Optimization study of a hybrid powertrain

Optimization of the system components and energy management of a zero-emission hydrogen powered boat

Bouke Teertstra

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Thesis report

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Preface

In front of you lies a thesis about the optimization of a hybrid powertrain. The subject of this thesis is a real case study about the H2C boat of the company H2 Marine Solutions. This is one of the first zero-emission hydrogen powered boats in the Netherlands.
This thesis is part of my graduation for the Master of Sustainable Energy Technology at Delft University of Technology. During this Master's, I learned a lot about the challenges that exist in the energy transition. With this graduation project, I had the opportunity to work with real sustainable technology. I had the opportunity to research some challenges that we face in this transition to zero-emission. Because of my background in the Royal Netherlands Navy, I especially had an interest in sustainable developments in the maritime sector. With this project, I had the opportunity to broaden my knowledge in this discipline.

I hope this thesis is a contribution to the developments in the design of hybrid powertrains. I also hope that this thesis is a contribution to the sustainable energy technology development. I experienced how challenging it is to develop an optimal hybrid powertrain and I respect everybody who works in this field.

Above all, I want to thank the people from the company H2 Marine Solutions. Without them, this project would not have been possible. Especially Cees van Bladel, Pieter Lantermans and Niek van Prooien I would like to thank. I wish them all the best with the challenges they face when designing zero-emission boats. Furthermore, I would like to thank my supervisors Henk Polinder, Rinze Geertsma, and Foivos Mylonopoulos. They guided me through the project and gave me valuable feedback. I was always welcome to discuss my problems with them and therefore I am very grateful. Finally, I would like to thank Andrea Coraddu for participating in the thesis committee.

I hope you enjoy reading my thesis,

Bouke Teertstra

Den Helder, September 2023

Summary

The company H2 Marine Solutions has designed a zero-emission hydrogen powered boat. This boat is compared to its fossil fuel counterpart more than twice as heavy. The reason for this is that the system components that are used in the hybrid powertrain of the hydrogen powered boat are heavier. The main question of this research is: How can we establish the optimal energy and power of the system components of a hybrid power system with optimal energy management for a zero-emission hydrogen powered boat for different operational profiles? This results in a sizing and control optimization problem. Because these two problems are coupled this is a multi-objective double-layer optimization problem. The most popular strategy to solve this problem is with the control problem nested in the sizing problem [1]. The most popular algorithms to solve these problems are evolutionary algorithms.

Unfortunately due to the complexity of these algorithms and due to lack of time the sizing and control problems are solved separately in this research. First, the system components of the plant are described and modeled. The components that are modeled are the battery, the fuel cells, and the DC/DC converter. To find the optimal energy management strategy an online optimization strategy is used. This is done because the problem is solved in real-time than and could be used in a real application. The strategy that is chosen to solve the control problem is the Equivalent Consumption Minimization Strategy (ECMS). This strategy translates the electrical energy from the battery into equivalent hydrogen consumption. For every timestep, the equivalent consumption is minimized by the ECMS. Because there are different variants of ECMS three of these variants are discussed and compared in the research. Also, two rule-based energy management strategies are compared. The sizing problem is described by linear equality and inequality constraints. The problem is solved by the Linprog function in Matlab. The objective of the sizing problem is to minimize the weight of the system components. The input in the sizing problem is the energy and power demand of the most energy intensive operational profile. After solving the sizing and control problem the results are combined and the different operational profiles are used as input to show the robustness of the optimization.

The three different energy management strategies all minimize the instantaneous equivalent consumption but show different behaviors when controlling the system components. The optimal energy management strategy is the Smooth Adaptive Penalty (SAP)-ECMS. With this controller, the fuel cells work on a steady operating point and ramp up and down the output power smoothly when necessary. Due to this behavior, the average efficiency of the fuel cell is the highest, and the hydrogen consumption is the lowest compared to the other controllers. The results of the sizing problem show that the weight will decrease when a bigger fuel cell is used in combination with a smaller battery. The consideration between a bigger fuel cell and a smaller battery is a consideration between lower weight and more hydrogen consumption. When a bigger fuel cell is used it is recommended to implement an optimal energy management strategy such as the SAP-ECMS to control the output power of the system components. This is preferable above a rule-based controller which can not find the optimal operating point at all timesteps. Even better energy management strategies may exist or could be made by combining different ECMS's. When the sizing and control problem are solved in a nested strategy more accurate results could be achieved.

Contents

List of Symbols

β Chosen factor in LAP-ECMS

δSOC Penalty factor

η_{bat} Efficiency of the battery

η_{con} Efficiency of the DC/DC converter

σ Constant in LAP/SAP-ECMS

$\triangle t$ Timestep

a Chosen factor in SAP-ECMS

C Usable battery capacity

C_{bat} Equivalent battery consumption

C_{rate} C-rate of the battery

E_{bat} Rated energy capacity of the battery

E_{demand} Total demanded energy

EF Equivalent Factor

H_2 Hydrogen consumption

I_{bat} Current of the battery

k Chosen factor in SAP-ECMS

M Chosen factor in AP-ECMS

m kWh to kg conversion coefficient of hydrogen

N Chosen factor in AP-ECMS

P_{bat} Output power of the battery

P_{dem} Demanded power

P_{fceff} Most efficient operating point of the fuel cell

P_{fcr} Rated power of the fuel cell

P_{fc} Output power of the fuel cell

P_{in} Input power of the fuel cell

P_{loss} Power loss of the battery

P_{max} Maximum demanded power

Q_{lhv} Lower heating value of hydrogen

R_{int} Internal resistance of the battery

SOC The State Of Charge of the battery

SOC_a Lower SOC limit in SAP-ECMS

SOC_b Upper SOC limit in SAP-ECMS

SOC_{max} Upper SOC constraint

SOC_{min} Lower SOC constraint

SOC_{ref} Reference SOC in AP-ECMS

T Operating time

u_c Control variables of the control optimization problem

V_{nom} Nominal voltage of the battery

W_b Weight factor of the battery

w_e Exogenous inputs of the control optimization problem

W_{fc} Weight factor of the fuel cell

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1 Introduction

In times when sustainability is very important sailing is praised to be a clean sport. Unfortunately, this image is not completely true, because at official competitions a lot of coach boats are used to coach the competitors. These coach boats are almost all powered by fossil fuels. To change this polluting part of the sport the company H2 Marine Solutions has built a zero-emission hydrogen powered coach boat. The goal is that with this system the sailing sport could live up to its clean image. This H2C boat is not only suitable to coach professional sailors but could also be used by other users of RIBs (Rigid Inflatable Boat), like the police, the navy, or the coast guard [2]. By making use of this zero-emission boat the users could reduce their carbon emissions. By doing this the users would contribute to a sustainable maritime sector and to the goals of for example the GD230 Green Deal in the Netherlands [3].

The powertrain in the boat consists of different components which are the hydrogen storage, the fuel cell, the battery, and the electric propulsion motor. The fuel cells convert the hydrogen into electricity. This electricity could be used to charge the batteries or to power the motor. The hydrogen in this system is used as a range extender. The boat is designed to sail at a speed of 25 knots for approximately one hour. In total the boat is able to sail for five and a half hours at 6.5 knots [4]. At this moment the components that are used in the powertrain of the H2C boat are very heavy in comparison with a fossil fuel-powered coach boat. The difference can be seen in Table 1.1. To make the system as light as possible it is essential to find their optimal size. Another very important aspect is that during the operation, the demanded power is split between the systems in an optimal way. In other words, systems need to have optimal energy management to reduce fuel consumption and component size. The objectives of this research are therefore to minimize the weight of the system components and to find the optimal energy management strategy.

Table 1.1: Comparison between a fossil fuel powered coach boat and the H2C boat.

Fossil:	Weight:	Zero-emission:	Weight:
Motor(60pk)	110 kg	Motor(80pk)	80 kg
Petrol	66.5 kg	Battery	284 kg
		Fuel cells	40 kg
		Hydrogen tank	59 kg
Total:	176.5 kg	Total:	463 kg
Max speed	30 knots	Max speed	25 knots

This sizing of components and optimizing energy management control are coupled with each other [1]. The control layer is dependent on the physical system, but it can not change the physical

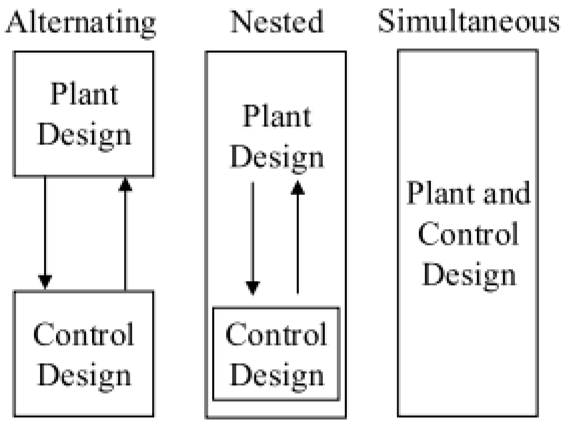

Figure 1.1: Optimization strategies for system level design [5].

parameters because they act as bounds [5]. The physical system is also dependent on the energy management system for the control of the components. This creates a multi-objective optimization problem that spreads over two levels namely sizing and control. If the optimization problems are solved sequentially then the solutions are by definition sub-optimal [5]. There are three ways to solve the coupled optimization problem and they are shown in Figure 1.1. They are widely used in the automotive industry and the most popular is the nested architecture with the control design in the plant design [1].

An optimization problem consists of objective(s), constraints, and variables. To solve the optimization problem different algorithms could be used, like Sequential Quadratic Programming (SQP), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), DIviding RECTangles (DIRECT), or others. Once the sizes of the components are selected it is essential that they are properly controlled. This is done by splitting the power between the components in an optimal way. For the control problem, two different methods are used in the literature: rule-based and optimization-based. The rule-based strategies are based on expert knowledge and are easy to implement. However, they are sub-optimal and require a lot of tuning effort [5]. For optimization-based control, two categories could be distinguished: real-time and offline optimization. Dynamic programming is widely used for offline optimization. For online optimization equivalent consumption minimization strategy (ECMS), stochastic DP (SDP) strategies, or model predictive control (MPC) strategies are used [5].

Various research has been done on the coupled optimization problem of sizing and control for hybrid power systems. In [5] an overview is given of the methodologies used to optimally design a Hybrid Electric Vehicle (HEV). This research states that Dynamic Programming is the most popular algorithm to solve the control problem. For the sizing problem, it is the trend to use an evolutionary algorithm. In [6] the powertrain of a hybrid mining truck is optimized. The hybrid system consists of fuel cells, batteries, a brake resistor, and a motor. To solve the problem an advanced global optimization search algorithm, Hybrid and Adaptive Metamodel (HAM) search is used. For the control problem, an Equivalent Consumption Minimization Strategy (ECMS) is used in combination with the shooting method to find the equivalent factors. The problem is solved in a nested way. The objective of this study is to minimize the lifecycle cost considering both system energy efficiency and performance degradation costs. Also, the size of the fuel cells is already fixed and the focus is on finding the optimal size of the batteries. In [7] a Plug-in Fuel Cell Urban Logistic Vehicle (PFCULV) is optimized. The difference between this system with the system in [6] is that the batteries could be charged by a separate power source because of the plug-in option. The objective of this research is to minimize the costs. All the constraints and the objective are convex and therefore the problem is solved by convex optimization in a simultaneous way.

There is also research on the optimization of hybrid power systems for maritime applications. Research on the optimization of a hybrid ship propulsion system is done in [1]. In this research, the powertrain of an offshore support vessel is optimized. The hybrid system in this research consists of diesel generators, fuel cells, and batteries. For the sizing problem, the Non-dominant Sorting Genetic Algorithm 2 (NSGA-2) is used, and for the control problem Mixed Integer Linear Programming (MILP). The problem is solved in a nested way. In [8] a completely zero-emission hybrid system is optimized for a ferry. The system consists of fuel cells, batteries, and an electric propulsion motor. In the problem the ship makes use of cold ironing to charge the batteries during the stops. The optimization problem is solved simultaneously by an Improved Sine-Cosine Algorithm (ISCA). There is also research on the optimal sizing and energy management of hybrid electric propulsion systems which is not specific to an application. In [9] a system that consists of diesel generators, an Energy Storage System (ESS), and shore power is optimized simultaneously. For the sizing problem, the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm is used. For the control part, a Modified Adaptive Equivalent Consumption Minimization Strategy (MA-ECMS) is used.

Out of all the mentioned researches the system of [8] is most similar to the system optimized in this research. The algorithm that is used to solve the optimization problem, namely ISCA is only able to work with one objective and therefore not suitable to use in this research [10]. In [5] and [1] the algorithm used to optimize the control part is Dynamic Programming. This is an offline optimization algorithm and therefore less suitable to use in this optimization study, because it is not able to execute a real-time optimization. Another conclusion from [5] is to use an evolutionary algorithm to solve the sizing problem. The studies [6] and [9] use evolutionary algorithms to solve the sizing problem and an Equivalent Consumption Minimization Strategy for the control problem. The hybrid system in [9] is different from the H2C boat because it includes diesel generators and no fuel cells. The system in [6] is similar, but the size of the fuel cells is fixed before the optimization. The optimization strategy of [7] is interesting if the optimization problem of this study could be solved in a convex way. In all of the mentioned references the objective was to minimize the costs. None of the studies optimizes the weight of the system components in combination with optimal energy management.

The aim of this research is to establish the optimal energy and power of the system components of a hybrid power system with optimal energy management for a zero-emission hydrogen powered boat for different operational profiles. The objective is to minimize the system components' weight with optimal energy management. This is a novelty in the optimization studies that combine sizing and control. The first goal of this research is to find an optimization strategy to establish the optimal energy and power of the system components of a hybrid power system with optimal energy management for a zero-emission hydrogen powered boat. This will be done through a literature study. Next to this, a model of the powertrain of a hydrogen powered boat will be used to validate the optimization results. The last goal of this research is to make the optimization robust. This means that for different operational profiles, the results of the optimization are still suitable.

The main question of this research is: How can we establish the optimal energy and power of the system components of a hybrid power system with optimal energy management for a zero-emission hydrogen powered boat for different operational profiles? Out of this question, the next questions follow:

- What are the system components of a hydrogen powered boat?

- What model to use to model the system components to validate the optimization results?
- What is the best strategy to solve the optimization problem?
- Which algorithm to use to solve the optimization problems?
- What are the different operational profiles?
- What is the optimal energy management of the systems of a hydrogen powered boat for different operational profiles?
- What is the optimal energy and power of the system components of a hybrid power system of a hydrogen powered boat for different operational profiles?

These questions will be answered in this research.

To answer the questions first a literature study on combined sizing and control optimization is executed. From this literature study, we learned that the combined optimization problem has to be solved by an evolutionary algorithm. Furthermore, the best way to achieve real-time optimal energy management is by using an online optimization algorithm for example ECMS. It was found that there are different variants of ECMS and therefore they are compared with each other. To solve the optimization problem, first, the case study is described and a model of the system components is made. Also, different operational profiles are made and with data measured from the H2C boat, a powerprofile is made to convert the speed data into demanded power. With these different operational profiles and the model, the optimal energy management is investigated. Unfortunately, due to the complex nature of evolutionary algorithms and lack of time, the sizing and control problems are solved separately. The sizing problem is solved by a linear solver in Matlab, namely Linprog. With the optimal size of the system components, the optimal energy management strategy, and the different operational profiles the final result is obtained.

The research is structured in the following way. First, an analysis of research on combined optimization of sizing and control is given in Chapter 2. Out of this analysis, a strategy follows on how to solve the combined optimization problem. This is explained in Chapter 3. After this part, the case study and the model of the system components are described in Chapters 4 and 5. The energy management optimization problem is described in Chapter 6 and the sizing optimization problem is described in Chapter 7. After this, the results of the optimization are presented and discussed in Chapter 8. The last part of the research consists of a conclusion and reflection in Chapters 9 and 10.

2
Analysis of optimization strategies

The goal of this research is to establish the optimal energy and power of the system components of a hybrid power system with optimal energy management for a zero-emission hydrogen powered boat for different operational profiles. The question to answer in this chapter is: What is the best strategy to find the optimal energy and power of the system components of a hybrid power system with optimal energy management for a zero-emission hydrogen powered boat? And what algorithms are suitable to solve the optimization problems? These questions will be answered by a literature study. In this study, different researches are analyzed in which the optimal sizing and control of hybrid power systems are investigated. By analyzing these studies the best strategy and algorithm to optimize the zero-emission hydrogen powered boat will be chosen.

2.1. Combined sizing and control optimization

The optimization problem in this research is a combined sizing and control optimization problem. This is the case because the sizing of components and optimizing energy management control are coupled with each other [1]. The control layer is dependent on the physical system, but it can not change the physical parameters because they act as bounds [5]. The physical components are also dependent on the energy management system. This creates a multi-objective optimization problem that spreads over two levels namely sizing and control. If the optimization problems are solved sequentially then the solutions are by definition sub-optimal [5]. There are three ways to solve the coupled optimization problem and they are shown in Figure 1.1. They are widely used in the automotive industry and the most popular is the nested architecture with the control design in the plant design [1]. The researches which are investigated in this study use different strategies. Some make use of the simultaneous strategy and others use the nested strategy.

2.2. Size optimization algorithms

For the sizing problem algorithms like Sequential Quadratic Programming (SQP), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), DIviding RECTangles (DIRECT), or others could be used. One can distinguish between derivative-free algorithms and gradient-based algorithms. Examples of derivative-free algorithms are Dividing Rectangles (DIRECT), Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Simulated Annealing (SA). Gradient-based algorithms include Sequential Quadratic Programming (SQP) or Convex Optimization (CO) [5]. The advantage of derivative-free algorithms is that they can handle non-linear cost functions and constraints. When the cost function behaves smoothly a gradient-based algorithm will offer a faster solution.

2.3. Control optimization algorithms

For the control problem, two different methods are used in the literature: rule-based and optimization-based. The rule-based strategies are based on expert knowledge and are easy to implement. However, they are sub-optimal and require a lot of tuning effort [5]. For optimization-based algorithms, two categories could be distinguished: real-time and offline algorithms. Dynamic programming is widely used for offline optimization. For online optimization the equivalent consumption minimization strategy (ECMS), stochastic DP (SDP) strategies, or model predictive control (MPC) strategies are used [5]. The downside of offline optimization algorithms is that the optimization can not be done in real-time. When this is the case the strategy can not be used in a real application. Therefore offline algorithms are mostly used as a benchmark to evaluate other real-time algorithms.

2.4. Analysis of optimization strategies

Several research studies have been done on the combined problem of optimal sizing and optimal energy management of hybrid power systems. In Table 2.1 an overview is given of the studies which are analyzed in this research. This is not a complete list of studies on combined optimization problems. In the table, the strategies and algorithms that these studies use to solve the optimization problem are shown.

Table 2.1: Comparison of combined optimization studies.

Studies:	Algorithm sizing:	Algorithm control:	Strategie:
Hybrid offshore support vessel [1]	NSGA-2	MILP (DP)	nested
Zero-emission ferry [8]	ISCA	ISCA	simultaneous
Hybrid cars [5]	GA/PSO	DP	nested
Hybrid electric propulsion system [9]	MO-PSO	MA-ECMS	simultaneous
Hybrid mining truck [6]	HAM Search	ECMS/shooting	nested
Plug-in fuel cell vehicle [7]	Convex (CVX)	Convex (CVX)	simultaneous

The table shows that the algorithms used to optimize the size of the components and the energy management can be different. Two different strategies are used to solve the problem namely simultaneous and nested. In the next part, the methods used in the different research are analyzed.

In [1] the powertrain of a hybrid offshore support vessel is optimized. The proposed hybrid system consists of diesel generators (DG's), batteries, and fuel cells. Because of the Diesel Generators, the system is more complex than the system which is optimized in this research. The problem is a multi-objective double-layer optimization problem (sizing and control). The objectives to be minimized are the CAPEX, OPEX, and fuel consumption. These objectives are different from the objectives in this research, but the amount is the same. The problem is solved in a nested way. This means that for every evaluation of the plant, a full optimization of the control design is researched. The algorithms used to solve the problem are: Non-dominant Sorting Genetic Algorithm 2 (NSGA-2) for the sizing and Mixed Integer Linear Programming (MILP) for the control problem. MILP is a dynamic programming algorithm and this means that it is an offline algorithm and not suitable to use in this study.

In [8] the hybrid power system of a completely zero-emission ferry is optimized. The powertrain consists of fuel cells and batteries and is very similar to the power system in this research. The ship travels a specific route and during the stops, it can charge the batteries by cold ironing. This is different from the situation in this optimization study because the boat does not stop and cannot be charged during the operation. The optimization problem is solved simultaneously. The objective is to minimize the costs divided into operation and investment costs. An Improved Sine-Cosine Algorithm is used to solve the problem. A novel enhancement that uses Harmony Search is considered in this work to increase the seeking capability of the SCA, which prevents it from trapping in local optima. So, each solution is improved based on memory consideration, pitch adjustment, and random selection. Studies show that the SCA algorithm is substantially faster than most of the meta-heuristic methods like Genetic Algorithms, Particle Swarm Optimization, Gravitational Search Algorithms, and so on. Unfortunately, this algorithm is only able to solve optimization problems with one objective and therefore it is not suitable to use in this research [10].

In [5] an overview is given of the methodologies used to optimally design a HEV (Hybrid Electric Vehicle). According to this research, the most popular strategy to solve the combined optimization problem is the nested variant. Furthermore, Dynamic Program (DP) is the most popular way to solve the control problem. The limitation of DP is that it is offline and therefore not able to solve a real-time optimization problem. For the sizing problem, there is no widely used algorithm. However, the trend is to use evolutionary optimization algorithms. The most commonly used algorithms are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Furthermore, multiple researches report the computational inefficiency of the exhaustive search. Depending on the shape of the optimization function, as well as the types of constraints, an optimization algorithm may prove to be better than others. Some general rules are given:

- When a problem is solved with Convex optimization it is required that the problem is convexicated to guarantee finding the global optimum.
- When SQP is used, for the original problem (nonconvex), the initial point can be varied to test the reach of local or global minimum.
- When evolutionary algorithms are used, various parameters have to be tuned (population size).

In [9] a way to solve sizing and control of hybrid systems simultaneously is proposed. For the sizing problem, the Multi-Objective Particle Swarm Optimization algorithm is used, because of its merits in computational time and generational distance. An Adaptive Equivalent Consumption Minimization strategy (A-ECMS), which has a light computational load, has been modified for the control problem by updating the equivalence factor based on the battery stage of charge and engine efficiency. The MA-ECMS can improve the traditional A-ECMS by adaptively adjusting the equivalence factor according to the instantaneous operation of the battery and diesel engines. This strategy could be used in this optimization study. Real-time Hardware In the Loop (HIL) experiments are used to validate the results. The results are compared with two independent single-level optimizations. The objectives of this study are to minimize: fuel consumption, greenhouse gasses, and net present costs. The system consists of diesel engines, energy storage systems, and shore power. This makes the system more complex than the system in this research. The bi-level optimization proposed in this paper integrates component sizing and energy management into a single algorithm. The equivalence factors are minimized by the upper-level optimization, which calls for the results of the lower-level optimization in each iteration. The lower level is required only to minimize the fuel consumption because the amount of fuel consumption on a voyage determines the greenhouse gas emission and the operation cost away from the shore power station.

In [6] the aim of the study is to optimize the powertrain of a hybrid mining truck. The objective of the optimization is to minimize the mining costs. The method considers the system energy efficiency and the performance degradation of the systems while minimizing the life cycle costs. This is a different objective than the ones in this research. The powertrain of the truck consists of the following components: fuel cells, batteries, brake resistor, and electric motors. The system looks similar to the system optimized in this research apart from the brake resistor. The braking resistors are used to supplement the electric energy absorbing capability of the regenerative braking. The fuel cells generate the primary propulsion power. The power of the fuel cell is already chosen before the optimization at 150kW. This is different from the method in this optimization study. The optimization is done by minimizing the amount of hydrogen fuel consumption. The integrated and nested design optimization problem is a typical computation-intensive, black-box global optimization problem. To solve this complex problem, an advanced, surrogate model (SM) based global optimization search algorithm, Hybrid and Adaptive Metamodel (HAM) search, is applied to find the solution. The optimal power control and energy management at the lower level further require two levels of optimization. The very bottom level optimization uses the ECMS method to realize optimal powertrain system control, while the higher-level optimization applies the shooting method to search for the equivalent factor needed by ECMS.

In [7] a hybrid plug-in fuel cell urban logistic vehicle (PFCULV) is optimized. The optimization is done by convex optimization. This is possible because all the formulas and constraints are convex. If this is the case in this research this strategy could be used. The objectives are to minimize the operational and initial costs while satisfying vehicle power demand and battery health requirements. The powertrain consists of an H2 tank, fuel cells, batteries an inverter, and an electric motor. A fuel cell system model and a convex battery health model are used. The problem is solved in a simultaneous way in the Matlab environment. By varying the driving cycles only the size of the fuel cell system is affected.

2.5. Outcomes

The questions to answer in this chapter were: What is the best strategy to find the optimal energy and power of the system components of a hybrid power system with optimal energy management for a zero-emission hydrogen powered boat? And what algorithms are suitable to solve the optimization problems? The above mentioned researches use different strategies and algorithms to solve the optimization problems of different hybrid systems. Some of the strategies could be suitable for this optimization, but others are not. According to [5] the most popular strategy to solve a combined optimization problem is in a nested way. Furthermore, Dynamic Programming is most popular for solving the control problem and an evolutionary algorithm to solve the sizing problem. Because Dynamic Programming is an offline algorithm and is not able to solve a real-time optimization problem, it is not suitable to use in this research. Therefore an Equivalent Consumption Minimization Strategy is a better option to solve the control problem. For the sizing problem, different algorithms could be used like, the NSGA-2 algorithm or the MO-PSO algorithm. Both algorithms are able to solve a multi-objective double-layer optimization problem.

2.6. Gaps in the analyzed literature

The analyzed studies of combined optimal sizing and control of hybrid power systems cover a lot of subjects. However, some gaps remain unfilled in the analyzed literature. None of the studies has the minimization of the system components' weight as an objective. Furthermore, none of the studies compare different ECMS strategies with each other. This research tries to fill these gaps and in the next chapter, the novelty of this research will be explained.

3
Methodology

In this chapter, the method used in this research to solve the sizing and control optimization problem is described. First, the structure of the methodology is explained. After this, the chosen method is explained. The last section elaborates on the novelty of the research.

3.1. Structure

The first step in solving the optimization problem is to define the case study, this is done in Chapter 4. After this the system components of the case study have to be modeled, this is done in Chapter 5. To find the optimal energy management an ECMS will be used. Because there are different variants of ECMS these strategies are compared in Chapter 6. In this chapter also the problem definition and the constraints of the control problem are described. After this, the objectives, variables, and constraints of the sizing optimization problem are defined in Chapter 7. Chapter 8 shows the results of the solved optimization problems with different operational profiles. The structure of the methodology is also shown in Figure 3.1.

Figure 3.1: Structure of methodology used in this research.

3.2. Method used to solve the optimization problem

As explained in Chapter 2 the multi-objective double-layer optimization problem can be solved by an evolutionary algorithm. This algorithm could be a Genetic Algorithm (GA) or a Particle Swarm Optimization (PSO). Unfortunately due to the complex nature of evolutionary algorithms and lack of time, it was not feasible to use one of these algorithms. Therefore a different method was chosen. First, the control problem is described and the different variants of ECMS are compared with each other in Chapter 6. Then the sizing optimization problem with objectives, variables, and constraints is described in Chapter 7. The sizing and control problem are separated and the sizing problem has one objective and only linear equality and inequality constraints. Therefore the problem can be solved by the Linprog function of Matlab. In Chapter 8 the results of the different ECMS's are shown and the optimal strategy is chosen. Separate from this, the sizing problem is solved and optimal sizes for the system components are obtained. The last step is to combine the solutions of the sizing and control problem into a final solution. This solution is tested for different operational profiles and the results are shown in Chapter 8.

3.3. Novelty

One of the novelties of this research is the comparison of the different ECMS's. All the other studies that are analyzed and that use ECMS to control the system components in a combined optimization study describe their ECMS but do not compare it with other variants. By comparing the different strategies and showing the different outcomes the optimal strategy can be chosen. This is a novel contribution of this research. The next novelty lies in the use of different operational profiles to validate the results. Most studies only use one profile to find the optimal size and control for the system components. By using multiple profiles the optimization is made robust. Furthermore, the objective of minimizing the weight of the system components is a novelty.

4
Plant description

The goal of this research is to find the optimal energy and power of the system components of a hybrid power system with optimal energy management. The system that is optimized is the powerplant of the H2C boat of the company H2 marine solutions. The system components of the powertrain in this boat are the hydrogen storage, the fuel cells, the battery, converters, and the electric propulsion motor. The weight of these components compared to the weight of the system components of a fossil fuel-powered RIB are shown in Table 1.1. Because the total weight of the system components of the hydrogen-powered boat that are used in this plant is more than twice the weight of system components of the fossil-powered boat it is necessary to find the optimal size for the system components and minimize the weight. To control these system components it is also necessary to find the optimal energy management. In Figure 4.1 a picture of the system is shown. In this chapter, the system components of the H2C boat are described and shown.

Figure 4.1: The H2C boat in Den Helder.

4.1. Hydrogen storage

Under normal temperature and pressure conditions, hydrogen is a colorless and flammable gas. Under these conditions hydrogen has the lowest volumetric energy density of any fuel [11]. To compensate for this negative characteristic the hydrogen that is used in the H2C boat is compressed. It can be stored under a pressure of 700 bar. This causes the volumetric energy density to increase almost 450 times compared to hydrogen at 1 bar [12]. The hydrogen is used as a range extender for the vessel. The tank has a volume of 76 liters which is approximately 3.1 kilograms of compressed hydrogen. In Figure 4.2 a picture of the hydrogen storage tank in the H2C boat is shown.

Figure 4.2: Hydrogen storage tank with fuel cap.

4.2. Fuel cell

The fuel cell that is used in the H2C boat is a Proton Exchange Membrane Fuel Cell (PEMFC). This system converts hydrogen and oxygen into water and electricity [13]. This electricity can be used directly by the propulsion motor or it can charge the battery. In Figure 4.3 a fuel cell system of the H2C boat is shown. There are two fuel cell systems on board the H2C boat which both have a rated power of 4 kW [14]. The mass of the fuel cell is 20 kilograms each. The fuel cells operate at 48V and this is converted by a DC/DC converter to the desired voltage.

Figure 4.3: Fuel cell system with air filter.

4.3. Battery

The battery system in the vessel provides the propulsion motor with electrical energy. The battery system used in this plant is a lithium battery system with an energy capacity of 38 kWh and a nominal voltage of 350V [15]. The maximum continuous power the battery can deliver is 55 kW. The C_{rate} the battery is the maximum power divided by the energy capacity. This gives a C_{rate} of 1.45. The weight of the battery system is 284 kilograms in total. In Figure 4.4 a picture of the battery system which is used in the vessel is shown.

Figure 4.4: Lithium battery system.

4.4. Propulsion motor

The propulsion motor converts the electrical energy into mechanical energy to propel the vessel. The motor used in the H2C boat is the Deep Blue 50 electric outboard motor of Torqeedo [15]. It is an AC motor and has a peak input power of 55 kW. Because the motor is AC-powered the voltage of the DC bus had to be converted by a DC/AC converter. In Figure 4.5 a picture of the propulsion motor is shown.

4.5. Schematic presentation

In Figure 4.6 a schematic presentation of the hybrid energy system of the H2C boat is shown. The black lines represent the minus connection and the red lines the plus connection. The blue lines represent the hydrogen connection. The DC-bus voltage is controlled by the battery. The voltage that comes out of the fuel cells is converted by a DC/DC converter. The voltage to the propulsion motor is controlled by a DC/AC converter.

Figure 4.5: Outboard electric propulsion motor Deep Blue 50 Torqeedo.

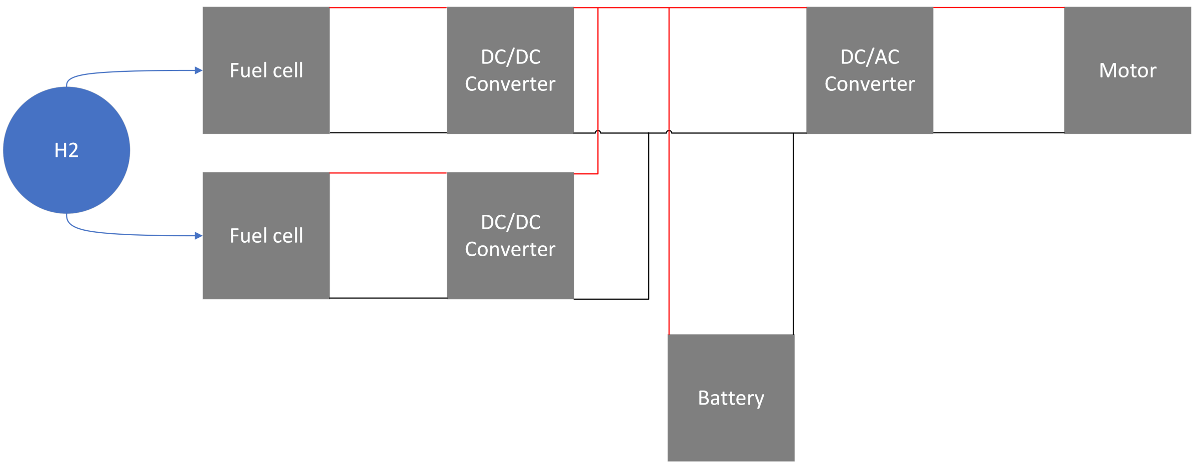

Figure 4.6: Line diagram of the system components of the H2C boat.

5 Modelling

To solve the optimization problem it is necessary to model the system components of the H2C boat. The components that are modeled in this research are the battery and the fuel cell. It is chosen to model the systems in an analytical way and not with Simulink for example.

5.1. Battery

The battery is the main power source of the H2C boat at this moment. The power of the battery depends on the demanded power and the power of the fuel cell. Also, the power losses have to be compensated. The relation is described with the following equation:

$$P_{bat}(t) = P_{dem}(t) - P_{fc}(t) + P_{loss}(t) \tag{5.1}$$

In this equation $P_{dem}(t)$ is the demanded power and $P_{fc}(t)$ is the output power of the fuel cell. $P_{loss}(t)$ is the power that is lost and that has to be compensated. $P_{bat}(t)$ is the power that has to be delivered by the battery. The amount of energy a battery has left can be described by a SOC. In the optimization study of [1] the following equation is used to describe the SOC of a battery.

$$SOC(t) = SOC(t-1) - \frac{P_{bat}(t) \cdot \triangle t}{E_{bat}} \tag{5.2}$$

In this formula $SOC(t)$ is the SOC at every time step and $SOC(t-1)$ is the SOC of the time step before. $P_{bat}(t)$ can have a positive or a negative value, this depends on the output power of the fuel cell and the demanded power. When $P_{bat}(t)$ is negative the battery is charging and the SOC will rise and when $P_{bat}(t)$ is positive the battery will discharge. E_{bat} is the rated energy of the battery. The optimal value of E_{bat} depends on the solution of the size optimization. To calculate the losses of the battery the efficiency is used. To find the efficiency of the battery the energy efficiencies map of [16] is used. The average efficiency for the different Lithium batteries with a C-rate and capacity of the battery described in Section 4.3 is 98.5 percent. The model that is used to calculate the losses is the battery Internal Resistance model (IR). In this model the internal resistance and the nominal voltage are constant. The losses are only resistance losses and these losses can be calculated by the following equation:

$$P_{loss} = I_{bat}^2 \cdot R_{int} \tag{5.3}$$

The current can be calculated by the following equation.

$$I_{bat} = \frac{P_{bat}}{V_{nom}} \tag{5.4}$$

V_{nom} in this equation is a constant and is 350 V. R_{int} can be calculated by Equation 5.5 from [17]. In this equation, the internal resistance can be calculated with the efficiency, the energy capacity, the C-rate, and the nominal voltage. Because these values are all known the R_{int} can be calculated and becomes 95.3 $m\Omega$. This value will be used in this research and the internal resistance will be constant. In a real battery, the resistance is highly dependent on SOC, SOH, and temperature and becomes higher when these values become lower [18].

$$R_{int} = V_{nom} \cdot \frac{1 - \eta_{bat}}{C_{rate} \cdot E_{bat}} \tag{5.5}$$

5.2. Fuel cell

A fuel cell converts hydrogen and oxygen into electricity and water [13]. Unfortunately, not all the power generated by the fuel cells is delivered to the load, but some of it disappears in the form of losses. The efficiency of a PEMFC is the highest when it operates between 10 and 90 percent of its output power [19]. This range is called the operation range and is shown in Figure 5.1. To model the fuel cell system, it is important to take the efficiency into account. The fuel cell's efficiency depends on the percentage of the rated power that is used [20]. A typical efficiency curve of a fuel cell system is shown in Figure 5.1. The input power can be calculated with the relation between the percentage of the used power and the efficiency. The input power is the output power divided by the efficiency. With this relation a power curve can be made and this curve can be described by a second-degree polynomial function [20],[1]. Because the efficiency of a fuel cell is the highest between 10 and 90 percent and because of degradation purposes only this part of the power curve is used. The second-degree polynomial function has the following form:

$$P_{in}(t) = P_{fc}(t)^2 \cdot a + P_{fc}(t) \cdot b + c \tag{5.6}$$

$P_{in}(t)$ is the input power of the fuel cell in this equation and $P_{fc}(t)$ is the output power. The coefficients a, b, c can be derived from the fitted curve which is derived from the efficiency related to the output power. Because the rated power of the fuel cell changes during the sizing optimization it is necessary to normalize the function. This can be done by dividing the output power in Function 5.6 by the rated power. After this, the whole function has to be multiplied by the rated power to calculate the input power. The function becomes then:

$$P_{in}(t) = ((P_{fc}(t)/P_{fcr})^2 \cdot a + (P_{fc}(t)/P_{fcr}) \cdot b + c) \cdot P_{fcr} \tag{5.7}$$

P_{fcr} in this function is the rated power of the fuel cell. The normalized power curve is shown in Figure 5.2. The coefficients a, b, and c are respectively 0.855, 0.89, and 0.1123 and they are obtained with the Curve Fitting tool in Matlab. The x represents the percentage of output power of the fuel cell and the y is the corresponding normalized input power of the fuel cell. This function is used to model the fuel cell in this optimization study. The approximation has an accuracy of 99.55 Percent with the data used in [20]. After the power leaves the fuel cell, the voltage is converted by a DC/DC converter. In this process also some energy is lost and the efficiency of this converter is chosen to be constant at 95 percent [21]. The output power of the fuel cell after the converter is therefore:

$$P_{fc}(t) = P_{fc}(t) * \eta_{con} \tag{5.8}$$

η_{con} in this equation is the efficiency of the DC/DC converter.

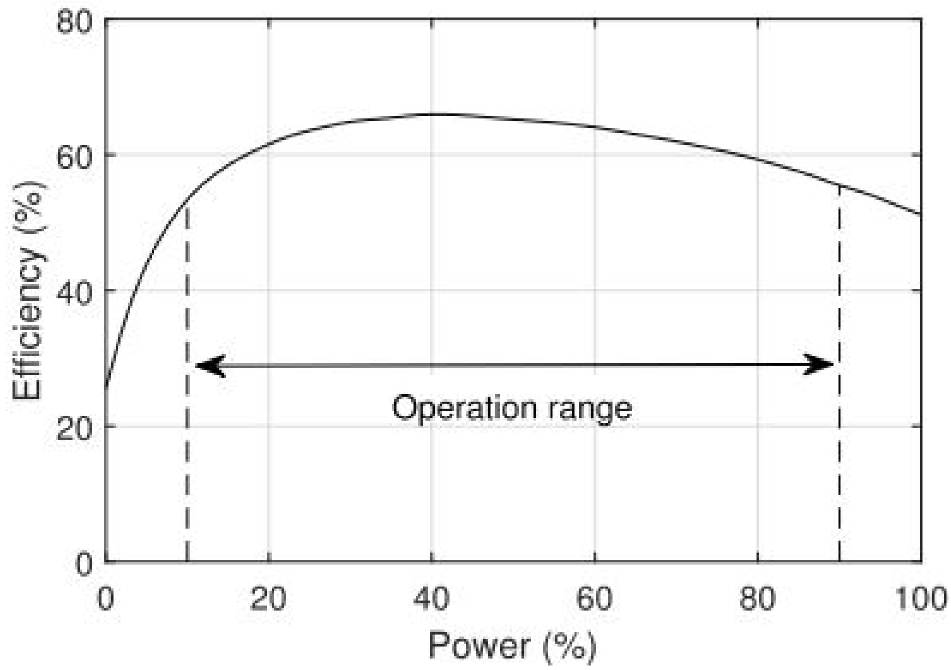

Figure 5.1: Typical efficiency curve of fuel cell systems [1].

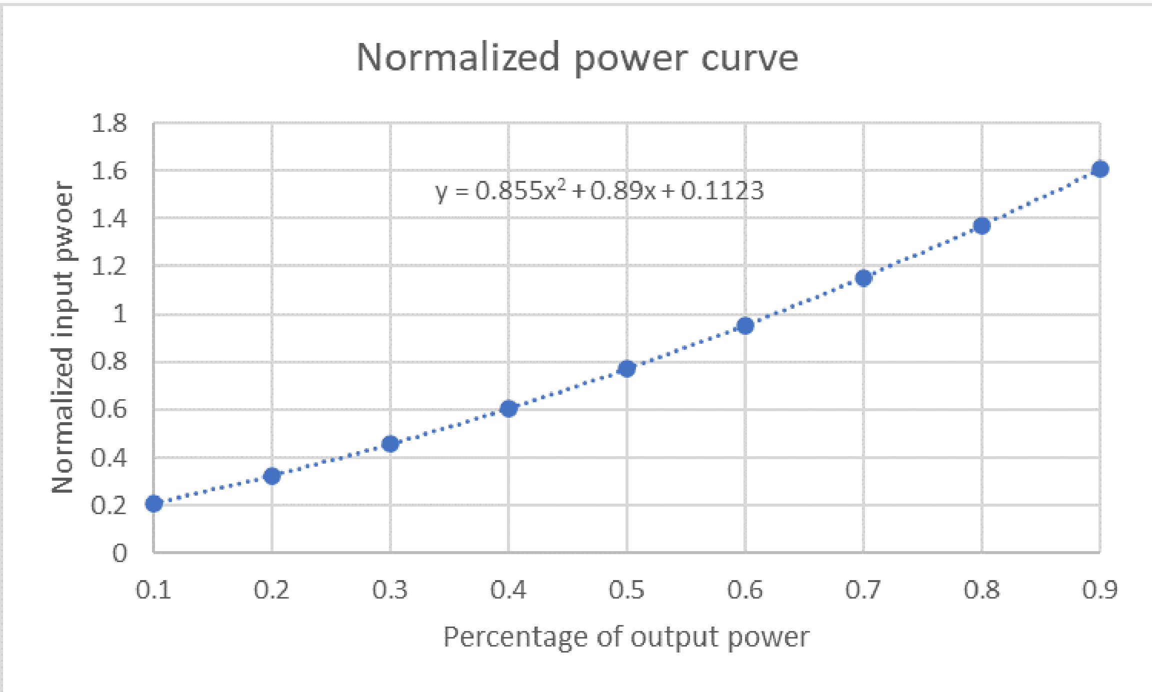

Figure 5.2: Normalized power curve of a fuel cell system.

5.2.1. Hydrogen consumption

The system components are controlled by an ECMS which minimizes the equivalent consumption. To do this it is necessary to calculate the instantaneous hydrogen consumption. This is done by using the following equation:

$$H_2(t) = P_{in}(t)\triangle t \cdot m \tag{5.9}$$

In this equation, $H_2(t)$ is the instantaneous hydrogen consumption, and $P_{in}(t)$ is the input power of the fuel cell which is calculated with Equation 5.7. m is the kWh to kg conversion coefficient of hydrogen and is 0.03 kg/kWh [20]. The total hydrogen consumption is the sum of the instantaneous hydrogen consumption at all timesteps.

5.3. Operational profile

All ships have a certain power that is needed to achieve a certain speed. When this power and corresponding speed are measured a power profile can be made. In this research, such a profile is made with data measured from the H2C boat. During this measurement, the H2C boat sailed in two opposite directions with the same speed. This is done to take into account the differences in circumstances that could exist when sailing in different directions. Factors that could be of influence are for example wind and tide. With these power and corresponding speed measurements a power profile is made. This graph is shown in Figure 5.3. The blue dots are the measured points. The blue line is the curve fitted through these points. The first part of the curve from 0 to approximately 4 m/s is described by a polynomial. The second part is described by a linear function. The functions are:

$$P_{dem} = 0.258 \cdot v^2 + -0.0311 \cdot v + 1.17 \cdot 10^{-13} \tag{5.10}$$

$$P_{dem} = 2.9045 \cdot v - 7.051 \tag{5.11}$$

In these equations, P_{dem} is the demanded power in kW that corresponds to the speed v that is asked. With this power profile and the corresponding formulas, an operational profile can be made. Because the maximum power of the motor of the H2C boat is 55 kW, this is also the maximum of the operational profile.

To solve the optimization problem an operational profile is needed as input. The operational profiles used in this research are obtained out of a feasibility study from Tu Delft students [22]. The four different profiles are obtained with measured data from different training sessions with a fossil fuel-powered coach boat. The measured data is speed over time and when this data is converted to power over time the profiles in Figures 5.4, 5.5, 5.6 and 5.7 are obtained. The total demanded energy in these profiles are respectively: 59.13 kWh, 22.11 kWh, 13.26 kWh, and 44.52 kWh.

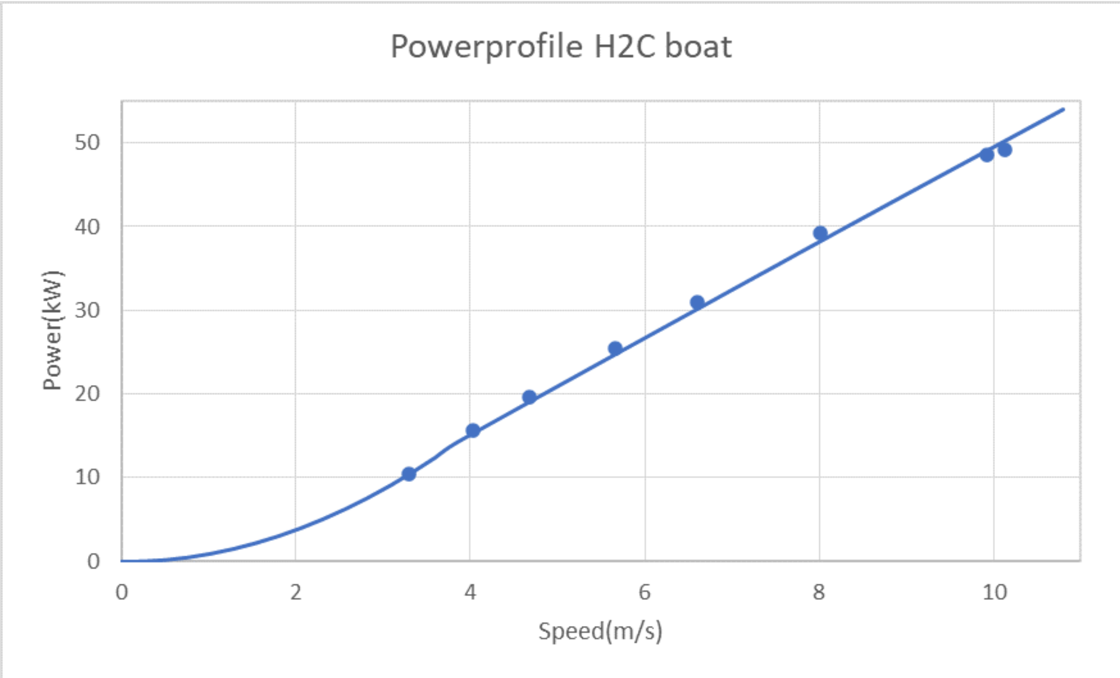

Figure 5.3: Power profile of the H2C boat with measured data.

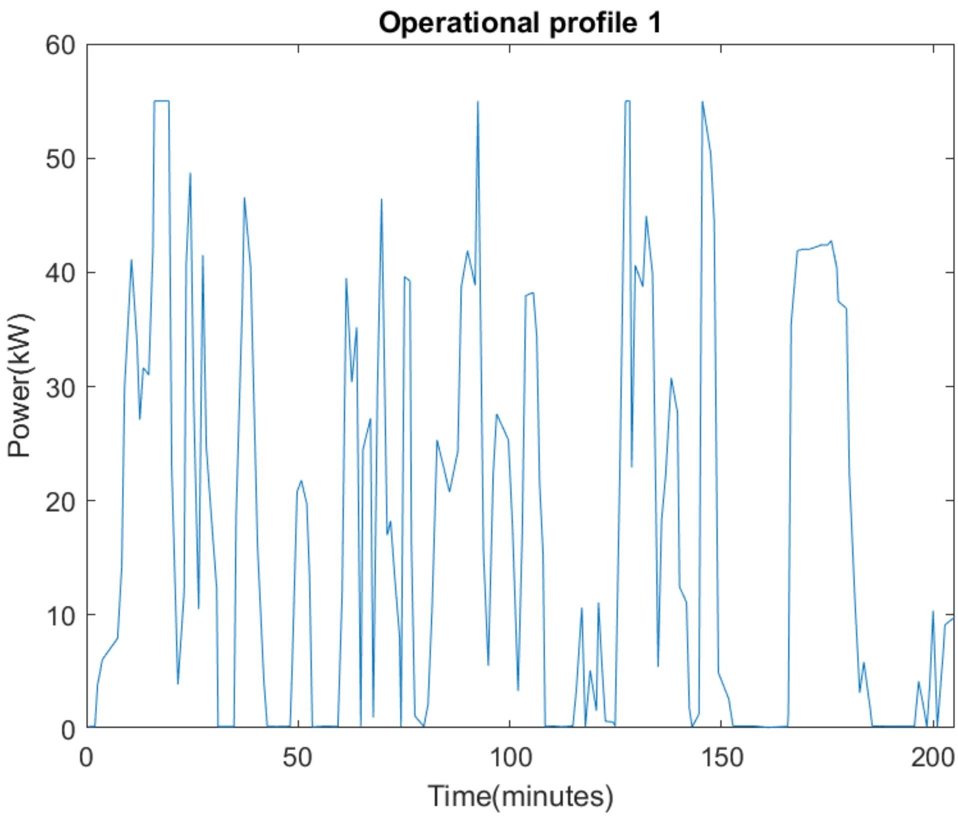

Figure 5.4: Operational profile 1 with a total energy demand of 55.13 kWh.

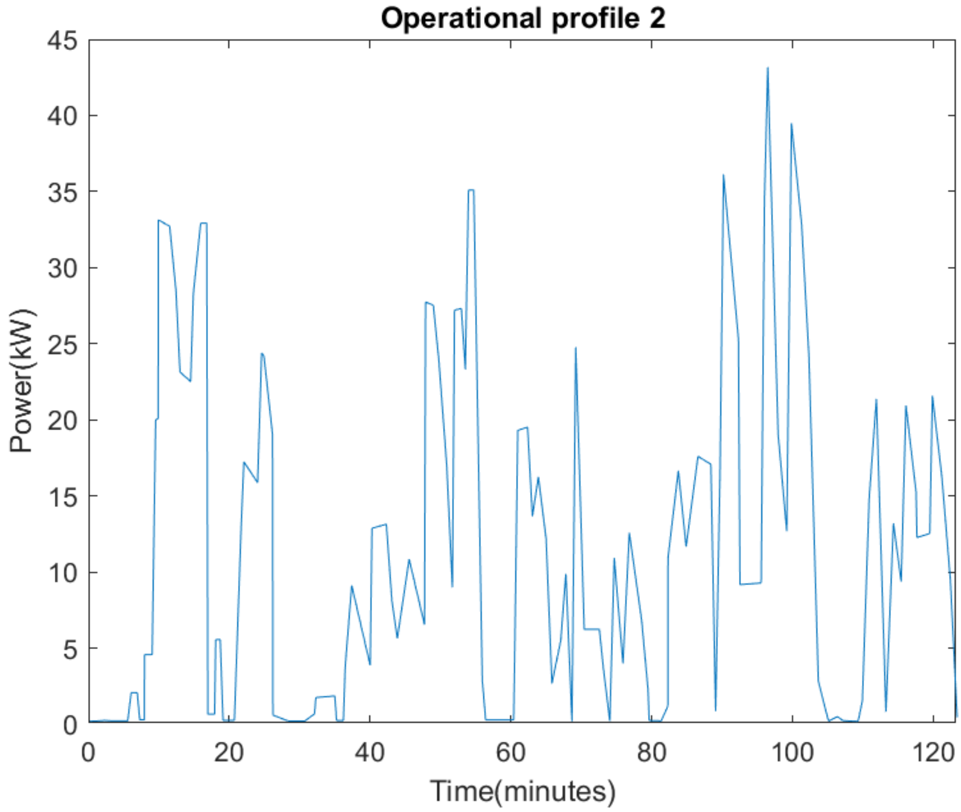

Figure 5.5: Operational profile 2 with a total energy demand of 22.11 kWh.

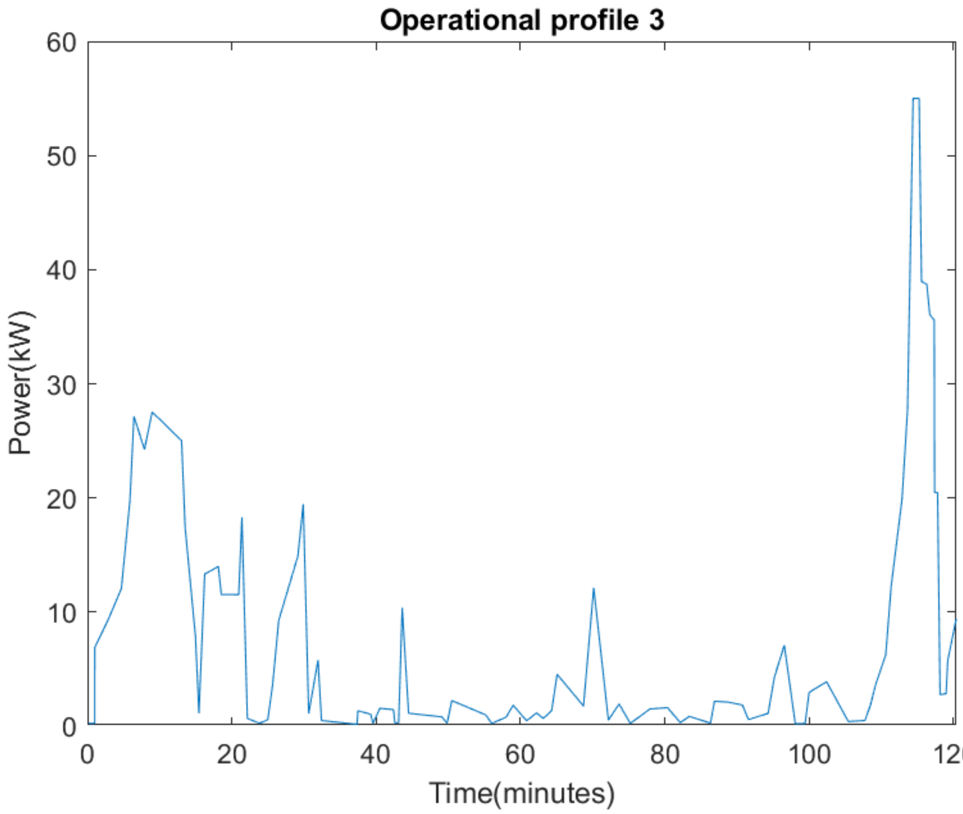

Figure 5.6: Operational profile 3 with a total energy demand of 13.26 kWh.

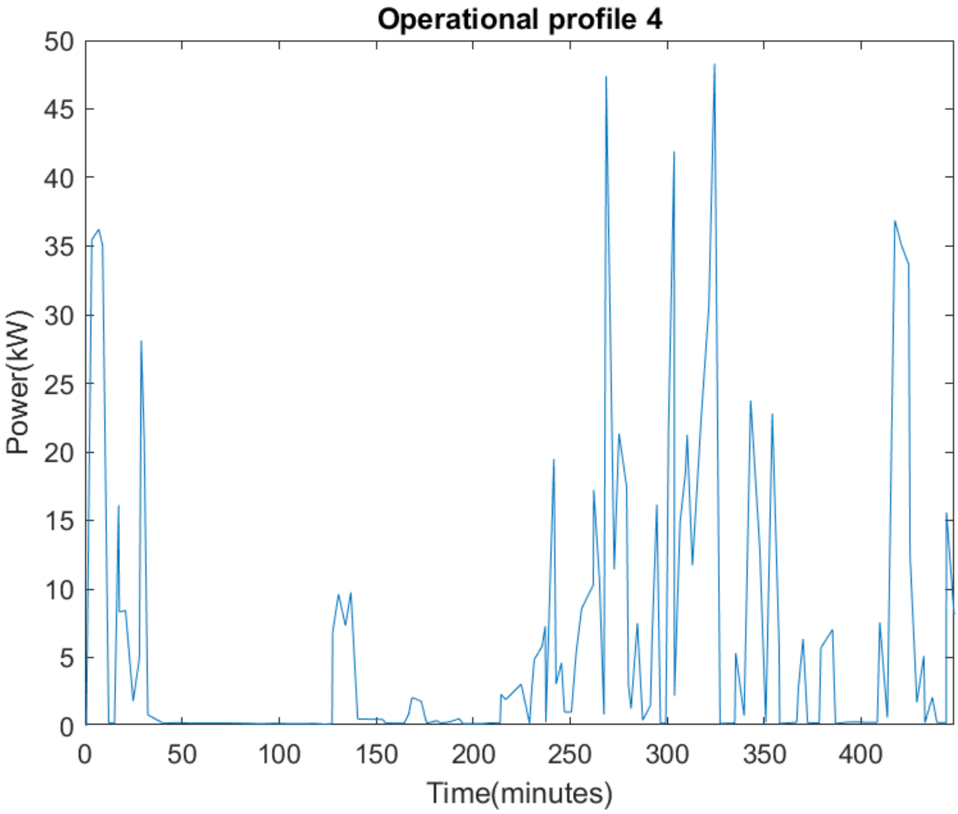

Figure 5.7: Operational profile 4 with a total energy demand of 44.52 kWh.

6
Equivalent Consumption Minimization Strategy

As mentioned in the outcomes of Chapter 2 the strategy to control the system components will be an ECMS. In this chapter, the general principle of ECMS are explained. Also, the problem definition of the optimization problem and the constraints are described. After this different three variants of ECMS are described.

6.1. Objective function and variables

To control the system components of a vessel, an energy management strategy has to be implemented. In this research, an Equivalent Consumption Minimization Strategy (ECMS) is chosen to control the system components of the hybrid powertrain. The objective of the ECMS is to minimize the equivalent fuel consumption of the hybrid power system. ECMS is an online optimization control method and therefore suitable to use in this study [23]. Online means that the energy management strategy solves the optimization with real-time available data. It does not need information about future working conditions but solves the optimization problem with the instantaneous available data. In theory, it can be applied to actual ship control [24]. The core idea is to convert electric energy into equivalent fuel consumption and minimize the total consumption for every timestep. In general, the ECMS seeks the optimal power allocation between the fuel cell and the battery by finding the minimal instantaneous equivalent fuel consumption for every time step [25]. The optimization definition for the ECMS is given in Equation 6.1 [26].

$$u_c(t) = arg \min_{u_c} M_{f,eqv}(u_c, w_e(t), EF(t)) \tag{6.1}$$

In this equation u_c are the control variables, $u_c = [P_{fc}(t)]$, w_e the exogenous inputs $w_e = f(P_{dem}(t), SOC(t))$ and $EF(t)$ the instantaneous Equivalent Factor. To calculate the instantaneous equivalent fuel consumption the following formula is used:

$$M_{f,eqv} = H_2 + C_{bat} \tag{6.2}$$

In this equation $M_{f,eqv}$ is the instantaneous equivalent fuel consumption, H_2 is the instantaneous hydrogen consumption which is calculated by Equation 5.9 and C_{bat} is the instantaneous equivalent battery consumption. C_{bat} is calculated by the following equation [25]:

$$C_{bat}(t) = EF(t) \cdot \frac{(P_{bat}(t) \cdot \triangle t)}{Q_{lhv}} \tag{6.3}$$

EF(t) is the instantaneous Equivalent Factor which can be calculated in different ways depending on the ECMS variant. The Equivalent Factor is always a combination between a chosen factor and a penalty factor. The penalty factor has to make sure that the battery SOC does not exceed its constraints [26]. There are different methods to calculate this penalty factor and three of these methods are explained in Sections 6.3, 6.4, and 6.5. $P_{bat}(t)$ is the power of the battery and Q_{lhv} is the lower heating value of hydrogen which is $1.19 \cdot 10^8 J/kg$ [12]. $P_{bat}(t)$ is not a control variable but is dependent on the demanded power and the output power of the fuel cells as stated in Equation 5.1 and shown in Figure 6.1. The ECMS chooses the output power of the fuel cells for every timestep in such a way that the equivalent consumption is minimal. The optimization is also subject to constraints which are defined in Section 6.2.

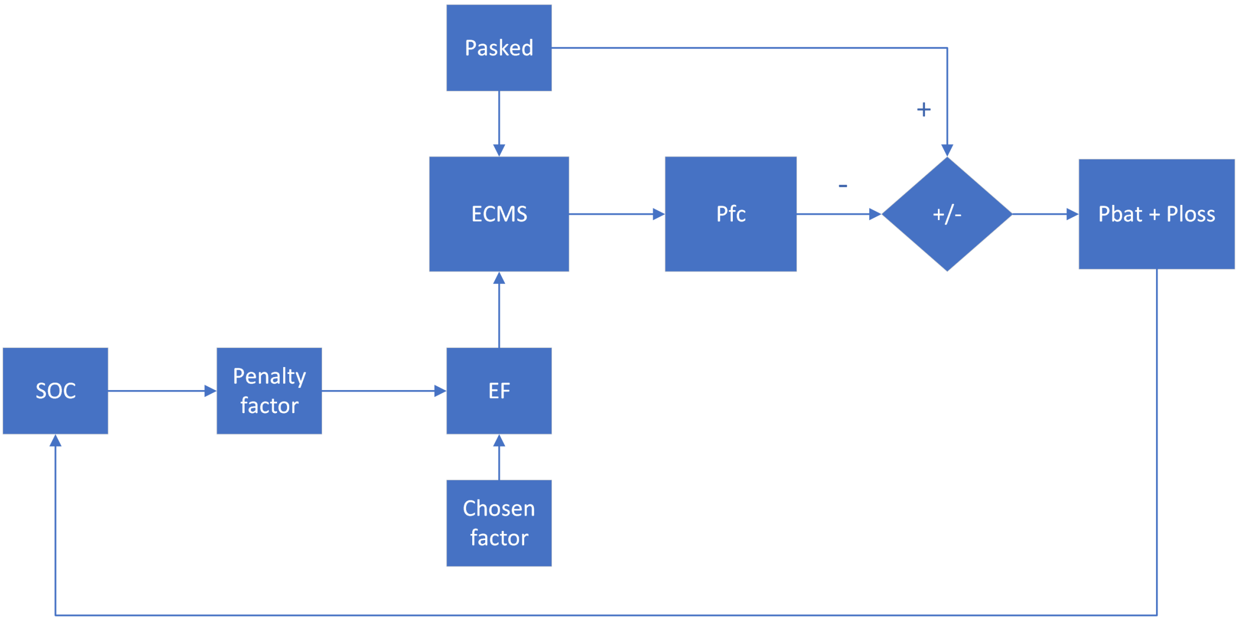

Figure 6.1: Block scheme of the working principle of ECMS.

6.2. Constraints

To determine the optimal energy management the optimization problem is subject to constraints. The input to solve the control optimization problem is an operational profile which is a matrix with timesteps and corresponding power demand. For the control problem the following constraints are applied. The first constraint is that the power demand has to be satisfied. The total demanded power should be in balance with the generated power at all times.

$$P_{dem}(t) = P_{fc}(t) + P_{bat}(t) - P_{loss}(t) \tag{6.4}$$

In this equation is $P_{dem}(t)$ the demanded power at time step t. The power is supplied by the fuel cell system and the battery. $P_{fc}(t)$ is the output power of the fuel cell system and $P_{bat}(t)$ is the output power of the battery. $P_{loss}(t)$ are the losses that have to be compensated by the battery. The next constraint is related to the battery system. The battery SOC always has to stay between certain limits.

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{6.5}$$

The maximum and minimum levels of SOC are respectively 100 and 12.5 percent. Below this level the motor limits itself.

Because of the big difference in efficiency with the corresponding operating point the fuel cells are constrained. Therefore the next constraint is applied.

$$0.1 \cdot P_{fcr} \leq P_{fc}(t) \leq 0.9 \cdot P_{fcr} \tag{6.6}$$

P_{fcr} is the rated power of the fuel cell which is a variable of the sizing optimization problem. The minimum and maximum percentages of output power for the fuel cell are respectively 10 and 90 percent as stated in Chapter 5. Below 10 percent the fuel cell shuts off.
Because the hydrogen storage has a limited capacity the total hydrogen consumption is constrained. The maximum capacity of the tank is 3.1 kg of compressed hydrogen as explained in Chapter 4. The instantaneous hydrogen consumption is calculated by Equation 5.9. When this instantaneous consumption is added up for every timestep the total hydrogen consumption is calculated.

$$\sum_{t=0}^{t=t_f} H_2 \leq 3.1\ kg \tag{6.7}$$

6.3. AP-ECMS

The Equivalent Factor is a combination between chosen factors and a penalty factor. The Equivalent Factor in [25] is calculated with Equation 6.8. This variant of ECMS is called AP-ECMS in this research. AP stands for Adaptive Penalty factor.

$$EF(t) = \delta SOC(t) \cdot M + \int_{t_0}^{t} \delta SOC(t) dt \cdot N \tag{6.8}$$

In this formula, $\delta SOC(t)$ is the penalty factor and M and N are the chosen factors. M and N reflect the adjusting intensity of the fuel cell. These chosen factors can be optimized to find the optimal behavior for the fuel cell. With a higher chosen factor M, the EF will be bigger when $\delta SOC(t)$ is bigger. With a bigger EF, it will be more expensive to use the battery because C_{bat} will be higher as shown in Equation 6.3. The integral from t_0 till t is the sum of $\delta SOC(t)$ from $t = 0$ till the actual timestep. Chosen factor N has more impact on the EF at the end of the cycle. The bigger the sum of $\delta SOC(t)$ is the more impact N has on the EF. Therefore, M and N have a great influence on C_{bat} and thus the behavior of the ECMS. The $\delta SOC(t)$ in this equation is the difference between the reference SOC and the real SOC and is functioning as a penalty factor. $\delta SOC(t)$ is described by Equation 6.9.

$$\delta SOC(t) = SOCref(t) - SOC(t) \tag{6.9}$$

The real SOC is calculated by Equation 5.2 and the reference SOC is calculated by the following equation:

$$SOCref(t) = SOC(0) - \frac{t}{T} \cdot (SOC(0) - SOC(t_f)) \tag{6.10}$$

In this equation SOC(0) is the initial State Of Charge and $SOC(t_f)$ is the desired SOC at the end of the cycle. T is the total duration of the cycle. By calculating the $SOCref(t)$ in this way it will decrease from $SOC(0)$ till $SOC(t_f)$ in a linear way over time. With every timestep the $SOCref(t)$ will decrease. The goal of this method is to let the real SOC decrease over time until the desired $SOC(t_f)$ at the end of the cycle. The more $SOC(t)$ differs from $SOCref(t)$ the higher or lower $\delta SOC(t)$ will be. This effect can be seen in Figure 6.2. In this figure, the reference SOC is 50 at this timestep and is marked with a red dot. If the real SOC is for example 30 at this timestep then the penalty factor is 20. The high penalty factor causes the EF to become bigger and this causes the cost of using the battery will be higher. When these costs are higher than the costs of using the fuel cell, the fuel cell will be used. When the $SOC(t)$ is higher than the reference SOC the penalty factor is negative. This causes a negative cost for using the battery and therefore the battery will be used to cover the demanded power.

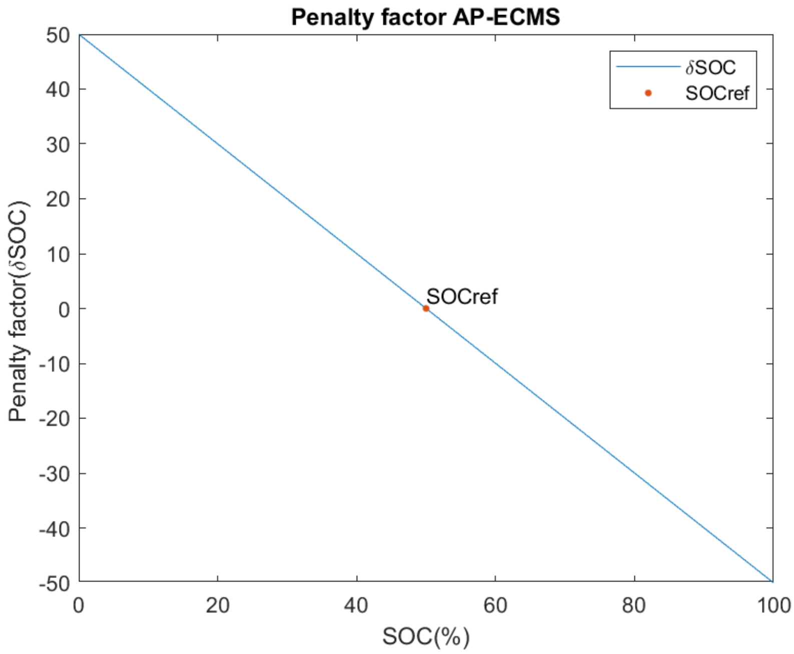

Figure 6.2: Changing penalty factor with changing SOC with a reference SOC of 50 percent at this timestep.

6.4. LAP-ECMS

In [27] the Equivalent Factor is calculated with Equations 6.11, 6.12 and 6.13. This variant of ECMS is called LAP-ECMS in this research. LAP stands for Low Adaptive Penalty function.

$$\delta SOC(t) = \frac{SOC(t) - \sigma}{SOC_{max} - SOC_{min}} \tag{6.11}$$

$$\sigma = \frac{SOC_{max} - SOC_{min}}{2} \tag{6.12}$$

$$EF(t) = 1 - \beta \cdot \delta SOC(t) \tag{6.13}$$

$\delta SOC(t)$ is the penalty factor and is calculated with Equation 6.11. The penalty factor changes when the SOC changes. The penalty factor stays between 1 and -1 when $SOC(t)$ stays between its boundaries. When $SOC(t)$ hits the upper bound, $\delta SOC(t)$ is 1, and when it hits the lower bound -1. This effect can be seen with changing SOC in Figure 6.4. σ is a constant that is calculated by subtracting the SOC boundaries and dividing them by 2 as shown in Equation 6.12. β is the chosen factor and reflects the adjusting intensity of the ECMS. When β is bigger the EF will be bigger with a change in SOC and penalty factor. The EF is calculated by Equation 6.13. The effect of a changing SOC on the EF with $\beta = 1$ can be seen in Figure 6.4. When $SOC(t)$ hits the lower bound the EF is 2 and when it hits the upper bound the EF is 0. This means that with a high SOC the EF is low and the costs of using the battery are low. The lower the EF the lower C_{bat} is and when C_{bat} is lower than the cost of using the fuel cell the battery will be used.

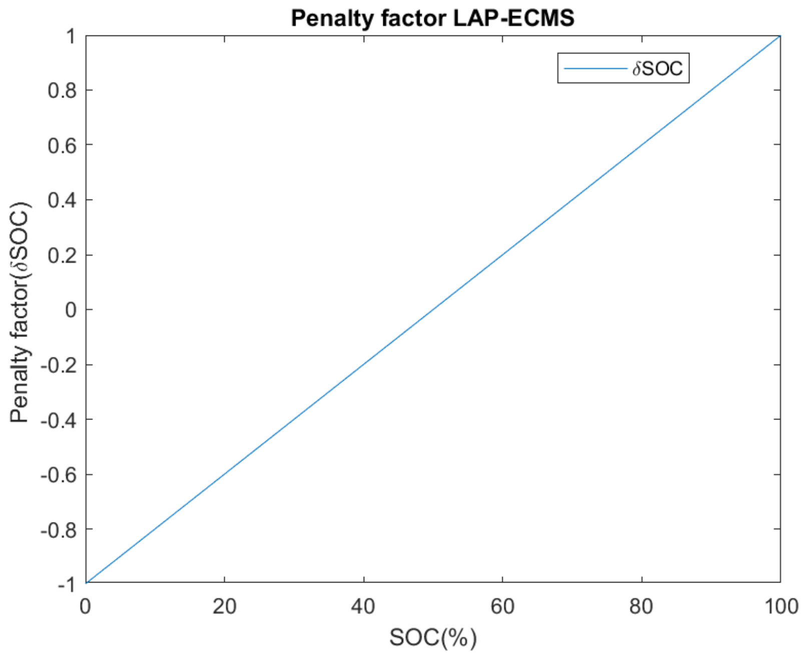

Figure 6.3: Changing penalty factor with changing SOC.

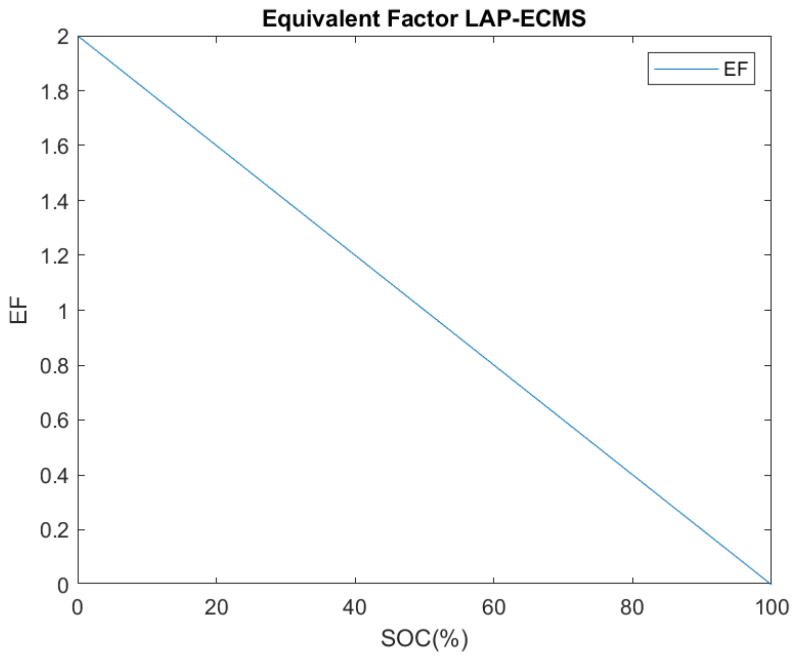

Figure 6.4: Changing Equivalent Factor with changing penalty factor(δSOC) and $\beta = 1$.

6.5. SAP-ECMS

In [26] the penalty function is calculated with Equations 6.15, 6.16, and 6.17. The Equivalent Factor is calculated with Equation 6.14. This ECMS is called SAP-ECMS in this research. SAP stands for Smooth Adaptive Penalty factor.

$$EF(t) = k \cdot \delta SOC(t) \tag{6.14}$$

$$\delta SOC(t) = 1 + (\frac{SOC_a - SOC(t)}{\sigma})^a : SOC(t) < SOC_a \tag{6.15}$$

$$\delta SOC(t) = 1 : SOC_b < SOC(t) < SOC_a \tag{6.16}$$

$$\delta SOC(t) = 1 - (\frac{SOC(t) - SOC_b}{\sigma})^a : SOC(t) > SOC_b \tag{6.17}$$

k in Equation 6.14 is the chosen factor that can be optimized to find the optimal behavior for the fuel cells. $\delta SOC(t)$ is the penalty factor which is dependent on the $SOC(t)$, SOC_a, and, SOC_b. SOC_a and SOC_b are chosen limits of the penalty factor. When the SOC is between the limits SOC_a and SOC_b Equation 6.16 is in effect and $\delta SOC(t) = 1$. When the SOC exceeds the limits SOC_a or SOC_b the penalty factor is calculated by Equations 6.15 or 6.17. σ is the same constant as used in LAP-ECMS and is calculated by Equation 6.12. a is a chosen factor that reflects the adjusting intensity of the penalty factor. The effect of this penalty factor with $a = 1$ can be seen in Figure 6.5. a determines the slope of the penalty factor when the SOC exceeds the limits SOC_a or SOC_b. With a different a the slope of the penalty factor will be different and the ECMS will react differently to changes in SOC. The penalty factor becomes higher when the SOC exceeds the lower limit SOC_a and becomes lower when it exceeds the upper limit SOC_b. This means that the EF becomes higher when the $SOC(t)$ exceeds SOC_a and therefore the cost of using the battery will be higher. The more $SOC(t)$ exceeds SOC_a the higher $\delta SOC(t)$ will become and the higher the EF will become. How fast $\delta SOC(t)$ becomes higher depends on the slope of the penalty factor and this depends on the chosen factor a. It is necessary to choose the SOC_a and SOC_b with distance from the SOC constraints SOC_{min} and SOC_{max}. By doing this the penalty factor can grow smoothly before $SOC(t)$ hits the final boundaries and the ECMS can react in a smooth way. The goal of this ECMS is that the energy management system reacts smoothly to changes in SOC so that the fuel cell system can also react smoothly. The benefit of this is that the system can work as efficiently as possible. In Chapter 8 the results and effects of these different energy management strategies are compared and discussed.

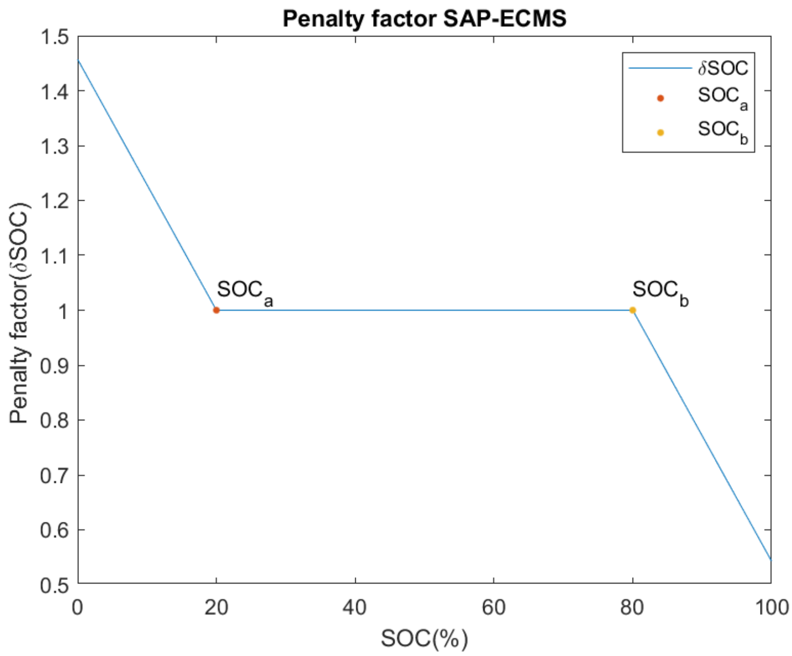

Figure 6.5: Effect of multiplicative penalty function with $a = 1$.

7
Sizing optimization

In this chapter, the sizing optimization problem is described. First, the objectives and variables are defined. After this, the constraints for the sizing problem are described.

7.1. Objective function and variables

The objective of the sizing problem is to minimize the weight of the system components. The problem definition is given in Equation 7.1.

$$S = arg\ min\ W(P_{fcr}, E_{bat}) \tag{7.1}$$

The control variables in this optimization problem are the rated power of the fuel cell P_{fcr} and the rated energy of the battery E_{bat}. These variables are respectively in kW and kWh. In this problem, there are no exogenous input parameters. The function to calculate the total weight is defined by the following equation.

$$W = W_b \cdot E_{bat} + W_{fc} \cdot P_{fcr} \tag{7.2}$$

In this equation W_b and W_{fc} are the weight factors of the rated power and energy of respectively the fuel cell and the battery. W_b is calculated by dividing the original battery weight by its energy capacity. These factors are given in Chapter 4 and W_b is therefore 7.1 $\frac{Kg}{kWh}$. For calculating W_{fc} the same method is applied with data given in Chapter 4 only now the power is used instead of the energy. W_{fc} is therefore 5 $\frac{Kg}{kW}$.

7.2. Constraints

To solve the optimization problem it is necessary to have constraints. The sizing problem is solved with a linear programming algorithm in Matlab named Linprog. All constraints are therefore linear equality or inequality constraints. The first constraint is the maximum power demand constraint. The battery and the fuel cell together have to be able to deliver the maximum output power of the motor.

$$E_{bat} \cdot C_{rate} + P_{fcr} \cdot 0.9 \geq P_{max} \tag{7.3}$$

In this equation, the battery rated energy is multiplied by the C-rate to obtain the maximum output power. The rated power of the fuel cell is multiplied by the maximum percentage of the output power of the fuel cell to obtain the maximum output power. P_{max} is the maximum continuous input power of the motor. The second constraint is related to the operational profile. To be able to satisfy the energy demand required to perform a certain profile, the battery and the fuel cell have to be able to deliver this demanded energy. To make sure this is the case for all profiles, the profile with the highest power and energy demand is used.

$$E_{bat} \cdot 0.875 + P_{fcr} \cdot 0.35 \cdot T \geq E_{demand} \tag{7.4}$$

In this equation, the battery rated energy is multiplied by 87.5 percent of its maximum capacity. Because of SOC limits not the complete energy capacity of the battery can be used. The rated power of the fuel cell is multiplied by its most efficient powerpoint. Ideally, the fuel cell works on this point all the time. T is the total time that is required to perform the operational profile.

8
Results and discussion

In this chapter, the results of the research are shown and discussed. The first section discusses the results of the different energy management strategies to control the hybrid power system. The second section shows the results of solving the sizing problem. The third section combines the results of the control and sizing problem and shows their impact on different operational profiles. In the last section, the results are verified.

8.1. Results of energy management strategies

There are different ways to control the system components of a hybrid power system. In this section, the results of different energy management systems are shown and discussed. First, two rule-based strategies are shown and after this, the results of the three different variants of ECMS are shown. To compare the results of the different strategies the operational profile with the highest energy demand, profile 1, is used. The sizes of the battery system and fuel cell system that are used are respectively 20 kWh and 32 kW. The original sizes of 40 kWh for the battery and 8 kW fuel cell system are not used because the energy management strategies would not have much effect with these sizes and operational profile 1 as input.

8.1.1. EMS H2C boat

The original controller of the H2C boat is a rule-based controller. The rules of this controller are that the fuel cells are switched on when the SOC is below 85 percent and that they are off when the SOC is above 95 Percent. When the fuel cells are on they work at their maximum operating point. The effect of this controller can be seen in Figure 8.1. In this figure, the demanded power is represented by the red line. The blue line shows the output power of the fuel cells and the yellow line the output power of the batteries. The total hydrogen consumption is 3.09 kg with this energy management strategy. In Figure 8.2 the SOC of the battery during the same cycle is shown. It can be seen that the SOC stays always between 70 and 100 percent. The effect of these rules is that the battery SOC will always be high until the hydrogen runs out. The downside is that it costs a lot of hydrogen to keep the battery SOC at this level. The other downside is that using the fuel cell at its maximum operating point is not efficient. The average efficiency with this energy management strategy is 53 percent for the fuel cells. Another downside of the rule-based controller is that it uses hard boundaries to control the fuel cell systems. By using these hard boundaries the fuel cells have to ramp up and down the power very fast.

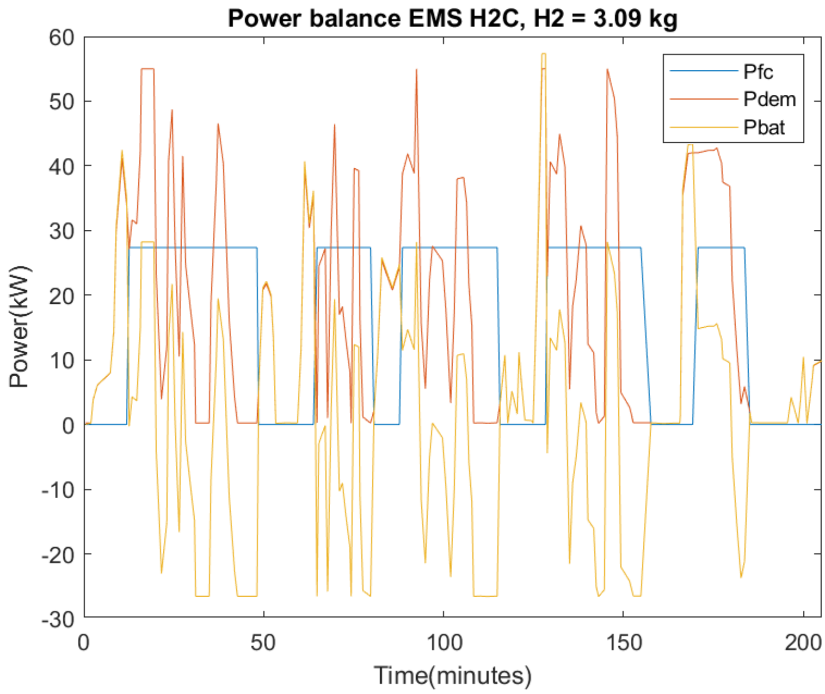

Figure 8.1: Output power of the system components controlled by the EMS of the H2C boat with operational profile 1 as input.

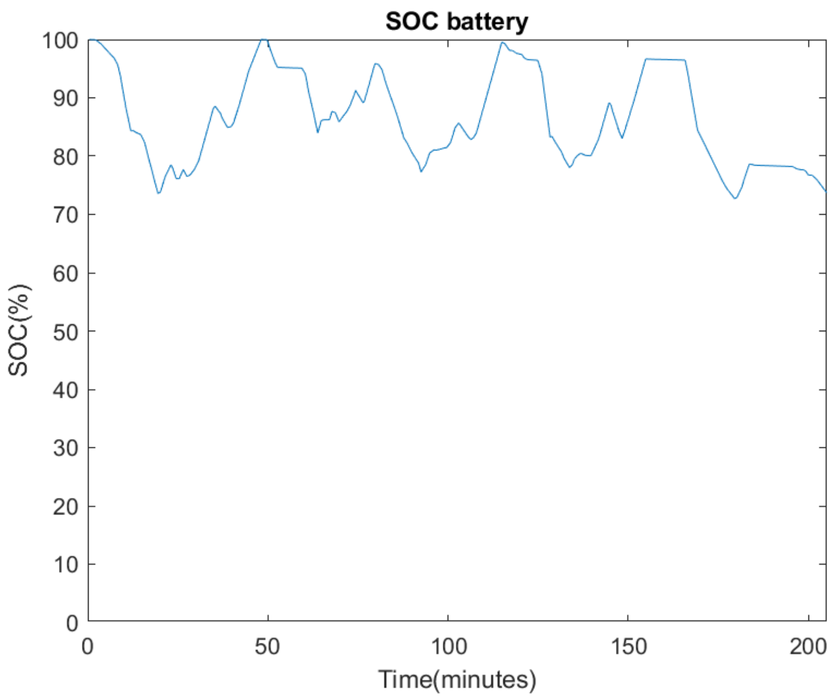

Figure 8.2: SOC of the battery during the cycle shown in Figure 8.1.

8.1.2. Rule-based controller

To show that the rule-based controller of the H2C boat is not the most efficient and uses a lot of hydrogen another rule-based controller is designed. The rules of this controller are that the fuel cells are off when the SOC is above 95 percent. The fuel cells work at their most efficient operating point when the SOC is between 30 and 90 percent and at their maximum operating point when the SOC is below 30 percent. The most efficient operating point is 35 percent of the fuel cells rated power. The efficiency at this operating point is 63 percent. The effect of this controller can be seen in Figure 8.3. The input is again operational profile 1. The total hydrogen consumption with this controller is 2.51 kg. The average efficiency of the fuel cells is 58 percent. These results show that the fuel cells work more efficiently with this controller and use less hydrogen than with the original controller of the H2C boat. In Figure 8.4 the SOC of the batteries during the cycle is shown. The downside of this rule-based controller is that it only uses two different operating points for the fuel cells. Because of this, the fuel cells can not work at their optimal operating point at all times. To make this possible for the fuel cells a lot more rules have to be implemented and this makes a rule-based controller complex and not optimal.

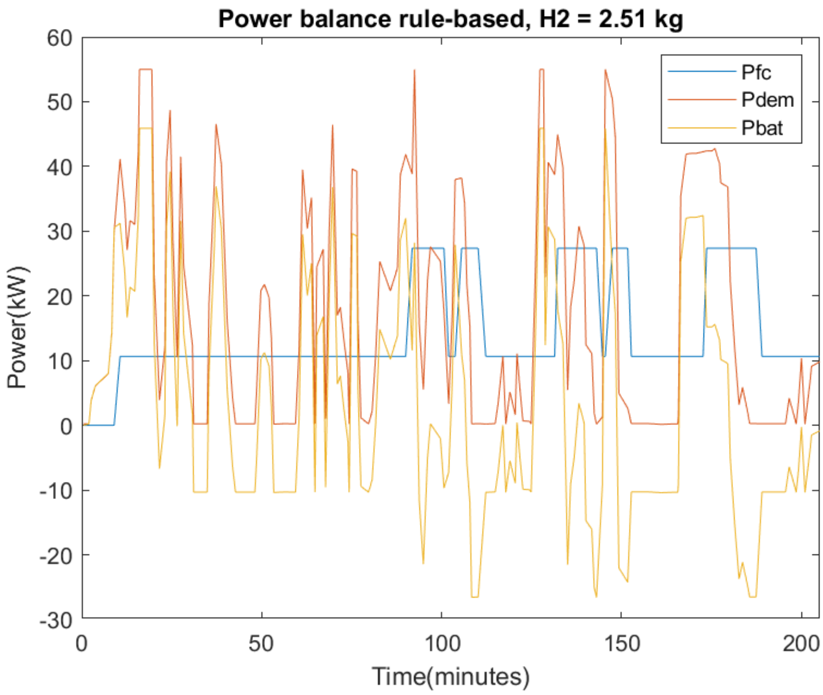

Figure 8.3: Output power of the system components controlled by a rule-based controller with operational profile 1 as input.

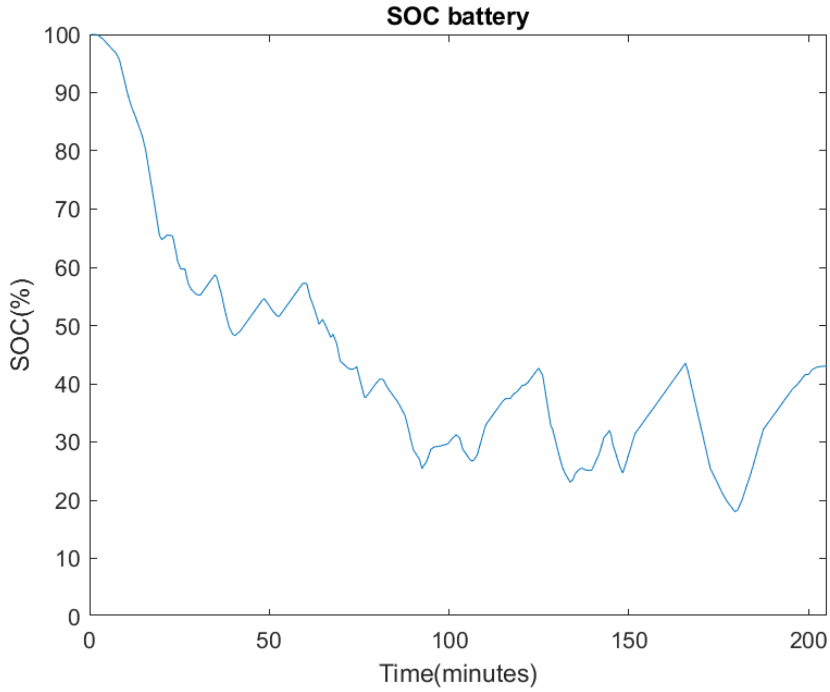

Figure 8.4: SOC of the battery during the cycle shown in Figure 8.3.

8.1.3. AP-ECMS

When the systems are controlled by the AP-ECMS the system components behave as shown in Figure 8.5 with operational profile 1 as input. The blue line represents the output power of the fuel cells and it can be seen that they ramp up and down the output power very fast. This behavior is caused by the penalty factor calculated with Equation 6.9. The penalty factor becomes bigger when the SOC is lower than the reference SOC and lower when the SOC is higher than the reference SOC. This growing and shrinking of the penalty factor causes the EF to grow or shrink and this causes a change in the costs of using the battery. When the costs of using the battery are higher than the costs of using the fuel cell, the fuel cell will be used. When the costs of using the battery are lower, the battery will be used as power source. This effect can be seen in Figures 8.5 and 8.6. When the SOC(blue line in Figure 8.6) is close to or higher than the reference SOC(red line in Figure 8.6) the costs of using the battery are low and the fuel cells are off. When the SOC is lower than the reference SOC the costs of using the battery are high and the fuel cells are turned on. The ECMS minimizes the equivalent consumption for every timestep. The calculation of the costs with this ECMS and penalty factor causes the costs to change a lot and this causes the fuel cells output power to ramp up and down fast. This behavior is not beneficial for the fuel cell's efficiency and the average efficiency is 53,98 percent. In Figure 8.6 it can also be seen that the SOC follows the reference SOC. This shows that the SOC can be controlled during the cycle with this controller. The result of this is that the SOC at the end of the cycle is very low, namely 21,67 percent. The downside of this strategy is that the operating time has to be known in advance to calculate the reference SOC during the operation. Due to this the ECMS does not completely work in real-time but needs knowledge in advance. The other parameters to influence the calculation of the EF and therefore the behavior of the ECMS are the chosen factors M and N. By changing these factors the calculation of the costs of using the battery is influenced. This influence of calculating the costs influences the adjusting intensity of the ECMS. This means that when the costs grow faster the fuel cells ramp up faster and vice-versa. In general, it can be said that the lower M and N are the slower the ECMS reacts to changes in SOC because the EF grows slower. This causes the fuel cells to be turned on later and the SOC can differ more from the reference SOC. This causes less hydrogen to be used. When M and N are too low the fuel cell reacts too slowly to changes in SOC and the SOC constraints can not be satisfied. The changes in hydrogen consumption with different M and N are shown in Figures 8.7 and 8.8. The M and N with the lowest hydrogen consumption found for this operational profile are respectively 22 and 0.3 and the hydrogen consumption is then 2.46 kg. The differences in hydrogen consumption are very small with different M and N and also the overall behavior of the controller does not change. In Figure 8.7 it can be seen that the hydrogen consumption is lower for a lower M factor. The lowest possible M factor with an N of 0.3 and this operational profile is 22. When a lower M factor is used the SOC limits are exceeded. In Figure 8.8 the hydrogen consumption for different N factors and their lowest possible M factor is shown. It can be seen that for very low N factors the M factor has to be very high to make sure the ECMS reacts fast enough with changing SOC to keep the SOC between the boundaries. When the results of this ECMS are compared with the rule-based controllers less hydrogen is consumed and the SOC is controlled very well.

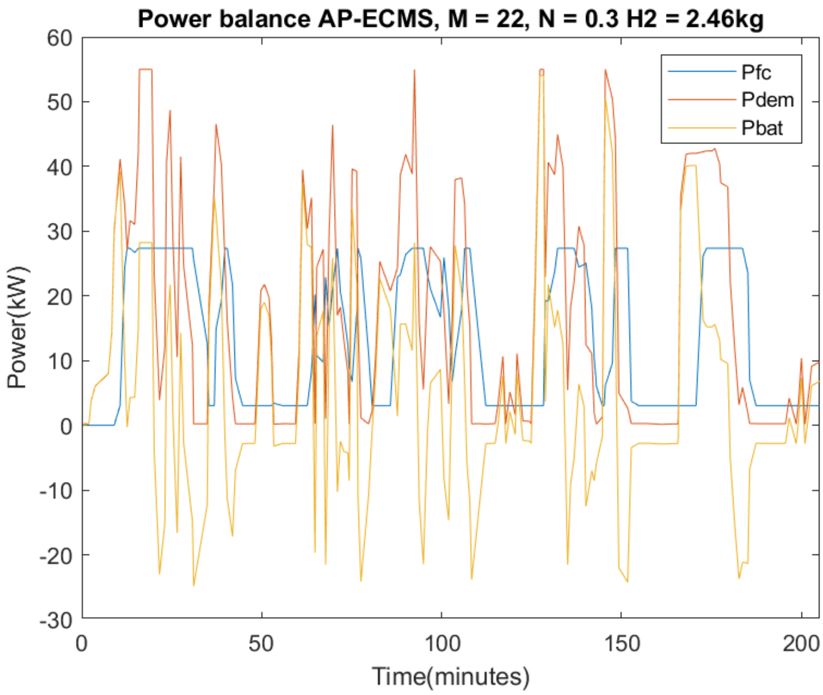

Figure 8.5: Output power of the system components controlled by AP-ECMS with operational profile 1 as input.

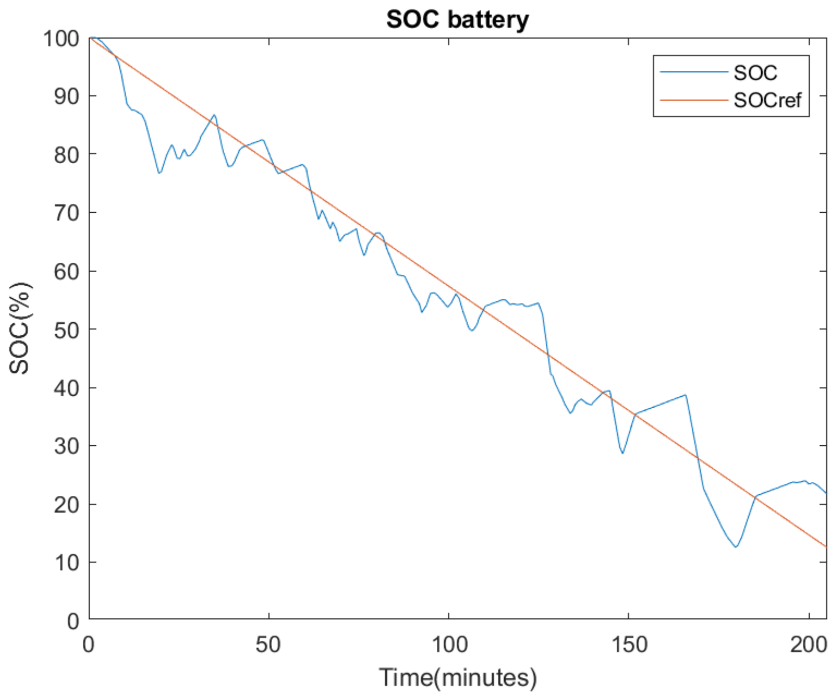

Figure 8.6: SOC of the battery during the cycle shown in Figure 8.5 and reference SOC.

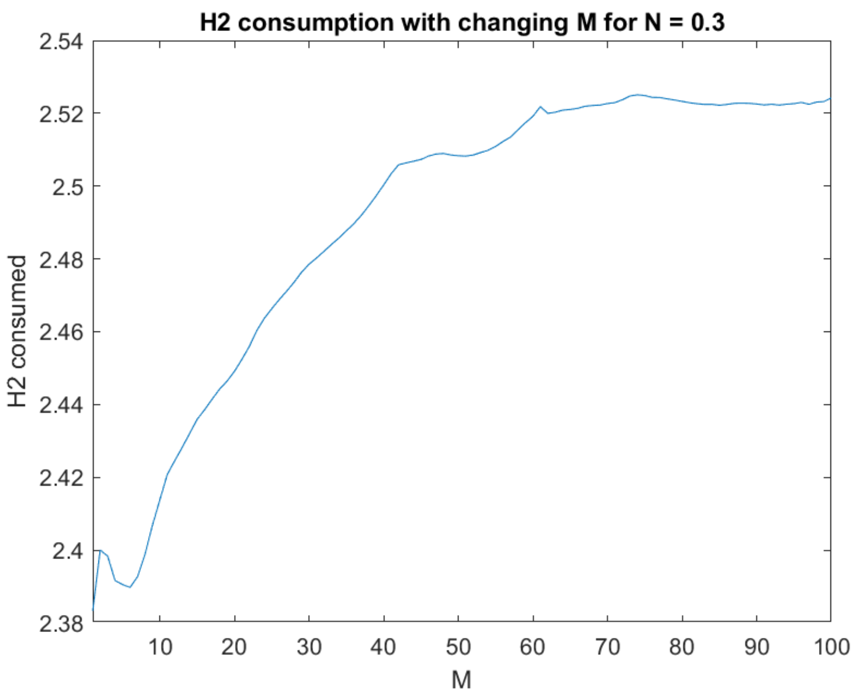

Figure 8.7: Changing H2 consumption for changing M factor.

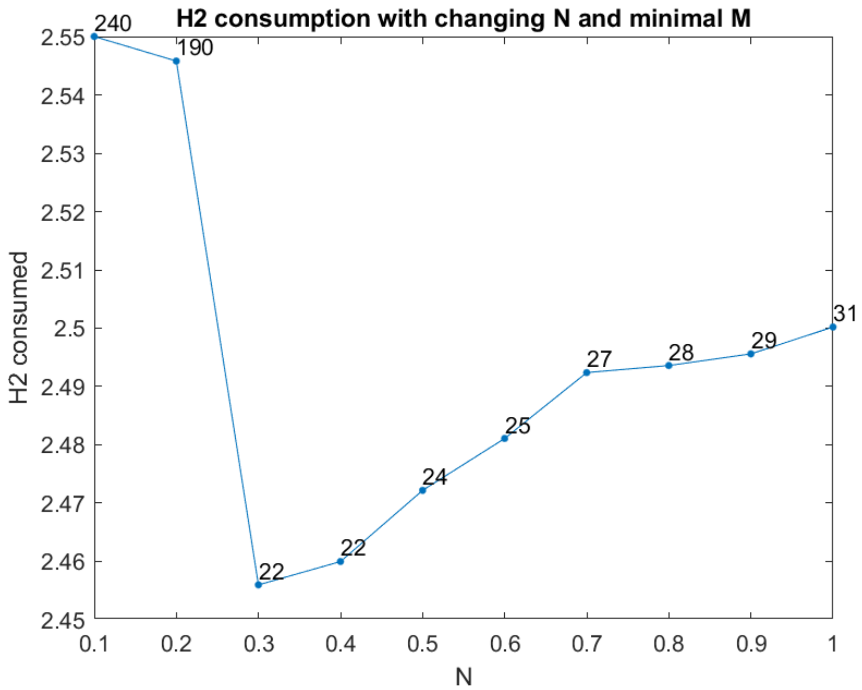

Figure 8.8: Changing H2 consumption for changing N factor.

8.1.4. LAP-ECMS

In Figure 8.9 the output power of the system components controlled by the LAP-ECMS with operational profile 1 as input is shown. In Figure 8.10 the SOC of the battery during the operation is shown. From this figure, it can be seen that the SOC drops fast at the beginning of the cycle. It can also be seen that the fuel cells are off or working at a low operating point in the beginning. The reason for this is that the cost of using the batteries is low at the beginning of the cycle when the SOC is high. When the SOC reaches the lower limit the costs of using the batteries grow. Around this time the fuel cells ramp up the output power and the batteries are charged. From this moment the SOC of the batteries balances around 30 percent. The average efficiency of the fuel cells with this controller is 57 percent. The total hydrogen consumption is 2.45 kg. In comparison with the AP-ECMS, the fuel cells have a higher average efficiency but the total hydrogen consumption is almost the same. The reason for this is that the SOC at the end of the cycle for this ECMS is higher, namely 34 percent. This means that more hydrogen is used to charge the batteries. This causes almost the same amount of hydrogen to be consumed for both controllers. A downside of this controller is that the SOC drops fast at the beginning of the cycle. If later during the operation more power is demanded than the fuel cells can deliver and if the batteries are empty then the power has to be constrained and the demanded power can not be delivered. To calculate the EF with this ECMS a factor β has to be chosen. In Figure 8.11 it can be seen that with a lower β less hydrogen is consumed. With a lower β the EF grows less with changes in SOC and this causes the cost of using the batteries to grow less. Because the cost of using the batteries grows less they are used more and the fuel cells are used less. This causes the SOC to drop more and with a too low β the SOC constraints are exceeded. Therefore the chosen factor β can not be too low and for this operational profile, the minimal β is 170.

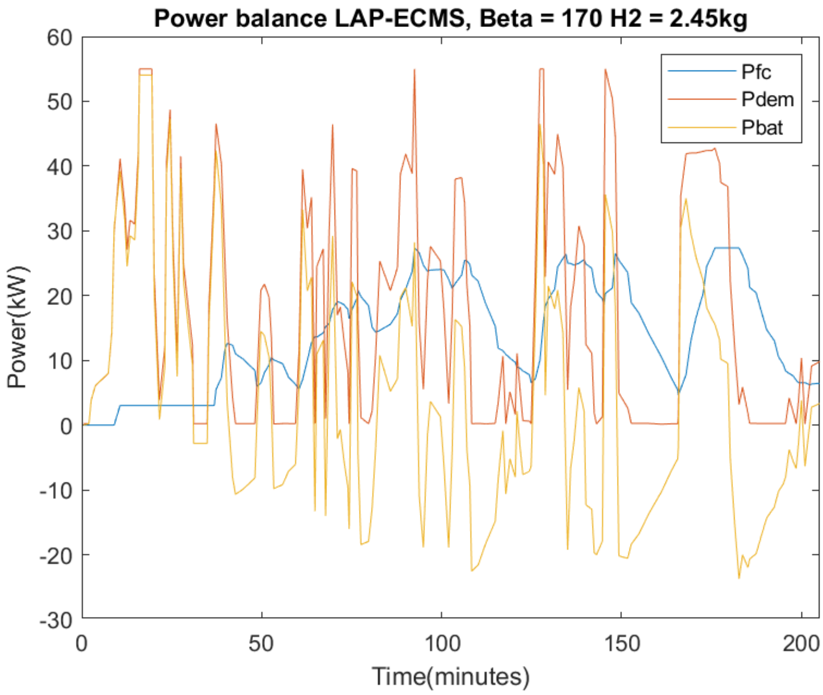

Figure 8.9: Output power of the system components controlled by LAP-ECMS with operational profile 1 as input.

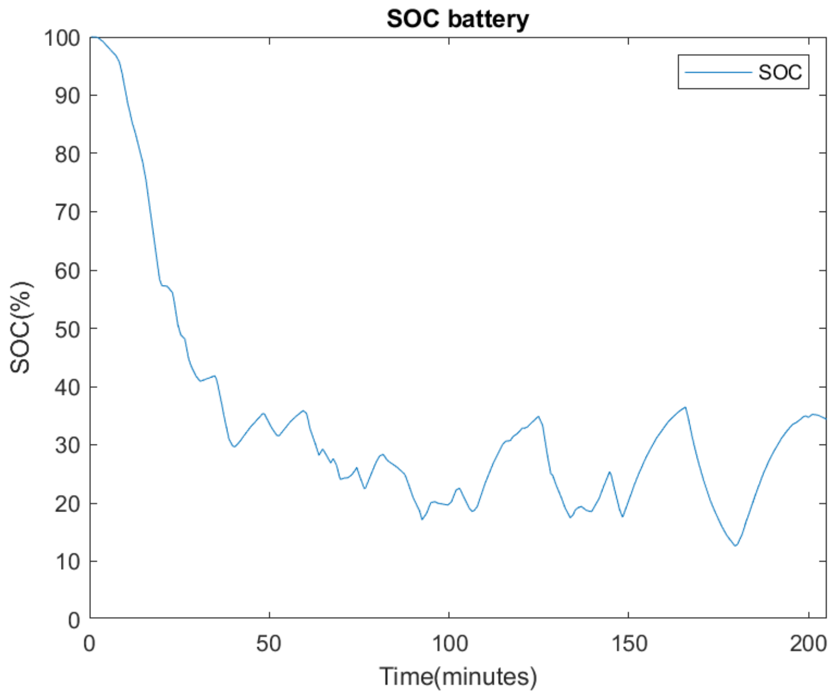

Figure 8.10: SOC of the battery during the cycle shown in Figure 8.9 controlled by LAP-ECMS.

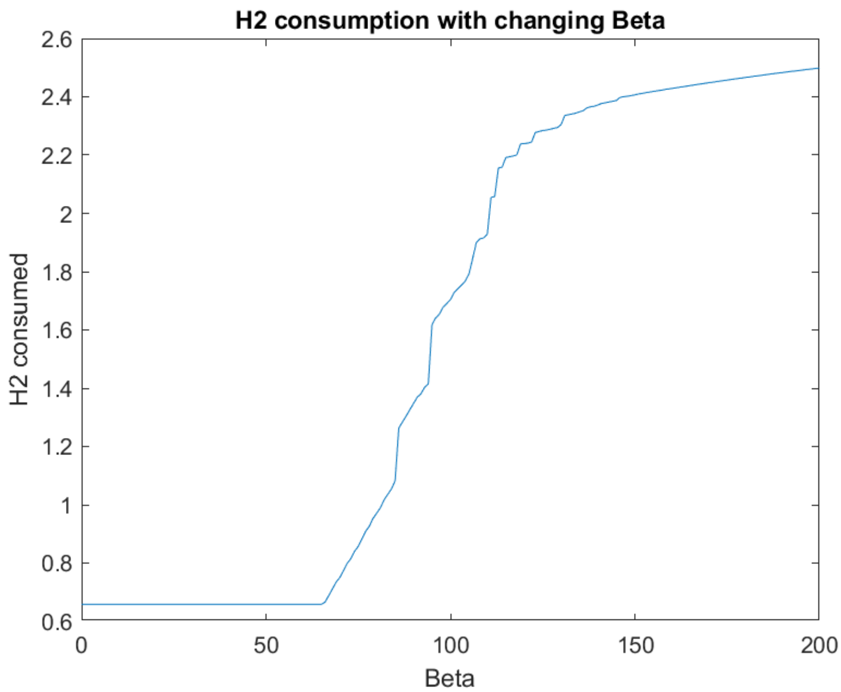

Figure 8.11: Changing H2 consumption for changing Beta factor.

8.1.5. SAP-ECMS

In Figure 8.12 the output power of the system components controlled by SAP-ECMS and with operational profile 1 as input is shown. In Figure 8.13 the SOC of the batteries during the operation can be seen. The blue line in Figure 8.12 represents the output power of the fuel cells. It can be seen that the fuel cells work around a constant operating point most of the time. This operating point is determined by the chosen factor k. It is found that the fuel cells work around their most efficient operating point when k is 93. The EF is calculated with a chosen factor and a penalty factor. When the SOC is between the limits SOC_a and SOC_b the penalty factor of this controller is one and the fuel cells work around a constant operating point. These limits have to be chosen before the SOC constraints so that the fuel cells can adjust the output power when the constraints are getting closer. The values of these limits are chosen to be 45 and 70 percent respectively. When these limits are exceeded the operating point of the fuel cell changes. This behavior is caused by the calculation of the penalty factor with Equations 6.15 and 6.17. When the SOC becomes higher than SOC_b the fuel cell power is ramped down and when the SOC is lower than SOC_a the output power of the fuel cell is ramped up. This ramping up and down goes smoothly because the penalty factor changes smoothly. How fast the penalty factor changes is dependent on the chosen factor a. In Figure 8.14 the total hydrogen consumption with changing a factor is shown. The a factor influences the slope of the penalty factor after the SOC limits. With a higher a factor the slope of the penalty factor becomes smoother. When the slope becomes smoother the EF reacts less to changes in SOC and the costs of using the battery change less. When the costs of using the battery change less the output power of the fuel cell also changes less. With higher a therefore less hydrogen is consumed but when a is too high the controller reacts too slowly and the SOC constraints are exceeded. The highest a for this operating profile with a factor k of 93 is 1.95. With these factors, the total hydrogen consumption is 2.36 kg. The SOC at the end of the cycle is 38 percent and the average efficiency of the fuel cell is 60,3 percent.

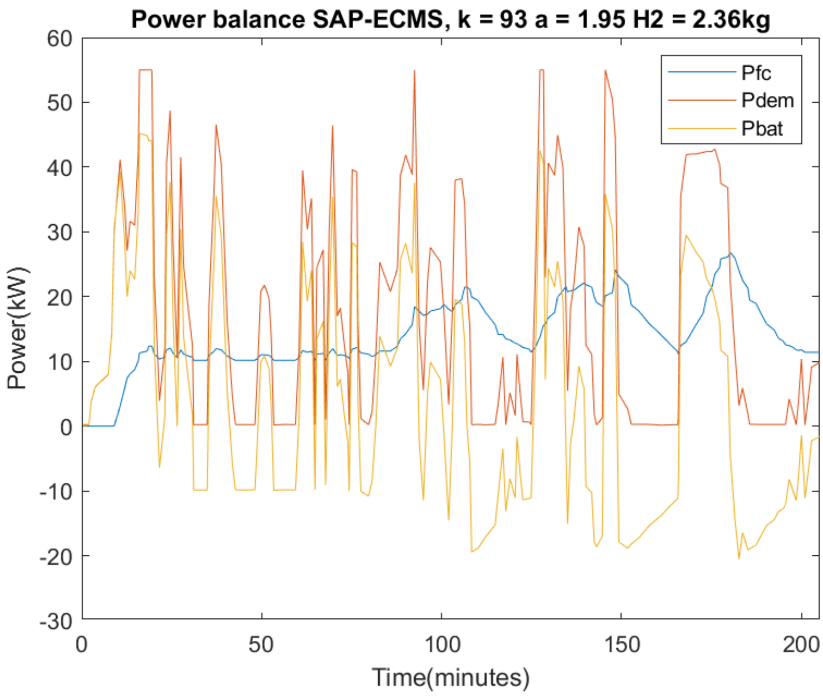

Figure 8.12: Output power of the system components controlled by SAP-ECMS with operational profile 1 as input.

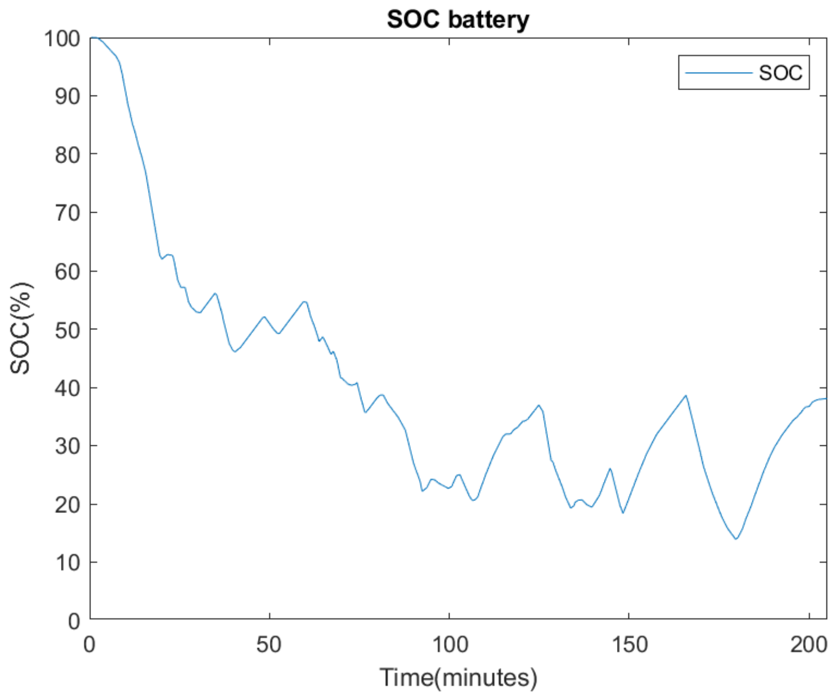

Figure 8.13: SOC of the battery during the cycle shown in Figure 8.12 controlled by SAP-ECMS.

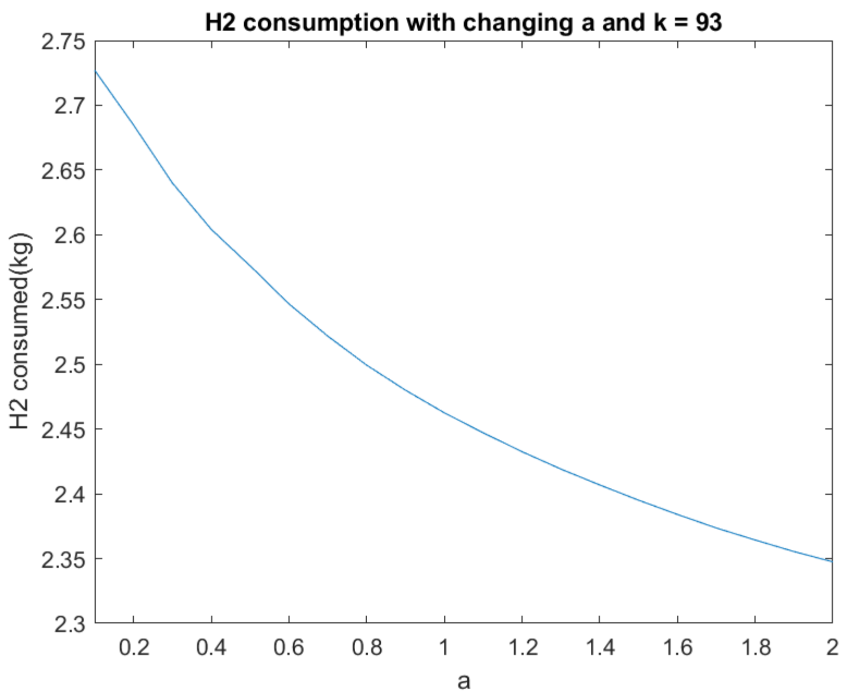

Figure 8.14: Changing H2 consumption for changing a with chosen factor k = 93.

8.1.6. Comparison of different Energy Management Strategies

In this section, different energy management strategies to control the system components of a hybrid power system of a hydrogen powered boat are compared. The results of the different control strategies are shown in Table 8.1. The first two control strategies that are used are rule-based and the last three are different versions of an ECMS. The rule-based controllers are by definition not optimal. The reason for this is that the controllers are based on a limited amount of rules and they cannot find the optimal operating point for the system components for every timestep. The first rule-based controller is the EMS of the H2C boat. With this controller, the fuel cells ramp up and down their output power very fast. The reason for this is that the fuel cells operate at their maximum operating point when the SOC is below 85 percent and they are off when the SOC is higher than 95 percent. This behavior of the fuel cells is not beneficial for the average efficiency and therefore much hydrogen is consumed. With the second rule-based controller, the fuel cells work most of the time on their most efficient operating point. This causes the average efficiency to be much higher when compared to the EMS of the H2C boat. Therefore the hydrogen consumption is also lower. When the SOC is below 30 percent the fuel cells ramp up to their maximum operating point. This ramping up of the output power does not go smoothly and therefore the fuel cells show some quick changes in output power. With this controller, the most efficient operating point for the fuel cells can not be found at all timesteps. The three ECMS variants work in different ways, but all versions minimize the equivalent consumption for every timestep. Because of their different calculations of the penalty factor their behavior is different. With the AP-ECMS as controller, the fuel cells ramp up and down the output power very fast. The reason for this is that the ECMS reacts fast to changes in SOC. This behavior is not beneficial for the efficiency of the fuel cells. The benefit of this controller is that the SOC can be controlled very well. Therefore the SOC at the end is very low and the hydrogen consumption is less than with the rule-based controllers. With the LAP-ECMS as controller, the fuel cells ramp up and down the output power smoothly. The controller lets the SOC drop at the beginning of the cycle and ramps up the output power of the fuel cells when the SOC constraint is close. This ramping up of the fuel cells goes smoothly and the average efficiency of the fuel cells is higher than with the AP-ECMS. With SAP-ECMS as a control strategy, the fuel cells work most of the time around a constant operating point. This operating point is chosen to be the most efficient operating point. If the SOC limits are exceeded the fuel cells ramp their power up or down smoothly due to the penalty factor. Due to this behavior and the chosen operating point, the average efficiency of the fuel cells is the highest for this controller. Due to this also the hydrogen consumption is the lowest. Therefore this controller is chosen to be the optimal controller compared to the other controllers.

Table 8.1: Results of the different energy management strategies with operating profile 1 as input.

EMS:	Hydrogen consumption(kg):	SOC end(%):	Average efficiency fuel cells(%):
H2C	3.09	73,71	53,24
Rule-based	2.51	43,07	58,01
AP-ECMS	2.46	21,67	53,98
LAP-ECMS	2.45	34,39	57,46
SAP-ECMS	2.36	38,08	60,35

8.2. Results of sizing optimization

To solve the sizing problem the objectives, variables, and constraints stated in Chapter 7 are used. The objective is to minimize the weight of the components as defined in Equation 7.2. The control variables are the energy capacity of the battery and the rated power of the fuel cell. To solve the sizing optimization problem the linprog function in Matlab is used. The code used to solve the problem is shown in Appendix A in Figure A.1. For the optimization, the most energy intensive operational profile is used as input. This is operational profile 1 and is shown in Figure 5.4. This is the worst-case scenario and the system components that can cover the energy and power demand of this profile can also cover the other profiles. The total energy demand, E_{demand} is 59.13 kWh. The total duration T of this profile is 3.4 hours. The C_{rate} used to convert the battery energy into power is the same as the C_{rate} of the battery used in the original plant and is 1.45. The usable battery capacity C is 87.5 percent. The reason that it is not 100 percent is because of the SOC constraint of 12.5 percent. The most efficient operating point of the fuel cell P_{fceff} is 35 percent. The results of the sizing optimization problem are shown in Figure 8.15. The blue line shows the Pareto front of all the possible size combinations of the battery and the fuel cell. The red line shows the total weight of the system for the different combinations of battery and fuel cells. The optimal combination with the lowest weight is a battery with 13.17 kWh energy capacity and a fuel cell with a rated power of 39.90 kW. With a lower battery energy capacity the fuel cell rated power has to be bigger to cover the power demand. This causes the total system to be heavier. With a higher battery energy capacity the fuel cell system can be smaller, but to cover the energy demand it cannot be much smaller. Therefore the total weight of the system will increase with a bigger battery. The total weight of this combination of system components is 293 kg. This is a reduction of weight of almost 10 percent compared with the original system. The consequence of this combination of system components is that the battery capacity is more than 50 percent smaller than the original battery and the fuel cell rated power is 5 times bigger than the original system. This means that the fuel cells are now the main power source. The consequence of this is that when the batteries are empty the system can still work with a power of approximately 35 kW. The other consequence of this is that the system consumes more hydrogen. This consideration can be seen in Figure 8.16. In this figure, the blue line shows the weight of the system components with different battery capacities and the corresponding fuel cells. It can be seen that with higher battery capacity the weight of the system components increases after the optimal solution. The red line shows the minimal hydrogen consumption with different battery capacities. It can be seen that with a higher battery capacity, less hydrogen is consumed. This consideration is also shown in Figure 8.17. With a higher weight of the system components, less hydrogen is consumed.

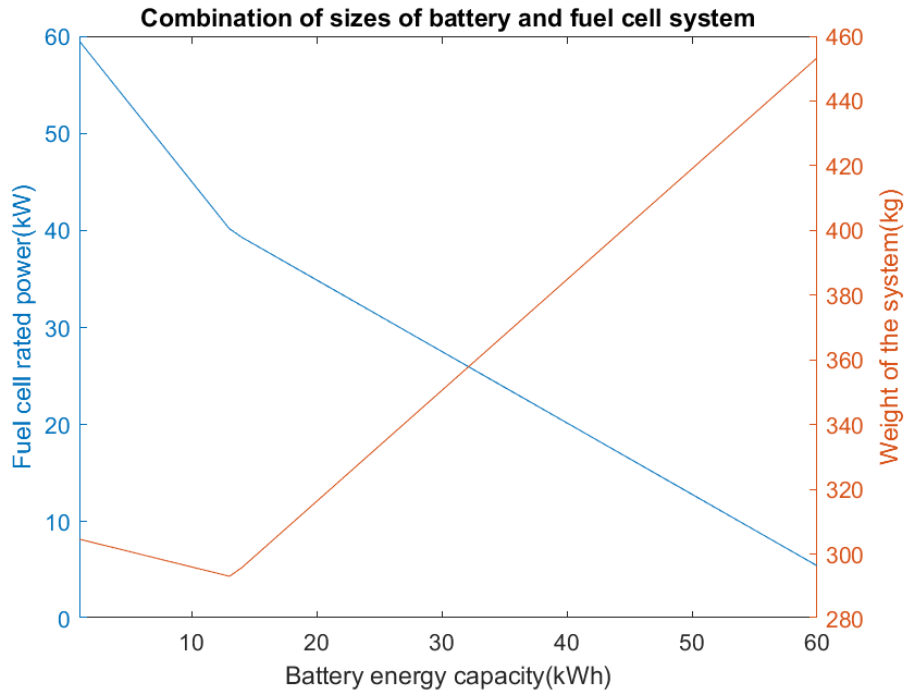

Figure 8.15: Pareto front of optimal size combinations of battery and fuel cell with corresponding weight.

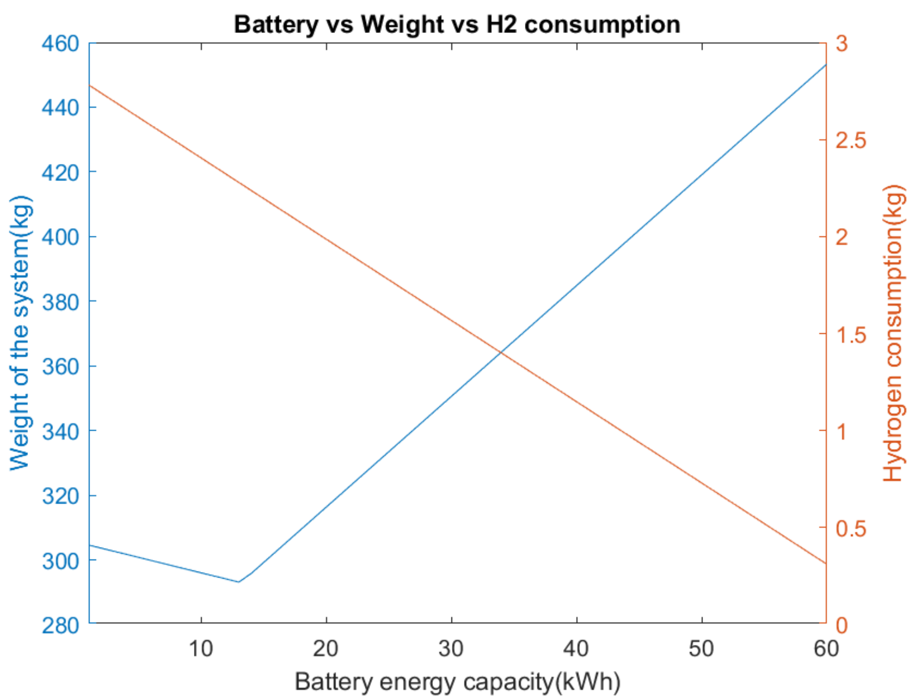

Figure 8.16: Weight and minimal hydrogen consumption for different battery energy capacities.

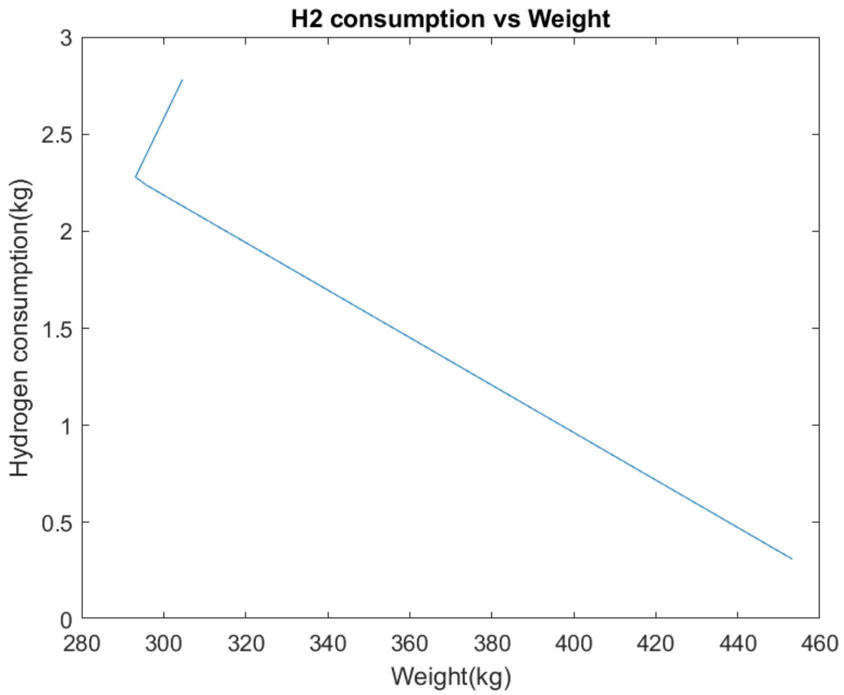

Figure 8.17: Weight and minimal hydrogen consumption.

8.2.1. Discussion of sizing optimization results

The sizing problem is constrained by the energy and power demand of the most energy intensive operational profile. One of the factors that influence the size of the components is the C_{rate} of the battery. With a higher C_{rate} the battery can produce more power with the same energy capacity. Therefore a smaller battery could be used to cover the power demand and the total weight of the system decreases. In the sizing optimization problem, it is chosen to let the fuel cells work at their optimal operating point at all times. This means that they work at 35 percent of their rated power at all times to cover the energy demand. When a higher operating point is chosen the fuel cells rated power could be lower and the total weight would decrease. To calculate the weight of the system components weight factors are used as explained in Chapter 7. For the calculation of the weight factor of the fuel cells, the original system of 4 kW is used. When a bigger fuel cell is used this weight factor can be lower. For example, a fuel cell of 40 kW with a weight of 48 kg exists [28]. This would give a weight factor of 0.833 $\frac{kg}{kW}$ instead of 5 $\frac{kg}{kW}$. When a bigger fuel cell system is used the total weight could decrease therefore.

8.3. Results of combined sizing and control

In this section, the system components with optimal sizes are controlled by the SAP-ECMS controller. The different operational profiles are used as input. This is done to show the robustness of the optimization results. In Figures 8.18, 8.20, 8.22, and 8.24 the output power of the fuel cell and the battery with the different operational profiles used as input are shown. In Figures 8.19, 8.21, 8.23, and 8.25 the SOC of the battery during the different operations are shown. In Table 8.2 the results of the system components controlled by the SAP-ECMS with the different operational profiles as input are shown. Profile 1 is the most energy intensive profile and was used to find the optimal sizes of the system components. According to Figure 8.17 the minimal hydrogen consumption for the optimal sizes is around 2.25 kg with operational profile 1 as input. The hydrogen consumption for the optimal sizes controlled by the SAP-ECMS is around 2.64 kg. The difference is caused by the fact that for the sizing problem, it is assumed that the fuel cells work at their optimal operating point at all times. When the fuel cells are controlled by the SAP-ECMS this is not the case and this can be seen in Figure 8.18. This difference in hydrogen consumption could be used to improve the sizing optimization problem. In Figures 8.22 and 8.24 the output power of the system components with operational profiles 3 and 4 as input is shown. In these figures, it can be seen that the fuel cells operate at their minimum operating point or sometimes shut off. The reason for this is that almost no power is demanded and the SOC reaches its maximum constraint. This behavior causes the average efficiency with these profiles as input to be lower than with operational profiles 1 and 2 as input. A solution to prevent this behavior is to shut the fuel cells off when no power is demanded. Table 8.2 shows that the average efficiency for the fuel cells is above 55 percent for all different profiles. Also the SOC at the end of the cycle is above 50 percent. This means that the battery is always still available at the end of the cycle and the maximum power of the battery combined with the fuel cells can be reached at all times. The hydrogen consumption for all profiles is below 3.1 kg and therefore this controller in combination with the sizes of the system components is suitable to use with the current hydrogen storage of 3.1 kg. The hydrogen consumption for profile 1 is higher than the results shown in 1.1. The reason for this is that the sizes of the system components that are used are different. Therefore more hydrogen is used and less energy is provided by the battery.

Table 8.2: Results for the optimal sizes of the system components controlled by the SAP-ECMS with different operational profiles used as input.

Operational profile:	Hydrogen consumption(kg):	SOC end(%):	Average efficiency fuel cells(%):
Profile 1	2.64	54,87	61,41
Profile 2	0.94	77,67	61,55
Profile 3	0.53	73,99	56,00
Profile 4	2.17	83,79	59,26

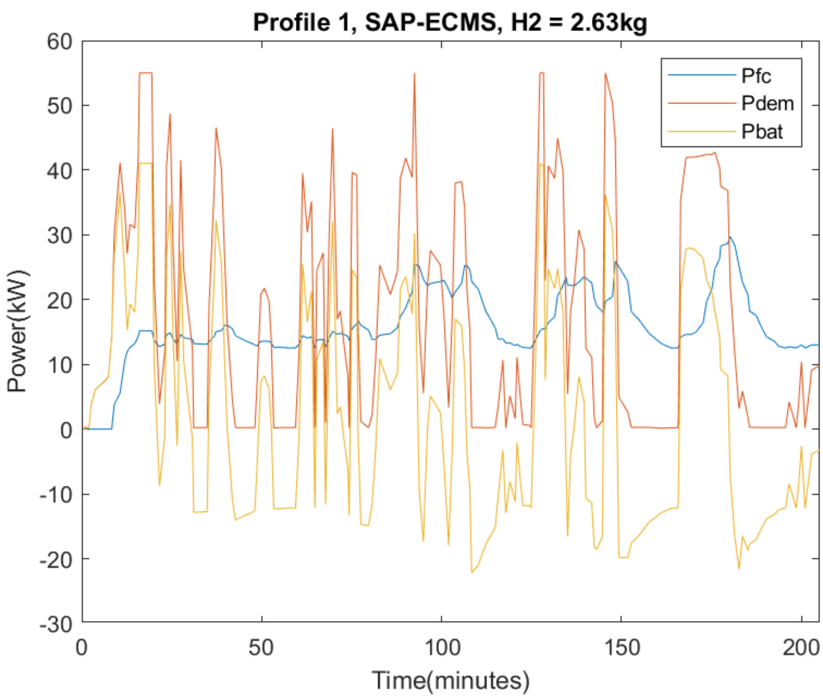

Figure 8.18: Output power of the system components with optimal sizes controlled by SAP-ECMS with operational profile 1 as input.

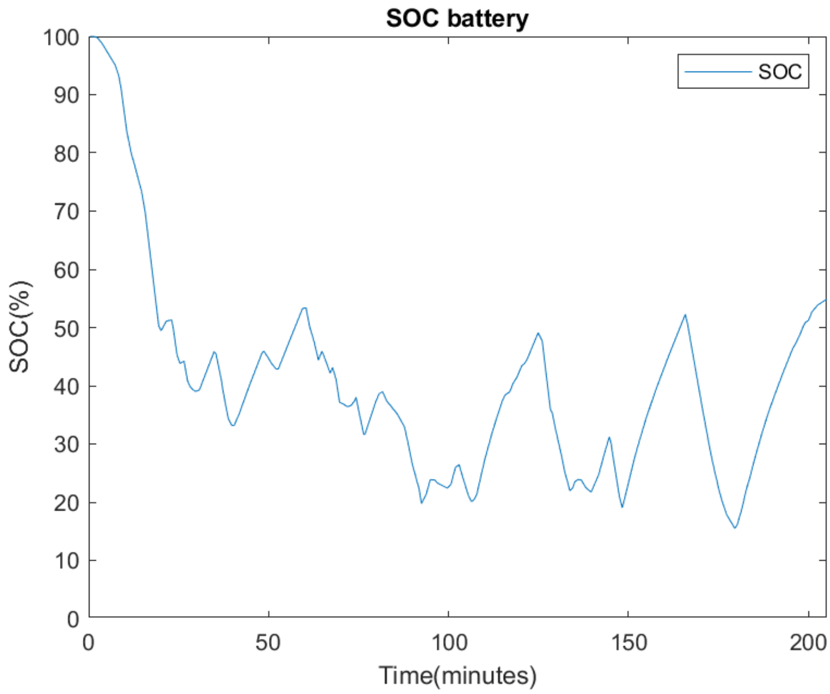

Figure 8.19: SOC of the battery during the cycle shown in Figure 8.18.

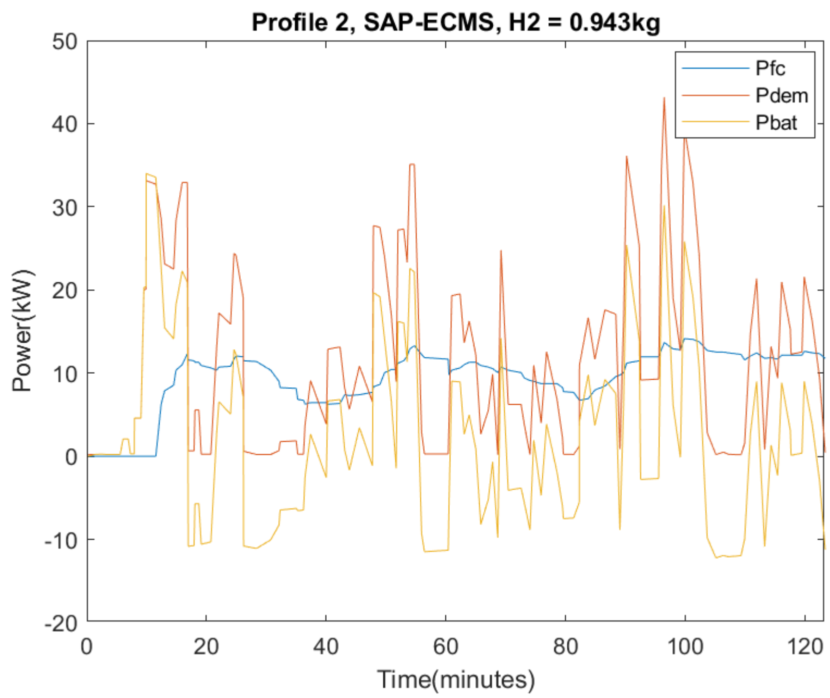

Figure 8.20: Output power of the system components with optimal sizes controlled by SAP-ECMS with operational profile 2 as input.

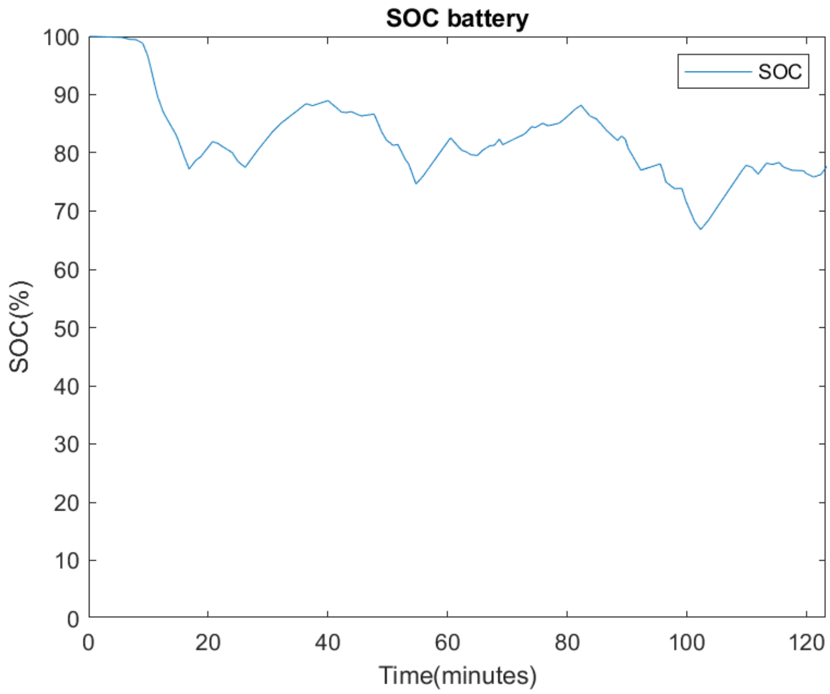

Figure 8.21: SOC of the battery during the cycle shown in Figure 8.20.

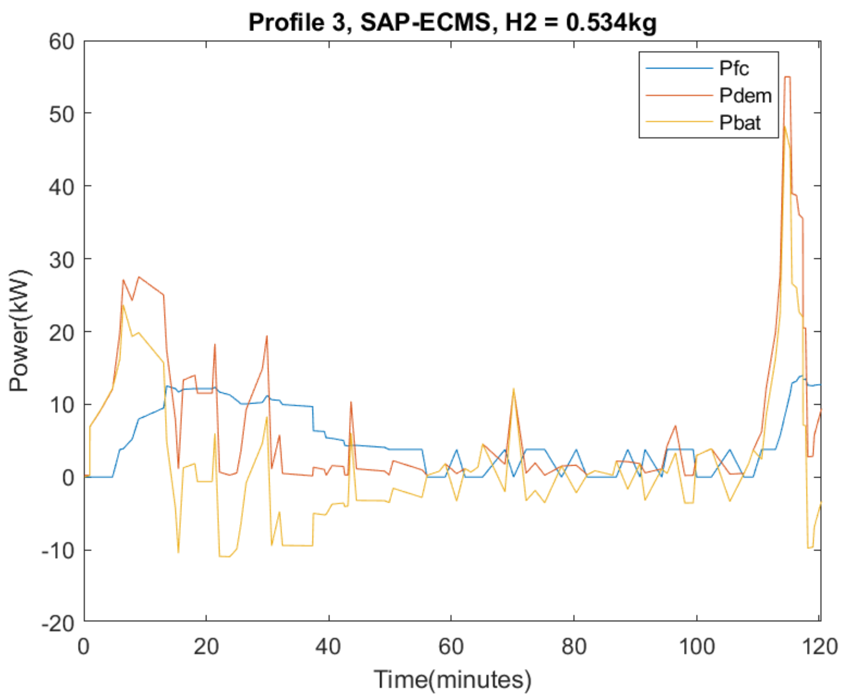

Figure 8.22: Output power of the system components with optimal sizes controlled by SAP-ECMS with operational profile 3 as input.

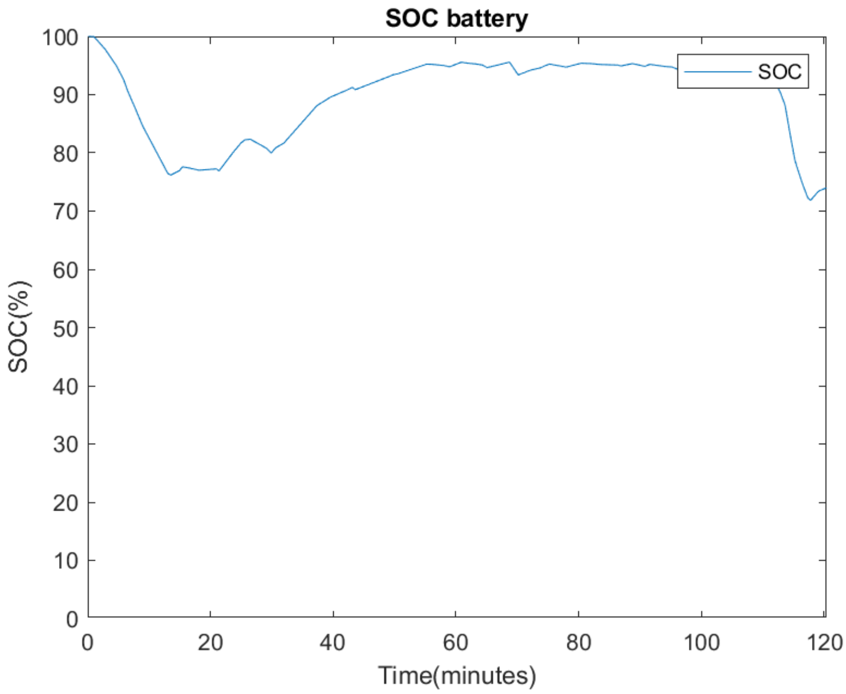

Figure 8.23: SOC of the battery during the cycle shown in Figure 8.22.

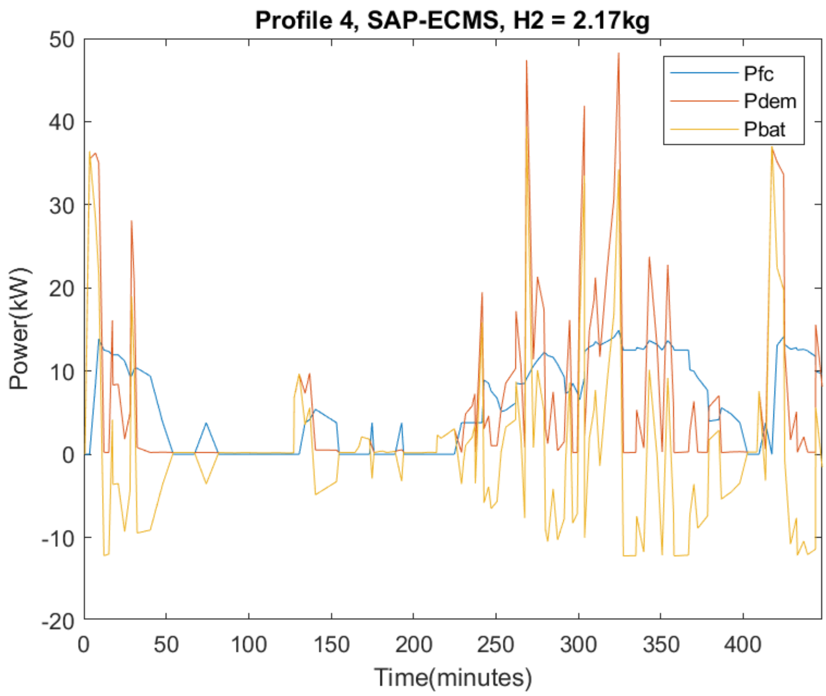

Figure 8.24: Output power of the system components with optimal sizes controlled by SAP-ECMS with operational profile 4 as input.

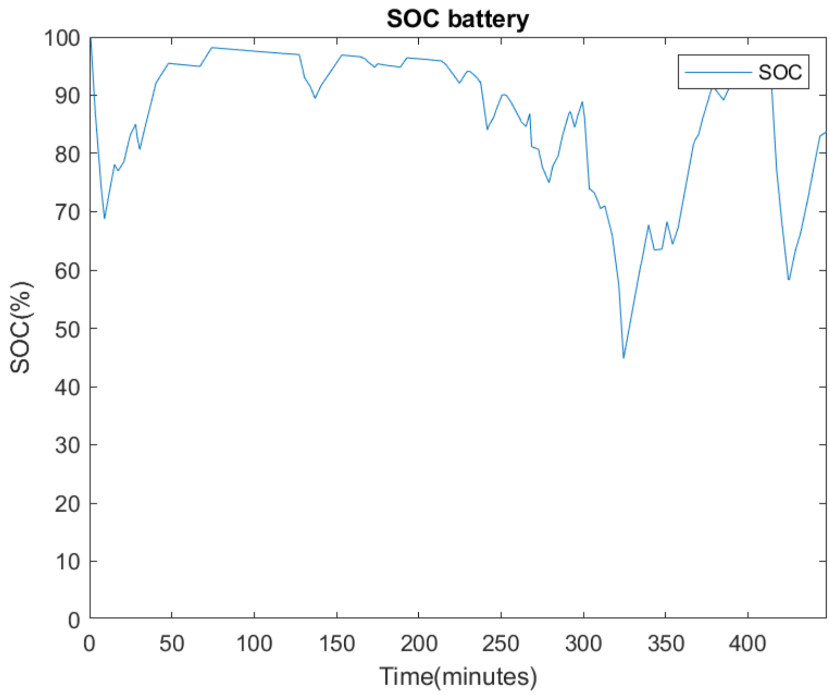

Figure 8.25: SOC of the battery during the cycle shown in Figure 8.24.

8.4. Verification of results

In the section above the results of the output power of the system components controlled by the SAP-ECMS are shown. In this section, the results are verified. In Figures 8.26, 8.27, 8.28 and 8.29 the demanded power and the output power of the battery and the fuel cell added together are shown with the different operational profiles used as input. From these figures, it can be seen that the output power of the system components always matches the demanded power or is higher. This shows that the results of the optimization are robust and that the sizes of system components controlled by the SAP-ECMS are suitable to use to cover the power and energy demand of the operational profiles. The difference between the output power and the demanded power is caused by the losses of the battery. Because of these losses, the battery has to produce more power to provide the demanded power. The percentage of lost energy is 1,05 percent on average for all profiles.

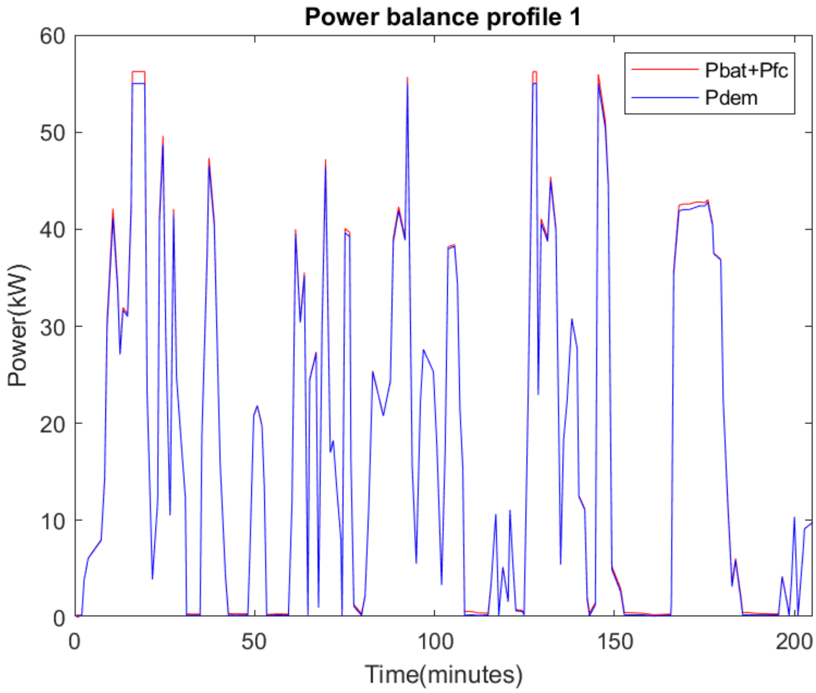

Figure 8.26: Verification of the power balance with profile 1 used as input.

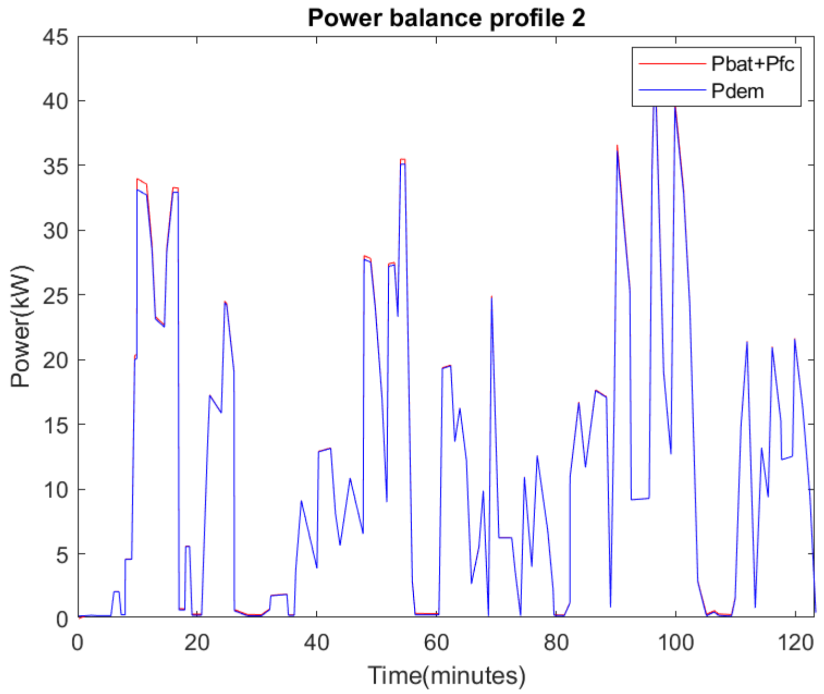

Figure 8.27: Verification of the power balance with profile 2 used as input.

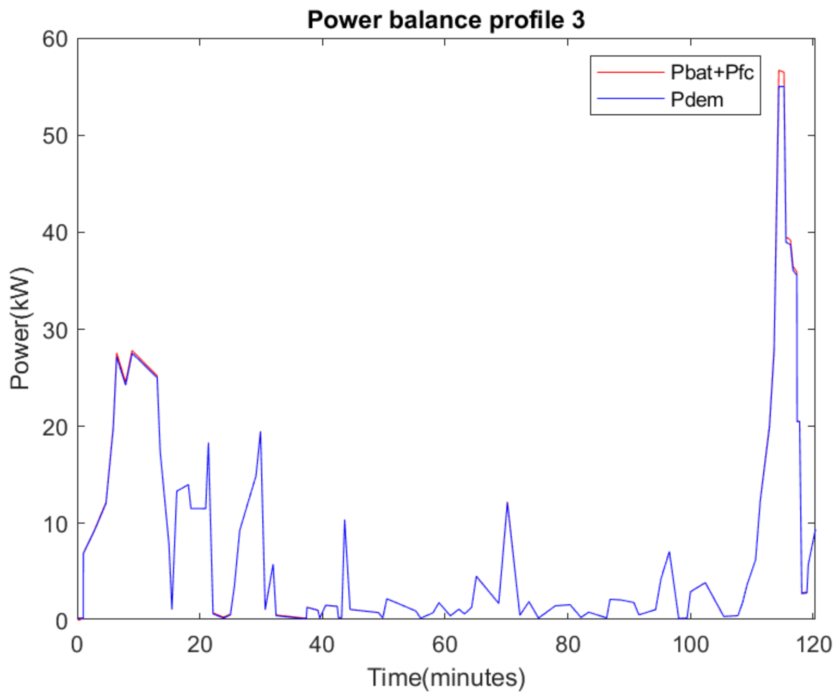

Figure 8.28: Verification of the power balance with profile 3 used as input.

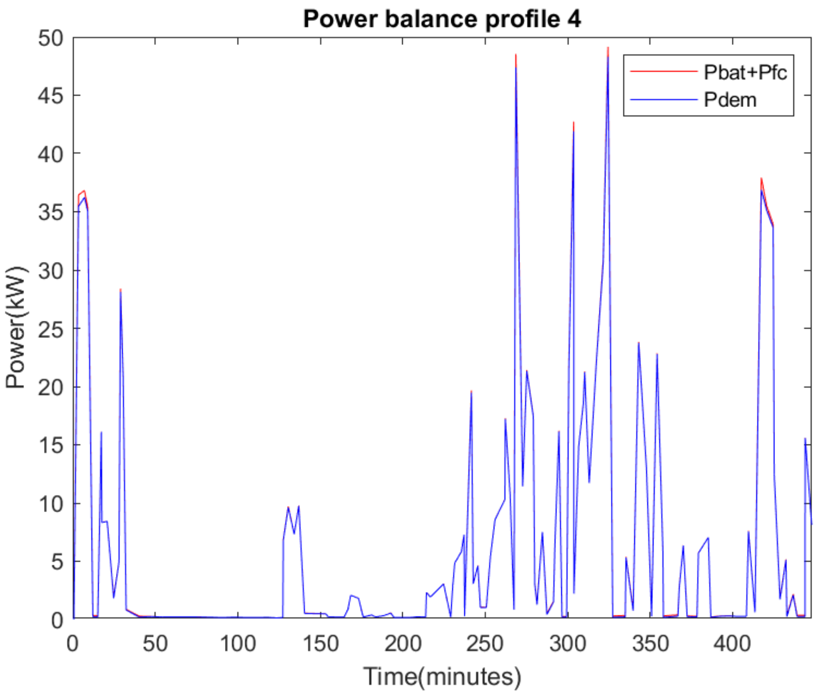

Figure 8.29: Verification of the power balance with profile 4 used as input.

9 Conclusion

This research is based on a real project, namely the H2C boat of the company H2 Marine Solutions. The H2C boat is one of the first zero-emission hydrogen powered vessels in the Netherlands. The system components of the hybrid powersystem are more than twice as heavy as their fossil fuel powered counterpart. The main question of this research is: How can we establish the optimal energy and power of the system components of a hybrid power system with optimal energy management for a zero-emission hydrogen powered boat for different operational profiles? This is a multi-objective double-layer optimization problem. To execute this project different steps are taken. First, different studies on double-layer optimization problems are analyzed in Chapter 2. The outcome of this analysis is that different methods and strategies are used to solve a combined sizing and control problem. The most popular strategy is the nested strategy where the control design is nested in the plant design. Also, different algorithms are used to solve the optimization problem and the most popular is to use an evolutionary algorithm. Unfortunately because of the complexity of solving the combined optimization problem with an evolutionary algorithm and due to lack of time a different strategy is chosen. The sizing and control problems are solved separately and the results are combined. To solve the control problem two different options are possible namely, online or offline optimization. In this research, it is chosen to solve the optimization problem in real-time because then the controller could be used in an actual application. Therefore, an online optimization method, the Equivalent Consumption Minimization Strategy (ECMS) is used.

To solve the optimization problem, first, the case study is described. After this, a model of the system components of the plant is built. The hybrid powertrain consists of fuel cells, a battery system, hydrogen storage, different converters, and a motor. The system components that are modeled in this research are the battery, the fuel cell, and the DC/DC converter. The different operational profiles used in the optimization are made with measured data from the H2C boat. With this data, a powerprofile is made and the speed data is converted into demanded power. Four different operational profiles are used in the optimization to make the result robust.

To find the optimal energy management an ECMS is used. Because there are different variants of ECMS three of them are compared with each other. All ECMS's minimize the instantaneous equivalent consumption. This equivalent consumption is calculated by converting the electric energy of the battery into equivalent hydrogen consumption. By adding this equivalent consumption to the hydrogen consumption the minimum equivalent consumption for every timestep can be found. To convert the battery power into equivalent hydrogen consumption an Equivalent Factor (EF) is used. This EF is a combination between a chosen factor and a penalty factor. The differences between the three ECMS's are mainly in the calculation of the penalty factor. This penalty factor makes sure that the State Of Charge (SOC) of the battery stays between its constraints. The different ECMS's are compared with each other and also with two rule-based controllers. The two rule-based controllers are by definition sub-optimal. The reason for this is that they use rules to control the system components and can not find the optimal operating point for every timestep. The first rule-based controller is the EMS of the H2C boat. When the system components are controlled by this controller, the average efficiency of the fuel cells is the lowest. Also, the hydrogen consumption is the highest compared to the other controllers. With the second rule-based controller, the average efficiency of the fuel cells is higher. Also, the hydrogen consumption is lower compared to the other rule-based controller. With this controller, the fuel cells work on their most efficient operating point most of the time. But still applies to this rule-based controller that it cannot find the optimal operating point for the system components for every timestep. The different ECMS's show different behavior when controlling the system components. With AP-ECMS as the controller, the fuel cells ramp up and down their output power fast. This causes a low average efficiency for the fuel cells. The benefit of this controller is that the SOC can be controlled very well and therefore the hydrogen consumption is low. With LAP-ECMS as the controller, the SOC drops very fast at the beginning of the cycle and the fuel cells are off. When the SOC reaches its constraint the fuel cell output power is ramped up smoothly. With this controller, the fuel cells have a higher average efficiency than with the AP-ECMS but almost the same amount of hydrogen consumption. The downside of this controller is that the battery SOC lowers very fast in the beginning and when the battery is empty only the fuel cell output power can be used. With SAP-ECMS as the controller, the fuel cell works around a steady operating point most of the time. When this operating point is chosen to be the most efficient operating point the average efficiency of the fuel cells is the highest and the hydrogen consumption the lowest compared to the other controllers. With this controller, the output power of the fuel cells is ramped up or down smoothly when the SOC comes close to the constraints. By doing this in a smooth way the optimal operating point is found for every timestep. Therefore the SAP-ECMS is chosen as the optimal controller.

To establish the optimal energy and power of the system components the optimization problem is described with linear objectives and constraints. The sizing problem is solved by the linprog function in Matlab. To find the optimal sizes the most energy intensive operational profile is used as input. This is done to make sure that the system components are able to cover the energy and power demands of all profiles. The objective of the sizing problem is to minimize the weight of the system components. The results of this problem show that the weight of the system components can be decreased by using a bigger fuel cell and a smaller battery than the original system. The consideration between a bigger fuel cell and a smaller battery is a consideration between lower weight and more hydrogen consumption. The optimal solution to the optimization problem is a rated power of 39.90 kW for the fuel cell system and an energy capacity of 13.17 kWh for the battery system. With a smaller battery energy capacity the fuel cell rated power has to be bigger to cover the power demand and the total weight becomes higher. With a bigger battery, the fuel cell can be smaller but not much smaller because the energy demand has to be satisfied and therefore the total weight will be higher. The weight of the optimal combination of system components is 293 kg in total and this is a reduction of 10 percent compared to the weight of the original combination of system components used in the H2C boat. A battery system with a higher C-rate could even lead to a smaller battery and a lower weight of the total system. The weight could also be lowered when a different and bigger fuel cell system is used than the original 4 kW fuel cell systems. When a bigger fuel cell is implemented it is recommended to use an optimal energy management strategy such as the SAP-ECMS to control the system components and to minimize the equivalent consumption. This could lead to a higher average efficiency for the fuel cells and lower hydrogen consumption. This is preferable above a rule-based controller which can not find the optimal operating point at all timesteps for the system components.

10 Reflection and recommendations

In this chapter, a reflection is given on the research. Also, recommendations to improve the research are given. The first section reflects on the model used in this research. After this, the method to solve the optimization problem is reflected. The last part gives some recommendations about the ECMS.

10.1. Model

The model used to simulate the system components is described in Chapter 5. This model is kept simple to focus more on solving the optimization problem. By improving the model the optimization result could be more accurate. The model can be improved in different ways for the different components. Not al components that are in the plant are modeled. For example, the AC motor of the plant is not modeled. Also, the DC/AC converter is missing. The DC/DC converter is modeled but in a very simple way considering an efficiency of 95 percent. For the battery model, a very simple model based on internal resistance is used. To improve this model a more accurate model could be used where the internal resistance is influenced by the SOC, SOH, and temperature. Such a model would improve the accuracy of the efficiency of the battery. For the fuel cell, the efficiency is modeled, but not validated with measurements of a real fuel cell. To improve the model the components could be validated with measurements from the real components. To achieve the operational profile measurements are used to achieve reliable data. The operational profiles that are used could be more accurate with smaller timesteps to improve the results.

10.2. Methodology

The methodology to solve the optimization problem is described in Chapter 3. The problem is a multi-objective double-layer optimization problem. The original idea was to solve this problem combined in a nested structure. Unfortunately, this problem was too complex to solve in the remaining time. Therefore the sizing and control problems are separated. The sizing problem is solved by a linear solver, namely linprog in Matlab. The control problem is solved by an ECMS. By separating the sizing and control problem the results become less accurate. The results of the sizing problem influence the results of the control problem and also the other way around. A recommendation is therefore to solve the sizing and control problem combined in a nested structure. This could improve the accuracy of the results.

10.3. ECMS

It was chosen to solve the control problem in real-time because the controller could then be used in a real application. To do this an online optimization strategy has to be used and it was chosen to use an ECMS. During the research, it was found that there are different variants of

ECMS, and therefore they are researched and compared in Chapter 6. Most likely more variants of ECMS exist and therefore it could be beneficial to also investigate these. Due to lack of time, not more EMCS's are investigated in this research. A better version of ECMS could exist when the AP-ECMS and SAP-ECMS are combined. This could lead to a smooth adaptive ECMS in which the SOC is controlled very well.

References

[1] Xuezhou Wang et al. “Sizing and Control of a Hybrid Ship Propulsion System Using Multi-Objective Double-Layer Optimization”. In: *IEEE Access* 9 (2021), pp. 72587–72601. DOI: 10.1109/ACCESS.2021.3080195.

[2] Cees van Bladel. *H2 marine solutions*. URL: https://h2marinesolutions.com/.

[3] *C-230 Green Deal on Maritime and Inland Shipping and Ports The parties*. Tech. rep. URL: https://www.greendeals.nl/green-deals/green-deal-zeevaart-binnenvaart-en-havens.

[4] *BN250 H2C boat (hydrogen)*. URL: https://www.habbeke.nl/project/bn250-h2c-boat-hydrogen/.

[5] Emilia Silvas et al. *Review of Optimization Strategies for System-Level Design in Hybrid Electric Vehicles*. Jan. 2016. DOI: 10.1109/TVT.2016.2547897.

[6] Yanbiao Feng et al. “Integrated design and control optimization of fuel cell hybrid mining truck with minimized lifecycle cost”. In: *Applied Energy* 270 (July 2020). DOI: 10.1016/j.apenergy.2020.115164.

[7] Xiaohua Wu et al. “Convex programming energy management and components sizing of a plug-in fuel cell urban logistics vehicle”. In: *Journal of Power Sources* 423 (May 2019), pp. 358–366. DOI: 10.1016/j.jpowsour.2019.03.044.

[8] Armin Letafat et al. “Simultaneous energy management and optimal components sizing of a zero-emission ferry boat”. In: *Journal of Energy Storage* 28 (Apr. 2020). DOI: 10.1016/j.est.2020.101215.

[9] Jianyun Zhu et al. “Bi-level optimal sizing and energy management of hybrid electric propulsion systems”. In: *Applied Energy* 260 (Feb. 2020). DOI: 10.1016/j.apenergy.2019.114134.

[10] Seyedali Mirjalili. “SCA: A Sine Cosine Algorithm for solving optimization problems”. In: *Knowledge-Based Systems* 96 (Mar. 2016), pp. 120–133. DOI: 10.1016/j.knosys.2015.12.022.

[11] E. Tzimas et al. *Hydrogen storage : state-of-the-art and future perspective*. European Commission, Directorate-General, Joint Research Centre, 2003.

[12] Office of Energy Efficiency Renewable Energy. U.S. Department of Energy. *Hydrogen Fuel Cell Engines MODULE 1: HYDROGEN PROPERTIES CONTENTS*. Tech. rep. URL: https://www.energy.gov/eere/fuelcells/articles/hydrogen-fuel-cell-engines-and-related-technologies-course-manual.

[13] Tomas Tronstad et al. *Study on the use of fuel cells in shipping DNV GL 1 MARITIME STUDY ON THE USE OF FUEL CELLS IN SHIPPING*. Tech. rep. EMSA European Maritime Safety Agency.

[14] Intelligent energy. *Fuel cell H2C*. URL: https://www.intelligent-energy.com/our-products/ie-power-hydrogen-fuel-cell-module/power-4/.

[15] Torqeedo. *Deep Blue 50 RXL System*. URL: https://www.torqeedo.com/en/products/outboards/deep-blue/deep-blue-50-r/M-3201-00.html.

[16] Siamak Farhad et al. "Introducing the energy efficiency map of lithium-ion batteries". In: *International Journal of Energy Research* 43.2 (Feb. 2019), pp. 931–944. DOI: 10.1002/er.4332.

[17] Olivier Tremblay et al. "A generic battery model for the dynamic simulation of hybrid electric vehicles". In: *VPPC 2007 - Proceedings of the 2007 IEEE Vehicle Power and Propulsion Conference*. 2007, pp. 284–289. DOI: 10.1109/VPPC.2007.4544139.

[18] Gaizka Saldaña et al. "Analysis of the current electric battery models for electric vehicle simulation". In: *Energies* 12.14 (2019). DOI: 10.3390/en12142750.

[19] Ronald M. Dell et al. "Hydrogen, Fuel Cells and Fuel Cell Vehicles". In: *Towards Sustainable Road Transport*. Elsevier, 2014, pp. 260–295. DOI: 10.1016/b978-0-12-404616-0.00008-6.

[20] Mohsen Banaei et al. "A Comparative Analysis of Optimal Operation Scenarios in Hybrid Emission-Free Ferry Ships". In: *IEEE Transactions on Transportation Electrification* 6.1 (Mar. 2020), pp. 318–333. DOI: 10.1109/TTE.2020.2970674.

[21] Ameen M. Bassam et al. "Development of a multi-scheme energy management strategy for a hybrid fuel cell driven passenger ship". In: *International Journal of Hydrogen Energy* 42.1 (Jan. 2017), pp. 623–635. DOI: 10.1016/j.ijhydene.2016.08.209.

[22] B C W Visser et al. *The Clean RHIB Challenge Haalbaarheidsonderzoek naar een emissieloze volgboot*. Tech. rep.

[23] Ameen M. Bassam et al. "Development of a multi-scheme energy management strategy for a hybrid fuel cell driven passenger ship". In: *International Journal of Hydrogen Energy* 42.1 (Jan. 2017), pp. 623–635. DOI: 10.1016/j.ijhydene.2016.08.209.

[24] Yongbing Xiang et al. "An ecms for multi-objective energy management strategy of parallel diesel electric hybrid ship based on ant colony optimization algorithm". In: *Energies* 14.4 (Feb. 2021). DOI: 10.3390/en14040810.

[25] Huizhong Gao et al. "Adaptive real-time optimal energy management strategy based on equivalent factors optimization for hybrid fuel cell system". In: *International Journal of Hydrogen Energy* 46.5 (Jan. 2021), pp. 4329–4338. DOI: 10.1016/j.ijhydene.2020.10.205.

[26] M. Kalikatzarakis et al. "Ship energy management for hybrid propulsion and power supply with shore charging". In: *Control Engineering Practice* 76 (July 2018), pp. 133–154. DOI: 10.1016/j.conengprac.2018.04.009.

[27] B He et al. *Optimisation-based energy management of series hybrid vehicles considering transient behaviour*. Tech. rep. 1. 2006, pp. 79–96.

[28] Hyfindr. *Fuel cell stack EH-81 40 kW*. URL: https://hyfindr.com/marketplace/components/fuel-cell-stacks/pem-stacks/fuel-cell-stack-eh-81-40-kw/.

A

Matlab code sizing optimization

```
%% Size optimization
%Energy and power demand of operational profile 1:
E = 59;                   %Required energy(kWh)
T = 3.4;                  %Time(hours)
P = 55;                   %Maximum demanded power(kW)

%Battery characteristics
Ebatmax = 60;             %Max size battery(kWh)
Ebatmin = 1;              %Min size battery(kWh)
Ecapacity = 0.875;        %Capacity battery(%)
Crate = 1.45;             %Tune parameter voor de power constraint
Wb = 7.1;                 %Weight factor(kg/kWh)

%Fuel cell characteristics
Pfcmax = 60;              %Max size fuel cell(kW)
Pfcmin = 1;               %Min size fuel cell(kW)
Peff = 0.35;              %Most efficient operating point
Efc = T*Peff;             %Time multiplied with most efficient operating point
MaxPPfc = 0.9;            %Maximum operating point
Wfc = 5;                  %Weight factor(kg/kW)

% %energy constraint
% -Ebat*Ecapacity -Pfc*Efc <= -E;

% %power constraint
% -Ebat*Crate - Pfc*Pfcmax <= -P

% %objective function
% Wb*Ebat + Wfc*Pfc == W

W = [Wb Wfc];
A = [-1 0; 1 0; 0 -1; 0 1; -Ecapacity -Efc;-Crate -MaxPPfc];
b = [-Ebatmin Ebatmax -Pfcmin Pfcmax -E -P];
[x, fval, exitflag] = linprog(W,A,b)
```

Figure A.1: Matlab code of size optimization problem.