New developments in Energy Management – battery lifetime incorporation and power consumption forecasting

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Synopsis

In the context of a continuously developing electrical world where the systems are becoming more complex, the demands on fuel consumption and greenhouse gases reduction are also becoming stricter. Additionally, more vessels are looking into using various energy sources – batteries, variable speed generators, etc. – to improve their operation. For such systems, an energy management system (EMS) becomes a vital component. The task of an EMS is to optimize the operation based on a specific goal or goals. Mostly it is the optimization of fuel consumption, and thus also the exhaust pollution reduction, that the EMS is striving to achieve. After implementing the EMS on seagoing ferries (predictable load cycle) and a super yacht (non-predictable load cycle), RH Marine has analysed the measured data and has seen a considerable reduction of fuel consumption, of even up to 38%. With the initial goals achieved, the EMS operation can now be expanded to include more tasks.

A further development of the EMS is to incorporate lifetime, wear and tear, and maintenance requirements of equipment into it. Doing so makes it possible to optimise on total cost of ownership (TCO). As a proof of concept the battery lifetime has been incorporated. Extensive simulations demonstrate that the battery lifetime can be extended, or better: a required lifetime can be reached. This can be realised by carefully observing lifetime determining quantities, like state of charge (SOC), magnitude of charging and discharging currents. This is achieved with a minimal impact on the previously obtained reduction in fuel consumption. The same is valid for other energy sources, such as diesel-generator sets (DGs). By incorporating effects of start-stop cycles on wear and tear, the use of these can be optimised regarding TCO as well.

The better the load can be predicted, the better the EMS will perform. The self-learning function of the EMS will make use of all available data, both from past and future, like a planned combat mode. The paper describes how the above has been integrated into the EMS. The simulations that were performed to prove the concept as described are presented and further developments in the near future will be announced.

Keywords: Energy Management; Hybrid Propulsion; Optimisation; Battery Lifetime; Consumption Forecasting

1. Introduction: Towards the global optimum

On the basis of achieving optimal power system operation on board a ship, generating the required power at the most efficient point can be considered the foundation of the most optimal way of operation. This can be achieved by means of the Lagrange algorithm which decides the power generation set-points of the sources for a given operational profile. The optimization algorithm deciding upon the energy generation allocation is called Energy Management System.

The main task of the EMS is to optimize the operation based on a specific goal or goals mainly focusing on the minimization of fuel consumption. However, for global optimal performance on board a ship many more factors should be taken into account. Optimizing the fuel consumption is a goal which could lead in decisions against the optimal operation of other equipment. In order to optimise the total performance of a ship, one should not neglect the operation and maintenance of on board assets.

A battery energy storage system, for example, is often regarded as a relatively cheap source of energy on hybrid systems because it can be a means to realize fuel saving. Because such a system is a costly investment the optimal operation for the maximization of the battery lifetime should also be considered. It can be argued that there is a trade-off between the battery lifetime maximization and fuel consumption minimization; thus both should be taken into account when striving for maximal cost efficiency. Therefore, as a first step towards optimising TCO, this paper presents an EMS which integrates the battery lifetime of a hybrid super yacht.

In addition, unpredictable load profile is one of the challenges to achieve minimization of TCO. In the operational profile of a yacht, for example, there is little to no predictability. However, on a naval vessel or a ferry there are planned missions, where more accurate power consumption can be achieved. A model for power consumption prediction was developed and operational results on board of a ferry where used to validate the accuracy. In this paper, the model from which results were implemented in the EMS on board a ferry and the actual operational results are explained.

An EMS with battery lifetime incorporated was developed and tested using simulations. The results of these simulations gave new insights in the performance and limitations of energy management systems in general and provide indispensable knowledge for the development of future energy management systems.

2. Optimization algorithm adaptation

Whereas in most current energy management systems the only aim is to save fuel costs, this paper presents the adaptation of the optimization algorithm to also consider the battery lifetime as an important goal. Initially, by considering an unpredictable load profile, a modification is made to a coefficient in the Lagrange algorithm to include the TCO. In order to do this, both the fuel consumption and the battery lifetime are used in the optimisation algorithm.

In case of a forecasted load, such as the one on a ferry, the optimization algorithm is adapted to achieve the desired behaviour of the battery. The forecasted load was used to adapt the Lagrange coefficient to reflect the TCO. For this scenario, operational results of the battery behaviour are shown.

2.1. Optimising fuel consumption

In order to optimise the fuel consumption, the Equivalent Consumption Minimisation System (ECMS) is used. This method has proven to be suitable for application with unknown load profiles (Berecibar, et al., 2016). When using the ECMS, second order cost functions are defined for every generating unit, then the cheapest solution is found using Lagrange relaxation. This method has been used for many optimising applications in a wide variety of systems and has proven successful in practice. Therefore this paper will not give an in depth analysis of the method itself, but instead will focus on the unique integration of the battery lifetime and desired behaviour in the system. The cost functions for the diesel generators can be found by fitting a second order polynomial on the fuel consumption curve; thus, cost functions of the following general form can be found.

$$f(P) = aP^2 + bP + c \tag{1}$$

Whereby *f(P)* equals SFC in g/kWh, *P* DG power in kW.

The fuel costs for charging the batteries, corrected with estimated battery losses, should also be expressed in an equation of a similar form. As published earlier in (Breijs & Al Amam, 2016), this can be done using the following equations:

$$a = \frac{\left(\frac{1}{\eta} - 1\right)}{P_{nom}} \times SFC_{batt}(t) \tag{2}$$

$$b = SFC_{batt}(t) \tag{3}$$

$$c = 0 \tag{4}$$

If you assume that stored battery energy is charged from ship born DG's or shore side power, the equivalent battery SFC_{batt} is expressed according to:

$$SFC_{batt}(t) = \frac{SFC_{batt}(t-1) \times SOC + \overline{SFC_p} \times \Delta SOC}{SOC + \Delta SOC} \tag{5}$$

Whereby η equals battery (dis-)charge efficiency, SOC represents the percentage of stored capacity and ΔSOC the state of charge increase. Where the $\overline{SFC_p}$ equals an average over all power sources supplying energy; weighted by the actual power they deliver, according to:

$$\overline{SFC_p} = \frac{\Delta\left(\mathrm{SFC_{DG1}} \times \frac{P_{DG1}}{P_{plant}} + \mathrm{SFC_{DG2}} \times \frac{P_{DG2}}{P_{plant}} + \mathrm{SFC_{DG3}} \times \frac{P_{DG3}}{P_{plant}}\right)}{\Delta t} \tag{6}$$

With P_{plant} as total plant power and DG_1 as *1st* SFC power source correspondingly.

The cost of charging energy for the batteries is dependent on the operating conditions of the vessel. In the case of the hybrid yacht, the batteries are currently considered to be only charged by the DGs, as defined in Equation (6). This formula is not valid for the ferry case, since the ferry will charge the batteries on shore power. In reality the price of the battery energy should be defined in such a way that would result in the desired battery behaviour, with respect to discharge duration and battery lifetime. In the future, the power consumption forecast for a yacht will result in charging decisions for achieving higher efficiency.

2.2. *Battery fuel cost price modification*

The aim is to incorporate factors which would lead to a longer battery lifetime and desired behaviour, in the optimisation algorithm. Since previously the equations only included the fuel consumption they required modification, to include the battery lifetime for the first case. In the second case, the equations were defined in a way that results in the battery desired behaviour. For both approaches, the factor b was modified in the battery cost function (Breijs & Al Amam, 2016).

$$b(t) = b(t-1) \times \left(1 + b_{offset}\right) \tag{7}$$

$$b_{offset} = \text{Penalty Factor [-]}$$

The resulting EMS is shown below in Figure 1, where the red blocks define the conventional version. The Lagrange multiplier method is used to optimize fuel economy, respecting the operational constraints of the generating units. In the improved EMS, the Lagrange multiplier is adapted with a variable cost function. For the first approach, the value is defined on desired battery lifetime (Approach 1) and on the second approach on desired battery behaviour (Approach 2).

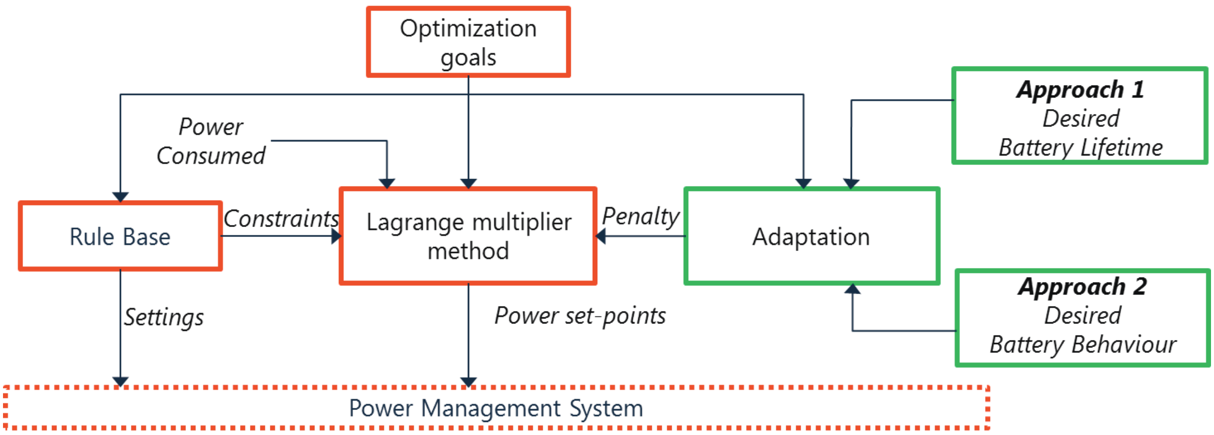

Figure 1: Adapted Energy Management System

2.3. *Approach 1 – Desired Battery lifetime*

2.3.1. *System description –Unpredictable load profile*

To simulate the performance of the improved EMS on an unpredictable operational profile, a case study of a super yacht has been used. Where many current hybrid vessels such as ferry's and tugs have a more or less repetitive and predictable load pattern, this is not the case for a super yacht. Optimising for unpredictable load patterns requires the EMS to provide the optimal solution for a wide range of load patterns.

The system model of the super yacht consists of three diesel generators and two battery energy storage systems, see Figure 2. A load profile is created, using real life data samples. In these data samples the time spent berthed is filtered out, resulting in an eleven day load profile shown in Figure 3. The demand shown includes the propulsion load, hotel load and bow and stern thrusters. For the simulations, different multiple day extractions from this load profile have been used to analyse the system performance.

2.3.2. *Predicting battery lifetime*

To include the battery lifetime in the optimization process, its definition and the influencing factors need to be identified and quantified. When predicting the battery lifetime a distinction can be made between experimental and adaptive battery models. Adaptive battery models measure parameters that are sensitive to battery degradation. Experimental techniques analyse the historical data of the battery. The degradation is estimated from data gathered through experiments.

Theoretically adaptive battery models can give a very accurate estimate since it identifies the key principles (Berecibar, et al., 2016). However, for lithium-ion batteries, adaptive models with sufficient accuracy are not available. Factors involved in the degradation of such batteries and their relationships have not been accurately identified yet. On the other hand plenty of research has been done on experimental methods resulting in relatively accurate models, which provide sufficient accuracy for practical use. Therefore an experimental method such as developed by (Li, Gee, Zhang, & Yuan, 2015) is used in this research. This method combines both the charge and discharge rate and the number of charge discharge cycles to determine the remaining lifetime of the battery. The input for this method is the SOC which is relatively simple to measure. A block diagram of the prediction method is shown in Figure 4.

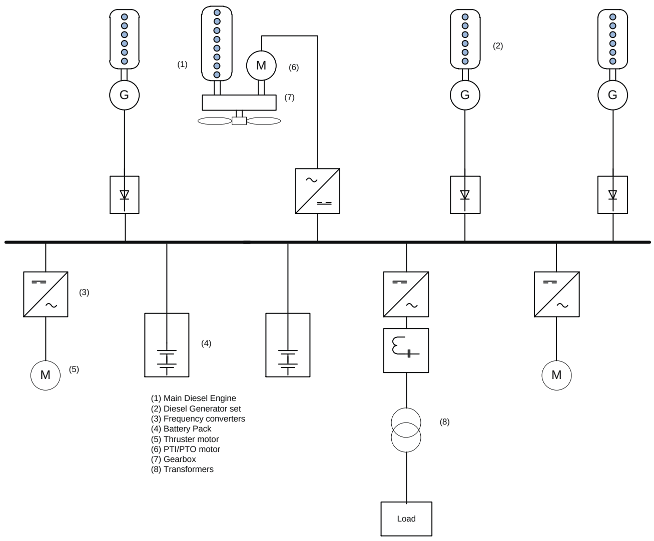

Figure 2: Hybrid super yacht system

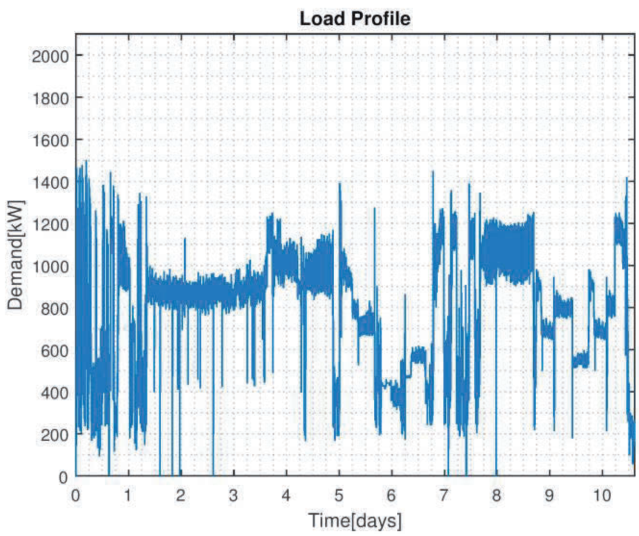

Figure 3: Load Profile of the hybrid yacht

The first step in predicting the battery lifetime is analysing the SOC with the help of rainflow counting. This algorithm determines the number of half and full-cycles and their amplitudes. Half cycles are assumed to have half of the effect on the lifetime, compared to their full cycle counterpart. The battery lifetime prediction algorithm can be seen in Figure 4, while the resulting equation for correction factor ε is shown in Equation (8) (Elling, 2017). The result of Figure 4 represents the input for the EMS, where C-rate is the (dis)-charge rate and CTF the cycles to failure.

$$\varepsilon = 0.8466 + 0.0892\, e^{-\left[\frac{Crate+0.0639}{-1.377}\right]^2} \tag{8}$$

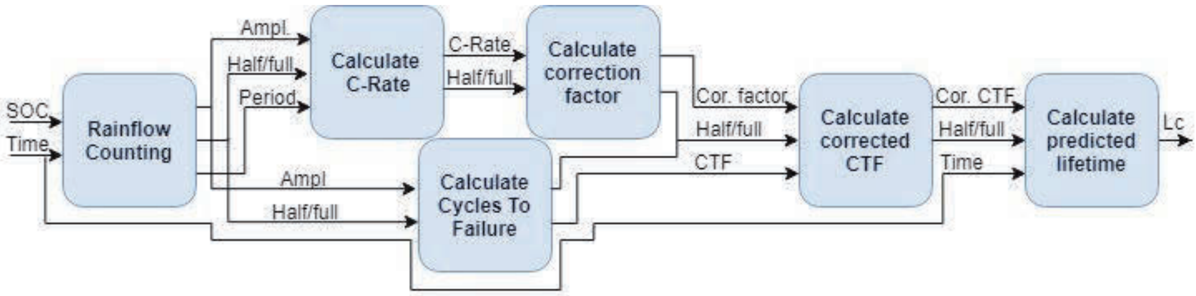

Figure 4: Battery Lifetime Prediction Block Diagram

2.3.3. Incorporating battery lifetime

The improved EMS is adapted with a variable cost function. This variable cost function is created by defining the penalty factor, b_{offset}, as a function of the desired (L_d[years]) and predicted battery lifetime (L_c[years])and a penalty gain (K_P[-]). The resulting set-points are sent to the power management system which controls the generating units.

$$b_{offset} = K_P(L_d - L_c) \tag{9}$$

In the case of the predicted battery lifetime being greater than the desired lifetime, the battery cost function is reduced leading to a greater use of the battery. This results in a reduction in battery lifetime and reduction in fuel costs. If the battery lifetime is smaller than the desired lifetime the battery cost function is increased. This leads to a decrease in battery usage and therefore to increase in battery lifetime. The penalty gain can be used to make the system more or less sensitive for a deviation from the desired lifetime. The resulted EMS in detail is shown in Figure 5.

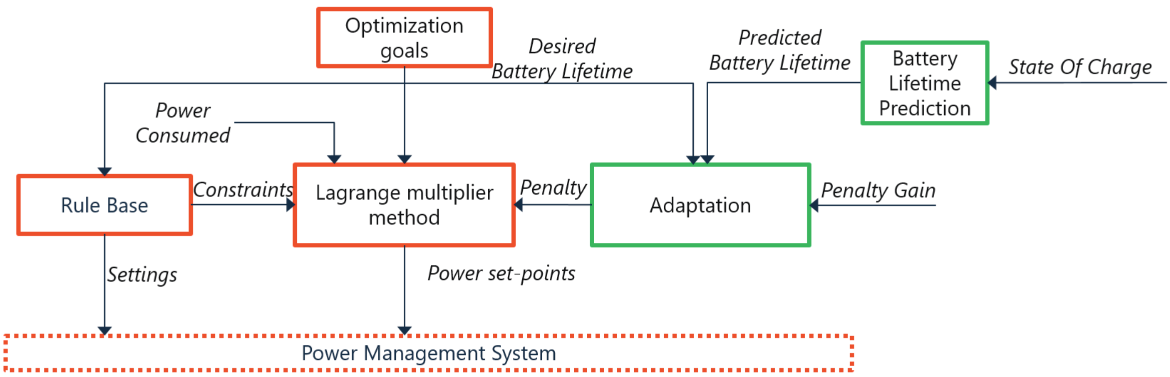

Figure 5: EMS including battery lifetime

2.4. Approach 2 – Desired battery behaviour

2.4.1. System description - Predictable load profile

A predictable load allows the EMS to adapt its optimization algorithm in such a way that the battery usage is optimal for the load pattern. This is ideal for achieving short-term goals, such as optimal discharge battery curves. For this approach, operational data of a ferry with a forecasted load is used and operational data of the battery behaviour are shown as a result of the forecasted load profile.

The system model of the ferry also consists of three diesel generators and two battery energy storage systems too, see Figure 6. The real propulsion load profile for a normal weekday was used, see Figure 7.

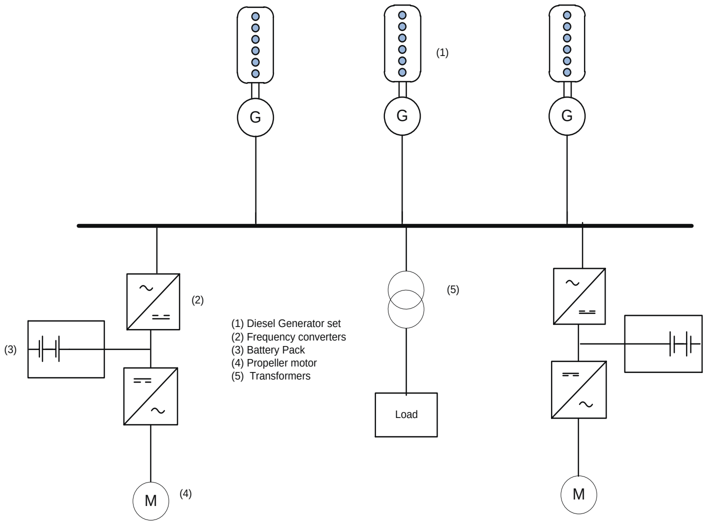

Figure 6: Hybrid ferry system

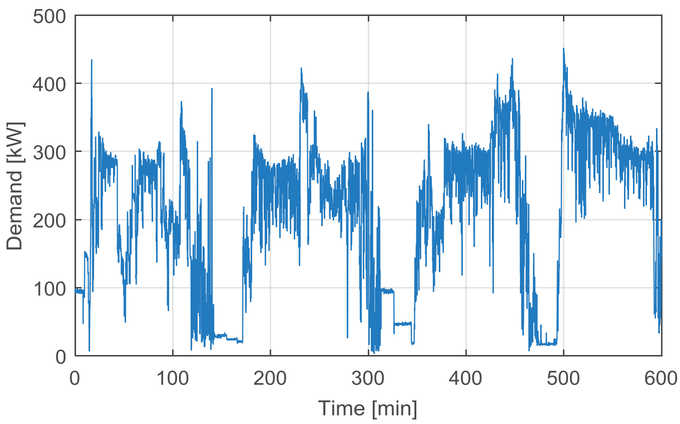

Figure 7: Propulsion load profile of a standard weekday

2.4.2. Power consumption forecasting

The hybrid ferry has a defined schedule during winter and summer time, thus forecast of the load profile is relatively easy. In this case a model was made calculating the *b* coefficient, see Equation (7), in order to obtain the desired battery behaviour. All sources implement the power set-points calculated by the Lagrange algorithm. Since the battery does not have a straight forward relationship to the fuel consumption, a function needs to be created and tuned in such a way that the battery will be used during the complete schedule in the desired way.

The load profile of the ferry consists of the propulsion load and the hotel load, see Figure 8. From historic data can be seen that the percentage of the propulsion over the total load is quite high. A model is made for the prediction of the propulsion load by using design specifications regarding the speed in order to define a nominal profile. Forecasting for the hotel load is not considered in this paper. In case of yachts, the hotel load would be quite significant, for future research a stochastic model for this prediction will be created. Because the majority of the hotel load consists of HVAC loads and this depends strongly on external factors, such as temperatures and humidity levels. These should be considered in the research.

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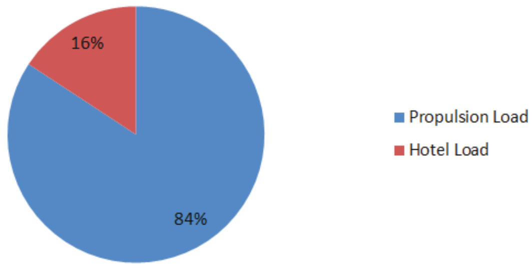

Figure 8: Load profile ratio

The propulsion power for a ship adheres to the following equation:

$$P_{prop} = C_{eq} \cdot V^3 \tag{10}$$

$$C_{eq} = \text{Coefficient of a ship}$$

$$V = \text{Sailing Speed}$$

For a ferry the sailing time and the design speed are known, thus an empirical method was used to define the C_{eq} in Equation (10) and as a result a predicted nominal profile. In reality, the actual load profile will not be nominal but perturbed due to several significant factors, such as weather which can lead to higher propulsion loads and should therefore be taken into account. To obtain a more robust load profile, a perturbation coefficient is created for every day (d) which results in a deviation percentage of the nominal prediction profile. The same is considered for every hour (h), so the predicted load per day and hour is calculated as:

$$\bar{P}_{prop}\,(d,h) = \beta_d \cdot \beta_h \cdot P_{prop}\,(d,h) \tag{11}$$

The above coefficients$(\beta_d, \cdot\, \beta_h)$ used in the predictor model, are taken as a normal distribution with mean value $\mu = 1$ and standard deviation $\sigma = 0.1$.

2.4.3. Power consumption forecasting incorporation

The intention of predicting the load profile is to discharge the battery in an optimal way over the complete scheduled time of the ferry operation. There is a maximum power that the battery can deliver in one hour over the n hour schedule which would still result in an evenly distributed discharge power, see Equation (12). This maximum power is set as a constraint, not only for maintaining the desired discharge duration, but to also include the battery lifetime in the control algorithm.

$$P_{max} = \frac{E\,[kWh]}{t[h]} \tag{12}$$

Where E is the battery capacity in kWh and t the time in hours.

To realise this, the factor in Equation (7), is calculated and penalized with an offset due to a-priori (predicted) knowledge. The implementation of this approach is shown in Figure 9. The operational goal is the usage of the max possible shore power charge and at the end of the day to have a SOC of 20%.

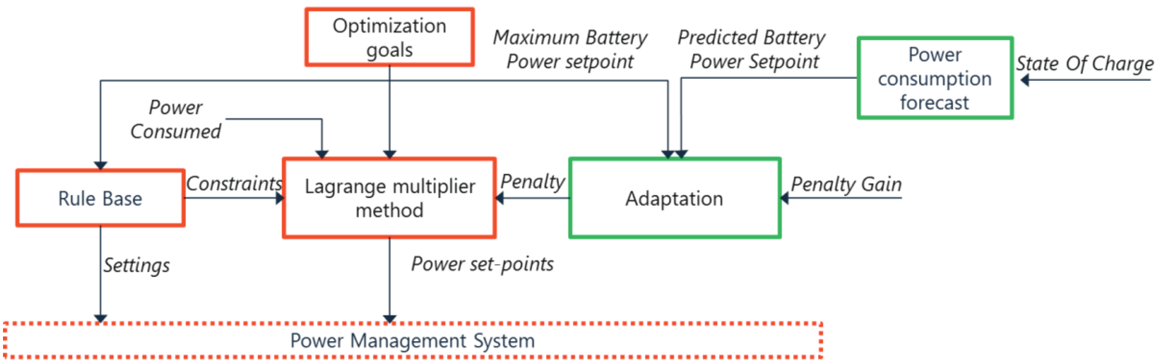

Figure 9: EMS including consumption forecasting

3. Results & Discussion

After validation of the system, the improved EMS for the first approach is simulated using several samples of the load profile shown previously. The results of these simulations are presented and discussed in section 3.1. In section 3.2, the operational results of the second approach, i.e. the battery behaviour as a result of the incorporation of the consumption forecasting are presented.

3.1. Approach 1- Simulation results

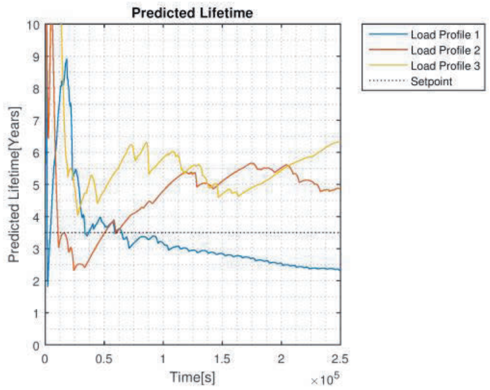

Figure 10: Conventional EMS

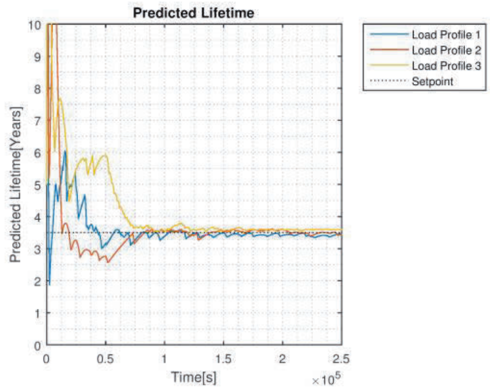

Figure 11: Improved EMS

Initially the improved EMS was tested using three different extracts from the load profile shown before. The resulting predicted battery lifetime for the conventional EMS is shown in Figure 10. The predicted lifetime at a moment t[s] is based on previously obtained information up to that given point in time. This explains the rather unstable behaviour in the beginning since at that time to little historical data was available for a reliable prediction.

The improved EMS, in Figure 11, uses a penalty gain $K_p = 1$ and a set-point of 3.5 years. The graph shows that for each load profile the system is capable of reaching the desired battery lifetime. Table 1 shows the mean and standard deviation for the improved EMS and shows that the system is capable of reaching the desired value for each load profile.

To further analyse the system performance the set-point and gain K_p are varied, as shown in Figure 12 and Figure 13. To compare the results for every set-point the deviation from it is plotted.

Table 1: Results Varying Load Profile

Load Profile	**Mean**	**Std. Deviation**
1	3.4349	0.0486
2	3.5121	0.0640
3	3.6065	0.0434

The deviation is calculated as shown below:

$$\text{Deviation} = \frac{\text{Observed Lifetime} - \text{Setpoint}}{\text{Setpoint}} \times 100\% \qquad (13)$$

The graphs show that initially a higher gain leads to a smaller deviation. It is apparent that for a smaller gain a large steady-state error is present. For set-point 7 years a steady-state error is present for every gain.

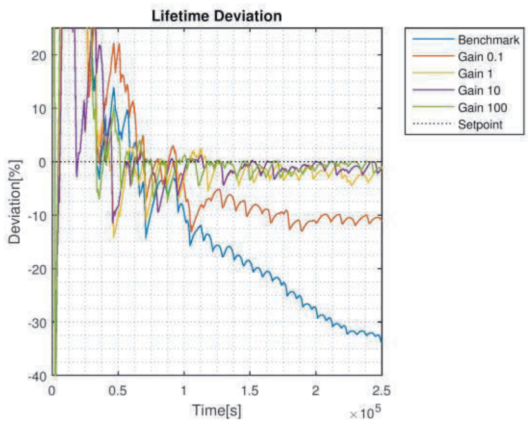

Figure 12: Set-point 3.5 years

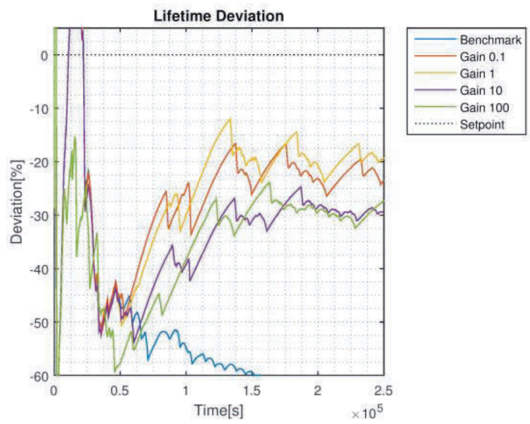

Figure 13: Set-point 7 years

The mean deviation shown in Table 2 gives more insight in the steady state error. It shows that the steady state error generally decreases while increasing the gain. It also shows that with increasing set-point the deviation increases. Especially for a set-point of 7 years (Figure 13) a considerable steady state error is present.

Table 2: Mean Deviation

	Set-point			
Gain	**3**	**3.5**	**4**	**7**
0.1	-6.75%	-9.61%	-12.55%	-22.58%
1	-1.87%	-1.86%	-1.76%	-19.47%
10	-1.07%	-1.01%	-1.70%	-30.46%
100	-0.76%	-0.99%	-1.57%	-29.72%

After closer analysis it was observed that for set-points that greatly differ from the uncontrolled set-point the system can become unstable. In this case the limits of the SOC and the improved EMS counteract each other resulting in a large steady state-error. A flowchart explaining this phenomenon is shown in Figure 14. If during normal operation, the lower or upper SOC limit is reached the battery set-point is limited such that the battery is charged or discharged. As the flowchart shows, in the case of the lower SOC limit being reached the system has the potential of becoming unstable. If for example the lifetime would be greater than desired, the battery cost function is reduced making the battery relatively cheap. Since the system aims to use the cheapest source of energy the system will tend to discharge the battery which is not allowed because of the SOC limit. The operational limits of the battery will only allow for slowly charging in order to prevent violation of the SOC limit. This results in a further increase of battery lifetime and thus error. This phenomenon occurs only for a large penalty factor, which can only be initiated by a large penalty gain or great difference between desired and predicted lifetime.

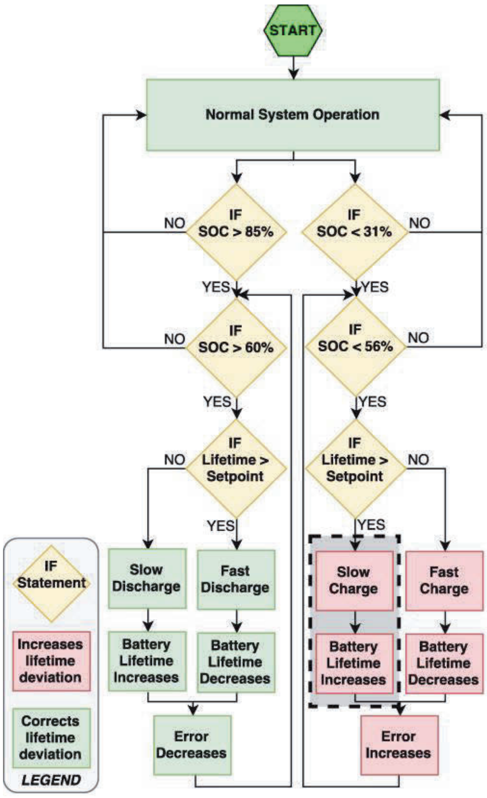

Figure 14: Flowchart Unstable System

Although this phenomenon can decrease the overall system performance as was observed for set-point 7, a fairly simple solution can be found. As shown in the flowchart the reaction is exactly the opposite of what is desired. Therefore the system response is negated after the lower SOC limit is violated; by doing so the battery lifetime can be controlled as desired.

3.2. Approach 2 – Operational results

The presented approach regarding power consumption forecasting, has been in operation in three hybrid ferries. The operator has the possibility of importing planned routes, so at the start of each day the total number of return journeys is defined. The number of return journeys is used by the automation to define a predicted load profile in order to calculate the *b* coefficient which will ensure that the batteries are at 20% SOC at the end of a working day. This value is used to decide on the battery discharge curve for that day.

For each new sailing route, the EMS resets the data stored and begins the self-learning mechanism. The EMS requires one week to develop an optimized battery discharge curve for each new route. During sailing the automation will compensate for several unknown factors (factors that are not measured by the automation), such as weather and crew behaviour. The goal of this is to ensure just 20% SOC at the end of a working day. Therefore the automation will compensate the battery discharge curves:

- During a working day - The weight of compensation will increase as the day comes to an end. Unexpected weather influences, and crew behaviour trigger this compensation.
- During the season - Compensation is made for seasonal weather changes.

In Table 3 resulting calculated *b* coefficients are presented as a function of different consumptions for propulsion and hotel load. The b values are increased with higher propulsion loads, since the price of the battery becomes higher when there is higher load demand, in order to keep a balance on the power delivered by the storage unit. In Figure 15, the operational results for a normal week day on the hybrid ferry are shown. In the first graph, one can see that the propulsion load is dominant in relation to the hotel load for a ferry, as described in section

2.4.1. Finally in the third graph, the battery behaviour is presented for a day, and it shows the adaptation of the battery coefficient to result in an empty battery by the end of the day.

Table 3: Calculated coefficients on different load profiles

Battery coefficient b	Propulsion load consumption [kWh/day]	Hotel load consumption [kWh/day]
205	2158	473
212	2800	450
204	2058	433
213	3050	490

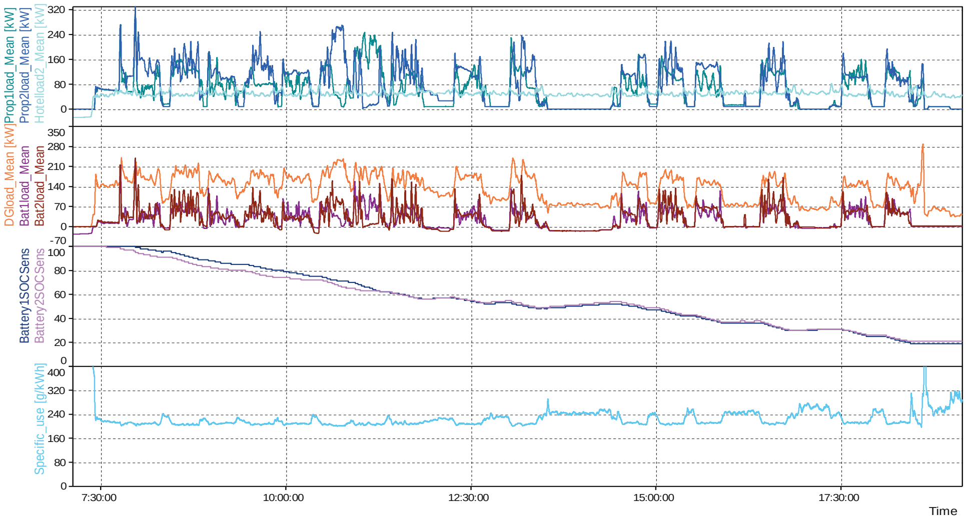

Figure 15: Operational results on a weekday

4. Conclusion

As a first step in the transition towards optimizing the TCO, the battery lifetime is incorporated in the EMS of a hybrid super yacht. Lagrange relaxation with a dynamic battery cost function is used to find the cheapest solution for any load demand. Based on a novel battery lifetime prediction method for Li-ion batteries, the battery lifetime was predicted and the battery cost function was influenced to reach the desired battery lifetime. This method was tested through simulations and resulted in the battery achieving its requested lifetime, without any major impact on the fuel consumption. However, it did also show that interaction with rule based constraints can lead to instability. Simulations showed that the number of start-stop cycles increase enormously with higher gains and set-point, possibly leading to an undesired increase in maintenance costs. This paper has also identified new challenges such as including the SOC and the number of start stop cycles in the optimisation process. It is questionable it can be properly achieved for each generating unit. Research for alternative algorithms for optimising the TCO is recommended.

In addition, power consumption forecast can improve the desired operation. Sailing with a ferry on an unknown route would require time to optimize the battery behaviour. Load profile prediction and as a result influence of the Lagrange coefficient, make the ship ready for every operation. Such a prediction can be used for more than influencing the expected battery charge/discharge behaviour. Consumers which can be controlled and energy to be stored when optimal, in order to maintain a stable grid is the next application of the power consumption forecasting approach.

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