Applied Energy 189 (2017) 640–653

Contents lists available at ScienceDirect

Applied Energy

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

Energy management of a dual-mode power-split hybrid electric vehicle based on velocity prediction and nonlinear model predictive control

Changle Xiang, Feng Ding, Weida Wang *, Wei He

School of Mechanical Engineering, Beijing Institute of Technology, 5 South Zhongguancun Street, Beijing 100081, China

HIGHLIGHTS

- A new cascaded real time energy management strategy is proposed.
- A velocity predictor is proposed based on radial basis function neural network.
- Forward dynamic programming is employed in nonlinear model predictive control to improve efficiency.
- Engine and motors are coordinated with fast sampling time.
- Results of simulation and experiments showed that fuel economy was improved compared with other methods.

ARTICLE INFO

Article history:
Received 1 July 2016
Received in revised form 25 November 2016
Accepted 11 December 2016

Keywords:
Hybrid electric vehicle
Dual-mode
Energy management
Velocity prediction
Neural network
Nonlinear model predictive control

ABSTRACT

In this paper, a real time energy management strategy (EMS) is proposed for a dual-mode power-split hybrid electric vehicle in order to improve the fuel economy and maintain proper battery's state of charge (SOC) while satisfying all the constraints and the driving demands. The EMS employs a cascaded control concept which includes a velocity predictor, a master controller and a slave controller. The short term vehicle velocity predictor is developed to improve the controller performance based on radial basis function neural network. The master controller based on nonlinear model predictive control is developed with slow sampling time to sustain SOC and to reduce fuel consumption. Forward dynamic programming is employed here to solve the optimal problem. And the PID-based slave controller is developed with fast sampling time to coordinate the engine and the two motors. Simulation and testbed experiments are performed to verify it and the results demonstrate the effectiveness of the proposed approach compared with other methods.

1. Introduction

Over the years, due to the shortage of fuel resources and the concerns of environmental impacts, the demand of electric power has become more and more important. Meanwhile, automotive customers' demands in terms of performance, safety and comfort for their new cars can be satisfied better in electric vehicles. Hence, many different types of electric vehicles are developed by enthusiastic automotive companies. But as the market shows, hybrid electric vehicles (HEVs) seem to be the most short-term promising solution [1]. An HEV adds an electric power path to the conventional powertrain to improve its performance and fuel economy. With the help of electric power, an HEV's engine can be better sized and work more efficiently, since the power needed can be compensated by electric motor generators (MGs). Also, when the vehicle is decelerating, the MGs can capture part of the vehicle kinetic energy and recharge the battery [2].

Based on the hybrid configuration, there are different types of HEVs, such as series, parallel and power-split, which can be used for different purposes. The Toyota Hybrid System (THS) is the most successful single-mode power-spit configuration used in small power vehicles. It enables the engine to operate at its efficient regions, independent of the vehicle speed, which also means an electronically controlled continuously variable transmission (E-CVT). Dual-mode power-split configuration is an extended version, and it is often used in heavy duty vehicles, like trucks and SUVs. Compared with single-mode HEVs, dual-mode power-split HEVs can provide larger power with two MGs of the same size. Because the peak power of the two MGs can partly be decoupled from the engine power. Also, dual-mode power-split HEVs can achieve higher efficiency through the overall vehicle velocity range [3–5].

In order to fully exploit the capabilities of the HEV, an appropriate energy management strategy (EMS) is necessary. The primary

* Corresponding author.
E-mail address: wangwd0430@163.com (W. Wang).

http://dx.doi.org/10.1016/j.apenergy.2016.12.056
0306-2619/

Nomenclature

A_f	frontal area of the vehicle
C_{batt}	battery capacity
C_d	drag coefficient
c_i	neural net center
f_e	fuel consumption look-up table
g	gravity acceleration
h	number of NN hidden layer nodes
i_f	gear ratio of final drive
J_e	rotational inertia of engine
J_{MG1}	rotational inertia of MG1
J_{MG2}	rotational inertia of MG2
k_1	PG1 inherent parameter
k_2	PG2 inherent parameter
k_3	PG3 inherent parameter
m	vehicle mass
m_f	fuel consumption
N_p	prediction horizon
P_{batt}	battery power
P_{load}	actual load disturbance
P_{MG1}	MG1 power
P_{MG2}	MG2 power
P_{MG1}^{loss}	MG1 power losses
P_{MG2}^{loss}	MG2 power losses
p	number of NN outputs
R_{batt}	battery internal resistance
r_w	radius of wheels
SOC_0	initial SOC value
SOC_r	reference SOC value
T_{brake}	friction brake torque
T_{demand}	future vehicle torque demand
T_{drive}	torque acting on the wheels
T_e	engine torque
T_{e_d}	demand engine torque
T_{MG1}	MG1 torque
T_{MG2}	MG2 torque
T_{out}	output torque
t_0	current time
t_h	prediction horizon
V	vehicle velocity
V_{demand}	future vehicle velocity demand
V_{oc}	battery open circuit voltage
w_h	final penalty weight
w_m	fuel penalty weight
w_s	SOC penalty weight
w_t	torque penalty weight
w_w	speed penalty weight
Z_r	ring gear teeth number
Z_s	sun gear teeth number
α	driver's pedal position
θ	road grade
μ	friction coefficient
ρ	air density
σ	spread width
ω_c	carrier gear speed
ω_e	engine speed
ω_{e_d}	demand engine speed
ω_{MG1}	MG1 speed
ω_{MG1_d}	desired MG1 speed
ω_{MG2}	MG2 speed
ω_{MG2_d}	desired MG2 speed
ω_{out}	output speed
ω_s	sun gear speed
ω_r	ring gear speed
DP	dynamic programming
EMS	energy management strategy
HEV	hybrid electric vehicle
MG	electric motor generators
MPC	model predictive control
NMPC	nonlinear model predictive control
NN	neural network
PG	planetary gear set
RBF	radial basis function
SOC	state of charge
VP	velocity predictor

objectives of EMS are to minimize fuel consumption, to fully take advantage of batteries and to take into account all physical constraints of the system. Current existing strategies are largely based on heuristic rules. Defining a set of thresholds to build a rule-based control strategy like [6–11], or using fuzzy logic for control algorithm development like [12–15], is relatively easy to achieve. These methods mostly stem from engineering intuition, which are sometimes far from the actual optimal solution. An alternative approach is optimization-based control strategy [16–20]. Recently, many researches have been done using optimal control methods like dynamic programming (DP) [21–23] and Pontryagin's Minimum Principle (PMP) [24,25]. These techniques require the full knowledge of entire driving cycle in advance, so they can only be used in off-line simulation. However, since DP results are global optimal, they are always used as benchmarks for the best achievable performance. Methods that are implementable in real time have also been developed. Equivalent consumption minimization strategy (ECMS) [2] defines an equivalent fuel cost for the battery energy, so it can be solved at each sampling time which makes it capable of being applied online. But it is quite sensitive to its tuning parameters and the dynamics of the system are not considered. Ref. [26] proposes a new ECMS which takes into account not only fuel consumption, but also emissions and battery aging. Ref. [27] proposes a total cost minimization strategy (TCMS) as least costly energy management considering the grid energy, the battery life and the fuel consumption. Besides these methods, multiple advanced algorithms such as particle swarm optimization [28], machine learning [29], genetic algorithm [30] and simulated annealing [31] are also employed to develop various strategies.

Model predictive control (MPC) is also proposed in some references to build a controller. This MPC-based controller can offer an optimal solution in real time and is implementable with limited computation and memory resources. Ref. [32] presents an energy management strategy based on linear time-varying MPC without a priori knowledge of the future load demand. Ref. [33] proposes a model predictive controller to extend battery life for a system with the combination of battery and supercapacitor. These methods need to linearize the system so the solution is not always the optimal. Ref. [34] proposes nonlinear model predictive control (NMPC) to further improve fuel economy. In order to fully take advantage of MPC algorithm, some approaches are developed to predict the future demand of vehicles. Ref. [35–38] propose an exponentially varying velocity predictor. This method is simple and provides an intuitive understanding of how velocity prediction affects fuel economy. Ref. [39] proposes path-forecasting for trajectory planning based on GPS data, but such an approach is not feasible everywhere due to some missing map information. Ref. [40] implements a Markov chain to represent driver behavior. And