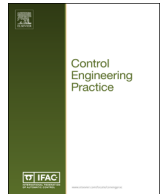




Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

Predictive planning of optimal velocity and state of charge trajectories for hybrid electric vehicles ☆

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ARTICLE INFO

Article history:

Received 15 May 2015

Received in revised form

1 July 2016

Accepted 2 July 2016

Keywords:

Hybrid vehicles

Dynamic programming

Sequential quadratic programming

Energy management

Potential analysis

Velocity optimization

Predictive control

Economic driving

ABSTRACT

The combination of electric motors and internal combustion engines in hybrid electric vehicles (HEV) can considerably improve the fuel efficiency compared to conventional vehicles. In order to use its full potential, a predictive intelligent control system using information about impending driving situations has to be developed, to determine the optimal gear shifting strategy and the torque split between the combustion engine and the electric motor. To further increase fuel efficiency, the vehicle velocity can be used as an additional degree of freedom and the development of a predictive algorithm calculating good choices for all degrees of freedom over time is necessary.

In this paper, an optimization-based algorithm for combined energy management and economic driving over a limited horizon is proposed. The results are compared with results from an offline calculation, which determine the overall fuel savings potential through the use of a discrete dynamic programming algorithm.

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1. Introduction

Over the last few decades, reducing fuel consumption for vehicles has become a more and more important field of research. Reasons for this development are increasing environmental awareness accompanied by stricter regulations and rising fuel costs. One technology emerging from this research is the hybrid electric vehicle (HEV), combining electric batteries and motors with the internal combustion engine (ICE) in one powertrain. There exists a wide variety of HEVs with different structures, e.g. parallel hybrid vehicles or series hybrid vehicles, and different degrees of hybridization, e.g. micro-hybrids, which are characterized by small batteries and electric motors (EM) whose main purpose is to implement an automatic engine start/stop function. At the other end of the scale plug-in hybrid vehicles with large batteries and motors facilitate long all-electric range and the possibility to charge the battery from the power grid (Guzzella and Sciarretta, 2013).

To achieve the best fuel efficiency, an optimal energy management system (EMS) is necessary to coordinate both power

sources. Since an optimal control strategy depends on the driving cycle, this poses two main challenges: firstly, the parameters of the driving cycle are not necessarily known and, secondly, finding a global, optimal solution for the resulting nonlinear optimal control problem is numerically challenging. Therefore, this is a demanding field of research. For previous work in this field, see Sciarretta and Guzzella (2007), Pisu and Rizzoni (2007), Johannesson and Egardt (2008), Bender, Kaszynski, and Sawodny (2013) and Panday and Bansal (2014).

Another approach is economic driving, i.e., using the velocity as an additional degree of freedom to reduce fuel consumption. In recent years, work for different types of vehicles, such as conventional cars and trucks (e.g. Hellström, Åslund, and Nielsen, 2010; Hooker, 1988; Kamal, Mukai, Murata, and Kawabe, 2013; Llamas, Eriksson, and Sundström, 2013; Terwen, Back, and Krebs, 2004), fuel-cell cars (Sciarretta, Guzzella, and van Baalen, 2004) and electric cars (Petit and Sciarretta, 2011) has been published.

The next step to increasing fuel efficiency is to combine both economic driving and predictive EMS. In van Keulen et al. (2009, 2010), the velocity profiles for a hybrid electric truck are optimized. Therefore, the driving cycle is partitioned into segments of constant power request and each of these segments is divided into four phases: max. power acceleration, constant velocity, coasting and max. power deceleration. The parameters of these phases are then optimized to maximize power recovery and minimize fuel consumption. In Kim, Manzie, and Sharma (2009), a model

☆This work is part of the "Promotionskolleg Hybrid", a cooperation between science and industry, funded by the Ministry of Science, Research and the Arts of the State of Baden-Württemberg, Germany and the Daimler AG.

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Nomenclature

Δd	discretization of the short horizon optimization	m	vehicle mass
ΔJ_{SHO}	stage transition costs for the short horizon optimization	m_{eff}	effective vehicle mass, including all inertias
Δp	phase length	N_{LHBP}	number of use cases in the long horizon battery planning
Δp_{max}	maximum phase length	N_{p}	number of phases in the short horizon optimization
Δp_{min}	minimum phase length	$N_{\text{S},j}$	number of stages in phase j
Δv_{ex}	maximum allowed velocity exceedance	N_{S}	number of stages in short horizon optimization
Δv_{off}	offset between reference and maximum velocity	\mathbf{p}	parameter vector
Δv_{safety}	security offset to the maximum possible curve velocity	P_{aux}	electric power consumed by the auxiliaries
$\Delta x_{\text{SoC,max}}$	maximum SoC change for a use case in long horizon battery planning	P_{bat}	battery power
$\Delta x_{\text{SoC,min}}$	minimum SoC change for a use case in long horizon battery planning	P_{brk}	braking power
\dot{m}_{f}	fuel consumption per second of the internal combustion engine	P_{el}	power demand of power electric loads
$\dot{m}_{\text{f,save}}$	fuel saved per second for a certain engine and motor operation point	$P_{\text{EM,el}}$	electric power of the electric motor
γ	road grade	$P_{\text{EM,max}}$	maximum EM power
κ	road curvature	$P_{\text{EM,min}}$	minimum EM power
λ	equivalence factor of the ECMS	$P_{\text{ICE,max}}$	maximum ICE power
\mathcal{U}	use case in the long horizon battery planning	$P_{\text{ICE,min}}$	minimum ICE power
μ	friction coefficient between road and wheels	P_{lim}	power limits for long horizon battery planning
μ_{R}	rolling coefficient	P_{req}	predicted power demand for long horizon battery planning
ω_{EM}	speed of the electric motor	Q_{bat}	battery capacity
ω_{ICE}	speed of the internal combustion engine	R_{EM}	torque derivatives of the electric motor
ω_{prop}	speed of the propshaft	R_{ICE}	torque derivatives of the internal combustion engine
ω_{whl}	speed of the wheel	R_{i}	battery resistance
ζ_{i}	weighting factors in the cost functions of the short horizon optimization	r_{whl}	wheel radius
ξ_{i}	weighting factors in the cost functions of the long horizon battery planning	s	position
a	vehicle acceleration	$s_{\text{p},j}$	starting position of phase j
b_{clt}	state of the clutch (open or closed)	s_{SBS}	battery power substitution benefit
b_{ICE}	engine on/off state	t	time
C_{Air}	air drag coefficient	T_{brk}	service brake torque
F_{drag}	air drag resistance force	T_{des}	desired torque from driver model
F_{grade}	grade resistance force	T_{drag}	air drag resistance torque
F_{roll}	rolling resistance force	$T_{\text{EM,high}}$	highest possible EM torque for SoC change limit calculation in LHBP
\mathbf{f}_{SHO}	position derivative of the states \mathbf{x}_{SHO}	$T_{\text{EM,low}}$	lowest possible EM torque for SoC change limit calculation in LHBP
\mathbf{f}_{s}	vector of time derivatives for the vehicle states \mathbf{x}_{s}	T_{EM}	electric motor torque
\mathbf{f}_{t}	vector of time derivatives for the vehicle states \mathbf{x}_{t}	$T_{\text{G,in}}$	torque transmitted from the motor side to the gearbox
g	gravitational acceleration	$T_{\text{G,out}}$	torque transmitted from the gear box to the propshaft
h	physical constraints of the short horizon optimization problem	T_{grade}	grade resistance torque
$I_{\text{bat,max}}$	maximum battery current	T_{ICE}	internal combustion engine torque
$I_{\text{bat,min}}$	minimum battery current	$T_{\text{loss,clt}}$	torque loss in the clutch
I_{bat}	battery current	$T_{\text{loss,G}}$	torque loss in the gear box
i_{G}	gear transmission ratio	$T_{\text{loss,RA}}$	torque loss in the rear axle
i_{RA}	rear axle transmission ratio	T_{resist}	driving resistance torque
J_{eff}	effective vehicle inertia, inertias of all rotating parts	T_{roll}	rolling resistance torque
J_{EM}	inertia of the electric motor	T_{whl}	accumulated torque at the wheels
J_{G}	inertia of the gear box	\mathbf{u}	vector of model inputs
J_{ICE}	inertia of the internal combustion engine	U_0	open circuit voltage of the battery
J_{RA}	inertia of the rear axle	U_{bat}	battery voltage
J_{whl}	inertia of the wheels	u_{clt}	clutch open/close command
$J_{\text{LHBP,fuel}}$	cost during use cases in LHBP except recuperation	u_{G}	desired gear
$J_{\text{LHBP,f}}$	final costs for the long horizon battery planning	u_{ICE}	engine on/off command
$J_{\text{LHBP,recup}}$	cost during recuperation use cases in LHBP	\mathbf{u}_{SHO}	input vector for short horizon optimization
$J_{\text{LHBP,k}}$	cost functions for the long horizon battery planning	v	vehicle velocity
$J_{\text{SHO,f}}$	final costs for the short horizon optimization	v_{corr}	merged velocity limits
$k_{\text{p},j}$	phase transition stage j	$v_{\text{curve,max}}$	curve velocity limit
		v_{des}	desired velocity
		v_{law}	speed limit
		$v_{\text{lim,min}}$	lowest curve velocity limit
		v_{max}	maximum velocity
		v_{min}	minimum velocity

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