ORIGINAL ARTICLE

Dual-Objective Energy Management Strategy for HEV

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Abstract: Based on equivalent consumption minimization strategy (ECMS), the approaches by genetic algorithm (GA), learning vector quantization neural networks (LVQ NNs) and fuzzy logic algorithm (FLA) are integrated to adjust/tune the power split ratio between internal combustion engines (ICE) and belt-driven starter generators (BSG). The proposed bi-object equivalent consumption minimization strategy (BOECMS) possesses three key features: being real-time, causal and capable of fulfilling two objects, namely, (i) minimizing fuel consumption, and (ii) ensuring a stable battery state of charge (SOC) within a relatively narrow range. A hybrid electric vehicle (HEV) model and its corresponding power split strategy are developed and verified by using the vehicle simulator ***ADVISOR*** (ad*vanced vehicle simulator*) and ***Simulink*** at the design stage. For practicality, the proposed control strategy, BOECMS, is converted into C code and then written into the embedded micro-processor to conduct the necessary hardware-in-the-loop (HIL) experiments at the verification stage. According to computer simulation results, fuel economy improved by 40.39 % over pure ICE vehicles for the "MANHATTAN" drive cycle. In addition, the SOC can be retained within a relatively narrow range: [0.4, 0.6]. Finally and significantly, the experimental results by HIL converge well with computer simulation results using ***Simulink***, implying BOECMS can potentially be applied to the real-world driving in the future.

Keywords: hybrid electric vehicle, real-time control strategy, equivalent consumption minimization strategy, fuzzy logic

Introduction

A well-designed energy management strategy (EMS) is critical for superior hybrid electric vehicle (HEV) performance in terms of drivability, fuel economy and emissions reduction. Therefore, how to allocate power generation between the internal combustion engine (ICE) and electric motor (EM) is a very important issue. This work is aimed at suboptimal control strategy to overcome disadvantages found in other solutions including the inherent ineffectiveness of heuristic control strategies and the low feasibility of optimal control strategies in practice [1]. Numerous suboptimal control strategies [1-12], e.g., equivalent consumption minimization strategy (ECMS) and adaptive-pontryagin's maximum principle (PMP) have been presented. To enhance adaptivity, He *et al*. [8] use driving cycle recognition (DCR) to tune the parameters embedded in ECMS. However, previous studies of ECMS have largely overlooked stabilizing the battery state of charge (SOC). Considering both fuel consumption and SOC, quickly identifying a correct globally optimal solution is a significant issue for developing highly effective ECMS. To emphasize HEVs, a bi-objective ECMS (BOECMS) to concurrently consider SOC and fuel consumption is proposed by this work. The relevant literature review suggests the minimization method for BOECMS has been overlooked so far [1, 12]. To sum up, a genetic algorithm (GA) [13], a learning vector quantization neural network (LVQNN) [14, 15] and a fuzzy logic algorithm (FLA) [16, 17] are integrated as the BOECMS adjustment algorithm such that the driving pattern can be real-time recognized and the equivalent factors for charge/discharge cycles, gear ratio and output torque of ICE can be obtained to achieve an optimal power split ratio. Finally, the hardware-in-the-loop (HIL) experiments are undertaken to verify the effectiveness of the proposed BOECMS for realistic driving scenarios.

BSG HEV Model

Figure 1 shows the configuration of the belt-driven starter generator (BSG) parallel hybrid powertrain system, and the basic parameters of the vehicle are summarized in Table 1. It is noted that the BSG is primarily applied to assist the internal combustion engine (ICE) to start up the vehicle or power the vehicle together with ICE.

Table 1. Parameters of BSG HEV.

Item	Value
Total Vehicle Mass	1000 kg
Engine Peak Power	29 kW @ 3990 rpm
Engine Peak Torque	81 Nm @ 2434 rpm
BSG Peak Power	12 kW
Battery Capacity	6 Ah

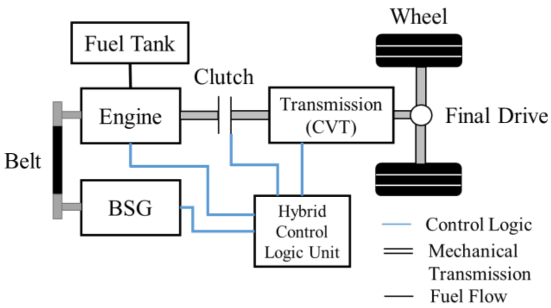


Figure 1. Configuration of BSG HEV.

A backward-facing model features a running-backward time frame, making it suitable for the optimization approach. On the contrary, HIL has to be conducted using a running-forward time frame to examine the effectiveness of BOECMS applied to real-world driving. Thus a BSG HEV model based on a forward-facing approach is also established using ***Simulink/MATLAB*** to simulate real-world driving conditions.

Control Stragegy

A novel real-time minimization strategy for a mild-parallel-hybrid electric vehicle equipped with a BSG is proposed by this paper. The control strategy for BOECMS is designed to minimize fuel consumption while keeping SOC for the battery within a prescribed range.

Control Strategy Structure

Figure 2 shows the configuration of the power split strategy, where Δs, $s_{nominal}$ and s respectively are corrections of equivalent factors, nominal equivalent factors and adjusted equivalent factors. $P_{CS,req}$ and PSR are respectively the required power at the crank shaft and the power split ratio.

To achieve BOECMS, a genetic algorithm (GA), instead of dynamic programming, is used to optimize the operating points of ICE and the gear ratio of a continuously variable transmission (CVT) due to its quick decision and timely subtle mutation. However, a designated driving cycle directly and significantly determines the fuel consumption and emission of toxic substances. Therefore, a driving cycle recognition (DCR) algorithm, based on a learning vector quantization neural network (i.e., ***LVQ NN #1*** in Fig. 2), is developed to adjust the parameters of BOECMS such that they comply with various road and driving conditions. The SOC deviation can be severe while still falling within the prescribed (wide) range: [0.2, 0.8]. Numerous studies have shown that significant deviation of SOC will seriously reduce battery lifetimes. Therefore, BOECMS includes a fuzzy logic algorithm (FLA), shown in Fig. 2, to fine-tuning the equivalent factors for charge/discharge cycles. This allows real-time BOECMS to adaptively learn to comply with realistic driving conditions, improve fuel efficiency and stabilize the battery SOC within a relatively narrow range [0.4, 0.6].

BOECMS

In every time epoch BOECMS generates a real-time power split ratio between ICE and BSG, based on the instantaneous minimization of a preset cost function.

BOECMS sums up all consumed electrical and thermal power through the electrical fashion and thermal path, i.e., the sum of electric power consumption, (called "***equivalent***" fuel consumption) and fuel consumption by

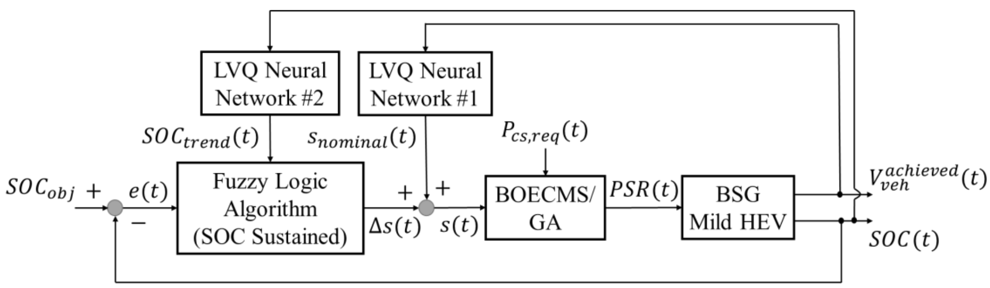


Figure 2. Power Split Strategy.

ICE. Accordingly, the cost function can be defined as follows [1]:

$$J_t = \dot{m}_{ice}(\omega_{ice}(t), T_{ice}(t)) + \dot{m}_{bsg\_equ}(\omega_{bsg}(t), T_{bsg}(t)) \quad (1)$$

where $\dot{m}_{ice}$ and $\dot{m}_{bsg\_equ}$ are respectively the fuel flow rate (g/s) and BSG equivalent fuel flow rate (g/s). Equation must be under 8 constraints defined by below:

$$\begin{cases} P_{cs,req}(t) = P_{ice}(t) + \eta_{belt} P_{bsg}(t) \\ SOC_{\min} < SOC(t) < SOC_{\max} \\ SOC_{ini} = SOC_{final} \\ \omega_{ice\_\min} \le \omega_{ice}(t) \le \omega_{ice\_\max} \\ T_{ice\_\min}(\omega_{ice}(t)) \le T_{ice}(t) \le T_{ice\_\max}(\omega_{ice}(t)) \\ \omega_{bsg\_\min} \le \omega_{bsg}(t) \le \omega_{bsg\_\max} \\ T_{bsg\_\min}(\omega_{bsg}(t)) \le T_{bsg}(t) \le T_{bsg\_\max}(\omega_{bsg}(t)) \\ \rho_{gb\_\min} \le \rho_{gb}(t) \le \rho_{gb\_\max} \end{cases} \quad (2)$$

where ω_{ice}, $\omega_{ice\_\min}$ and $\omega_{ice\_\max}$ are respectively engine speed (rad/s), minimum speed and maximum speed of engine. ω_{bsg}, $\omega_{bsg\_\min}$ and $\omega_{bsg\_\max}$ are respectively BSG speed (rad/s), minimum speed and maximum speed of BSG. T_{ice}, $T_{ice\_\min}$ and $T_{ice\_\max}$ are respectively engine torque (N-m), minimum torque and maximum torque of engine. T_{bsg}, $T_{bsg\_\min}$ and $T_{bsg\_\max}$ are respectively BSG torque (N-m), minimum torque and maximum torque of BSG. P_{ice} and P_{bsg} are respectively output power (W) of engine and BSG. η_{belt} is the belt efficiency between engine and BSG. $SOC_{\min}$, $SOC_{\max}$, SOC_{ini} and SOC_{final} respectively are prescribed minimum, maximum, initial and final SOC. ρ_{gb}, $\rho_{gb\_\min}$ and $\rho_{gb\_\max}$ are respectively the actual gear ratio of CVT, lowest and highest gear ratio of CVT. To be more specific and explicit on the second term of Eq. (1), the equivalent fuel consumption of BSG can be described as below [1]:

$$\begin{aligned} &\dot{m}_{bsg\_equ}(\omega_{bsg}(t), T_{bsg}(t)) \\ &= \gamma \cdot s_{dis} \cdot (1+k_p) \cdot \frac{1}{\eta_{batt}(V_{oc}, R_{dis}, P_{batt}) \cdot \eta_{bsg}(\omega_{bsg}, T_{bsg})} \cdot \frac{P_{bsg}(t)}{H_{LHV}} \\ &\quad + (1-\gamma) \cdot s_{chg} \cdot (1+k_p) \cdot \eta_{batt}(V_{oc}, R_{chg}, P_{batt}) \cdot \eta_{bsg}(\omega_{bsg}, T_{bsg}) \cdot \frac{P_{bsg}(t)}{H_{LHV}} \end{aligned} \quad (3)$$

$$\gamma = \frac{1+\operatorname{sgn}(P_{bsg}(t))}{2} \quad (4)$$

where V_{OC}, R_{dis} and R_{chg} are respectively the open-circuit voltage, internal resistance for discharge cycle, internal resistance for charge cycle of battery. P_{batt} is referred to the batter output power. S_{dis} and S_{chg} are respectively the equivalent factors in terms of discharge and charge operations. k_p is the adjusted coefficient, tuned by ***FLA*** (see Fig. 2). η_{bsg} and η_{batt} are respectively the efficiencies of BSG and battery. "***sgn***" is the Sign function. In Eq. (3), the equivalent factors for discharge/charge cycles, (S_{dis} , S_{chg}), must be appropriately tuned to comply with the real-time driving cycle recognized by ***LVQ NN#1*** in Fig. 2.

Roughly speaking, there are four major dominator parameters to be adaptively tuned. The first pair is: output torque of ICE and gear ratio of CVT: (T_{ice}, ρ_{gb}). In other words, it directly controls the operating points of ICE. The second pair is: equivalent factor for discharge and equivalent factor for charge: (S_{dis}, S_{chg}) . Similarly, this pair directly controls the battery SOC. The role of GA is to determine the key manipulation parameters: output torque of ICE and gear ratio of CVT: (T_{ice}, ρ_{gb}). On the other hand, the SOC is coarsely tuned by ***LVQ NN#1*** at first and later fine-turned by ***FLA/LVQ NN#2***. Nevertheless, these four major dominant parameters are all embedded into the same BOECMS (see Eq. (1) and Ineq. (2)). These two pairs of parameters mutually affect each other.

Genetic Algorithm for BSG (GAFBSG)

Since the cost function J_t in Eq. (1) is a function of the engine torque and gear ratio of CVT, for each time interval, the cost function of BOECMS is to be optimized to tune the quantities of key manipulation parameters (namely, engine torque and gear ratio of CVT). GAFBSG is hereby applied to optimize the objective function of BOECMS. Since the objective function is piecewise-continuous, multiple local optimums can be expected so that GA is employed to find the global fittest. The conceptual process of GA is schematically shown in Fig. 3. Initial parameters or population (first generation) are generated by a random number generator and imported to the cost function of BOECMS to obtain the fitness value of the populations (namely, engine torque and gear ratio of CVT) at the preliminary step. The iteration is repeated until the iteration criterion is achieved. In other words, if the criterion has not been achieved, then the key manipulation parameters are tuned by the operators selection, crossover and mutation, to find the next-generation quantities of required key manipulation parameters.

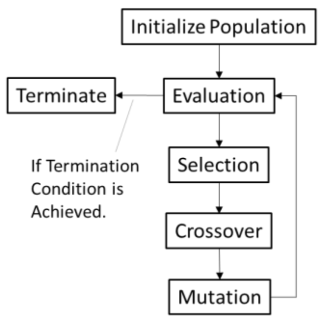
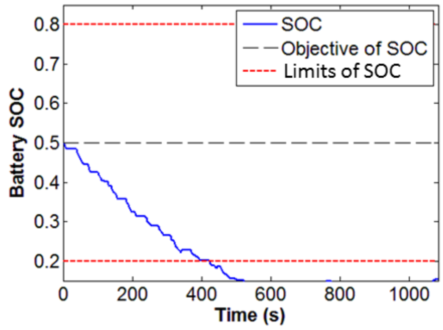


Figure 3. Flow chart of genetic algorithm.

As shown in Fig. 4, to maintain the battery SOC, the equivalent factors (i.e., S_{dis} and S_{chg} in Eq. (3)) must be tuned in real-time to cope with drastic variation in driving conditions. Consequently, more adjustment mechanisms, namely, ***LVQ NN#1*** and ***FLA***/***LVQ NN#2***, are needed to maintain the battery SOC within a relatively narrow range: [0.4, 0.6]. This will be discussed in the following sections.

(a) NurembergR36, $S_{dis} = S_{chg}$ =2.5



(b) MIXED, $S_{dis} = S_{chg}$ =2.5

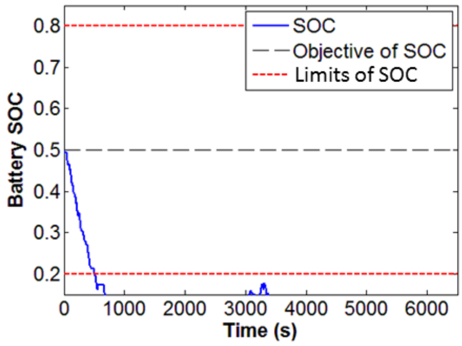


Figure 4. Variation of aattery SOC if discharge/charge equivalent factors are un-tuned: $S_{dis} = S_{chg}$ =2.5 (a) NurembergR36 (b) MIXED.

Driving Pattern Recognition (DPR)

A driving cycle recognition (DCR) algorithm, constituted by a learning vector quantization neural network (named as ***LVQ NN #1*** hereafter), is established to adjust the torque output of ICE and gear ratio of CVT and coarsely maintain the battery SOC. As shown in Fig. 5, the network configuration has a hidden layer constituted by 60 hidden nodes between the input and output layers. The input and output layers respectively have 7 and 6 layers due to the 7 representative features extracted from 6 typical specific driving cycles. In other words, the 7 features are fed to the network and one of the nodes of the output layer will be 1 in quantity if one of the typical specific driving cycles numbered by 1~6 is recognized.

Once the on-going driving pattern is recognized, the equivalent factors (namely, the discharge and charge equivalent factors S_{dis} and S_{chg}) in BOECMS can be adjusted on-line to coarsely maintain battery SOC within an appropriate range. As shown in Fig. 6, using the DCR algorithm described above, the SOC fluctuation is significantly decreased from "severe" down to "intermediate". However, the deviation and drift of SOC is still relatively unacceptable despite being within the prescribed range: [0.2, 0.8]. Hence a fuzzy logic algorithm (FLA) is introduced to reduce the degree of SOC fluctuation.

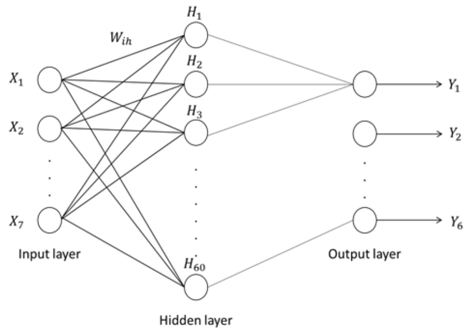
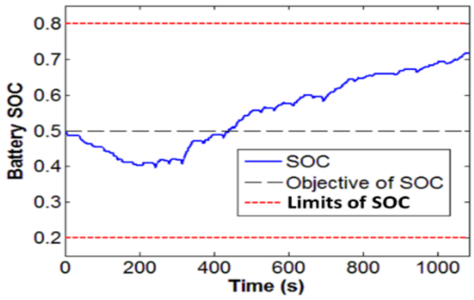


Figure 5. Configuration of the LVQ NN.

(a) NurembergR36, with DPR



(b) MIXED, with DPR

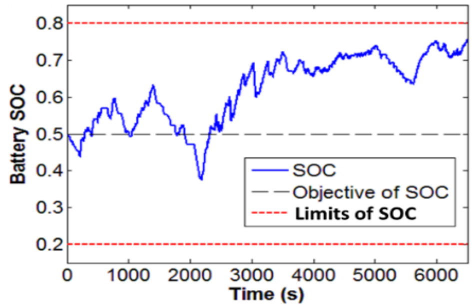


Figure 6. Battery SOC tuned By DCR under various driving cycles: (a)NurembergR36, (b) MIXED.

Fuzzy Logic Algorithm (FLA)

A fuzzy logic algorithm (FLA) is included to reduce the fluctuation of the battery charge status. In addition, another well-trained neural network, hereafter named ***LVQ NN #2***, is established to predict the variation trend of SOC. Consequently, inputs of FLA are: (i) the error between SOC and desired SOC, and (ii) the outputs of ***LVQ NN #2*** as shown in Fig. 7. The quantity of adjustment gain, k_p, is determined by the real-time feedback of SOC error (E_{SOC}) and SOC trend (TR_{SOC}). The rule-base table of FLA is conventionally summarized in Fig. 8.

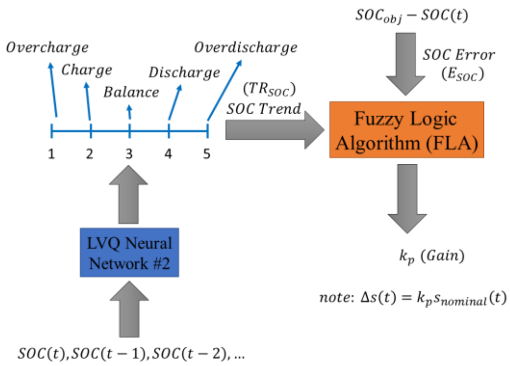


Figure 7. Inputs and output of FLA.

k_p (TR_{SOC} / E_{SOC})	CB	C	BL	D	DB
NB	NB	NB	NB	NM	NM
NM	NB	NB	NM	NM	NM
NS	NB	NM	NM	NM	NM
ZE	ZE	ZE	ZE	ZE	ZE
PS	ZE	ZE	PS	PS	PS
PM	ZE	PS	PS	PS	PM
PB	PS	PM	PM	PB	PB

(TR_{SOC} : Trend of SOC, E_{SOC} : SOC error)

Figure 8. Ruled Based table for FLA.

By incorporating ***FLA*** and ***LVQ NN#2***, SOC is steadily retained within a narrow range. As shown in Fig. 9, the fluctuation of SOC becomes relatively mild and is narrowed to within a fairly limited band: [0.45, 0.55].

Hardware-In-the-Loop (HIL) Experiments

To be more practical, the proposed power split strategy is converted into C code and burned onto a DSP (Texas Instruments TMS320F28335) chip for hardware-in-the-loop (HIL) experiments (Fig. 10).

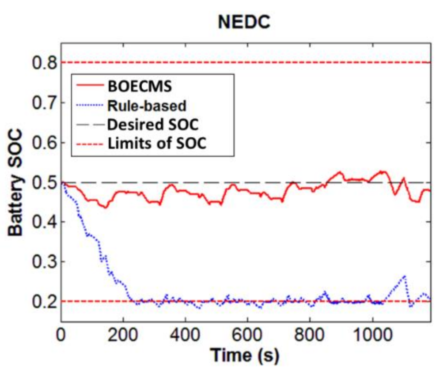


Figure 9. Fluctuation of SOC reduced by fuzzy logic algorithm.

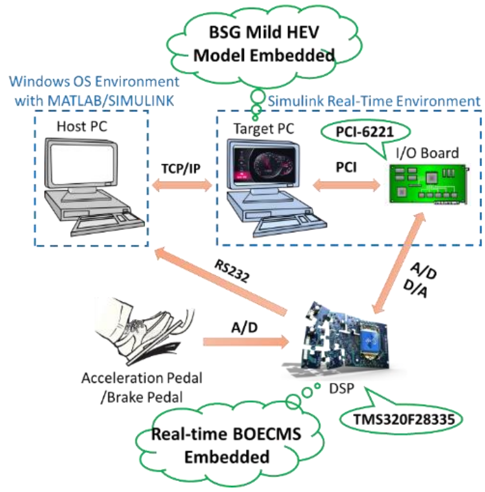


Figure 10. Schematic configuration of hardware-in-the-loop experiments.

The HIL experiments are conducted *via* communications of two PCs: one host and one target. The host PC runs in Windows environment and communicates with the target PC by TCP/IP. The belt-driven starter generator (BSG) hybrid electric vehicle (HEV) model is embedded in the target PC to create a ***virtual*** HEV (VHEV). Finally, the DSP chip with the BOECMS receives acceleration and braking data from the target PC to determine the power split ratio between ICE and BSG, and generate the required control commands.

Results and Discussions

This section presents the results of computer simulations and experiments by hardware-in-the-loop (HIL).

Computer Simulations

Table 2 summarizes computer simulation results for fuel economy on conventional pure ICE vehicle, rule-based-strategy-embedded BSG HEV and BOECMS-embedded BSG HEV.

BOECMS provides a significant improvement to fuel economy for both urban (40.39% improvement for the MANHATTAN driving cycle) and suburban driving cycles, but less improvement for highway driving cycles. This is because urban driving cycles feature a higher proportion of idling time. However, BOECMS fuel consumption is greater than that of the rule-based strategy which tends to discharge battery power down to 0.2 as the driving cycle SC03 starts (Fig. 9), thus significantly reducing fuel consumption for this time interval. Highway (SC03) speeds are generally higher than that in urban-type driving cycles. That is, the corresponding time period for the whole SC03 cycle is too short to manifest the superiority of BOECMS. In this case, SOC for SC03 under the rule-based strategy is slowly decayed, but remains above 0.2 by the end of SC03 cycle. That is, if the time period is prolonged, as shown in Fig. 11, the rule-based strategy will consume more fuel to charge the battery, due to battery SOC decayed down to 0.2. Thus BOECMS consumes less fuel than the rule-based strategy if the SC03 cycle lengthed is increased by 100% or is repeated.

Table 2. Fuel economy simulations.

Driving Cycle	Conventional ICE	Rule-based HEV		BOECMS	
	L/100km	L/100km	Improv.	L/100km	Improv.
MANHATTAN (Urban)	10.4542	8.0400	23.09 %	6.2318	40.39 %
NYCC (Urban)	10.4145	7.0681	32.13 %	6.4114	38.44 %
NurembergR36 (Urban)	8.1623	5.8916	27.82 %	5.3525	34.42 %
WVUSUB (Suburban)	5.6093	5.2535	6.34 %	4.1618	25.81 %
CSHVR (Suburban)	6.0724	5.8890	3.02 %	4.2990	29.20 %
INDIA_URBAN_SAMPLE (Suburban)	5.8405	6.5461	-12.08 %	4.4011	24.65 %
HWFET (Highway)	4.6645	4.6558	0.19 %	4.4824	3.90 %
SC03 (Highway)	5.7607	4.5903	20.32 %	4.6691	18.95 %
NEDC	5.9410	5.3550	9.86 %	4.8170	18.92 %
MIXED	5.5270	5.9038	-6.82 %	4.4705	19.12 %

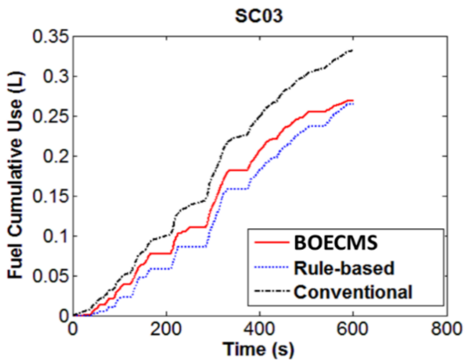


Figure 11. Comparison of fuel consumption for SC03 Driving cycle.

On the other hand, for the INDIA_URBAN_SAMPLE and MIXED driving samples, the rule-based power split strategy underperforms the conventional pure ICE because the rule-based algorithm only considers ICE efficiency rather than fuel consumption. In Fig. 12, the higher the mean of engine efficiency, the more operation points are located near the centroid of the distribution map. However, the higher the engine efficiency, the more fuel is consumed. Consequently, enhancing engine efficiency alone tends to result in more fuel consumption, with performance inferior to even the conventional pure ICE vehicles.

Figure 13 shows the alternation of battery SOC under various power-split strategies for MIXED driving cycles. Based on the rule-based power-split strategy, the battery SOC fluctuates considerably and occasionally falls below the minimum allowable level. In contrast, under the BOECMS strategy, SOC is stable and varies slightly, and the final SOC converges closely to the initial SOC as expected (see Sec. 3.5).

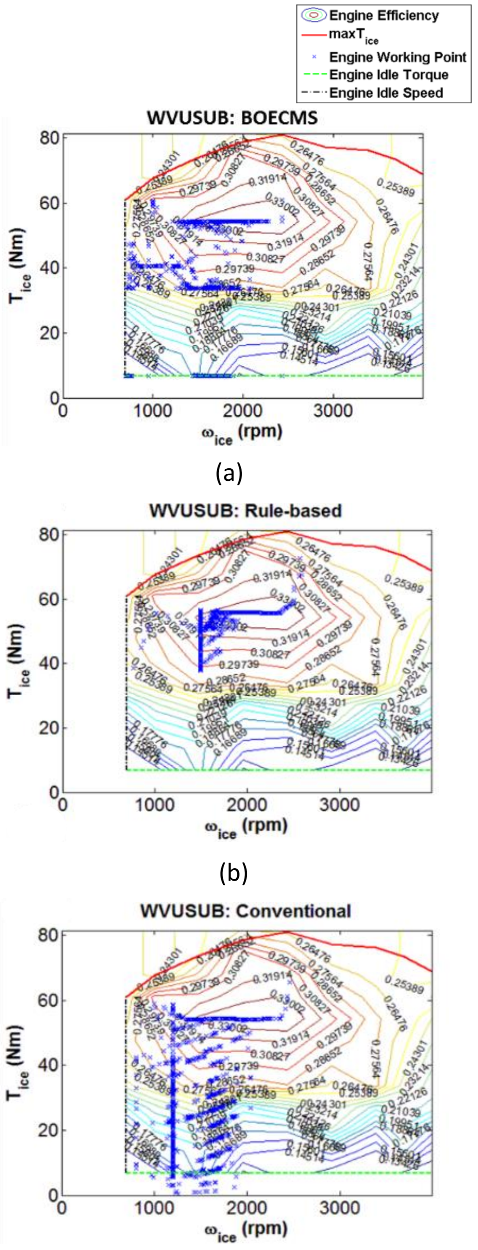


Figure 12. Engine operation points under WVUSUB driving cycle:(a)BOECMS, (b) Rule-based, (c) Conventional pure ICE vehicle.

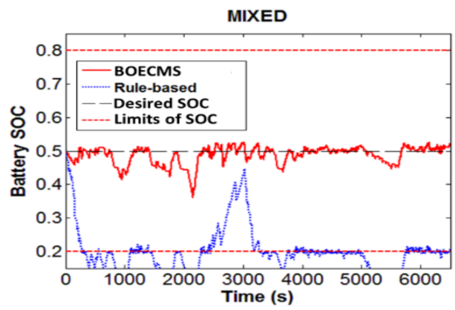
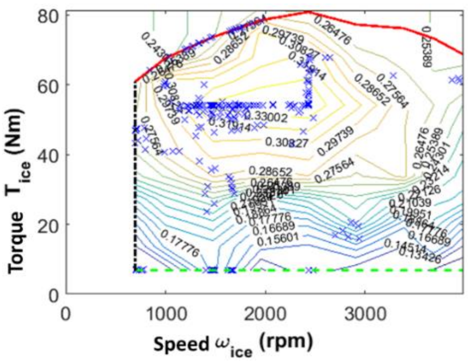


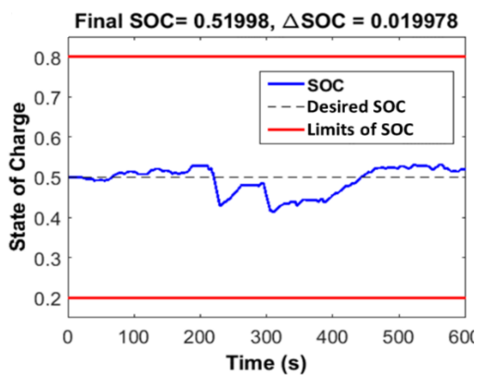
Figure 13. Battery SOC for MIXED drive cycle.

Experimental Results for Hardware-in-the-loop

Experimental results for BOECMS by hardware-in-the-loop experiments are quite consistent with computer simulation results conducted using ***Simulink***. In other words, the advantages of BOECMS cited here appear also in the HIL experiments, namely, (i) the engine operation points tend to be located near the high-efficiency zone, (ii) the battery SOC can be sustained within a relatively narrow range, (iii) a fuel consumption savings of 39.25% is obtained for the MANHATTAN driving cycle over the rule-based strategy, and (iv) the final SOC converges to the initial SOC (see Fig. 14). Thus, the HIL experimental results are highly consistent with computer simulation results.



(a)



(b)

Figure 14. Experimental results for SC03 driving cycle: (a) Operation points, (b) Battery SOC.

Conclusions

A combined forward/backward-facing BSG HEV model is established and the effectiveness of proposed control strategy, BOECMS, is verified by simulations and experiments. Intensive simulations show that the proposed power allocation strategy can effectively improve fuel economy, compared with conventional pure ICE vehicles and the popular rule-based strategy. BOECMS also maintains the battery SOC within a relatively narrow range: [0.4, 0.6].

Simulation results show the proposed approach produces fuel savings for the MANHATTAN drive cycle of 40.39 % and 23.09 %, respectively, over the conventional pure ICE vehicles and the rule-based strategy. In addition, the SOC can be held within a relatively narrow range [0.4, 0.6] without significant fluctuations. Furthermore, the final SOC converges well with the initial SOC for the illustrative drive cycles NEDC and SC03 in earlier computer simulations and later by hardware-in-the-loop (HIL) experiments. In addition, engine operation efficiency improves by 45.97 % over conventional pure ICE vehicles for the New York City Cycle.

To be more practical, the corresponding HIL experimental test rig is successfully set up to verify BOECMS for BSG HEVs. HIL experimental results show that BOECMS is potentially applicable to real-world driving conditions and may be particularly beneficial to extending the lifespan of both the electric motors (EM) and ICEs.

Acknowledgement

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