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Calibration methodology for energy management system of a plug-in hybrid electric vehicle

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ABSTRACT

This paper presents a new analytical calibration method for energy management strategy designed for a plug-in hybrid electric vehicle. This method improves the actual calibration efficiency to reach a compromise among the conflicting calibration requirements (e.g. emissions and economy). A comprehensive evaluating indicator covering emissions and economic performance is constructed by using a radar chart method. A radial basis functions (RBFs) neural network model is proposed to establish a precise model among control parameters and the comprehensive evaluation indicator. The optimal Latin hypercube design is introduced to obtain the experimental data to train the RBFs neural network model. And multi-island genetic algorithm is used to solve the optimization model. Finally, an offline calibration example is conducted. Results validate the effectiveness of the proposed calibration approach in improving vehicle performance and calibration efficiency.

1. Introduction

The increasing new forms of energy demands and global environmental concerns are the main challenges in automotive industry [1,2]. Plug-in hybrid electric vehicles (PHEVs) integrate the advantages of both electric and conventional vehicles. These advantages include emission reduction, low fuel consumption and long endurance mileage [3,4]. Recent trends suggest that PHEVs are lead into the commercial domain by advanced technologies in electronics and energy storage [5–7].

The Energy Management System (EMS) technology has significantly improved the driving and economic performance of vehicles to meet the increasingly becoming stringent emission standards [8–10]. However, this improvement leads to an increased complexity in powertrain, and an effective procedure must be applied to develop EMS [11]. V-cycle development process is an efficient approach to develop EMS. This process involves several stages, including functional design, rapid control prototyping, production code generation, hardware-in-loop simulation, and calibration [12]. Calibration is a process where the optimal values of control parameters are chosen to achieve minimum fuel and electricity consumption, and exhaust emissions are depressed under satisfying vehicle dynamic performance. Calibration is a trial and error process in the classic sense, and it has characteristics of low efficiency and high costs. Although numerous mature calibration tools are commercially available and widely used by automobile manufacturers, nearly all calibration work is based on the try-error way. The calibration rules do not have theoretical foundation. Finding means to improve the calibration process is thus urgently needed.

In fact, some parameters in the EMS, such as thresholds and curves, can be obtained through theoretical analysis and optimization. Numerous studies have investigated the design and optimization EMS: in [13], a rule-based energy management for parallel hybrid electric vehicles (HEVs) is presented, and this EMS is based on principles describing optimal control behavior. In [14], optimization of key component sizes and control strategy for PHEVs by using bees algorithm is presented. Few studies have investigated component calibration. A method for automated engine calibration by optimizing engine management settings and power-split control of an HEV is proposed in [11]. In [15], motor automatic calibration of resolver offset in an HEV is studied. Surprisingly, few theoretical studies on EMS calibration method for HEV have been conducted to improve the calibration efficiency.

This paper tries to explore a method to help the calibration become a time-saving and low-cost process. It is organized as follows. Section 2 introduces the proposed calibration methodology which includes a comprehensive evaluating method for economy and emissions characteristics, a Radial Basis Function (RBFs) neural

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Nomenclature

EM	electric machine (–)
ICE	gasoline-fueled internal combustion engine (–)
BATT	battery pack (–)
ISG	integrated starter generator (–)
CS	Charge Sustaining (–)
CD	Charge Depleting (–)
fe	fuel consumption equivalence factor of electricity consumption (–)
fc_d	direct fuel consumption (L/100 km)
ec	direct electricity consumption (kW h/100 km)
fc_e	equivalent fuel consumption (L/100 km)
x_i^j	value of the ith response in the jth sample set (–)
y_i^j	relative value of the ith response in the jth sample set (–)
$\max(x_i)$	maximum value of the ith response (–)
$\min(x_i)$	minimum value of the ith response (–)
S_j	total sector area of the jth sample set (–)
L_j	total arc length of the jth sample set (–)
f_{1j}	relative area value of the jth sample set, which indicates the overall benefit (–)
f_{2j}	relative arc length value of the jth sample set, which indicates the balance of indicators (–)
f_j	comprehensive evaluation value of the jth sample set (–)
$\boldsymbol{p}$	input vector of RBF neural network model (–)
$f(\boldsymbol{p})$	outputs of RBF neural network model (–)
$h_j(\boldsymbol{p})$	output of jth neuron in the hidden layer of RBF neural network model (–)
MSE	Mean Square Error of RBF neural network model (–)
T_{req}	demand torque on the wheels (Nm)
T_m	output torque of EM (Nm)
T_e	output torque of ICE (Nm)
b_e	brake specific fuel consumption of ICE (g/kW h)
P_{m_e}	electric power of EM (kw)
SOC	state of charge of the BATT (–)
$v_{cdev\_\lim}$	vehicle velocity threshold for entering EV mode in CD mode (km/h)
$p_{cdev\_\lim}$	demanded power threshold for entering EV mode in CD mode (kw)
$p_{cdhy\_\lim}$	demanded power threshold for entering Hybrid mode in CD mode (kw)
v_{cden}	the lower limit vehicle velocity threshold for entering Engine mode in CD mode (km/h)
SOC_{CS}	the SOC threshold for entering CS mode from CD mode (–)
$SOC_{ass\_\lim}$	the SOC lower limit of available motor power in CS mode (–)
$SOC_{cha\_\lim}$	the SOC upper limit of available battery charge in CS mode (–)
$v_{csev\_\lim}$	vehicle velocity threshold for entering EV mode in CS mode (km/h)
v_{csen}	vehicle velocity threshold for entering Engine mode in CS mode (km/h)
η	system efficiency (–)

network and the optimal Latin hypercube design approach. Section 3 is an application example. In this section the modeling and operational modes of a plug-in hybrid electric vehicle is introduced, based on which the calibrating parameters are extracted. Section 4 implements the offline calibration. Section 5 presents the conclusions.

2. Calibration methodology

2.1. Method of radar chart comprehensive evaluation

The most attractive features of the HEV are its high fuel and electricity economy and low emissions. However, they are always conflicting with each other (i.e. it is always a trade-off within them during the calibration) [16].

2.1.1. Economy

According to the Revisions and Additions to Motor Vehicle Fuel Economy Label from Environmental Protection Agency (EPA) and National Highway Traffic Safety Administration (NHTSA) (2010), a gallon of gasoline is equivalent to 33.7 kW h of energy, and any value expressed in kilowatt-hours can be converted into an energy-equivalent value of gallons of gasoline. It is a simple and effective method to measure the fuel economy performance of hybrid vehicles. The basic idea of this method is that electricity consumption is converted into fuel consumption by using an equivalence factor [17–19]. The equivalence factor fe can be expressed as follows

$$fe = 3.785/33.7 = 0.1123 \tag{1}$$

And the total equivalent fuel consumption fc (L/100 km) can be calculated as

$$\begin{cases} fc = fc\_d + fc\_e \\ fc\_e = fe * ec \end{cases} \tag{2}$$

where fc_d is the direct fuel consumption, L/100 km; fc_e is the equivalent fuel consumption, L/100 km; ec is the direct electricity consumption, kW h/100 km.

2.1.2. Emissions

Normally the main exhaust emissions of engine include Carbon Monoxide (CO), Hydrocarbons (HC) and Nitrous Oxides (NOx) [8].

2.1.3. Comprehensive performance

The above evaluation indicators show that calibration remains a multi-objective problem. Thus, a reasonable comprehensive evaluation indicator is urgently needed to simplify the optimization model. The improved radar chart evaluation method is proven to be an ideal way for calibration [20]. It is shown in Fig. 1.

The steps to transform multi-objective into a single objective problem using improved radar chart evaluating method are as follows:

(1) Normalization

Normalization is required to obtain the dimensionless value and unify the magnitude of the responses. It is shown in following equation

$$y_i^j = \begin{cases} \frac{x_i^j - \min(x_i)}{\max(x_i) - \min(x_i)}, & x_i \text{ is a positive indicator} \\ \frac{\max(x_i) - x_i^j}{\max(x_i) - \min(x_i)}, & x_i \text{ is a negative indicator} \end{cases} \tag{3}$$

where x_i^j is the value of the ith response in the jth sample set; y_i^j is the relative value; and $\max(x_i)$ and $\min(x_i)$ are the maximum and minimum values of the ith response, respectively.