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Hybrid Control of Container Cranes

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Abstract: Hybrid cranes use ultracapacitors to store energy that is regenerated when lowering a container or during braking, and reuses this energy to assist the engine later on. A hybrid crane needs a system that optimizes the fuel cost by controlling in real time the two available power sources. Currently, the crane uses a rule-based heuristic strategy, which does not achieve optimal results and is difficult to tune. An alternative approach is Equivalent Consumption Minimization Strategy (ECMS), an optimization-based strategy of limited complexity that assigns a weight to the usage of the ultracapacitors that represents the equivalent ‘future fuel cost’. Two new strategies are presented that each have their own approach to this issue. The first uses feedback from the state of the ultracapacitors, the second uses predictions about the upcoming power demand. The new strategies are compared with the current system. The new strategies consistently outperform the current system, significantly improve the fuel savings, and increase the operational profits.

Keywords: Hybrid control, Energy management, Ultracapacitors.

1. INTRODUCTION

Hybrid cars are popular today. A driving car has potential energy that can be recuperated when the car is breaking or has to decelerate downhill. An interesting question for hybrid cars is how and when to discharge the battery. If it discharges too quickly, it cannot use the battery at the next acceleration, if it does not discharge enough, it probably cannot store the energy from the next brake. (Hofman (2007)).

Container cranes raise and stack containers and are naturally more appropriate for hybrid applications than cars, therefore, hybrid containers are also popular today. A hybrid container crane has a conventional diesel engine and an energy storage system that together deliver energy to the hoist mechanism, the wheels, the trolley, and all auxiliary systems such as heating, ventilating, and air conditioning. The diesel engine delivers its energy via variable speed generators and rectifiers, because all equipment is driven by electric motors. The energy storage system can be based on batteries (lead-acid, lithium-ion, (Sumitomo Heavy Industries (2008))), on flywheels (VYCON (2008)), or on ultracapacitors (Schneuwly et al. (2002)). We have used ultracapacitors because they have high lifting power and a long life expectancy.

A simple strategy would be to load the ultracapacitor when a container is let down and to unload the capacitor when lifting another container. When the ultracapacitor is running down, the diesel engine takes over gradually. For several reasons, this is a bad strategy from an energy management point of view. This paper presents properties of a good strategy and a method to achieve a nearly optimal strategy.

The paper is organized as follows. In Section 2 we describe the power demand and supply model. Section 3 describes the energy management strategy. Section 4 describes a case study and results.

2. POWER DEMAND AND SUPPLY

A rubber-tired gantry (RTG) straddles multiple lanes of stacked containers, and can move 20 or 40ft long containers weighing up to 65t. As the name suggests, rubber-tired gantry cranes have rubber tires that enable them to move from one line of stacked containers to another. RTG’s are not connected to the grid and are responsible for their own power system. The complete power system of the ECO-RTG is shown in Fig. 1. The top half of the figure shows the power supply, the bottom half shows the power demand or the power consumers. The power demand is due to a combination of the following subsystems:

- The hoist mechanism, powered by a single electric motor capable of peaks of 200-400kW.
- The wheels for moving the complete crane around the yard, driven by four heavy-duty motors, capable of 40kW 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 on rails at the top of the crane and is driven by two trolley motors with 20kW nominal power each.
- The auxiliary systems, such as the heating, ventilating, air conditioning, and lighting. These systems have a more or less constant power demand of 10-30 kW, depending on, 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 crane’s normal operation is discussed in the next section.

The crane’s movements during the unloading of a truck are depicted in the movements ‘A’ to ‘F’ in Fig. 2. The power demand during each section ‘A’ to ‘F’ depends on the required

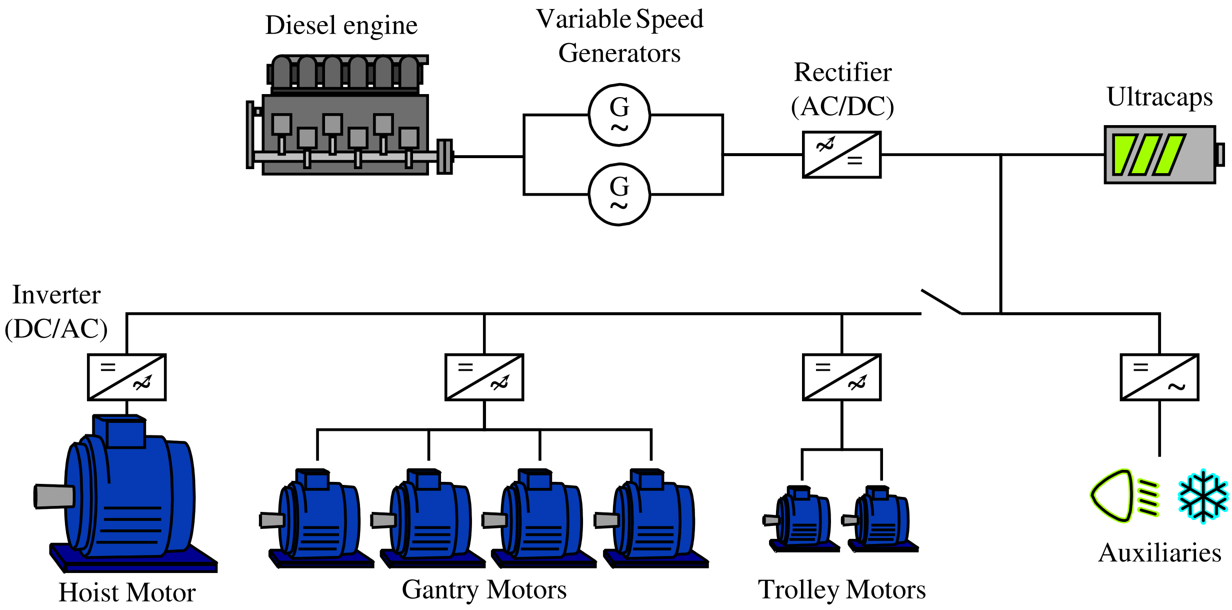

Fig. 1. Power architecture of the ECO-RTG

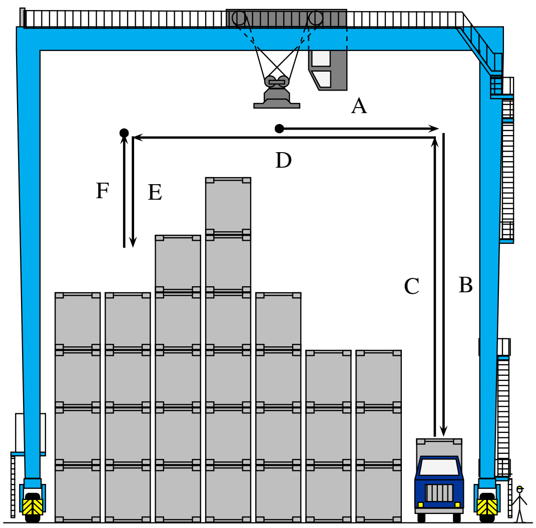

Fig. 2. Movements of an RTG crane unloading a truck

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:

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

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 two power sources of the hybrid ECO-RTG crane each have their own energy 'reservoir', the diesel generator set (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.

The task of the energy management strategy is to optimize the fuel cost and ultracapacitor storage power, $C(k)$ and $P_s(k)$. This is done by controlling the setpoints for the GenSet and ultracapacitors, $P_G(k)$, $P_{uc}(k)$. Therefore, the model that is

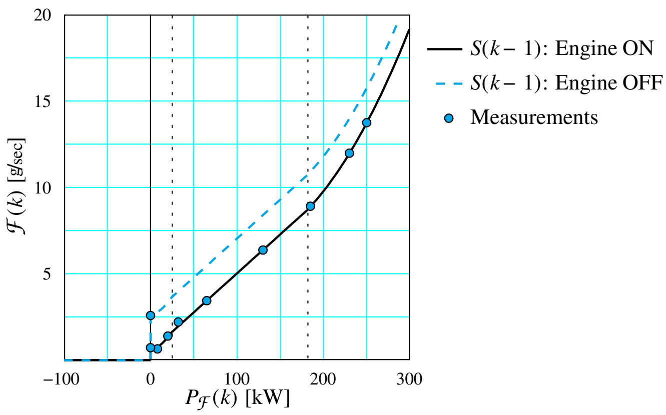

Fig. 3. GenSet fuel consumption measurements and model

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 $C(k)$ and $P_G(k)$, 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, cf. Powell et al. (1998). 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, cf. Gao et al. (2007). The alternative approach is using a quasi-static model as in Guzzella and Sciaretta (2005). 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 Koot et al. (2005); Kessels (2007); Sciarretta et al. (2004).

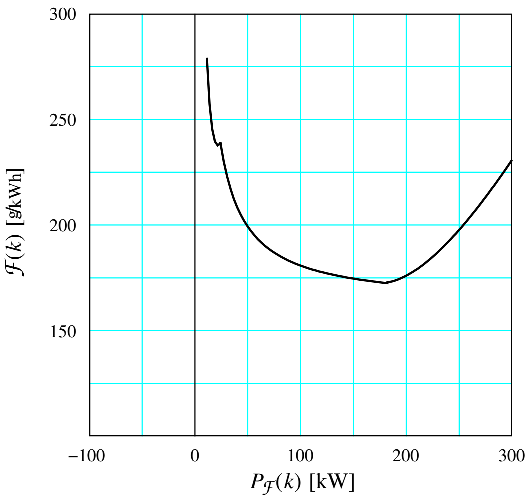

Fig. 4. Specific fuel consumption of the GenSet

Figure 3 shows the measurement data and the model that was created based on laboratory tests on the diesel engine. 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 F_{st} added to the fuel cost.

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

$$\mathscr{F}(k) = \begin{cases} a_2 P_G(k)^2 + a_1 P_G(k) + a_0 & \text{if ON} \\ a_2 P_G(k)^2 + a_1 P_G(k) + a_0 + F_{\text{st}} & \text{if OFF} \end{cases} \quad (2)$$

where ON/OFF denotes $S(k-1) = \text{ON/OFF}$.

In the region between 25-182kW, the quadratic term $a_2 P_G(k)^2$ is equal to zero, to create a linear behavior in that region. To get some insight in the efficiency of the GenSet, Fig. 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 150-200kW, 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.

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 also known as supercapacitors or double-layer capacitors. Schneuwly et al. (2002) provide a more in-depth description of the technology. 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 150–200kW or even switching it off.

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:

$$E_{\text{uc}}(k) = \frac{1}{2} C \cdot u_{\text{int}}(k)^2 \quad (3)$$

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

$$E_{\text{uc}}(k+1) = E_{\text{uc}}(k) - P_s(k) \cdot h \quad (4)$$

where h is the sample time, 1s. The above equation can also be expressed non-recursively:

$$E_{\text{uc}}(k) = E_{\text{uc}}(1) - \sum_{i=1}^{k-1} P_s(i) \quad (5)$$

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 first component where losses occur is the DC/DC converter. These losses are modeled by a static efficiency factor $\eta = 0.92$ between the power at the side of the ultracapacitor bank, and the power at the crane side. When the ultracapacitors are being charged, i.e. $P_{\text{uc}}(k) < 0$, the input and output of the DC/DC converter switch sides, so $P_{\text{dc}}(k)$ is related to the ultracapacitor setpoint as follows, cf. (1):

$$P_{\text{dc}}(k) = \begin{cases} \frac{1}{\eta} P_{\text{uc}}(k) & \text{if} P_{\text{uc}}(k) > 0 \\ \eta P_{\text{uc}}(k) & \text{if} P_{\text{uc}}(k) \leq 0 \end{cases} \quad (6)$$

The second source of energy losses is the 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:

$$P_{\text{dc}}(k) = u_{\text{dc}}(k) \cdot i_{\text{dc}}(k) \quad (7)$$

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

$$P_{\text{loss}}(k) = R_{\text{int}} \cdot i_{\text{dc}}(k)^2 \quad (8)$$

Combining the last equation with (3) and (7) results in:

$$P_{\text{loss}}(k) = R_{\text{int}} \cdot \frac{P_{\text{dc}}(k)^2}{u_{\text{dc}}(k)^2} = \frac{1}{2} R_{\text{int}} C \cdot \frac{P_{\text{dc}}(k)^2}{E_{\text{uc}}(k)} \quad (9)$$

Finally, the losses in the ultracapacitors can be combined with the losses in the DC/DC converter from (6). This gives the relation between $P_s(k)$ and $P_{\text{uc}}(k)$, i.e., the efficiency of the total ultracapacitor:

$$P_s(k) = \begin{cases} \frac{1}{\eta} \left(1 + \frac{1}{2} R_{\text{int}} C \frac{P_{\text{uc}}(k)}{E_{\text{uc}}(k)}\right) P_{\text{uc}}(k) & \text{if} P_{\text{uc}}(k) > 0; \\ \eta \left(1 + \frac{1}{2} R_{\text{int}} C \frac{P_{\text{uc}}(k)}{E_{\text{uc}}(k)}\right) P_{\text{uc}}(k) & \text{if} P_{\text{uc}}(k) \leq 0. \end{cases} \quad (10)$$

The efficiency of the ultracapacitor bank is depicted in Fig. 5. 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 150–200kW.

The influence of the energy level is also clearly visible in Fig. 6. The more energy is stored in the ultracapacitor, the smaller the currents are, and so the efficiency becomes higher.

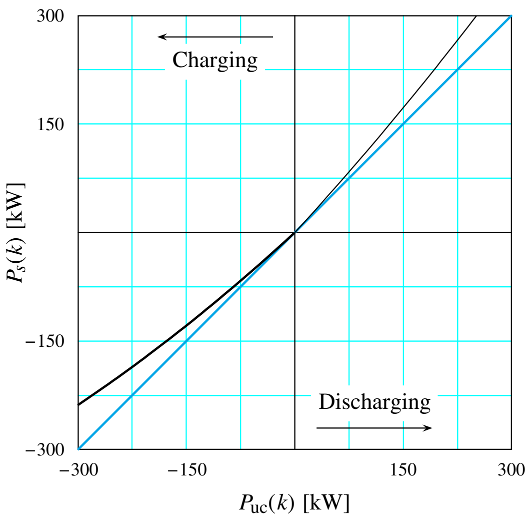

Fig. 5. Nonlinear relation between $P_s(k)$ and $P_{uc}(k)$

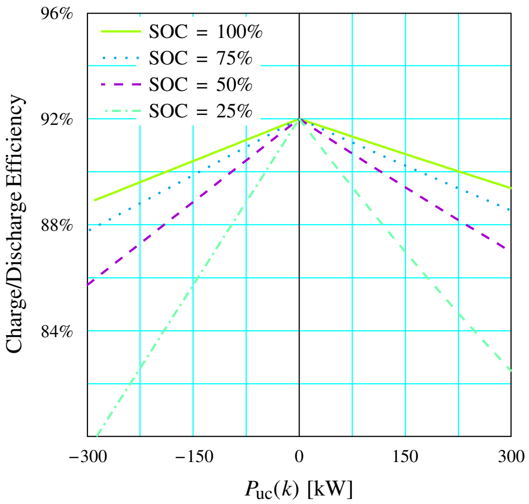

Fig. 6. Ultracapacitor efficiency model — Charge/Discharge efficiency

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. ENERGY MANAGEMENT STRATEGY

3.1 Goal

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 150s and the sample frequency is 5Hz.

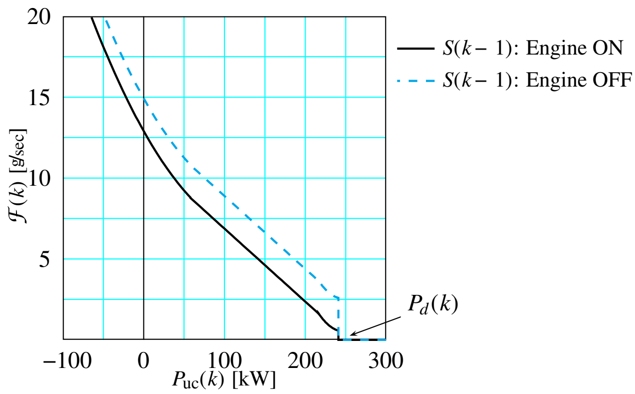

Fig. 7. The fuel cost for a single time step, for $P_d(k) = 241\text{kW}$

Now that the optimization goal is determined, next come 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 $P_G(k)$, because of the relation $P_G(k) = P_d(k) - P_{uc}(k)$. That means that it is not necessary to include $P_G(k)$ 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.

The resulting optimization goal becomes:

$$\min_{P_{uc}(k),S(k)} J(P_{uc}(k), S(k)) = \min_{P_{uc}(k),S(k)} \sum_{k=1}^{N} \mathcal{F}(P_d(k) - P_{uc}(k), S(k)) \quad (11)$$

where $N = 750$, $\mathcal{F}$ denotes the fuel consumption. 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.

The shape of the objective function has a big influence on the results of the optimization problem. The minimum is 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. 7 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, 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 a 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.

3.2 Constraints

The physical constraints for the GenSet are defined by the maximum and minimum amount of power it can deliver:

$$0\text{kW} \le P_{\mathscr{T}}(k) \le 350\text{kW (peak power)}$$

The ultracapacitor bank is limited by its maximum allowed current i_{int}:

$$i_{\text{int}}(k) \le 750\text{A (1s peak current)}$$
$$i_{\text{int}}(k) \le 150\text{A (1s continuous current)}$$

The voltage can be expressed in terms of the stored energy, so it can be written as:

$$P_s(k) \cdot \sqrt{\frac{\frac{1}{2}C}{E_{\text{uc}}(k)}} \le i_{\max} \tag{12}$$

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

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:

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

The energy balance constraint also has to be formulated in terms of the ultracapacitor power, hence:

$$\sum_{k=1}^{N} P_s(k) = 0 \tag{13}$$

The storage capacity of the ultracapacitors is relatively small, just enough for hoisting one container from the bottom to the top of the crane, and therefore plays an important role in the optimization problem. The constraints on the storage are:

$$E_{\min} \le E_{\text{uc}}(k) \le E_{\max} \tag{14}$$

where $E_{\min} = 0.32$kWh, and $E_{\max} = 1.38$kWh. 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:

$$-P_s(k) \le E_{\max} - E_{\text{uc}}(1) + \sum_{i=1}^{k-1} P_s(i) \tag{15}$$

3.3 Equivalent consumption minimization strategy

An optimization-based approach that has proven successful is ECMS from Guzzella and Sciaretta (2005). Of course, changing the formulation of the goal and the constraints can also change the outcome of the optimization algorithm. Hofman (2007) 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 subsection, resulting in two new energy management strategies.

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 $P_{\text{uc}}(k)$ for a single time instance depends on both the instantaneous and the future fuel consumption:

$$\mathscr{T}_{\text{ecms}}\left(P_{\text{uc}}(k), \lambda_{\text{uc}}\right) = \mathscr{T}\left(P_d(k) - P_{\text{uc}}(k)\right) + \lambda_{\text{uc}} P_{\text{uc}}(k)$$

where $\mathscr{T}_{\text{ecms}}$ 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.

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 literature. 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:

$$\begin{aligned}&\mathscr{T}_{\text{ecms}}\left(P_{\text{uc}}(k), S(k), \lambda_{\text{uc}}, \lambda_{\text{st}}\right) = \\ &\mathscr{T}\left(P_d(k) - P_{\text{uc}}(k)\right) + \lambda_{\text{uc}} \cdot P_{\text{uc}}(k) + \lambda_{\text{st}} \cdot g(S(k))\end{aligned} \tag{16}$$

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

To improve the notion of equivalent fuel cost of ultracapacitor power, the losses inside the ultracapacitor should also be taken into account, e.g. by using the equivalent fuel cost of the internal ultracapacitor power $P_s(k)$ instead of $P_{\text{uc}}(k)$ in (16).

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 150s, 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 $\mathscr{T}_{\text{ecms}}(k)$ for each time step.

Selecting an optimal value for λ_{st} is relatively straightforward. It is intuitive to choose the weight as some fraction of the startup cost $\mathscr{T}_{\text{st}}$. If λ_{st} is too high, the strategy becomes overly conservative, if it is too low, there is a risk that 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 $0.02 \cdot \mathscr{T}_{\text{st}}$ and $0.03 \cdot \mathscr{T}_{\text{st}}$ will give the best possible results.

Finding a good value for λ_{uc} is more involving. A first approach is using feedback as proposed by Kessels (2007). A second approach is using a heuristic controller based on fuzzy logic

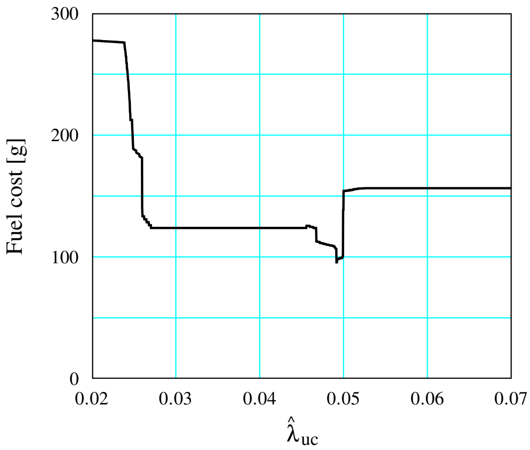

Fig. 8. Typical shape of the objective function for the $\hat{\lambda}_{uc}$ optimization

as proposed by George (2008). We propose to approximate λ_{uc} with prediction. The basic approach is similar to the way $\hat{\lambda}_{uc}$ is found for off-line applications. 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:

$$\min_{\hat{\lambda}_{uc}} \sum_{k=1}^{N} \mathscr{T}\left(P_d(k) - P_{uc}^*(k)\right) \text{ s.t. } \sum_{k=1}^{N} P_{uc}(k) = 0 \qquad (17)$$

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

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 (17) is shown in Fig. 8. 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.

4. CASE STUDY

To get an indication of the fuel consumption gain that can be achieved with the two new strategies, the performance has to be compared to the performance of the rule-based strategy that is currently in place. In total, four case studies were carried out in order to make a well-founded comparison between the

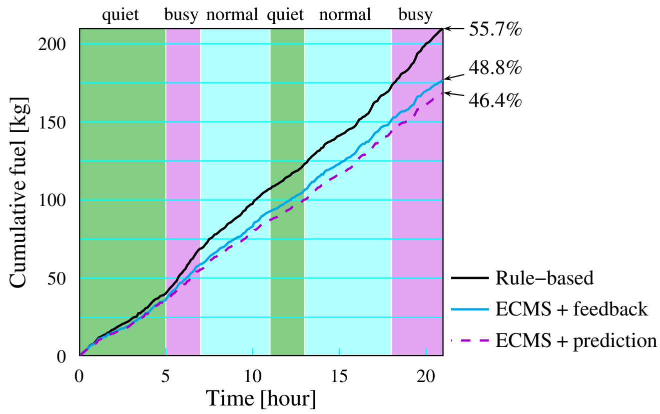

Fig. 9. Cumulative fuel consumption over 21 hour day with varying activity

performance of the energy management strategies. The case studies concerned four situations:

(1) Quiet/busy/normal activity
(2) Load/unload activity
(3) Sudden busyness changes
(4) Different ultracapacitor sizes

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% when it is busy. The second case shows a 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 the predictive approach can adequately anticipate on each peak of regenerated energy. The third case shows one of the limitations of the predictive strategy. 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 150s, which means that the prediction does not extend far enough to notice much difference between quiet and busy periods. 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 1.4kWh, the relative difference between the strategies is more than 10% (60.8 versus 53.9), but at 2.4kWh 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.

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 ECO-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.

Table 1. Calculation of the profits for the hybrid ECO-RTG with different strategies

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

[1] diesel price 0.84$/l

Fig. 9 shows the day's schedule and the cumulative fuel consumption. 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.

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.

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 1. It shows that the feedback and predictive strategies cut the payback time by 17% and 21% respectively.

5. CONCLUSIONS

The two new ECMS-strategies consistently outperform the non-hybrid and rule-based approaches. The differences in performance lead to significant long-term gains, and also reduce 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 can have large effects in the long run, so it might still be interesting to research the prediction system.

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