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MODEL PREDICTIVE CONTROL AS AN ENERGY MANAGEMENT STRATEGY FOR HYBRID ELECTRIC VEHICLES

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ABSTRACT

The energy management strategy in a hybrid electric vehicle is viewed as an optimal control problem and is solved using Model Predictve Control (MPC). The method is applied to a series hybrid electric vehicle, using a linearized model in state space formulation and a linear MPC algorithm, based on quadratic programming, to find a feasible suboptimal solution. The significance of the results lies in obtaining a real-time implementable control law. The MPC algorithm is applied using a quasi-static simulator developed in the MATLAB environment. The MPC solution is compared with the dynamic programming solution (offline optimization). The dynamic programming algorithm, which requires the entire driving cycle to be known a-priori, guarantees the optimality and is used here as the benchmark solution. The effect of the parameters of the MPC (length of prediction horizon, type of prediction) is also investigated.

1 Introduction

Hybrid electric vehicles (HEV) have found their place in the automobile industry due to their potential to reduce fuel consumption and emissions in comparison to conventional vehicles. The presence of a battery pack and one or more electric machines gives rise to a new degree of freedom, thanks to the possibility for the electric actuators and storage system to operate bidirectionally. The addition of these devices offers idle off capability, regenerative braking, power assist ability and potential for engine downsizing. The problem of finding the most efficient way of splitting the power between the engine and the battery pack is addressed by the energy management strategy. The main objective of the energy management strategy is to minimize fuel consumption and possibly emissions over a driving cycle, without compromising the driveability of the vehicle. Several strategies have been proposed in literature to solve this optimal control problem (see [1] for an overview). The energy management strategies for HEVs can be classified in three categories, on the basis of the amount of information used. The first category assumes the complete knowledge of the past, present and future values of the external variables involved in the optimization; in other words, the driving cycle is assumed to be known a priori, leading to control strategy not realizable in practice, but only in simulation. This category includes dynamic programming [2, 3] and analytical optimal control techniques [4,5], which use a simplified, analytical model of the powertrain.

The second category assumes the knowledge of only past and present values, and uses some kind of prediction for the future values. These strategies include adaptive equivalent consumption minimization strategy (A-ECMS) [6, 7], receding-horizon control [8], and stochastic dynamic programming [9].

The third category assumes knowledge only of past and present information, and includes standard ECMS [10], which reformulates the global problem to a local one, minimizing at each instant a cost function opportunely defined, and heuristic control strategies, which implement energy management with rules based on engineering intuition, but often fail to fully exploit the potential of the hybrid electric architecture.

In formal terms, the optimal control problem in a hybrid electric vehicle corresponds to the minimization of the integral cost, or performance index, given by:

$$J = \int_{t_0}^{t_f} L(x,u,t)dt \tag{1}$$

where t represents, the time, $u(t)$ is the control action, $T = t_f - t_0$ is the duration of the optimization horizon (ideally corresponding to the length of the trip), and L is the cost function. If minimization of fuel consumption is the only objective of the controller (as it is assumed in this work), then L is the instantaneous fuel flow rate: $L = \dot{m}_f(t, u(t))$. On the other hand, if pollutant emissions are also a concern, then L can be a weighted average of fuel consumption and emission rates. The minimization problem is solved under several constraints, both integral (charge-sustainability, i.e. the state of charge at the end of the trip must be nominally equal to the initial value) and local (instantaneous power limits, state of charge boundaries).

In this paper, model predictive control (MPC) is proposed as an energy management strategy for hybrid vehicles and applied to a series HEV configuration. MPC is an advanced control technique frequently used in the process control industry for constrained optimization problems in multivariable plants [11]. It is based on the receding horizon concept: the control sequence is calculated, at each instant, in order to minimize a cost defined over an optimization horizon which extends into the future. The cost (in this case, the fuel consumption) is predicted as a function of the future control inputs by using a model of the system (hence the name model predictive control) and approximate prediction of the relevant external inputs. Only the first control value is applied at the current time step, and the procedure is repeated at the following time step to calculate the subsequent value of the control, updating the model with the measured states. In this way, a feedback loop is introduced in the open-loop control resulting from the optimization. The minimization is subject to several constraints on the control and the states. A linear MPC formulation is used here, using a linearized model of the system for prediction; this allows to obtain the sequence of control during the prediction horizon from the solution of a quadratic programming problem, which is easily obtained with commercial code (function `quadprog` in *Matlab*).

The paper is organized as follows: In Section 3, the HEV architecture and the nonlinear model used for simulation are explained. In section 4, the MPC theory is recalled, followed by the standard linear MPC algorithm. Section 5 describes the MPC algorithm as applied to the architecture described in Section 3, and the linearization of the model. Section 6 shows the simulation results of MPC for various standard driving cycles and the results are compared with the optimal solution obtained with dynamic programming.

2 Energy management controller

The general control scheme of a hybrid electric vehicle (series architecture) is shown in Figure 1. Two control layers are represented. The outer layer is the speed control, which is the human driver in a real vehicle and a driver model (typically a PI controller) in simulation. The speed controller decides the total power request P_{req} that the powertrain must deliver in order to follow the prescribed velocity profile. The inner layer is the energy management strategy, which decides how to split the total power request between the energy sources present on-board (the battery and the generator in a series HEV). Given that the architecture considered in this paper presents a single degree of freedom in the power split, the energy management only needs to decide the value of one between the generator power $P_{gen,e}$ and the battery power P_{batt}; the other is obtained by difference with the total power request. The separation of the two control layers allows to consider only the battery state of energy dynamics in the energy management strategy, while the vehicle speed does not need to be treated as a state of the system, since it is controlled independently. Model predictive control is used as the energy management strategy which decides the power split between the battery and the generator set (*genset*). The control is implemented with the following steps:

1. A nonlinear vehicle and powertrain model is developed, assuming that the dynamics of the engine and electric machine are fast in comparison to the battery state of charge and vehicle longitudinal dynamics.
2. The linear MPC algorithm for a standard linear model with linear constraints is developed.
3. The nonlinear model is linearized at each sample time and used as the embedded control model for the MPC.

3 HEV System Architecture and Model

A series hybrid electric vehicle incorporates a fuel converter (internal combustion engine), a generator, battery, and an electric traction motor, as shown in Figure 2. The engine does not drive the wheels directly, but it drives the generator to convert mechanical power into the electrical energy. The electric energy can also be saved in the energy storage system (battery). The torque required to drive the vehicle is supplied entirely by the electric motor. The presence of a purely electric transmission path between the prime mover and the driven wheels allows the genset (set resulting from the coupling of engine and generator) to operate in its optimal efficiency range, along the maximum efficiency

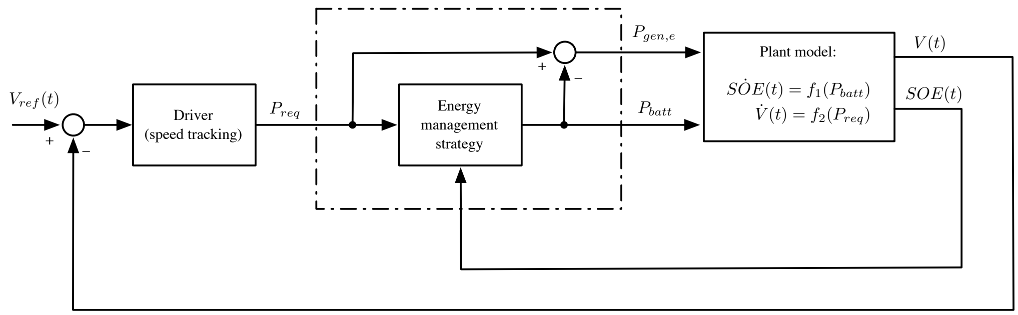

Figure 1. Control scheme of a hybrid electric vehicle

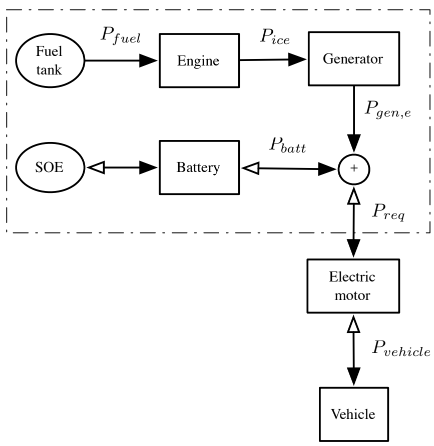

Figure 2. Series Hybrid Architecture

line. In general, the energy management strategy in a series hybrid vehicle can be interpreted on the engine speed/torque map as shifting the engine operation from an iso-power curve to a different one, while remaining on the maximum efficiency line. The deviation from the power level corresponding to the total power demand translates into a charge or discharge of the battery and must be compensated at a later time. Since the engine does not directly drive the wheels, the need for a complicated multi-speed transmission and clutch is eliminated. Because series drivetrains perform best in stop-and-go driving they are primarily being considered for buses and other urban vehicles.

3.1 HEV Plant Model

The major components of the series hybrid architecture are the genset (combination of engine and generator), the battery pack, the traction motor. Since the model is to be used for estimation of fuel consumption, a quasi-static model is sufficient [12]. Therefore, the equations describing the components are developed with the assumption that the only relevant dynamics are the vehicle longitudinal dynamics and the battery state of charge. This makes the quasi-static model fairly simple, yet complete enough for the energy management problem. The plant model represents the HEV in the simulator used to obtain the implementation results of Section 6. The control model that has been used in the MPC algorithm is described in section 5.

3.1.1 Genset Model The engine and the generator are modeled using quasi-static efficiency maps. The engine map represents the fuel consumption as a function of mechanical power and speed, the generator map represents the mechanical power as a function of electrical power and speed. Mechanical power and speed are the same for both machines. Assuming that it is possible to control the genset in order to make it operate along the maximum efficiency line, the fuel consumption $\dot{m}_f$ is a function only of the net electrical power delivered, $P_{gen,e}$:

$$\dot{m}_f = \dot{m}_f \left(P_{gen,e}\right) \tag{2}$$

The genset is constrained to operate within its power limits:

$$P_{gen,min}(t) \le P_{gen,e}(t) \le P_{gen,max}(t) \tag{3}$$

3.1.2 Battery Model The battery pack can be modeled in various ways depending on the energy management problem formulation, with either the battery state of charge SOC or its state of energy SOE as system state. These are defined as:

$$SOC(t) = \frac{Q(t)}{Q_{max}} \tag{4}$$

$$SOE(t) = \frac{E(t)}{E_{max}} \tag{5}$$

where Q_{max} (measured in Ah) and E_{max} are the total amount of charge and energy that can be stored in the battery, and $Q(t)$ and $E(t)$ the amount of charge and energy currently stored. Both current and power are assumed to be positive during discharge, and negative during charge. The two quantities are related by the fact that the energy stored is the product of the electrical charge and of the open circuit voltage V_0. Therefore,

$$SOE(t) = \frac{E_{batt}(t)}{E_{max}} = \frac{Q_{batt}(t)V_0\left(SOC(t)\right)}{Q_{max}V_{0,max}} = SOC(t)\frac{V_0\left(SOC(t)\right)}{V_{0,max}}$$

For a typical HEV battery, the open circuit voltage remains almost constant during operation in the nominal range of state of charge (typically 0.5-0.8), therefore the quantity $V_0(t)/V_{0,max}$, which is "conversion factor" from SOC to SOE, is constant and thus the two quantities are proportional (not strictly equal because the open circuit voltage characteristic is nonlinear and the value at 100% SOC is higher than the value taken for SOE between 0.5 and 0.8). While the state of charge is the more common method the express the state of the battery, since it has a clear physical meaning and can be related to quantities directly measurable, such as current and open circuit voltage, the state of energy is used in this paper for all modeling and simulation purposes, because its dynamics are related to battery power, which is the most immediate control variable for a HEV.

The variation of SOE with respect to time is expressed using the dynamic equation

$$S\dot{O}E(t) = -\frac{P_{batt}}{E_{max}}\left(1 + \frac{R_0}{V_0^2}P_{batt}\right) \tag{6}$$

where R_0 is the internal resistance, V_0 is the open circuit voltage. Both parameters are assumed to be constant. This description is derived using a simple circuit model including the voltage source E_0 in series with the resistance R_0.

The power balance equation for the electrical summation node in Figure 2, in which the power from the genset, the battery and the electric motor are summed, is:

$$P_{batt} = P_{gen,e} + P_{req} \tag{7}$$

from which the following constraints on the battery power are derived:

$$P_{req}(t) - P_{gen,e,max} \leq P_{batt}(t) \leq P_{req}(t) - P_{gen,e,min} \tag{8}$$

which must be satisfied together with the physical constraints

$$P_{batt,min}(t) \leq P_{batt}(t) \leq P_{batt,max}(t). \tag{9}$$

In addition to this, the state of energy must remain within an upper and a lower boundary values:

$$SOE_{min} \leq SOE(t) \leq SOE_{max} \tag{10}$$

3.1.3 Electric Motor Model

The electric traction motor in Figure 2 model computes the electrical power that the bus must provide. The electrical power is a function of the torque and speed (related to the vehicle driving cycle) and of the efficiency:

$$P_{req} = \begin{cases} \frac{T_{em}\omega_{em}}{\eta_{em}(T_{em}\omega_{em})} & if\, P_{em,m} \geq 0 \\ T_{em}\omega_{em}\eta_{em}\left(T_{em},\omega_{em}\right) & if\, P_{em,m} < 0 \end{cases} \tag{11}$$

where ω_{em}, T_{em}, η_{em} are the speed, torque and efficiency of the electric motor, and $P_{req} = P_{em,e}$ is the motor electrical power, corresponding to the power request at the bus. The motor torque and speed are calculated using the vehicle model.

Table 1. Vehicle and Transmission Parameters

Parameter	Value in SI units
Total mass	6350 kg
Aerodynamic resistance coefficients	$C_d = 0.4$ $A_f = 0.4m^2$
Rolling resistance coefficients	$r_0 = 0.012$ $r_1 = 0$
Final gearing ratio	$g_r = 10$
Wheel radius	$R_w = 0.6$ m

3.1.4 Vehicle Model

Two different approaches to the HEV modeling can be adopted: the backward and forward modeling with respect to the physical causality principles [13]. The former makes the assumption that the vehicle meets the target performance, so that the vehicle speed is supposed known and the power request is calculated using the kinematical relationships imposed by the drivetrain. Forward modeling, on the contrary, takes as inputs the driver commands and, simulating the physical behaviors of each component, generates the vehicle performance as output. In this paper, a backward model is used to calculate the power demanded by the driver. Given the velocity profile that the vehicle is intended to follow, the torque that would be necessary at the input of the electric motor, T_{em}, is calculated at each time instant using the backward dynamics model of the vehicle.

The force necessary to follow a driving cycle is given by

$$F_{vehicle} = F_{rr} + F_{aero} + F_{grade} + m\dot{V} \tag{12}$$

with: $F_{rr} = r_0 + r_1 V$, $F_{aero} = \frac{1}{2}\rho_{air}C_d V^2$, and $F_{grade} = mg\sin\gamma$, where m is the mass of the vehicle, γ is the road slope angle and r_0, r_1, ρ_{air}, C_d are constant coefficients. The torque is related to the force by the wheel rolling radius R_w and the gear ratio g_r between the motor and the wheels: $T_{em} = F_{vehicle}R_w/g_r$. The vehicle and transmission parameters used to generate the power request are listed in Table 1.

4 Linear Model Predictive Control

This section describes the general problem formulation of the standard linear MPC [14] which is used as the basic framework for developing the MPC problem for a series HEV architecture described in Section 5. The standard linear MPC formulation described here consists in finding a control law which minimizes the quadratic cost:

$$\begin{aligned} J = \sum_{i=1}^{P-1} [w_{i+1}^{y} & \left\| y(k+i+1|k) - y_{ref}(k+i+1|k) \right\|^2 \\ + w_i^{\Delta u} & \left\| \Delta u(k+i|k) \right\|^2 \\ + w_i^{u} & \left\| u(k+i|k) - u_{ref}(k) \right\|^2] \end{aligned} \tag{13}$$

subject to the linear system dynamics:

$$\begin{cases} x(k+1) = Ax(k) + B_u u(k) + B_v v(k) \\ y(k) = Cx(k) + D_u u(k) + D_v v(k) \end{cases} \tag{14}$$

and the linear constraints

$$\begin{cases} u_i^{min} \leq u(k+i|k) \leq u_i^{max} \\ \Delta u_{i-1}^{min} \leq \Delta u(k+i|k) \leq \Delta u_{i-1}^{max} \\ y_i^{min} \leq y(k+i+1|k) \leq y_i^{max} \\ \Delta u(k+i|k) = 0 \; for \; i = M+1, \ldots P \end{cases}$$

where $\|\cdot\|^2$ is the euclidean norm, $P, M < P$ are the prediction and control horizon respectively, $\Delta U = [\Delta u(k|k), \ldots, \Delta u(k+P-1|k)]^T$ is the sequence of control input increments with respect to which the optimization is performed,$w_{i+1}^y, w_i^{\Delta u}, w_i^u$ are the weighting factors of the output, control input increment and control input respectively, $x(k) \in R^n$ is the State vector, $u(k) \in R^m$ is the vector of control variables of the system and $y(k) \in R^p$ is the output vector, $v(k) \in R^q$ is the vector of measured inputs. By $q(k+i|k)$ is indicated the value of the variable q at the $k+i$ time step given the value at time step k. $u_{ref}(k)$, $y_{ref}(k)$ are the control reference and output reference trajectory, respectively.

In a typical MPC fashion, the above optimization procedure is solved at time k, and the result of the optimization is the optimal control input increment $\Delta u^{opt}(k|k)$ at time k. The control input at time k is calculated as

$$u(k|k) = u(k-1) + \Delta u^{opt}(k|k) \tag{15}$$

This is applied to the process and the procedure is repeated at subsequent times $k+1, k+2$, etc. The above formulation necessitates the use of the predicted outputs over the prediction horizon which can be calculated by substituting equation(15) into equation (14) as:

$$\begin{aligned} y(k+i|k) = {} & C\left[A^i x(k) + B_v v(k+m|k)\right] + D_v v(k) \\ & + C\sum_{m=0}^{i-1}\left(A^{i-1}B_u u(k-1)\right) \\ & + C\sum_{m=0}^{i-1}\left(A^{i-1}B_u \sum_{j=0}^{m} \Delta u(k+j|k)]\right) \end{aligned} \tag{16}$$

The predicted output, which is now an explicit function of the control input increment vector $\Delta U = \{\Delta u(k|k), \Delta u(k+1|k), ..., \Delta u(k+P-1|k)\}$, is substituted into the performance objective function J given by equation (13) to rewrite the problem as a quadratic programming (QP) optimization problem:

$$\Delta U^{opt} = arg\min_{\Delta U}\left[\frac{1}{2}\Delta U^T H \Delta U + F^T \Delta U\right] \tag{17}$$

under the constraints

$$G_u \Delta U \leq W + Sx(k) \tag{18}$$

where H, F, G_u, W, S are constant matrices and functions of desired references, measured inputs, input targets, the last control input and the measured or estimated states at current sample time.The solution of the QP gives the optimal control input increment sequences ΔU^{opt}, out of which only the first element $\Delta u^{opt}(k|k)$ is used to find the control input at time k. The control is applied to the plant and the procedure is repeated for the subsequent time steps, shifting the prediction horizon forward by one time step (*receding horizon method*).

5 MPC problem formulation for series HEV

The system used in the MPC problem is given by the quasi-static model that describes the battery dynamics, i.e.:

$$\dot{x} = -\frac{u(t)}{E_{max}}\left(1 + \frac{R_0}{N_p N_s E_0^2}u(t)\right) \tag{19}$$

where $x = SOE$ is the state of energy of the battery, and $u = P_{batt}$ is the control input.

The output y is given by both tracked outputs and constrained outputs. The tracked outputs of the system are the fuel consumption, which has to be minimized (i.e., tracked to zero), and the state of energy which has to be kept around its nominal value. The constrained outputs specify the physical constraints of the devices used, and include the battery power P_{batt} and the genset electrical power $P_{gen,e}$.

Let us define the vectors of state, control inputs, measured inputs, and outputs as:

$$x = SOE, \; u = P_{batt}, \; v = P_{req}, \; y = \begin{bmatrix} \dot{m}_f \\ P_{gen,e} \\ P_{batt} \\ SOE \end{bmatrix} \tag{20}$$

The output vector is expressed as a function of the control input and state as follows:

$$y(t) = \begin{bmatrix} \dot{m}_f\left(P_{req}(t) - P_{batt}(t)\right) \\ P_{req}(t) - P_{batt}(t) \\ P_{batt}(t) \\ SOE(t) \end{bmatrix} \tag{21}$$

and the cost function to be minimized is

$$L(x,u,v) = \begin{bmatrix} w^f \dot{m}_f \\ w^{SOE}\left(SOE(t) - SOE_{ref}\right) \end{bmatrix} \tag{22}$$

where w^f and w^{SOE} are the penalty weights for the fuel consumption and SOE variation respectively.

The nonlinear first order equations (19), (21) are linearized around an operating point and discretized in order to follow the linear MPC algorithm implementation. The linearized and discretized model of the system is

$$\begin{Bmatrix} x(k+1) = Ax(k) + B_u u(k) + B_v v(t) + \bar{F} \\ y(k) = Cx(k) + D_u u(k) + D_v v(k) + \bar{G} \end{Bmatrix} \tag{23}$$

where

$$A = 1; \quad B_u = -\tfrac{1}{E_{max}}\left(1 + \tfrac{R_0}{N_p N_s E_0^2} u_0\right); \quad B_v = 0;$$

$$C = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}; \qquad D_u = \begin{bmatrix} -m_1 \\ -1 \\ 1 \\ 0 \end{bmatrix}; \qquad D_v = \begin{bmatrix} m_1 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

$$\bar{F} = \tfrac{1}{E_{max}}\left(1 + \tfrac{R_0}{N_p N_s E_0^2} u_0^2\right); \; \bar{G} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

Using (16), the predicted output of the system over the prediction horizon P can be written as

$$\begin{aligned} Y &= Cx(k) + D_{u(k-1)} u(k-1) \\ &+ D_{\Delta U} \Delta U + D_V V + D_{\bar{F}} \end{aligned} \tag{24}$$

where $Y = \left[y(k+1) \; y(k+2) \; \cdots \; y(k+P) \right]^T$ is the set of predicted outputs over the prediction horizon P, $x(k)$ is the measured /estimated SOE of the battery, $u(k-1)$ is the control input at the previous time step, $\Delta U = \left[\Delta u(k) \; \Delta u(k+1) \; \cdots \; \Delta u(k+P-1) \right]^T$ is the input increment sequence over P that needs to be optimized, $V = \left[v(k+1) \; v(k+2) \; \cdots \; v(k+P) \right]^T$ is the set of measured inputs over P. $D_{\Delta U}$, D_V and $D_{\bar{F}}$ are functions of the matrices A, B_u, B_v, C, D_u, D_v; their explicit expression is not reported here for brevity.

5.1 Cost Function and Optimization

The performance objective function or the cost function that was defined in (13) has to reformulated for the energy management problem. The main objective of the problem is to minimize the fuel consumption (22) and keep the SOE around its reference value. The reference trajectory for the fuel consumption (first output) is taken as zero, i.e $y_{ref}^{(1)}(k+i|k) = 0 \, \forall \, i = 1,2,\dots P$. The reference trajectory for the SOE (fourth output) is also constant, and equal to the reference value SOE_{ref}: $y_{ref}^{(4)}(k+i|k) = SOE_{ref} \, \forall \, i = 1,2,\dots P$. There is no reference trajectory for the control input P_{batt} in our case and the constraints on the control effort involved are imposed by enforcing (8) and (9) at each time. Therefore, in the cost function (13), the weights on the control are $w_i^{\Delta u} = 0$ and $w_i^u = 0$, and $u_{ref}(k) = 0$. The weights on the tracked outputs are $w_i^y = [1 \; 0 \; 0 \; 0.001]$ (the weight on the fuel consumption, i.e. the first element, is much higher than the weight on the SOE variation, which is the fourth element). The predicted outputs of the system Y as a function of the control input increment vector ΔU given by (24) are then substituted into the above defined cost function to obtain the explicit form of (17), in which

$$H = D_{\Delta U}^T D_{\Delta U}$$

$$F = f\left(C_x, x(k), D_{u(k-1)} u(k-1), u(k-1), D_V, V\right)$$

$$C = g\left(C_x, x(k), D_{u(k-1)} u(k-1), u(k-1), D_V, V\right)$$

f, g being nonlinear functions. G_u is a coefficient matrix for the constants and W is a matrix containing the limits of ΔU. The term S is zero, since the constraints on the control do not depend on the state.

The energy management problem is now in the form required by the quadratic programming solver in MATLAB. The optimal control input increment sequence ΔU^{opt} is obtained from the solver, and the first element of this vector $\Delta u^{opt}(k|k)$ is applied to the plant model of HEV. At the subsequent time step, the updated value of the system state is obtained. This procedure is repeated during the subsequent time steps to implement the receding control strategy.

6 Simulation Results

The MPC algorithm is implemented using a vehicle simulator that implements the model described in Section 3.1. The vehicle modeled is a medium-duty series hybrid truck, used for pickup and delivery, i.e. mainly for urban, stop-and-go driving cycles. The results of the control strategy implementation are presented here for two driving cycles: a test cycle with two acceleration-deceleration profiles, which allows to analyze the MPC behavior and extract some information about the effect of the algorithm parameters, and a real-world cycle with stop-and-go characteristics. In both cases, the MPC solution is compared with the optimal solution obtained using dynamic programming [3]. Obviously, the plant model is identical for both strategies. The time step for the simulation and the MPC algorithm is 1 s.

6.1 Effect of prediction horizon and prediction accuracy

In order to assess the effect of the prediction horizon length, as well as the effect of the accuracy in predicting the future power demand (or, equivalently, velocity profile), the simple driving cycle shown in Figure 3 was used. The cycle includes two acceleration/deceleration sequences. The MPC parameters that affect the solution are the length of the prediction horizon, P, and the type of prediction. In the figure, two extreme cases are presented for each of the parameters. The prediction horizon can be either 5 s or 100 s: in the first case, the algorithm only predicts a few steps ahead, while in the latter case it has a vision of the entire cycle.

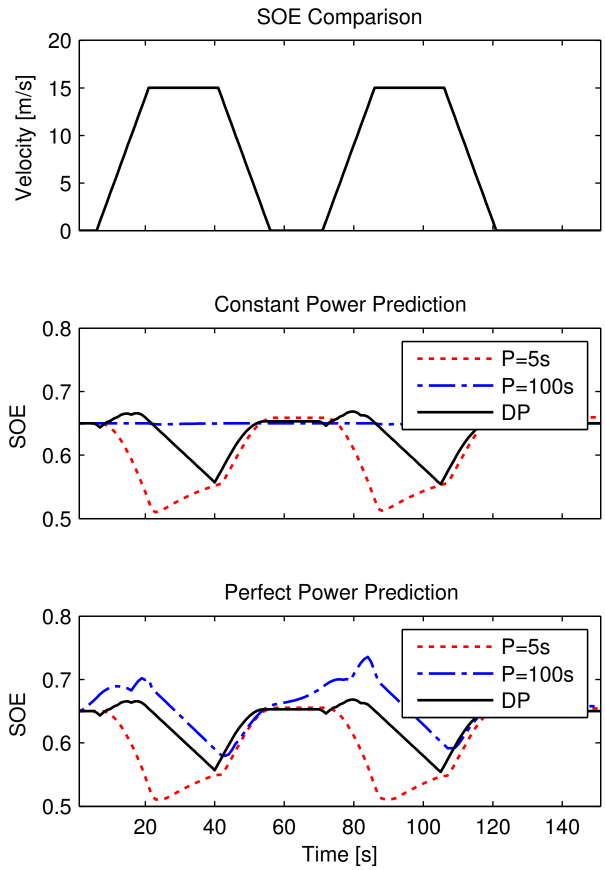

Figure 3. Simplified cycle used for testing and SOE profile with different length of prediction horizon and different prediction accuracy

The prediction of power request (P_{req} in (11)) can be, in the simplest case, based on the assumption that the future power request remains constant (equal to the last measured value); or, in the best-case scenario, matches perfectly the actual values for the entire prediction horizon. Figure 3 shows the SOE profile corresponding to the various cases, and the optimal solution obtained with dynamic programming. It can be noticed how the prediction accuracy does not affect the results obtained with the small prediction horizon, while it changes completely the behavior in the case of a long prediction horizon. In fact, as it is intuitive, assuming a constant power demand for 5 s is more realistic than it is to assume it constant for 100 s. The MPC with long prediction horizon and constant power request does not work effectively, because it is too conservative in terms of battery usage. On the other hand, the MPC with perfect prediction and a receding horizon of 100 s is the closest to the optimal solution. The differences with respect to DP can be attributed to the fact that MPC uses a linearized system model, as opposed to the fully nonlinear model of DP. Figure 4 shows the battery power for the same cycle. It can be concluded that a long prediction horizon is not useful unless a very reliable prediction algorithm is used, and that a short prediction horizon, even with a simplified prediction that assumes

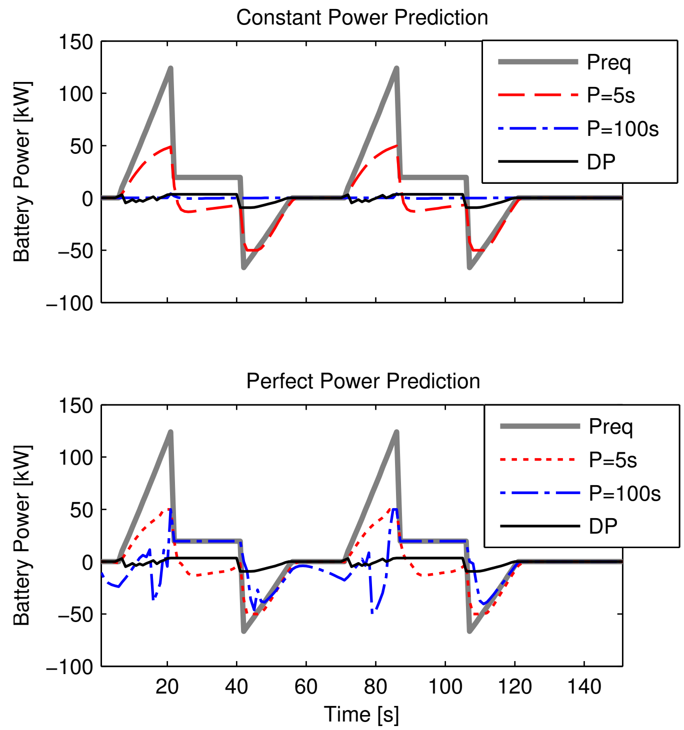

Figure 4. Battery power relative to the cycle of Figure 3

constant power, can be quite effective.

6.2 Application on actual driving cycle

MPC is compared to DP in relation to a real-world driving cycle, as shown in Figure 5. In this case, even the longest prediction horizon with perfect power prediction generates a solution that does not reproduce the trend of the SOE profile obtained with DP. This can be attributed to the fact that, despite the long prediction horizon, MPC still lacks the knowledge of the entire cycle, and therefore the solution it generates mimics the optimal solution only in the relatively short term. Again, the quality of prediction makes very little difference in the case of the short prediction horizon (5 s), but it changes the behavior of the solution with long prediction horizon (100 s).

In terms of computational time, this MPC algorithm is rather efficient. For a 1000 s driving cycle, the case with P = 5 s is solved in roughly 20 seconds, while the case with P = 100 s requires almost 540 s, on a standard desktop PC. By comparison, the DP solution for the same cycle is computed in 1200 s. In terms of final results, i.e. fuel consumption, the MPC algorithm is between 17 and 30 % worse than DP, depending on the case, as shown in Table 2. From the results in this table, it appears that increasing the length of the prediction horizon does not improve the performance (it actually makes the fuel consumption higher), probably due to the fact that the linearization is more effective in the short-term than it is over a large prediction horizon. Furthermore, the perfect power prediction is not necessarily

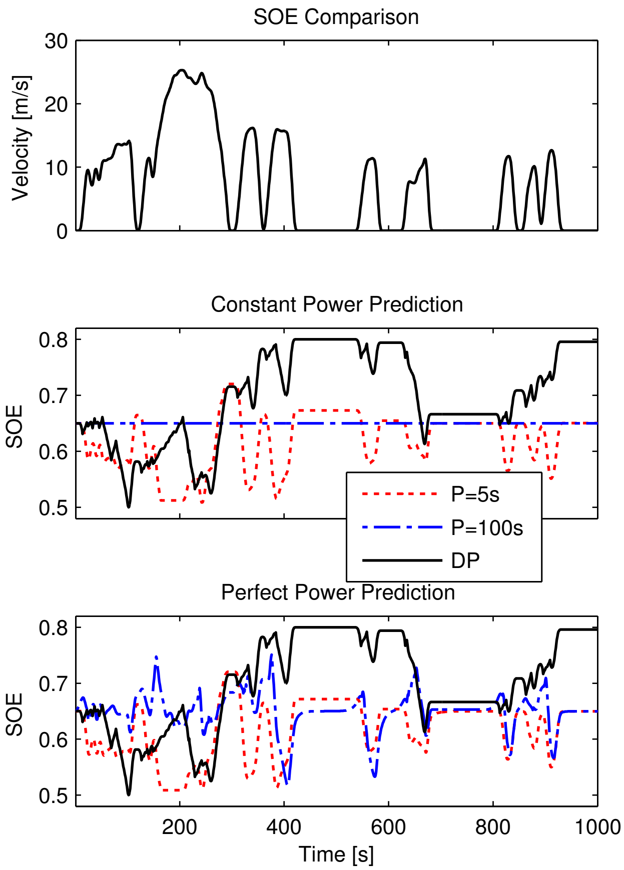

Figure 5. Results in a real-world cycle

advantageous in comparison to the constant power prediction, in fact the same fuel consumption is achieved for both cases (for P = 5 s).

Table 2. Results of MPC implementation compared with dynamic programming

Strategy	MPC, Constant		MPC, Perfect		DP
Prediction horizon [s]	5 s	100 s	5s	100 s	-
Execution time	19 s	73 s	19 s	540 s	1200 s
Fuel consumption (normalized)	1.17	1.30	1.18	1.23	1

7 Conclusion

The application of model predictive control to energy management of hybrid electric vehicle has been presented, showing a suitable problem formulation and solution method. The effect of the most important MPC parameters has also been investigated, showing that a long prediction horizon and high prediction accuracy do not yield better results than a shorter horizon, but also that the prediction accuracy is meaningful only for long prediction horizon.

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