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A model-based supervisory energy management strategy for a 12 V vehicle electrical system

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ABSTRACT

This paper describes the development, implementation, and experimental verification of a supervisory energy management strategy for the vehicle electrical system of a passenger car. The control strategy commands the alternator duty cycle such that vehicle fuel economy is optimized whilst the instantaneous load current demand is met and constraints on the system voltage and battery state of charge are satisfied.

The work is based on a control-oriented model of the vehicle electrical system, experimentally validated against vehicle data. Then, a constrained global optimal control problem is formulated for the energy management of the electrical system, and analytically solved using the Pontryagin's Minimum Principle (PMP). The optimal solution obtained is evaluated for a range of different driving cycles and electrical load current profiles, leading to the formulation of an adaptive supervisory control strategy that is implemented and tested in vehicle.

1. Introduction

In an effort to comply to the stringent government mandates on fuel economy and CO_2 emissions without compromising on vehicle performance and customer acceptability, the automotive industry is striving to rapidly develop and implement a range of design, system integration and control solutions for increasing the energy conversion efficiency of engines and powertrain systems.

The vehicle ancillary loads represent a considerable source of energy dissipation. Reducing these losses provides the opportunity to achieve FE benefits at a relatively low cost. Managing the energy consumption of the vehicle loads, such as the air conditioning system, fans and blowers, or the alternator, has in fact been explored recently as a direction towards vehicle fuel economy improvement, see for instance Silva, Ross, and Farias (2009), Chiara and Canova (2013), Lyu, Doo, and Ku (2007).

In particular, the vehicle electrical system presents interesting opportunities for energy optimization. In its simplest form, the system consists of a belt driven alternator integrated with a voltage regulator, and a lead–acid battery as the energy storage device. During vehicle operation, the electrical system supplies the electrical power required for the actuation of several vehicle subsystems or components, such as lighting and infotainment, cabin blower, radiator fan, defroster and heated seats.

The alternator is typically controlled to fulfill the demand of the vehicle electrical loads, as well as to recharge the battery whenever needed. Therefore, the battery is minimally utilized, and limited to starting the engine and to supplement the alternator when high electric load demands occur. However, the energy storage capacity provided by the battery could be exploited for achieving potential fuel savings.

Conceptually, the topology of a vehicle electrical system resembles the architecture of a parallel mild hybrid-electric vehicle, with the exception that the alternator can only absorb power. It is therefore evident that supervisory energy management strategies, such as those developed for the control of hybrid vehicles, could be applied to the vehicle electrical system to improve fuel economy (Shen, Masrur, Garg, & Monroe, 2003). To this extent, an energy-based approach to the control of the vehicle electrical system was proposed initially by Koot et al. (2005) and Kessels et al. (2007), where optimization techniques have been applied to design an optimal offline strategy as well as a causal (implementable) strategy. Experimental results obtained on a chassis dynamometer pointed to fuel economy improvement of up to 2.6% on the New European Driving Cycle (NEDC).

More recently, Couch, Fiorentini, and Canova (2013) proposed a model-based approach for the energy optimization of a vehicle electrical system, based upon the Equivalent Consumption Minimization Strategy (ECMS), an approach initially developed for the supervisory energy management of charge-sustaining HEVs

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(Paganelli, Ercole, Brahma, Guezennec, & Rizzoni, 2000a, 2000b; Pisu & Rizzoni, 2007; Sciarretta, Back, & Guzzella, 2004). The simulation results presented show a reduction of engine fuel consumption of up to 1.5% on the FTP driving cycle.

This paper describes the development and vehicle implementation of a supervisory energy management strategy for a vehicle electrical system, which controls the alternator duty cycle to minimize the energy consumption while meeting the load current demand from the auxiliary loads. The work is based on a control-oriented model of the 12 V electrical system of a passenger car, which captures the dynamics of the bus voltage, battery state of charge, and the energy consumed by the alternator.

The supervisory control design is approached by formulating a constrained global optimal control problem, for which an analytical solution is obtained through the Pontryagin's Minimum Principle (PMP) . While the procedure adopted leverages an established procedure for energy management of hybrid and plug-in hybrid vehicles, see for instance Stockar, Marano, Rizzoni, and and Guzzella (2010), Serrao, Onori, and Rizzoni (2011), Stockar, Marano, Canova, Rizzoni, and Guzzella (2011), and Kim, Cha, and Peng (2011), the application to ancillary loads reduction is novel and presents significant differences in the formulation of input constraints.

Since the PMP theorem provides an optimal solution only with full information on the driving cycle and load current profile, a thorough analysis is conducted to formulate an Adaptive PMP control strategy that can be implemented in real time on a rapid prototyping ECU. Results from vehicle testing are benchmarked against the production control strategy.

2. Model of the vehicle electrical system

The electrical system of a conventional (non-hybrid) passenger car typically consists of three main components, namely the battery, the alternator and the electrical loads. As shown in Fig. 1, regardless of the specific control strategy implemented, the Vehicle Electrical System (VES) control commands the alternator duty cycle (DC), which in turn generates a field current (I_f) within the alternator. The field current determines the amount of current produced by the alternator (I_{alt}), in relation to the engine speed (N_{eng}) and the battery voltage (V_{bat}). The battery current (I_{bat}) is the difference between the load current (I_{loads}) and the alternator current. Depending on this current balance, the battery either accepts or supplies current, hence setting the voltage of the system.

Fig. 1 presents a block diagram showing the cause and effect relationships of the three interconnected models.

The work presented in this paper was developed for the electrical system of a passenger car. To this extent, the electrical system of a test vehicle was fully instrumented to allow for real-time measurement and acquisition of the most important

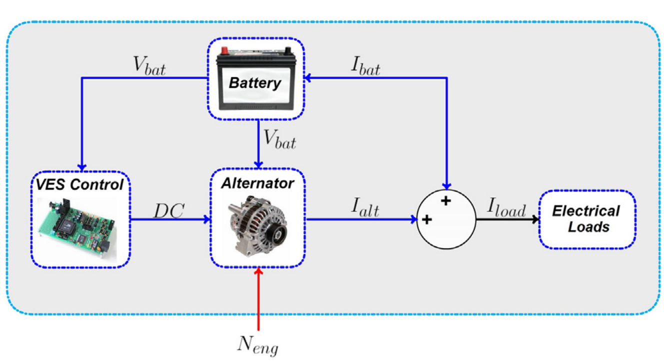

Fig. 1. Schematic of the vehicle electrical system.

operating variables. The models of the alternator and the battery, together with the baseline VES control strategy (Electrical Voltage Regulation, or EVR), will be described in further detail in the following sections.

2.1. Alternator model

A heuristic, map-based model of the alternator was developed for integration into the comprehensive VES model. The alternator model consists of three interconnected look-up tables, which characterize the alternator torque, output current, and field current. The general form of the look-up tables is described in implicit form as

$$T_{alt} = T_{alt}(N_{eng}, I_f, V_{bat}) \tag{1}$$

$$I_{alt} = I_{alt}(N_{eng}, DC, V_{bat}) \tag{2}$$

$$I_f = I_f(N_{eng}, DC, V_{bat}) \tag{3}$$

illustrates each output variable for a fixed battery voltage.

The alternator model was identified from experimental data collected on the test vehicle on a chassis dynamometer. The vehicle electrical system was instrumented with shunts to monitor the alternator current, while a programmable load was used to set the battery voltage and the duty cycle was imposed by bypassing the ECU. Fig. 2 illustrates the alternator maps obtained experimentally for fixed bus voltage conditions.

2.2. Battery model

The battery is modeled by considering a simple equivalent circuit, as commonly done in applications related to vehicle system energy management, see for instance Kessels et al. (2007), Serrao et al. (2011), and Couch et al. (2013). In this study, a standard 12 V lead–acid battery is considered, and its specifications are summarized in Table 1.

Assuming a first-order equivalent circuit model as a reasonable approximation of the battery low-frequency behavior, the terminal voltage is expressed as

$$V_{bat} = E_0 - RI_{bat} - V_{C0} \tag{4}$$

$$\frac{dV_{C0}}{dt} = -\frac{V_{C0}}{R_0 C_0} + \frac{I_{bat}}{C_0} \tag{5}$$

where V_{C0} is the potential difference across the capacitance C_0, E_0 is the open-circuit voltage, R the internal resistance and R_0 the over-voltage resistance.

The parameters in Eq. (4) are functions of several operating variables:

$$E_0 = f(T_{bat}, SOC) \tag{6}$$

$$R, R_0, C_0 = f(T_{bat}, SOC, I_{bat}) \tag{7}$$

where T_{bat} is the battery temperature; and the state of charge (SOC) of the battery is simply computed through current integration:

$$SOC(t) = SOC_0 - \frac{1}{Ah_{nom}} \int_{t_0}^{t} I_{bat}\, dt \tag{8}$$

where SOC_0 is the SOC at time t_0 and Ah_{nom} is the nominal battery capacity.

The parameters shown in Eqs. (6) and (7) were identified from experimental data. The experimental setup utilized consists of a programmable load and supply system, alongside an environmental chamber to control the temperature throughout the test. Tests were performed at several temperatures, from −10 °C to 50 °C at equal intervals of 5 °C.