Proceeding of the 2004 American Control Conference
Boston, Massachusetts June 30 - July 2, 2004

Energy Management Strategies for Vehicle Power Nets

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Abstract— **In the near future a significant increase in electric power consumption in vehicles is to be expected. To limit the associated increase in fuel consumption and exhaust emissions, smart strategies for the generation, storage/retrieval, distribution, and consumption of the electric power can be used. This paper presents a case study on controlling the vehicle power net using knowledge of the driving pattern to minimize fuel use, by generating and storing extra energy only at the most suitable moments. For this purpose, both off-line and online optimization methods are developed and tested in a simulation environment. Results show a reduction in fuel use, even without an accurate prediction of the drive cycle.**

I. INTRODUCTION

The electric power consumption in standard road vehicles has increased significantly over the past twenty years (approximately four percent every year) and in the near future, even higher power demands are expected [7]. Reasons for this trend are:

- Today's customers expect more performance, comfort, and safety from new vehicles.
- Electrical devices replace mechanical or hydraulic components in the vehicle (e.g., the drive-by-wire concept).

To keep up with future power demands, the automobile industry has suggested new 42V power net topologies which should extend (or replace) the traditional 14V power net from present vehicles [4], [7]. Although these advanced power nets will be able to meet tomorrow's power requirements, a problem that arises is how to control the power net, in order to obtain maximum energy efficiency within the vehicle.

Following the considerations in [9], [3] and [8], this paper presents the results from a study on controlling the power delivered by the alternator using optimization techniques and knowledge of the driving pattern. Eventually, such a controller can become part of an overall *Energy Management System* incorporating several control systems.

This paper is built up as follows: The vehicle will be modelled in Section II. In Section III, the energy management problem will be formulated. Several strategies for solving this problem off-line and online will be presented in Section IV, V and VI. Their performance will be compared by simulations in Section VII. Conclusions are given in Section VIII.

II. VEHICLE MODEL

The type of vehicles considered in this paper are vehicles with a conventional drive train and a manual transmission. In Fig. 1 the structure of such a vehicle is represented as a power-based model. The drive train block contains all drive train components including clutch, gears, wheels, and inertia. The alternator is connected to the engine with a fixed gear ratio.

The power flow in the vehicle starts with fuel that goes into the internal combustion engine (ICE). The mechanical power that comes out of the engine splits up into two directions: one part goes to the mechanical drive train for vehicle propulsion, whereas the other part goes to the alternator. Next, the alternator provides electric power for the electric loads but also takes care of charging the battery. Contrary to the other components, the power flow through the battery can be positive as well as negative. In the end, the power becomes available for vehicle propulsion and for electric loads connected to the power net.

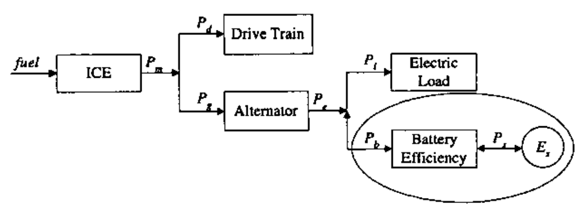

Fig. 1. Block diagram of vehicle's power flow

The goal of energy management is to control the alternator power such that the fuel consumption is reduced, while the drivability remains unaffected, i.e., the driver should not experience different vehicle behavior when the controller is applied. This requirement greatly reduces the problem complexity. It implies that the vehicle speed and thus the drive train torque and engine speed remain unaffected and therefore it is possible to use them as given information.

The remaining components of interest are the engine, the alternator, and the battery. Using discrete time optimization with a sampling interval of 1 second or larger, their dynamic behavior is neglected, so their characteristics are represented by static models. The only remaining dynamics in the model is the integrator of the battery storage.

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The internal combustion engine can be represented by a nonlinear static map which describes the relation between fuel consumption, engine speed, and engine power:

$$fuelrate = f(P_m, \omega) \quad \text{where} \quad P_m = P_d + P_g \tag{1}$$

Note that the engine torque can be derived from the engine power if the engine speed is known.

A characteristic fuel map of a Spark Ignition (SI) engine is displayed in Fig. 2. In this figure, fuel consumption curves $f(P_m, \omega)$ are drawn for different engine speeds ω as function of mechanical power P_m.

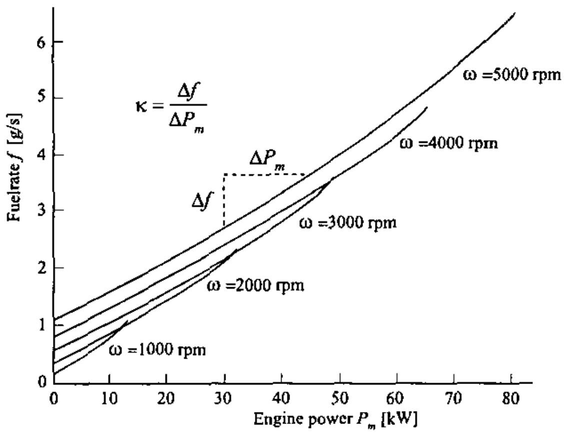

Fig. 2. Characteristic fuel map of an SI-engine

Using a similar approximation, the alternator model reduces to a static nonlinear map:

$$P_g = g(P_e, \omega) \quad \text{where} \quad P_e = P_l + P_b \tag{2}$$

The battery characteristics can be modelled by:

$$P_b = P_s + P_{loss}(P_s, E_s, T) \tag{3}$$

P_b represents the power entering or leaving the battery terminals, and P_s represents the power actually stored in the battery. P_{loss} represents the battery losses that depend on the storage power, the energy level in the battery E_s, and the temperature T. A typical charge/discharge power storage curve is shown in Fig. 3.

The battery energy level is given by a simple integrator:

$$E_s(t) = E_s(0) + \int_0^t P_s(\tau)\,\mathrm{d}\tau \tag{4}$$

The state of charge (SOC) is the relative energy level:

$$SOC = \frac{E_s}{E_{cap}} \cdot 100\% \tag{5}$$

where E_{cap} is the energy capacity of the battery.

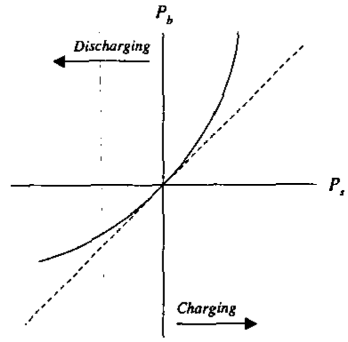

Fig. 3. Battery Power Map

III. PROBLEM DEFINITION

The idea of controlling the alternator power is initiated by the fact that energy losses in the internal combustion engine, alternator, and battery change according to their operating point. Minimizing these energy losses will result in an energy management strategy achieving higher fuel economy.

To explain the basic idea behind this control strategy, consider, for convenience, the fuel map given in Fig. 2, although the actual strategy also involves the alternator and battery characteristics.

As driver requests have to be fulfilled, one cannot change the power to the drive train P_d nor the engine speed ω (assuming manual gearshifts). However, the storage capacity of the battery allows changes in the alternator's setpoint while still all electric load requests are fulfilled. It is clear that such control actions introduce freedom in shifting the operating point of the engine to other regions. Intuitively, one can find profitable control actions for the alternator by considering the gradient of the fuel map curves, the so called *incremental fuel rate* κ:

$$\kappa = \frac{\Delta f}{\Delta P_m} \tag{6}$$

At points where κ is small, it is relatively cheap to generate electric energy. This energy will be stored in the battery and can be used at moments when it is less profitable (i.e., κ large) to activate the alternator. To yield a positive effect on the total fuel economy of the vehicle, energy losses in the battery must be small with respect to the profits obtained in the fuel map.

Control Objective and Constraints

The intention of energy management is to improve the fuel economy of the vehicle, so the control objective is to minimize the fuel consumption while satisfying several constraints. This control problem can be described as an optimization problem.

$$\min_{\underline{x}} J(\underline{x}) \quad \text{subject to} \quad G(\underline{x}) \leq \underline{b} \tag{7}$$

A cost function is chosen that expresses the fuel use over the drive cycle as function of the battery storage power. This way, the characteristics of all components can be combined into a singe cost function over time interval $[0, t_e]$:

$$J = fuel(P_s) = \int_0^{t_e} fuelrate(P_s)\,\mathrm{d}t \qquad (8)$$

Although P_s represents the design variable, the actual controlled input is P_e. Because the relation between P_s and P_e is known, P_e can be computed easily afterwards.

The operating range of the components is limited, so bounds have to be set on the engine power, electrical power, battery power throughput and battery energy level. This can be done using the following constraints:

$$P_{m\,min} \leq P_m \leq P_{m\,max} \qquad (9)$$

$$P_{e\,min} \leq P_e \leq P_{e\,max} \qquad (10)$$

$$P_{b\,min} \leq P_b \leq P_{b\,max} \qquad (11)$$

$$E_{s\,min} \leq E_s \leq E_{s\,max} \qquad (12)$$

Using (1)-(4), these constraints can be expressed as nonlinear functions of P_s.

A charge-sustaining vehicle requires some kind of end-point penalty to guarantee that the state of charge of the battery remains in a neighborhood around a desired value. An endpoint constraint will be used here, requiring the state of charge at the end of the cycle to be the same as at the beginning:

$$E_s(t_e) = E_s(0) \quad \Rightarrow \quad \int_0^{t_e} P_s(t)\,\mathrm{d}t = 0 \qquad (13)$$

Applied Control Techniques

The nonlinear optimization problem can be carried out using nonlinear problem solvers. For practical data, the problem is convex, which makes solution easier.

Assuming the complete drive cycle, specified by the signals $\omega(t)$, $P_d(t)$, and $P_l(t)$, to be known for $t \in [0, t_e]$, it is possible to calculate the optimal control sequence for the alternator over the trajectory. This provides an indication of the potential performance of an energy management strategy.

The problem is defined such that it can be easily incorporated into an optimization technique called *Dynamic Programming* (DP) [2] as will be done in Section IV.

Because computation time is limited in online applications, the nonlinear optimization problem will be approximated by a Quadratic Programming problem in Section V.

In reality, only a limited prediction of the future drive cycle will be available. A possible control technique that is able to use this prediction is *Model Predictive Control* (MPC) [6], which will be the topic of Section VI.

IV. DYNAMIC PROGRAMMING

Using discrete time, the optimization problem formulated in the previous section can be seen as a multi-step decision problem: each time step, one has to decide which alternator setpoint will achieve the highest fuel economy over a certain trajectory, while respecting the constraints. To find this optimal control sequence, Dynamic Programming will be applied.

Implementation DP Algorithm

Equations (1)-(4) define the fuel consumption of a dynamic system consisting of one control input P_s and one state variable E_s. Both quantities are mapped onto a fixed grid with distance ΔP_s and ΔE_s respectively, where:

$$\Delta P_s = \frac{\Delta E_s}{\Delta t} \qquad (14)$$

To keep track of the energy level in the battery, a discrete version of (4) is used:

$$E_s(k+1) = E_s(k) + P_s(k)\Delta t \qquad (15)$$

Due to the bounds (12), only energy levels between $E_{s\,min}$ and $E_{s\,max}$ are used. The sample time Δt is fixed, whereas signals are kept constant in between.

A cost matrix $\mathbf{R} \in \mathbb{R}^{m \times n}$ is created with:

$$m = \left\lceil \frac{E_{s\,max} - E_{s\,min}}{\Delta E_s} \right\rceil \quad \text{and} \quad n = \left\lceil \frac{t_e}{\Delta t} \right\rceil \qquad (16)$$

After selecting a desired end state $E_s(t_e)$, the DP algorithm will fill matrix $\mathbf{R}$ for $k = [n, \ldots, 1]$ and $e = [1, \ldots, m]$ as follows:

$\mathbf{R}_{e,k}$ = the minimum cumulative fuel consumption for driving the remainder of the drive cycle starting at $t = k\Delta t$ with an initial state $E_s(k\Delta t) = E_{s\,min} + e\Delta E_s$

The alternator setpoints which achieve minimum fuel consumption are not stored in $\mathbf{R}$, but are calculated afterwards for $k = [1, \ldots, n]$, using the information from $\mathbf{R}$ and a desired starting point $E_s(0)$.

V. QUADRATIC PROGRAMMING

Dynamic Programming is very time consuming, so for real-time implementation other methods need to be considered. In this section, simplifications will be introduced to achieve a Quadratic Programming structure (QP), which has the advantage that a global minimum is guaranteed and short computation times can be achieved.

A QP problem is given by a quadratic cost criterion subject to linear constraints:

$$\min_{\underline{x}} \; J(\underline{x}) = \tfrac{1}{2}\,\underline{x}^T H\,\underline{x} + \underline{h}^T\underline{x} + h_0 \qquad (17)$$

$$\text{subject to} \quad A\,\underline{x} \leq \underline{b}$$

Model Approximation

To obtain a quadratic cost function, the nonlinear component models are approximated as quadratic relations between incoming and outgoing power and then combined into a single expression, again simplified to be quadratic.

The fuel map of the engine is approximated by:

$$fuelrate(P_m, \omega) \approx \alpha_2(\omega)\,P_m^2 + \alpha_1(\omega)\,P_m + \alpha_0(\omega) \qquad (18)$$

where the parameters α_i depend on the engine speed.

Similarly, the alternator map is approximated by:

$$P_g(P_e, \omega) \approx \gamma_2(\omega)\, P_e^2 + \gamma_1(\omega)\, P_e + \gamma_0(\omega) \qquad (19)$$

The losses in the battery are positive for both charging and discharging. This can be obtained by making the losses quadratic with the storage power:

$$P_b(P_s) \approx P_s + \beta\, P_s^2 \qquad (20)$$

For simplicity the influence of E_s and T and differences between charging and discharging are neglected here. This model can be extended using piecewise linear terms for charging and discharging to obtain closer approximations of a real battery, within a QP framework [3].

Cost Function

Combining the quadratic relations for the engine, the alternator, and the battery results in an 8^{th}-order relation describing the fuel use as function of P_s. Because the cost function may only be quadratic, the higher order terms are omitted. The expression for the fuel use then becomes:

$$fuelrate(P_s) \approx \varphi_2\, P_s^2 + \varphi_1\, P_s + \varphi_0 \qquad (21)$$

where parameters φ_i depend on ω, P_d, and P_l.

The cost function is the fuel use over the cycle. By discretization one may obtain:

$$J = fuel(n) = \sum_{k=1}^{n} fuelrate(P_s(k))\, \Delta t \qquad (22)$$

The sample time Δt may be omitted, since it is constant.

Returning to (17), this means that H is diagonal with:

$$H(k,k) = 2\, \varphi_2(k) \qquad (23)$$

The other terms become:

$$\underline{h}(k) = \varphi_1(k) \quad \text{and} \quad h_0 = \sum_{k=1}^{n} \varphi_0(k) \qquad (24)$$

Constraints

Using the quadratic relations for the components and the drive cycle info, the constraints on P_m, P_e, and P_b can be rewritten as linear constraints on P_s, assuming the solution for P_e from (19) and P_s from (20) can be uniquely selected.

Combining them leads to one lower and upper bound for P_s at each time instant:

$$P_{s\,min}(k) \le P_s(k) \le P_{s\,max}(k) \qquad (25)$$

The bounds on E_s can also be written as linear constraints on P_s, by using the following discretization:

$$E_s(k) = E_s(0) + \sum_{i=1}^{k} P_s(i)\, \Delta t \qquad (26)$$

The equality constraint (13) becomes:

$$E_s(n) = E_s(0) \quad \Rightarrow \quad \sum_{k=1}^{n} P_s(k) = 0 \qquad (27)$$

From (25-27) it is easy to construct A and b in (17).

VI. MODEL PREDICTIVE CONTROL

When the complete drive cycle is known a priori, the optimization problem has to be solved only once. However, if only a limited prediction horizon is available, both the DP and QP problem can be used within an MPC structure using a receding horizon.

This means that the optimization is carried out at each time step over a limited prediction horizon. The first value of the optimal control sequence is implemented. The next time step a new optimization is done using an updated prediction and new measurement data.

As already shown in [8], for short prediction horizons, the variation in P_s and thus the performance is limited by the endpoint constraint on E_s. Therefore, a new approach based on QP that does not rely on an accurate prediction has been developed.

Reduction of the QP Problem

If only the cost function and the equality constraint are considered, the QP problem can be solved analytically by introducing the Lagrange function, as is also done in [10]:

$$L(\underline{P}_s, \lambda) = \sum_{k=1}^{n} \{\, \varphi_2(k)\, P_s(k)^2 + \varphi_1(k)\, P_s(k) + \varphi_0(k) \,\} - \lambda \sum_{k=1}^{n} P_s(k) \qquad (28)$$

The optimal solution can be calculated by solving:

$$\frac{\partial L(\underline{P}_s, \lambda)}{\partial \underline{P}_s} = 0 \quad \text{and} \quad \frac{\partial L(\underline{P}_s, \lambda)}{\partial \lambda} = 0 \qquad (29)$$

The solution is given by:

$$P_s^o(k) = \frac{\lambda - \varphi_1(k)}{2\, \varphi_2(k)} \qquad (30)$$

where:

$$\lambda = \sum_{k=1}^{n} \frac{\varphi_1(k)}{2\, \varphi_2(k)} \Big/ \sum_{k=1}^{n} \frac{1}{2\, \varphi_2(k)} \qquad (31)$$

This requires that $\varphi_2 > 0$, so the cost function J must be convex. From (30) follows that in the optimal solution, all n periods have the same incremental cost, namely λ.

When the upper and lower bounds on P_s are taken into account, the problem can still be solved efficiently with a routine described in [10]. If the upper and lower bound on E_s or other constraints are added, a general QP solver must be used.

Elimination of the Prediction Horizon

Although for the computation of $P_s^o(k)$ only current values $\varphi_1(k)$ and $\varphi_2(k)$ are needed, computation of the value of λ requires knowledge of φ_1 and φ_2 over the entire drive cycle.

When a prediction of the complete cycle is not available, λ can be estimated or adapted online, for instance by using the following PI-type controller:

$$\lambda(k+1) = \lambda_0 + K_P(E_{ref} - E_s(k)) + K_I \sum_{i=1}^{k} (E_{ref} - E_s(i))\Delta t \quad (32)$$

where λ_0 is an initial guess.

Because P_s is proportional with λ, and E_s is the integral of P_s, the closed loop becomes a time varying second order dynamic system.

The feedback of E_s is meant to avoid draining or overcharging the battery in the long run, but short term fluctuations of E_s should still be possible, so the bandwidth of the PI-controller should be chosen rather low.

For given λ, computing $P_s^o(k)$ using (30) is equivalent to solving at each time instant k:

$$P_s^o(k) = \arg \min_{P_s(k)} \{ \varphi_2(k) P_s(k)^2 + \varphi_1(k) P_s(k) + \varphi_0(k) - \lambda P_s(k) \} \quad (33)$$

Instead of the quadratic approximation, the original nonlinear cost function can also be used:

$$P_s^o(k) = \arg \min_{P_s(k)} \{ fuelrate(P_s(k)) - \lambda P_s(k) \} \quad (34)$$

The bounds on P_s can be respected by saturation:

$$P_s'(k) = \min(\max(P_{s\,min}(k), P_s^o(k)), P_{s\,max}(k)) \quad (35)$$

Equation (34) provides a nice physical interpretation of the strategy. At each time instant the actual incremental cost for storing energy is compared with the average incremental cost. Energy is stored when generating now is cheaper than average, whereas it is retrieved when it is more expensive.

VII. SIMULATION

Simulation Model

Simulations are done for a conventional vehicle equipped with a 100kW 2.0 liter SI engine and a manual transmission with 5 gears. A 42V 5kW alternator and a 36V 30Ah lead-acid battery make up the alternator and storage components of the 42V power net.

The battery has an energy capacity of $E_{cap} = 4 \cdot 10^6$ J and is operated around 70% SOC, because the efficiencies for both charging and discharging in this range are acceptable. The simplified battery model (20) is also used for the DP strategy. Parameter β has a value of $5 \cdot 10^{-5}$ W^{-1}, which gives an efficiency of 95% at 1000 W and 90% at 2000 W.

For a given speed profile and selected gears, the corresponding engine speed and torque needed for propulsion can be calculated using the following formulas:

$$\omega(t) = \frac{f_r}{w_r} g_r(t)\, v(t) \quad (36)$$

$$\tau_d(t) = \frac{w_r}{f_r} \frac{1}{g_r(t)} F_d(t) \quad (37)$$

$$F_d(t) = m\,\dot{v}(t) + \tfrac{1}{2} \rho\, C_d\, A_d\, v(t)^2 + m\, g\, C_r \quad (38)$$

The parameters and their values are given in Table I.

When the engine speed drops below a certain value, the clutch is opened. Then the drive train torque becomes zero and the engine speed drops to an idle speed of 700 rpm.

When the drive train torque is negative, it is partly delivered by the ICE (which has a negative drag torque), by the alternator, and by the brakes. Because regenerative braking delivers electrical power without extra fuel use, it will be used as much as possible. The brakes are only used when the desired deceleration torque is larger than the maximum negative torque that can be delivered by the engine and the alternator.

Simulations are done for the New European Driving Cycle (NEDC) [1], of which the vehicle speed is shown in Fig. 4. For the electric power request, constant loads of 500, 1000, and 2000 W are used.

TABLE I

PARAMETERS OF THE SIMULATION MODEL

Quantity	*Symbol*	*Value*	*Unit*
Mass	m	1400	kg
Frontal area	A_d	2	m^2
Air drag coefficient	C_d	0.3	-
Rolling resistance	C_r	0.015	-
Air density	ρ	1.2	kg/m^3
Gravity	g	9.8	m/s^2
Wheel radius	w_r	0.3	m
Final drive ratio	f_r	4.0	-
Gear ratio	g_r	3.4 - 2.1 - 1.4 - 1.0 - 0.77	-

Strategies

The following strategies are implemented on simulation level and their results will be compared:

- *BL* Baseline strategy where the alternator power is equal to the requested load.
- *RGB* Regenerative braking strategy that stores free energy during braking and uses it directly afterwards.
- *DP* This strategy calculates the DP problem once for the complete drive cycle.
- *QP* This strategy calculates the QP problem once for the complete drive cycle.
- *QP1* QP at each time step using (30), (35), and (32).
- *DP1* DP at each time step using (34), (35), and (32).

The DP strategy is used with an input grid of 100 W and a state grid of 100 J. The DP1 strategy is used with an input grid of 10 W and does not need a state grid.

K_P and K_I are tuned such that for average values of $\varphi_1(t)$ and $\varphi_2(t)$ a bandwidth of 10^{-3} rad/s is obtained.

The QP1 and DP1 strategy do not guarantee that the endpoint constraint is satisfied. The difference in SOC is accounted for in the fuel consumption using the average value of λ.

Results

The resulting sequences of P_s and SOC using the DP optimization with $P_l = 1000$ W are shown in Fig. 4.

As can be seen, the optimization anticipates on regenerative braking phases and generates less in between. No electricity is generated during stand still, because the slope of the fuel map is higher at very low engine speeds.

The variation in SOC is small, because of the large capacity of the battery. This justifies that for this simulation, the battery efficiency is chosen independently of E_s.

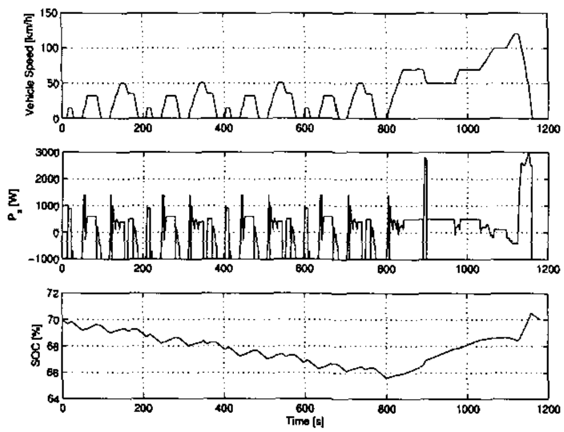

Fig. 4. Simulation results for $P_l = 1000$ W

The power needed for propulsion has an average of 10 kW for the NEDC with this vehicle. The fuel needed for propulsion cannot be influenced, so for a fair comparison of the strategies, only the additional fuel use needed for the electric power is of interest.

The fuel savings on the electric power with respect to the baseline strategy are presented in Table II.

TABLE II

FUEL SAVINGS ON THE ELECTRIC POWER

Saving [%]	500 W	1000 W	2000 W
RGB	37.52	20.00	10.49
DP	42.40	24.24	11.74
QP	41.93	23.53	11.55
QP1	42.19	23.03	11.20
DP1	43.32	24.35	11.72

Evaluation

The simulations show that the concept is working. Most of the profit comes from regenerative braking, which delivers a certain amount of energy for free. Therefore the relative fuel savings are higher at low electric powers.

Both Dynamic Programming and Quadratic Programming do not find the global optimal solution of the nonlinear optimization problem. The DP algorithm uses the original nonlinear cost criterium, but restricts itself to a grid, whereas the QP algorithm finds the global optimum of a quadratic approximation of the original problem. The small difference between DP and QP indicates that the nonlinear problem is approximated accurately by a QP problem.

The adaptive strategies without future knowledge perform equally well. For some loads, the DP1 strategy outscores the DP strategy, because of its finer grid.

Apart from regenerative braking, the strategy presented here benefits from differences in the incremental fuel rate at various operating points. For the fuel map used here, this variation in slope is rather low, which limits the improvement that can be made with an energy management strategy on top of regenerative braking.

The performance is also limited by the losses that occur during charging and discharging of the battery. As an alternative, an ultra capacitor can be used, which has a much higher efficiency, but also a lower capacity.

A detailed analysis on how the performance depends on the component characteristics is presented in [5].

VIII. CONCLUSIONS AND FUTURE RESEARCH

Several possible energy management strategies for the electrical power net are presented, that use either a prediction of the future or only current information to minimize the fuel consumption over a drive cycle.

Simulations show that the concept is working. However, for the configuration considered here, only a limited fuel reduction can be obtained.

More freedom in control, and thus more potential improvement is possible when using other drive train configurations, e.g., where variation in both engine torque and speed is possible.

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