 it means that it is right on the point related to $\lambda_{gen,1,2}$. Thus, only consecutive λ values can be non-zero, otherwise values far out from the approximated curve can be chosen. This is ensured by the $z_{gen,i,n}$ variables. Each point n for genset i has a related $z_{gen,i,n}$ binary variable, and only one $z_{gen,i,n}$ is allowed to be non-zero. Constraints are made such that if e.g $z_{gen,1,3} = 1$, only $\lambda_{gen,1,2}$ and $\lambda_{gen,1,3}$ can have non-zero values, and thus it is ensured that only values on the right line segment can be chosen.

B. Battery degrading term

The cost of using the battery is largely related to the degradation of the battery. When the battery degrades it both loses energy storing capacity as well as the internal resistance is increasing [16]. This results in the battery eventually not being able to deliver the needed performance both in terms of power output and amount of energy stored, the battery has then reached end-of-life (EOL). When the battery pack reaches EOL it must be replaced with a new battery pack, which comes with a large cost.

The battery ageing includes both calendar ageing and cyclic ageing. Calendar ageing is time dependent degrading taking effect even when the battery is not used. The calendar ageing is related to the formation of a solid electrolyte interphase (SEI), which consumes lithium when formed. The calendar ageing is dependent on the SOC of the battery at rest and the temperature [16]. Cyclic ageing is related to the degrading of the battery due to the stresses in the material induced by the charging and discharging of the battery. Due to no temperature information on the battery and difficulty of assessing calendar ageing online, only the cyclic ageing is considered in the EMS algorithm in this paper.

The cyclic degradation is complex and has many influential factors, e.g depth of discharge (DOD), C-rate and temperature. The battery degrading term is simplified to account only for the C-rate when assessing the degradation. In [17] the degradation of batteries under different charging stresses are tested, in fig. 5 results from the tests can be seen. The degradation stages marked in fig. 5 describes how far the battery is in the degrading process, stage I: $0-4\%$ capacity loss, stage II: $4-13\%$ and stage III: $> 13\%$. Hence, the cyclic degradation is larger when the battery is new compared to later. For simplification it was assumed that the cyclic degradation curve is constant throughout the battery's lifetime. Thus, to estimate the cyclic degradation, values from stage II, i.e the red line, in fig. 5 was extracted. Several points from the curve was plotted in excel and curve fitted with a 4th degree polynomial. Based

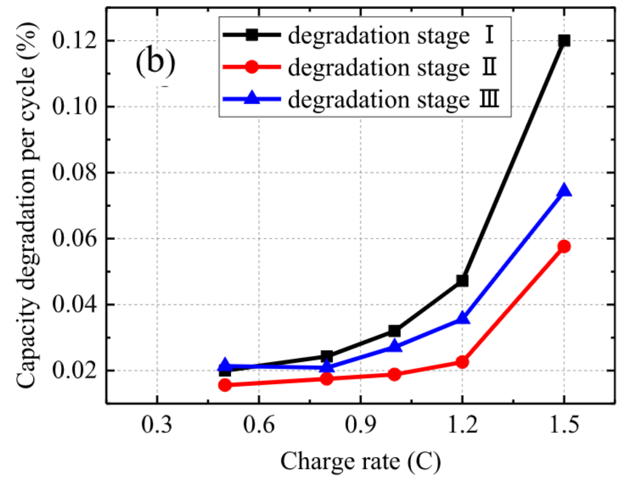

Fig. 5: Relation between charging rate and capacity loss per cycle for lithium-ion battery, from [17].

on the polynomial a curve was created for C-rates from 0 to 1.5C. Since no data was found on degradation effects when discharging with different rates, the same values are used for both charging and discharging. And the curve was mirrored about the y-axis, making a curve for C-rates from -1.5C to 1.5C. However, since the data describes degrading per cycle, the values was divided by two, i.e. half the degradation per cycle is assumed to happen during charging and half during discharging.

As seen in the second term in eq. (1), the battery degrading is calculated as the product of capacity loss per cycle and the fraction of an equivalent cycle that is undergone in this time step. One equivalent cycle is set as one $0-100\%$ charge-discharge cycle, and thus the expression becomes as seen in eq. (1), exchanged energy divided by two times the battery size. In difference from the fuel consumption calculations, the battery is only allowed to charge or discharge with power equivalent to C-rates with increments of 0.1C. This is due to the calculation time becoming very high when allowed to interpolate between the values, and increments of 0.1C is thought to be sufficient. The decision variable is $\lambda_{bat,n}$, which is a binary variable, and the constraint $\sum_{n=0}^{N_b} \lambda_{bat,n} = 1$ ensures that only one λ_{bat} is non-zero and thus only one value can be chosen for P_{bat} at each time step. Since both the expression for fraction of equivalent cycles and the cyclic loss is dependent on λ_{bat}, the term for battery degrading makes the objective function quadratic.

C. Maintenance term

An estimation of the maintenance cost related to the gensets was found in [18]. It can be calculated as the product of the rated power of the genset, the number of running hours and a constant describing maintenance cost in $\frac{USD}{kWh}$. This is included as the third term in eq. (1), where the number of active gensets is minimized and the different gensets have relative weights corresponding to their rated power.

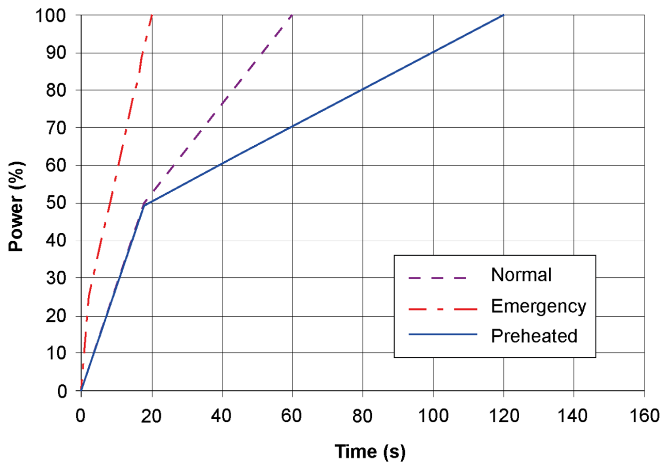

Fig. 6: Ramp rate limitations for gensets, from [19].

D. Load variation term

The gensets has limitations on the load dynamics. They need a certain time to react to load variations, and cannot go from 0 to 100% in an instant. In order to reduce the transients in the loading of the gensets, a penalty on load variation was added. This penalty is the third term in eq. (1) and it minimizes the sum of change in load for all gensets, multiplied with an associated weight w_{ramp}.

In addition to the term reducing transients in the objective function, a constraint on ramp-up time was added. The constraint is based on fig. 6. As seen in the figure the ramp limit is higher for load levels below 50% of rated power compared to load levels above 50%. Thus, two different constraints were added for the two cases. Below 50% load we have that the slopes are the same for normal operation and preheated engine, and the constraint is set such that the genset can reach 50% load in 20 seconds(Δ_{low}). For loads above 50% we have that the slope for normal and preheated engine are different, preheated means that the high temperature cooling water and lubrication oil has been preheated, but the temperature throughout the engine is not as in normal operation. Preheated engine uses 100 seconds to increase 50%, while at normal operation is uses 40 seconds to increase 50%. For this case a value in between was chosen for the constraint. It was chosen such that the gensets can increase the load with a slope of 50% increase in 60 seconds(Δ_{high}).

E. SOC variation term

When the algorithm was tested with only the battery degrading term related to battery usage, the algorithm would not utilize the battery very well. It would discharge the battery when the power was needed, but not charge it up again. In order to induce the algorithm to utilize the battery more, a SOC variation term was added in the objective function. The term is the last term in the objective function eq. (1), it penalizes deviation from a set reference for the SOC multiplied with an associated weight w_{soc}. By adding this term to the objective function, you also penalize deep discharges, which is desirable to reduce degrading of the battery. Although, the battery degrading calculation does not consider the depth of discharge when the total degradation is calculated, and thus these effects are not reflected in the battery degrading cost.

TABLE I: Notation and description of the parameters used in the optimization algorithm.

Notation	Description
$J(k)$	Objective function to be solved at time k
$P_{gen,i}(k)$	Power produced by genset i at time k
$P_{bat}(k)$	Power produced by battery pack at time k
$y_i(k)$	Binary decision variable for genset i at time k
Δt	Time step for optimization algorithm
$P_{dem}(k)$	Total power demand at time k
$P_{max,i}$	Rated power for genset i
$SOC(k)$	SOC at time step k
SOC_{min}	Minimum value for SOC
SOC_{max}	Maximum value for SOC
SOC_{ref}	Reference value for SOC
Q_{bat}	Battery capacity
$\lambda_{bat,n}$	Selection variable for piecewise linear battery degradation
$\lambda_{gen,i,n}$	Selection variable for piecewise linear fuel consumption
$Fc_{i,n}$	Fuel consumption in $\frac{kg}{h}$ at different load levels for genset i
$C_{loss,n}$	Capacity loss per cycle at different c-rates
N_g	Number of data points in $Fc_{i,n}$
N_b	Number of data points in $C_{loss,n}$
Lp_b	Array of C-rates with length N_b
Δ_{high}	Ramp limit for gensets above 50% load
Δ_{low}	Ramp limit for gensets below 50% load
$w_{bat,deg}$	Weighting factor for battery degrading
$w_{gen,i}$	Weighting factor for genset i
$w_{maintenance,i}$	Weighting factor for maintenance for genset i
w_{ramp}	Weighting factor for ramp term in objective
w_{soc}	Weighting factor for soc variation term in objective

$$
\begin{aligned}
\min \quad J(k) = & \\
& \frac{\Delta t}{3600} \sum_{i}^{Gensets} \sum_{n}^{N_g} w_{gen,i} \cdot \lambda_{gen,i,n} \cdot Fc_{i,n} \\
& + w_{bat,deg} \cdot \frac{|P_{bat}| \cdot \frac{\Delta t}{3600}}{2 \cdot Q_{bat}} \cdot \sum_{n}^{N_b} \lambda_{bat,n} \cdot C_{loss,n} \\
& + \sum_{i}^{Gensets} w_{maintenance,i} \cdot y_i \\
& + w_{ramp} \sum_{i}^{Gensets} |P_{gen,i}(k) - P_{gen,i}(k-1)| \\
& + w_{soc} \cdot |SOC(k) - SOC_{ref}|
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
\text{s.t.} \quad & \sum_i P_{gen,i}(k) + P_{bat}(k) = P_{dem}(k) \\
& P_{gen,i}(k) \geq 0.1 \cdot P_{max,i} \cdot y_i(k) \\
& P_{gen,i}(k) \leq 0.9 \cdot P_{max,i} \cdot y_i(k) \\
& P_{gen,i} = \sum_n^{N_g} \lambda_{gen,i,n} \cdot fc_{i,n} \quad \forall \ i \in gensets \\
& \sum_{n=0}^{N_g} \lambda_{gen,i,n} = 1 \ \forall \ i \in gensets \\
& \sum_{n=0}^{N_g} z_{gen,i,n} = 1 \quad \forall \ i \in gensets \\
& \lambda_{gen,i,n} \leq z_{gen,i,n} + z_{gen,i,n+1} \quad \forall \ i \in gensets, \\
& \qquad \qquad n = 1, .., N_g \\
& \lambda_{i,0} \leq z_{gen,i,1} \quad \forall \ i \in gensets \\
& \lambda_{i,N_g} \leq z_{gen,i,N_g} \quad \forall \ i \in gensets \\
& \lambda_{gen,i,n} \geq 0 \ \forall \ n, i \\
& z_{gen,i,n} \in \{0, 1\} \ \forall \ n, i \\
& P_{bat} = Q_{bat} \cdot Lp_b \cdot \lambda_{bat} \\
& \lambda_{bat,n} \in \{0, 1\} \ \forall \ n \\
& \sum_{n=0}^{N_b} \lambda_{bat,n} = 1 \\
& SOC(k) = SOC(k-1) - P_{bat}(k) \cdot \frac{\Delta t}{3600 \cdot Q_{bat}} \\
& 0.2 \leq SOC(k) \leq 0.9 \\
& -1.5 \cdot Q_{bat} \leq P_{bat} \leq 1.5 \cdot Q_{bat} \\
& P_{gen,i}(k) - P_{gen,i}(k-1) \leq \Delta_{limit} \ \forall \ i \in gensets \\
& \Delta_{limit} = \Delta_{high}, \quad if \quad P_{gen,i} > 0.5 \cdot P_{max,i} \\
& \Delta_{limit} = \Delta_{low}, \quad if \quad P_{gen,i} < 0.5 \cdot P_{max,i}
\end{aligned}
\tag{2}
$$

IV. Data

The data used for assessing the algorithm was provided by Blue Ctrl AS and Ulstein Design & Solutions AS. The data includes a data set from a ferry and data set from a platform supply vessel (PSV).

A. PSV

The data from the PSV was recorded from operation between 20.08.2015 and 02.10.2015, and the PSV has a power and propulsion system configuration as listed in table II

TABLE II: Configuration of power and propulsion system for the PSV.

Power generation	Rating	Propulsion	Rating
Genset 1	2250 kW	Azipull 1 & 2	2200 kW each
Genset 2	2250 kW	Bow thruster 1 & 2	880 kW each
Genset 3	940 kW	Retractable Azimuth	880 kW
Genset 4	940 kW		

The data set includes generated power for each genset, the power used by each thruster and positional data. The difference between the power generated and the power used by the propulsion represents the auxiliary loads and the losses in the system, e.g power conversion losses. The sampling rate of the data is 0.2 Hz and consist of 760 302 data points, which constitutes a time span of ∼1055 hours. The data set includes some low values that are constant over many time steps, e.g -2 and 3, these values are assumed to be faulty and thus all values below 10 was set to zero. The power delivered by each genset throughout the data set can be seen in fig. 7.

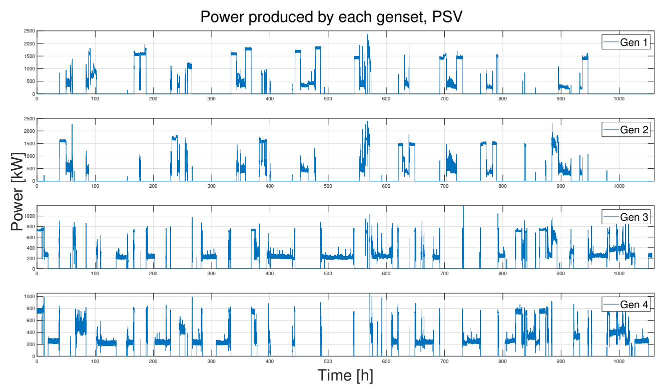

Fig. 7: Measured ship data from the PSV in operation.

For the case study the sum of power generated power from all gensets was used as the power demand at each time step. Hence, producing the power needed for the operation including the auxiliary loads and losses in the power system. It was not logged any information about the kind of operation the PSV was conducting at the different times, hence, the different operational profiles cannot be assessed directly againts a specific PSV operation. Since the data set is quite long, and the load profile is cyclic, a section of ∼112 hours was chosen for the case study. The section chosen includes two large peaks as well as various load levels. The total power demand needed throughout the test section can be seen in fig. 8.

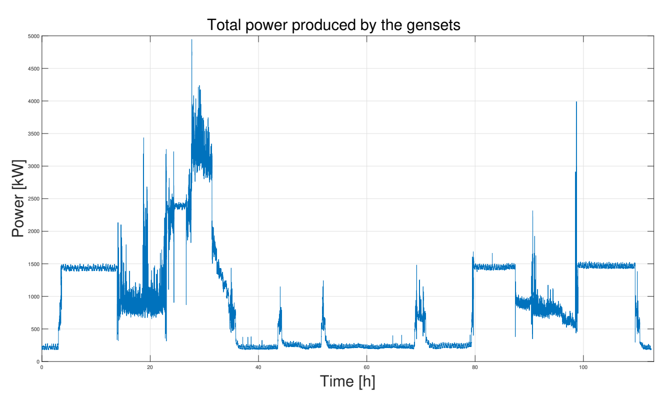

Fig. 8: Total power produced by the gensets for the PSV, 57 hour section used as power demand in the case study.

B. Ferry

The ferry has a power and propulsion system configuration as listed in table III. The data set was extracted from ferry operation. The data set only includes data on produced power by each genset, and no information on the load share between propulsion loads and other loads. The data does however represent the power demand for a typical ferry operation. The data set has 601 201 data points with a sampling rate of 1 Hz, hence, constituting a time span of ∼167 hours. The ferry data set also included some constant and low values which are assumed to be faulty, and thus also for this data set all values below 10 was set to zero. Similarly to the PSV case, the sum of power delivered by all gensets was used as power demand. The ferry data is very cyclic and thus only a smaller section was chosen for the case study. The ∼15.3 hour section chosen includes about 30 cycles and the highest load peak. The load demand throughout this section can be seen in fig. 9.

TABLE III: Configuration of power and propulsion system for the Ferry.

Power generation	Rating	Propulsion	Rating
Genset 1	1200 kW	Main propeller 1	1200 kW
Genset 2	1200 kW	Main propeller 2	1200 kW
Genset 3	640 kW		
Genset 4	640 kW		

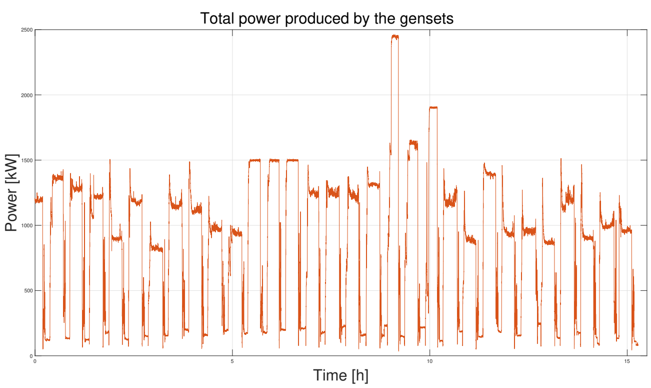

Fig. 9: Total power produced by the gensets for the ferry. 15.3 hour section used as power demand in the case study.

As seen in fig. 9 the power demand for the ferry has a cyclic load demand with two main loading conditions, in transit and at quay. The low load periods in fig. 9 is when the ferry is at quay, and the high load levels represent transit. The load demand is highest with peak loads at the beginning of the transit periods, this is probably due to the extra power needed to accelerate the ferry. A varying load demand can also be seen for different transits, this is likely due to varying weather conditions throughout the day.

V. Results

The proposed EMS algorithm was tested using the data extracted from vessel operation. The algorithm was implemented using MATLAB and the YALMIP package, which is a framework for optimization. Both the MIQP formulation for the cases with battery and the MILP formulation for the cases without battery was solved using the CPLEX solver.

Due to genset 1 and 2, and 3 and 4 having the same rated power and SFOC curves, the algorithm would switch very frequently between using the different gensets. Thus, a varying weight was set on the gensets in order to avoid frequent switching between similar gensets as well as letting all gensets be used. The reference value for the SOC, SOC_{ref}, was set to 60%. The weights related to the maintenance term was set based on the rated power of the gensets, where the weighting is relative to the cost of running the different sized gensets. The weights are similar for both the PSV and ferry, except for the maintenance weights which are sligthly different, due to different relative sizes of the genset. The weights was set trough trial and error and the values used was as follows

$$\begin{aligned}
&w_{gen,1,2,3,4} = [10, 10.02, 10, 10.01] \\
&\text{if } |T_1 - T_2| > 50 \\
&\ \text{switch} \quad w_{gen,1} \ and \ w_{gen,2} \\
&\text{if } |T_3 - T_4| > 50 \\
&\ \text{switch} \quad w_{gen,3} \ and \ w_{gen,4} \\
&w_{maintenance,1,2,3,4} = [107.2, 107.2, 103, 103] \\
&w_{bat,deg} = 1 \\
&w_{ramp} = 1 \\
&w_{soc} = 50
\end{aligned} \tag{3}$$

To evaluate the performance of the algorithm a few key values was considered. Mainly the cost of operation, which is the fuel cost, the maintenance cost and CO_2 taxes for the cases without battery. For the cases with battery, the battery degrading cost is also included. The maintenance cost was estimated based on the power rating of the gensets and number of running hours, and was set to $0.0032 \ \frac{USD}{kWh}$ based on data from [18]. For the fuel cost calculations, the fuel cost was set to $230\frac{USD}{ton}$ based on data from May 2019 [20]. The CO_2 taxes in 2019 was $508\frac{kr}{tonne}$ [21], which equals $54.58\frac{USD}{tonne}$ based on today's exchange rates. The CO_2 emissions are directly related to the fuel consumption as $CO_2[kg] = Q_{fuel}[kg]{\cdot}3.667{\cdot}0.867$. Hence, the fuel costs and emission costs are related to fuel consumption and the maintenance cost to the running hours.

The battery degrading cost was calculated based on the total degradation throughout the test section and the size of the battery pack. Assuming the EOL is when the battery has degraded 40% [22], the total degradation was divided by 0.4 to find the amount of the batteries lifetime that had been used. By multiplying this with the cost of the battery pack, the cost of battery usage for the period is estimated. The DNV GL report from 2015 [23], states that batteries of automotive quality is expected to drop from the $500\frac{USD}{kWh}$ cost of 2015 to $200\frac{USD}{kWh}$ in 2020, and batteries for maritime applications to reach $500\frac{USD}{kWh}$. These values were conservative as reported prices of 2019 for automotive batteries were $156\frac{USD}{kWh}$ [24]. Thus, the battery cost used in the cost calculations was set to $500\frac{USD}{kWh}$.

The real fuel consumption from the operational data is not known, and for comparison purposes the fuel consumption for vessel operation is thus calculated based on the same SFOC curve used in the EMS algorithm. The fact that this SFOC curve are not exact for the different genset sizes adds uncertainty to the results. The EMS algorithm calculates set points for every 10 seconds. For the PSV data with 0.2 Hz sampling rate this means it calculates for every other data point. And for the ferry data with 1 Hz sampling rate it calculates for every 10th data point. Hence, it is assumed that the fast load dynamics within the 10 second periods can be covered by the lower control levels, i.e PMS and converter control.

For all cases with battery the initial SOC was set to 50%, and thus for a fair comparison the difference between initial and final SOC is added to or subtracted from the total fuel consumption, depending on whether the final SOC is below or above 50%, the adjusted fuel consumption can be seen in the $\sum_{SOC}$-rows in the result tables. For these calculation a specific fuel consumption of 180 $\frac{g}{kWh}$ was used.

A. PSV

Results extracted from the vessel operation data is used as a benchmark performance and is compared with four cases of optimal control, one without battery, and three cases with battery of different sizes, $500kWh$, $1000kWh$ and $1500kWh$, respectively. Results from the different cases in terms of running hours, T_i, and fuel consumption, Q_{fuel} can be seen in table IV and table V. A total cost comparison for all cases can be seen in table VI.

Results showed that optimal control without battery successfully reduce the fuel consumption with 3.2%. The maintenance cost is also slightly reduced, and the different cost reductions combines to a total cost reduction of 2.8%. All cases with battery showed a reduction in fuel consumption ranging from 2.2% to 3.7% compared to the vessel operation, with better performance for smaller battery. Hence, the worst case with the largest battery has higher fuel consumption than optimal control without battery. The maintenance cost does also see large reductions compared to the vessel operation, ranging from 16.4% to 27.9%. The larger batteries showed less reduction in maintenance cost. The battery degrading costs are however quite large and the reductions in the other expenses are cancelled out, resulting in an increase of total costs compared to the vessel operation. The increase in total cost for the battery cases range from 0.5% to 2.2%, with the case with the smallest battery showing the best results. However, the total degradation of the smallest battery was 0.0875%, which would result in a battery lifetime of just below six years, assuming EOL at 40% degradation and that similar operation was conducted throughout its lifetime. In comparison the $1000kWh$ battery would have a lifetime of 11 years and the $1500kWh$ would have a lifetime of right above 18 years.

TABLE IV: Results from vessel operation compared with optimal control without battery for PSV.

	Vessel operation		Optimal control, no battery	
	T_i [h]	Q_{fuel} [kg]	T_i [h]	Q_{fuel} [kg]
G1	33.10	5444.16	12.14	3410.02
G2	45.90	9027.30	48.63	6355.11
G3	49.59	3017.30	95.39	7722.34
G4	22.68	1514.46	18.50	903.16
$\sum$	151.27	19003.23	174.66	18390.64

B. Ferry

The cases investigated for the ferry are similar to the PSV, using the vessel operation as benchmark. However, the battery sizes used are slightly different with, $500kWh$, $750kWh$ and $1000kWh$. The running hours and fuel consumption for the different cases can be seen in table IX and table VII. A total cost comparison can be seen in table VIII.

Results from optimal control without battery shows almost identical fuel consumption to the vessel operation. The maintenance cost is however reduced significantly with 7.9%. This results in a slight reduction of the total cost with 0.8%. All the cases with battery shows reductions in fuel consumption, although, not very large as they range from 1.2% to 2.1%. The maintenance cost, however, sees large reductions with the $750kWh$ battery resulting in a 32.3% reduction in maintenance cost. The $500kWh$ and $1000kWh$ batteries gives a 26.8% and 16.7% reduction, respectively. Despite the reductions in fuel, emission and maintenance cost, the total cost sees large increases for all the ferry cases with battery, ranging from 23.3% to 27.2%. The best case is for a battery size of $750kWh$, with the 23.3% increase in total cost. This is due to the estimated battery degrading, and thereby degrading cost, becoming very high. The degrading percentage for the three cases are 0.0540%, 0.0324% and 0.0242%, which results in a expected lifetime for of only 1.3, 2.2 and 2.9 years, respectively.

VI. Discussion

For both the PSV and the ferry the lowest total cost is obtained by optimal control without battery. However, the improvements are smaller for the ferry compared to the PSV with cost savings around 0.8% compared to 2.8%. This could be because the load profile for the ferry is more predictable than the load profile for the PSV, and thus the ferry was operated more efficiently to begin with.

The addition of batteries for the PSV load profile improves the fuel consumption slightly and the maintenance cost significantly. However, the estimated battery cost is too large compared to the savings, resulting in higher total cost. The best case with battery use is the $500kWh$ case, which is just slightly more expensive than the results from vessel operation. Also, for the battery degrading cost, the second hand price of batteries is not considered. And the difference in total price for the optimal control case without battery and the $500kWh$ case is about half the battery degrading cost. Hence, if the battery

TABLE V: Results from vessel operation compared with optimal control with battery for PSV.

	Vessel operation		Optimal control, $Q_{bat} = 500kWh$		Optimal control, $Q_{bat} = 1000kWh$		Optimal control, $Q_{bat} = 1500kWh$	
	T_i [h]	Q_{fuel} [kg]	T_i [h]	Q_{fuel} [kg]	T_i [h]	Q_{fuel} [kg]	T_i [h]	Q_{fuel} [kg]
G1	33.10	5444.16	0.26	40.67	2.74	558.26	23.39	5754.52
G2	45.90	9027.30	24.75	5822.94	30.59	5315.23	11.63	1354.93
G3	49.59	3017.30	96.58	8562.44	106.59	9757.68	109.90	8839.09
G4	22.68	1514.46	31.95	3855.49	23.34	2764.42	24.67	2596.1
$\sum$	151.27	19003.23	153.54	18281.54	163.26	18395.60	169.60	18544.55
$\sum_{SOC}$	-	-	-	18307.29	-	18339.35	-	18436.56
$\%_{degrade}$	-		0.0875%		0.0467%		0.0281%	
$\%_{yearly}$	-		6.81%		3.64%		2.19%	

TABLE VI: Total cost comparison for PSV. OC = optimal control.

	Vessel operation	OC, no battery	OC, $Q_{bat} = 500kWh$	OC, $Q_{bat} = 1000kWh$	OC, $Q_{bat} = 1500kWh$
Fuel cost	4370.74	4229.85	4210.68	4218.05	4240.41
Battery degrading cost	-	-	546.87	584.07	526.40
Maintenance cost	786.17	780.13	566.71	630.81	656.98
CO_2 tax cost	3297.55	3191.24	3172.32	3192.11	3217.96
Total operational cost	8454.46	8201.22	8496.57	8625.03	8641.75

TABLE VII: Results from vessel operation compared with optimal control with battery for ferry.

	Vessel operation		Optimal control, $Q_{bat} = 500kWh$		Optimal control, $Q_{bat} = 750kWh$		Optimal control, $Q_{bat} = 1000kWh$	
	T_i [h]	Q_{fuel} [kg]	T_i [h]	Q_{fuel} [kg]	T_i [h]	Q_{fuel} [kg]	T_i [h]	Q_{fuel} [kg]
G1	14.26	1379.76	2.17	278.65	0.36	27.94	7.59	851.31
G2	2.33	237.31	2.23	165.59	6.73	880.11	3.61	424.78
G3	1.03	59.38	14.19	1176.23	9.81	835.21	11.80	761.29
G4	12.27	740.17	10.79	738.44	9.81	595.79	5.03	356.21
$\sum$	30.88	2416.62	29.38	2358.92	24.54	2239.05	28.03	2393.60
$\sum_{SOC}$	-	-	-	2366.55	-	2365.83	-	2388.80
$\%_{degrade}$	-		0.0540%		0.0324%		0.0242%	
$\%_{yearly}$	-		30.92%		18.55%		13.85%	

TABLE VIII: Total cost comparison for ferry. OC = optimal control.

	Vessel operation	OC, no battery	OC, $Q_{bat} = 500kWh$	OC, $Q_{bat} = 750kWh$	OC, $Q_{bat} = 1000kWh$
Fuel cost	555.82	555.22	542.55	544.14	549.42
Battery degrading cost	-	-	337.32	304.07	302.12
Maintenance cost	92.97	85.62	68.07	62.94	77.48
CO_2 tax cost	419.35	418.89	409.33	405.89	415.35
Total operational cost	1068.14	1059.73	1359.03	1317.03	1344.37

TABLE IX: Results from vessel operation compared with optimal control without battery for ferry.

	Vessel operation		Optimal control, no battery	
	T_i [h]	Q_{fuel} [kg]	T_i [h]	Q_{fuel} [kg]
G1	14.26	1379.76	1.98	333.00
G2	2.33	237.31	7.64	369.13
G3	1.03	59.38	11.92	861.67
G4	13.27	740.17	11.85	850.21
$\sum$	30.88	2416.62	33.39	2414.01

can be resold at half the price when it has reached EOL for this purpose, i.e. at 60% capacity, the total price would become equal. And with less fuel consumption and emissions, the use of battery would be favourable. As the battery price is not exact, and a large decrease has been seen for battery prices in recent years, and even further drops is expected, the calculation will favour batteries more and more.

The performance with battery use for the ferry case is quite poor compared to the PSV. Less reduction in fuel consumption is seen in addition to larger degradation on the batteries. Resulting in large total cost increases. Further, the expected lifetime of less than 3 years is not very sustainable from an environmental point of view. However, some infeasibility issues were seen for the ferry load profile. They occur at times where the battery is delivering high power and eventually reaches the lower SOC limit. Then, high power must be produced instantly by the gensets, and due to the ramp limitations, the problem becomes infeasible. At these points the ramp limitation was relaxed in order to produce a solution, which can give suboptimal results.

The results indicate that battery/genset hybrid solutions is not ideal for ferries. This can make sense as the load profile is such that the load demand is quite stable, with few peak loads where the battery can be used to avoid starting gensets. When active gensets often is required in transit anyway and the battery use must be charged by the gensets, the potential savings may be limited. Since ferries are so often at quay, shore-charging solutions may be more beneficial.

The different battery sizes gives slightly different results, e.g. for the PSV case the smallest battery gave slightly lower costs than the two larger batteries. The cost differences are noticable, however, the largest difference is in the yearly degradation percent and thereby expected lifetime for operation of this type. If for instance you are expecting to operate the PSV for 15 years, then the largest battery would be beneficial as it would not need a replacement during this time. This would remove the battery degrading cost, giving it the lowest total cost. Thus, the operational lifetime must be considered when selecting the battery size.

VII. Conclusion

In this work an energy management algorithm for a battery/genset hybrid ship has been proposed in order to reduce the cost of operation. The algorithm is based on Mixed-Integer Quadratic Programming (MIQP). It considers a piecewise linear specific fuel oil consumption curve to minimize the fuel consumption, the cyclic battery degrading is minimized based on cyclic degradation for different C-rates and the maintenance cost is minimized by minimizing the active gensets with weighting relative to their rated power. The algorithm was tested on two different load profiles extracted from vessels in operation, a PSV and a ferry. Four different cases was tested for both vessels, one case with optimal control without battery and three cases with batteries of different size. The performance was compared to the performance extracted from vessel operation.

Results showed that the lowest costs was obtained with optimal control without battery for both the PSV and the ferry. However, the best PSV case with battery showed similar costs to the vessel operation with lower fuel consumption and thereby emissions. Considering selling the battery second hand combined with reducing battery prices, it can be argued that the battery use will be favourable. The cases with battery for the ferry showed large battery degrading costs, and battery hybrid solutions with this algorithm does not seem viable for such load profiles.

The algorithm is based on certain simplifications, and needs further work. In order to more accurately assess the fuel consumption, the exact SFOC curves for the gensets in consideration should be used. The starting and stopping of gensets affects wear and tear, which need further attention. The battery degrading estimations does not include calendar effects, and the cyclic degradation is assumed to be the same throughout the battery lifetime, which is inaccurate. Thus, further development of the battery degrading model should be considered. The algorithm should also be improved to better handle various load profiles, like the one extracted from ferry operation. In addition to that the investment costs of the power system is not considered, the battery installation cost and the potential reductions in installed genset power would need further investigation to truly evaluate the different options.

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Norwegian University of
Science and Technology