International Conference on Applied Energy 2021
Nov. 29 - Dec. 5, 2021, Thailand/Virtual
Paper ID: 346

# Intelligent SOC Reference Planning for Hybrid Electric Bus: A Hierarchical Predictive Energy Management Strategy

Ruchen Huang [1], Hongwen He [1*], Xiangfei Meng [1]

1 National Engineering Laboratory for Electric Vehicles, School of Mechanical Engineering,

Beijing Institute of Technology, Beijing 100081, China

## ABSTRACT

This paper proposes a hierarchical predictive energy management strategy (EMS) for hybrid electric bus (HEB) with an intelligent state of charge (*SOC*) reference planning method. In the cloud layer, future driving cycle is acquired through the intelligent transportation system (ITS) and well-trained neutral networks of deep deterministic policy gradient (DDPG) are extracted to plan the *SOC* reference trajectory quickly. In the vehicle layer, back propagation neutral network (BP-NN) is used to predict the velocity in a short term and an optimal controller is designed to distribute power flows optimally. Simulation results show that the fuel economy is improved by 2.12% compared with DDPG and reaches 97.43% of dynamic programming (DP).

**Keywords:** hybrid electric bus, energy management, intelligent *SOC* reference planning, model predictive control, deep deterministic policy gradient

## NONMENCLATURE

*Abbreviations*

| | |
|---|---|
| EMS | Energy management strategy |
| HEB | Hybrid electric bus |
| *SOC* | State of charge |
| ITS | Intelligent transportation system |
| DDPG | Deep deterministic policy gradient |
| BP-NN | Back propagation neutral network |
| MPC | Model predictive control |
| DP | Dynamic programming |
| DRL | Deep reinforcement learning |
| RMSE | Root mean square error |

*Symbols*

| | |
|---|---|
| $F_t$ | Driving force demand |
| $P_d$ | Driving power demand |
| $m$ | Vehicle mass |
| $g$ | Gravity acceleration |
| $f$ | Rolling resistance coefficient |
| $\varphi$ | Angle of road slope |
| $C_d$ | Drag coefficient |
| $A$ | Front area |
| $v$ | Velocity |
| $a$ | Acceleration |
| $\dot{m}_{fuel}$ | Fuel consumption rate |
| $\eta$ | Efficiency |
| $T$ | Torque |
| $\omega$ | Rotational speed |
| $I_{bat}$ | Current of the battery |
| $V_{oc}$ | Open-circuit voltage |
| $R_0$ | Internal resistance |
| $SOC_0$ | Initial value of *SOC* |
| $Q$ | Nominal battery capacity |
| $\alpha$ | Weight factor of fuel consumption |
| $\beta$ | Weight factor of *SOC* maintaining |
| $SOC_{tar}$ | *SOC* target value |
| $J_k$ | Total cost in the *k*-th time step |
| $\Delta t$ | Sampling time step size |
| $N_p$ | Prediction horizon |
| $SOC_{ref}$ | *SOC* reference value |

## 1. INTRODUCTION

Active development of hybrid electric bus (HEB) is an effective way to solve urban air pollution and traffic congestion. Energy management strategy (EMS) is

Selection and peer-review under responsibility of the scientific committee of the 13th Int. Conf. on Applied Energy (ICAE2021).

crucial for the fuel economy of the HEB [1]. There are multifarious kinds of EMSs that have been proposed yet, and EMSs based on model predictive control (MPC) and deep reinforcement learning (DRL) have been widely studied in recent years.

MPC-based EMSs convert global optimization into local and adjust the allocation of power flows in advance actively by taking advantage of the future distribution of driving power demand in the prediction horizon, thus achieving a favorable fuel economy [2]. It is of great importance to obtain a *SOC* reference trajectory to guide the MPC controller to distribute power flows optimally, however, the *SOC* reference trajectories lack adaptability to changeable driving cycles, limiting the improvement of the fuel economy [3].

DRL based EMSs have gradually flourished with a promising prospect, showing an impressive optimization performance with great adaptability and robustness for HEB [4]. However, most of the researches on DRL-based EMSs never take the uncertainty of future driving cycles into consideration, which is an inherent attribute of the driving cycles, leading to an adverse effect on the fuel economy [5].

Accordingly, it is more significative to combine the MPC-based EMSs with DRL algorithms for the energy management of HEB, so as to give full play to the advantages of these two types of strategies. Besides, with the prosperity of the intelligent transportation system (ITS), the whole driving cycle in the future can be obtained, and then the global *SOC* reference trajectory can be planned before departure. To this end, this paper proposes a hierarchical EMS under the MPC framework with an intelligent *SOC* reference planning method of a HEB for favorable fuel economy.

## 2. HEB POWERTRAIN MODELLING

### 2.1 HEB configuration

The HEB in this paper adopts the power-split configuration to control the engine working in the high efficiency area. The powertrain configuration is shown in Fig. 1, and the main parameters of the HEB are listed in our previous research [6].

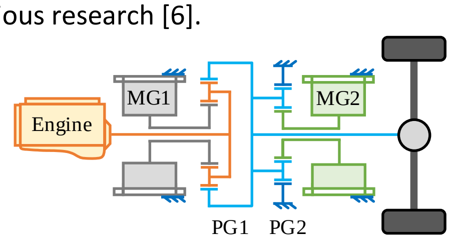


Fig. 1. HEB Powertrain configuration

### 2.2 Vehicle dynamics model

The driving power demand can be calculated as:

$$\begin{cases} F_t = mgf\cos\varphi + mg\sin\varphi + \dfrac{C_d A}{21.15}v^2 + ma \\ P_d = F_t v \end{cases} \tag{1}$$

### 2.3 Power units model

The efficiency of engine, MG1 and MG2 are functions of speed and torque, which can be formulated as:

$$\begin{cases} \dot{m}_{fuel} = f\left(T_{eng}, \omega_{eng}\right) \\ \eta_{mg1} = f\left(T_{mg1}, \omega_{mg1}\right) \\ \eta_{mg2} = f\left(T_{mg2}, \omega_{mg2}\right) \end{cases} \tag{2}$$

The battery theoretical model is formulated as:

$$\begin{cases} I_{bat} = \dfrac{V_{oc} - \sqrt{V_{oc}^2 - 4R_0(V_{oc}I_{bat} - I_{bat}^2 R_0)}}{2R_0} \\ SOC = SOC_0 - \dfrac{\int_0^t I_{bat}\,dt}{Q} \end{cases} \tag{3}$$

## 3. HIERARCHICAL PREDICTIVE EMS

### 3.1 Training of DDPG

Deep deterministic policy gradient (DDPG) is a state-of-art DRL algorithm [7], which is used in this research. The state space *S*, action space *A* and reward function *R* are respectively defined as:

$$\begin{cases} S = \{SOC, v, a\} \\ A = \{T_{eng}, \omega_{eng}\} \\ R = \alpha \cdot \dot{m}_{fuel} + \beta\left(SOC_{tar} - SOC(t)\right)^2 \end{cases} \tag{4}$$

The training dataset is real velocity data collected from a fixed bus route with a 15-km distance shown in Fig. 2, and the testing dataset is shown in Fig. 3.

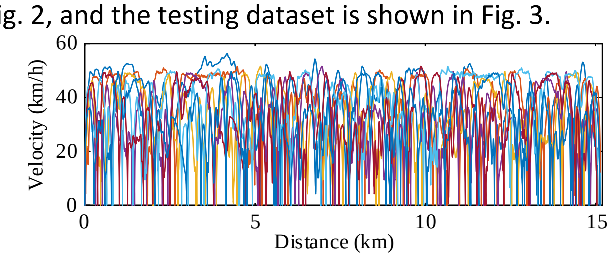


Fig. 2. Training dataset

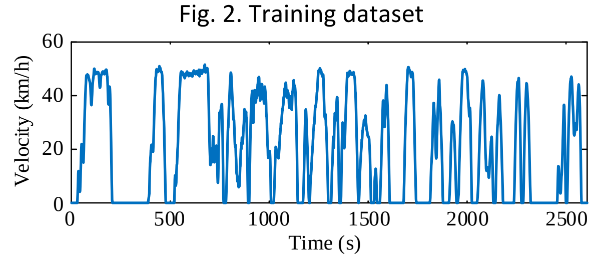


Fig. 3. Testing dataset

Fig. 4 shows the mean reward and final *SOC* of each episode during training. It can be seen that after 15 episodes, the DDPG algorithm converges completely, and the final *SOC* of each episode is close to 0.5, which is the *SOC* target value in equation (4). Fig. 4 indicates a favorable training effect of the DDPG algorithm.

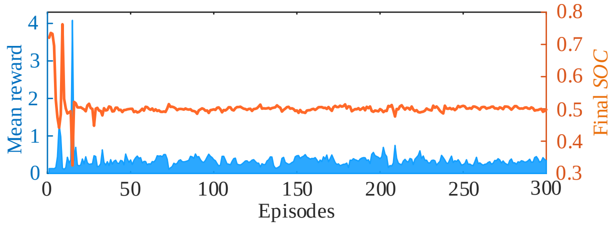

Fig. 4. Mean reward and final *SOC* of each episode.

### *3.2 Velocity prediction*

Back propagation neutral network (BP-NN) is utilized to predict the future velocity in the next 10 seconds. The velocity data shown in Fig. 2 and Fig. 3 are also used as the training and testing datasets for BP-NN.

The velocity prediction result is shown in Fig. 5, and the root mean square error (RMSE) is shown in Fig. 6. It can be seen that the predicted velocity is smoothly close to the real velocity, and the average RMSE is 1.05 m/s, showing a favorable prediction performance.

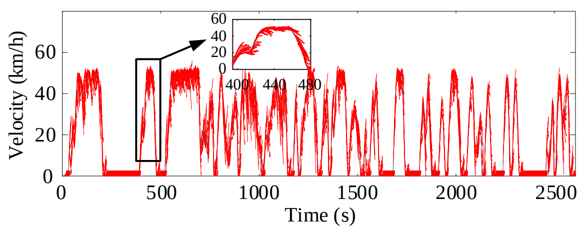

Fig. 5. Velocity prediction result

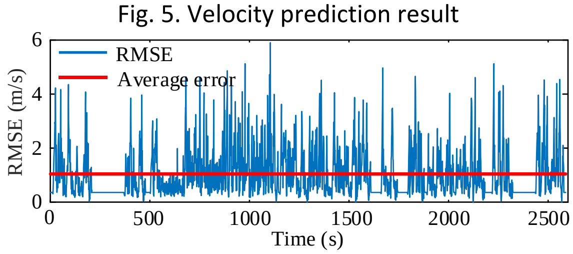

Fig. 6. RMSE

### *3.3 Hierarchical control scheme*

This research adopts dynamic programming (DP) as the MPC optimal controller to calculate the optimal control sequences during the rolling optimization process so as to maximize the optimization effect. The cost function of the proposed strategy is:

$$J_k = \sum_{t=k\Delta t}^{(k+N_p)\Delta t} \dot{m}_{fuel} + \phi\left[SOC(t) - SOC_{ref}\left(k+N_p\right)\right]^2 \quad (5)$$

According to the description above, the hierarchical control scheme of the proposed strategy in this research is shown in Fig. 7.

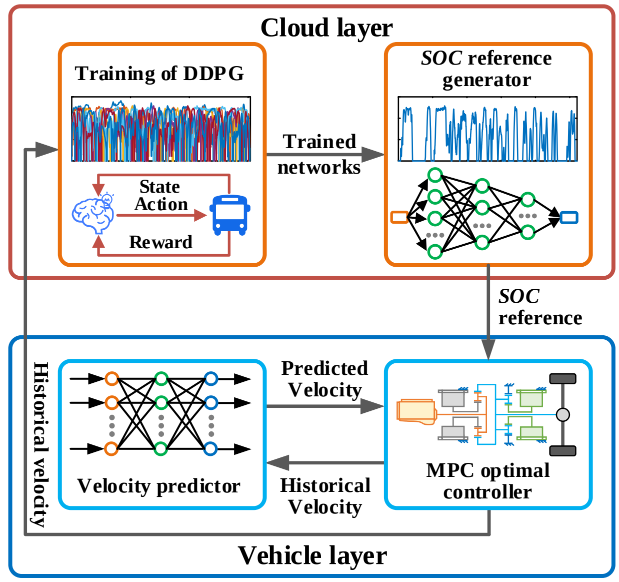

Fig. 7. Hierarchical control scheme

## 4. SIMULATION RESULTS AND DISCUSSION

### *4.1 Fuel economy improvement*

The testing dataset shown in Fig. 3 is leveraged as the pre-known cycle acquired by ITS. Note that the proposed strategy is represented as SOC@DDPG, and the method uses constant 0.5 as the *SOC* reference is SOC@Cons.

Simulation results of the fuel economy are listed in Table 1. The final SOC of both the SOC@DDPG and SOC@Cons are constrained about 0.5, and SOC@DDPG improves the fuel economy by 2.12% than DDPG, showing a superior fuel economy performance. More importantly, it only takes 1.08 s to generate the global *SOC* reference trajectory of the SOC@DDPG strategy, which is also more conducive to the practical application of the proposed strategy in this research.

Table 1. Simulation results of fuel economy.

| Strategies | Final *SOC* | Fuel consumption (L/100km) | Fuel economy[1] |
|---|---|---|---|
| SOC@DDPG | 0.4977 | 23.37 | 97.43% |
| SOC@Cons | 0.5011 | 24.05 | 94.68% |
| DDPG | 0.5000 | 23.89 | 95.31% |
| DP | 0.5000 | 22.77 | 100% |

[1] Compared with DP.

Engine working points of the four strategies above are shown in Fig. 8. There are more working points of SOC@DDPG and DP distributed in the high-efficiency area. In contrast, much more points of SOC@Cons are distributed in the area that consumes more fuel. It is worth noting that the points of DDPG are almost completely distributed along the optimal operation line of the engine owing to the great self-learning ability, however, there are still many low efficiency points need to be further optimized.

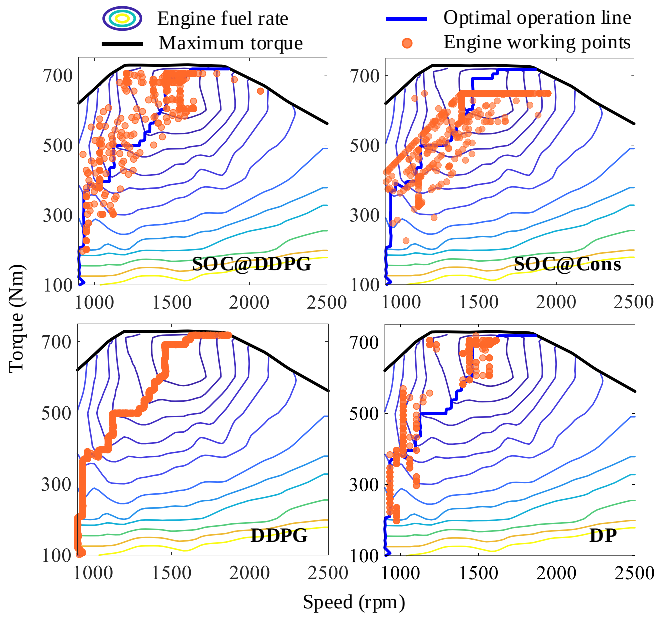


Fig. 8. Engine working points

### 4.2 *SOC* tracking performance

The HEB do not need external charging for battery, so it is of great importance to keep *SOC* close to the reference value. The *SOC* tracking results and deviations of SOC@DDPG and SOC@Cons are shown in Fig. 9 and Fig. 10 respectively. It can be seen that the MPC optimal controller has the ability to track the *SOC* reference trajectories closely. The maximum absolute deviations of SOC@DDPG and SOC@Cons are 0.0063 and 0.0087, and the mean absolute deviations are 0.0021 and 0.0024 respectively, indicating that the *SOC* tracking performance of SOC@DDPG is better than SOC@Cons. This is because that the DDPG algorithm takes the nonlinear characteristics of driving cycles into consideration during training by taking advantage of the powerful generalization ability while DP only conducts the calculation passively.

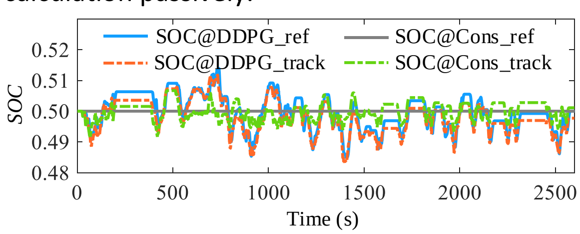


Fig. 9. *SOC* tracking results

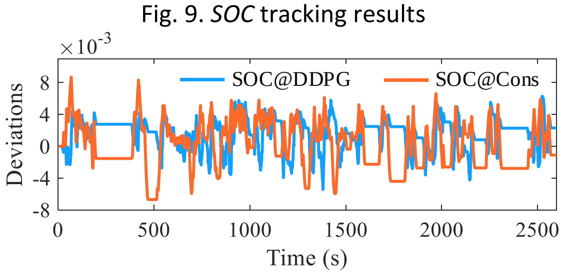


Fig. 10. Deviations

## 5. CONCLUSION

This paper proposes an intelligent *SOC* reference planning method within a hierarchical MPC-based EMS for HEB for favorable fuel economy. DDPG is trained to plan the global *SOC* reference quickly after acquiring the driving cycle in a fixed bus route through ITS. BP-NN is utilized to predict the short-term velocity and an MPC optimal controller is designed to distribute power flows optimally. Comparative simulation results indicate that the proposed strategy only takes 1.08 s to generate the *SOC* reference trajectory for a 15-km bus route and improves fuel economy by 2.12% with a superior *SOC* tracking performance compared with DDPG.

## ACKNOWLEDGEMENT

This work was supported in part by the National Natural Science Foundation of China (Grant No. U1864205 & Grant No. 52172377), and the Scientific and Technological Innovation Project of Shandong Province in China in part (Grant No. 2019JZZY020814).

## REFERENCE

[1] Peng J, He H, Xiong R. Rule based energy management strategy for a series–parallel plug-in hybrid electric bus optimized by dynamic programming. Applied Energy. 2017; 185: 1633-1643.

[2] Zhou Y, Ravey A, Péra M-C. A survey on driving prediction techniques for predictive energy management of plug-in hybrid electric vehicles. Journal of Power Sources. 2019; 412: 480-495.

[3] Zhang H, Peng J, Tan H, et al. Tackling SOC long-term dynamic for energy management of hybrid electric buses via adaptive policy optimization. Applied Energy. 2020; 269.

[4] Li Y, He H, Khajepour A, et al. Energy management for a power-split hybrid electric bus via deep reinforcement learning with terrain information. Applied Energy. 2019; 255.

[5] Wu J, Wei Z, Li W, et al. Battery Thermal- and Health-Constrained Energy Management for Hybrid Electric Bus Based on Soft Actor-Critic DRL Algorithm. IEEE Transactions on Industrial Informatics. 2021; 17(6): 3751-3761.

[6] Wu J, He H, Peng J, et al. Continuous reinforcement learning of energy management with deep Q network for a power split hybrid electric bus. Applied Energy. 2018; 222: 799-811.

[7] Wu Y, Tan H, Peng J, et al. Deep reinforcement learning of energy management with continuous control strategy and traffic information for a series-parallel plug-in hybrid electric bus. Applied Energy. 2019; 247: 454-66.

 