ISSN 2004-2965 Energy Proceedings, Vol. 20, 2021

International Conference on Applied Energy 2021
Nov. 29 - Dec. 5, 2021, Thailand/Virtual
Paper ID: 544

A DRL-based Ecological Driving Strategy for Series Hybrid Energy Vehicle Including Battery Degradation

Yi Fan[1], Hongwen He[2], Zexing Wang[3], Jiankun Peng[1*], Hailong Zhang[1], Weiqi Chen[1]

1 School of Transportation, Southeast Unversity, Nanjing , 211189,China

2 National Engineering Laboratory for Electric Vehicles, Beijing Institute of Technology, Beijing, 100081, China

3 National New Energy Vehicle Technology lnnovation Center,Beijing, 100176, China

ABSTRACT

An ecological driving strategy considered battery State-of-Health is proposed based on Deep reinforcement learning. Not only does this strategy try to minimize fuel consumption while maintaining the safe car-following sate, it also seeks to lower the battery aging speed. In order to optimize the car-following and energy management performance, reward functions are developed by combing driving features of car-following, engine and battery characteristics. The agent maximizes the accumulated reward by interacting with the simulation environment to explore the action space. While controlling the SHEV to maintain a safe car-following distance, the proposed method reduces the effective Ah-throughput by 15 - 57.6% and only increases the fuel consumption within 5% compared with the case of achieving the best fuel economy. In addition, this method is proven to achieve similar results in different driving cycles.

Keywords: Energy management strategy;Car-following; Battery State-of-Health; Deep reinforcement learning

1. INTRODUCTION

Although the driver's behavior is generally considered to be one of the most important factors affecting vehicle fuel consumption, the development of energy management strategies for powertrain devices has never stopped [1] . First, dynamic programming is used to control the gear-shifting sequence and the power split [2]. Paganelli et al. proposed the equivalent consumption minimization strategy which comes down to a single goal with electric and energy consumption [3]. In addition to the characteristics of the vehicle itself, traffic information is also critical to EMS. Model Predictive Control incorporates future operating conditions into the calculation process, and its optimization is solved over a future prediction horizon [4].

In order to make vehicles have higher fuel economy, the concept of ecological driving that takes into account more influencing factors is proposed. These factors include driving speed, acceleration, deceleration, route choice, idling and vehicle accessories [5]. Adaptive cruise control technology enables the vehicle to keep stable speed ,acceleration and deceleration performance under complex traffic conditions , therefore using cruise control when possible is commonly recommended for eco-driving [6]. Dahmane et al. studied using stochastic model predictive control (SMPC) to solve the global optimization problem of the combination of ACC with Stop&Go and energy management strategies [7], and innovatively regarded the required power of the vehicle as a random Markov process. Based on Markov property of the power required by hybrid electric vehicles, Hu et al. firstly applied deep reinforcement learning to the energy management strategy of HEVs [8]. Compared with conventional method,learning-based methods have higher adaptability under complex driving cycles and consumer less computational resources [9]. Therefore, the longitudinal control task of the vehicle can also be completed by the deep reinforcement learning algorithm, as shown in [10,11].

In summary, it is feasible to use deep reinforcement learning to solve the global optimization problem combining SHEVs energy management strategy and adaptive cruise control. However, extreme fuel economy means shorter battery life, and a tradeoff exists between better fuel economy and longer battery life [12]. Therefore, in this paper, a DRL-based ecological driving strategy considering battery aging is proposed. The rest of paper is organized as following: section 2 shows car following system, SHEV system and control algorithm of eco-driving in detail; in section 3, simulation results are analyzed and discussed; section 4 finally concludes the paper.

2. THE ECO-DRIVING STRATEGY INCLUDING BATTERY DEGRADATION

A complete eco-driving strategy consists of vehicle adaptive cruise control and energy management strategies. In other words, the car-following system and powertrain system are the control objects of the eco-driving strategy. Since the focus of our research is not on the structure of vehicle's powertrain system, we select SHEVs as the target vehicle.

2.1 Car-following system

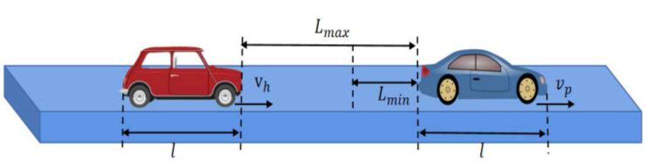

Figure1. Car-following system

The car-following system usually describes the scene where the target car follows the preceding car on a one-way road that cannot be overtaken, as shown in Fig.1. v_p, a_p and x_p are the speed, acceleration, and distance traveled by the proceeding vehicle. v_r, a_r and x_r are the speed, acceleration and travel distance of the target vehicle. l and L are the vehicle length and car-following distance, and L is defined as $\mathrm{L} = \mathrm{x_p} - \mathrm{x_t} - \mathrm{l}$. Besides, the target vehicle satisfies the following mathematical relationship:

$$\begin{cases} x_r = \int v_r\,dt \\ v_r = \int a_r\,dt \\ a_r = \dfrac{F - Gf\cos\alpha - G\sin\alpha - \dfrac{C_D A(3.6v_r)^2}{21.15}}{\delta m} \end{cases} \tag{1}$$

where F is the driving force of the vehicle, G is the gravity of the vehicle, f is the rolling resistance coefficient, C_D is the air resistance coefficient, A is the windward area, δ indicates the rotation mass conversion coefficient, m is the body mass, and α indicates the road gradient angle whose default value is 0.

If the velocity of the target vehicle is not restricted, collisions will still occur during the training process. Therefore, we define the minimum car-following distance and the maximum car-following distance on the basis of the braking distance [13].They are estimated as

$$\begin{cases} L_{min} = v_r(t_r + \dfrac{t_b}{2}) + \dfrac{v_r^2}{a_{max}} \\ L_{max} = 10 + 3.6 \cdot v_r + 0.0825 \cdot v_r^2 \end{cases} \tag{2}$$

where t_r is the driver's reaction time, taking 0.8s, t_b is the acceleration change time, taking 0.1s, and a_{max} is the emergency deceleration of the target vehicle, taking 7.5m/s^2.

2.2 SHEV powertrain system

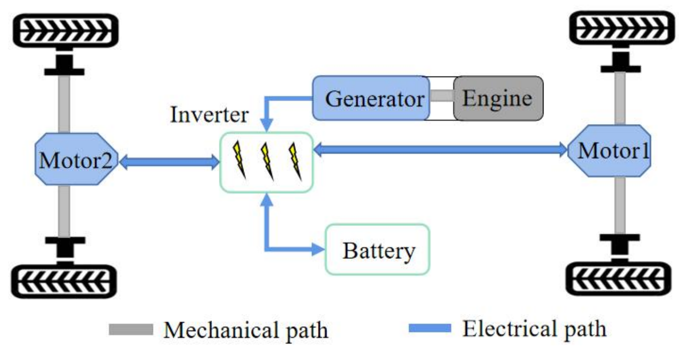

Figure2. SHEV configuration

The vehicle studied is equipped with two identical electric propulsion systems,as shown in Fig.2.Engine-generator set(EGS) and the battery pack are equipped as power sources for the vehicle.Their energy distribution should satisfy the following relationship to provide the required power $\mathrm{P_{req}}$:

$$\mathrm{P_{req}} = \begin{cases} (P_{batt} - P_{EGS}) \cdot \eta_{inverter}\ , \mathrm{P_{req}} \geq 0 \\ (P_{batt} - P_{EGS}) / \eta_{inverter}\ , \mathrm{P_{req}} < 0 \end{cases} \tag{3}$$

where $\mathrm{P_{batt}}$ is terminal power of the battery pack,$\mathrm{P_{EGS}}$ is output power of generator,and η_{inverter} presents efficiency of inverter .Other parameters of this series hybrid electric vehicle are provided in Table 1.

Table1.Vehicle parameters of the SHEV

Vehicle	Curb Weight	3500kg
	Rolling radius	0.447m
Engine	Maximum power	62kW
	Maximum torque	227Nm

Generator	Maximum speed Maximum torque	4000rpm 277Nm
Front/Rear motor	Maximum speed Maximum torque	7200rpm 320Nm
Battery pack	Capacity Voltage	25Ah 347.8V

The deep reinforcement learning algorithm mainly finds the optimal engine power by controlling the EGS. The generator and the engine are connected by mechanical transmission, so their torque and speed ($T_{gen}, W_{gen}, T_{eng}, W_{eng}$)satisfy the following relationship:

$$\begin{cases} T_{gen} = T_{eng}, W_{gen} = W_{eng} \\ P_{EGS} = P_{gen} = T_{gen} \cdot W_{gen} \cdot \eta_{gen} \\ P_{eng} = T_{eng} \cdot W_{eng} \\ m_{fuel} = \dot{P_{eng}}/(E\eta_{eng}) \end{cases} \quad (4)$$

where η_{gen} and η_{eng} are the efficiency of generator and engine;E is the gasoline lower heating value(4.25×10^7J/kg) .

As another important power source, energy of battery pack is established as an equivalent circuit model by

$$\begin{cases} P_{batt} = V_{oc} - RI^2 \\ I = \dfrac{V_{oc} - \sqrt{V_{oc}^2 - 4RP_{batt}}}{2R} \\ SoC = \dfrac{Q_0 - \int I dt}{Q} \end{cases} \quad (5)$$

where P_{batt} is the power of the battery,V_{oc} is the open circuit voltage,R is the internal resistance,I is the battery current,SoC is the state of charge, Q_0 is the initial battery capacity,and Q is the nominal battery capacity.

State-of-Health(SoH) is an important parameter that characterizes the current state of the battery. However, there is currently no clear definition of SoH. Identifying the aging mechanism in the battery is very challenging [14].Identified aging model [15] we selected has the form of

$$Q_{loss\%} = (\alpha \cdot SoC + \beta) \cdot exp(\frac{-31700 + 163.3 \cdot I_c}{R \cdot \theta}) \cdot Ah^{0.57}$$
$$\alpha = \begin{cases} 1287.6, \ \mathrm{SoC} \le 0.45 \\ 1385.5, \ \mathrm{Soc} > 0.45 \end{cases} \quad (6)$$
$$\beta = \begin{cases} 6356.3, \ \mathrm{SoC} \le 0.45 \\ 4193, \ \mathrm{SoC} > 0.45 \end{cases}$$

where $Q_{loss\%}$ is the battery capacity loss in percentage with respect to the nominal capacity,R is the gas constant, θ is the battery temperature expressed in Kelvin, I_c is the battery current rate,Ah is the Ah-throughput,and α , β guarantee SoC dependence.In this study, we only considered the working condition of the battery at nominal temperature θ_{nom} of 25 ℃.

Reducing the effective Ah-throughput of the battery is equivalent to delaying the aging of the battery [16], therefore we define Ah-through as

$$\begin{cases} \Gamma = \left[\dfrac{20}{(\alpha \cdot SoC_{nom} + \beta) \cdot exp(\frac{-31700 + 163.3 \cdot I_{c,nom}}{R \cdot \theta_{nom}})}\right]^{\frac{1}{0.57}} \\ \gamma = \left[\dfrac{20}{(\alpha \cdot SoC + \beta) \cdot exp(\frac{-31700 + 163.3 \cdot I_c}{R \cdot \theta})}\right]^{\frac{1}{0.57}} \\ \delta = \dfrac{\Gamma}{\gamma} \\ Ah_{eff}(t) = \int_0^t \delta \cdot |I(t)| \, dt \end{cases} \quad (7)$$

where Γ the nominal battery life, γ is the battery life in specific operating conditions,and δ is severity factor.

2.3 Control algorithm

We select Deep Deterministic Policy Gradient (DDPG) algorithm as the control algorithm of the agent, which can conduct stable training in the continuous action space. After observing the state of the environment, the agent performs optimal control actions based on the reward function.

$$\begin{cases} state = \{a_r, v_r, SoC, L, a_p, v_p\} \\ r_{follow} = \begin{cases} -80 \cdot v_r \ if \ L = 0 \\ -30 \cdot v_r \ if \ L < L_{min} \\ -15 \cdot (33.4 - v_r) \ if \ L > L_{max} \\ \begin{cases} log(\frac{TTC}{4}) \ \ if \ 0 < TTC < 4 \\ 0 \quad otherwise \end{cases} \end{cases} \\ r_{energy} = -\left\{\left[fuel(t) + 360 \cdot \left[SoC_{ref} - SoC\right]^2\right]\right\} \\ r_{battery} = \dfrac{\Gamma}{\gamma} \cdot |I| \\ reward\ function = \delta \cdot r_{follow} + \varepsilon \cdot r_{energy} + \beta \cdot r_{battery} \\ action = \{a_r, e_r\} \end{cases} \quad (8)$$

where r_{follow} , r_{energy} and $r_{battery}$ are reward functions, involving car-following, energy management and battery aging respectively, SoC_{ref} is the reference value of SoC, TTC(Time to Collision) is directly captured from the simulation platform, e_r is the engine power of target vehicle, and β controls influences of SoH on the agent.Through the comparison of multiple experiments, δ=-4, and ε=1 can achieve the global optimization.

3. RESULTS AND DISCUSSIONS

We firstly set the driving cycle of the preceding vehicle to US06_2 in the simulation platform to evaluate the performance of the proposed strategy. When using ChinaCity and JN1015 driving cycles to test the robustness of the strategy, the parameters of the neural network are adopted from pre-trained algorithm.

3.1 The strategy on-design evaluation

Fig.2 shows the simulation results of adaptive cruise control under the control of DDPG.The target vehicle successfully completed the car-following task, and its actual car-following distance is maintained between the maximum car-following distance and the minimum car-following distance at every time step.It is worth noting that the car-following distance of the target vehicle changes with the velocity, which effectively prevents the appearance of dangerous driving behavior.

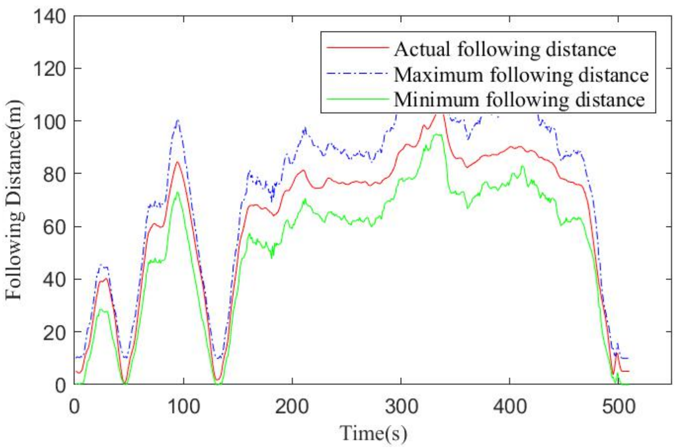

Figure2.The following distance between preceding vehicle and target vehicle(US06_2)

Motor torque and SoC trajectories are presented in Fig.3.When the agent considers the reward function of battery(β = 1), the torque of the motor changes more smoothly, while when β= 0, the torque of the motor changes drastically,which means that the target vehicle frequently request high C-rate of battery to achieve best fuel economy.When β= 1, the effective Ah-throughput decreases by 15.7%;however, the fuel consumption increases only by 3.6%, as shown in Table2. In addition, when β= 1, the SoC value is below the case of β= 0 most of time.This can be explained by the aging model (7), that is, lower SoC means slower aging speed.

Table1.Fuel and battery economy comparisons

The Value of β	Fuel consumption(L/100km)	Terminal SoC	Effective Ah
1	3.74	0.32	10.2
0	3.61	0.32	12.1

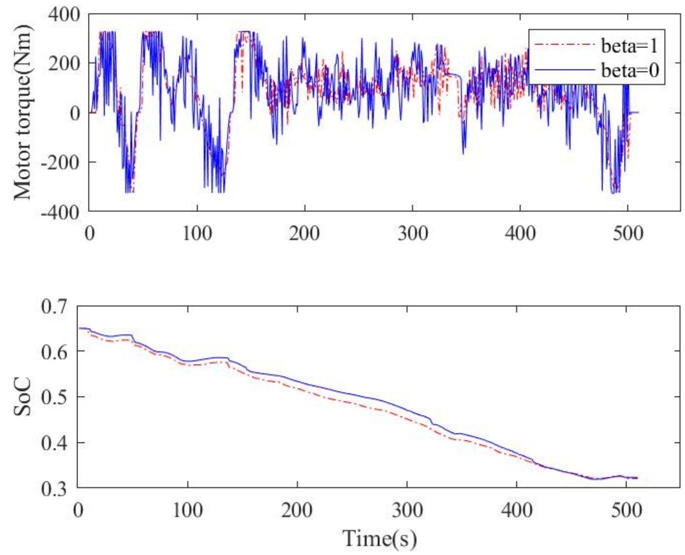

Figure3.Comparisons of motor torque and SoC trajectories

3.2 *Robustness analysis of proposed strategy*

When the driving cycle of preceding car is modified to JN1015 and ChinaCity, the following car can still maintain good car-following performance, as shown in Figure 3 and Figure 4.

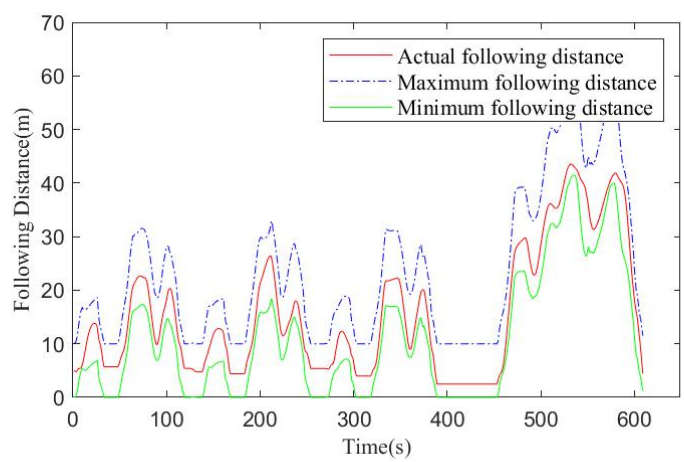

Figure3.The following distance between preceding vehicle and target vehicle(JN1015)

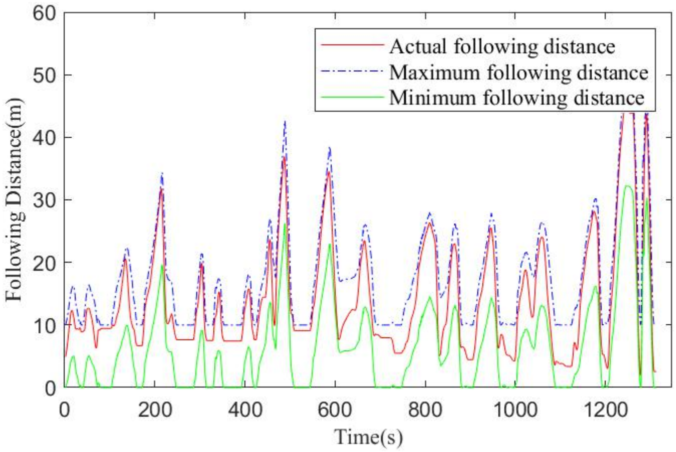

Figure4.The following distance between preceding vehicle and target vehicle(ChinaCity)

Compared with the optimal fuel economy case under JN1015 driving cycle, the effective Ah-throughput decreases by 57.6%, and the fuel consumption increases 4.7%.Under China-City driving cycle, regarding the best fuel economy case as a benchmark, the effective Ah-throughput decreases by 17.1%, and the fuel consumption increases 2.9%. Since the speed and acceleration characteristics of JN1015 are easier to learn by the agent, the effective Ah-throughput under this driving cycle is reduced by more than half.

Table3.Fuel and battery economy comparisons under different driving cycles

Driving cycles	Fuel consumption(L/100km)	Terminal SoC	Effective Ah
JN1015($\beta = 1$)	2.63	0.57	1.4
JN1015($\beta = 0$)	2.51	0.56	3.3
China-City($\beta = 1$)	4.49	0.54	2.9
China-City($\beta = 0$)	4.36	0.54	3.5

4. CONCLUSIONS

In this work, a DRL-based ecological driving strategy for SHEVs including battery aging is implemented under different driving cycles, and the main research findings can be outlined as follows:

(1)Battery SoH is firstly considered in the ecological driving strategy based on deep reinforcement learning, and multi-objective collaborative optimization of car-following and energy management strategies that considers battery aging is proven to be meaningful;

(2)The proposed strategy reduces the effective Ah-throughput by 15.7-57.6%; however, the sacrifice in fuel economy does not exceed 5%. Experiments under more driving cycles can help determine a more accurate range of Ah-throughput reduction and fuel consumption increase.

(3)The proposed strategy shows excellent car-following and energy management performance under different typical driving cycles, and is applicable for delaying battery aging.

ACKNOWLEDGEMENT

This work was supported in part by the National Natural Science Foundation of China (Grant No.52072074), the Fundamental Research Funds for the Central Universities (Grant No. 2242021R40007).

REFERENCES

[1]Ke Huang, Xianfeng Yang, Yang Lu, Chunting Chris Mi, Prathyusha Kondlapudi. Ecological driving system for connected/automated vehicles using a two-stage control hierarchy. IEEE Transactions on Intelligent Transportation Systems 2018;19(7):2373-84.

[2]Chan-Chao Lin, Huei Peng, Jessy W.Grizzle, Jun-Mo Kang. Power management strategy for a parallel Hybrid electric truck. IEEE Transactions on Control System Technology 2003;11(6):839-49.

[3]G.Paganelli, S. Deprat, T. Guerra, J. Rimaux, J J. Santin. Equivalent consumption minimization strategy for parallel hybrid powertrains. IEEE Vehicular Technology Conference 2002;4:2076-81.

[4]H. Ali Borhan, Ardalan Vahidi, Anthony M. Philips, Ming L. Kuang, Ilya V. Kolmanovsky. Predictive energy management of a power-split hybrid electric vehicle. American Control Conference 2009;3970-76.

[5]Yuhan Huang, Elvin C.Y. Ng, John L. Zhou, Nic C. Surawski, Edward F.C. Chan, Guang Yong. Eco-driving technology for sustainable road transport: A review. Renewable and Sustainable Energy Reviews 2018;93:596-609.

[6]Michael Sivak, Brandon Schoettle. Eco-driving: Strategic, tactical, and operational decisions of the driver thatinfluence vehicle fuel economy. Transport Policy 2012;22:96-9.

[7]Yassir Dahmane, Rustem Abdrakhmanov, Lounis Adouane. Stochastic MPC for optimal energy management strategy of hybrid vehicle performing ACC with stop&go maneuvers. IFAC 2018;51(9):223-29.

[8]Yue Hu, Weimin Li, Kun Xu, Taimoor Zahid, Feiyan Qin, Chenming Li. Energy management strategy for a hybrid electric vehicle based on deep reinforcement learning. Applied Sciences 2018;187(8):1-15.

[9]Renzong Lian, Jiankun Peng, Yuankai Wu, Huachun Tan, Hailong Zhang. Rule-interposing deep reinforcement learning based energy management strategy for power-split. Energy 2020;197(3):Article 117297.

[10]Meixin Zhu, Xuesong Wang, Yinhai Wang. Human-like autonomous car-following model with deep reinforcement learning. Transportation Research Part C 2018;97:348-368.

[11]Minxin Zhu, Yinhai Wang, Ziyuan Pu, Jingyun Hu, Xuesong Wang, Ruimin Ke. Safe, efficient, and comfort velocity control based on reinforcement learning for autonomous driving. Transportation Research Part C 2020;117:Article 102662.

[12]Soren Ebesen, Philipp Elbert, Lino Guzzella. Battery state-of-health perspective energy management for hybrid electric vehicles. IEEE Transactions on Vehicular Technology 2012;61(7):2893-2900.

[13]Qiang Luo, Lunhui Xun, Zhihui Cao, Yangguo Huang. Simulation analysis and study on car-following safety distance model based on braking process of leading vehicle. Proceedings of the 8th Word Congress on Intelligent Control and Automation 2011; 740-3.

[14]Cheng Lin, Aihua Tang, Wenwei Wang. A review of SOH estimation methods in lithium-ion batteries for electric vehicle applications. Energy Procedia 2015;75:1920-25.

[15]Girish Suri, Simona Onori. A control-oriented cycle-life model for hybrid electric vehicle lithium-ion batteries. Energy 2016;96:644-53.