



Advanced 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 CO₂ emission), smart strategies for the generation, storage/retrieval, distribution and consumption of the electric power can be used.

This paper presents a preliminary case study based on a Model Predictive Control-based strategy that uses a prediction of the future driving pattern and load request in order to minimize fuel use by generating only at the most efficient moments. The strategy is tested in a simulation environment, showing a decrease in fuel consumption compared to a baseline strategy.

Index Terms— electric power management, model predictive control.

I. INTRODUCTION

Every year, the electric power consumption in automobiles increases significantly. Over the years, this has led to several modifications of the vehicle's power net, in order to keep up with more stringent electric power demands. A major turning point occurred around the year 1955 when car manufacturers started to replace the existing 6V power net by a new 12V system with 14V regulation. This system has become the standard in today's passenger cars.

Over the last two decades, the electric power consumption in vehicles increased even more (approximately four percent every year) and in the near future, researchers expect again much higher power demands due to several aspects:

- Electrical devices replace traditionally mechanical and hydraulic components. A good example for this trend is the drive-by-wire concept.
- The market expects more performance, comfort and safety from new vehicles. Here, one should think of functions like electric active suspension but also of video entertainment at the backseat.

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Today, the average electric power consumption of a regular vehicle is between 750W and 1kW with peak loads up to 2kW, depending on the vehicle and its accessories [1]. Taking into account that a belt driven 14V alternator typically supplies 1.2kW, power limitations will become an important issue within the next years.

Already in the mid-1990's, several automobile manufactures realized this problem and started considering new topologies of the vehicle's power net. Under the name "42V PowerNet" they proposed a class of systems that seems to meet tomorrow's power requirements. All these systems have in common that they share a power net with a nominal voltage of 42V. It can be easily seen that the introduction of a power net operating at a higher voltage level, leads to better efficiencies when supplying power to the electric loads [2]. However, in the field of control strategies several uncertainties exist about how the alternator (including the voltage regulator) should operate in order to obtain maximum energy efficiency within the vehicle. This paper presents a preliminary study on one possible control strategy based on model predictive control (MPC) and discusses the benefits of such an *advanced energy management strategy* with respect to the fuel economy of the total vehicle.

II. CONTROL STRATEGY

Present vehicles are equipped with an alternator in combination with a 14V regulator, to maintain a constant voltage at the power net when the engine is running. In this way, the alternator supplies continuously power to all electric loads as well as the 12V battery. Conversely, the battery provides energy to the loads only during peak-power demands or when the engine is turned off. Regulating the voltage at 14V means that the battery is always operated at almost 100% state of charge, where energy is lost due to gassing reactions. This is one disadvantage of the conventional control strategy.

The vehicle considered in this paper is a conventional series-production vehicle that was equipped with a 42V power net for research purposes. An advanced alternator (belt driven) replaces the conventional alternator and a 36V lead-acid

battery takes the place of the 12V battery. Figure 1 shows a schematic diagram of this new power net. One can see that the alternator (A) and the battery are directly coupled to the power net. Using an advanced alternator, it is possible to control power flow. Finally, the 42V loads (currently implemented in the vehicle by means of a programmable load box) are connected to the power net by means of fuses and switches.

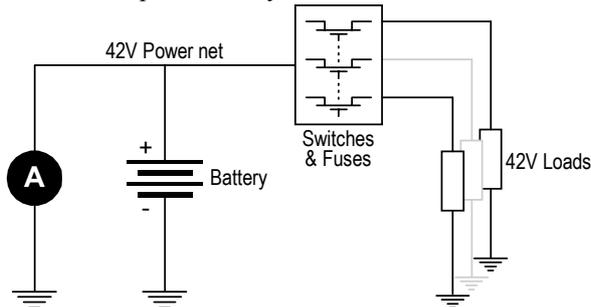


Figure 1: Topology 42V power net

Still the question remains what type of control should be selected to obtain the most optimal set points for the alternator? Ultimately, it is the internal combustion engine that delivers all necessary power requested by the electric loads. For that reason, the control strategy for the alternator will be called optimal, if it establishes minimal fuel consumption over a given drive cycle, with no shortcomings on the driver's requests.

It is common knowledge that the efficiency of a combustion engine depends on its operating point, i.e. the engine speed and torque at the crankshaft [4]. Taking into account this efficiency and the fact that the mechanical driveline (and indirectly the driver) enforces a set-point for the engine, it should be possible to increase the total efficiency of the engine by activating the alternator at the right moment (see Figure 2). On average, the engine will run in a more efficient operating point and hence, accomplish fuel reduction.

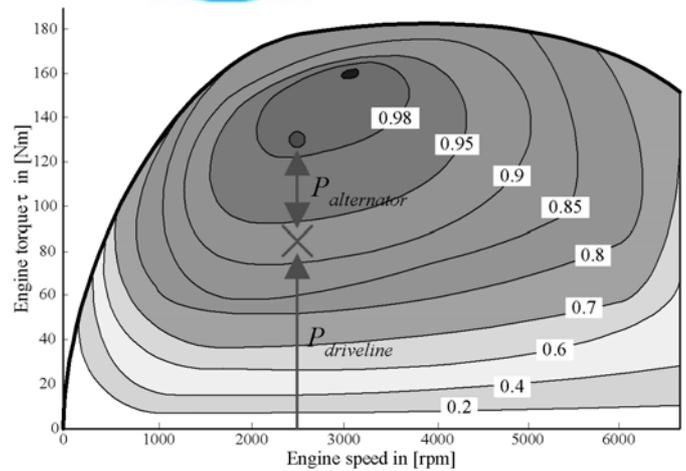


Figure 2: Normalized efficiency map of the engine

Considering the efficiency of the combustion engine solely will not be enough to find the optimal control strategy for the alternator. The efficiency of the alternator strongly depends on its operating point as well and also the battery has a time-varying efficiency that cannot be neglected. A possible control strategy has to take all these efficiencies into account because the speed of the engine, alternator and the vehicle itself are directly related to each other. Information about the vehicle speed (but also the electric load request) in the near future will help to improve the performance of the control strategy. Besides efficiencies, the control strategy has to take into account that the components in the system will operate safely only within certain operating limits.

A general control technique to find the optimal solution but still satisfying all the boundary conditions as mentioned above, is called *model predictive control* (MPC). As will be explained later, this technique uses a model of the system to calculate the most optimal control action, given the present state of the system and some prediction of the system in future. This control technique has been applied in this research, following the considerations of Tate and Boyd [3].

III. VEHICLE MODEL

A basic necessity for controller design is a good model of the system. Since this model should represent a complete vehicle, a fundamental approach is suggested. All parts of interest are placed in separate (power-based) input/output blocks (see Figure 3). The interconnection of these blocks will be done according to the power flow in a real vehicle, starting with fuel that goes into the combustion engine. The mechanical power that comes out of the engine splits up into two directions: one part goes to the mechanical driveline 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 blocks, the power flow through the battery can be positive as well as negative. In the end, the useful energy comes available for vehicle propulsion and for activating electric devices connected to the power net.

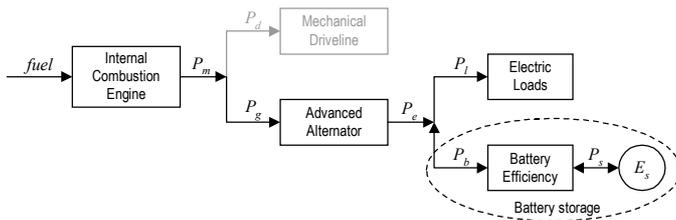


Figure 3: Block diagram of vehicle's power flow

IV. MODEL PREDICTIVE CONTROL

Introduction

MPC has become quite popular in the process industry due to its ability to control plants within tight time-varying constraints and meeting desired optimal operating conditions. In industrial environments MPC prediction information can often be obtained by using measurement information from earlier stages in the manufacturing line. Due to increasing computational capabilities of microprocessors it is now even possible to apply simple MPC techniques online in servo-based applications. New technological developments such as GPS, navigation systems and information exchange between vehicles and traffic control systems increase the possibilities of using MPC in automotive applications.

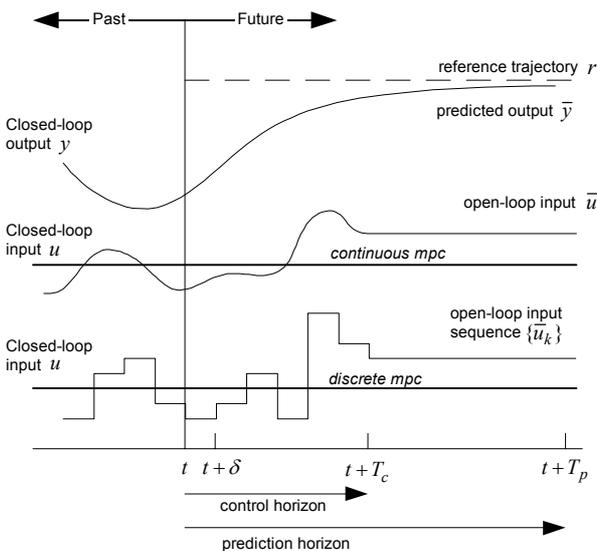


Figure 4: MPC principle

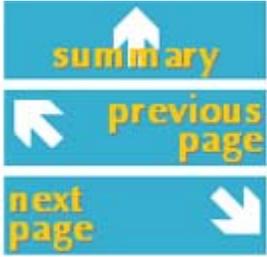
Model Predictive Control Concept

In general, the Model Predictive Control problem can be formulated as solving on-line a finite horizon open-loop optimal control problem subject to system dynamics and constraints involving states and controls. Figure 4 shows the basic principle. Based on measurements obtained at time t , the controller predicts the future dynamic behavior of the system over a prediction horizon T_p and determines the input \bar{u} such that a predetermined open-loop performance objective function is optimized. If there were no disturbances and no model mismatches and if it would be possible to optimize over an infinite horizon, then one could apply the optimal control sequence found at $t = t_0$ to the system for all times $t > t_0$. In general this is not the case and therefore feedback methods need to be used. An MPC system implements the obtained open-loop input function at time t until new measurement information becomes available at time $t + \delta$. At every interval of length δ a new prediction and optimization is performed using updated models. This control algorithm is frequently referred to as the receding horizon principle.

To obtain numerical solutions on the open loop optimization problem it is often necessary to parameterize the input u in an appropriate way. This can for example be done using a finite set of basis functions. A frequently used method is approximation of intervals of length δ by a piecewise constant value. This way a discrete time Model Predictive Controller can be introduced. Figure 4 shows both a continuous and discrete trajectory of input u for an MPC cost function penalizing differences between r and \bar{y} .

As was mentioned earlier, calculation of the control input can be subject to constraints put on states, inputs and outputs of the predicted system as well as subject to the optimization of a given cost function. In general, the predicted system behavior will differ from the closed-loop one. This implies that precautions must be taken to achieve closed loop stability. Various methods exist for this purpose. They include implementing control horizons limiting the region in which control actions are allowed along the prediction horizon, endpoint constraints demanding state or output value to reach a given value at the end of the prediction horizon, rate limits or special design methods for stabilizing cost functions.

A simplified framework for implementation of cost-function, constraints and system dynamics is shown in Figure 5. Here $e(t)$ is considered to be an unknown disturbance known only at time t which is often considered to be zero mean white noise and $\omega(\tau)$ models known disturbances. The variable



$v(\tau)$ defines the inputs of the system which can be either $u(\tau)$ or $\dot{u}(\tau)$ and $x(\tau)$ represents the system's states. All expressions containing a bar on top are dependent of the optimization process. System states are passed through the equality constraint $\bar{x}(t) = x(t)$. System dynamics are implemented by introducing equality constraints representing the system's behavior.

$$\begin{aligned} & \text{find } \min_{\bar{v}(\cdot)} J(x(t), \bar{v}(\cdot); T_p) \\ & \text{with } J(x(t), \bar{v}(\cdot); T_p) := \int_t^{t+T_p} F(\bar{x}(\tau), \bar{v}(\tau)) d\tau \\ & \text{subject to} \\ & \quad \bar{\dot{x}}(\tau) = f(\bar{x}(\tau), e(t), \omega(\tau), \bar{v}(\tau), \tau), \quad \forall \tau \in [t, t+T_p] \\ & \quad g(\bar{x}(\tau), e(t), \omega(\tau), \bar{v}(\tau), \tau) = 0, \quad \forall \tau \in [t, t+T_p] \\ & \quad h(\bar{x}(\tau), e(t), \omega(\tau), \bar{v}(\tau), \tau) \leq \Psi(\tau), \quad \forall \tau \in [t, t+T_p] \\ & \quad \bar{x}(t) = x(t) \end{aligned}$$

Figure 5: MPC framework

The reader who is interested in more details on MPC, is referred to [5].

V. APPLICATION ON THE FUEL REDUCTION PROBLEM

MPC has one big disadvantage. Solving an optimization problem might require a prohibitive amount of computation time with this technique. Therefore a model structure is required, that is accurate enough to model all desired properties and fast enough for real-time calculation.

Figure 3 describes the structure of the used vehicle in the following examination of an MPC-based optimization. The generator is connected to the engine with a gear ratio $1 : N_g$. The driveline block contains all driveline components including clutch and gears. This is a typical structure for a conventional vehicle.

The target is to apply an MPC scheme in such a way that drivability remains unaffected. Stated otherwise, the driver should not experience different vehicle behavior when using the MPC approach. This assumption greatly reduces the problem complexity. It implies that the driveline torque and speed remain unaffected and therefore it is possible to use them as prediction information. As a consequence, the engine will have to compensate all generator actions and vice versa. This requires both fuel injection and generated power to be controlled by the MPC.

The remaining dynamic components include the engine, generator and battery. Using discrete time MPC with a sampling interval of 1 second or larger, the engine and generator dynamics can be excluded. Also the battery dynamics are neglected.

A nonlinear static map can be used to represent the Internal Combustion Engine (ICE). This map describes the relation between fuel consumption and engine speed and engine torque. Note that the engine torque can be derived from the engine power if the engine speed is known. A fuel consumption map can be used as displayed in Figure 6.

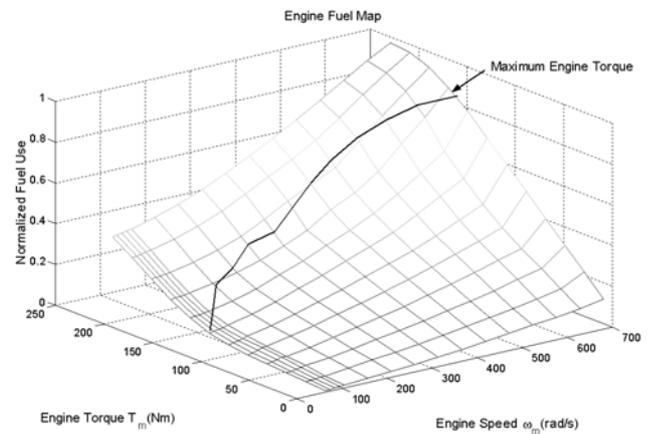


Figure 6: Normalized Fuel Use

For now this map will be represented by the following equation:

$$\text{fuelrate} = f(\omega_m, P_m) \quad (1)$$

Using a similar approximation, the generator model reduces to a static nonlinear map (Equation 2). Again the speed information can be used to describe the speed dependent behavior of the device.

$$P_g = g(\omega_g, P_e) \quad (2)$$

$$P_m = P_d + P_g \quad (3)$$

For the alternator used in the simulation, g shows smooth and almost linear behavior within the area of interest. For a constant value of ω_g a curve for this function is shown in Figure 7.

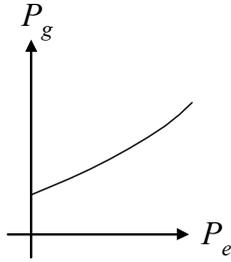


Figure 7: Generator Power Map

When the electrical loads P_l are predicted, Equations 4-6 can be used to model the electrical circuit. Here P_b represents the power entering or leaving the battery terminals, and E_s represents the energy stored in the battery.

$$P_e = P_l + P_b \quad (4)$$

$$P_b = P_s + P_{loss}(P_s, E_s, T) \quad (5)$$

$$\dot{E}_s = P_s \quad (6)$$

Function P_{loss} represents the battery losses. Figure 8 shows a typical charge/discharge power transfer curve for a constant state of charge.

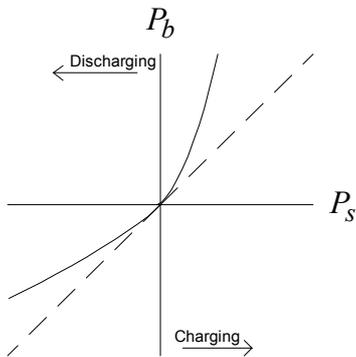


Figure 8: Battery Power Map

Using P_s as the optimization variable, the efficiencies of all components can be included into a cost function based on fuel use:

$$J = \min_{P_s} \text{fuel}(P_s) = \min_{P_s} \int_t^{t+T_p} \text{fuelrate}(P_s) dt \quad (7)$$

To get a useful control strategy, constraints have to be added. For example, draining the battery could reduce fuel use, but such a solution would be unacceptable in a vehicle. In

addition, constraints need to be applied to set bounds on allowable values for the battery's state of charge. Extra constraints prohibit the optimization to reach invalid or unwanted operating conditions such as overcharging or allowing the SOC (State of Charge) to drop dangerously low. Constraints are set on engine torque T_m (by constraining the engine power for known engine speed), electrical power P_e , battery power throughput P_b and energy stored in the battery E_s . For the sake of brevity those constraints are written out later on.

The variable optimized in Equation 7 is different to the ones used to control the vehicle. To derive the correct control variables, the structure presented in Figure 9 is used. These signals will not be used directly but will be fed through low-level controllers capable of stabilizing the dynamic behavior between engine and generator.

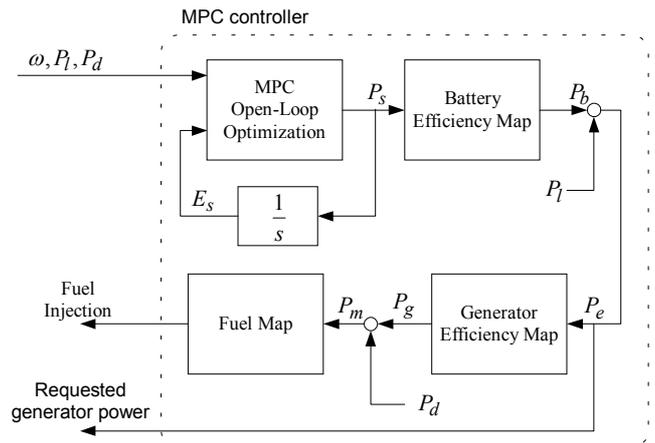


Figure 9: MPC controller implementation, using prediction information of ω , P_l and P_d .

For real-time implementation of this MPC controller further simplifications are necessary, the optimization described by Equation 7 must be carried out using nonlinear (in general non-convex) problem solvers. Optimizing nonlinear problems is very time consuming and other methods need to be considered. In the next section simplifications will be introduced to achieve a quadratic problem structure, which has a great computational advantage.

VI. IMPLEMENTATION

Quadratic Programming

It is preferable to structure the optimization as a Quadratic Programming problem because doing so, 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.

$$\min_x J(x) = x^T H x + f^T x + f_0 \quad , \quad A x \leq b \quad (8)$$

Cost criterion

Because the main goal is to reduce fuel consumption, a cost function is chosen that expresses the fuel use over the horizon as function of the battery storage power P_s . This way, losses in the ICE, the alternator and the battery will all be included in the cost function. Other cost criteria could be implemented here as well.

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

Engine

The fuel map of the engine is approximated by a quadratic fit. The parameters α_i depend on the engine speed for which a lookup table can be used.

$$\begin{aligned} \text{fuelrate} &= f(\omega, P_m) \approx \\ &\alpha_2(\omega) \cdot P_m^2 + \alpha_1(\omega) \cdot P_m + \alpha_0(\omega) \end{aligned} \quad (9)$$

where $P_m = P_d + P_g$

Alternator

The alternator map is also approximated by a quadratic fit where the parameters γ_i depend on the engine speed.

$$\begin{aligned} P_g &= g(\omega, P_e) \approx \\ &\gamma_2(\omega) \cdot P_e^2 + \gamma_1(\omega) \cdot P_e + \gamma_0(\omega) \end{aligned} \quad (10)$$

where $P_e = P_l + P_b$

Battery

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

$$P_b = P_s + P_{loss}(P_s, E_s, T) \approx P_s + \beta_2(E_s, T) \cdot P_s^2 \quad (11)$$

This model can be extended using piecewise linear terms for charging and discharging to obtain closer approximations to a real battery. This concept can still be handled within a QP framework [6]. For simplicity differences in losses are here

assumed to average out.

Cost function

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

$$\text{fuelrate} \approx \lambda_2 \cdot P_s^2 + \lambda_1 \cdot P_s + \lambda_0 \quad (12)$$

In Equation 12, the parameters λ_i depend on the following parameters:

$$\lambda_i \equiv \lambda_i(\alpha_j(\omega), \gamma_j(\omega), \beta_j(E_s, T), P_d, P_l) \quad (13)$$

The variable P_s used in equation 12 represents the design variable, whereas the actual controlled input is P_e . Because the relation between P_s and P_e is straightforward, P_e can be computed easily for each optimization step using the structure described in Figure 9.

The cost function is the fuel use integrated over the prediction horizon. By discretization one may obtain:

$$J = \text{fuel}(N_p) = \sum_{k=1}^{N_p} \text{fuelrate}(k) \cdot \Delta t \quad (14)$$

Constraints

The components are subject to the following limitations:

$$\begin{aligned} P_{m,\min}(\omega) &\leq P_m \leq P_{m,\max}(\omega) \\ P_{e,\min}(\omega) &\leq P_e \leq P_{e,\max}(\omega) \\ P_{b,\min} &\leq P_b \leq P_{b,\max} \\ E_{s,\min} &\leq E_s \leq E_{s,\max} \end{aligned} \quad (15)$$

Using the quadratic relations for the components, the constraints on P_m , P_e and P_b can be rewritten as linear constraints on P_s . Combining them leads to one lower and upper bound for P_s at each time instant.

$$P_{s,\min}(\omega, P_d, P_l) \leq P_s \leq P_{s,\max}(\omega, P_d, P_l) \quad (16)$$

The lower and upper bound of E_s , which represents the state of charge, can also be written as linear constraints of P_s , by



using the following discretization:

$$E_s(k) = \sum_{q=1}^k P_s(q) \cdot \Delta t + E_s(0) \quad (17)$$

End-point constraint

A charge-sustaining vehicle requires some kind of endpoint penalty in order to guarantee that the state of charge remains in a neighborhood around a desired value. The value may be chosen with an eye on maximizing battery efficiency or expectation of battery life. Here an endpoint constraint is implemented requiring the state of charge at the end of the horizon to be the same as or larger than at the beginning. A drawback of this method is that it will limit the variation in P_s and thus the performance when using short prediction horizons. An advantage is that for all simulations the SOC at the end is equal, so there is no need for SOC compensation in the calculation of the fuel use.

This equality constraint for $E_s(N_p)$ can also be written as a linear function of P_s , by using the following relation:

$$\begin{aligned} E_s(N_p) &= \sum_{i=1}^{N_p} P_s(i) \cdot \Delta t + E_s(0) = E_s(0) \\ \Rightarrow \sum_{i=1}^{N_p} P_s(i) &= 0 \end{aligned} \quad (18)$$

VII. SIMULATION MODEL

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

The operating range of the battery is limited between 60% and 80% SOC, because the efficiencies for both charging and discharging in this range are acceptable. The parameter $\beta_2(E_s, T)$ is chosen to be independent of E_s and T and has a constant value of $5 \cdot 10^{-5}$ (Equation 11). The battery is parameterized to provide an efficiency of 95% at 1000 W and 90% at 2000 W.

When the speed profile and the selected gear are known beforehand, the corresponding engine speed and torque needed for propulsion can be calculated using the following formulas:

$$\begin{aligned} \tau_d(t) &= \frac{1}{\mu_d} \frac{w_r}{f_r} \cdot \frac{1}{g_r(t)} (m \cdot \dot{v}(t) + \\ &\quad \frac{1}{2} \cdot \rho \cdot C_d \cdot A_d \cdot v(t)^2 + m \cdot g \cdot C_r) \\ \omega(t) &= \frac{f_r}{w_r} \cdot g_r(t) \cdot v(t) \end{aligned} \quad (19)$$

The parameter values for the simulation model are given in Table 1.

Mass	m	1200 kg
Frontal area	A_d	2 m ²
Air friction coefficient	C_d	0.3
Rolling resistance	C_r	0.015
Air density	ρ	1.2 kg/m ³
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
Driveline efficiency	μ_d	0.9

Table 1: Parameter values for the simulation model

When the vehicle is standing still, the driveline torque is zero and the engine runs at an idle speed of 700 rpm (73 rad/s).

When the driveline torque is negative, it is partly delivered by the ICE (which has a negative drag torque during vehicle deceleration), the alternator and by the brakes. Because regenerative braking delivers electrical power with no extra fuel use, it is used as much as possible. The brakes are only used when the desired deceleration torque is greater than the maximum negative torque that could be delivered by the engine and the alternator: $\tau_d < \tau_{m,\min} - \tau_{g,\max}$.

Driving cycle

Simulations are done for the NEDC cycle, which consist of an urban and an extra-urban part. The vehicle speed of this cycle and the corresponding engine speed and driveline torque and gear number, are given in Figure 10. The electric power request is a constant load of 1000 W.

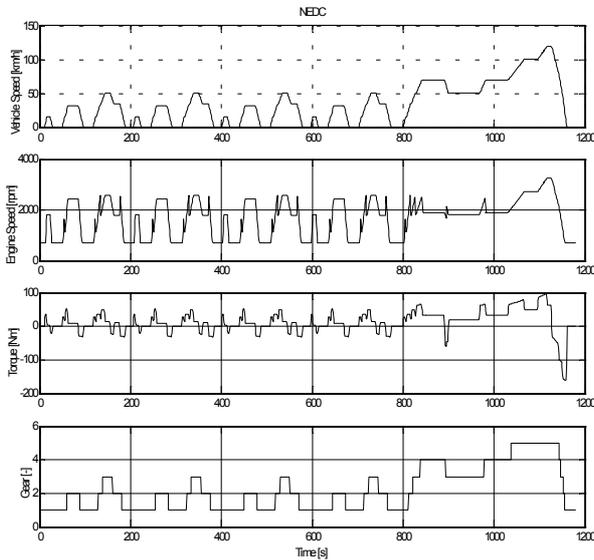


Figure 10: Applied vehicle speed, engine speed, engine torque and gear shifting during simulations

VIII. PRELIMINARY RESULTS

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

- Baseline 1: No electric load. This indicates how much fuel is needed for propulsion only.
- Baseline 2: The power provided by the alternator is equal to the requested load. This indicates how much fuel is needed in the normal situation. This strategy does not include regenerative braking.
- MPC: Optimization at every time step over a receding horizon with limited length.
- Optimal: This strategy calculates the QP problem once for the complete cycle. The resulting control signal is implemented afterwards. This should give the lowest fuel consumption.

The MPC controller is used with prediction horizons of 10, 30, 100 and 300s. Towards the end of the simulation, the prediction horizon is limited to the end of the cycle.

An ideal integrator on the signal P_s is used to accomplish the feedback of E_s in the simulation model, as shown in Figure 9.

For the optimal strategy, the resulting sequence of the battery's SOC is shown in Figure 11. As can be seen, the optimization seems to anticipate on regeneration phases and generates between them as little as possible. The variation in SOC is very low, because of the large capacity of the battery. This justifies that for this simulation, the battery efficiency is chosen independently of E_s .

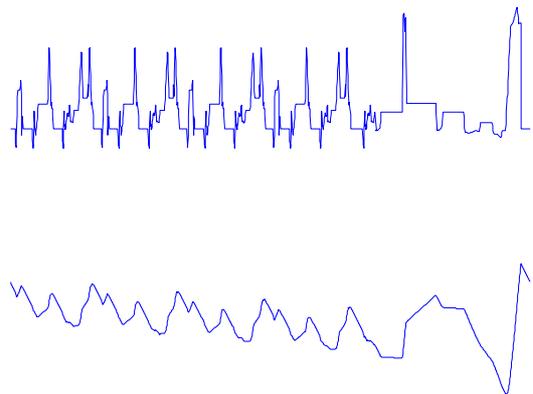


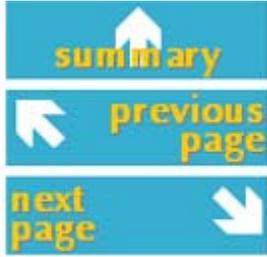
Figure 11: Simulation results optimal strategy

The fuel use over the entire cycle is computed afterwards using three methods:

- Using the quadratic cost function
- Using the 8th order expression
- Using the measured fuel map, and alternator map and the quadratic battery model

By comparing these values, the influence of the model reduction can be studied.

The normalized fuel use is presented in Table 2. The differences between the 8th order and the quadratic fit are marginal, which justifies the omission of the higher order terms in the cost function. Both show a difference of ca. 2 % compared to the fuel use computed with the measured data.



Normalized Fuel Use	Quadratic	8 th order	Measured maps
Baseline 1	100	100	101.17
Baseline 2	111.21	111.21	114.02
MPC $N_p = 10$	110.53	110.58	112.48
MPC $N_p = 30$	110.25	110.31	112.31
MPC $N_p = 100$	109.87	109.92	111.92
MPC $N_p = 300$	109.84	109.89	111.91
Optimal	109.83	109.88	111.89

Table 2: Influence of model reduction on performance

In Table 3, the fuel savings with respect to the Baseline 2 strategy are given. As can be seen, the savings based on the measured data are even higher than for the reduced model that is used in the optimization. The maximum saving based on measured data is 1.90 %. This can already be achieved with a prediction horizon of 100 s, while 1.37 % is already obtained with a prediction horizon of only 10 s.

Saving [%]	Quadratic	8 th order	Measured maps
Baseline 1	-	-	-
Baseline 2	-	-	-
MPC $N_p = 10$	0.61	0.57	1.37
MPC $N_p = 30$	0.86	0.81	1.52
MPC $N_p = 100$	1.22	1.17	1.88
MPC $N_p = 300$	1.25	1.20	1.89
Optimal	1.25	1.21	1.90

Table 3: Fuel savings with respect to baseline 2 strategy

Evaluation

The simulations show that the concept is working, although the fuel savings are rather small. There are several explanations for this.

Although the efficiency of the fuel converter varies drastically over the driving cycle, this is merely caused by the off-set (zero torque corresponds with positive fuel use, while zero fuel use corresponds with negative torque), whereas the strategy presented here only benefits from differences in (the increments of) the fuel rate at various operating points. For modern engines, this change in slope is rather low, because of electronic ignition, fuel injection, and advanced motor management. Although this improves the efficiency of the engine in general, it limits the extra improvement that can be made with this strategy.

Furthermore, significant losses occur during charging and discharging of the battery. This is disadvantageous compared to the baseline strategy, where the battery is not used. As an

alternative for the battery, an ultra capacitor can be used, which has a lower capacity but on the other hand it has a higher efficiency. The lower capacity will not be a limitation since the variations in SOC are very small.

Another reason for the small improvement is that the NEDC is a rather conservative cycle. For the test vehicle use here, the NEDC cycle requires an average power of 10 kW and peaks of 40 kW, while the engine is capable of delivering 100 kW. When using a driving cycle that covers the whole operation range of the engine, more profit is likely to be made.

Furthermore it should be mentioned, that for this preliminary case study, the results based on measured maps turned out to be better than with the reduced model, but in general this will not be the case.

IX. CONCLUSIONS

An MPC-based energy management strategy for the electrical power net is presented, that uses future knowledge of the driving pattern to minimize the fuel consumption over a driving cycle.

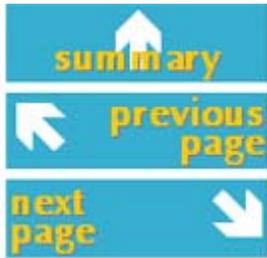
The initial simulations show that the concept is working, although fuel savings are lower than expected. However, as a preliminary study this looks quite promising. A further in depth investigation should reveal the real potential of this approach.

X. FURTHER RESEARCH

A next step before implementing the strategy in a real vehicle would be implementation on a hardware-in-the-loop test setup consisting of a software emulation of the drive train and real electrical components.

Another interesting topic is to adapt the concept behind the strategy for other power net or drive train configurations. The strategy can be extended to a vehicle with a dual voltage power net (14V and 42V) with one or two generators, two electrical power storage devices (batteries and/or super capacitors) and a DC/DC-converter. The strategy can easily be adapted to be used for parallel hybrid electric vehicles, where the alternator can also be used as a motor. This way, the operating range of the alternator is much larger, so more profit can be made.

Other directions for extension lie in the direction of series hybrid electric vehicles, vehicles that use a flywheel for temporary energy storage and vehicles with a CVT, where variation in both engine torque and speed is possible.



Furthermore, the strategy can be expanded with priority control. This is a power scheduling system that can postpone or quicken the electric power requests.

REFERENCES

- [1] J. G. Kassakian, J. M. Miller, and N. Traub, "Automotive electronics power up", IEEE spectrum, pp. 34-39, May 2000.
- [2] P. Nicastrì, and H. Huang, "42V powernet: Providing the vehicle electrical power for the 21st century", SAE, Future Transportation Technology Conference and Exposition, Costa Mesa, Aug. 21-23, 2000.
- [3] E. D. Tate, and S. P. Boyd, "Finding ultimate limits of performance for hybrid electric vehicles", SAE, Future Transportation Technology Conference and Exposition, Costa Mesa, Aug. 21-23, 2000.
- [4] V. H. Johnson, K. B. Wipke, and D. J. Rausen, "HEV control strategy for real-time optimization of fuel economy and emissions", SAE, Future Car Congress, Arlington, Virginia, USA, Feb. 2-6, 2000.
- [5] E. F. Camacho, and C. Bordons, "Model predictive control", Springer-Verlag, London, 1999.
- [6] Bram de Jager, "Predictive storage control for a class of power conversion systems", submitted to the ECC 2003 conference, Cambridge, UK.

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