Predictive Control for Fuel Consumption of Hybrid Solar Vehicles

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Abstract: Hybrid solar vehicles (HSVs), having multiple main energy sources and a photovoltaic panel, are an attractive alternative to conventional vehicles. The paper presents a study on modelling a series HSV and minimization of the energy consumption in such a vehicle. The presented model is used for the development of optimal control strategies which minimize the vehicle's fuel consumption. The presented control strategy to minimize fuel consumtion is Model Predictive Control (MPC). Simulations were performed using Matlab – Simulink for testing the model and the control strategy.

Keywords: hybrid solar vehicles (HSVs), component models, Model Predictive Control (MPC)

1 Introduction

Hybrid electric vehicles (HEVs), having multiple main energy sources, are an attractive alternative to conventional vehicles. These energy sources are the conventional fuel tank and a battery. If a photovoltaic panel is also added, a Hybrid Solar Vehicle (HSV) is obtained. HSVs can be seen as a transition from conventional vehicles to fully electric vehicles. HSVs can have different architectures, depending on the imposed requirements [1], [2]. Basic drivetrain structures for HSVs are: series, parallel, series/parallel and complex hybrids. Series HSVs are optimal solutions for urban traffic applications where the vehicle starts and stops frequently during a drive cycle. So regenerative braking can be often used, which substantially improves the fuel economy of the vehicle. Since the target of the research is optimization of fuel consumption in case of urban drive cycles, a series architecture was chosen for this study, this proving to be optimal in this case. A basic diagram of the series HSV is depicted in Figure 1.

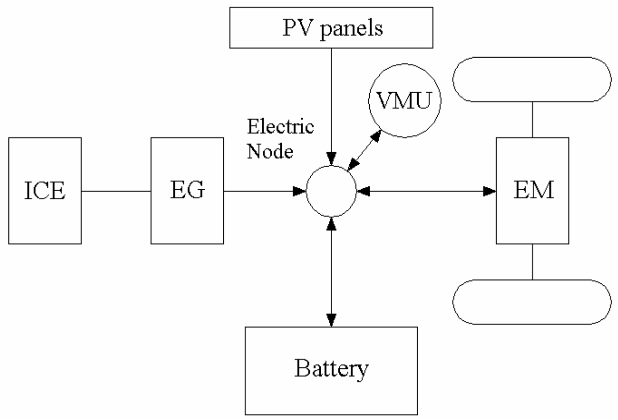

Figure 1
Series hybrid architecture

The HSV model is based on the component modelling that takes into accout fuel minimization aspects. Model Predictive Control (MPC) is applied for fuel minimization. The numerical data used for simulation is taken from the literature.

2 Series Hybrid Architecture Component Modelling

2.1 Introduction

The architecture of a series HSV is depicted in Figure 1. The fuel consumption minimization relevant components are as follows: the electric motor (EM) which drives the wheels or works as a generator during regenerative braking; the electrical energy for the EM is delivered by the electric generator (EG); the photovoltaic (PV) panel and battery; the electric generator is in rigid connection with the internal combustion engine (ICE). The vehicle management unit (VMU) is used for control and coordination of the components.

2.2 Electric Motor

For electric vehicles and HEV driving systems the Brushless DC machines (BLDC-m) are often used [3]. They can work both in motor and generator regimes. The BLDC can function in four quadrants: forward motoring, forward breaking, reverse motoring and reverse braking [4].

A qualitative modelling is achieved by presenting the characteristic steady-state curves (Figure 2), for normalized values of the torque and speed, for the first quadrant of forward motoring. The steady-state speed-torque curves $M = f(\omega; U - parameter)$ are obtained the relation:

$$M = \frac{K_t}{1.1R_m}[U - K_e\omega] \tag{1}$$

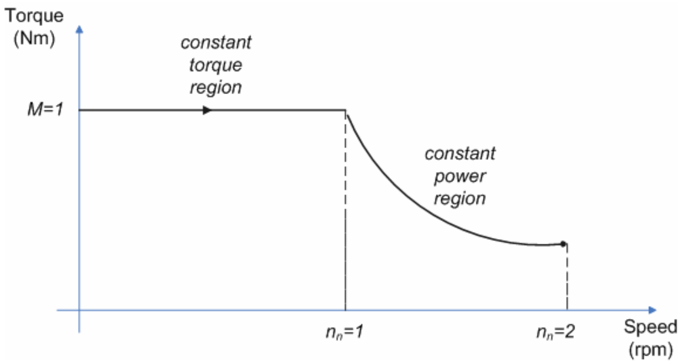

Figure 2
Torque-speed characteristics in normalized values

Here n_n is the nominal resolution. The power balance between the electrical and mechanical powers is (2).

$$P_{el}=P_m/\eta \tag{2}$$

The efficiency balance is valid also at breaking.

2.3 Photovoltaic Panel

The PV panel is independent from the other components. It can be chosen so that it has maximum efficiency and a maintenance free robust structure [5]. The model used for PV panel power is:

$$P_{PV} = U_{opt}(\lambda) \cdot K(\lambda) \cdot \left(1 - e^{\frac{U_{opt}(\lambda) - U_{\max}(\lambda)}{T_U(\lambda)}}\right) \cdot (1 + K_P(T - 25)) \tag{3}$$

Where I_0 is the output current, U is the output voltage, $U_{\max}$ is the maximum possible output voltage, K and T_U are parameters to be calculated (they are λ insolation dependent), T is the actual cell temperature.

2.4 Battery

A relatively complex battery model is presented, which models the battery as a real voltage generator considering the change in open circuit voltage when the battery state of charge (SOC) changes. Based on [6] the efficiency of the battery is modelled as follows:

$$P_b = \frac{1-\sqrt{1-6\cdot 10^{-5}\cdot P_{bn}}}{3\cdot 10^{-5}} \tag{4}$$

With P_{bn} meaning nominal battery power. In this type of formulation positive P_b (battery power) means battery discharge, while negative P_b means battery charge. The overall structure of the battery model is presented in Figure 3.

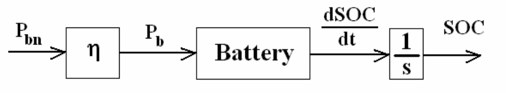

Figure 3
Battery simulation structure

The resultant battery model reflects all the important characteristics of a battery.

2.5 Internal Combustion Engine and Electric Generator

The electric generator (EG) and internal combustion engine (ICE) must be fitted to the electric motor and to each other using the maximum efficiency region for both of them. This way the EG can be described by a single characteristic curve, between input mechanical and output electrical power (Figure 4).

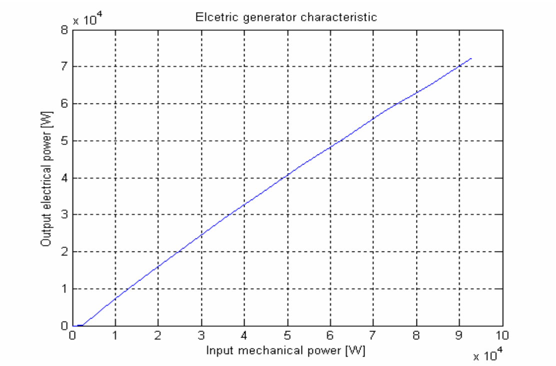

Figure 4
Electric generator characteristic curve

For the ICE, the quotient of output and input power is the ICE efficiency. The efficiency map is plotted against torque and angular velocity values (Figure 5).

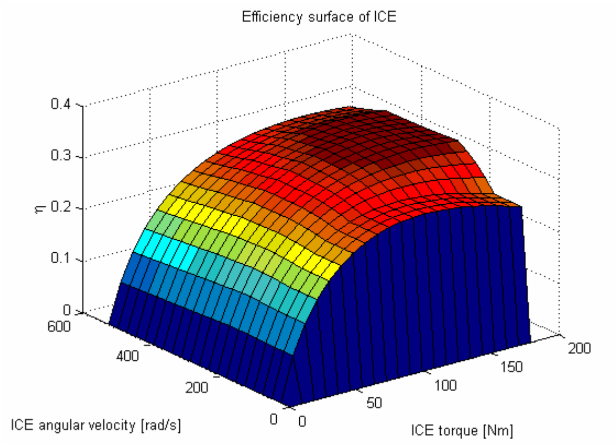

Figure 5
ICE efficiency map

2.7 Vehicle Model and Drive Cycle

The resulting vehicle model is a non-linear model. In order to apply MPC a linearization was performed, keeping the state variables of the system [7]. The resulting linear model has the following inputs, outputs and states:

- State variables: - x_1: ICE power state,
  - x_2: SOC,
  - x_3: EM power state;
- Inputs: - u_1: ICE power,
  - u_2: Battery nominal power;
- Controlled outputs: - o_1: Drive power,
  - o_2: SOC,
  - o_3: Fuel rate;
- Measured disturbance input: - d_m: PV panel power.

In this model the PV power is considered a measured disturbance (depending on the actual insolation which is an external factor). The numerical data was taken from the literature, based on real data [6], and is presented in the chapter dealing with control. The simulations were performed for the New European Drive Cycle (NEDC), depicted in Figure 6.

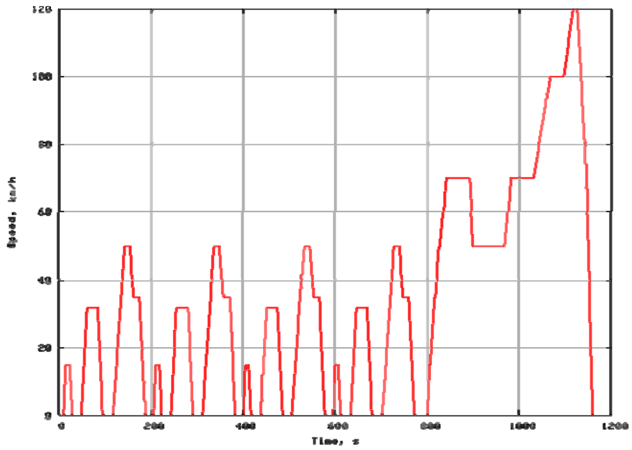

Figure 6
New European Drive Cycle

3 Fuel Consumption Minimization using Predictive Control

3.1 Introduction

The task presented in this paragraph is to minimize the fuel consumption of a HSV during a given driven cycle (NEDC), while the SOC is kept between well defined boundaries: the minimal and maximal SOC values are 0.6 and 0.8, from [8].

The applied control strategy for the series HSV architecture is Model Predictive Control (MPC), as used also for a hybrid vehicle in [9],[10]. MPC is an advanced control strategy which had spread significantly during the past years in industry as well, due also to the computational capacity of nowadays machines [11], [12], [13].

3.2 Problem Formulation and Simulation Results

The numerical values for the HSV are as follows (resulting from literature, based on real data [7]):

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ x_3(k+1) \end{bmatrix} = \begin{bmatrix} 0.3679 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0.9048 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \end{bmatrix} +$$

$$+ \begin{bmatrix} 3.78 \cdot 10^{-6} & 6.321 \cdot 10^{-4} \\ 0 & -1.517 \cdot 10^{-11} \\ 2.638 \cdot 10^{-7} & 0 \end{bmatrix} \begin{bmatrix} u_1(k) \\ u_2(k) \end{bmatrix} + \begin{bmatrix} 6.321 \cdot 10^{-4} \\ 0 \\ 0 \end{bmatrix} d_m(k) \tag{5}$$

$$\begin{bmatrix} y_1(k) \\ y_2(k) \\ y_3(k) \end{bmatrix} = \begin{bmatrix} 800 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 100 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) + \end{bmatrix}$$

A sampling time of $T_s=0.001$ sec was used. The constraints acting upon the system are:

$$\begin{cases} 0 \le u_1 \le 93000 \\ -26000 \le u_2 \le 14000 \\ -40000 \le y_1 \le 58000 \\ 0.6 \le y_2 \le 0.8 \\ 0 \le y_3 \le 7.3 \end{cases} \tag{6}$$

A quadratic cost function is assumed that has the following form:

$$J(k) = \sum_{i=1}^{N} \left\| \hat{y}(k+i|k) - r(k+i|k) \right\|^2_{Q(i)} + \sum_{i=0}^{N_u} \left\| \Delta\hat{u}(k+i|k) \right\|^2_{R(i)} \tag{7}$$

Where $\hat{y}(k+i|k)$ are the predictions, at time k, of the output y, $r(k+i|k)$ is the reference trajectory vector, $\Delta\hat{u}(k+i|k)$ are the changes of the future input vector.

The tuning parameters of the cost function are: the prediction horizon N=10 and the control horizon N_u=4. Constant Q and R weights were chosen:

$$Q = \begin{bmatrix} 10^{-4} & 0 & 0 \\ 0 & 1000 & 0 \\ 0 & 0 & 0.01 \end{bmatrix}, \quad R = \begin{bmatrix} 10^{-15} & 0 \\ 0 & 10^{-15} \end{bmatrix} \tag{8}$$

The values of the weighting factors were chosen taking into account their inpact on the state variable which they are referring to. In this sense, the SOC in highly weighted, since one of the main tasks is to keep its value as close as possible to 0.7, the other states are more lighter. The control inputs are not so severly weighted in this case.

Simulations were performed, the presented one consists in applying the NEDC drive cycle (Figure 6) as reference, transposed into its equivalent of drive power need for r_1. Also, for the SOC the constant reference of $r_2=0.7$ was prescribed, the third reference was $r_3=0$ (for fuel rate).

Simulation results are presented in Figure 7 (P_d reference tracking), Figure 8 (SOC and total fuel) and Figure 9 (control signals ICE power and battery nominal power).

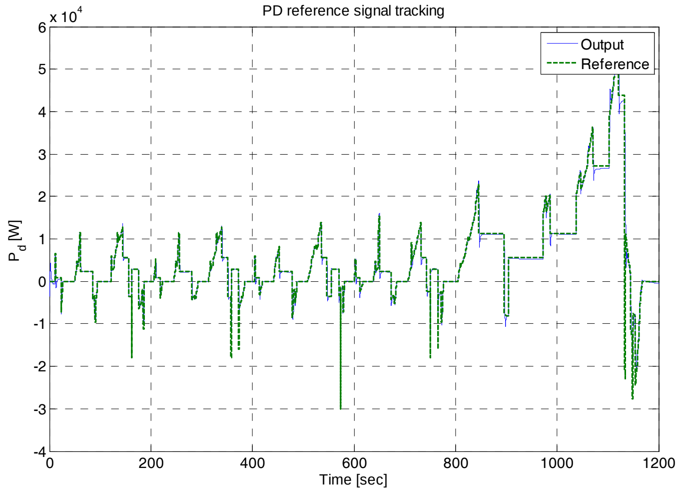

Figure 7

P_d reference tracking

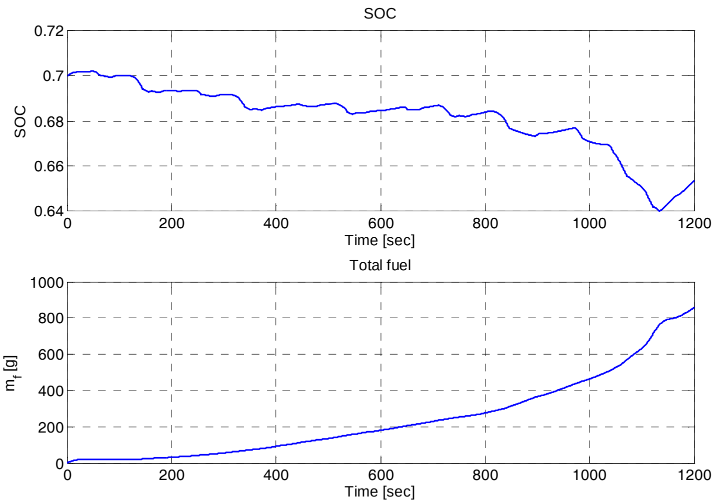

Figure 8

SOC and total fuel consumption

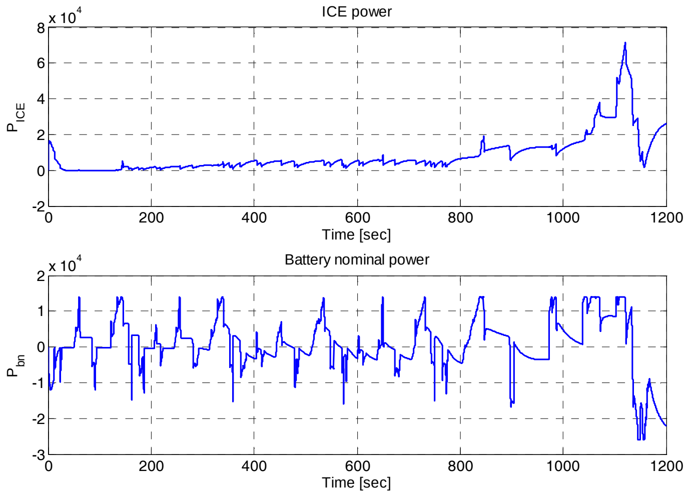

Figure 9
ICE power and nominal battery power

It can be seen that the P_d drive power reference tracking is ensured by the predictive controller. The fuel consumption is between the global optimum value and the value calculated without controller, as expected.

For the SOC it can be remarked that a certain degree of constraint violation in the SOC level. This is due to the fact that the optimization was performed only for a limited horizon. In this particular case, a rise in the SOC can be achieved during parking, when the PV panel can function and load the battery.

The battery nominal power is varying between the prescribed bounds (-26000 W and 14000 W). In the time interval of [1000 , 1100] the drive cycle should necessitate more power, but due to the hard constraint on the MPC controller, only 14000 W are used.

Conclusions

The paper presents a modelling for a series Hybrid Solar Vehicle (HSV) based on fuel optimization aspects, followed by Model Predictive Control (MPC) for fuel consumption minimization. The model of the HSV is based on modelling its components that are necessary for the control, from the point of view of power balance. Then MPC is applied using the MPC Toolbox of Matlab. Simulations were performed so a pre-defined standars drive cycle, namely the New European Drive Cycle (NEDC), in this case both reference tracking and fuel consumption minimization give promising results. MPC strategies can be applied also for real HSVs as well. The simulations were performed using the Matlab-Simulink environment.

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