Abstract—In a Hybrid Electric Vehicle (HEV), the main task of an Energy Management Strategy (EMS) is to determine the power-split of the total power demand into a power requests to the internal combustion engine and the electro motor. In this work, real-time implementable previewing strategies (utilizing Model Predictive Control (MPC) and Dynamic Programming (DP)) are applied to a hybrid commercial vehicle. Based on simulations, a comparison of these strategies with non-previewing heuristics and Equivalent Consumption Minimization Strategies (ECMS) is made.

I. INTRODUCTION

Hybrid electric vehicles (HEV’s) have more than one power source to propel the vehicle. Smart combination of these power sources will result in reduced fuel consumption, emissions, and increased drivability. A supervisory control algorithm determines the optimal use of the power sources and is referred to as the Energy Management Strategy (EMS).

EMS’s can be divided into three categories dependent on the route information available: reactive, adaptive and predictive.

Reactive EMS’s use only current information to determine the power-split, where several techniques can be used to implement the strategy, e.g. heuristics [1], ECMS [2] and MPC [3].

Adaptive EMS’s use current and past information to determine the power-split, based on e.g. transport mission identification [4] or equivalent cost learning [5].

Predictive EMS’s use future route information to calculate the best power-split. Information from Geographical Information Systems (GIS) (speed limits, slopes), traffic information services, vehicle to vehicle (V2V) communication (radar, vision), vehicle characteristics (friction, mass) is combined to predict the future power demand. As the optimal power-split problem is non-linear [4], most strategies in literature use Dynamic Programming (DP) to solve the optimization problem. In its basic formulation DP is non causal as it needs full knowledge of the route. Several attempts have been made to make DP real time tractable, by reducing the horizon and simplifying the problem, e.g. [6], [7], [8].

Most investigations focus on light passenger car applications e.g. [4], [9], [10]. Some research is performed on medium duty applications such as city distribution [2] and public transport busses [11]. In this paper we focus on a heavy duty long haulage mission, where fuel reduction is essential, but with relative small components. We compare two real-time implementable predicting EMS’s that use DP or MPC [12].

II. MODELING THE HEV

The HEV has a parallel topology as depicted in Fig. 1. The internal combustion engine (ICE) is coupled via a clutch to the electromotor / generator (EM) which is directly coupled to the input shaft of the gearbox (GB). The output shaft of the GB is connected to the wheels through a fixed ratio.

![Fig. 1. Topology of parallel HEV](image_url)

The power demand P is calculated based on a prescribed route cycle and a model of the 40 ton vehicle incorporating air drag and rolling resistance. In the next paragraphs the modeling of the components and the route cycle are explained.
**A. Internal Combustion Engine**

The internal combustion engine is a Willans approximation [17] of a PACCAR 300 kW diesel engine:

$$m = \frac{P_{\text{ICE}} + k_2 (w_{gb, in})^2}{\frac{P_{\text{ICE}} + k_2 (w_{gb, in})^2}{K_2}}$$

with $m$=fuel flow [g/s], $P_{\text{ICE}}$=power output [W], $w_{gb, in}$=engine speed [rad/s], $k_2$=combined friction constant, $K_2$=combined thermal efficiency. Start-stop is modeled as a fuel penalty at every start event.

**B. Electro Motor/Generator**

The electro motor/generator is based on the 'Powerphase 150' [13] and can deliver a peak power of 150 kW. The motor is connected to the driveline through a 2:1 reduction to match the speed range of the ICE. The model is implemented as the power conversion lines shown in Fig. 3.

**C. Battery**

The model of the battery is based on the MS-TiO battery in [14]. This model has dynamics with time constants $\tau_1$ of 10s and $\tau_2$ of 270s. If we assume that the typical usage of the battery lies in between these time constants, the model can be further simplified by short-circuiting the capacitor of $\tau_2$ and removing the capacitor of $\tau_1$. The model thus reduces to a quasi static model with a separate Recharge and Rdisharge as in Fig. 4. In [14] the State Of Charge (SOC) dependency of the Open Circuit Voltage (OCV) and the resistors are given, resulting for our model in the parameters in Table I.

**Fig. 2. Control loop definition**

**Fig. 3. Control to Power (model of roll, air and accelerations forces)**

**Fig. 3. Power conversion of the Powerphase 150 electro motor**

**Fig. 4. Simplified equivalent circuit of the battery**

**Table I: Parameters of Battery Model**

<table>
<thead>
<tr>
<th>SOC [%]</th>
<th>OCV [V]</th>
<th>Rdisharge [Ω]</th>
<th>Rcharge [Ω]</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>2.661</td>
<td>0.00540</td>
<td>0.01140</td>
</tr>
<tr>
<td>80</td>
<td>2.593</td>
<td>0.00529</td>
<td>0.00740</td>
</tr>
<tr>
<td>60</td>
<td>2.543</td>
<td>0.00550</td>
<td>0.00533</td>
</tr>
<tr>
<td>40</td>
<td>2.483</td>
<td>0.00533</td>
<td>0.00550</td>
</tr>
<tr>
<td>20</td>
<td>2.408</td>
<td>0.00740</td>
<td>0.00529</td>
</tr>
<tr>
<td>0</td>
<td>1.6</td>
<td>0.01140</td>
<td>0.00540</td>
</tr>
</tbody>
</table>

Output power $P_B$ of the battery is calculated with:

$$P_B = P_S - P_{\text{loss}}$$

$$P_B = V_L I_L$$

$$P_{\text{loss}} = R_{\text{discharge}} I_L^2$$

The resulting power conversion lines are shown in Fig. 5. It clearly shows the increasing losses at a combined high power output and low SOC. Stored energy is given by:

$$\int P_{\text{storage}} dt$$

The number of cells in the battery pack is chosen such that the total effective capacity is 4 kWh within a SOC range of 30% (empty) and 90% (full).

**Fig. 5. Power conversion of the battery**

It should be noted that the battery-capacity-to-vehicle-mass-ratio of our truck (0.1 Wh/kg) is low compared to e.g. the Toyota Prius (0.5 Wh/kg) [15], assuming an effective battery range of 50%, see Table II. For our route described in paragraph E this implies that not all energy from brake events fit into the battery.
### Table II

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>HD truck</td>
<td>4</td>
<td>40e3</td>
<td>0.1</td>
</tr>
<tr>
<td>Prius</td>
<td>0.7</td>
<td>1.4e3</td>
<td>0.5</td>
</tr>
</tbody>
</table>

**D. Gear Box**

The gearbox is modeled as a 12 speed Automated Manual Transmission without losses. It has a shift delay of one second and downshifting is penalized with an extra fuel cost. Final drive and wheel diameter are included into this model to provide the translation from vehicle speed to engine speed.

**E. Route**

The route used for our simulation is a flat long haulage motorway route with in the middle a large hilly segment. As shown in Fig. 2 the route is converted to a power demand trace, which the plant is able to track, i.e. the demanded powers are within the maximum rating of the components. The resulting power trace together with elevation and vehicle speed is shown in Fig. 6. For our simulation it is sampled with $T_s=1\text{s}$.

![Power demand $P_{\text{d}}$ [kW]](image1)

![Vehicle speed $v$ [m/s]](image2)

![Elevation $h$ [m]](image3)

**Fig. 6.** Power trace to be tracked by the EMS's

To have a fair comparison of the fuel consumption of different controllers, the difference in SOC between start and end of the route is compensated with some equivalent cost. The cost of this energy is assumed to be the same as for charging the battery in the best efficiency point of the ICE. To minimize the SOC differences between start and end every route is repeated once.

**III. Energy Management Control Concepts**

Two reactive control concepts are used as a reference for the predictive control concepts: a simple heuristic EMS providing insight and an ECMS that also serves as a building block for the predictive controllers. The first predictive controller is based on Dynamic Programming and the second on explicit linear MPC [16]. Both controllers use the same reactive ECMS controller for the final power-split.

The controller has to track the power demand $P_d$ and minimize the fuel consumption over the route while implementing the hybrid functions in Table III.

### Table III

**Hybrid Functions in the EMS’s**

<table>
<thead>
<tr>
<th>Hybrid Function</th>
<th>$P_{\text{ICE}}$</th>
<th>$P_{\text{EM}}$</th>
<th>Clutch Engaged</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICE-only</td>
<td>$P_u$</td>
<td>0</td>
<td>yes</td>
</tr>
<tr>
<td>BER</td>
<td>0</td>
<td>$&lt;0$</td>
<td>no</td>
</tr>
<tr>
<td>E-drive</td>
<td>0</td>
<td>$P_u$</td>
<td>no</td>
</tr>
<tr>
<td>E-boost</td>
<td>$&gt;0$</td>
<td>$&gt;0$</td>
<td>yes</td>
</tr>
<tr>
<td>E-charge</td>
<td>$&gt;0$</td>
<td>$&lt;0$</td>
<td>yes</td>
</tr>
</tbody>
</table>

**A. Reactive controller: Heuristic**

The heuristic controller implements the following rules:
- if (SOC<90 & $P_d<0$), {BER}
- if (SOC>30 & $P_d\geq 0$ & $P_d\leq P_{\text{EM max}}$), {E-drive}
- if (SOC>30 & $P_d\geq 0$ & $P_d>P_{\text{EM max}}$), {E-boost}

With this controller all electric energy will be used as soon as possible and as a consequence the battery will be depleted most of the time.

**B. Reactive controller: ECMS**

The ECMS controller has been elaborately described in literature, see e.g. [18], [19], [20]. Here it consists of two parts: an optimizer which calculates the best power split based on a cost equivalent factor (here: $\lambda$) and a feedback loop that steers the SOC to a nominal value by adjusting this $\lambda$, see Fig. 7. The relation between $\lambda$ and SOC is non-linear and its value is not known upfront [21]. As a result tuning of the feedback loop is not straightforward.

![ECMS control concept with feedback loop on SOC](image4)

**C. Predictive controller: DP**

The core of this predicting controller is provided by dynamic programming (DP) in a receding horizon manner: over a small part of the route-to-come an optimal control is calculated based on a model of the plant and the current...
As illustrated in Fig. 8, the preview vector $P_d$ is the input for the DP algorithm, which calculates a SOC trajectory for the future. This trajectory is used as $SOC_{des}$ for the ECMS feedback loop depicted in Fig. 7.

D. Predictive controller: MPC

The MPC predicting controller consists of a linear MPC controller [16] that calculates a $\lambda$ estimate based on the preview information and the current SOC. It uses simplified plant models, i.e. the EM is approximated with Willans lines, a fixed engine speed is chosen and for the battery a fixed average efficiency is assumed. The $\lambda$ estimate is directly connected to the ECMS controller in Fig. 7, which results in the system depicted in Fig. 9.

A conclusion from optimal ECMS theory is that $\lambda$ will be constant over a route, as long as no SOC limits are violated [2]. If however SOC limits are touched, we assume that $\lambda$ will still be constant between two consecutive limit touches, but remains to be proven. So if we know where the SOC constraint is touched, we are looking for a constant $\lambda$ in between. In MPC a mechanism called 'blocking' [22] is used to reduce the optimization effort by keeping the controlled variable (here: $\lambda$) constant during a given block in the horizon. Sizing the blocks according to constant $\lambda$ segments decreases the time needed for optimization, while maintaining the accuracy of the prediction.

The task of the MPC controller is to find the control variable $\lambda$ resulting in minimal costs over a limited horizon. The cost function consists of penalizing (in order of decreasing importance):
- $\lambda$ deviations.
- SOC boundary violations.
- $SOC_{des}$ deviation at the end of the horizon.

The dynamics in the MPC controller are linear, thus facilitating conversion to an explicit formulation [12].

IV. SIMULATION

A. Fuel consumption

The combination of route and component sizing determines the importance of dealing with battery limits in the EMS. Our route contains a significant amount of BER events, which contain more energy than can be stored in the battery (Fig. 10), which will favor predictive strategies [20].

On our route the simple reactive heuristic controller realizes 9% fuel reduction compared to a non-hybrid topology, see Fig. 11. It recuperates all energy possible with our components. The buffered energy is however immediately used by E-boost and E-drive, which is known to be not optimal.

The reactive ECMS controller can mimic the heuristic behavior by choosing the $SOC_{des}$ in Fig. 7 to be 30%. By varying $SOC_{des}$ and the PI settings, the ECMS controller is able to momentarily save fuel by better use of the buffered energy. Fig. 11 shows however that this fuel gain is at the cost of missing brake energy, which has a dominant influence on the total fuel reduction.

With predictive control it is possible to break with this trade-off and have both good recuperation and use of buffered energy. The MPC controller in Fig. 11 shows a better fuel reduction, even without recuperating the maximum amount of energy. In Fig. 12 a route segment is shown where the heuristic and the MPC controller recuperate the same amount of energy. MPC uses the buffered energy to E-drive at low power demands ($t=230..250s$) and E-boost to maintain a higher gear (e.g. $t=400..500s$), thus saving an extra 2% on the heuristic strategy. Another benefit is that the battery will not be
depleted most of the time, which adds robustness against unexpected electrical demands.

Fig. 11. In a reactive ECMS controller buffered energy use can be improved by tuning (curved line), but at a cost of missing brake energy, which has a dominant influence on fuel consumption. With predictive control both can be improved.

The predictive DP strategy did not perform as expected as shown in Fig. 11: it is hardly able to improve the reactive ECMS performance. This could be due to the choice of interfacing to the ECMS controller. No setting for the PI controller could be found that was fast enough to anticipate SOC violations without $\lambda$ oscillations in the remainder of the route. Besides prescribing a $\text{SOC}_{\text{des}}$ to the PI controller, a direct feed forward to $\lambda$ could be added in Fig. 8.

B. Length of preview horizon

BER has the largest influence on the fuel reduction of the previewing controller. The length of the horizon should cover both the brake energy recuperation and the use of the buffered energy. The power limits of the EM ($P_{\text{em, max}}$ and $P_{\text{em, min}}$) and the battery capacity ($Q_{\text{batt}}$) determine how little time is needed ($T_{\text{min, prev}}$) to drain a full battery and fill it again:

$$T_{\text{min, prev}} = \left[ \frac{Q_{\text{batt}}}{P_{\text{em, max}}} + \frac{Q_{\text{batt}}}{P_{\text{em, min}}} \right]$$

(6)

For our components this minimal time is approximately 200 seconds. The character of the route cycle will determine how much extra preview time is needed to prevent missing brake energy.

Varying the horizon length of the MPC controller shows that on our route 95% of the preview potential is obtained with a horizon of 250s (Fig. 13). It should be noted that reducing the horizon to zero, we converge to the reactive ECMS solution.

C. Gear shifts

Gear shifting is controlled by a separate shift strategy and not incorporated into the EMS’s. The EMS has however strong influence on the behavior of the shift strategy. In Fig. 14 a histogram is shown of the time between shift events for a conventional truck and an MPC controlled hybrid truck. The total number of shifts rises significantly and is most notable for segments where a gear is maintained less than 4 seconds. It is clear that some shifting awareness must be added to the EMS to reduce the number of shifts and a trade-
off must be found between reducing the number of shifts and increasing fuel cost. Because the ICE and EM have different characteristics with respect to optimal engine speed some increase in gearshifts seems inevitable: the gearbox must serve more power sources at both positive and negative power demands.

**D. Controller footprint**

The controller must be able to run on an embedded system, preferably shared with other control functions to reduce costs. To have a design limit on the CPU load, we demanded the controller to be at least 10 times faster than real-time (sample time / turnaround time) on our 2.5GHz simulation PC. The memory usage should be less than 1000 kB. All controllers comply, see Table IV. The predicting controllers are more demanding than the reactive controllers where especially the CPU load of DP is large. The MPC controller makes advantage of its explicit formulation, which saves CPU load at the cost of memory usage.

**Table IV**

<table>
<thead>
<tr>
<th>EMS</th>
<th>sample time / turnaround time [(s)]</th>
<th>Memory [kB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>heuristic</td>
<td>1e-5</td>
<td>0.1</td>
</tr>
<tr>
<td>ECMS</td>
<td>1e-5</td>
<td>10</td>
</tr>
<tr>
<td>DP</td>
<td>1e-5</td>
<td>10</td>
</tr>
<tr>
<td>MPC</td>
<td>1e-4</td>
<td>100</td>
</tr>
</tbody>
</table>

V. CONCLUSION+OUTLOOK

A predicting EMS with real-time capabilities is designed and simulated. It is able to outperform the reactive EMS’s with an extra 1% fuel reduction on top of the 8-9% obtained with reactive EMS. Due to the nature of the mission, many SOC limit violations occur and the reactive EMS’s are not able to both recuperate and use energy optimally. With prediction this trade-off can be broken.

In future work the influence of preview quality on the controller performance will be investigated. Gear shifting will be included in the EMS, as it is seen to strongly influence the behavior of the EMS.

**REFERENCES**


