

Energy Management Strategy for a Hybrid Container Crane

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Master of Science Thesis

Energy Management Strategy for a Hybrid Container Crane

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Abstract

Siemens has developed a hybrid drive system for rubber-tired gantry (RTG) cranes that drastically reduces their fuel consumption. The hybrid crane uses ultracapacitors to store energy that is regenerated when a container is lowered or during braking, and reuses this energy to assist the engine later on. The main goal of this thesis is improving the crane's energy management strategy. This is the system that optimizes the fuel cost by controlling in real time how and when the two available power sources of the hybrid crane are used.

Currently, the crane uses a rule-based heuristic strategy. This is reliable and predictable, but does not achieve optimal results and is difficult to tune. As an alternative, this thesis proposes to use an Equivalent Consumption Minimization Strategy (ECMS). This is an optimization-based strategy of limited complexity that revolves around assigning a weight to the usage of the ultracapacitors that represents the equivalent "future fuel cost". The idea is that using the ultracapacitors at one moment means that they cannot be used anymore in the next, which will then cost extra fuel.

The main issue for ECMS is selecting a proper way to assign the future fuel cost. In the end, two new strategies are presented that each have their own approach to this issue. The first uses feedback from the state of the ultracapacitors to assign a weight to the ultracapacitor power, the second uses predictions about the upcoming power demand.

The new strategies were compared to the current one using a custom-built RTG crane simulator. The simulation results show that new strategies consistently outperform the current system, significantly improving the fuel savings and therefore increasing the operational profits. Encouraged by these results, Siemens plans to test the new approach on hybrid cranes in the Port of Felixstowe (UK).

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Preface

Somehow, container cranes have managed to work their way into every major project I have performed during my studies. My final bachelor's project at Electrical Engineering—"IPP" for intimi—involved creating the electrical instrumentation for the simulator crane of the TU Delft department of Transport and Logistics. After this project, I made the jump from Electrical Engineering to Systems and Control. At the end of the first year, I was confronted with another container crane during the Integration Project. It seems inevitable that the subject of my final thesis also has to do with container cranes.

When I stepped into prof. Hans Hellendoorn's office in the end of 2007, the purpose of the visit was discussing the study tour to Israel that we were planning to organize in the following year. Over the course of a few more visits, this resulted in a number of valuable contacts for our study tour, including Thomas Cohn, ex-CEO of Siemens Nederland and the uncrowned king of Israeli startup companies. On top of this, professor Hans also went along with us to Israel, where we had a great time discovering the Israeli culture and technology.

During the preparation of the study tour, we also started talking about the possibility of graduating at Siemens. The initial plan was to work on model-based fault detection (applied to container cranes of course), but soon the choice was made to continue Joe George's work for the hybrid ECO-RTG. After a meeting with Rob Kuilboer at Siemens in The Hague, a formal assignment was drafted and I started my internship in august 2008.

During my internship, I learned a lot more than just designing energy management strategies. Actually, I think I learned far more about business politics and economics than I did about engineering. The crane department was just going through a reorganization and the management was partially moved to Germany. It seemed to me that no one in The Hague was completely happy with the way things were going.

At the same time, the global financial crisis broke out. For me, the crisis had two direct repercussions. First and foremost, the dropping oil prices meant that my fancy graph of exploding fuel costs became obsolete overnight. On the other hand, the topics for the lunchtime discussions did take a welcome diversion from the policy for flying business class and the confusion about everybody's job description to falling stocks and companies going bankrupt. Especially Rob turned out to have a wealth of macro-economic knowledge and little-known

statistics about world trade. I never would have guessed that the Baltic Dry Index had nothing to do with the Baltic countries.

Overall, I can look back at a very nice time at Siemens and I am quite proud of the end results. Before continuing to the rest of this thesis, I want to thank a number of people that have helped me along the way. First of all my supervisor, Hans Hellendoorn. You were a great support for me, especially during the final writing weeks where I was struggling to get anything on paper. The encouraging discussions about my progress really pulled me through, not to mention the weekly deadlines. I will be recommending you to anyone looking for a graduation supervisor.

Another important role was played by my supervisor at Siemens, Rob Kuilboer. I know you had a lot of other things on your mind (the ECO-RTG gearbox springs to mind), but you still were able to keep track of my progress and help me out wherever you could. I appreciate how you involved me in some projects besides my own thesis work, and also left me free to spend time on the organization of the study tour. Besides this, I also really enjoyed hearing about your experience as an expat in China.

Back in Delft, there are a number of fellow students that perhaps did not contribute directly to this thesis, but did make life a lot more fun while I was working on it. I have to thank my MTB241 flatmates Siebe and Tamar for always finding creative ways of dragging me away from the computer screen to (briefly) get my mind away from optimization algorithms. Even HJ Thijs contributed to this sometimes, although, really, you should have spent less time in your other “homes”. Tamar deserves a special mention for his part in the black gold alliance, keeping me supplied with coffee when I needed it most.

I also want to thank ex-*MTBewoner* Kenneth for keeping me active in sports throughout the project. Although the recent long distance running hype is a bridge too far for me, our traditional squash games were a great way to let off steam. I just wish you would let me win a little more often.

Finally, there is my eternal project partner Vincent. I have lost count of how many projects we did together during our six years together in Delft, but it seems like I completed at least 50 percent of my courses by working together with you in some way. It was quite a change to have to find all my own bugs in this project. I wish you a lot of success with completing your thesis on the Moving Base, I am sure you will manage without me.

A final, special word of thanks is meant for my family. To my parents, thank you for supporting me all these years of my studies. Mom, I always knew there was at least one person who was interested in what I was doing, even though sometimes I still struggle to properly explain it to you. Dad, thanks for your advice on many things, even proofreading my thesis. Iris, my big little sister, thanks for the long *Vogelpark Walsrode Verhalen* that kept me entertained when I didn't feel like writing. I wish you a lot of luck with the completion of your new Master. To Opa en Oma, I am really lucky to have you as grandparents. Thank you for always being there, from the bottom of my heart (and also from my wife's bottom). Finally, I want to thank Mieke for always supporting me and being so incredibly understanding whenever I decided I would go *kluizenaar* for the weekend. I love you, you mean the world to me.

Steven Mulder
Delft, June 30, 2009

“An algorithm must be seen to be believed.”

— *Donald E. Knuth*, The Art of Computer Programming

“Meer control is meer gaver.”

— *Siebe Krijgsman*, MSc (2008)

Chapter 1

General Introduction

This chapter serves as a general introduction for the rest of the thesis. Section 1.1 starts with some background information on the subject of container cranes and on the development of Siemens' hybrid ECO-RTG crane. This is followed in Section 1.2 by the definition of the problem that is going to be addressed in this thesis, along with the way this problem is split up into smaller subproblems. Finally, Section 1.3 outlines the way the rest of the thesis is structured.

1.1 Background

1.1.1 Container shipping

Millions of containers are transported all over the world, making over 200 million trips every year between seaports with container terminals such as the Port of Los Angeles in Fig. 1.1. Reliable and efficient handling of these containers is crucial, because the competition between container terminals is fierce.

Within a terminal, there are a couple of types of crane in operation, see Fig. 1.2. First there are the ship-to-shore (STS) cranes, that have to load or unload container ships as quickly as possible, usually with multiple cranes working on a single ship. The containers then have to be transported “horizontally” to the stacking yard behind the STS cranes. This is done by much smaller vehicles like container tractors, automated guided vehicles (AGVs) or straddle carriers. Finally, the containers are stacked for the most efficient use of space and time, before they are transferred onto trucks or trains that transport them over land. In smaller terminals, this stacking can also be done by straddle carriers, but usually this is done by larger rubber-tired gantry (RTG) or rail-mounted gantry (RMG) cranes.

This thesis focused solely on RTG cranes. The cranes straddle multiple lanes of stacked containers (see Fig. 1.3), and can move 20 or 40 ft long containers weighing up to 65 t. As the name suggests, rubber-tired gantry cranes have rubber tires that enable them to move from one line of stacked containers to another. This gives them an advantage over RMG cranes,

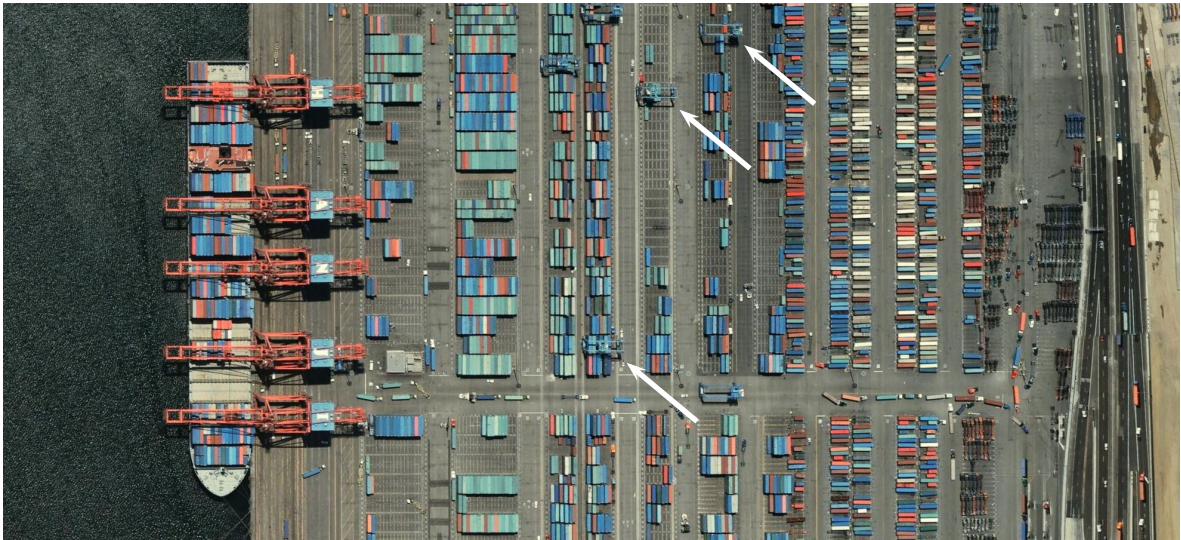


Figure 1.1: Top view of a container terminal in the Port of Los Angeles (some RTG cranes are denoted with arrows)



(a) STS crane



(b) AGV



(c) Container tractor



(d) Straddle carrier



(e) RTG crane



(f) RMG crane

Figure 1.2: Container handling vehicles

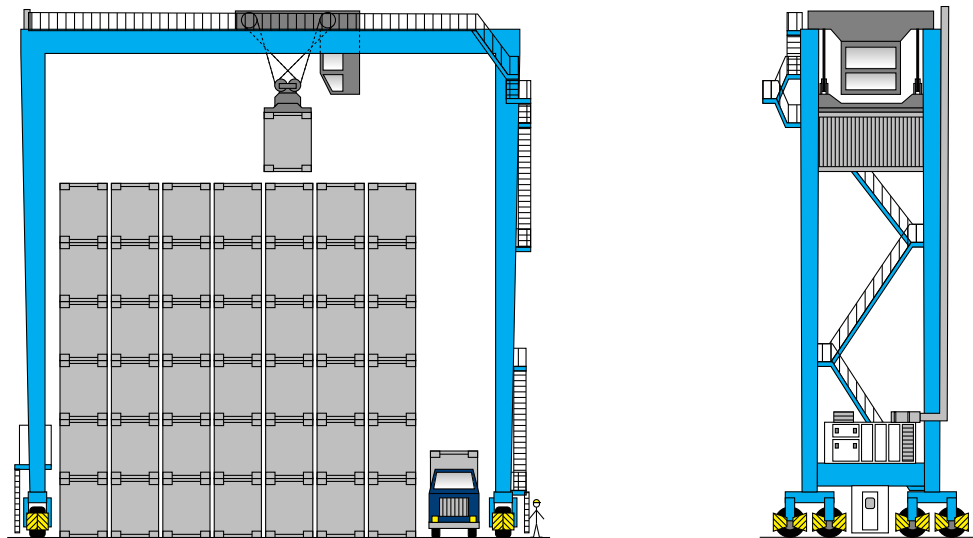


Figure 1.3: Front and side view of an RTG crane

which are limited to a single stack lane because of its rail tracks. The cranes are driven by an operator who is seated in a control cabin on the trolley at the top of the crane.

The vast majority of the cranes that are built today are manufactured by the Shanghai Zhenhua Heavy Industries Co. (formerly ZPMC). Siemens is one of the electrical suppliers for this company, selling the electrical drive systems, the power pack and also other electrical systems such as anti-sway control. Siemens is constantly striving to keep its place as one of the preferred suppliers for the OEM crane builders, against competition such as ABB from Switzerland and the Japanese Yaskawa and Fuji Electric.

1.1.2 Siemens hybrid ECO-RTG

Recently, Siemens laid out its long term view of the biggest challenges facing the world today. The coming decades will be dominated by three *megatrends*. One megatrend is demographic change, world population is growing and people are living longer. The second trend is urbanization, meaning the movement of people to large cities, and the third trend is climate change. If we wish to accommodate the future growing demand for energy while also limiting climate change, we will need a smart energy mix. After all, today's energy conservation is the most important, most secure and cheapest source of future energy.

As an exponent of this world view, Siemens developed an energy saving container crane, the ECO-RTG, which doubled fuel efficiency by using improved generators and engine management. The next step in the development of the ECO-RTG system is the production of a hybrid version. This hybrid crane is able to store regenerated energy in ultracapacitors and reuse it later on.

Other electrical suppliers are also developing their own hybrid RTG crane solutions. The Japanese manufacturer Sumitomo has developed a system based on lithium-ion batteries [1], and the Californian company VYCON has a system based on a flywheel battery [2]. All manufacturers are reporting impressive fuel economy figures, so it is vital for Siemens to stay ahead of the competition.

An important aspect of the hybrid system is the control policy that optimizes the use of the regenerated energy. By using a strategy that makes smart decisions about when and how to use the secondary ultracapacitor power source, the overall efficiency of the crane can be optimized. In the literature this is known as energy management. Due to the advent of hybrid cars, this has been a popular research subject in recent years. The challenge in energy management is making the best use of the limited storage capacity of the secondary source, so that the primary combustion engine runs as efficiently as possible. What makes improving the energy management strategy so interesting is that it only changes the software of the system, so no additional hardware costs are necessary.

This study focuses on the design of an optimal energy management strategy for Siemens' hybrid ECO-RTG crane. It is a continuation of the Master's Thesis work by Joe George [3]. In his project, Joe George developed a system that can calculate an optimal strategy for a given power demand, where the existing research into hybrid cars was used as a starting point. Although this particular system could not be directly applied in practice for various reasons, it did prove that improving the strategy can lead to significant fuel consumption gains.

1.2 Problem statement

1.2.1 Main thesis goal

With the tough competition in the "green" RTG business, Siemens wants to stay in the lead by achieving the best fuel economy at a relatively low cost. This leads to the following formal definition of the problem that is addressed in this thesis:

How can the energy management strategy of the Siemens hybrid ECO-RTG crane be improved in order to enhance its fuel economy?

An important constraint on the possible solutions is that the performance of the crane cannot be compromised. A fuel efficient crane that is much slower than a normal crane is not interesting for terminal operators, whose main concern is still container throughput.

1.2.2 Subproblems

At the start of the project it was not exactly clear to the people at Siemens what the performance of the hybrid ECO-RTG is, and whether it could be improved significantly. A prototype crane is in use at the Port of Algeciras (Spain), and it has shown promising fuel consumption figures, but essentially the hybrid crane remains a black box. The only way to see whether adjustments to the system improve the performance is by putting the crane into operation for a longer period of time. After this period, data about the total fuel consumption during that period can give an indication of the fuel efficiency. For structured improvements to the system is necessary to have some way of analyzing the crane's fuel consumption, so creating a simulator for this is the first subproblem to address in the thesis.

The simulator can be split up in two distinct parts. The first part is simulating the crane's power demand. There are some measurements available of the power flow when the crane is in action, but these are both limited in duration and in variety. A solution is required to make

it possible to simulate the crane's performance in any possible circumstance. For instance, to simulate the fuel consumption during a busy period, or while the crane is moving a series of very heavy containers.

The second part of the simulator is a model of the crane's power sources, which can simulate the fuel consumption of the crane given a certain power demand. This model also includes the behavior of the ultracapacitors, which function both as energy storage and as power source.

Summarizing, the first subproblem is:

1. Create a simulator to analyze the fuel consumption of the hybrid ECO-RTG crane.
 - (a) Create a system to mimic the power demand of the crane during specific types of operations.
 - (b) Create a model that simulates the total power system of the hybrid ECO-RTG, including the fuel consumption and the ultracapacitors.

When the simulator is available, the focus can be on the energy management strategies. The first step in improving the strategy is looking at the current situation, and analyzing what is good and what is not. Based on this information, a choice can be made on how to proceed in order to improve the current situation. The final step is actually implementing these improvements in a new strategy, so the second subproblem is formulated as:

2. Design a system that improves the current energy management strategy.
 - (a) Analyze the current strategy to find its strong points and weaknesses.
 - (b) Find an approach to improve the weaknesses of the current strategy
 - (c) Implement the improved strategy so it can be tested in the simulator.

It turns out—perhaps unsurprisingly—that there is no definitive best approach to improve the current energy management strategy. In the end, the choice was made to implement two new strategies and compare them using the simulator. Of course, the original strategy should also be taken into account in this comparison, so in total there are three alternatives. To make a good comparison of the strategies, well-designed experiments are necessary. The experiments have to uncover as much relevant information about the strategies as possible, so a well-founded choice for the best strategy can be made in the end. This task forms the third and final subproblem of this thesis:

3. Select the best strategy from the three alternatives.
 - (a) Design experiments that show relevant characteristics of the strategies.
 - (b) Analyze the simulation results to find the best strategy.

1.3 Outline

The contents of the rest of this thesis are structured much in the same way as the three subproblems. In the first two chapters, the simulator is discussed. Chapter 2 explains the

power consumption of RTG cranes, leading to a system that simulates the power demand during operation. Chapter 3 then deals with the mathematical model that is created of the crane's power sources. This model serves both as a simulation model and as the basis for the energy management strategy.

In Chapter 4 the actual design of the strategy is explained, which corresponds with the second subproblem. The chapter starts with a brief discussion of the current strategy. The performance of this strategy will function as a benchmark for the new designs. Next, a brief survey is given of the various alternative approaches that are available in the literature, and the choice for an optimization-based strategy is explained. The final two sections of Chapter 4 explain the implementation of the two new strategies.

The third subproblem is next. The comparison of the different strategies is handled in Chapter 5. Simulation results of the different strategies under various circumstances are presented in this chapter, so they can be compared and the best strategy is found.

Finally, Chapter 6 draws conclusions about the success of the project, and gives some recommendations about possibilities for further improvement.

Chapter 2

Power Demand Model

The first step in the design process of any technical system is understanding the way it is going to be used. The energy management strategy that we want to design will control the power supply for a larger system, the rubber-tired gantry (RTG) crane. Therefore it is necessary to research the RTG crane's typical power demand.

The complete power system of the ECO-RTG is shown in Fig. 2.1. This chapter is only concerned with the bottom half of the system, i.e., the power consumers. The goal is to create a model of the typical power consumption of the crane during operation. Section 2.1 explains the different subsystems that consume power on the crane. Next, Section 2.2 explains how these subsystems are used during typical operation, which leads to a model of the typical power demand of an RTG crane. This system will be combined with a model of the crane's power sources—the top half of Fig. 2.1—to form the simulation framework in which the strategies are tested.

2.1 Power consuming subsystems

It is often easy to relate an unknown drivetrain to that of a standard personal car. Unlike the situation on a car, an RTG crane moves using electric motors, its combustion engine is only used to generate electrical energy for these motors. Another thing that is different from a car's power system is that the power demand is dominated by only the propulsion system, there are several major power consumers on an RTG crane. The power demand is due to a combination of the following subsystems, which are also depicted in Fig. 2.1.

- The hoist mechanism, powered by a single electric motor capable of peaks of 200–400 kW.
- The wheels for moving the complete crane around the yard, driven by the gantry motors. These motors are typically four heavy-duty motors capable of 40 kW of power each.
- The trolley with the control cabin, and the spreader suspended beneath it. The spreader is the part of the crane that attaches to the top of a container. The trolley can move

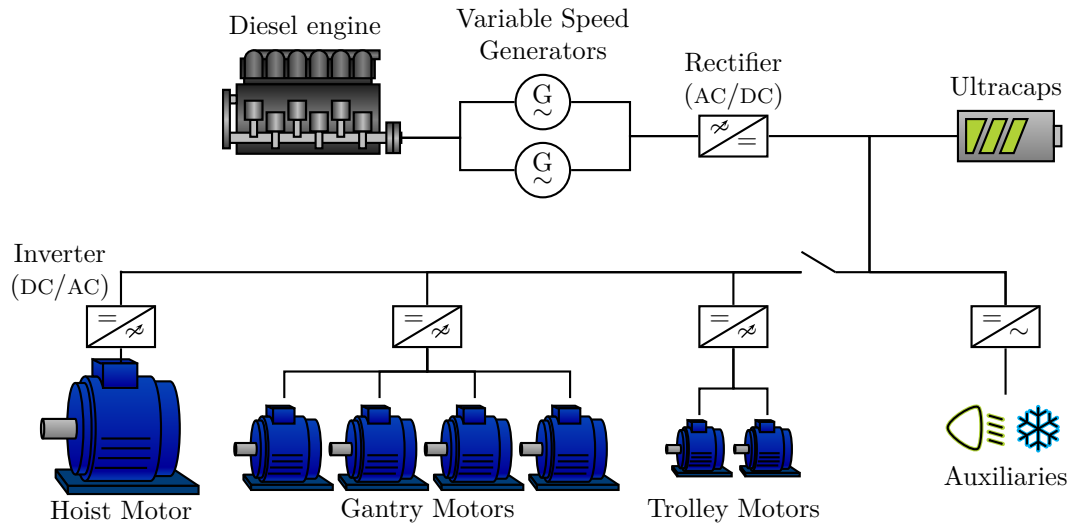


Figure 2.1: Power architecture of the ECO-RTG

on rails at the top of the crane and is driven by two trolley motors with 20 kW nominal power each.

- The auxiliary systems, such as the heating, ventilating, and air conditioning (HVAC) systems, the big lights for night time operation, and the crane's computer system. These systems have a more or less constant power demand of 10–30 kW, depending on the circumstances, e.g., temperature or daylight.

During operation of the crane, all subsystems contribute to the total power demand. The hoist, gantry and trolley motors only need power when they are moving, while the auxiliary systems are always on. The specific usage of the subsystems during the cranes normal operation is discussed in the next section.

2.2 Typical operation

The activities of an RTG crane can be separated in four categories:

- Loading a container from the stack down to a truck.
- Unloading a container from a truck onto the stack.
- Gantry movement from one row of stacked containers to another.
- Idling.

The loading or unloading of a container is usually called a “move”. The gantry movement will not be considered specifically in this thesis, because this operation is not done very often compared to the other three activities. In general, the contribution of the gantry movements to the power demand is very similar to that of the trolley system.

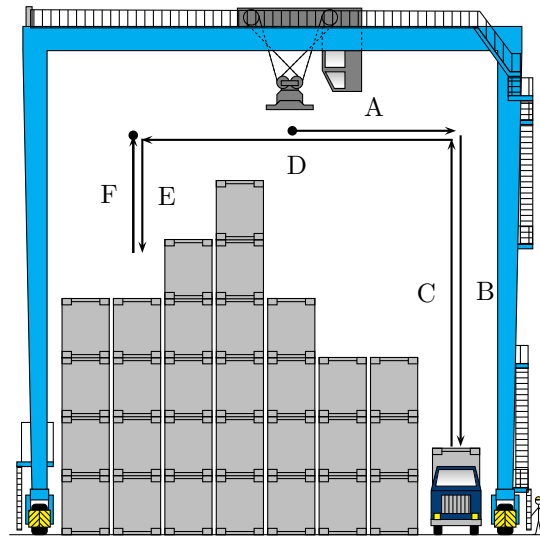


Figure 2.2: Movements of an RTG crane unloading a truck

2.2.1 Crane movements during operation

Figure 2.2 shows the crane's movements during the unloading of a truck:

- A. move the trolley over the pick-up point (either above the stack or a truck);
- B. lower the empty spreader onto the container;
- C. hoist the container up to clear the top of the stack;
- D. move the container over the release point;
- E. lower the container to the release point;
- F. lift the empty spreader from the container.

The basic movements during a container move cycle are identical for both loading and unloading. The only difference between the two is the height of the pickup and release points, i.e., the length of the “B–C” and “E–F” sections. In general, unloading a truck costs more net energy because the container is moved up to the stack.

2.2.2 Power demand for one move

The power demand during each section “A” to “F” depends on the required force, the speed of the movement and the efficiency of the motors and inverters. The required force can also be negative when the container is lowered or during braking, so the power demand is modeled as:

$$P_d(k) = \begin{cases} \eta \cdot F(k) \cdot v(k) & \text{if } F(k) \geq 0 \\ \frac{1}{\eta} \cdot F(k) \cdot v(k) & \text{if } F(k) < 0 \end{cases}$$

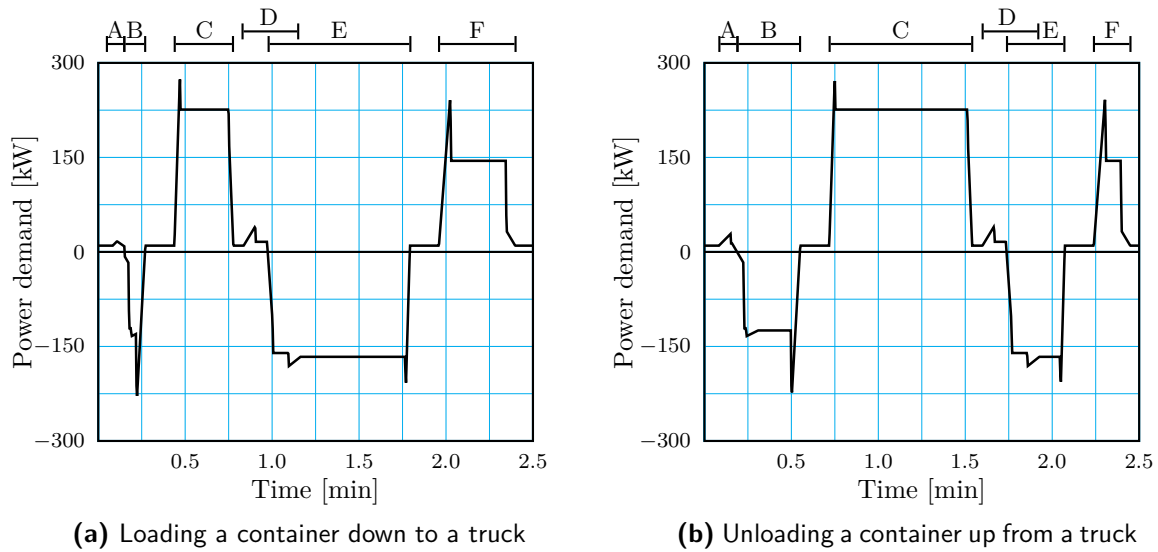


Figure 2.3: Typical power demand during loading and unloading of a 40 t container from a truck onto the stack (row 6, height 5)

Note that the model is in discrete time. This is the most logical choice, because the simulator will be implemented on a computer. The final energy management strategies will also be implemented in discrete time.

The motor efficiency η is assumed to be a fixed value that depends on whether the crane is hoisting or using the trolley or gantry motors. The required force $F(k)$ depends on the weight of the load that the crane is carrying. This weight determines the gravitational force that the hoist motors need to overcome, and also the frictional forces for the trolley and gantry movements. To limit the required power for very heavy containers, the speed $v(k)$ of the movements is adjusted by the crane software according to the weight of the load. This means that moving heavy containers takes more time, but the maximum power demand is not too high for the generator to handle.

Besides the continuous power during each move, the motors need to accelerate and overcome the inertia of the crane's moving parts such as the big cable reels. This creates a peak of extra power demand at the start of each movement. On the other hand, there also is a peak of negative power each time the crane decelerates at the end of each movement, albeit somewhat smaller because of the losses in the electric motors and inverters.

Figure 2.3 shows the modeled power demand during both loading and unloading moves. When the power demand is positive, the crane has to supply power to the electric motors. During the sections where the power demand is negative, energy is released to the crane, e.g., during braking or lowering of the container. In regular cranes this energy is dissipated by the brakes, but the hybrid ECO-RTG can store it in the ultracapacitors so it can be reused later on. It is clear that the hoist movements dominate the power demand of the crane. The influence of the speed of the movements is visible by relatively small difference in the height of the peaks when the crane is empty and when it is full, e.g., between “B” and “E”. The peaks in the demand during acceleration and deceleration are also visible.

Table 2.1: Key figures for the three general activity profiles

Profile	Avg. move duration	Avg. idle time per move	Avg. moves per hour
Quiet	150 sec	200 sec	10 move/hr
Normal	150 sec	100 sec	14 move/hr
Busy	150 sec	< 10 sec	23 move/hr

2.2.3 Varying level of busyness

Over the course of a day of activities, the number of container moves per hour will vary according to the level of activity in the container terminal. When a ship is docked, containers are loaded or unloaded as quickly as possible, creating a peak of activity in the terminal. Conversely, there can also be relatively quiet periods during which the crane spends a lot of time idling between moves. Table 2.1 shows the average idle times and number of cranes per hour for three general activity profiles, which will be used in simulations of the crane's power demand. Figure 2.4 shows the power demand for three levels of activity in simulations.

The varying idle times can have an important effect on the choice for the best strategy. To save fuel, the engine of the diesel generator set (GenSet) is usually shut off during idle periods in hybrid cranes. Even though the power demand is only 10–30 kW, during longer idle times this can significantly decrease the energy level of the ultracapacitors at the start of a new move. Sometimes it is even necessary to restart the diesel generator set and briefly recharge the ultracapacitors.

It has to be noted that the power demand model is not validated in the sense that it is guaranteed to mimic the crane's power demand for each specific movement 100% accurately. After all, this is not the goal of the model, it will only be used as a simulation of the power demand of the crane while it is loading and unloading different containers, so the energy management strategy have realistic input signals to work with. In this sense, the power demand model is sufficiently accurate.

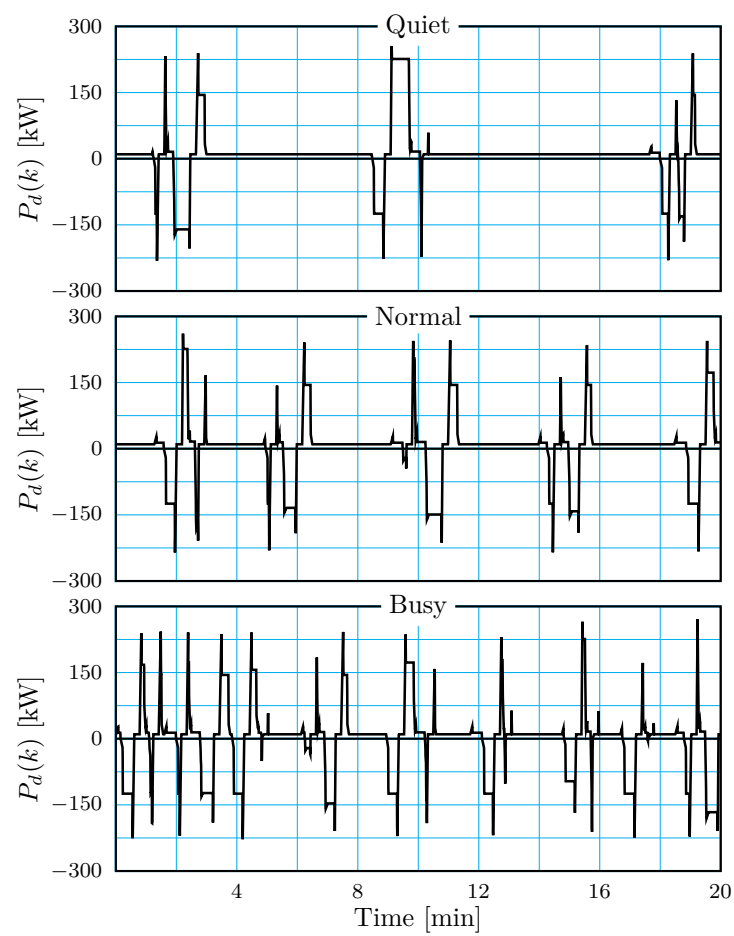


Figure 2.4: Power demand during quiet, normal, and busy operational activity

Chapter 3

Power Supply Model

The previous chapter set the first steps toward the creation of a simulator for the hybrid ECO-RTG. The power system was discussed in general and a model for the power demand was developed. The next step for the simulator is creating a model for the power generating system of the crane. The model of the power system is also needed for the design of an optimal energy management strategy. The model should simulate the power behavior of the real crane, i.e., the electrical power use and fuel consumption.

The hybrid ECO-RTG crane has two power sources on board: the diesel generator set (GenSet) and the ultracapacitor bank. This chapter is split up in a similar way: after the introduction of the model goals and approach in Section 3.1, Section 3.2 discusses the model of the GenSet, and Section 3.3 the ultracapacitors. After this, Section 3.4 concludes with an overview of the complete crane simulator model.

3.1 Introduction

3.1.1 Power system overview

Figure 3.1 shows a schematic overview of the power system in the hybrid ECO-RTG crane. On the right side there are the power consumers: the electric motors and the auxiliary systems like the lighting and the air-conditioning. The power demand of these systems was discussed in the previous chapter. On the left side there are the GenSet and the ultracapacitors, which have to fulfill the power demand.

The two power sources of the hybrid ECO-RTG crane each have their own energy “reservoir”, the GenSet has its diesel fuel tank and the ultracapacitors have electrical charge stored in the capacitors. The ultracapacitors also have the ability to store regenerated energy coming from the electric motors, increasing the amount of stored charge. Obviously the GenSet cannot store regenerated energy and convert it back into fuel.

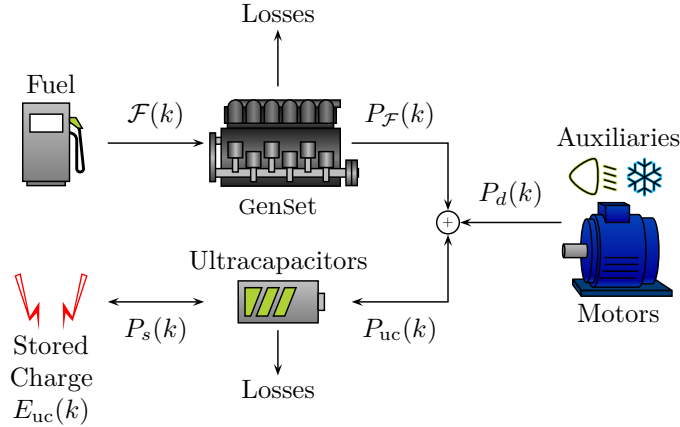


Figure 3.1: Overview of the power system in the hybrid ECO-RTG

3.1.2 Model goals and approach

The task of the energy management strategy is to optimize the fuel cost and ultracapacitor storage power, $\mathcal{F}(k)$ and $P_s(k)$. This is done by controlling the setpoints for the GenSet and ultracapacitors, $P_F(k)$, $P_{uc}(k)$. Therefore, the model that is developed in this chapter is concerned with the efficiency with which the energy from the fuel and the charge reservoirs is delivered to the crane, i.e., the relation between $\mathcal{F}(k)$ and $P_F(k)$, and between $P_s(k)$ and $P_{uc}(k)$. However, the application of the model in the calculation of the new strategies means that there are limits on the time it costs to calculate the simulated power flows.

The most accurate modeling results can be achieved by describing the system as a set of differential equations [4]. In this way all dynamics of the system can be captured in the model. However, this approach has a major drawback: it has a relatively high computational complexity so it is unsuited for application in real-time strategies [5].

The alternative approach is using a quasi-static model [6]. Instead of incorporating all the dynamics of the system in the model, the power flows are modeled using static mappings. Some dynamic effects can still be incorporated in the model, such as the startup fuel cost of the engine or the influence of the state of charge of the ultracapacitors. This approach has been successfully used for energy management design in the past, see for instance [7, 8, 9]. Therefore, the same approach is used in this thesis.

3.2 Diesel generator set

3.2.1 Introduction

Most cranes in container terminals are connected to a fixed electrical power grid. rubber-tired gantry (RTG) cranes are an exception to this rule, because they have to be able to move around and switch from one stack lane to another, making it difficult to connect them to a fixed grid. There are projects to fit yards with conducting rails to remove this problem, e.g., Conductix-Wampfler [10], but this limits mobility and is not practical in a lot of cases. Therefore RTG cranes are traditionally equipped with a large diesel generator set (GenSet).

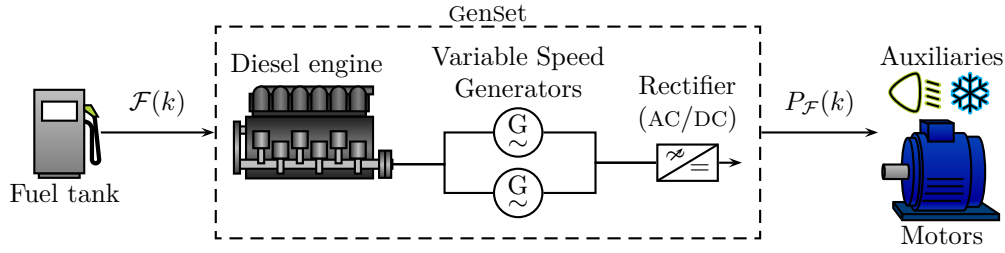


Figure 3.2: Schematic of the GenSet model

The GenSet system is comprised of a large diesel internal combustion engine, which is connected to one or more electric generators via a step-up gearbox. Finally, a rectifier converts the generated current from AC to DC, before it is distributed to the various motors and other systems.

Traditional RTG cranes use the GenSet very inefficiently. The GenSet engine runs at a constant speed of 1500 or 1800 rpm regardless of whether the crane is moving containers or simply idling momentarily. Having the engine run at constant high speeds when there is only little power demand means that it is often used in an inefficient working point. Therefore, when the crane is idling it consumes a lot of unnecessary fuel, even though it is only supplying power to the auxiliary systems like heating, ventilating, and air conditioning (HVAC) and the computer system.

In an attempt to solve the problem of the inefficient GenSet working point, Siemens and terminal operator APM have developed their ECO-RTG solution. Its main improvement lies in the introduction of a variable speed generator (VSG) and a smart engine controller. Thanks to these innovations, the engine can run at variable speed according to the power demand from the system. This way, when the crane is idling, the speed of the VSG can be lowered and so fuel consumption can be reduced drastically. Field tests in the Port of Algeciras APM container terminal in Spain have shown that the ECO-RTG lowers fuel consumption by 50 percent compared to traditional RTG cranes [11].

3.2.2 Diesel generator set model

The complete GenSet system is taken as a single block box during modeling, as depicted in Fig. 3.2. It is not necessary to model all the individual subsystems separately, because the energy management strategy will only act as a global controller. In other words, the specific speed and current setpoints of the subsystems are not within the scope of the model, only the global relation between the delivered power $P_{\mathcal{F}}(k)$ and the fuel consumption $\mathcal{F}(k)$ is considered.

Measurements

Siemens recently switched engine suppliers for the ECO-RTG from MAN to SCANIA. To perform some performance and robustness tests (on subjects unrelated to this thesis) on the new power pack, a single GenSet module was installed at the Siemens facility in Zoetermeer. In between the regular testing there was an opportunity to do some measurements on the fuel consumption of the GenSet.

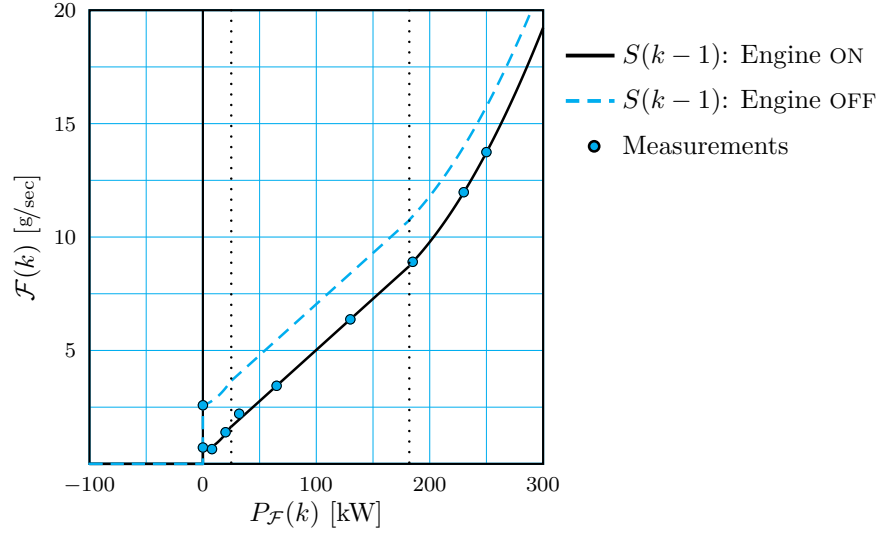


Figure 3.3: GenSet fuel consumption measurements (circles) and model

The fuel consumption experiment is set up as follows: the GenSet is used to power a large electric motor, which is in turn connected to a second electric motor. The second motor is used to supply a counterforce to the first motor, so the power demand of the first motor can be adjusted at will.

Using this setup, engineers took measurements of the steady-state fuel consumption at nine different power delivery setpoints. In the SCANIA engine, the fuel consumption can be read directly from the engine control software. Ideally, even more measurements would have been taken, but measuring the fuel consumption was not the main purpose of the test sessions, so this data is all that is available.

Aside from the steady-state measurements, the engineers observed that the GenSet consumes extra fuel when starting up from standstill. Overcoming the initial inertia of the engine and generators costs 2.6 g of extra diesel, equivalent to producing 50 kJ of energy for the electric motors.

Modeling

Figure 3.3 shows the measurement data and the model that was created based on these measurements. The model is split up in two cases, depending on the ON/OFF state of the engine, $S(k)$. When $S(k-1) = \text{OFF}$, there is an extra startup fuel penalty $\mathcal{F}_{\text{st}}$ added to the fuel cost.

The model is created by performing a piecewise quadratic fit in the regions 0–25 kW, 25–182 kW and >182 kW. In each region, the fuel consumption is modeled as:

$$\mathcal{F}(k) = \begin{cases} a_2 \cdot P_{\mathcal{F}}(k)^2 + a_1 \cdot P_{\mathcal{F}}(k) + a_0 & \text{if } S(k-1) = \text{ON} \\ a_2 \cdot P_{\mathcal{F}}(k)^2 + a_1 \cdot P_{\mathcal{F}}(k) + a_0 + \mathcal{F}_{\text{st}} & \text{if } S(k-1) = \text{OFF} \end{cases}$$

In the region between 25–182 kW, the quadratic term $a_2 \cdot P_{\mathcal{F}}(k)$ is actually equal to zero, to keep the model as simple as possible.

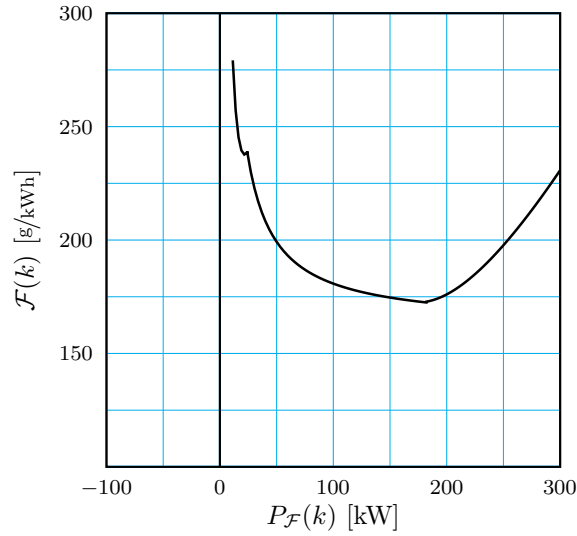


Figure 3.4: Specific fuel consumption of the GenSet

To get some insight in the efficiency of the GenSet, Fig. 3.4 shows the fuel cost per kWh of produced energy, also known as the specific fuel consumption. It shows that the GenSet is most efficient in the region 150–200 kW, and the performance rapidly deteriorates for lower and higher power delivery. This is typical behavior for combustion engines. The energy management strategy will try to keep the engine running inside this region as much as possible. This explains why it is so beneficial to switch off the engine during the idle periods of the crane, when the power demand is low.

3.3 Ultracapacitor bank model

The ultracapacitor bank forms the second power source of the hybrid ECO-RTG crane. Ultracapacitors are a type of capacitors with very high energy density thanks to very porous carbon electrodes and special double-layer dielectric material. They are sometimes also known as supercapacitors or double-layer capacitors. Schneuwly et al. provide a more in-depth description of the technology [12]. Current ultracapacitors can have capacitance values that are literally thousands times higher than conventional capacitors. Compared to batteries and flywheels they can handle higher peaks in power, which makes them especially suited for use in container cranes.

During the operation of an RTG crane, there are a lot of opportunities to capture regenerated energy, for example when lowering of the containers or during braking of the crane. This regenerated energy can then be reused to assist the GenSet later on during operation, keeping it in its most efficient region of 150–200 kW or even switching it off.

3.3.1 Ultracapacitor data

Siemens uses custom-made Maxwell ultracapacitor banks with 1.38 kWh maximum storage capacity, of which only 1.1 kWh is actually usable. Without assistance of the GenSet, this is enough for about 10 min of idling, or hoisting a single container to the top of the crane.

Table 3.1: Ultracapacitor data

Capacitance	C	25.2 F
Internal resistance	R_{int}	42.5 m Ω
Maximum voltage	$v_{\text{uc, max}}$	630 V
Minimum voltage	$v_{\text{uc, min}}$	300 V
Maximum current (1 sec peak)	i_{peak}	750 A
Maximum current (continuous)	i_{max}	150 A
DC-DC-converter efficiency	η_{dc}	0.92 per unit

When the energy level is too low, the current through the ultracapacitors will be too large for safe operation.

No measurements were performed to test the performance of these banks, so the power flow model has to be based on some fundamental physics and data from Maxwell. The most important data for the ultracapacitor model is collected in Table 3.1.

3.3.2 Ultracapacitor bank model

The ultracapacitor stores energy using the same principle as regular capacitors, by collecting charge on its two conducting plates, which generates a voltage across them:

$$E_{\text{uc}}(k) = \frac{1}{2} C \cdot u_{\text{int}}(k)^2 \quad (3.1)$$

When the ultracapacitors are charged or discharged during a time step, the energy level changes as follows:

$$E_{\text{uc}}(k+1) = E_{\text{uc}}(k) - P_s(k) \cdot h$$

where h is the sample time. In the rest of this thesis, h is chosen as 1 sec, so it can be dropped from further equations. The above equation can also be expressed non-recursively:

$$E_{\text{uc}}(k) = E_{\text{uc}}(1) - \sum_{i=1}^{k-1} P_s(i) \quad (3.2)$$

where $E_{\text{uc}}(1)$ is the energy level at the start of the simulation. In order to arrive at the relation between $E_{\text{uc}}(k)$ and the true ultracapacitor power $P_{\text{uc}}(k)$, the efficiency of the ultracapacitors needs to be discussed first.

The efficiency of the ultracapacitors is defined by the relationship between $P_{\text{uc}}(k)$, the power delivered to or from the crane's motors, and $P_s(k)$, the power going in or out of the energy storage. Between the ultracapacitors' energy storage and the motors there are two components where losses occur: inside the DC/DC converter, which maintains the constant output voltage of the unit; and in the ultracapacitor bank itself. Figure 3.5 shows the schematic of the ultracapacitor power model.

The first component where losses occur is the DC/DC converter. These losses are modeled by a static efficiency factor $\eta_{\text{dcdc}} = 0.92$ between the power at the side of the ultracapacitor

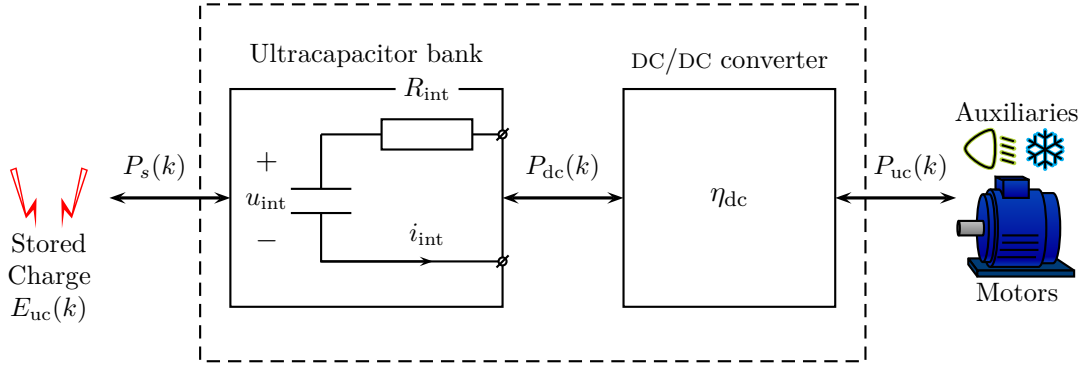


Figure 3.5: Schematic of ultracapacitor bank model

bank, and the power at the crane side. When the ultracapacitors are being charged, i.e., $P_{uc}(k) < 0$, the input and output of the DC/DC converter switch sides, so $P_{dc}(k)$ is related to the ultracapacitor setpoint as follows:

$$P_{dc}(k) = \begin{cases} \frac{1}{\eta_{dc}} P_{uc}(k) & \text{if } P_{uc}(k) > 0 \\ \eta_{dc} P_{uc}(k) & \text{if } P_{uc}(k) \leq 0 \end{cases} \quad (3.3)$$

The second contribution to the energy losses is due to heating of the internal resistance R_{int} of the ultracapacitors. Obviously, the heating is related to the amount of power that is being delivered. The power is a function of the voltage and the current:

$$P_{dc}(k) = u_{dc}(k) \cdot i_{dc}(k) \quad (3.4)$$

The losses in the internal resistance increase with the square of the current:

$$P_{loss}(k) = R_{int} \cdot i_{dc}(k)^2$$

Combining the last equation with (3.1) and (3.4) results in:

$$P_{loss}(k) = \frac{1}{2} R_{int} \cdot \frac{P_{dc}(k)^2}{u_{dc}(k)^2} = \frac{1}{2} R_{int} C \cdot \frac{P_{dc}(k)^2}{E_{uc}(k)}$$

Finally, the losses in the ultracapacitors can be combined with the losses in the DC/DC converter from (3.3). This gives the relation between $P_s(k)$ and $P_{uc}(k)$, i.e., the efficiency of the total ultracapacitor:

$$P_s(k) = \begin{cases} \frac{1}{\eta_{dc}} \left(1 + \frac{1}{2} R_{int} C \cdot \frac{P_{uc}(k)}{E_{uc}(k)} \right) P_{uc}(k) & \text{if } P_{uc}(k) > 0; \\ \eta_{dc} \left(1 + \frac{1}{2} R_{int} C \cdot \frac{P_{uc}(k)}{E_{uc}(k)} \right) P_{uc}(k) & \text{if } P_{uc}(k) \leq 0. \end{cases} \quad (3.5)$$

The efficiency of the ultracapacitor bank is depicted in Fig. 3.6. As the energy level decreases the currents in the ultracapacitors get larger, so the losses due to heating also increase. For the most efficient use of the ultracapacitors, the energy management strategy should avoid delivering large peaks of power with them. This behavior is quite different from the GenSet, which is most efficient in the range of 150–200 kW.

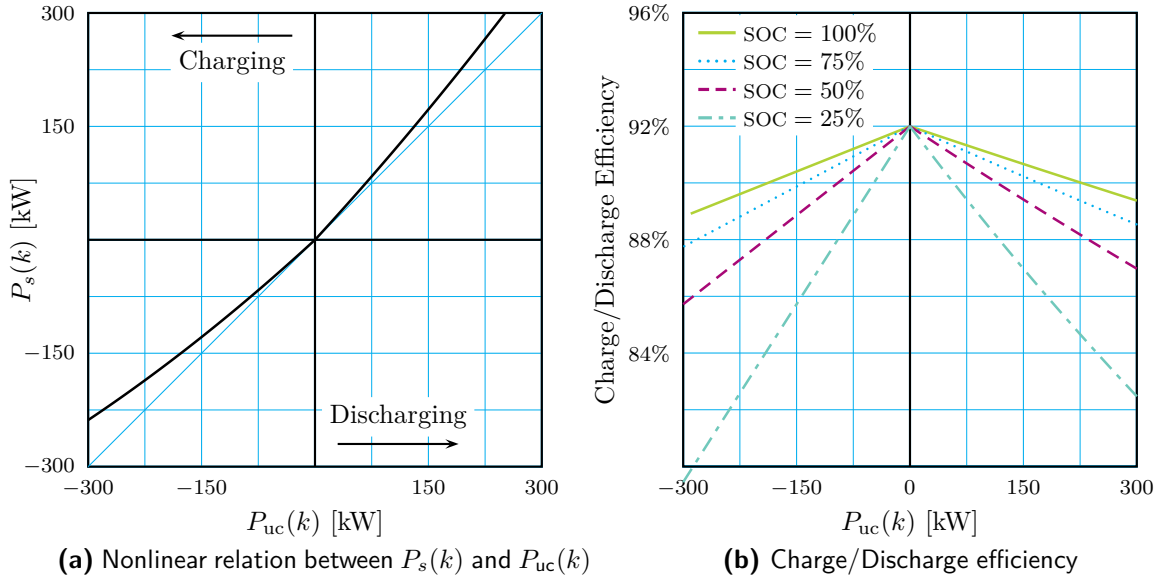


Figure 3.6: Ultracapacitor efficiency model

The influence of the energy level is also clearly visible in Fig. 3.6(b). The more energy is stored in the ultracapacitor, the smaller the currents are, and so the efficiency becomes higher. It is interesting to note that the impact of the energy level on the efficiency is a lot larger for ultracapacitors than it is for batteries, where the voltage does not drop as much when they become drained.

3.4 The complete simulator

With the model of the power demand and of the power supply ready, the simulator is complete. First, the power demand for the desired circumstances can be generated, e.g., a busy schedule with a lot of unloading trucks. This power demand is passed on to the energy management strategy, which calculates the setpoints $P_{\mathcal{F}}(k)$ and $P_{uc}(k)$ for the GenSet and ultracapacitors. These setpoints are used by the model of the two power sources to find the resulting fuel cost and change in the stored charge. By supplying the same power demand to different strategies, the performance can be compared.

Figure 3.7 shows a simulation of how the current strategy uses the hybrid ECO-RTG's two power sources together to supply the crane with power. In this example, the ultracapacitor is used to supply the power during the initial peaks in the demand, after which the GenSet gradually takes over. Just after the 2.5 min mark, the GenSet is used to recharge the ultracapacitors. Note that this is only intended as an example of the two power sources working together, it is not a demonstration of the optimal strategy for the distribution of the load over the two sources.

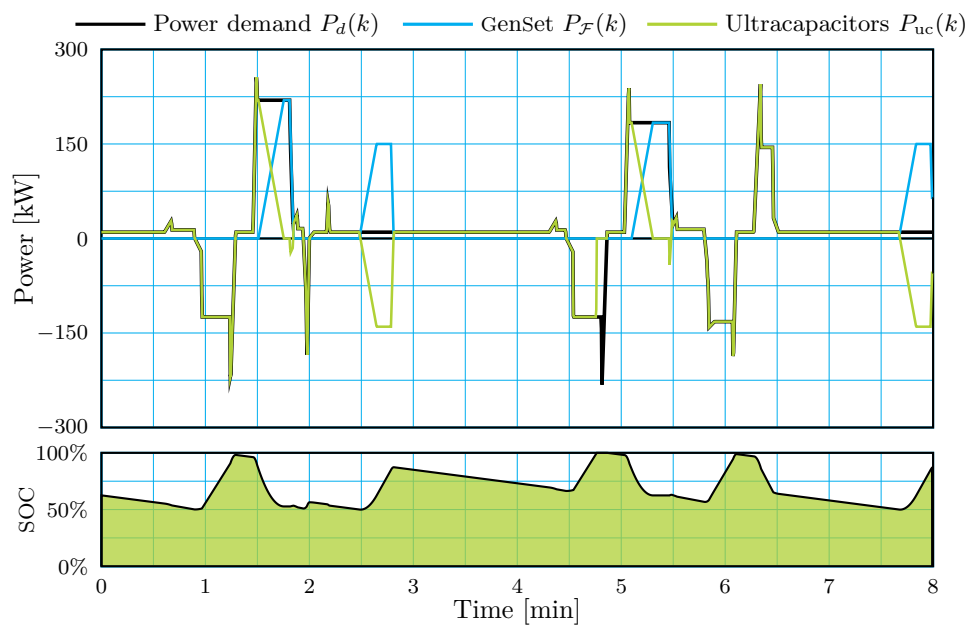


Figure 3.7: Example of the GenSet and ultracapacitors working together

Energy Management Strategy

The previous chapters laid the groundwork for the design of the energy management strategy. The intended usage of the strategy in the hybrid ECO-RTG crane is clear, and the mathematical model of the crane shows some important characteristics of the crane's power system. In this chapter the steps taken in the design of the new energy management strategies are explained, which is the second subproblem of this thesis after the simulator.

Because the energy management strategy is the main subject of this thesis, this chapter runs quite a bit longer than the previous ones. First, Section 4.1 gives a short introduction of energy management strategies in general. The workings of the current strategy, which will function as a benchmark, are outlined in Section 4.2. There are some fundamental problems with the current strategy, so in Section 4.3 an alternative approach is presented: optimization-based strategies. Unfortunately, this new formulation has some challenges of its own, which are also explained in this section. As a result of these problems, the optimization needs to be adjusted to be feasible in practice. This leads to the Equivalent Consumption Minimization Strategy (ECMS) approach, which is presented in Section 4.4. In this section the two new strategies that were designed for the hybrid ECO-RTG are explained in detail. Finally, the chapter is rounded off by a brief summary in Section 4.5.

4.1 Introduction

The goal of the energy management strategy is to minimize the fuel consumption of the hybrid ECO-RTG crane during operation. This can be achieved by constantly controlling the amount of power supplied by the diesel generator set (GenSet) and by the ultracapacitors, while they work together to meet the power demand. The two power sources should always supply at least as much power as is currently demanded, so $P_{\mathcal{F}}(k) + P_{uc}(k) \geq P_d(k)$. Any excess power will be burnt off in braking resistors, so usually it is most efficient to have $P_{\mathcal{F}}(k) + P_{uc}(k) = P_d(k)$.

The most straightforward way to save fuel is by turning off the GenSet engine and only using the ultracapacitors to power the crane. Unfortunately the energy storage capacity of the

ultracapacitors is not big enough for this simple strategy, so it is necessary to use the GenSet at least part of the time when the crane is in operation. The challenge is to use the GenSet as efficiently as possible, by selecting the best time to turn the GenSet on and off, and by using it in its most efficient operating range.

It is clear from the previous chapter that, when the engine is running, the GenSet is most efficient when it delivers 150–200 kW (cf. Fig. 3.4 on page 17) of power, while the ultracapacitors perform best when they are delivering small amounts of power. The energy level of the ultracapacitors is also important, because they are more efficient when the energy level is high, as was shown in Fig. 3.6 on page 20.

Selecting the best time to shut the GenSet engine off and when to turn it back on again, presents the strategy with a crucial dilemma. This can be compared to the automatic stop/start mechanism in some modern cars: when a car spends two minutes standing in front of an opened bridge, it is best to turn the engine off and save fuel; on the other hand, when the car is in a traffic jam, it would be disadvantageous for the fuel consumption to switch off the engine every time it came to a stop. The same decision of when to switch the engine on and off has to be made for the hybrid ECO-RTG crane.

With the use of the model crane's power supply systems from Chapter 3, it is theoretically possible to calculate the optimal solution to the fuel consumption problem. It is even possible that multiple optimal solutions exist for a given power demand cycle. The difficulty lies in the fact that optimal solution has to be found in real time, so there is limited calculation time available. Furthermore, the exact power demand for each move is not known in advance. The crane software does not know the locations where the containers have to be picked up or released, or even the weight of the container is unknown until it is picked up.

Even more importantly, the software also does not know when the crane is going to start a move or when it going to be idle for some time. This is crucial in trying to decide when best to switch the GenSet engine off. Because of the lack of knowledge about the upcoming power demand, the energy management strategy has to react on the real-time power demand and also has to try to anticipate what will happen in the next two minutes—the average duration of a typical move.

There are a number of different techniques to design an energy management strategy, each with their own approach to find the best way to use the available power sources. The current strategy—which will act as a benchmark—will be presented in the next section. After this, the rest of this chapter explains the steps taken in the design of the two alternative strategies, which use an approach that is different from the current one.

4.2 Current approach: rule-based strategy

Siemens currently has a prototype hybrid ECO-RTG crane in operation in the Port of Algeciras (Spain). Of course, this prototype already has an energy management strategy on board. The current strategy is based on a set of rules that tries to determine the best strategy heuristically by looking at the current state of the crane. This section describes this strategy and its advantages and weaknesses.

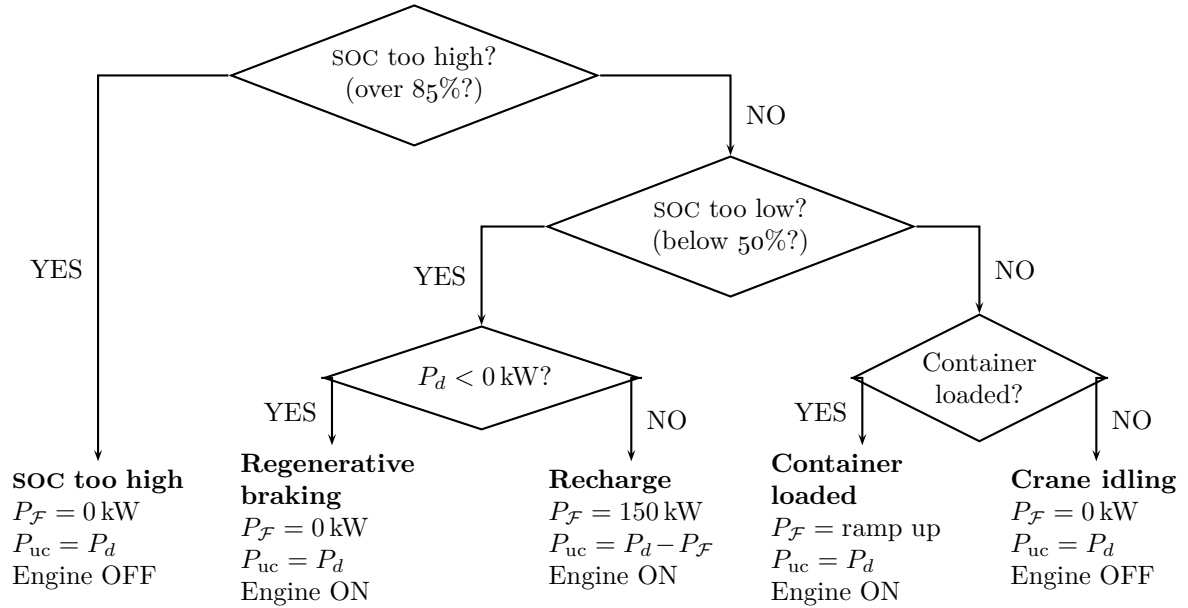


Figure 4.1: Flowchart of suboptimal rule-based strategy currently in use in the hybrid ECO-RTG

4.2.1 The decision making process

In Fig. 4.1 the decision making process of the current strategy is displayed. Every time step, the strategy starts at the top of the flowchart and decides on the best setpoint for $P_{\mathcal{F}}(k)$ by looking at the state of charge (SOC) of the ultracapacitors, the current power demand $P_d(k)$, and whether the spreader is currently connected to a container or not.

This rule-based strategy has the advantage that it is relatively easy to understand what is happening in the process of selecting the setpoints for $P_{\mathcal{F}}(k)$ and $P_{uc}(k)$. The main principles of the strategy are as follows.

1. If the ultracapacitors' energy level is close to the maximum, the engine is shut off to save fuel.
2. If the engine is running, it should produce 150–200 kW in order to stay in its most efficient operating region, cf. Fig. 3.4 on page 17.
3. If no container is loaded, the power demand will probably be relatively small. Therefore the ultracapacitors supply all the power, preventing the GenSet from having to operate in an inefficient working point.
4. If a container is loaded, the crane can expect a large power demand and the GenSet should start to speed up towards its efficient working point.
5. If the ultracapacitors are close to the minimum SOC (i.e., below 50%), they are recharged back to 85% SOC. This can be achieved either by regenerative braking or by charging the ultracapacitors using the GenSet. Once again, the GenSet is used in its most efficient region while charging (150 kW).

4.2.2 Advantages and drawbacks

A rule-based strategy is a good choice for many applications, and especially for prototype systems. This is mainly because the reasoning behind the strategy is immediately clear from the rule base, which results in reliable and predictable behavior of the crane. Besides this, it is also easy to implement the strategy in the crane software, saving development time and cost.

On the other hand, rule-based systems also have certain drawbacks. The most important drawback is the performance. Without expert knowledge of the system to be controlled, it is very difficult to construct a rule base that achieves optimal performance. Even when expert knowledge of the system is available, it is often still difficult to produce a good controller. All the different rules need to be tuned to fit all possible circumstances, so there are many threshold values and output parameters that can influence the performance of the system.

4.3 Alternative approach: optimization-based strategies

To improve the current strategy, it might seem appealing to start a thorough analysis of the rule base and to tune the threshold values for each rule and the resulting setpoints to see how each of these affect the performance. There are also a number of other rule-based approaches found in literature, see for instance [13, 14, 15]. Nonetheless, a completely different approach is needed to overcome the main structural drawback of rule-based strategies, namely the large number of parameters that can influence the performance of the system.

The most commonly used alternative is an optimization-based approach, where hand-tuning of the parameters is no longer needed. This section presents the optimization framework and how it can be applied to energy management strategies. Unfortunately, there are also some difficulties associated with the initial formulation of the optimization-based approach. The details of these problems are discussed at the end of this section. Afterwards, Section 4.4 will explain a new strategy that is also based on the optimization framework, but uses a different formulation of the optimization goals.

4.3.1 Optimization framework

According to Van den Boom and De Schutter, a general optimization problem consists of four separate characteristics [16].

- J or $J(\theta)$, the objective function or criterion that expresses the intention or goal.
- θ , the parameter vector that can be used to optimize the objective function $J(\theta)$.
- $H(\theta) = 0$, (optional) equality constraints that bound the solution to a certain subset of the parameter space.
- $G(\theta) \leq 0$, (optional) inequality constraints that bound the solution to a certain allowed region in the parameter space.

The optimization problem is defined as a search for the combination of parameters that minimize the objective function $J(\theta)$:

$$J(\theta^*) = \min_{\theta} J(\theta) \quad \text{subject to} \quad H(\theta) = 0 \text{ and } G(\theta) \leq 0$$

where

$$\theta^* = \arg \min_{\theta} J(\theta)$$

Finding θ^* is done using optimization algorithms. There are many algorithms available, ranging from basic solvers like the Simplex Method to complex nonlinear solvers like Genetic Algorithms. The optimization algorithm determines the computational complexity of the solution. Simpler solvers generally need less calculation steps, but they are not always applicable for each optimization problem.

Before an optimization algorithm is selected, the first important step in the design of an optimization problem is the selection of an appropriate objective function and constraints. The objective function not only determines the desired goal, but its shape in the parameter space also influences how difficult it will be for an optimization algorithm to find the optimal solution. In the end, the type of solver depends on the characteristics of the objective function and the constraints, i.e., on the application for which the optimization is used.

4.3.2 Objective function for energy management strategies

The goal for the energy management strategy is to minimize the fuel consumption of the crane, so this has to be expressed in the objective function. Furthermore, the strategy should not only minimize the fuel consumption for a single time instant, but it should do a cumulative optimization over a longer period of time. The time it takes to do a single load/unload move is a good choice for this time period. Selecting a shorter time period would cause part of the typical power demand cycle to be ignored in the optimization, yielding suboptimal results. On the other hand, selecting the time period too long would result in unnecessary calculation, because the load demand is quasi-periodic thanks to the repetitive activities of the crane. Overall, the objective function should take 750 time samples into account, because an average move takes up to 150 sec and the sample frequency is 5 Hz.

Now that the optimization goal is determined, the next step are the optimization parameters, i.e., the parameters that are used to achieve the optimization goal. The set of parameters that is used to minimize the cumulative fuel cost is the amount of ultracapacitor power at each time step: $P_{uc}(k)$. The ultracapacitor power directly influences the GenSet power $P_{\mathcal{F}}(k)$, because of the relation $P_{\mathcal{F}}(k) = P_d(k) - P_{uc}(k)$. That means that it is not necessary to include $P_{\mathcal{F}}(k)$ as a parameter.

In addition to $P_{uc}(k)$, there is one other parameter that influences the fuel consumption: the state of the engine, or rather the fact whether it is running or not. When the engine is switched off, it obviously does not use any fuel. However, switching on the engine from standstill requires extra fuel, so deciding when to turn the engine on or off is an important issue. The on/off state of the engine is defined by the boolean signal $S(k)$, which is the second set of optimization parameters.

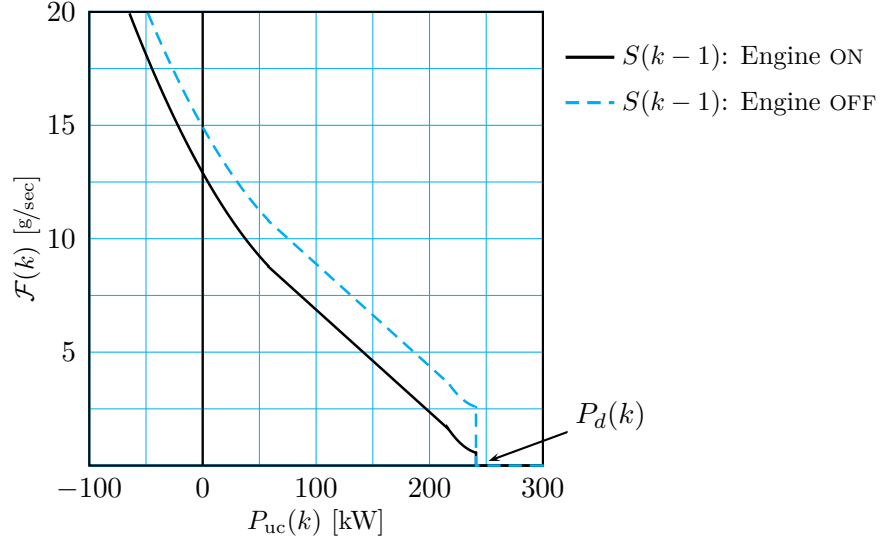


Figure 4.2: The fuel cost for a single time step, for $P_d(k) = 241$ kW

The resulting optimization goal becomes:

$$\min_{P_{uc}(k), S(k)} J(P_{uc}(k), S(k)) = \min_{P_{uc}(k), S(k)} \sum_{k=1}^N \mathcal{F}(P_d(k) - P_{uc}(k), S(k)) \quad \text{where } N = 750 \quad (4.1)$$

Note that the power demand $P_d(k)$ cannot be influenced by the strategy, because it is determined by the way the driver moves the crane. Therefore $P_d(k)$ cannot act as an optimization parameter, although it does determine the eventual optimal strategy.

Shape of the objective function

The shape of the objective function in the parameter space has a big influence on the results of the optimization problem. The minimum will be more difficult to find in an irregular nonlinear function than in a straightforward linear function. To give a better impression of the objective function, Fig. 4.2 shows $\mathcal{F}(P_d(k) - P_{uc}(k), S(k))$, i.e., the fuel cost for a single time step. The shape is a mirrored image of the GenSet fuel consumption model of Fig. 3.3, shifted right or left according to $P_d(k)$.

There are two notable things about the shape of the fuel cost. First there is the influence of $S(k-1)$, which makes using the GenSet more costly when the engine was previously switched off. It also shows that switching the engine off is beneficial for a single time instance, but it will hurt performance at the future time step. The second thing to note is the discontinuity at $P_{uc}(k) = P_d(k)$ when the engine is switched off. While the rest of the shape is a nice piecewise quadratic function, the discontinuity makes the shape non-convex, and therefore the total objective function will also be non-convex. Non-convex objective functions are more difficult to optimize than convex functions. They have the drawback that the function can have multiple local minima, so the result of the optimization is not guaranteed to be the global minimum.

Figure 4.3 shows the shape of the fuel cost during a complete container move. Essentially, it is built up using the shape from Fig. 4.2 and shifting it according to the varying $P_d(k)$.

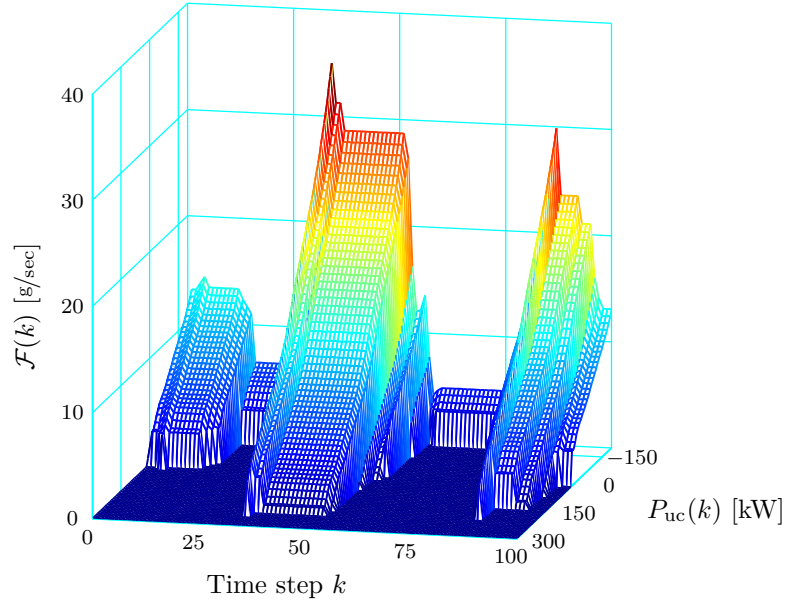


Figure 4.3: The fuel cost for each time step during a complete move, without engine startup penalty

The influence of $S(k)$ cannot be seen in the graph, because it is not known in advance when the engine will be on or off. If the engine would be switched off at some point during the move, the cost for using the GenSet in all the following time steps would be increased, until the point where the engine is switched back on.

Besides the objective function that was formulated in this subsection, an optimization-based energy management strategy also has to take some constraints into account. The next subsection discusses these constraints.

4.3.3 Constraints for energy management strategies

An energy management strategy is constrained in the actions it can take to reach the goal defined by the objective function. In this subsection three types of constraints are covered: constraints on the peak power, a constraint on the balance of the total power flows, and constraints on the ultracapacitor energy limits.

Peak power constraints

Obviously the two major crane components have some physical limitations that constrain the possible actions of the energy management strategy. The physical constraints for the GenSet are defined by the maximum and minimum amount of power it can deliver:

$$0 \text{ kW} \leq P_{\mathcal{F}}(k) \leq 350 \text{ kW (peak power)}$$

It is interesting to note that the power demand $P_d(k)$ does not play a role in these constraints. That means that GenSet can supply more power than required for the motors, so it can simultaneously power the motors and recharge the ultracapacitors. Besides this, peaks in

the power demand of more than 300 kW are very rare in normal operation. Therefore, the constraints on the GenSet do not play an important role in the solution of the optimization problem.

In addition to the limitations of the GenSet, the ultracapacitor bank is limited by its maximum allowed current:

$$\begin{aligned} i_{\text{int}}(k) &\leq 750 \text{ A (1 sec peak current)} \\ i_{\text{int}}(k) &\leq 150 \text{ A (continuous current)} \end{aligned}$$

For the optimization framework, these constraints need to be reformulated in terms of the ultracapacitor power instead of the current. Of course, the ultracapacitor power and the current are related by the voltage. Furthermore, the voltage can be expressed in terms of the stored energy (cf. (3.1) in the previous chapter), so it can be written as:

$$P_s(k) \cdot \sqrt{\frac{\frac{1}{2}C}{E_{\text{uc}}(k)}} \leq i_{\text{max}} \quad (4.2)$$

where i_{max} is either 750 A or 150 A, depending on whether the peak power or the continuous power is considered. In practice, these constraints have the effect that the ultracapacitors are limited to 45 kW of continuous power when they are empty, while they can handle 95 kW of continuous power when they are completely full.

Energy balance constraint

The second set of constraints does not have to do with physical limitations, but instead is due to the limited number time steps that are considered in the optimization. The formal optimization objective is to minimize the fuel consumption during a single container loading/unloading move, but another container move will begin after the end of the optimized move cycle. In order to make sure that the ultracapacitor storage is not completely drained at the end of the cycle—which would create a difficult situation for the next cycle—the following constraint is added on the ultracapacitor energy level:

$$E_{\text{uc}}(1) = E_{\text{uc}}(N)$$

In other words, over the course of the container move, the total amount of energy going out of the ultracapacitors has to be balanced with the energy flowing back. This can be achieved by regenerative braking or by charging the ultracapacitors with the GenSet. This constraint ensures that the strategy does not drain the ultracapacitors for short-term gains.

The energy balance constraint also has to be formulated in terms of the ultracapacitor power. The relation between the ultracapacitor power and energy was discussed in the previous chapter. From (3.2) it immediately follows that the constraint can be rewritten as:

$$\sum_{k=1}^N P_s(k) = 0 \quad (4.3)$$

Energy storage constraints

The final constraining issue are the bounds on the amount of energy that is stored in the ultracapacitors. Because the storage capacity is relatively small—just enough for hoisting one container from the bottom to the top of the crane—this constraint plays an important role in the optimization problem. The constraints on the storage are:

$$E_{\min} \leq E_{\text{uc}}(k) \leq E_{\max}$$

where $E_{\min} = 0.32 \text{ kWh}$ (1 152 kJ), and $E_{\max} = 1.38 \text{ kWh}$ (4 968 kJ). For the sake of legibility, only the upper bound will be discussed in detail. The lower bound can be handled exactly the same as the upper bound.

Just like in the discussion of the energy balance constraint, (3.2) is used to reformulate the constraints in terms of the ultracapacitor power. The constraints for each time step are as follows.

$$\begin{aligned} E_{\text{uc}}(1) - P_s(1) &\leq E_{\max} \\ E_{\text{uc}}(1) - P_s(1) - P_s(2) &\leq E_{\max} \\ E_{\text{uc}}(1) - P_s(1) - P_s(2) - P_s(3) &\leq E_{\max} \quad \text{etc.} \end{aligned}$$

In general, the constraint means that the upper bound on the ultracapacitor power for each time step is given by the maximum energy level, the energy at the start of the simulation and the change in the energy due to the power flow in the previous time steps:

$$-P_s(k) \leq E_{\max} - E_{\text{uc}}(1) + \sum_{i=1}^{k-1} P_s(i) \quad (4.4)$$

4.3.4 Feasibility of the optimization-based approach

Now that the optimization objective and the constraints are formulated as best as possible, the feasibility of an optimization-based strategy with this formulation can be examined. The optimization problem needs to be solvable in reasonable time for it to be useful in practice. For instance, in an optimization-based model-based predictive control (MPC) strategy, the optimization process needs to start and finish within a single time step. This makes the complexity of the optimization problem a critical issue. Unfortunately, the formulation that was discussed in the previous sections is too complex for practical applications.

First of all, the influence of $S(k)$ on the objective function of (4.1) has a negative effect on the solvability of the optimization problem. The possibility to switch the GenSet off complicates the objective function by introducing a “dent” in the fuel consumption when the engine is switched off. This gives $\mathcal{F}(P_d(k) - P_{\text{uc}}(k), S(k))$ a non-convex shape. The startup fuel penalty creates further complications in the shape of the objective function. As a result of the non-convexity, the objective function will have multiple local minima, complicating the solving algorithm and increasing the chance of a suboptimal solution.

Another challenge is posed by the constraints. Note that all the constraints (4.2), (4.3) and (4.4) are actually constraints on $P_s(k)$ instead of on the true optimization parameter $P_{\text{uc}}(k)$. To use the constraints in the optimization framework, they need to be reformulated

in terms of $P_{uc}(k)$. However, in Section 3.3 it was discussed that the relation between $P_s(k)$ and $P_{uc}(k)$, i.e., the efficiency of the ultracapacitors, depends strongly on the energy level $E_{uc}(k)$.

The problem is that $E_{uc}(k)$ in turn depends on $P_{uc}(k)$ in the previous time steps. That means that for each time step, the ultracapacitor efficiency can only be calculated using the values of $P_{uc}(k)$ in the earlier time steps. This creates the strange situation that the constraints on $P_{uc}(k)$ are unknown until $P_{uc}(k)$ itself is known. It is needless to say that it is very difficult to solve an optimization problem when the constraints on the optimization parameter are only gradually becoming known during the optimization.

In the light of these calculation problems, the conclusion is as follows. To accomplish feasibility of the optimization-based approach in practice, the formulation of the objective and the constraints needs to be changed in some way to avoid the problems that were just discussed. Section 4.4 will show how this is done by the new energy management strategy, which features a different choice for the objective function. That said, Section 4.3.5 first discusses an off-line solution of the optimization problem, to discover what performance might be achieved when given enough time and computing power.

4.3.5 Off-line solution: dynamic programming

The challenges that were just discussed are important issues for an on-line solution, where computational time is an important factor. Nevertheless, it is also interesting to see what performance could theoretically be achieved. This would give some insight on what performance gain to expect, before making a lot of effort to design a new strategy. By disregarding calculation time and the fact that we do not know exactly what the future power demand will be, it should be possible to find the absolute optimal strategy. Unfortunately, unexpected problems forced this project to be abandoned without actually producing results.

The Dynamic Programming algorithm

In the literature on energy management strategies for hybrid vehicles, an off-line solution is often used as a benchmark to show the best possible results with a certain hybrid system. Richard Bellman's Dynamic Programming (DP) algorithm [17] is well-suited for this task, since it is able to handle the complex constraints, and is guaranteed to find the optimal solution with a certain accuracy. This subsection applies the DP algorithm to an energy management as explained by Koot et al. [7].

As depicted in Fig. 4.4, Dynamic Programming works by putting a grid on the feasible solution-space, i.e., all values for $P_s(k)$ and $S(k)$ that result in energy levels within the bounds of the ultracapacitors. Then, starting at the desired finishing point $E_{uc}(N) = E_{uc}(1)$, the algorithm calculates the minimum cumulative cost of getting from each point to the desired end point. By working its way "back in time", the algorithm eventually finds the minimum cumulative cost to get from start to finish. Depending on the density of the grid, the global optimum is guaranteed to be found with a certain accuracy.

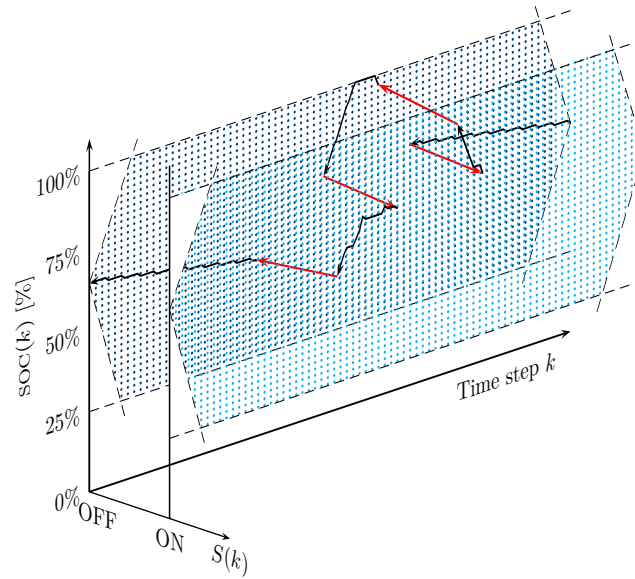


Figure 4.4: The grid on the energy levels for the DP algorithm. Every dot represents a feasible energy level in the grid. The red arrows indicate ON/OFF switching of the engine, the diamond shape is due to constraints on $P_{uc}(k)$

Challenges for the DP approach

The downside of the grid-based approach is that it involves a lot of calculations, and that the amount of calculations rises rapidly when the desired accuracy increases. The problem lies in the fact that when the grid density is increased, not only the number of points gets bigger, but also the amount of calculation per point increases.

As a calculating example, suppose the feasible energy levels are divided into 100 sections by the grid and the algorithm simulates 150 sec of crane operation with a sample time of 1 sec. A grid with 100 sections in the energy level means that the step size between these sections is 38 kJ, and therefore—the sample time is 1 sec in this example—the step size for $P_s(k)$ is also 38 kW. Due to this large step size, there is only a handful of points that are reachable within the peak power constraints on $P_s(k)$. The peak power also depends on the energy level, but on average there are 10 possible choices for $P_s(k)$. The choice between having the engine running or not ($S(k)$ true or false) adds another possible decision, so we have to calculate the cost to get to 11 points. For the total simulation, this would result in running a loop of 0.1 ms running $150 \times 100 \times 2 \times 11 = 330\,000$ times, taking only 33 sec.

For this example, the step size for $P_s(k)$ was chosen 38 kW. Of course, this is a very large step size compared to the changes in the power demand. This means that the resulting strategy is not close the true optimal solution at all. If the grid is chosen more accurate, for instance 3 800 sections, the step size for $P_s(k)$ becomes 1 kW and the average number of reachable points within the constraints becomes 450. The finer grid means that a lot more calculation steps are necessary, $150 \times 3\,800 \times 2 \times 450 \approx 500\,000\,000$ in total. A trial run of this algorithm on a state-of-the-art desktop computer showed that calculation would take 14 hours to complete, for only 150 sec of simulated operation.

For the off-line strategy to be useful as a benchmark for real-time strategies, a single simulation

of a 150 sec movement is not enough. Ideally, a simulation of a full day of operation with many different container move operations would be used. This would best emulate the true application, where the container movements vary, and the idling times can vary as well. At the rate that was discussed above, simulating a full day with 21 hr of operations would take 295 days to complete.

In the end, because of the problems with the calculation time, the DP off-line strategy was abandoned in favor of getting results with the real time strategies. While it is unfortunate that the invested efforts did not pay off, it has little influence the main goal of the project: improving the real time strategy. It only means that the new strategies can only be compared to the original rule based strategy, and not to a truly optimal solution.

4.4 Equivalent consumption minimization strategy

Section 4.3 applied the optimization framework to the design of an energy management strategy. The section was concluded with a discussion of calculation difficulties that make it impossible to use the defined objective function and constraints for a real-time implementation: the non-convex shape of the objective function due to the on/off state of the engine, and the fact that the constraints on the ultracapacitor power are unknown at the start of the optimization. A way to solve this is altering the objecting function, making it less complex, and at the same time removing some of the constraints.

A optimization-based approach that has proven successful is ECMS from Guzzella and Sciarretta [6]. Of course, changing the formulation of the goal and the constraints can also change the outcome of the optimization algorithm. Hofman [18] and others have shown that formulating the optimization as an ECMS can still yield results that are very close to the absolute optimal strategy found using DP. The application of ECMS for the hybrid ECO-RTG crane is discussed in this section, resulting in two new energy management strategies.

4.4.1 Change of the objective function

The general idea behind ECMS is the fact that all the energy that the ultracapacitors supply to the crane has to be balanced in the future by energy that is stored back in the ultracapacitors, either using regenerated energy or using excess power from the GenSet. Recharging the ultracapacitors add to the fuel cost, so the power that the ultracapacitors supply can be expressed in terms of its “equivalent fuel cost”.

Basically, ECMS considers the power from the ultracapacitors not as “free energy” as it would seem from the original objective function, but it will cost some fuel in the future. The argument is the same when energy is stored instead of spent: storing energy right now will save fuel in the future. As a result of this, the fuel cost/saving that is associated with $P_{uc}(k)$ for a single time instance depends on both the instantaneous and the future fuel consumption:

$$\mathcal{F}_{ecms}(P_{uc}(k), \lambda_{uc}) = \underbrace{\mathcal{F}(P_d(k) - P_{uc}(k))}_{\text{current fuel cost}} + \underbrace{\lambda_{uc} \cdot P_{uc}(k)}_{\text{future fuel cost/saving}}$$

Where $\mathcal{F}_{\text{ecms}}$ is called the “equivalent fuel cost”, and λ_{uc} is called the “equivalent fuel cost weight”. By adjusting the value of λ_{uc} , the equivalent fuel cost of ultracapacitor power can be changed, making ultracapacitor power worth more (or less) fuel.

The same reasoning of “future fuel cost” can be applied to switching the engine on and off, something that has not been considered in this way in any other work before. If the engine is switched off at a certain point in time, this is beneficial for the fuel cost in that time step, but it will cost extra fuel to start the engine back up again in the future. Therefore, when the engine is switched off, the future fuel cost of switching it back on is incorporated in the equivalent fuel cost in the same way as before:

$$\mathcal{F}_{\text{ecms}}(P_{\text{uc}}(k), S(k), \lambda_{\text{uc}}, \lambda_{\text{st}}) = \underbrace{\mathcal{F}(P_d(k) - P_{\text{uc}}(k))}_{\text{current fuel cost}} + \underbrace{\lambda_{\text{uc}} \cdot P_{\text{uc}}(k) + \lambda_{\text{st}} \cdot g(S(k))}_{\text{future fuel cost/saving}}$$

where $g(S(k))$ is a penalty function that is only nonzero when the engine is being switched off.

Including the losses in the ultracapacitors

To improve the notion of equivalent fuel cost of ultracapacitor power, the losses inside the ultracapacitor should also be taken into account. The inefficiency of the ultracapacitor costs some energy, which should also be expressed in terms of its equivalent fuel cost. The losses are taken into account by using the equivalent fuel cost of the internal ultracapacitor power $P_s(k)$ instead of $P_{\text{uc}}(k)$:

$$\mathcal{F}_{\text{ecms}}(P_{\text{uc}}(k), P_s(k), S(k), \lambda_{\text{uc}}, \lambda_{\text{st}}) = \mathcal{F}(P_d(k) - P_{\text{uc}}(k)) + \lambda_{\text{uc}} \cdot \underline{P_s(k)} + \lambda_{\text{st}} \cdot g(S(k))$$

$P_s(k)$ can be removed from the equation again by using the relation from (3.5) to express it in terms of $P_{\text{uc}}(k)$:

$$\begin{aligned} \mathcal{F}_{\text{ecms}}(P_{\text{uc}}(k), S(k), \lambda_{\text{uc}}, \lambda_{\text{st}}) &= \mathcal{F}(P_d(k) - P_{\text{uc}}(k)) + \dots \\ &\quad + \lambda_{\text{uc}} \cdot \frac{1}{\eta_{\text{dc}}} \left(1 + \frac{1}{2} \frac{R_{\text{int}} C}{E_{\text{uc}}(k)} P_{\text{uc}}(k)\right) P_{\text{uc}}(k) + \lambda_{\text{st}} \cdot g(S(k)) \quad \text{if } P_{\text{uc}}(k) > 0 \\ \mathcal{F}_{\text{ecms}}(P_{\text{uc}}(k), S(k), \lambda_{\text{uc}}, \lambda_{\text{st}}) &= \mathcal{F}(P_d(k) - P_{\text{uc}}(k)) + \dots \\ &\quad + \lambda_{\text{uc}} \cdot \eta_{\text{dc}} \left(1 + \frac{1}{2} \frac{R_{\text{int}} C}{E_{\text{uc}}(k)} P_{\text{uc}}(k)\right) P_{\text{uc}}(k) + \lambda_{\text{st}} \cdot g(S(k)) \quad \text{if } P_{\text{uc}}(k) \leq 0 \end{aligned}$$

Obviously, this notation is not very efficient, so instead the original expression with $P_s(k)$ will be used in the rest of this thesis.

Reformulating the optimization problem using the equivalent fuel cost

By adding the future effect of using ultracapacitor power to the fuel cost, the need for knowledge about future power demand is removed. If λ_{uc} and λ_{st} are chosen correctly, the future fuel consumption is already discounted in the fuel cost for each individual time step. This means the optimization solver no longer needs to know what will happen in the next 150 sec,

instead it can optimize each time instance separately. The ECMS no longer has the cumulative fuel consumption for 750 time steps as objective function, but instead minimizes only the equivalent fuel consumption $\mathcal{F}_{\text{ecms}}(k)$ for each time step:

$$\begin{aligned} \min_{P_{\text{uc}}(k), S(k), \lambda_{\text{uc}}, \lambda_{\text{st}}} \mathcal{F}_{\text{ecms}}(P_{\text{uc}}(k), S(k), \lambda_{\text{uc}}, \lambda_{\text{st}}) &= \dots \\ &= \min_{P_{\text{uc}}(k), S(k), \lambda_{\text{uc}}, \lambda_{\text{st}}} \mathcal{F}(P_d(k) - P_{\text{uc}}(k)) + \lambda_{\text{uc}} \cdot P_s(k) + \lambda_{\text{st}} \cdot g(S(k)) \quad (4.5) \end{aligned}$$

The new objective function makes the decision of switching the engine on or off a lot easier, because there is only a single time step to take into account during optimization. The shape of the objective function is also simplified to the point that the optimum choice for $P_{\text{uc}}(k)$, $S(k)$ can be found analytically, which will be demonstrated in a following section.

Another benefit has to do with the optimization constraints. Because of the new formulation, finding a balance between spending and using ultracapacitor energy is enclosed within the optimization goal. If the weights λ_{uc} and λ_{st} are chosen correctly, the problem of keeping the ultracapacitor power balanced is solved, without the need for explicitly formulating this as a constraint.

At the same time, the constraints on the peak power and the bounds on the amount of stored energy are also less problematic. Because there is only a single time step to optimize, the influence of $E_{\text{uc}}(k)$ on the ultracapacitor efficiency does not cause any trouble. The new constraints follow directly from the original (4.2) and (4.4):

$$\begin{aligned} P_s(k) &\leq \min \left(i_{\text{max}} \cdot \sqrt{2 \frac{E_{\text{uc}}(k)}{C}}, E_{\text{uc}}(k) - E_{\text{min}} \right) \\ P_s(k) &\geq \max \left(-i_{\text{max}} \cdot \sqrt{2 \frac{E_{\text{uc}}(k)}{C}}, E_{\text{uc}}(k) - E_{\text{max}} \right) \end{aligned}$$

These constraints still have to be rewritten in terms of the true ultracapacitor power $P_{\text{uc}}(k)$ to fit them in the optimization framework. Using (3.5), the final set of constraints is:

$$\begin{aligned} \frac{1}{\eta_{\text{dc}}} \left(1 + \frac{1}{2} \frac{R_{\text{int}} C}{E_{\text{uc}}(k)} P_{\text{uc}}(k) \right) P_{\text{uc}}(k) &\leq \min \left(i_{\text{max}} \sqrt{2 \frac{E_{\text{uc}}(k)}{C}}, E_{\text{uc}}(k) - E_{\text{min}} \right) \quad \text{if } P_{\text{uc}}(k) > 0 \\ \eta_{\text{dc}} \left(1 + \frac{1}{2} \frac{R_{\text{int}} C}{E_{\text{uc}}(k)} P_{\text{uc}}(k) \right) P_{\text{uc}}(k) &\geq \max \left(-i_{\text{max}} \sqrt{2 \frac{E_{\text{uc}}(k)}{C}}, E_{\text{uc}}(k) - E_{\text{max}} \right) \quad \text{if } P_{\text{uc}}(k) \leq 0 \end{aligned}$$

A new challenge

Although the formulation of ECMS removes the original problems with the complex objective and incalculable constraints, it also presents a new challenge: finding the optimal value for the equivalent consumption weights λ_{uc} and λ_{st} . If either of the two is too large, the strategy will be too conservative with $P_{\text{uc}}(k)$ or $S(k)$, and use the GenSet too much. If it is too small, the

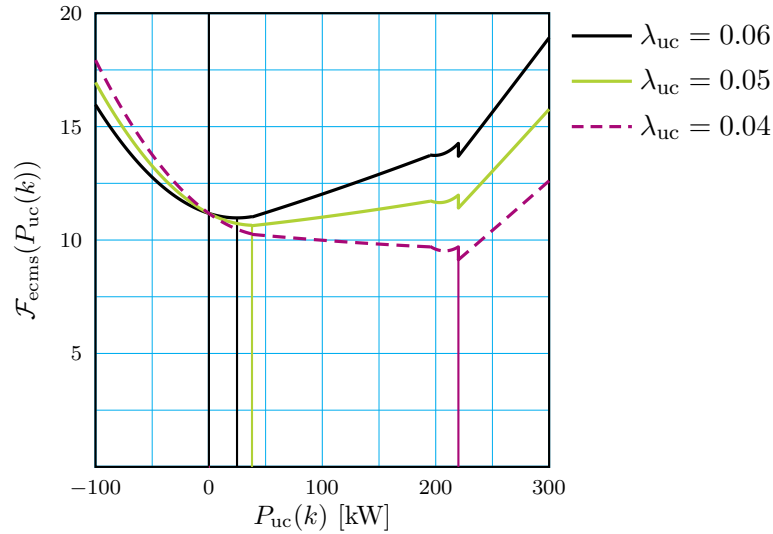


Figure 4.5: ECMS objective function, showing the influence of λ_{uc} on the optimal solutions

strategy will be too aggressive and the ultracapacitor storage will become drained. Therefore, estimating λ_{uc} and λ_{st} is extremely important for optimal behavior of the ECMS.

Selecting an optimal value for λ_{st} is relatively straightforward. It is intuitive to choose the weight as some fraction of the startup cost $\mathcal{F}_{st}$. If λ_{st} is too high, the strategy becomes overly conservative, if it is too low, there is a risk that the state of the strategy will start to “chatter”, constantly switching on and off. Around the optimal λ_{st} there is a comfortable margin where the performance is not noticeably degraded, possibly because $g(S(k))$ can take only two values. In fact, any value between $0.02 \cdot \mathcal{F}_{st}$ and $0.03 \cdot \mathcal{F}_{st}$ will give the best possible results.

Finding a good value for λ_{uc} is more involving. In Sections 4.4.2 and 4.4.3, two approaches to solve this will be presented. The first was previously proposed by Kessels [8], the second is a completely new contribution.

Solving the ECMS optimization problem

Thanks to the less complex new objective function and constraints, the solution to the ECMS optimization problem can be found analytically, so iterative solving algorithms are not necessary. The shape of the new objective function is shown in Fig. 4.5. Basically, the objective is formed by taking the single time step fuel cost from Fig. 4.2, with an added penalty for high values of $P_{uc}(k)$. The figure also demonstrates that the optimal solution depends on the value of λ_{uc} , as was discussed in the previous section. This section is only concerned with finding the optimal $P_{uc}(k)$ and $S(k)$ when λ_{uc} and λ_{st} are known. Selecting the optimal value for λ_{uc} is covered in the sections after this one.

In general, the solution can be located in one of two states: either the GenSet engine is running in optimal solution, or it is not. This corresponds with $S(k)$ being “ON” or “OFF”, respectively. For each of these two cases, the corresponding optimal $P_{uc}(k)$ can be found, each with an equivalent fuel cost associated with it. The optimal solution is found by comparing these two local minima.

The first possible solution uses both the GenSet and the ultracapacitors to power the crane, i.e., $S(k)$ is “ON”. That means that $\mathcal{F}_{\text{ecms}}(k)$ consists of both the true GenSet fuel cost and the equivalent fuel cost due to the ultracapacitors. In Section 3.2 on page 16, the GenSet fuel consumption was modeled by a (piecewise) quadratic equation:

$$\mathcal{F}(P_{\mathcal{F}}(k)) = a_2 \cdot P_{\mathcal{F}}(k)^2 + a_1 \cdot P_{\mathcal{F}}(k) + a_0$$

Using $P_{\mathcal{F}}(k) = P_d(k) - P_{\text{uc}}(k)$, the fuel consumption is formulated in terms of the ultracapacitor power:

$$\mathcal{F}(P_{\text{uc}}(k)) = a_2 \cdot (P_d(k) - P_{\text{uc}}(k))^2 + a_1 \cdot (P_d - P_{\text{uc}}) + a_0$$

With this expression for the fuel consumption, the ECMS objective is:

$$\min_{P_{\text{uc}}(k)} \mathcal{F}_{\text{ecms}}(P_{\text{uc}}(k), \text{ON}) = a_2(P_d(k) - P_{\text{uc}}(k))^2 + a_1(P_d - P_{\text{uc}}) + a_0 + \lambda_{\text{uc}} \cdot P_s(k)$$

Note that the $g(S(k)) = 0$ in this case, because the engine is not switched off in this situation.

In the previous equation, $P_s(k)$ still has to be substituted with the proper expression in $P_{\text{uc}}(k)$ so that the ultracapacitor efficiency is taken into account. After some rearranging of the terms, this results in the following quadratic programming problem:

$$\min_{P_{\text{uc}}(k)} b_2 \cdot P_{\text{uc}}(k)^2 + b_1 \cdot P_{\text{uc}}(k) + b_0$$

where,

$$\begin{aligned} b_2 &= a_2 + \lambda_{\text{uc}} \frac{1}{\eta_{\text{dc}}} \frac{1}{2} R_{\text{int}} C \frac{1}{E(k)} & \text{if } P_{\text{uc}} > 0 \\ b_2 &= a_2 + \lambda_{\text{uc}} \eta_{\text{dc}} \frac{1}{2} R_{\text{int}} C \frac{1}{E(k)} & \text{if } P_{\text{uc}} \leq 0 \\ b_1 &= -a_1 - 2a_2 P_d(k) + \lambda_{\text{uc}} \frac{1}{\eta_{\text{dc}}} & \text{if } P_{\text{uc}} > 0 \\ b_1 &= -a_1 - 2a_2 P_d(k) + \lambda_{\text{uc}} \eta_{\text{dc}} & \text{if } P_{\text{uc}} \leq 0 \\ b_0 &= a_2 P_d(k)^2 + a_1 P_d(k) + a_0 \end{aligned}$$

The minimum of this quadratic objective function is easily found:

$$P_{\text{uc}}^*(k) = \arg \min_{P_{\text{uc}}(k)} \mathcal{F}_{\text{ecms}}(P_{\text{uc}}(k), \text{ON}) = \frac{-b_1}{2b_2} \quad (4.6)$$

The second possible solution is turning off the GenSet, i.e., $S(k)$ is “OFF”, the ultracapacitors have to supply the complete power demand during this time step. Of course, this should be possible within the constraints on $P_{\text{uc}}(k)$, otherwise this is not a feasible solution. Because it is never beneficial to have the ultracapacitors supply more power than strictly necessary, the optimal ultracapacitor power is equal to the power demand, so the solution is immediately found as:

$$P_{\text{uc}}^*(k) = \arg \min_{P_{\text{uc}}(k)} \mathcal{F}_{\text{ecms}}(P_{\text{uc}}(k), \text{OFF}) = P_d(k) \quad (4.7)$$

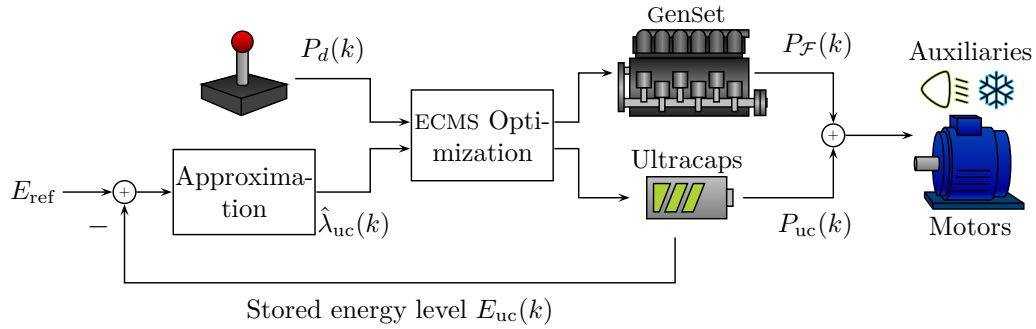


Figure 4.6: Block scheme of first new strategy, using SOC feedback to approximate $\hat{\lambda}_{uc}$ for ECMS

Finally, the optimal solution is found by comparing the equivalent fuel cost of both solutions (4.6) and (4.7), and selecting the one that yields the lowest cost. Since the optimization does not use any very complicated operations, this whole routine can very easily be used in practice to perform optimizations in real time.

4.4.2 Approximating λ_{uc} with feedback

The final piece in the design of the new ECMS strategies is selecting a good value for λ_{uc} . The strategy that is presented in this section was recommended by Joe George in his Master's Thesis on the ECO-RTG [3], and has also been implemented for personal cars by Kessels [8]. Section 4.4.3 discusses the second strategy, which is based on a different principle than the one in this section.

The influence of λ_{uc} on the use of stored energy can be used to approximate whether an optimal value for λ_{uc} is found or not. As discussed in the previous paragraphs, if λ_{uc} is too large or too small, the strategy will use too little or too much ultracapacitor energy, and the average energy level of the ultracapacitors will slowly drift away from its initial value.

By looking at slow variations in the energy level, the optimal value of λ_{uc} can be approximated. Figure 4.6 shows a schematic of this technique. The energy level of the ultracapacitors is compared to a reference level, for instance 65%. The approximation block consists of a PI-controller with a very small bandwidth, so only slow variations of the energy level are controlled. The resulting approximation of λ_{uc} is called $\hat{\lambda}_{uc}$.

The variation in $\hat{\lambda}_{uc}$ during operation is shown in Fig. 4.7. The initial value for $\hat{\lambda}_{uc}$ is not optimal, and because of this the ultracapacitors are not used at all by the strategy. As a result of this, the SOC of the ultracapacitors goes all the way to the maximum value. The PI-controller reacts to this by slowly changing $\hat{\lambda}_{uc}$ to get the average SOC back down to the reference value of 65%. In this implementation E_{ref} is fixed, but it is also possible to adjust the reference value, for instance when the amount of regenerated energy is expected to be larger or smaller than usual.

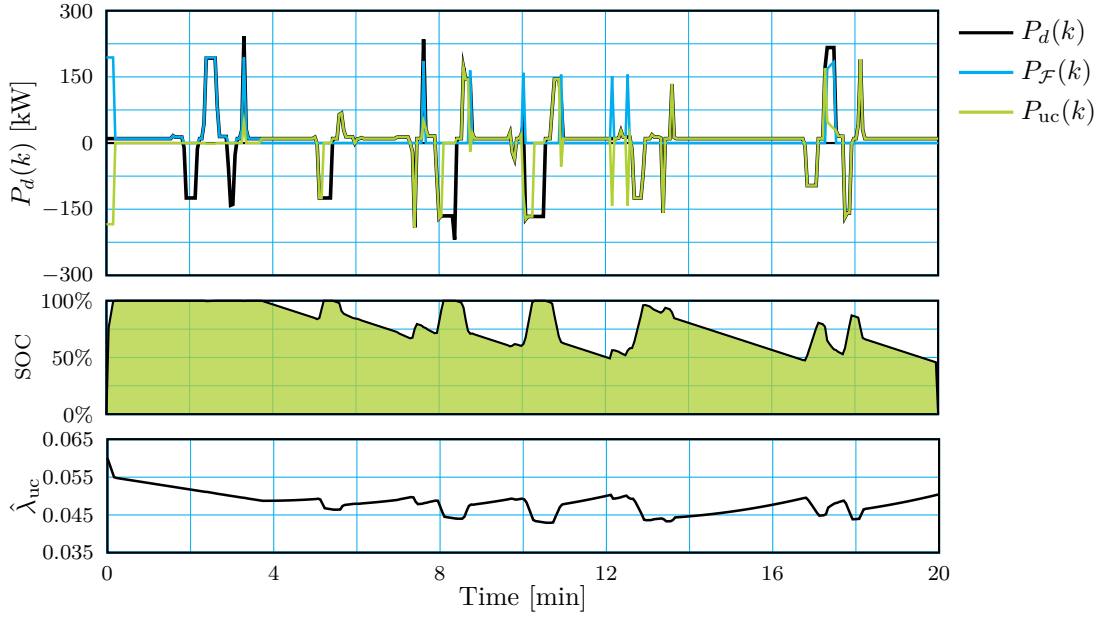


Figure 4.7: Variation of $\hat{\lambda}_{uc}$ during operation

Controller Bandwidth

As Kessels points out [8], the choice for the bandwidth of the PI-controller should depend on the frequency content of the power demand signal. If the bandwidth is too large, the controller will adapt $\hat{\lambda}_{uc}$ to all variations in the power demand, and $E_{uc}(k) = E_{ref}$. In other words, the ultracapacitor will not be used at all. Nevertheless, the bandwidth should also not be chosen too small. If this is the case, $\hat{\lambda}_{uc}$ will not adapt at all, and chances are that $E_{uc}(k)$ will drift to the upper or lower extremes of the energy level.

Since the bandwidth of the controller decides which frequency components of the power demand are suppressed and which are allowed to influence the ultracapacitors, it is important to investigate the power spectrum of the power demand. The main periodic contribution on the power demand is duration of a container movement, 150 sec on average. This means that the power demand signal has a peak in the power spectrum around $1/150 = 0.0067$ Hz, or 0.042 rad/s. The controller should have a bandwidth smaller than this, otherwise it will suppress the use of the ultracapacitors during container moves. On the other hand, the bandwidth should remain as large as possible, so as to keep a measure of adaptability in the system. Table 4.1 shows the fuel consumption figures for different controller bandwidths on a simulation of 21 hours of operation, demonstrating that 0.004 rad/s (10 times smaller than the main periodic component of the power demand) is a good choice for the controller bandwidth.

4.4.3 Approximating λ_{uc} with prediction

Although the SOC feedback approach is appealing because of its simplicity, it may not always produce the best possible results. Essentially it is constantly reacting on things that have already happened, because it relies on feedback from the ultracapacitor energy level. Especially when the average power demand of the crane abruptly changes, for instance when a

Table 4.1: Effect of controller bandwidth on the strategy performance

Bandwidth	Fuel consumption ¹
0.0002 rad/s	30.17 kg
0.0005 rad/s	25.21 kg
0.0010 rad/s	23.45 kg
0.0020 rad/s	23.24 kg
0.0040 rad/s	22.77 kg
0.0080 rad/s	23.37 kg
0.0160 rad/s	26.68 kg
0.0320 rad/s	38.95 kg
0.0640 rad/s	50.39 kg

¹ Fuel consumption during 10 hour operation with varying activities

ships arrives at the terminal and suddenly a lot of containers need to be moved, the feedback approach might react too slow to optimally deal with this change.

A predictive system is an obvious solution for this problem. As of yet, this approach has not been investigated by anyone for a real time application with ECMS. This is probably due to the fact that most research is related to hybrid automobiles, where it is difficult to make reliable predictions about the future power demand. For an RTG crane, making predictions is more feasible. In the near future, detailed information about the upcoming crane activity can be obtained by communicating with the terminal operation system (TOS). This is the complex logistic software system that controls the movement of all the cranes, containers and trucks on the container terminal. Based on this information, the software can make a reasonably accurate prediction of the power demand in the next few minutes. This information can then be used to optimize the current value for $\hat{\lambda}_{uc}$ in real time.

At the moment there is no communication link between the crane software and the TOS, but Siemens is investigating possibilities for closer integration of the two. In this light, the approach of finding $\hat{\lambda}_{uc}$ using predictions can only serve as a feasibility study and as demonstration of what might be possible with good prediction data. For the simulations, a perfect N steps ahead prediction of $P_d(k)$ was used for the optimization.

The basic approach is similar to the way $\hat{\lambda}_{uc}$ is found for off-line applications. Figure 4.8 shows the approximation routine as a block scheme. Using the estimate of the power demand $\hat{P}_d(k)$ a new optimization problem is formulated, that has the goal to find the optimal value for $\hat{\lambda}_{uc}$. The optimum is defined as the value for which the cumulative fuel cost over the predicted time period is minimized, while the energy in the ultracapacitors remains balanced:

$$\min_{\hat{\lambda}_{uc}} \sum_{k=1}^N \mathcal{F}(P_d(k) - P_{uc}^*(k)) \quad \text{subject to} \quad \sum_{k=1}^N P_{uc}(k) = 0 \quad (4.8)$$

where $P_{uc}^*(k)$ is the optimal value of $P_{uc}(k)$ according to the ECMS optimization, for a given value of $\hat{\lambda}_{uc}$. The constraints on the peak power and the energy storage bounds are implicitly satisfied by the ECMS algorithm simulator.

The energy management strategy now consists of two optimization routines. The first is trying to find the optimal $\hat{\lambda}_{uc}$ using the predicted $\hat{P}_d(k)$; and the second is the ECMS-routine

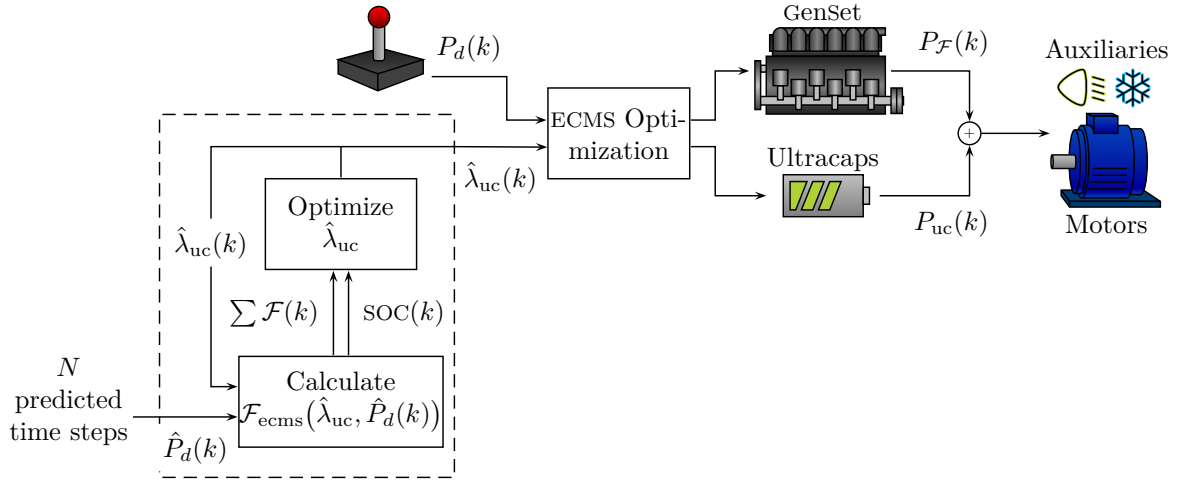


Figure 4.8: Block scheme of second new strategy, using prediction to approximate $\hat{\lambda}_{uc}$ for ECMS

that tries to find the optimal $P_{uc}(k)$, using the approximated $\hat{\lambda}_{uc}$ from the first optimization routine.

Solving the new optimization problem

Because $\hat{\lambda}_{uc}$ is only a scalar variable, the optimization problem can be solved using line search methods. A typical shape of the objective function (4.8) is shown in Fig. 4.9. The precise location of the optimum depends mainly on $\hat{P}_d(k)$, but in general the shape of the function is very similar for most cases. There is a relatively “flat” region, followed by a narrow dip in which the optimum is located, after which the objective function rises back up to higher values.

One notable exception to this general shape is when the crane is idling between moves. Because the power demand during idling is so small, it makes using the GenSet extremely unattractive because of its low efficiency for low power. That means that the choice for $\hat{\lambda}_{uc}$ hardly matters: the engine will not be used, unless the ultracapacitors are completely empty.

As a start location for the line search routine, a value slightly below the approximated $\hat{\lambda}_{uc}$ of the previous time step is used. Because the optimal value λ_{uc}^* usually does not move around very quickly, this ensures that the line search starts close to the optimum so it can quickly find it.

There are a number of line search algorithms available to solve the optimization problem. There is no gradient information available, so the algorithm can use only function evaluations. The key is to keep the number of function evaluations as low as possible, because each function evaluation means that the entire N time samples have to be simulated to find the cumulative fuel cost. However, a trade off has to be made between keeping the calculation time small and the reliability with which the optimization routine finds the optimum.

A comparison between fixed-step, variable-step, parabolic interpolation and golden section methods quickly showed the variable-step method to find the optimum quite quickly (5–6 function evaluations on average). Besides this, the variable-step method is also very reliable

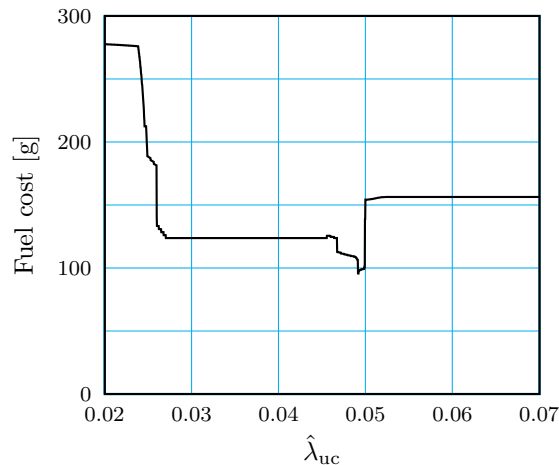


Figure 4.9: Typical shape of the objective function for the $\hat{\lambda}_{uc}$ optimization

in the sense that it always resulted in a value that is close to the optimum, while other methods sometimes came up with unexpectedly large or small values for $\hat{\lambda}_{uc}$.

Prediction horizon N

The number of time steps for which the power demand $P_d(k)$ is predicted is known as the prediction horizon. As discussed during the formulation of the original optimization problem, a prediction horizon of 150 sec will give the best results. On the other hand, the larger the prediction horizon is, the longer it will take to calculate the predicted fuel cost. Because the optimization takes place in real time, this means that it can happen that the optimal value for $\hat{\lambda}_{uc}$ is not found in time for the next time step. This situation is solved by keeping the “old” $\hat{\lambda}_{uc}$ a second time step. Because the prediction system is not in place yet, there is no point in discussing this subject in too much detail.

4.4.4 Idle mode

The initial experiments with ECMS and the original rule-based strategy exposed a weakness in the new strategies: when the crane is idling for a long time, the performance drops dramatically. What happens is that the engine is usually switched off when the crane is idling, because only the auxiliary systems are drawing power so the demand is only small.

During the idle periods, the ultracapacitors are slowly discharged while they power the auxiliaries. After some time the GenSet engine has to start back up and recharge the ultracapacitors. However, because the strategy has no sense of what activities the crane will perform in the near future, it often makes suboptimal decisions about when to start or stop recharging.

A solution was found by making the idle mode a special case in the strategy. When the power demand is small for over 30 sec and no container is loaded, a special routine is started that is hardcoded to deliver a better performance during idling. The routine is based on the original rule-based strategy so it can efficiently recharge the ultracapacitors if necessary. As soon as a container is picked up, or another activity demands extra power, the main optimization-based routine takes over again.

4.5 Summary

The goal of the energy management strategy is to minimize the fuel consumption of the hybrid ECO-RTG crane during operation. This is achieved by constantly controlling the amount of power supplied by the GenSet and ultracapacitors, while they work together to meet the crane's power demand.

Siemens currently uses a rule-based approach for the energy management of its hybrid systems. This approach is attractive because it results in reliable and predictable behavior of the crane. Unfortunately, it is very difficult to achieve optimal fuel efficiency with a rule-based strategy because of the many parameters that are involved that have to be tuned. To overcome the disadvantages with the rule-based strategy's performance, an alternative approach is proposed to achieve optimal fuel economy. The alternative is based on the optimization framework.

An optimization problem can be formulated that minimizes the cumulative fuel consumption over a container movement. The optimization parameters are the setpoints for the ultracapacitor power and the ON/OFF state of the GenSet engine in each time step of the move. Changing the amount of ultracapacitor power influences both the remaining power demand that the GenSet needs to supply, and the amount of stored energy in the ultracapacitors. Changing the ON/OFF state of the engine is more complex than it may seem. Switching the engine off makes it more costly to use the GenSet in the following time steps, due to the additional startup costs. The result is a non-convex objective function with multiple local minima that is difficult to use in optimization.

Furthermore, the optimization is bound by a couple of constraints that limit the possible actions of the energy management strategy. There are constraints on the peak power, the maximum and minimum ultracapacitor energy and on the ultracapacitor energy balance. An important factor in these constraints is the influence of the ultracapacitors' efficiency, which is in turn related to the level of energy in the ultracapacitors. This relation means that the efficiency of the ultracapacitors cannot be calculated until it is known how much power they have supplied, and so the constraints on the ultracapacitor power can only be calculated after the optimization has already finished.

In order to solve the difficulties with the non-convex objective and problematic constraints, the optimization problem is recast in the ECMS framework. The main idea of this strategy is that the use of ultracapacitor power can be expressed in terms of "equivalent fuel cost". This removes the need to optimize the strategy for a complete container move, reducing the optimization problem to a single time step. The traditional ECMS framework was extended to incorporate the "equivalent fuel cost" of switching the GenSet engine off.

The performance of the ECMS approach relies strongly on selecting a good value for the equivalent fuel cost weight λ_{uc} . Two approaches to solve this problem were presented. The first is based on a low-bandwidth PI controller, that adjusts the approximated $\hat{\lambda}_{uc}$ by comparing the ultracapacitor energy to a reference value.

Finally, the second approach attempts to find $\hat{\lambda}_{uc}$ by using predictions of the power demand in the upcoming time steps. This should improve the quality of the strategy compared to the feedback approach, because it can anticipate future events instead of only reacting on changes in the energy level. A line search routine is used to select the optimal value for $\hat{\lambda}_{uc}$, by optimizing the total fuel cost over the predicted time steps.

Simulation Results

The previous chapter proposed two new energy management strategies for the hybrid ECO-RTG crane, both based on the Equivalent Consumption Minimization Strategy (ECMS) approach. In this chapter the fuel economy achievements of these new strategies are presented and compared to the current rule-based strategy, based on simulations of the crane in operation. Section 5.1 introduces the chapter with a general overview of the simulation goals. Next, the three strategies are subjected to four different case studies in Section 5.2. The tests highlight the performance in specific situations such as peak busyness. After these case studies, Section 5.3 presents the results of a simulation of a complete day of operation. Next, Section 5.4 discusses the financial benefits that the three different strategies provide, arguably the most important issue for terminal operators. In Section 5.5 an overview of all simulation results can be found.

5.1 Introduction

To get an indication of the fuel consumption gain that can be achieved with the new strategies, the performance has to be compared to the performance of the rule-based strategy that is currently in place. Eventually this comparison should be made based on tests with a real crane in real operation, but setting up such a test requires a lot of planning and preliminary work. Furthermore, the terminal operator would need to be convinced to have one of its ECO-RTG cranes modified with experimental software. Before all of these steps are taken, computer simulations can give an indication whether these new strategies are worth going through all this trouble.

5.1.1 Simulation setup

The first step in performing the simulations is creating a simulator. This simulator is made up of two parts: a fuel consumption model, and a power demand model. The simulator was built in MATLAB, because the new strategies were also written in MATLAB. The rule-based

strategy was also implemented in MATLAB for this project in order to compare it to the other two.

The fuel consumption model consists of the model from Chapter 3, which mimics the power flows in the crane’s diesel generator set (GenSet) and ultracapacitor banks. The power demand model calculates the power demand of the crane for a given container move. Every important parameter for the move can be varied to simulate real-world conditions, such as the spreader’s start point, the container pickup and release points, the height of the stack and the weight of the container. By giving the model a sequence of move parameters, the power demand for that specific situation can be generated.

The simulated power demand is fed to the three energy management strategies, that calculate the corresponding setpoints for $P_{\mathcal{F}}(k)$ and $P_{uc}(k)$. These setpoints are then used by the fuel consumption model to calculate the fuel cost for each strategy. Finally, the fuel cost for a non-hybrid ECO-RTG is found by calculating the consumption for $P_{\mathcal{F}}(k) = P_d(k)$, i.e., without using the ultracapacitors.

The performance studies are all based on simulations of longer time periods, minimally to 10 hrs simulated operation. This was done to even out the influence of extreme situations, where one of the strategies makes a decision that turns out extremely bad, such as recharging the ultracapacitors right before a container is lowered. All three strategies sometimes make “stupid mistakes” like this, it is impossible to avoid this because the strategies simply cannot plan ahead far enough. Because of this, there deliberately is no discussion of specific behavior of the strategies in specific situations. The only metric of interest is the cumulative fuel consumption over a longer period of time.

5.1.2 Limitations

It is important to note that these simulations have certain limitations, even though a lot of effort was made to make sure the simulator is as close to reality as possible.

The limitations on the crane’s fuel consumption model the most important issue. For instance, the influence of the temperature and humidity is not included in the simulator, because no data for these situations was available. Furthermore, the decision was made not to perform formal verification of the model, because the focus of this project is demonstrating the use of alternative strategies compared to the current one. Gathering the required data for verification would simply take too much time away from developing the strategies, so the model’s accuracy has not been tested against fuel consumption data from the crane in operation. Of course, the model is based on real measurements of the GenSet, so it will definitely be able to give a reliable indication of which strategy gives the best performance in practice.

The power demand model is based on internal Siemens calculations for the crane’s power pack. The model has not been formally verified by comparing it to the power demand of a real crane during specific movements, but it was not the goal of the model to be 100 percent accurate. The simulated power demand should only give a representation of the average power demand and the variations in the demand between different moves, and in this respect the model performs very well. Nonetheless, the accuracy of the power demand model is somewhat limited by the lack of gantry movements, although these are arguably not very important for the total power demand of the crane.

5.2 Case studies

In total, four case studies were carried out to find out as much as possible about the performance of the energy management strategies, in order to make a well-founded comparison between the three. The setup and goals of the tests are described in Section 5.2.1, and the simulation results can be found in Section 5.2.2.

5.2.1 Test descriptions

Test 1: quiet/busy/normal activity

One of the factors worth studying is whether there is a difference in performance when the amount of moves per hour changes. If one of the strategies excels at quiet or busy ports, this information would be useful for container terminals with more (or less) than average activity. The test consist of 10 hours of randomized loading and unloading, with either “quiet”, “normal”, or “busy” operational activity.

Test 2: load/unload activity

Similar to the first test case, this case study does not look at the activity level but the difference between loading or unloading trucks. The difference between loading and unloading lies in the net amount of energy required for each move: lowering a container down from the stack onto a truck requires less energy than the other way around. By looking at the two situations separately, it is possible to see if there is a difference in the way the strategies handle these situations. A “normal” amount of containers per hour is used for the simulation.

Test 3: sudden busyness changes

This case tries to show the result of the different approximation methods. The amount of activity in the simulation switches every half an hour from “quiet” to “busy”, and the strategy has to adjust each time to the changing power demand. While the predictive approach can anticipate the changes, the feedback approach can only react on things that have already happened.

Test 4: different ultracapacitor sizes

The final case study highlights an important trade-off in the design of hybrid vehicles: the size of the energy storage versus the cost of the system. With the ECO-RTG, Siemens chooses to use a relatively small ultracapacitor bank to keep the initial purchase price as low as possible. The goal of this study is to find out whether the choice for a certain size of ultracapacitors has an influence on the best choice for the strategy.

5.2.2 Test results

Figure 5.1 shows the simulation results for the four case studies. The graphs show the total fuel cost over the 10 hours of simulated operation, relative to the (simulated) performance of the non-hybrid ECO-RTG. That means that the fuel cost of the non-hybrid crane represents 100%. As a general remark, the fuel cost for all tests is around 50–60%, which corresponds nicely with the performance figures that were reported for the real prototype crane.

Test 1: quiet/busy/normal activity

The first case study shows that the performance of all the strategies increases as the crane moves more containers per hour. Furthermore, the two new strategies show a small gain for quiet periods, but a very large gain of almost 10 percentage points when it is busy. The small difference for the quiet case is likely due to the fact that all three strategies have a very similar rule-based strategy when the crane is idling.

It is notable that while the fuel savings percentages improve with increasing activity, the total fuel cost also goes up. This means that the absolute improvements are even higher than the percentages indicate. During the 10 hours of busy activity, the ECMS strategies save close to 50 kg of diesel. That is 6 kg more fuel saved than the total fuel consumption of the non-hybrid crane during the quiet test.

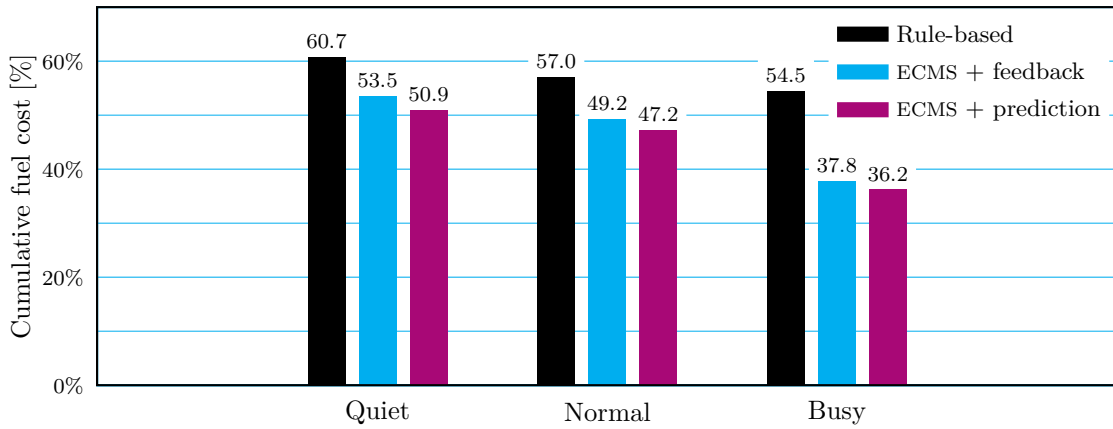
Test 2: load/unload activity

The test on the difference between loading and unloading shows interesting results. The fact that it is more costly to unload containers from the trucks up onto the stack is not surprising, there is less regenerative energy available because the containers are lowered less far in this case. What is surprising however, is the large difference between the three strategies during loading. It seems that the rule-based strategy is too conservative with its energy in this situation, while predictive approach can adequately anticipate on each peak of regenerated energy. This test most clearly shows the advantage of using a predictive strategy.

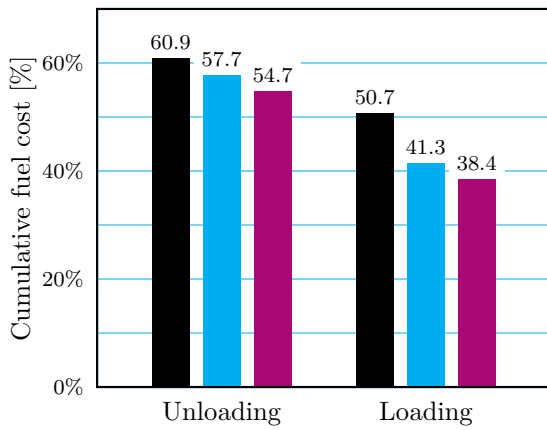
Test 3: sudden busyness changes

This test was intended to highlight the predictive capabilities of the second new strategy, but instead it shows one of its limitations. There is virtually no difference between the two new strategies, even though the expectation was that the predictive strategy should be able to better prepare for the change between busy and quiet periods. The cause for this unexpected result is the limited prediction horizon of only 150 sec, which means that the prediction does not extend far enough to notice much difference between quiet and busy periods.

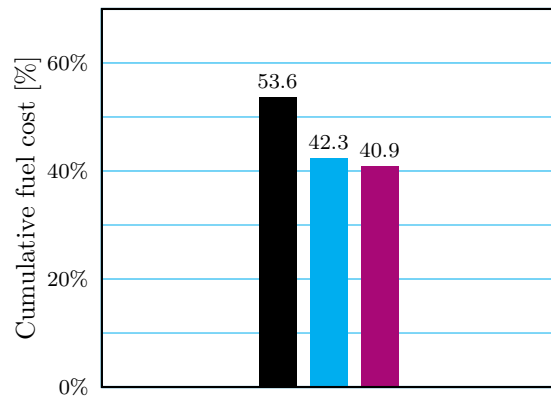
It is also interesting to see that all three strategies perform a lot better than what can be expected by looking at the results from the first test. Intuitively, a 50/50 mix of busy and quiet periods should result in a performance that is in the middle between the results of the two scenarios, but the simulations show that all three perform much better than that. This is due to the fact that the busy periods have a much larger influence on the total cost than the quiet periods. All three strategies have the best performance when it is busy, which explains why the results are better than expected.



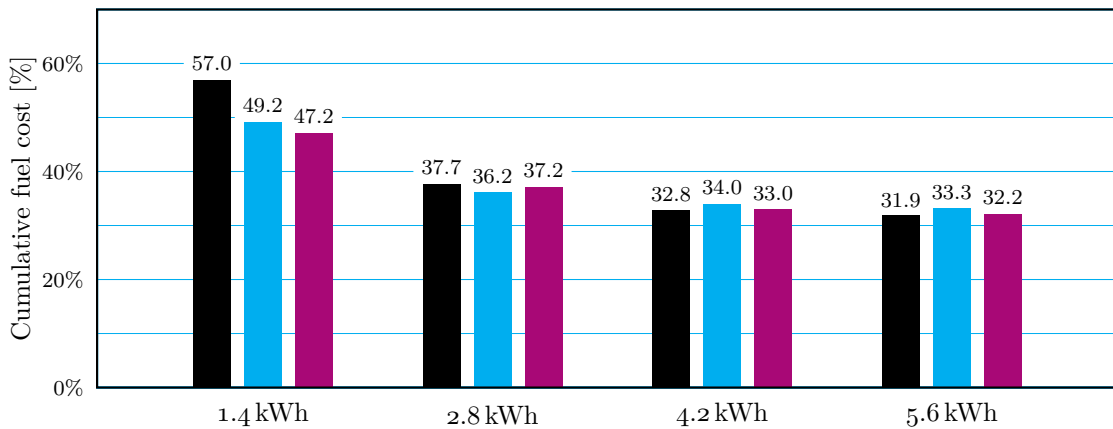
(a) case study 1: quiet/busy/normal activity



(b) case study 2: loading vs. unloading



(c) case study 3: changes in busyness level



(d) case study 4: different ultracapacitor sizes

Figure 5.1: Simulation results of the four case studies. The graphs show the relative fuel cost, where the fuel cost of the non-hybrid ECO-RTG crane represents 100%.

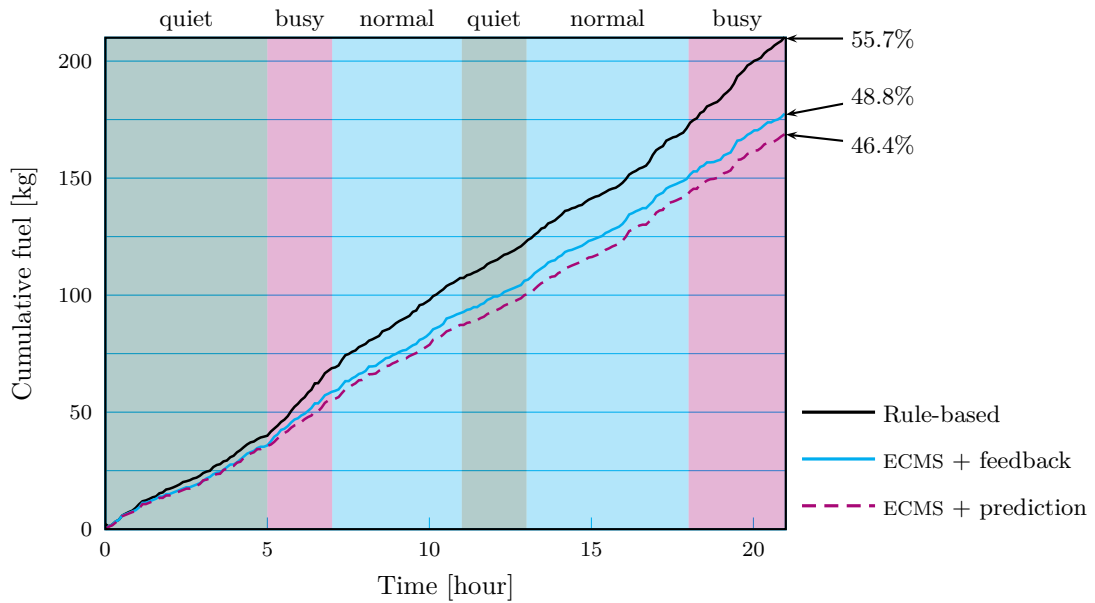


Figure 5.2: Cumulative fuel consumption over 21 hour day with varying activity

Test 4: different ultracapacitor sizes

Increasing the size of the ultracapacitor storage shows that the difference between the three strategies reduces to next-to-nothing when the capacity is large enough. With 1.4 kWh, the relative difference between the strategies is more than 10% (60.8 versus 53.9), but at 2.4 kWh this difference has disappeared. An explanation is that having more storage space means that there is more margin for error for the strategy, so the less sophisticated rule-based strategy is also able to achieve as well as the other two.

5.3 Simulation of real operation

Although the four case studies are useful for finding out where the differences between the three strategies lie, they do not represent real world scenarios. Therefore, as a final test, the strategies are used in a simulation of a complete 21 hour working day. The crane starts the day with its ultracapacitors almost empty, to mimic the self discharging effect of the ultracapacitors. Over the course of the day, the level of activity fluctuates just like the real workload of RTG cranes. On average, the crane does 15 moves per hour, which is almost the same as with the “normal” profile. The load/unload scheduling is completely random, so sometimes there might be a couple of trucks that need unloading, and other times the crane has to load a few containers from the stack.

Figure 5.2 shows the day’s schedule, and the cumulative fuel consumption during the day. The results for the quiet, normal and busy periods resurface in this graph: during quiet periods there is little difference between the strategies, but in more busy periods—when the fuel consumption is larger—the gap increases notably. This is best seen in the difference between the first quiet hours and the busy sections from 5–7 hours. This means that busier terminals will gain more from using the new strategies.

Table 5.1: Calculation of the profits for the hybrid ECO-RTG with different strategies

Strategy		Fuel/month	Profit/month ¹	Payback time	10 yr profit
Non-hybrid	100%	6 000 l	\$ 0.-	-	\$ 0.-
Rule-based	57.7%	3 460 l	\$ 2 130.-	38 months	\$ 176 000.-
ECMS + feedback	48.8%	2 930 l	\$ 2 580.-	31 months	\$ 230 000.-
ECMS + prediction	46.4%	2 780 l	\$ 2 700.-	30 months	\$ 244 000.-

¹ diesel price 0.84 \$/l

Overall, the new strategies consistently outperform the current strategy, as the gap between them never gets smaller but instead is continually growing. The simulation also shows that the two ECMS-based strategies stay very close together throughout the day. In the end, there is only 2.4 percentage points difference between the two. However, even such small differences can save the terminal operators large amounts of money, as will be shown in the following section.

5.4 Financial benefits

An important metric for the hybrid cranes is the time it takes for the hybrid system to earn back its initial investment costs. The more fuel the system saves, the quicker it becomes profitable. The hybrid crane costs US\$80 000 more than a regular ECO-RTG. The payback time is calculated in Table 5.1. It shows that the feedback and predictive strategies cut the payback time by 17% and 21% respectively.

After the strategies have paid off their initial investment, they start making a monthly profit. Over ten years, the total cost of ownership of the hybrid ECO-RTG cranes with the new feedback ECMS strategy is \$230 000.- less than a regular ECO-RTG. Compared to the current hybrid system, the new strategy saves \$55 000.- extra over ten years. A typical container terminal will have a fleet of rubber-tired gantry (RTG) cranes, so switching to the new strategy will literally save hundreds of thousands of dollars for the terminal operator.

Potentially, the predictive strategy could save even more, but since there is no prediction system available at the moment, this strategy cannot be directly implemented on a real crane. Hopefully, the results from these simulations will spur on development in this direction.

5.5 Conclusions

Table 5.2 summarizes the results of the simulations. Overall, the two new ECMS-based strategies consistently outperform the current rule-based strategy. The difference between the two new strategies is relatively small. Because they are both based on the same ECMS principle, this is not a big surprise. What is surprising however is that even in the test with the many sudden changes there is virtually no difference between the two. This is due to the fact that the power of the predictive strategy is hampered by its limited prediction horizon.

Table 5.2: Summary of the tests

		Rule-based	ECMS + feedback	ECMS + prediction
Test 1	Quiet	—	□	□
	Normal	—	□	□
	Busy	□	+	+
Test 2	Unloading	—	—	□
	Loading	□	+	+
Test 3	Busyness changes	□	+	+
Test 4	1.4 kWh	—	□	□
	2.8 kWh	+	+	+
	4.2 kWh	+	+	+
	5.6 kWh	+	+	+
Real operation		—	□	□
Financial gain	Monthly profit	\$ 2 130.-	\$ 2 580.-	\$ 2 700.-
	10 yr profit	\$ 176 000.-	\$ 230 000.-	\$ 244 000.-

In practice it will be the economic benefits that determine the feasibility of the developments. The results show that even a small improvement of the strategy can save the terminal operators hundreds of thousands of dollars in fuel costs. Therefore, the results of these tests are very encouraging for the practical implementation of the new strategies.

Conclusions and Recommendations

This chapter starts by presenting the conclusions of the previous chapters. Section 6.2 proposes some recommendations for further research in the subject of energy management for hybrid cranes.

6.1 Conclusions

As a supplier of electrical systems for container cranes, Siemens faces tough competition, forcing it to keep innovating in order to deliver superior products. A major innovation is the hybrid ECO-RTG crane, which uses an ultracapacitor bank that can store regenerated energy to assist the crane's diesel generator set (GenSet) during operation. This thesis focused on improving the energy management strategy, which is the system that governs the use of the ultracapacitor in combination with the GenSet. The main subject is formulated as follows.

How can the energy management strategy of the Siemens hybrid ECO-RTG crane be improved in order to enhance its fuel economy?

In order to answer this question, it was split up into three subproblems. These three subproblems will be discussed in the following three sections.

1. Create a simulator to analyze the fuel consumption of the hybrid ECO-RTG crane.
 - (a) Create a system to mimic the power demand of the crane during specific types of operations.
 - (b) Create a model that simulates the total power system of the hybrid ECO-RTG, including the fuel consumption and the ultracapacitors.
2. Design a system that improves the current energy management strategy.
 - (a) Analyze the current strategy to find its strong points and weaknesses.

- (b) Find an approach to improve the weaknesses of the current strategy
 - (c) Implement the improved strategy so it can be tested in the simulator.
3. Select the best strategy from the three alternatives.
 - (a) Design experiments that show relevant characteristics of the strategies.
 - (b) Analyze the simulation results to find the best strategy.

6.1.1 Simulator

Power demand simulator

The power demand of the crane was analyzed in Chapter 2. The motion of the crane is handled by a set of electric motors, of which the hoist motor is by far the largest. The power demand of the crane is also dominated by the hoist action, which creates 150–250 kW peaks in the power demand and also large amounts of regenerated power. There is a difference in the duration of these peaks for loading and unloading containers from trucks, due to the height difference between the truck and the stack. Unloading a truck generally requires more net energy than loading, where the container is moved “down” from the stack.

In between the moving of containers the crane is idling. During these periods, the auxiliary systems of the crane still demand 10–30 kW of power. The amount of idle time depends on the busyness of the container terminal: 200 sec during quiet periods, 100 sec for normal activity, and < 10 sec during busy periods. The long idle times have a large influence on the performance of the hybrid crane, because the ultracapacitors are gradually drained during idling.

Power supply model

The power system of the crane was modeled in Chapter 3. The model consists of two parts: the GenSet and the ultracapacitor bank. A quasi-static fuel consumption model of the GenSet was constructed, based on measurements of the ECO-RTG power pack. Overall, the GenSet is most efficient when it is generating power in the 150–200 kW range, and its efficiency drastically deteriorates outside this region. Furthermore, the ON/OFF state of the engine is also important. The engine burns extra diesel when cranking, which adds to the fuel cost right after startup.

The ultracapacitors can both store and deliver power. A model was created, based on data from the manufacturer. The efficiency of the ultracapacitor bank depends on the current flowing through it. This means that the ultracapacitors are most efficient when they supply low power. The energy level of the ultracapacitors is also a factor in the efficiency. A fully charged ultracapacitor is significantly more efficient than when it is nearly empty.

6.1.2 Energy management strategy

Two new energy management strategies were developed in Chapter 4. The strategy that is currently used in the prototype crane is a rule-based heuristic strategy that is reliable and

predictable, but is difficult to tune for optimal performance. An optimization-based strategy is better suited to achieve the best possible performance.

Initially, a strategy that optimizes the fuel cost for a complete move cycle was described, but this approach was unsuitable for implementation because of calculation issues. Instead, an Equivalent Consumption Minimization Strategy (ECMS) is proposed, which only takes a single time step into account for the optimization. The approach revolves around assigning an “equivalent fuel cost” weight $\hat{\lambda}_{uc}$ to the ultracapacitor power. The strategy was further expanded to also include the equivalent fuel cost of starting and stopping the GenSet engine.

The performance of ECMS depends heavily on the choice of the weight $\hat{\lambda}_{uc}$, because it determines how much the ultracapacitors will be used. The two new strategies each have a different approach to solve this issue. The first approach uses a low-bandwidth PI-controller that adjusts $\hat{\lambda}_{uc}$ to keep the ultracapacitor energy level near a set reference value.

The second approach does not rely on feedback to react on things that have already happened, but instead intends to use predictive information to anticipate upcoming power demand. As of yet, the required information about upcoming events is not available to the strategy, but this can be accomplished by connecting to the terminal operation system (TOS). The predictive strategy performs a line search optimization to select $\hat{\lambda}_{uc}$.

6.1.3 Simulation results

The current strategy and the two new alternatives are compared in Chapter 5. The results of the various tests and calculations is shown in Table 6.1. The new strategies consistently outperform the current one. This difference in performance leads to significant long-term gains, and also reduces the time it takes for the hybrid crane to break-even on its initial investment cost.

Between the two new strategies, the difference is small. The advantage of the more complex predictive strategy is small because of the limited prediction horizon. The relatively small storage size also makes long-term planning infeasible. However, because these cranes are used so much, even a small improvement in the strategy can have large effects in the long run, so it might still be interesting to research the prediction system.

6.2 Recommendations

The thesis work focused on researching feasibility of improving the current energy management strategy. The results are encouraging, but there are still a number of things left for future research.

First and foremost, a real life test of the new strategies should be performed to accurately measure the gains the new system during actual operation. The predictive system is still too immature for this step, but the combination of ECMS with SOC feedback should be relatively easy to implement into the crane software. Siemens is already planning to perform these tests using hybrid ECO-RTG cranes that are scheduled for delivery to the Port of Felixstowe.

While the ECMS/feedback strategy is ready for implementation on the crane, the predictive strategy cannot be implemented yet because there are no predictions available. The simulations showed that even a few percentage points improved performance can save large amounts

Table 6.1: Summary of the tests

		Rule-based	ECMS + feedback	ECMS + prediction
Test 1	Quiet	—	□	□
	Normal	—	□	□
	Busy	□	+	+
Test 2	Unloading	—	—	□
	Loading	□	+	+
Test 3	Busyness changes	□	+	+
Test 4	1.4 kWh	—	□	□
	2.8 kWh	+	+	+
	4.2 kWh	+	+	+
	5.6 kWh	+	+	+
Real operation		—	□	□
Financial gain	Monthly profit	\$ 2 130.-	\$ 2 580.-	\$ 2 700.-
	10 yr profit	\$ 176 000.-	\$ 230 000.-	\$ 244 000.-

of money in the long run, so getting the predictive system can be worth the effort. Since there already is a simulator that can predict the power demand for given movement setpoints, the main issue is setting up the communication with the terminal operation system to acquire these setpoints.

To get a better view of what to expect in the way of further improvements, the strategies should be compared to an off-line strategy that achieves the globally optimal fuel consumption. An attempt at this was made by using Dynamic Programming (DP), but this turned out to be too computationally demanding. As an alternative, Rule-Based Equivalent Consumption Minimization Strategy (RB-ECMS) [18] is an option. Although it is not truly a globally optimal strategy, it has proven to be extremely close to it. The earlier thesis work by Joe George [3] already made a start with RB-ECMS, but it used an incorrect model and ignored the importance of the ultracapacitor losses.

Although the model of the power system that was developed in this thesis is far more reliable than the previous one, it is still not perfect. To gain more confidence in the simulations, the model should be properly validated using measurements of the crane during dynamic operation. Because the ECMS strategies also depend on the accuracy of the model, improving it could also lead to better performance in practice.

Further improvements to the new strategies might also be possible. The feedback system currently uses a static reference value for the energy level of the ultracapacitors. This value could also be adjusted to the circumstances, for instance, by lowering the reference value during a move where more regenerated energy is expected. This can be easily predicted by looking at the height of the spreader when the container is picked up.

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Glossary

Abbreviations

AGV	Automated Guided Vehicle
DP	Dynamic Programming
ECMS	Equivalent Consumption Minimization Strategy
GenSet	(Diesel) Generator Set
HVAC	Heating, Ventilating, and Air Conditioning
MPC	Model-based Predictive Control
RB-ECMS	Rule-Based Equivalent Consumption Minimization Strategy
RMG	Rail-Mounted Gantry
RTG	Rubber-Tired Gantry
SOC	State Of Charge
STS	Ship-To-Shore
TOS	Terminal Operation System
VSG	Variable Speed Generator

Greek Symbols

η	Efficiency	pu
η_{dc}	DC/DC converter efficiency	pu
λ_{st}	Equivalent fuel cost weight for engine shutdown	g
λ_{uc}	Equivalent fuel cost weight for ultracapacitors	g/kW
$\hat{\lambda}_{uc}$	Approximated equivalent fuel cost weight for ultracapacitors	g/kW
θ	Generalized optimization parameter	-
θ^*	Generalized optimization solution	-

Latin Symbols

C	Capacitance	F
E_{uc}	Ultracapacitor energy	kWh
F	Force	N
$\mathcal{F}(k)$	GenSet fuel consumption	g
$\mathcal{F}_{ecms}(k)$	Equivalent fuel consumption	g
$\mathcal{F}_{st}$	GenSet startup fuel cost	g
$G(\theta)$	Generalized optimization inequality constraint	-
$H(\theta)$	Generalized optimization equality constraint	-
i_{int}	Ultracapacitor internal current	A
i_{uc}	Ultracapacitor current	A
$J(\theta)$	Generalized optimization objective function	-
k	Time step	-
N	Total number of time steps	-
$P_d(k)$	Combined power demand	kW
$\hat{P}_d(k)$	Predicted power demand	kW
$P_{dc}(k)$	DC/DC converter power	kW
$P_{\mathcal{F}}(k)$	GenSet power	kW
$P_{loss}(k)$	Power losses	kW
$P_s(k)$	Ultracapacitor power (internal)	kW
$P_{uc}(k)$	Ultracapacitor power	kW
R_{int}	Internal resistance	Ω
$S(k)$	ON/OFF state of the GenSet engine	-
v	Velocity	m/s
v_{int}	Ultracapacitor internal voltage	V
v_{uc}	Ultracapacitor voltage	V

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