Abstract: Hybrid vehicles require a supervisory algorithm, often referred to as energy management strategy, which governs the drivetrain components. In general the energy management strategy objective is to minimize the fuel consumption subject to constraints on the components, vehicle performance and driver comfort. Typically, we have to deal with two difficulties. The first difficulty is the design of an energy management strategy. Firstly, the nonlinear behavior of the components results in a nonconvex cost function, complicating the use of optimization methods. Different approaches to deal with the nonconvexity are discussed. Secondly, the future power and velocity trajectories are unknown. Prediction of the future trajectories, based upon either past or predicted vehicle velocity and road grade trajectories, could help in obtaining a solution close to optimal. The benefit of prediction, compared to a heuristic and an optimal control strategy that uses only actual vehicle data, is shown with an example of a hybrid truck at a highway trajectory in a hilly environment. Results indicate that prediction has benefits only when the slopes have sufficient grade and length, such that the battery state-of-charge boundaries are reached.

Keywords: Energy Management; Hybrid Configurations.

1. INTRODUCTION

Hybridization of drivetrains is an often proposed method for fuel consumption reduction in vehicles. Hybrid Electric Vehicles (HEVs) contain two or more power converters instead of one. Energy Management Strategy (EMS) in HEV is the supervisory control algorithm that attempts to minimize the fuel consumption by controlling the drivetrain components. We could divide EMS methods in two classes, firstly, noncausal methods that control the powersplit using exact knowledge of the power and velocity trajectories, and secondly, causal, real-time implementable methods, that control the powersplit without exact knowledge of these trajectories. In general the noncausal strategies are used to benchmark and design the real-time implementable strategies.

In literature several noncausal EMS methods can be found, using optimal control solutions with, e.g., Dynamic Programming (DP), see Lin et al. (2003) and Sundström et al. (2008), or a partly analytical solution derived using the Pontryagin Maximum Principle (PMP), see Delprat et al. (2001). Real-time strategies rely either on heuristic rules, see Guzzella and Sciarretta (2005) and Lin et al. (2003), or on optimal control, Delprat et al. (2001); van Keulen et al. (2008); Kleimaier and Schröder (2002); Koot et al. (2005) and van Mullem et al. (2010).

Recently, attention is paid to predictive EMS that exploit, either statistical properties, see Jeon et al. (2002); Lin et al. (2004); Musardo and Rizzoni (2005); Yokoi et al. (2004) or stochastic properties, Johannesson et al. (2007); Opila et al. (2008), of measured data from past routes or geographic information, see Katsargyi et al. (2009); Kessels and van den Bosch (2008) and van Keulen et al. (2009b), of the upcoming route, to predict the future velocity and power trajectories.

However, several papers, see Kessels and van den Bosch (2008) and van Keulen et al. (2009a), indicate that real-time implementable strategies, that use no prediction, but only actual vehicle conditions as battery SoC, obtain a fuel consumption close to the optimal calculated with DP. Indicating that, at least in these cases, the potential of prediction is limited. Therefore, it is unclear whether prediction is beneficial in the first place, and in case there is benefit: when and how large the fuel consumption benefit of prediction is.

This paper provides an overview of the state-of-the-art EMS, including predictive strategies. Recently, a method is proposed, see van Keulen et al. (2010), that deals with the optimization of vehicle velocity while accounting for the hybrid system, using information from a navigation system as input. This results in optimal velocity and power trajectories of the upcoming route. The benefit of prediction, using these predictions for powersplit optimization, is indicated in a simulation example. Based upon the simulation results, it is argued that prediction can offer considerable fuel savings only when the battery, vehicle, and road characteristics are such that the battery SoC boundaries are reached.

The paper is organized as follows: Section 2 presents a model of heavy-duty HEV longitudinal dynamics and drivetrain components, Section 3 gives an overview of EMS strategies, in Section 4 simulation results are presented, and finally, in Section 5, we summarize with conclusions and give an outlook on future research.

* Thijs van Keulen would like to thank Dominique van Mullem for the use of his simulation model.
2. VEHICLE MODEL

In this example a medium duty truck with a parallel electric drivetrain is used as carrier. The topology is schematically depicted in Fig. 1. The primary power converter is a diesel engine, and the secondary power converter is an electric machine with a lithium-ion battery as storage device. The engine and electric machine are situated in front of a six speed automated gearbox and run with the same rotational velocity. The engine can be decoupled using a clutch. The relation between fuel flow and output power of the diesel engine, depending on the power throughput and rotational velocity, is described in Fig. 2. The different lines show the influence of rotational velocity. Note that several of these lines are nonconvex functions. Moreover, transients effects and temperature influences are neglected. The electric machine can be modeled as a power converter as well, relating electric power to mechanical power at different rotational velocities, see Fig. 3. The SOC of the battery depends on the battery current $I_b$ according to:

$$ S\dot{O}C(t) = I_b(t) $$

For the losses in the battery, an internal resistance model is used, see Pop et al. (2008, p. 103):

$$ P_s = I_b V = I_b V + I_b^2 R $$

here, $I_b$ is the current throughput and $R$ is the battery internal resistance. The power request is described with a cubic function of the vehicle forward velocity:

$$ P_{req}(v, t) = m \frac{dv}{dt} v(t) + c_0 v(t) + c_1 v(t)^2 + c_2 v(t)^3 $$

in which $v$ is the vehicle velocity, $m$ is the vehicle mass, and $c_0$, $c_1$ and $c_2$ are the coefficients describing the vehicle drag and rolling resistance.
• the cost function \( \dot{m}_f(T_{em}) \) is nonconvex (see model description in Fig. 2 and 3),
• the future power trajectory \( P_{req}(v,t) \) is not known a priori.

In the next sections it is discussed how to deal with these difficulties.

### 3.2 Nonsensical Strategies

Provided that the power request trajectory \( P_{req}(v,t) \) is known a priori, a numerical solution for (6) and (7) can be obtained using DP, see Lin et al. (2003) and Sundström et al. (2008). DP is a powerful tool to solve general optimization problems; it can deal with nonlinear nonconvex optimization problems. However, the computation time increases strongly with the number of variables. Since (6) consist of only one optimization variable, the problem can, in general, be solved with acceptable computation time.

Another approach to solve (6) and (7), for a known trajectory \( P_{req}(v,t) \), is to use a partly analytical solution. Neglecting the boundaries on SoC, the Pontryagin Maximum Principle can be applied: the system dynamics (1) can be adjoined to the integrant of the cost function (6), using the multiplier function \( \lambda(t) \), leading to the Hamiltonian:

\[
H = \dot{m}_f(T_{em}) + \lambda(t)P_s(T_{em})
\]  

(8)

To minimize \( H \) subject to the boundary conditions (7), the PMP can be applied, which states that if the control is optimal, then there exists a nontrivial \( \lambda(t) \), such that the following necessary conditions are satisfied:

- the differential equation on the Lagrange multiplier holds:
  \[
  \dot{\lambda}(t) = -\frac{\partial H}{\partial SOC} = 0 \Rightarrow \lambda = const
  \]  
  (9)

- the Hamiltonian has a global minimum with respect to \( T_{em} \):
  \[
  u^* = \arg \min_{T_{em}} H(\lambda^*, T_{em})
  \]  
  (10)

This reduces the optimization, (6) subject to (7), to a stationary problem (independent of time). The Lagrange multiplier \( \lambda \) has a physical meaning: it represents the equivalent cost of stored electric energy in fuel. Therefore, \( \lambda \) is often referred to as equivalence factor. The function \( H \) is still nonconvex, however.

Note that, in case the value of \( \lambda \) is known, (10) can be solved with relatively low computational effort. In Delprat et al. (2001) a recursive method is suggested, where (1), (2) and (6) are solved for an initial value of \( \lambda \). In case the initial guess deviates from the optimal value, the battery will over charge or deplete. The error between initial and end SoC is used to update \( \lambda \). This is repeated until the SoC error is smaller than a certain threshold. Ref. Koot et al. (2005) suggests approximating (8) quadratically, in this way losing the nonconvex character, and using Quadratic Programming (QP) techniques to solve it. This leads to an analytical expression for \( \lambda \). In both methods the SoC boundaries are neglected, but the optimal solution for (6) subject to (7) is found in a much shorter computation time then with DP.

### 3.3 Real-Time Implementable Strategies

In practice, the exact power request trajectory \( P_{req}(v,t) \), is unknown. Therefore, real-time EMS are derived that can be implemented in the vehicle.

**Heuristic Strategies:** a rule-based structure can be employed, where the rules are developed with empirical considerations. In Guzzella and Sciarretta (2005, pp. 190) the following heuristic rules are proposed:

- below a velocity threshold, the electric motor is used alone,
- above a velocity threshold, and below a torque request threshold, the engine is used alone,
- above a torque request threshold, the engine maximum torque is required and the electric motor is used to assist the engine,
- if the SoC is below a threshold, the engine is forced to deliver excess torque to recharge the battery,
- if the SoC is too high, the electric motor is used alone.

A DP analysis Lin et al. (2003) shows that it is beneficial to recharge the battery especially in the low torque region. Besides these rules, that try to optimize the fuel consumption, in practice additional rules are used that ensure driver comfort and vehicle performance.

**Optimal Control Strategies:** the analytical solution obtained with optimal control, could be used to design a real-time strategy as well. It was acknowledged before, that the optimization of (6) subject to (7), simplifies considerably to an optimization that is independent of time (10). This important observation can be used by real-time implementable strategies, that estimate the Lagrange multiplier \( \lambda \). In literature these strategies are often referred to as Equivalent Consumption Minimization Strategies (ECMS). The optimal value of \( \lambda \) depends on the actual operating conditions such as vehicle mass, route characteristics and driving style. For instance if a long descent is present in the upcoming route, then the electric energy is relatively cheap (compared to fuel), and frequent use of the electric machine is more favorable. Several methods for the estimation of \( \lambda \) are proposed. In Kleinau and Schröder (2002) and Koot et al. (2005) it is suggested to apply feedback on the SoC, to prevent the battery from over or undercharging.

\[
s = s_0 + K (SOC_{ref} - SOC)
\]  

(11)

With \( s \) the estimation of \( \lambda \). The resulting optimization can be solved, in real-time, by numerical methods, or approximating (8) with \( s \) quadratically, and solving with QP, see Koot et al. (2005).

Finally, in van Keulen et al. (2008) it is suggested to use actual vehicle conditions as mass and velocity to further optimize the strategy described above. It is reasoned that the reversible energy contains, beside the battery stored electric energy, also kinetic and potential energy. By feedback control on the SoC, the amount of stored energy can be kept on a trajectory, such that the total amount of reversible energy, \( SOC_{ref} - SOC_{kin} \), remains constant:

\[
s = s_0 + K (SOC_{ref} - SOC_{kin} - SOC)
\]  

(12)

So far, EMS are discussed that use current vehicle conditions to estimate the Lagrange parameter \( s_0 \) and/or SoC reference trajectory \( SOC_{ref} - SOC_{kin} \). However, past or future information can also be used to improve the estimation. This is discussed in the next section.

### 3.4 Real-Time EMS Using Past Information

Considering the use of past information, measured power and velocity trajectories can be used to solve the optimization (6) and (7) offline. The optimal solution, for different operating conditions (drive patterns) can be stored in look-up tables. The strategies in Jeon et al. (2002); Lin et al. (2004); Musardo and Rizzoni (2005) and Yokoi et al.
(2004) use drive pattern recognition, and make use of, statistic, characteristic vehicle operating parameters, to chose from a set of representative driving patterns and adjust the EMS accordingly. Examples of characteristic operating parameters are average and standard deviation of: velocity, stop time, acceleration and deceleration, power request, etc. In Bartholomaeus et al. (2008) and Kermani et al. (2008) the special class of problems for vehicles operating in a fixed-route service are described, where past velocity information of the future route is available.

Another approach is to use the stochastic properties of the measured data. A characterization in terms of stochastic information considers the frequency distribution of the measured trajectories, and can be used to train Markov chains, see Johannesson et al. (2007) and Opila et al. (2008). The probability of the next power split command can then be estimated given, e.g., the current vehicle speed and the current power split.

3.5 Real-Time EMS Using Future Information

Besides measured data, characteristics of the future route can be exploited in case a GPS with navigation is available. A navigation system could provide information of road grades and velocity limitations. This information, together with vehicle road load parameters in (4), can be used to estimate the upcoming (optimal) velocity $v$ and power $P_{req}$ trajectories, as was done in van Keulen et al. (2010). One of the noncausal strategies, of Section 3.2, can be used as a tool to quantify the benefits offered by the route.

Other methods that decompose the route into segments with known properties are outlined in Katsargyri et al. (2009); Kessels and van den Bosch (2008) and van Keulen et al. (2009b). The segments are used then to construct an estimation of the future power and velocity trajectory. The idea of an active SoC reference trajectory, as in (12), can be further exploited by predicting the optimal SoC trajectory for the upcoming route.

In the next section, a method similar to van Keulen et al. (2009b) is used to estimate an optimal SOC reference trajectory for three different routes.

4. RESULTS

The benefit of prediction, of heavy-duty HEVs, in a hilly environment, is outlined in the next example. The simulation model described in Section 2 is used to evaluate three real-time implementable EMS with a nonhybrid baseline vehicle:

(1) a rule-based strategy, using the rules described in Section 3.3.1,
(2) an optimal control strategy with fixed reference, using (11),
(3) an optimal control strategy with SoC trajectory prediction, using (12),
(4) baseline vehicle.

The strategies are compared on highway trajectories of 40 km length, with three different height profiles, see Fig. 4. First, input grade 1, a trajectory with only mild grades of 2 % is considered. Secondly, input grade 2, a highway route with small lengths (1 km) of steep grades of 4 %. Finally, input grade 3, a route with long (5 km) and steep road grades of 4 %. Fig. 5 shows the velocity input trajectories with the same travel time: (A) using a constant velocity: and (B), a dynamic optimized velocity.

Fig. 6 to 11 show the simulated SoC and fuel consumption trajectories. Table 1 shows the fuel consumption results.

Here, the difference between initial and end SoC is accounted for by using an equivalence factor of 0.616 [L/-] to express the SoC difference in fuel consumption.

Table 1. Simulation results: the bar indicates that this are equivalent values, accounting for the difference between initial and final SoC.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>grade 1</th>
<th>grade 2</th>
<th>grade 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1A) rule-based</td>
<td>$\bar{m}_f = 6.04$ (-0.0%)</td>
<td>$\bar{m}_f = 5.88$ (-1.7%)</td>
<td>$\bar{m}_f = 6.23$ (-7.5%)</td>
</tr>
<tr>
<td>(2A) optimal control</td>
<td>$\bar{m}_f = 6.04$ (-0.0%)</td>
<td>$\bar{m}_f = 5.87$ (-1.9%)</td>
<td>$\bar{m}_f = 6.30$ (-6.5%)</td>
</tr>
<tr>
<td>(3A) prediction</td>
<td>$\bar{m}_f = 6.05$ (0.0%)</td>
<td>$\bar{m}_f = 5.89$ (-1.6%)</td>
<td>$\bar{m}_f = 6.13$ (-8.9%)</td>
</tr>
<tr>
<td>(3B) prediction</td>
<td>$\bar{m}_f = 6.04$ (-0.0%)</td>
<td>$\bar{m}_f = 5.98$ (-1.6%)</td>
<td>$\bar{m}_f = 6.02$ (-10.4%)</td>
</tr>
<tr>
<td>(4A) baseline</td>
<td>$\bar{m}_f = 6.04$</td>
<td>$\bar{m}_f = 5.98$</td>
<td>$\bar{m}_f = 6.73$</td>
</tr>
<tr>
<td>(4B) baseline</td>
<td>$\bar{m}_f = 6.04$</td>
<td>$\bar{m}_f = 5.98$</td>
<td>$\bar{m}_f = 6.59$</td>
</tr>
</tbody>
</table>
optimal control with prediction leads to a SoC end point closer to the initial SoC. However, this does not lead to an improved fuel economy compared to the rule-based or optimal control strategy with fixed reference, see Fig. 9 and 10.

A substantial benefit in fuel economy can be seen though for input grade 3, where the SoC reference trajectory causes a depletion of the battery in between the two descents, see Fig. 8. Velocity trajectory optimization offers a substantial fuel consumption reduction, both for the baseline as hybrid vehicle. The performance of the rule-based strategy and optimal control with fixed reference is practically the same.

Finally, note that the fuel consumption of the hybrid vehicle with predictive EMS, at the input grade 3 profile, deviates only marginally from input grade 1 profile, although the altitude was doubled. The travel time was a bit longer though.

5. CONCLUSION

During the last years, many strategies that deal with the powersplit between hybrid system and internal combustion engine are presented. Recently, it is suggested that prediction of the future power and velocity trajectories, based upon input from a geographical information system with GPS, could improve the result of the real-time strategies. The simulation example in this paper shows that one can find examples where the benefit of prediction ranges from marginal to substantial, depending upon the route and vehicle characteristics.

It is argued that prediction of the future power and velocity trajectories, for the EMS optimization has little
or no fuel consumption benefit on roads with mild grades, although it is possible to keep the state-of-charge closer to a preferred value of 50%. In practice benefits from prediction can be expected, only when driving in a hilly terrain with long and steep descends. This also implies that the use of stochastic or statistical properties of measured data from past routes, to optimize the future powersplit, offers limited benefits, unless it is connected to a GPS with navigation that can locate the vehicle in a map.

Future work will focus on an experimental validation of the results presented here.

ACKNOWLEDGEMENTS

The research leading to these results has received funding from the ENIAC Joint Undertaking and from SenterNovem in the Netherlands under Grant Agreement number 120009, and is part of a more extensive project in the development of advanced energy management control for urban distribution trucks which has been made possible by TNO Business Unit Automotive in cooperation with DAF Trucks NV.

REFERENCES