Research

Learning Based Energy Management Strategy for Hybrid Electric Vehicle

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May 20, 2020

Contents

Introduction

Energy management methods for hybrid electric vehicles(HEVs):

Rule-based methods

(deterministic /fuzzy rules, ...)

- Easy implementation for real industry
- Acceptable online calculation amount
- Tightly depending on a certain vehicle parameter / certain driving cycle

Optimization-based methods

(DP, ECMS, MPC, ...)

- Achieving optimal/suboptimal control strategies
- Rely on the priori knowledge (for global optimal methods like DP and MPC)
- Difficult for direct real-time implementation due to parameter tuning (like equivalence factor in ECMS) or calculation amount

Learning-based methods

(Q-learning, DQL, DDQL, DDPG, ...)

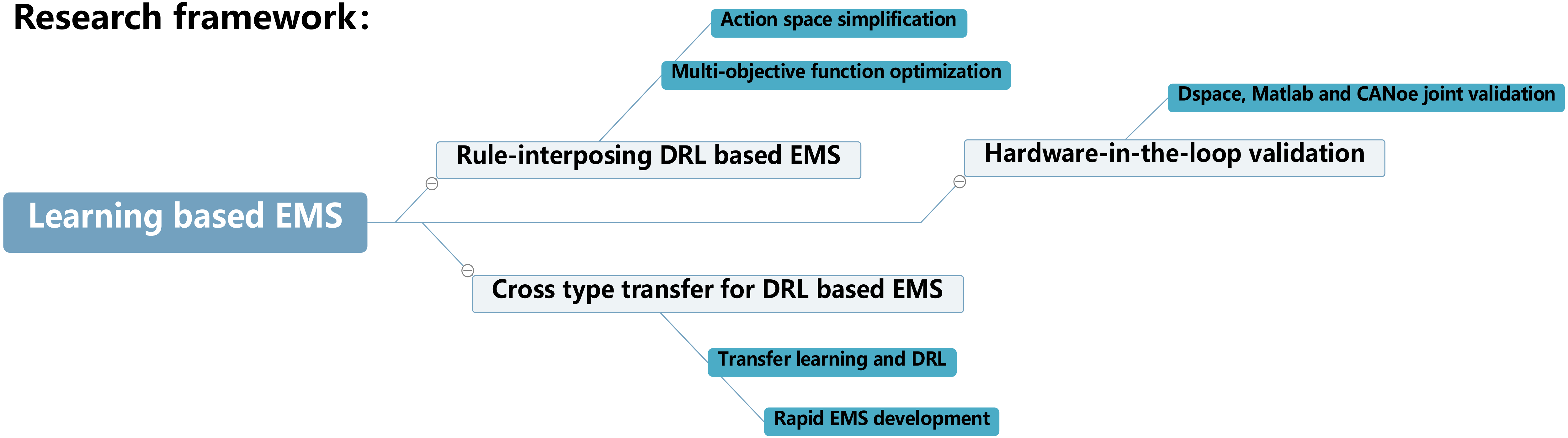
- Close to the global optimum
- Strong learning ability and adaptability under complex driving cycles
- Consume less computational resources

Introduction

Research motivation:

- Utilization of expert knowledge of HEV in deep reinforcement learning (DRL) based energy management strategy (EMS)
- Rapid development of EMS for different types of hybrid electric vehicles (HEVs)
- Real-world application of DRL-based EMS

Research framework:



HEV Powertrain Model

A **backward HEV model** is built for the training and evaluation of EMS. Energy management system mainly deals with the power allocation among multiple power sources.

Vehicle Dynamics

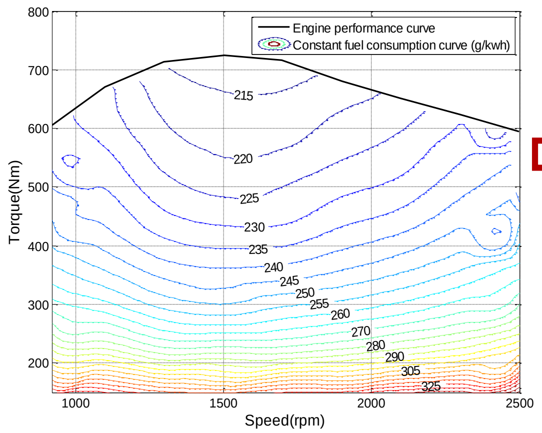
modeled by longitudinal force balance equation:

$$F_t = F_a + F_r + F_i + F_w$$

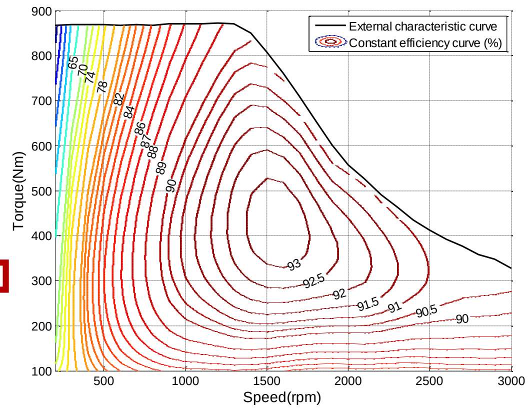
$$F_a = ma, F_r = mgf\cos\theta, F_i = mg\sin\theta, F_w = \frac{C_d A_f}{21.15} v^2$$

Engine, Generator, and Motors

modeled by corresponding efficiency maps from bench experiments



Engine fuel map

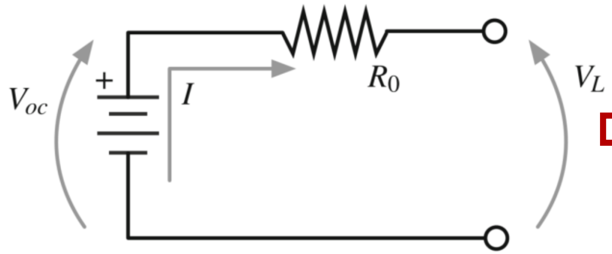


Motor/generator efficiency map

Battery Pack

modeled as equivalent circuit-based model:

$$\dot{SoC} = \frac{\left(V_{oc} - \sqrt{V_{oc}^2 - 4R_{batt}P_{batt}}\right)}{2R_{batt}C_{batt}}$$

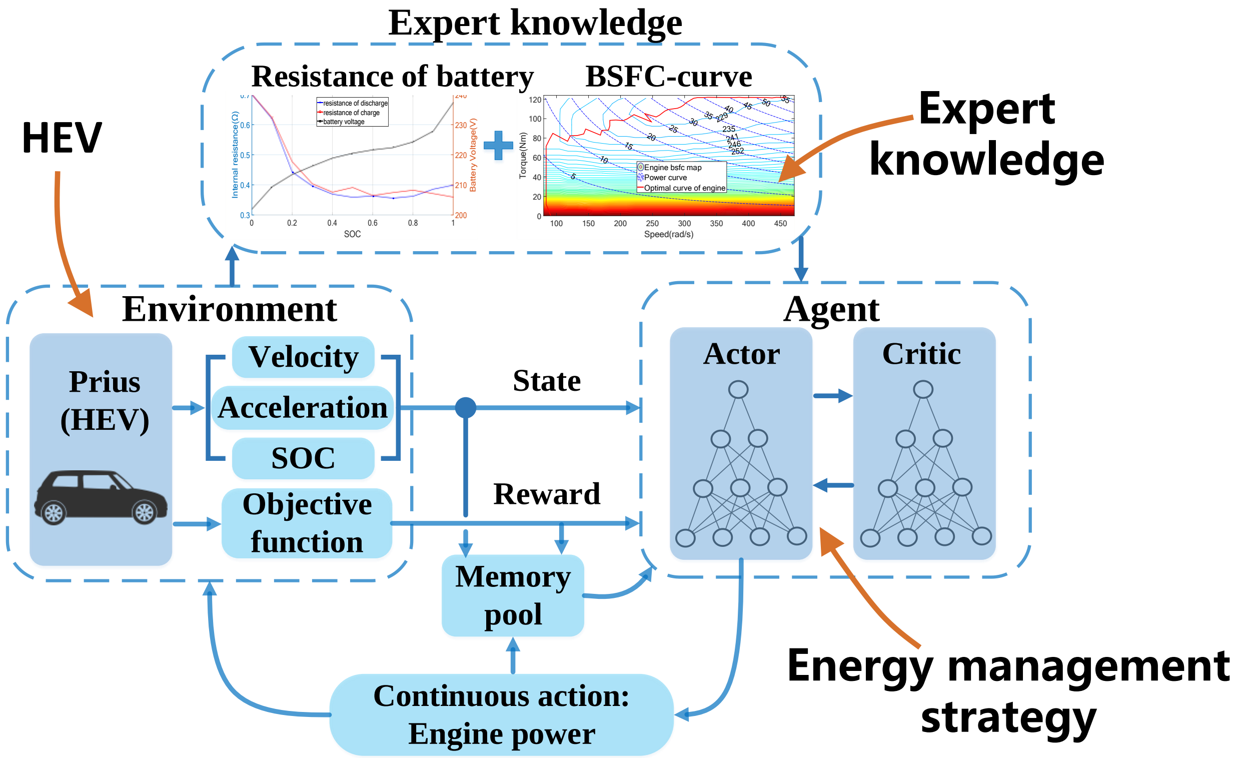


Battery equivalent circuit-based model

Rule-interposing DRL based EMS for power-split HEV

Given the slow and resource-intensive training processes of DRL, an improved energy management framework that embeds expert knowledge into DDPG is proposed.

Rule-interposing DRL based EMS



- **State** (input of DRL-based EMS)

$$state = \{SoC, velocity, acceleration\}$$

- **Action** (output of DRL-based EMS)

$$\boxed{action = \{engine\ power\}}$$

- **Multi-objective reward function:**

$$\boxed{reward = -\{\alpha[fuel(t)] + \beta[SoC_0 - SoC(t)]^2\}}$$

Charge-sustaining reference value of SoC (SoC_0)   **Current SoC** ($SoC(t)$)

R. Lian, J. Peng, Y. Wu, H. Tan, and H. Zhang, "Rule-interposing deep reinforcement learning based energy management strategy for power-split hybrid electric vehicle," Energy, vol. 197, p. 117297, 2020.

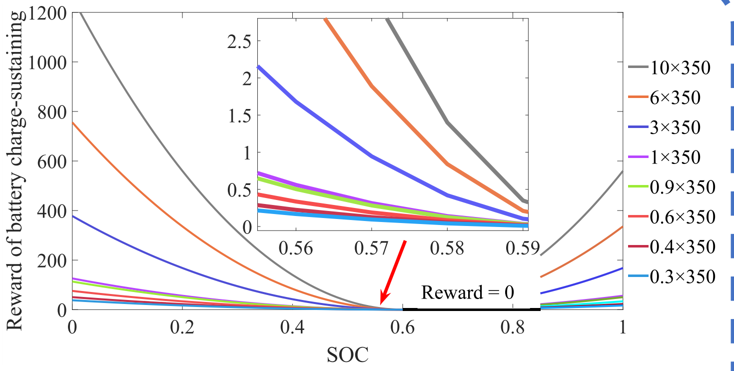
Rule-interposing DRL based EMS for power-split HEV

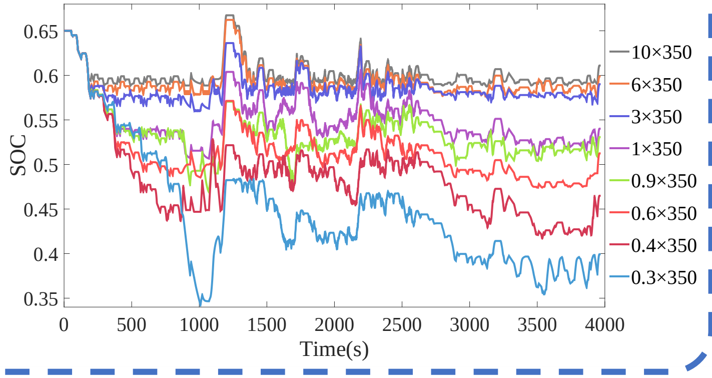
Multi-objective reward function: by allocating weights between the fuel consumption and the battery charge sustaining properly, fuel consumption can be significantly reduced by up to 4%.

α: fixed to 1

β: from 0.3×350 to 10×350

The higher the β, the better battery charge-sustaining effect the SoC trajectory shows.





Comparison of different weight settings

The weight of battery charge-sustaining (β)	Fuel consumption (L/100Km)	Terminal SoC	Fuel consumption of DP(L/100Km)	Fuel economy (%)
0.3 × 350	3.755	0.403	3.359	critical point 89.4 ×
0.4 × 350	3.704	0.466	3.428	92.5
0.6 × 350	3.721	0.509	3.474	93.4 √
0.9 × 350	3.758	0.531	3.503	93.2
1 × 350	3.795	0.541	3.506	92.4
3 × 350	3.925	0.590	3.563	critical point 90.8
6 × 350	3.942	0.603	3.585	90.9
10 × 350	3.958	0.611	3.602	91.0

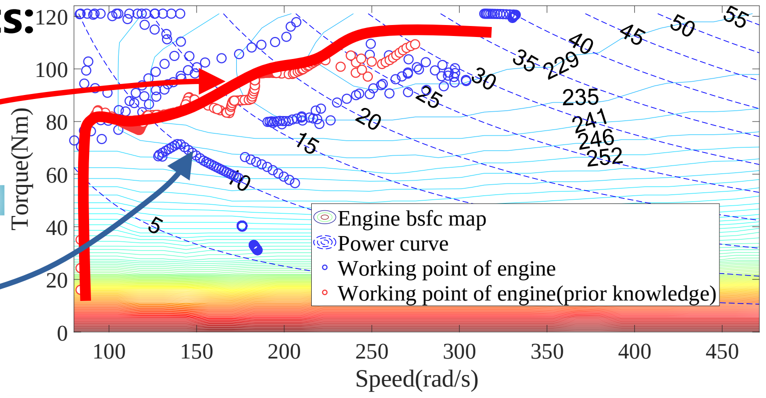
R. Lian, J. Peng, Y. Wu, H. Tan, and H. Zhang, "Rule-interposing deep reinforcement learning based energy management strategy for power-split hybrid electric vehicle," Energy, vol. 197, p. 117297, 2020.

Rule-interposing DRL based EMS for power-split HEV

Simplified action space: with a limited number of training episodes, the performance of improved DDPG is better than that of original DDPG.

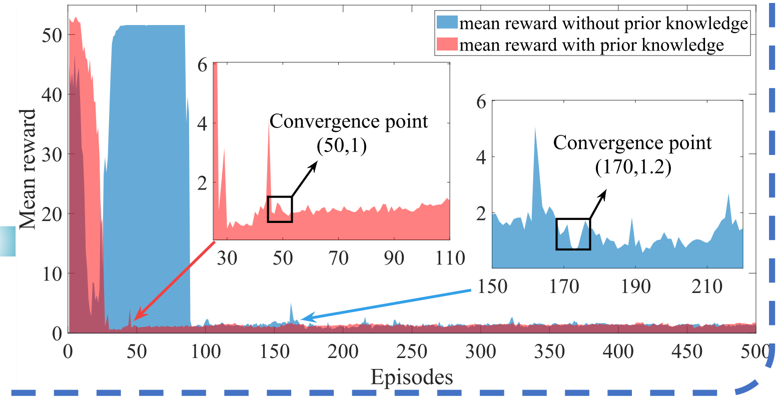
Distribution of engine working points:

- **Improved DDPG:** in the area of low fuel consumption rate
- **Original DDPG:** be scattered throughout the engine map



Convergence speed:

- **Improved DDPG:** 50th episode
- **Original DDPG:** 170th episode



Comparison between two DDPG algorithms

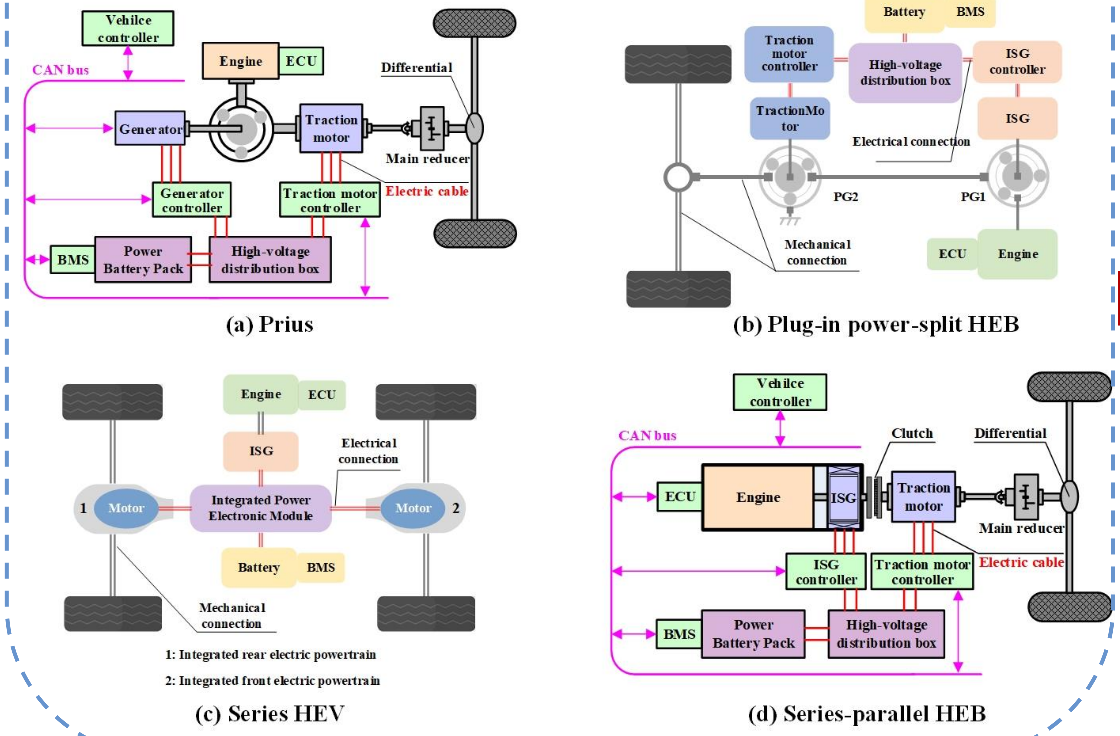
Algorithm	Improved DDPG	DDPG
Fuel consumption (L/100Km)	**3.64 √**	3.70
Terminal SoC	0.596	0.598
Fuel consumption of DP (L/100Km)	3.47	3.48
Fuel economy (%)	**95.3 √**	94.1
Convergence speed (episodes)	**50 √**	170

R. Lian, J. Peng, Y. Wu, H. Tan, and H. Zhang, "Rule-interposing deep reinforcement learning based energy management strategy for power-split hybrid electric vehicle," Energy, vol. 197, p. 117297, 2020.

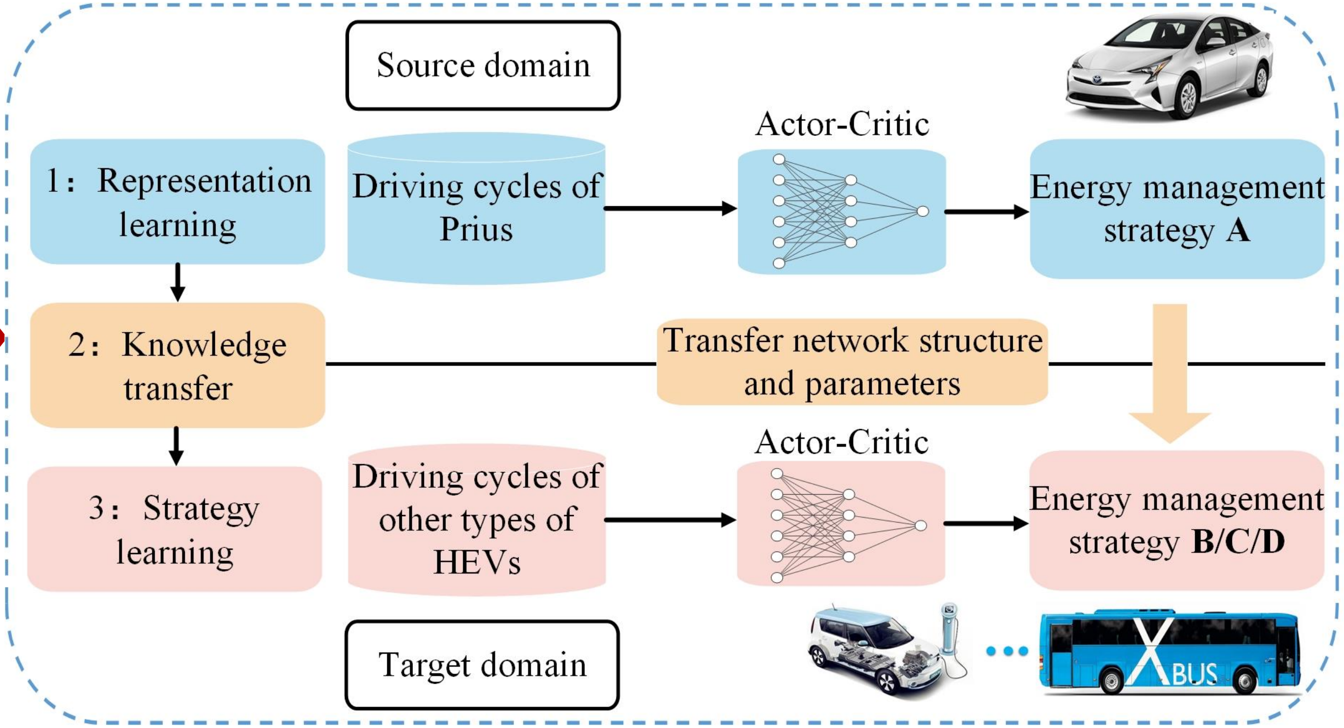
Cross-type transfer for DRL based HEV energy management

Due to the complicated and time-consuming development process of EMSs, deep transfer reinforcement learning is proposed to implement EMSs for different types of HEVs.

The diversity in powertrain structures of HEVs



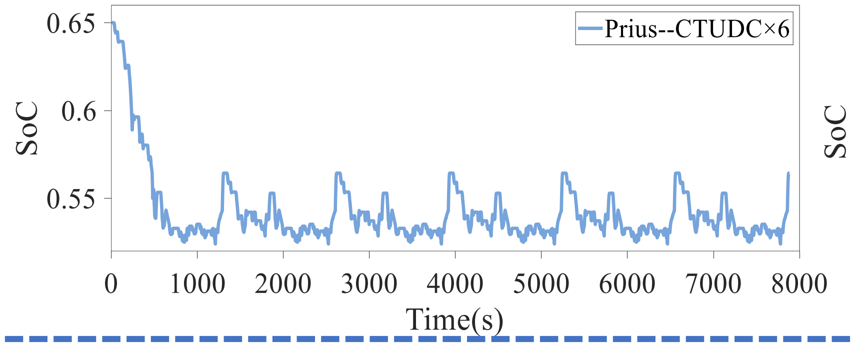
Sketch map of network-based deep transfer learning

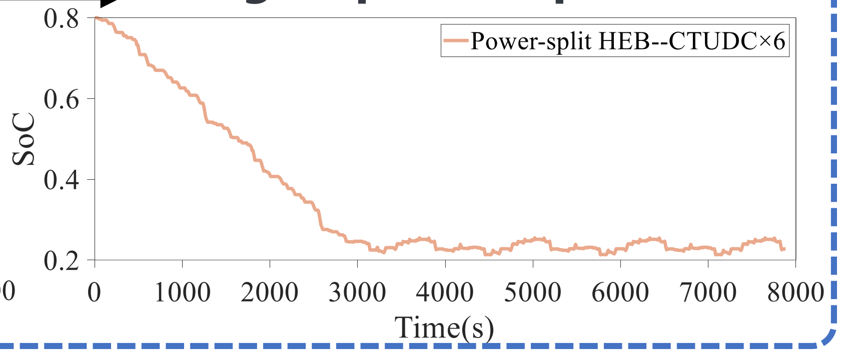


Cross-type transfer for DRL based HEV energy management

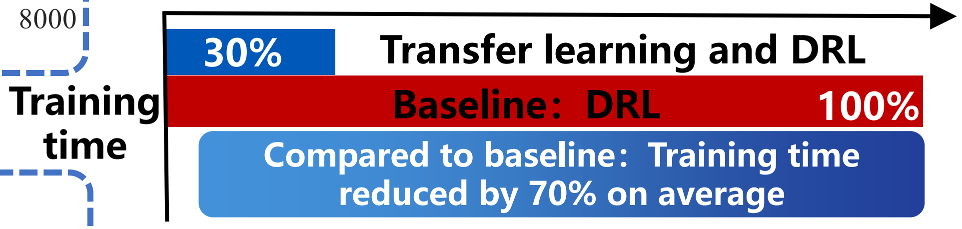
By incorporating transfer learning into DRL-based EMS for HEVs, an average 70% gap from the baseline in respect of convergence efficiency has been achieved.

Prius → EMS transfer → Plug-in power-split HEB

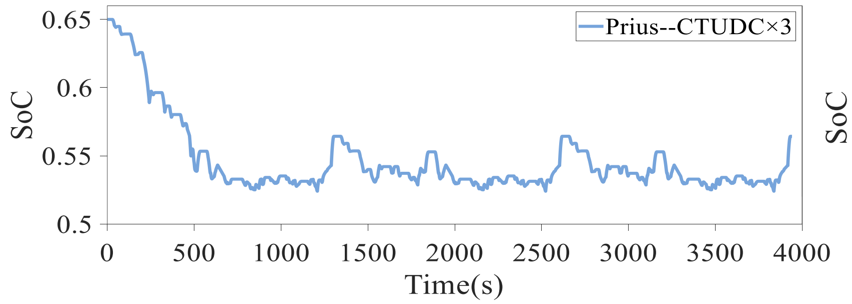


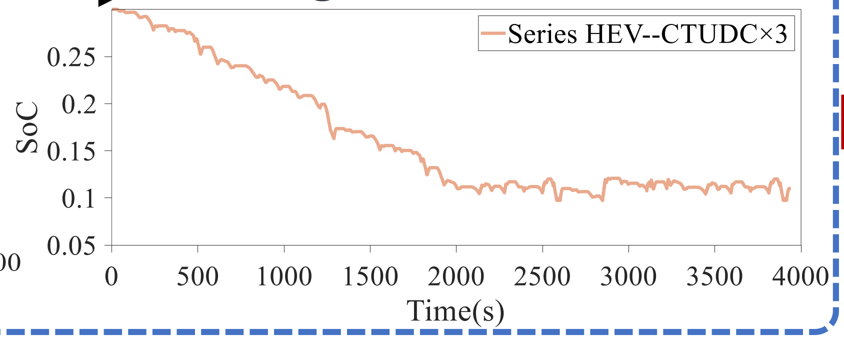


EMS	Training time
baseline	100%
Transfer the first layer	**45.5%**
Transfer the first two layers	36.4%
Transfer the first three layers	**20.0%**
Transfer all layers	**37.3%**



Prius → EMS transfer → Plug-in series HEV

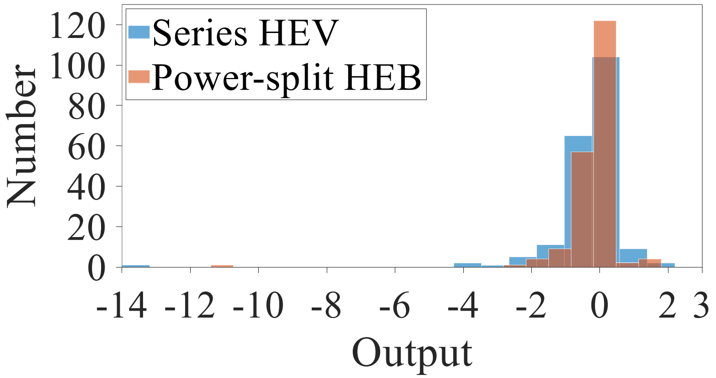




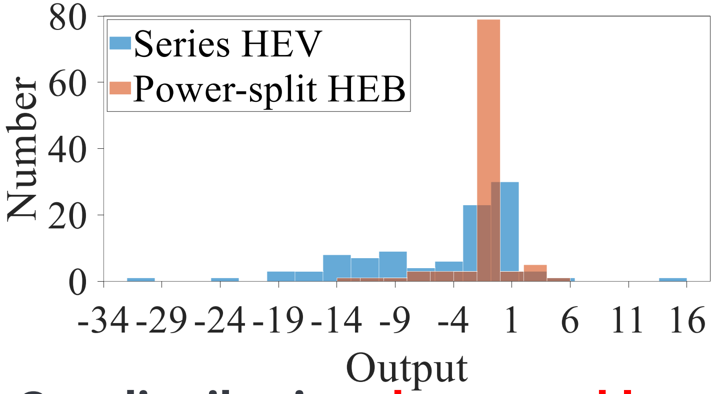
EMS	Training time
baseline	100%
Transfer the first layer	**30.5%**
Transfer the first two layers	22.5%
Transfer the first three layers	**19.5%**
Transfer all layers	**23.5%**

Cross-type transfer for DRL based HEV energy management

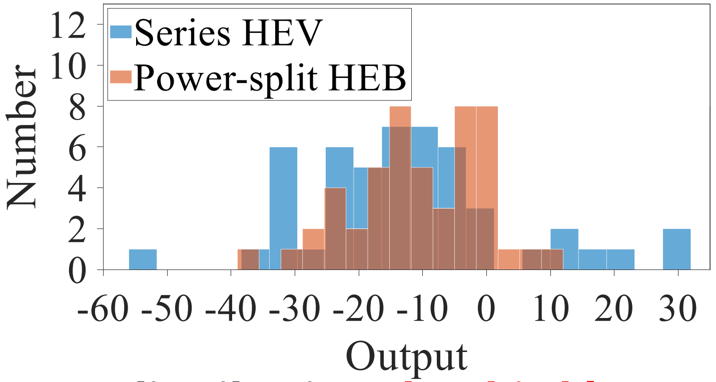
Interpretability of EMS transfer: representations will gradually transition from **general** to **specific** with the depth increase of neural network layers.



Out distribution **the first layer**



Out distribution **the second layer**



Out distribution **the third layer**

The similarity degrees of neural network outputs between the two HEVs decrease with the depth increase of neural network layers.

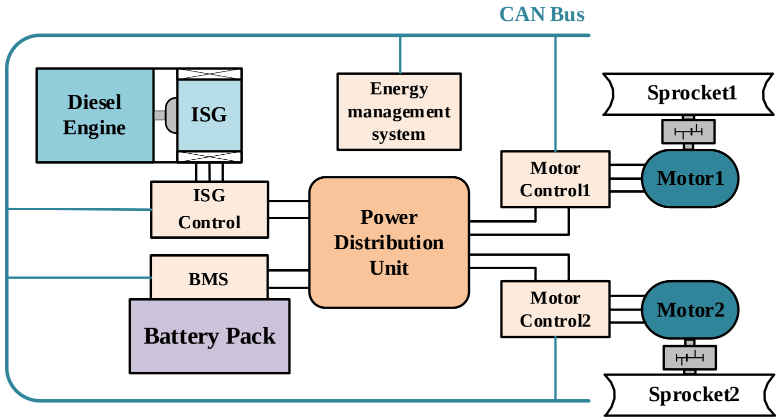
Output	Euclidean distance
Output of the first layer	20.9
Output of the second layer	82.7
Output of the third layer	146.1
Action	168.0

general

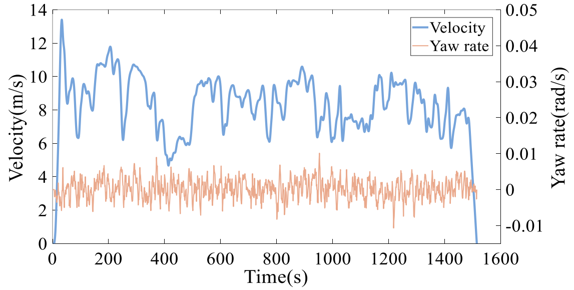
specific

Hardware-in-the-loop validation

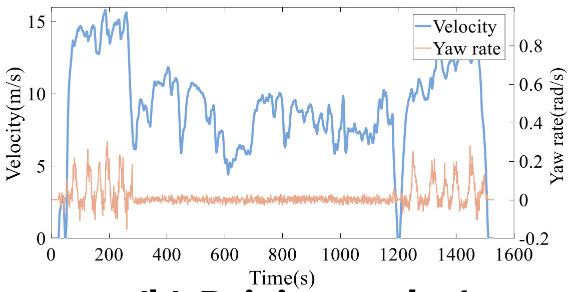
The real-world application of DRL-based EMSs is verified by a HiL platform through the Dspace, Matlab and CANoe joint validation method.



The series hybrid tracked vehicle



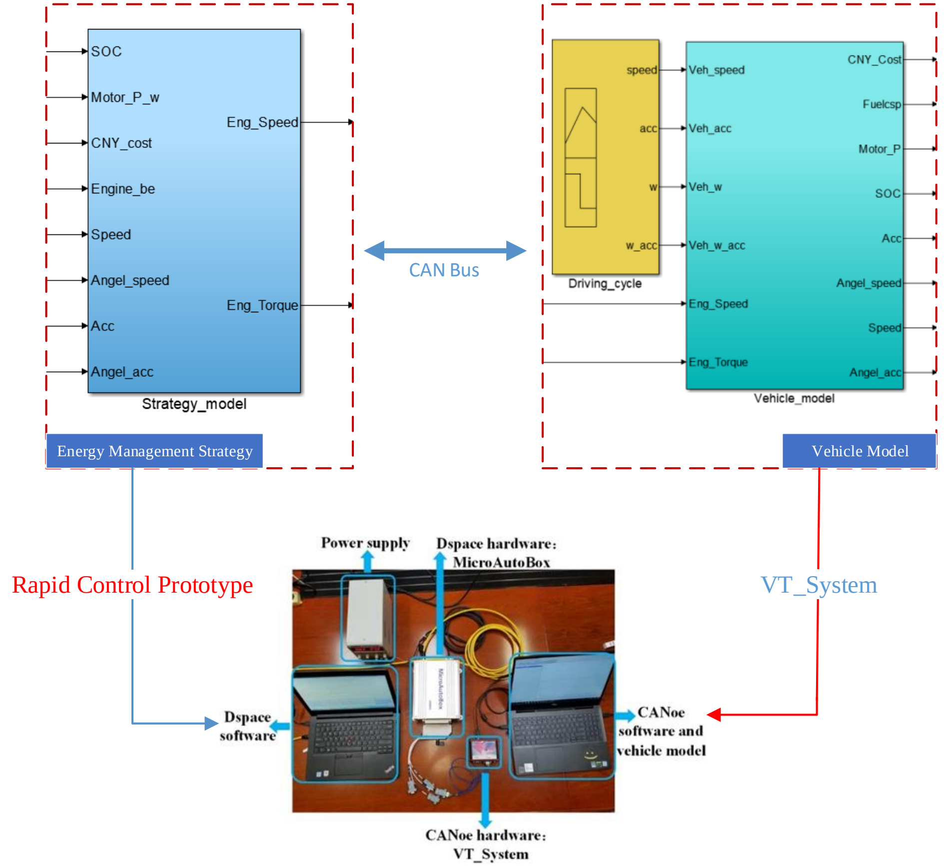
(a) Driving cycle 0



(b) Driving cycle 1

Real driving cycles

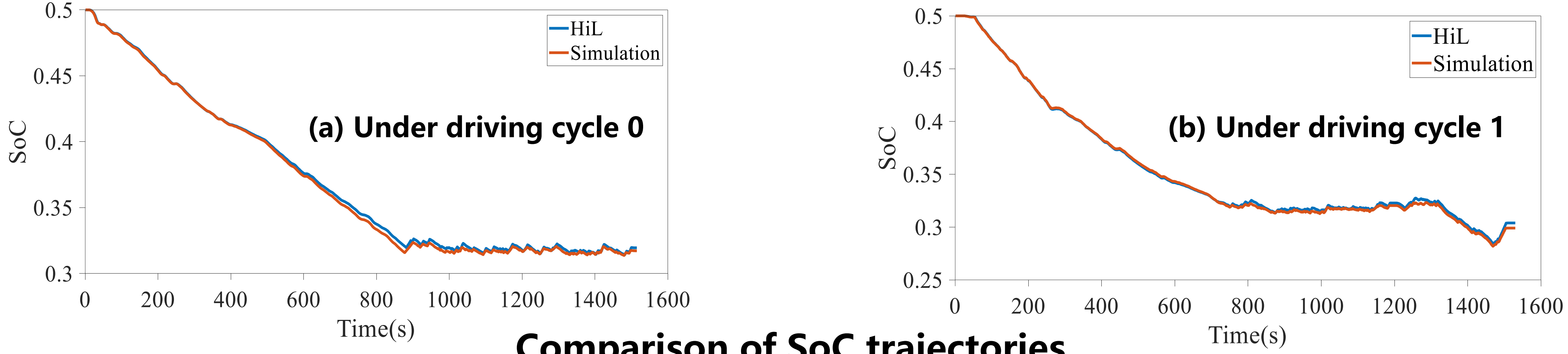
Strategy Validation



HiL Platform

Hardware-in-the-loop validation

The embedded EMS keeps the same level of the well-developed simulation EMS, which can ensure the performance of fuel economy and battery charge sustaining throughout the trip.



Comparison of SoC trajectories

Platform	Driving cycle	CNY cost (￥)
HiL	Driving cycle 0	16.86
	Driving cycle 1	20.28
Simulation	Driving cycle 0	17.64
	Driving cycle 1	20.75

Future work

Generating and deploying packages for DRL-based EMS at real HEVs

- **Cloud computing:** training and generating packages
- **Internet of vehicles:** communication
- **Vehicle:** implementation of EMS、collecting data

Human-like autonomous car-following model

- **Human-like driving study**
- **Vehicle longitudinal control**
- **Energy saving**

Publication

R. Lian, J. Peng, Y. Wu, H. Tan, and H. Zhang, "**Rule-interposing deep reinforcement learning based energy management strategy for power-split hybrid electric vehicle**," Energy, vol. 197, p. 117297, 2020.

- **Code:** https://github.com/lryz0612/DRL-Energy-Management

File(**Click to open**)

R. Lian, H. Tan, J. Peng, Q. Li, Y. Wu, "**Cross-type transfer for deep reinforcement learning based hybrid electric vehicle energy management**," IEEE Transactions on Vehicular Technology. (Under review)

File(**Click to open**)

R. Han, **R. Lian**, H. He, X. Han, "**Deep reinforcement learning based energy management strategy for a hybrid electric tracked vehicle including lateral dynamics**," Applied Energy. (Under review)

Thank you for your attention!

May 20, 2020