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ENERGY MANAGEMENT STRATEGY FOR HYBRID ELECTRIC VEHICLE BASED ON INTELLIGENT TRANSPORT SYSTEM

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Abstract: Hybrid electric vehicles (HEVs) have the potential to reduce fuel consumption and emissions while improving the performance of conventional vehicles. However, the design of an energy management strategy for HEVs is a challenging problem due to the complex interactions between the vehicle's power sources and the driving conditions. The study commences with a comprehensive understanding of the problem domain, emphasizing the need to balance the power allocation between the internal combustion engine (ICE) and the electric motor to meet performance requirements while minimizing fuel consumption. Data collected from various vehicle sensors are preprocessed and used to train a DRL agent, implemented through neural network architectures. In this paper, we propose a new energy management strategy for HEVs based on DRL. The proposed strategy uses a DRL agent to learn how to control the power flow between the HEV's power sources in order to minimize fuel consumption and maximize range. The DRL agent is trained using a dataset of driving cycles that are representative of the operating conditions of the HEV. The performance of the proposed strategy is evaluated on a variety of driving cycles and it is shown to be able to significantly improve the fuel economy of the HEV. The proposed strategy has several advantages over traditional energy management strategies. First, it is able to adapt to changes in the driving conditions. Second, it is able to learn the optimal control policy even in the presence of uncertainty. Third, it is able to handle complex interactions between the vehicle's power sources. The proposed strategy is a promising approach for developing energy management strategies for HEVs. The results of this study show that DRL can be used to develop efficient and robust energy management strategies for HEVs.

***Keywords* - Energy management strategy, Hybrid electric vehicle, DRL, Fuel economy, Range.**

I. INTRODUCTION

In the contemporary era of increasing environmental awareness and the pressing need to mitigate the adverse effects of greenhouse gas emissions, the transportation sector stands at the forefront of transformation. Hybrid Electric Vehicles (HEVs) have emerged as a promising solution, strategically combining conventional internal combustion engines (ICE) with electric propulsion systems to deliver superior fuel efficiency and reduced emissions. At the heart of this technological advancement lies the Energy Management Strategy (EMS), a pivotal component responsible for orchestrating the distribution of power between the ICE and the electric motor. This distribution, driven by the EMS, has a direct and profound impact on the vehicle's performance, fuel consumption, and environmental footprint. Traditionally, EMS development has relied on rule-based and heuristic control algorithms. While these approaches have proven effective to some extent, they often fall short in harnessing the full potential of HEV technology, particularly when confronted with the complexities of real-world driving scenarios. As a result, there exists a compelling need to explore more sophisticated and adaptive control methodologies capable of optimizing EMS in dynamic and uncertain environments.

In this context, the intersection of Deep Reinforcement Learning (DRL) and automotive technology offers an exciting frontier for research and innovation. DRL, a subset of machine learning, has demonstrated remarkable success in various domains, from playing complex games to optimizing financial portfolios. Its core strength lies in its ability to learn optimal control policies through interaction with an environment, a characteristic ideally suited for the dynamic and adaptive nature of EMS in HEVs. This research endeavor embarks on the journey to harness the potential of DRL in redefining EMS for HEVs. By integrating the power of neural networks, reinforcement learning algorithms, and a comprehensive simulation environment, we seek to develop an intelligent EMS that not only surpasses the performance of conventional strategies but also adapts seamlessly to diverse driving conditions, optimizing fuel efficiency while preserving vehicle performance and meeting environmental objectives. Throughout this research paper, we will delve into the intricacies of EMS design for HEVs using DRL techniques. We will explore the data collection and preprocessing steps, model selection, and the creation of a realistic simulation environment that captures the essence of HEV behavior. Key to this endeavor is the formulation of a reward function that motivates the DRL agent to make decisions that prioritize fuel efficiency and adhere to performance constraints. Training the DRL agent, validation, and testing are crucial milestones on our journey, ensuring that the intelligent EMS not only learns efficiently but also generalizes well to real-world driving conditions. We will also address safety and robustness concerns, recognizing the imperative of preventing risky behaviors and managing unforeseen challenges in the field. Furthermore, this research does not exist in isolation; it unfolds in a broader context of sustainable transportation and environmental responsibility. Thus, we will emphasize the importance of regulatory compliance, comprehensive documentation, and reporting, ensuring the seamless integration and widespread adoption of HEVs equipped with the proposed EMS.

II. FLOW DIAGRAM OF THE PROPOSED EMS

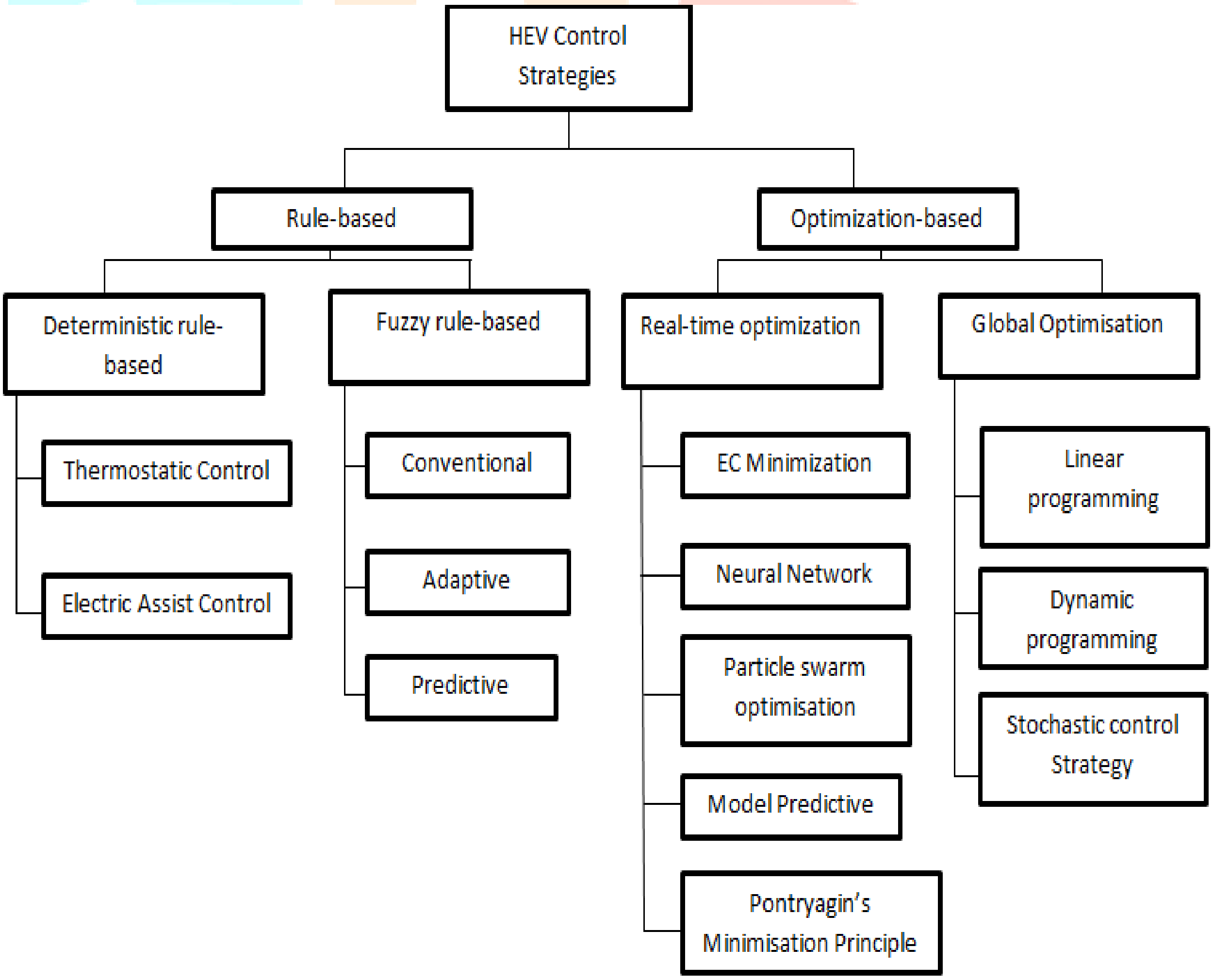

Fig. 1: Flow diagram of the proposed interleaved EMS

Hybrid Electric Vehicles (HEVs) have emerged as a promising solution to address the dual challenges of reducing fuel consumption and minimizing greenhouse gas emissions in the transportation sector. HEVs integrate both internal combustion engines (ICE) and electric propulsion systems, offering improved fuel efficiency and lower emissions compared to traditional vehicles. However, optimizing the allocation of power between the ICE and electric motor, known as the Energy Management Strategy (EMS), remains a complex and dynamic problem.

Traditional EMS approaches are often rule-based or heuristic, lacking the adaptability and optimization potential required to fully exploit the benefits of HEV technology. Real-world driving conditions, including varying traffic, road gradients, and driver behavior, necessitate an EMS that can make dynamic and informed decisions to maximize fuel efficiency while ensuring vehicle performance and adherence to environmental standards.

The primary objective of this research is to design, develop, and evaluate an intelligent Energy Management Strategy (EMS) for Hybrid Electric Vehicles (HEVs) using Deep Reinforcement Learning (DRL) techniques. The EMS should be capable of dynamically optimizing power distribution between the internal combustion engine (ICE) and the electric motor in real-time, considering factors such as vehicle speed, battery state of charge (SoC), road conditions, and driver behavior.

III. PROPOSED METHODOLOGY

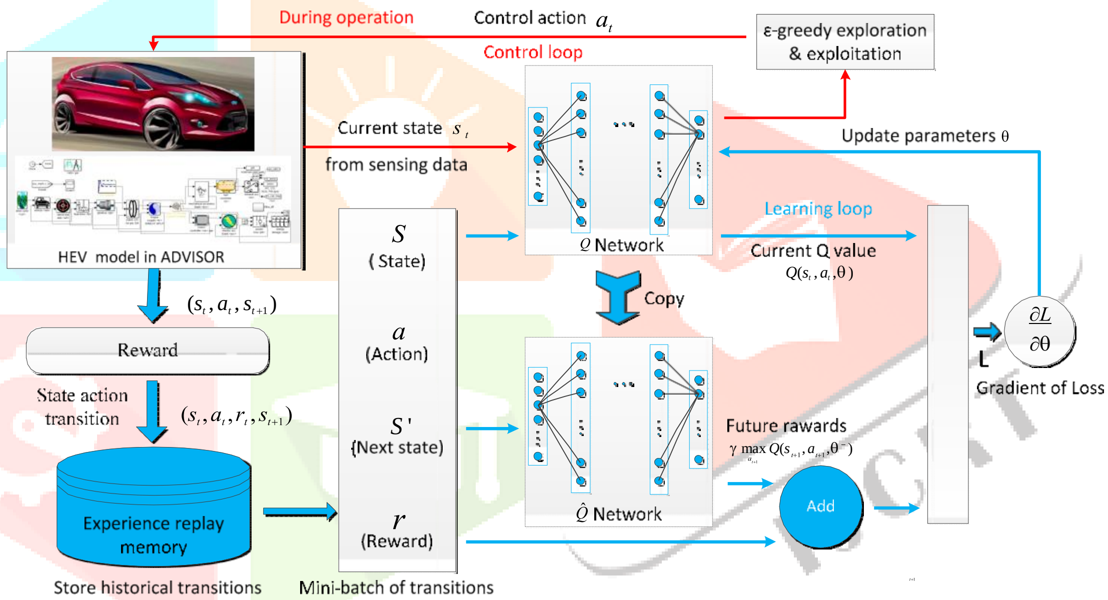

Figure 2: Deep reinforcement learning (DRL)-based framework for HEV EMS

PARAMETERS

Table 1. Summary of the HEV parameters.

Part or Vehicle	Parameters Value
Spark Ignition (SI) engine	Displacement: 1.0 L Maximum power: 50 kW/5700 r/min Maximum torque: 89.5 Nm/5600 r/min
Permanent magnet motor	Maximum power: 10 kW Maximum torque: 46.5 Nm
Advanced Ni-Hi battery	Capacity: 6.5 Ah Nominal cell voltage: 1.2 V Total cells: 120
Automated manual transmission	5-speed GR: 2.2791/2.7606/3.5310/5.6175/11.1066
Vehicle	Curb weight: 1000 kg

3.1. System State:

- In the DRL algorithm, control actions are determined based on the system states.
- The key system states selected in this study are the total required torque (Tdem) and the battery state-of-charge (SOC).
- The system state space is represented as s(t) = (Tdem(t), SOC(t))T, where Tdem(t) is the required torque at time t, and SOC(t) is the battery state of charge at time t.

3.2. Control Action:

- The core problem in HEV energy management is determining the torque-split ratio between the internal combustion engine (ICE) and the battery.
- The control action in this study is represented as A(t) = Te(t), where Te(t) is the output torque from the ICE.
- Te(t) is discretized to create an action space A = A1, A2, ..., An, where n is the degree of discretization (in this study, n = 24).

3.3. Immediate Reward:

- The immediate reward plays a crucial role in the DRL algorithm, as it guides the learning process.
- The objective of the HEV EMS is to minimize vehicle fuel consumption while maintaining drivability and battery health.
- The immediate reward is defined as the reciprocal of the ICE fuel consumption at each time step.
- A penalty value is introduced to penalize situations when the SOC exceeds a threshold.
- The immediate reward is defined using equations, ensuring lower ICE fuel consumption while satisfying SOC constraints.

3.4. Formulation of EMS as Dynamic Optimization:

- The goal of the EMS for the HEV is to find the optimal control strategy, π∗, that maps observed states to control actions.
- This control strategy is formulated as an infinite-horizon dynamic optimization problem, where the objective is to maximize the cumulative reward.
- The Bellman Equation is used to calculate the optimal value, Q∗(st, at), which represents the maximum accumulative reward.
- The Q-learning method is used to update the value estimation, facilitating the convergence to the optimal action value function.

$$Q^*(s_t, a_t) = E[r_{t+1} + \gamma \max_{a_{t+1}} Q^*(s_{t+1}, a_{t+1}) | s_t, a_t] \quad (3)$$

The Q-learning method is used to update the value estimation, as shown in Equation (4).

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \eta(r_{t+1} + \gamma \max_{a_{t+1}} Q_t(s_{t+1}, a_{t+1}) - Q_t(s_t, a_t))$$

Deep Reinforcement Learning-Based EMS

Deep reinforcement learning-based EMS is developed which combines a deep neural network and conventional reinforcement learning. The EMS makes decisions only based on the current system state since the proposed EMS is an end-to-end control strategy. This deep reinforcement neural network can also be called a deep Q-network (DQN). In the rest of this section, value function approximation, DRL algorithm design, and the DRL-based algorithm online learning application are presented.

3.4 Value Function Approximation

The state-action value is represented by a large, but limited, number of states and actions table, i.e., the Q table, in conventional reinforcement learning. However, a deep neural network is taken in this work to approximate the Q-value by Equation (3). As depicted in Figure 3, the inputs of the network are the system states.

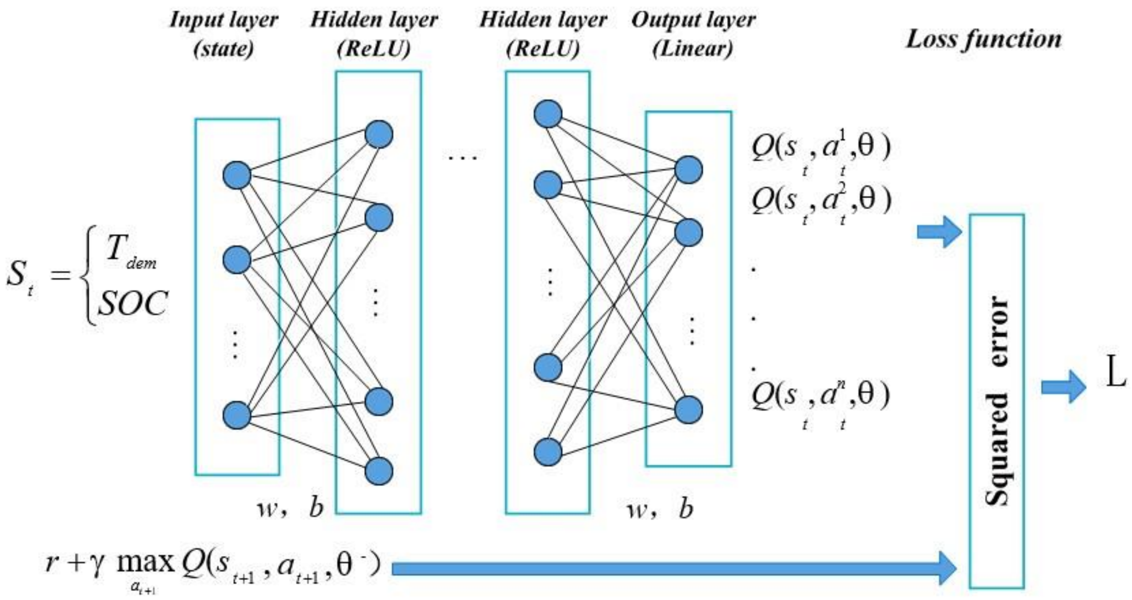

Figure 3. Structure of the neural network.

$$T_{dem} = \frac{T_{dem} - \min(T_{dem})}{\max(T_{dem}) - \min(T_{dem})}$$

3.5 DRL Algorithm Design

Algorithm 1: Deep Q-Learning with Experience Replay

Initialize replay memory D to capacity N

Initialize action-value function Q with random weights ϑ

Initialize target action-value function $\hat{Q}$ with weights $\vartheta^- =$

1: **For** episode = 1, M **do**
2: Reset environment: $s_0 = (SOC_{Initial}, T_0)$
3: **For** $t = 1, T$, **do**
4: With probability ε select a random action a_t
otherwise select $a_t = \max_a Q(s_t, a; \vartheta)$
5: Choose action a_t and observe the reward r_t
6: Set $s_{t+1} = (SOC_{t+1}, T_{t+1})$
7: Store (s_t, a_t, r_t, s_{t+1}) in memory D
8: Sample random mini-batch of (s_t, a_t, r_t, s_{t+1}) from D
9: **if** terminal s_{j+1}: Set $y_j = r_j$
else set $y_j = r_j + \gamma \max_a \hat{Q}(s_{j+1}, a_{j+1}; \vartheta^-)$
10: Perform a gradient descent step on $(y_j - Q(s_j a_j; \vartheta))^2$
11: Every C steps reset $\hat{Q} = Q$
12: **end for**

13: **end for**

IV EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Offline Application

4.1.1 Experiment Setup

In order to evaluate the effectiveness of proposed DRL-based algorithm, simulation experiments are done in MATLAB and the ADVISOR co-simulation environment. The offline learning application is evaluated firstly and the UDDS driving cycle is used in the learning process. The simulation model for the HEV mentioned is built in ADVISOR. Meanwhile, the hyper parameters of the DRL-based algorithm used in the simulations are summarized in Table 2.

Table 2. Summary of the DRL-based algorithm hyper parameters.

Hyper Parameters	Value
mini-batch size	32
replay memory size	1000
discount factor γ	0.99
learning rate	0.00025
initial exploration	1
final exploration	0.2
replay start size	200

In this application, the input layer of the network has two neurons, i.e., T_{dem} and SOC. There are three hidden layers having 20, 50, and 100 neurons, respectively. The output layer has 24 neurons representing the discrete ICE torque. All these layers are fully connected. The network is trained with 50 episodes and each episode means a trip (1369 s).

We evaluate the performance of DRL-based EMS by comparing them with the rule-based EMS known as "Parallel Electric Assist Control Strategy" [20]. The initial SOC is 0.8

4.1.2. Experimentation Findings

First, we assess how well the DRL-based algorithm performs in learning. In Figure 5, the average loss track is shown. It is evident that as training progresses, the average loss quickly falls. Figure 6 shows the progression of a single episode's total reward during the training process. The curve is undulating, but the overall direction of the track is upward. During the training phase, the overall payout also experiences some significant decreases. This is because when the algorithm chooses behaviors that violate the SOC restriction, a significant penalty is added.

Figure 5. Track of loss.

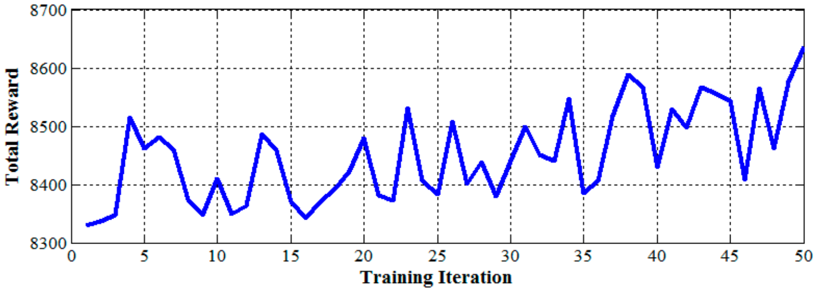

Figure 6. Track of the total reward.

Figure 6 then displays the simulation outcomes of the trained DRL-based EMS for the UDDS driving cycle. Table 3 compares the outcomes in order to assess the efficiency and performance of the trained DRL-based EMS. The conversion of power usage to gasoline consumption yields an equivalent

Adding the converted power consumption and fuel consumption yields the fuel consumption. The results of Table 3 demonstrate that the fuel consumption is reduced by 10.09%, which is a substantial improvement over the rule-based management technique. The equivalent fuel consumption is also down by 8.05% at the same time. The DRL-based EMS performs admirably. Notably, the DRL-based EMS only learns from the states and historical data whereas the rule-base EMS is created by specialists.

Table 3. Comparison of the results under UDDS.

Control Strategy	**Fuel Consumption (L/100 km)**	**Equivalent Fuel Consumption (L/100 km)**
Rule-Based	3.857	3.861
DRL-based	3.468	3.550

4.2 Online Application

4.1.1Experiment Setup

This experimental setup allows for the deployment and continuous improvement of the DRL-based EMS in real-world HEVs. It ensures that the EMS controller remains adaptive and effective in various driving scenarios, ultimately optimizing fuel efficiency and emissions reduction over time**.**

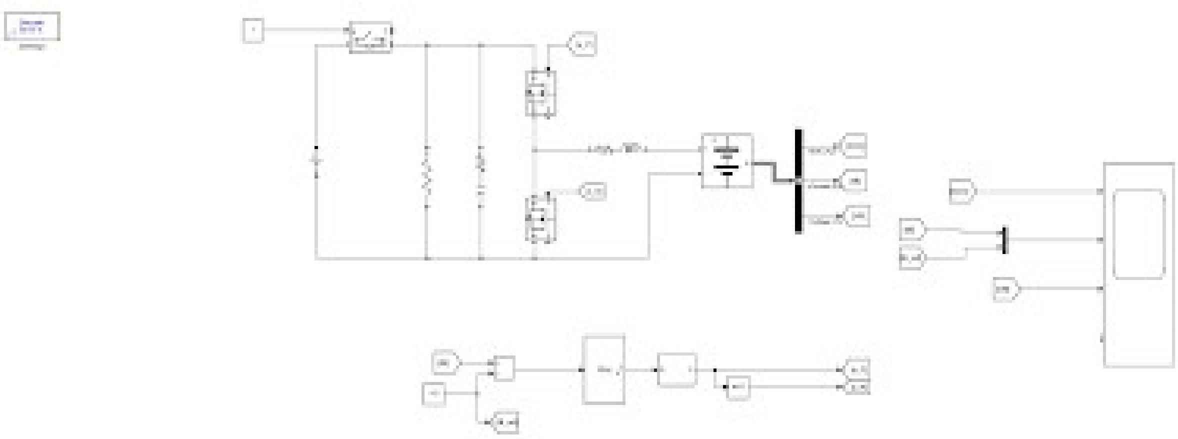

Figure 7. Simulation in the online application

4.2.2 Experimental Results

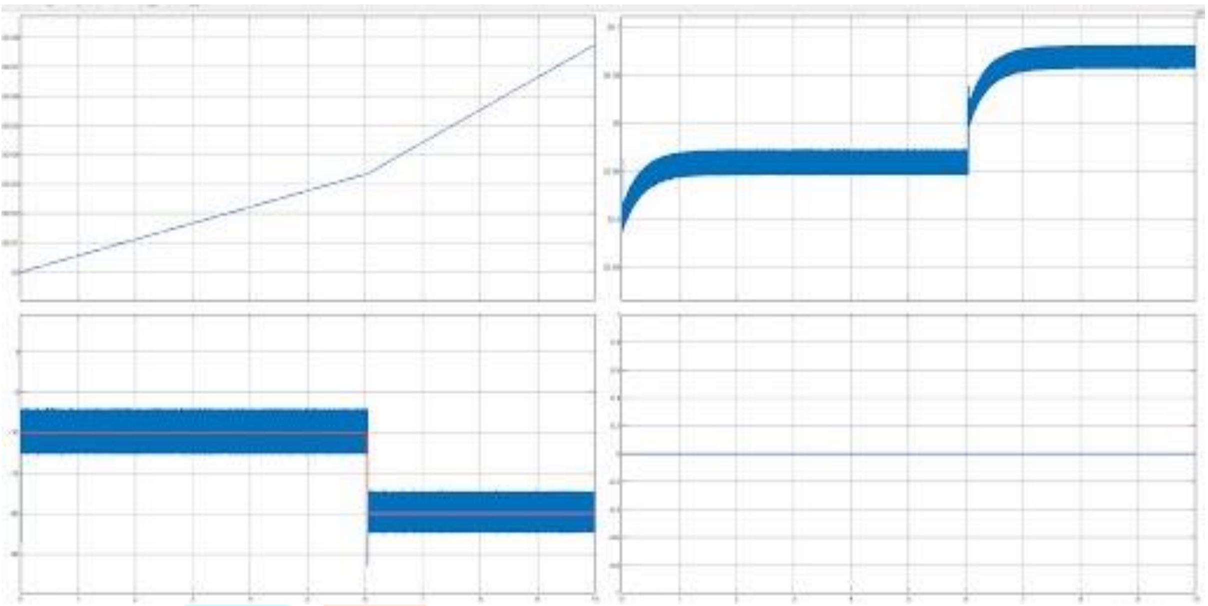

Figure 8. Simulation results of the trained EMS under NEDC.

IV. CONCLUTION

This paper presents a deep reinforcement learning-based data-driven approach to obtain an energy management strategy of a HEV.In order to develop a HEV's energy management strategy, this research introduces a deep reinforcement learning-based data-driven approach. The suggested method creates a deep Q network that can take action directly from the states by fusing Q learning and a deep neural network. The fundamental ideas of the DRL-based EMS have been developed. This paper provides a detailed description of the design of the DRL algorithm and the value function approximation. A DRL-based online learning architecture has been presented to help drivers adjust to different driving cycles. According to simulation data, the DRL-based EMS can achieve greater fuel economy than the rule-based EMS. Additionally, the online learning strategy can pick up knowledge from various driving scenarios. Future research will concentrate on ways to increase the effectiveness of online learning using a real car for testing. The ability to output continuous activities is a crucial concern. The output actions in this work are discretized, which may cause the ICE output torque to oscillate violently. This issue might be resolved using the deep deterministic policy gradient (DDPG) technique, which can generate continuous actions. This is a future piece of work. But DRL is also the foundation of DDPG. This paper's contribution will hasten the use of deep reinforcement learning techniques in HEV energy management.

Future works to be implemented

The future work of this study includes:

- Improving the performance of the DRL-based EMS by using a more complex DQN.
- Testing the DRL-based EMS in a real-world vehicle.
- Integrating the DRL-based EMS with other vehicle systems, such as the battery management system and the climate control system.

V. ACKNOWLEDGEMENT

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