Applied Energy Symposium 2021: Low carbon cities and urban energy systems
September 4-8, 2021, Matsue, Japan
Paper ID: 30

Global optimization energy management based on "Cyber-physical system - Dynamic Programming" (CPS-DP)

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ABSTRACT

With the Intelligent Connected Vehicle, Intelligent Transportation System and data mining technology, information sharing provides the feasibility for real-time application of global optimization energy management. To standardize the optimizing process, a framework of "Cyber-physical system - Dynamic Programming" (CPS-DP) is proposed. Based on the Internet of Vehicles, the information from various physical subjects (mainly refer to drivers, vehicles, and roads) can be acquired from different scenarios. For the stochastic information, the "drivers-vehicles-roads" co-constraint model is proposed to determine the speed limits. Based on the available information, optimal power distribution is determined in the control system. The keys are to determine feasible work modes based on the "kinetic/potential energy & onboard energy" conservation framework and develop an effective global domain-searching algorithm. To verify the proposed method, a case study (WLTP) is given. Simulation results demonstrate that the proposed method gains a better performance in both real-time performance and global optimality.

Keywords: cyber-physical system, standardization, real-time application, global optimization, energy management

1. INTRODUCTION

To deal with energy shortage, environmental pollution, and carbon neutral problem, developing new energy vehicles is an inevitable choice for global automotive industry in the 21st century. To maximum the energy-saving potential of the multi-energy source vehicles (MEVs), the global optimization energy management came into being.

Dynamic programming (DP) [1], as the typical optimization method, can obtain the theoretical optimal fuel economy. However, there exists four main challenges in practical application of DP strategy: standardization [2], real-time application, accuracy, and drivability. Owning to its reliance on future driving conditions (FDC) [3] and low computational efficiency, DP method can only be implemented offline.

With the intelligent transportation system (ITS) and traffic flow monitoring systems, real-time and historical traffic information can be obtained from roadside sensors. Meanwhile, thanks to C-V2X, such as V2V (Vehicle-to-vehicle), V2I (Vehicle-to-Infrastructure), the basic information, such as vehicle state, vehicle-to-vehicle communication, etc., are available. With the rapid development of data mining, the derived data, i.e., road characteristics, driving style, etc., can be extracted. The above information makes the acquired trip information more realistic and accurate. To avoid the adverse effects of optimal results against unknown cycles, the DP method is usually combined with global driving cycle construction [4], driving pattern recognition [5] or rule extraction [6] to develop an adaptive energy management strategy. According to the available information, access to future information can be classified into full, partial, or no future information. Under different information scenarios, how to acquire comprehensive and accurate information is the basis for implementing global optimization energy management.

With the development of artificial intelligence (AI), data-driven control strategies, such as neurodynamic programming (NDP) [7], reinforcement learning (RL) [8], and adaptive dynamic programming (ADP) [9], are emerged to improve real-time performance while ensuring the sub-optimality of energy management system. However, sufficient optimal results obtained by DP method are required as training samples. Thence, an efficient optimization algorithm is necessary to improve the real-time performance while ensuring the optimality.

To standardize DP model, a unified state space model of DP is established in Ref. [2] based on the work modes of EVs/HEVs. The main steps and technical routes of DP strategy are concluded in Ref. [10]. Currently, in the context of the Internet of Vehicles (IOV) and automotive big data, a global optimization energy management architecture is necessary to avoid repetitive case studies with different vehicle configurations.

To solve the above problems of DP strategy, a framework of “Cyber-physical system - Dynamic Programming” (CPS-DP) is proposed. The contribution of this paper mainly includes three aspects. First, a framework of CPS-DP is proposed to standardize the optimizing process of global energy management with informatization and intelligentization. For the stochastic information, a “drivers-vehicles-roads” co-constraint model is proposed to determine speed limits. Finally, under the “kinetic/potential energy & onboard energy” conservation framework, the optimal energy distribution is determined based on the global domain-searching algorithm.

The remainder of this paper is organized as follows: Section 2 introduces the global optimization framework of CPS-DP. The simulation results and analysis under WTLP cycle are described in Section 3, and conclusions are drawn in Section 4.

2. GLOBAL OPTIMIZATION FRAMEWORK

2.1 The overall framework

Essentially, global optimization energy management is based on the available trip information to produce the global optimal energy distribution by making full use of the characteristics of the vehicle.

Thus, we regard drivers, vehicles, roads, networks and clouds as a cyber-physical system (CPS), which is a standard concept in industrial automation. Based on hierarchical thinking, a framework of "Cyber-Physical Systems - dynamic programming" (CPS-DP) is proposed.

The framework consists of three main hierarchies, namely, cyber, physical, and control, and an application layer in the end. A schematic diagram is shown in Fig 1.

2.2 Physical

The physical refers to physical substances, mainly including drivers, vehicles, roads (environment). In terms of the roads, it mainly involves road infrastructures, traffic facilities, terrain, etc. Regarding the drivers, it reflects in different driving styles and driving habits.

In terms of the vehicle, multi-energy source vehicles usually consist of engine, drive motor, power battery, and electronic control system. The vehicle modeling is a prerequisite for global energy management. In the longitudinal direction, the driving force in the driving process can be expressed as:

$$F_D = mgf\cos\alpha + \frac{C_D A \cdot v_c^2}{21.15} + mg\sin\alpha + \delta \cdot m\frac{du}{dt} \quad (1)$$

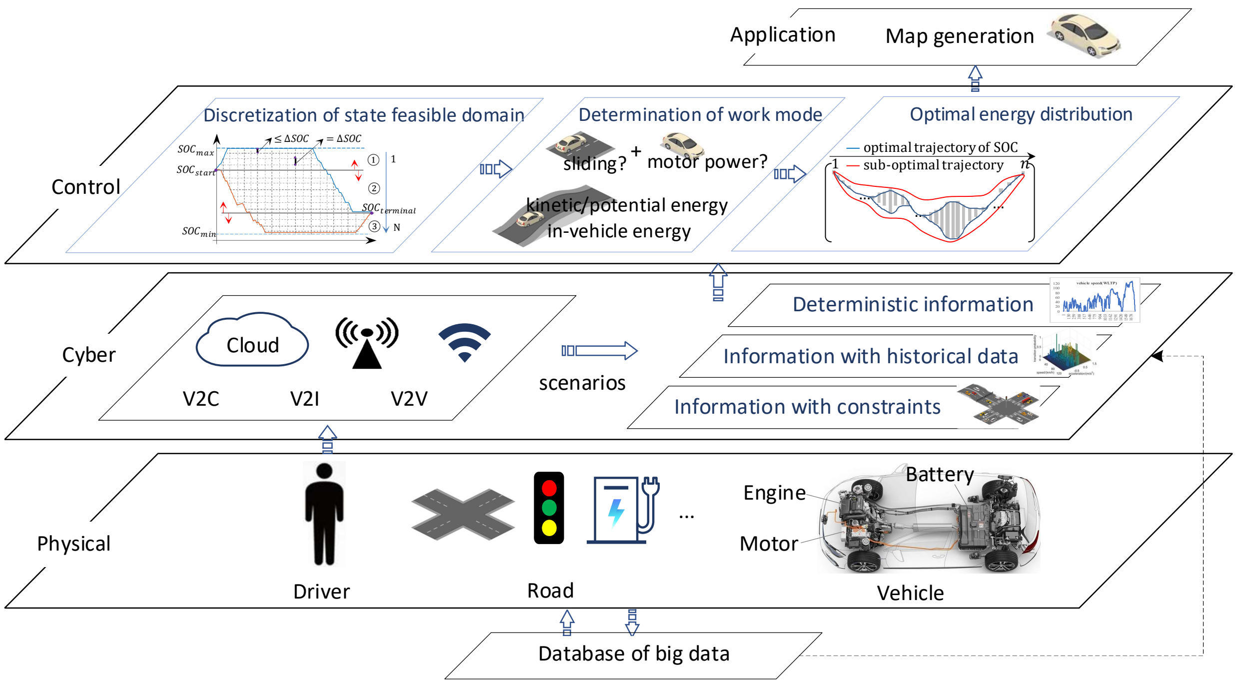


Fig 1 Schematic diagram of the global optimization framework (CPS-DP).

Where, F_D is the driving force, m is gross weight, g is gravity acceleration, f is rolling resistance coefficient, α is the road gradient, C_D is air resistance coefficient, A is windward area, v_c is vehicle speed, δ is the rotation mass conversion factor, and du/dt is longitudinal acceleration of the vehicle.

For the power components, the experimental modeling method is used to develop the engine model and motor model without considering its dynamic characteristics. The engine model is simplified as a quasi-static map to calculate the fuel consumption (Q_e), that is,

$$Q_e = F_{fuel}(T_e, n_e) \tag{2}$$

Where, n_e is engine speed, T_e is engine torque.

Similarly, the efficiency characteristics of motors can be formulated as:

$$\eta_m = f(T_m, n_m) \tag{3}$$

Where, η_m is motor efficiency, n_m is motor speed, and T_m is motor torque, which is defined as positive during propelling and negative during regenerative braking.

Without the consideration of temperature change and battery aging, an internal resistance battery model can be used to calculate the battery power. The state of charge (SOC) can be calculated by:

$$SOC_{k+1} - SOC_k = -\frac{U_{oc} - \sqrt{U_{oc}^2 - 4R_{int} \cdot P_{bat}}}{2R_{int} \cdot C} \tag{4}$$

Where, SOC_{k+1} is the battery SOC at the moment $(k+1)$, and $SOC_k, U_{oc}, P_{bat}, R_{int}$ are the SOC, open-circuit voltage, electric power and internal resistance of the battery at the moment k, respectively.

2.3 Cyber

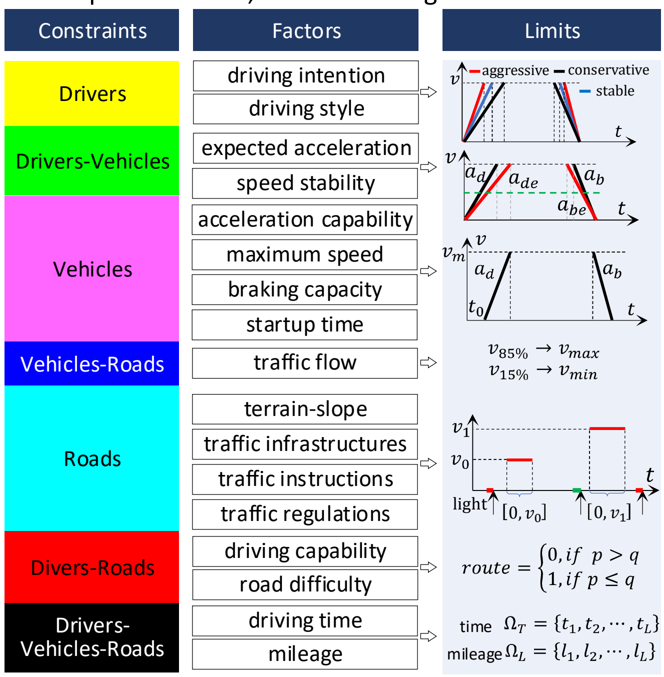
The cyber mainly refers to virtual substances, such as the internet and software. Based on the IOV, information from various physical subjects can be obtained. The trip information, including vehicle speed, slope, is the premise for global energy management. According to the available information, trip information is acquired from three scenarios: deterministic information, information with constraints, and information with historical data.

2.3.1 Deterministic information

For a MEV with a fixed line, trip information can be fully understood in advance with ITS and GPS (global positioning system). Simultaneously, the energy-saving potential of a certain vehicle configuration can be explored, which provides a benchmark for assessing the optimality of other energy management strategies.

2.3.2 Information with constraints

In real-world driving, the priori information generally depends on drivers, vehicles and roads, which are obtained by the telematics or the Internet. If the constraints on trip information are available, the possible value of the trip information at each moment (or location, the same as below) can be limited by constraints about the drivers, vehicles, roads, or combination constraints [11]. By comprehensively considering the constraints from the drivers' driving style, dynamic performances of the vehicle, traffic flow and road conditions, the "drivers-vehicles-roads" co-constraint model is proposed to determine the profile of each trip information, as shown in Fig 2.



*a_d, a_{de}, a_b, a_{be} represents the the maximum acceleration, the excepted acceleration, the maximum deceleration, the excepted deceleration, repectively; p represents the level of road difficulty, q represents the level of driving ability.

Fig 2 "Drivers-vehicles–roads" co-constraint model.

With regard to the vehicles, the constraints mainly arise from restrictions on vehicle dynamics, which are mainly characterized by maximum speed, acceleration capability, braking capability and startup time. In terms of the roads, the constraints mainly come from facilities (slope, intersections, turntables, gates, etc.), instructions (traffic lights, traffic signs, markings) and traffic regulations (i.e., speed restrictions). For example, according to traffic regulation of China, for expressways, the speed of three lanes (from left to right) cannot be lower than $110, 90, 60\ km/h$.

The constraints about drivers are reflected in different driving styles and driving intentions. Driving styles can be classified into three types: aggressive, conservative, and stable. Driving intention means that the driver makes normal choices based on the results of interactions with the environment.

By combining the vehicles with the drivers, constraints are caused by different driving styles, which can be characterized by the expected acceleration (or deceleration) and the speed stability. By combining the drivers with the roads, the constraints are reflected in screening feasible routes, which depends on driving capability and road difficulty. Regarding the combination constraints of vehicles and roads, traffic flow reflects the smooth traffic or traffic congestion. According to the cumulative frequency curve of vehicle speed, the 85% speed and 15% speed are regarded as the maximum and minimum speed limit on a certain route, respectively.

By comprehensively considering the drivers, vehicles and roads, the driving time and mileage of each feasible route are different.

2.3.3 Information supported by history data

Supported by historical driving data, the state transition probability matrix can be obtained to reflect the distribution of the trip information.

Considering that route selection at multiple junctions conforms to the Markov property, a state transition probability matrix can be constructed based on the relative altitude and slope within a certain range at intersections. The probability matrix is defined as

$$T_{ij} = P\left[\theta_{k+1} = \bar{\theta}_j | H_k = \overline{H}_i\right] \tag{5}$$

Where H_k is the relative altitude at the moment k, and θ_{k+1} is the slope at the moment $(k+1)$.

Similarly, the speed and acceleration are regarded as state variables to generate the state transition probability matrix for speed prediction. When the vehicle is driving, new driving data are used as training data to update the state transition probability matrix.

2.4 Control

DP, as a global optimization method, transforms a multiple-phases problem into multiple single-phase problems and solves optimization quickly through recurrence relation between each phase.

2.4.1 Discretization of state feasible domain

Since the DP model is a numerical solution, it is necessary to mesh the state feasible domain. It mainly includes determining: (1) the boundary of state feasible domain; (2) a suitable discrete interval (ΔSOC); (3) the number of state points; (4) the SOC matrix. To reduce the computational burden, a simplified state feasible domain is developed to narrow the exploring region. According to previous studies, we found that the optimal SOC trajectory obtained by DP strategy declines linearly as a whole. Thus, we set a reference SOC (SOC_r), defined as:

$$SOC_r(k) = SOC_0 - \left(SOC_0 - SOC_f\right) \cdot k/N \tag{6}$$

Where, SOC_0 is the initial SOC, SOC_f is the terminal SOC, N is the total driving time, k is the moment.

The SOC range is set to 0.0625. Under multiple standard driving cycles, the maximum interval between the optimal SOC trajectory and the reference SOC trajectory is concluded in Tab 1.

Tab 1 The interval between optimal and reference trajectory.

Cycles	CSUDC	UDDS	NEDC	WLTP	HWEET
width	0.0058	0.0088	0.0209	0.0245	0.019

Based on above analysis, the maximum interval between optimal SOC trajectory and reference SOC trajectory is basically no more than 0.025. Particularly, for the driving cycle with uniform speed distribution, the maximum interval is basically no more than 0.01. To make the statistical rule more universal, simulations are performed under different vehicle models and various standard driving cycles. Based on the statistical rules, the state feasible domain can be simplified. The process is:

(1) Regarding the reference SOC trajectory as the baseline, and the maximum internal width as the radius, a banded-searching domain is initially formed.

(2) The available trip information is introduced to limit the maximum charging and discharging current, and then the simplified state feasible domain is formed.

2.4.2 Determination of feasible work mode

Based on mathematical analysis, a "kinetic/potential energy & onboard energy" conservation framework is put forward to determine the work modes between any two reachable state points. It can realize the one-to-one mapping of work mode and trip information.

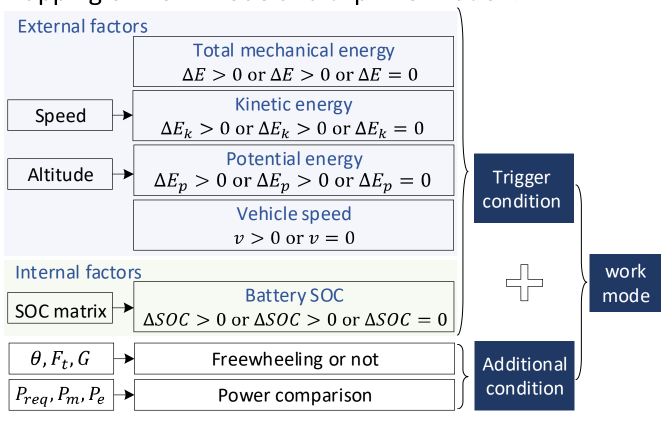


Fig 3 Energy conservation framework.

As shown in Fig 3, the vehicle speed and the change in mechanical energy (ΔE), kinetic energy (ΔE_k), and potential energy (ΔE_p) are regarded as external factors, while the change in battery SOC (ΔSOC) is taken as internal factor. The above factors are combined reasonably and feasibly to generate various trigger conditions. With each trigger condition, additional conditions can be added to determine the unique work mode of powertrain's controllable components. Regarding the additional conditions, it mainly takes the sliding conditions and power comparison (between the power demand and the maximum allowable power of the motor or the engine) into account.

Correspondingly, the fuel consumption and controls are determined under energy conservation framework, which are stored in the three-dimensional matrix.

2.4.3 Optimal energy distribution

By introducing the idea of graph theory, the optimal energy distribution problem is transformed into the shortest path problem from the starting point (initial SOC) to the ending point (terminal SOC).

To improve the computational efficiency of DP algorithm, a global-searching domain algorithm is developed to output all optimal state points, which form an optimal state trajectory domain. It mainly includes sequential calculation and reverse searching. The solution process is shown in Fig 4.

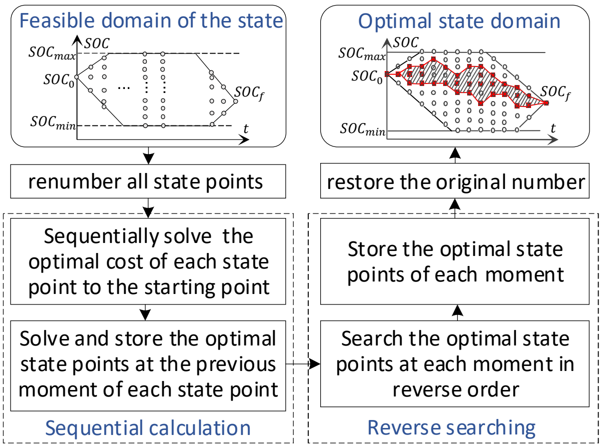


Fig 4 Solution process of global domain-searching algorithm.

2.5 *Application*

For the MEVs with single electric machine, the essence of energy management is to determine the optimal power split rate (PSR), which is defined as the ratio of engine power (P_e) and the required power (P_{req}).

Due to the diversity of driving cycles, a three-layer feed-forward neural network is applied to classify driving conditions. It inputs characteristic parameters of driving cycles, and outputs classification results (0/1/2), which correspond to urban, highway, and mixed driving conditions. To improve the real-time performance of DP strategy while ensuring the optimality, simulations are performed under multiple standard driving cycles. Then, the optimal results are regarded as samples to determine the optimal map (PSR graph), which takes vehicle speed, power demand and SOC as state variables.

3. RESULTS AND DISCUSSION

3.1 *Example*

A plug-in hybrid electric vehicle (PHEV) with P2 configuration is taken as the research object. Main component parameters of the PHEV are listed in Tab 2.

Tab 2 Main parameters of the PHEV model.

	Description	Value
Engine	Displacement	$1.5L$
	Maximum power/torque	$64kW/142Nm$
Motor	Maximum power/torque	$60\ kW/458Nm$
Battery	Voltage/capacity	$328V/10.57kw\cdot h$
Gear box	Gear	[3.45;1.98;1;0.75]
Vehicle	Gross mass/wheel radius	$1500kg/0.334m$
	Windward area	$2.25m^2$
	Final drive ratio	3.63
	Mechanical efficiency	0.92

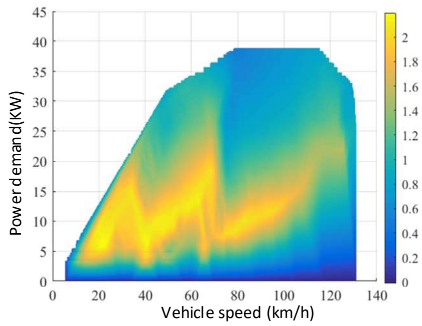
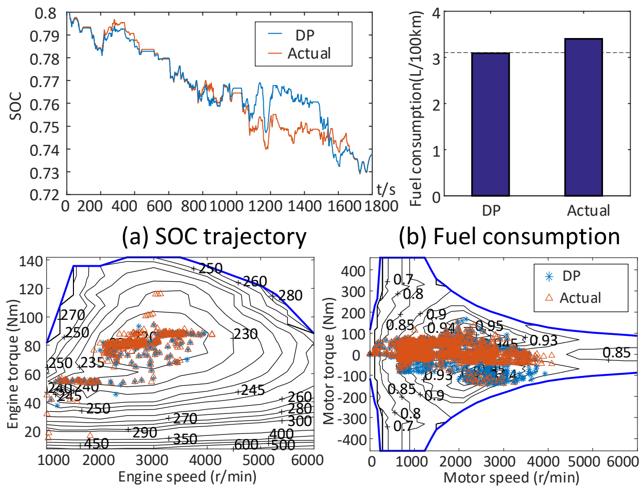


Fig 5 PSR graph (with sufficient SOC).



(a) SOC trajectory (b) Fuel consumption

(c) Engine (d) Motor

Fig 6 Optimal control results under WLTP cycle.

The WLTP cycle is regarded as a combined cycle of urban and highway driving. The fuel consumption for 100 kilometers under DP strategy is 2.2062 kg, equal to 3.0935 $L/100\ km$ (93#, $\rho = 0.725\ g/ml$). Based on the optimal results of simulations with different SOC range, the PSR map (with sufficient SOC) is generated to realize the practical application, as shown in Fig 5.

Compared with DP, the simulation results based on PSR map are shown in Fig 6.

3.2 Discussions

To evaluate the energy-saving potential of the proposed control strategy, that is, the ability to utilize global trip information, a comprehensive performance index (r) is proposed based on the statistical dispersion between actual operating points and optimal operating points obtained by DP strategy. Due that the essence of energy management is to allocate the power between various components, for the parallel hybrid configuration, the index is formulated as:

$$r = \frac{1}{2N}\sum_{k=1}^{N}\left[\frac{min\{P_E^k, P_{EDP}^k\}}{max\{P_E^k, P_{EDP}^k\}} + \frac{min\{|P_M^k|, |P_{MDP}^k|\}}{max\{|P_M^k|, |P_{MDP}^k|\}}\right] \quad (7)$$

Where P_{EDP}^k, P_{MDP}^k are the engine power and motor power at the moment k under DP strategy; P_E^k, P_M^k are the engine power and motor power at the moment k under the control strategy to be evaluated, respectively.

Based on the simulation results of the proposed mothed, the comprehensive index is $r = 0.8585$. That is, the energy-saving potential of this strategy reaches about 85% of DP strategy.

4. CONCLUSIONS

With the combination of drivers, vehicles, roads, networks and clouds, the real-time application of global optimization energy management becomes possible. A global optimization framework, namely “Cyber-physical system - Dynamic Programming” (CPS-DP), is proposed to standardize the optimizing process of DP strategy.

Drivers, vehicles, and roads are regarded as the main physical subjects. The acquisition of information from various physical subjects has been made realistic with the Internet of Vehicles (IOV). According to the available information, trip information is acquired from three scenarios: deterministic information, information with constraints or historical data. Specially, for the stochastic information, a “drivers-vehicles-roads” co-constraint model is proposed to determine speed limits. With the fixed vehicle configuration, the optimal energy distribution is achieved. It mainly includes: (1) meshing the state feasible domain; (2) Determining the feasible work mode based on energy conservation framework; (3) Developing a global domain-searching algorithm.

Simulations are performed under WLTP cycle. Regarding DP strategy as a benchmark, the energy-saving potential of the real-time control strategy can reach about 85% of DP strategy.

ACKNOWLEDGEMENT

This work was supported by the National Natural Science Foundation of China under Grant 51805201 and 52172365, Faw-volkswagen China Environmental Protection Foundation Automobile Environmental Protection Innovation Leading Program, International Clean Energy Talent Program (iCET2019) of China Scholarship Council under Grant 201904100052, and NDANEV OPENLAB.

REFERENCE

[1] Bertsekas, D.P. Dynamic Programming and Optimal Control, Volume I, 4th Edition, Athena Scientific: Belmont, MA, USA, 2017.

[2] Zhou W, Yang L, Cai YS, Ying TX. Dynamic programming for New Energy Vehicle based on their work modes part I: Electric Vehicles and Hybrid Electric Vehicles. J Pow Sour 2018; 406:151-166.

[3] Zhang C, Vahidi A. Real-Time Optimal Control of Plug-in Hybrid Vehicles with Trip Preview. Pro. American Control Conference 2010; 6917-6922.

[4] He HW, Guo JQ, Peng JK, Tan HC, Sun C. Real-time global driving cycle construction and the application to economy driving pro system in plug-in hybrid electric vehicles. Energy 2018; 152: 95-107.

[5] Lin CC, Jeon S, Peng H, Lee JM. Driving pattern recognition for control of hybrid electric trucks. Vehicle System Dynamic 2004; 42 (1-2): 41-58.

[6] Peng JK, He HW, Xiong R. Rule based energy management strategy for a series-parallel plug-in hybrid electric bus optimized by dynamic programming. Appl Energy 2017; 185: 1633-1643.

[7] Liu C, Murphey YL. Optimal Power Management Based on Q-Learning and Neuro-Dynamic Programming for Plug-in Hybrid Electric Vehicles. IEEE Trans Neural Netw Learn Syst 2020; 31(6): 1942-1954.

[8] Chen Z, Hu HJ, Wu YT, Zhang YJ, Li G, Liu YG. Stochastic model predictive control for energy management of power-split plug-in hybrid electric vehicles based on reinforcement learning. Energy 2020. 211: 118931.

[9] Liu JC, Chen YZ, Zhan JY, Shang F. Heuristic Dynamic Programming Based Online Energy Management Strategy for Plug-In Hybrid Electric Vehicles. IEEE Trans Veh Technol 2019; 68(5): 4479-4493.

[10] Xu N, Kong Y, Chu L, Ju H, Yang ZH, Xu Z, Xu ZQ. Towards a Smarter Energy Management System for Hybrid Vehicles: A Comprehensive Review of Control Strategies. Applied Sciences-Basel 2019; 9(10): 2026.

[11] Kong Y, Xu N, Zhang YJ, Sui Y, Ju H, Liu H, Xu Z. Acquisition of full-factor trip information for global optimization energy management in multi-energy source vehicles and the measure of the amount of information to be transmitted. Energy 2021; 236: 121423.