International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V71I5P223

Volume 71 Issue 5, 219-227, May 2023

Original Article

An Optimum E-Vehicle Energy Management System using Deep Reinforcement Learning

S. Manoj[1], S. Pradeep Kumar[2]

[1,2]Department of Electrical and Electronics Engineering, Vels Institute of Science, Technology and Advanced Studies, Tamilnadu, India.

[1]Corresponding Author : manojresearchscholar@gmail.com

Received: 20 January 2023 Revised: 17 April 2023 Accepted: 13 May 2023 Published: 25 May 2023

Abstract - *A growing body of evidence indicates that incorporating onboard computer vision hardware and software into modern automotive systems aids in the pursuit of eco-driving goals. Automotive engineers face a lengthy and tedious task when developing Energy Management Strategies (EMSs) for various hybrid electric vehicle configurations. By capitalizing on similarities between various hybrid electric vehicle EMSs, experienced engineers can shorten the development cycle. This automated EMS development framework aims to speed up the production of hybrid electric vehicles. The study presented here combines computer vision with deep reinforcement learning, which leads to an improvement in the fuel economy of hybrid electric cars. The proposed method can autonomously learn the best policy for control based on observed data. We employ the cutting-edge convolutional neural networks-based object detection technique to glean useful visual data from onboard cameras. A continuous deep reinforcement learning model takes the detected visual data as a state input and generates policies for conserving power. To be more precise, the sharing of information among four very different hybrid electric vehicle types is investigated. In this paper, we propose a transfer learning-based tactic to automate the improvement of hybrid electric vehicle EMSs through the exchange of cross-type knowledge between EMSs that employ various flavors of deep reinforcement learning. According to the findings, the proposed method achieves the highest possible fuel efficiency of the global optimization programming, and the depth reinforcement learning-based system with image perception uses less fuel than the one without visual information. Moreover, the system without visual information uses less fuel than the one with visual information. Battery modeling, accurate battery state of charge and state of health estimation, and the development of other advanced EMS in EVs can solve most of the problems, allowing for more precise driving range estimates and more efficient charging and discharging strategies. The proposed strategy was shown to be effective and reliable in reducing losses and increasing safety during training and validation. The proposed energy management strategy performed better than the methods that were based on deep learning in terms of the amount of time needed for computation and the amount of energy lost in the combination battery bank. This provides support for the utilization of this method in the development of future systems for managing energy.*

Keywords - *Electric Vehicle (EV), Computer vision, BMS, Deep Reinforcement Learning.*

1. Introduction

Due to concerns over depleting fossil fuels and global warming, battery electric vehicle development has received a lot of consideration over the past several decades. Compared to cars powered by internal combustion engines, BEVs are among the greenest options because of their zero-emissions driving, high powertrain competence, and potential for incorporation with renewable energy.

However, there are still obstacles to be overcome in the enterprise and process of battery systems in BEVs to decrease the cost further and increase the presentation and longevity of these vehicles. BEVs' battery systems shouldn't be excessively large for a number of reasons, including price and efficiency. However, the criteria for the potential for exerting force and energy must be met in all cases, particularly while working in cold temperatures and high states of charge (SoC). Multiple energy system integrations have been extensively discussed as a potential solution to the problems outlined above. Most hybrid energy storage systems use power electronics to pair two high-energy-density devices. Hybrid energy storage systems show a number of requirements have been satisfied through the use of several storage technologies, including supercapacitors [6]. Although supercapacitors have many positive attributes, such as high efficacy, long cycle life, and high-power density, even at low temperatures, they also have certain negative aspects. High-power lithium-ion batteries, such as those with a lithium-titanate-oxide anode, have just entered the market [7], and this has piqued the interest of the business community in hybrid battery systems (HBSs) [8,9,10].

Several circuits, components, power systems, detectors, actuators, transistors, resistors, inductors, transducers, valves, translators, and safety devices make up the BMS in electric cars. Several methods, models, and control signals quantify these factors [11]. A significant amount of investigation has been put into designing the right algorithms in BMS [12]. Model-based techniques and intelligent methods are the most often used methodologies in business performance management systems [13]. The compound, dynamic, and nonlinear features of lithium-ion batteries may be addressed by intelligent algorithms, which are ideal for use with these batteries.

There is an immediate need to manufacture more fuel-efficient automobiles due to the depletion of global oil sources and the more rigorous emissions rules throughout the world [1]. In the current technological context, hybrid electric vehicles (HEVs) are seen as an attractive option for reducing emissions and cutting energy use costs [2]. HEVs, which are seen as a bridge product between regular gasoline cars and zero-emission vehicles, combine the benefits of both fuel and electric vehicles to produce exceptional mileage and tailpipe emissions [3]. Thus, there has been a dramatic increase in both the quantity and variety of HEVs over the past several years, which has contributed to a rapidly expanding and successful industry [4, 5]. Concurrent HEVs, sequential HEVs, and energy HEVs are the three main subsets of HEVs based on their powertrains [3].

More recently, Deep Reinforcement Learning has been discussed as a way to overcome the constraints of real-time optimization approaches using scenario-action fitting [14,15]. This is due to the fact that Deep Learning Algorithm can better match circumstances to actions than can real-time optimization approaches. Modeling the EMS may be done with a Markov decision process (MDP) [16] because Deep Reinforcement Learning-based EMS can meet the Markov property. Using Q-learning and Deep As part of a Deep Reinforcement Learning-based energy management method for HEVs, Q-learning algorithms were developed by Wu J. et al. [17]; Deep Q-EMS learnings may be an inter-input and multi-information integration method, as the authors showed by analyzing traditional Q-learning under multi-state inputs, which can lead to dimensional disaster. These results were given in a publication by Tan H. et al. [18] titled "DRL-based energy management method for hybrid electric cars based on Q-learning and Deep Q Critic-Actor learning technique to address discretization errors and dimensional catastrophes. It has been demonstrated that this tactic performs similarly to DP. Learning in large discrete-continuous hybrid action spaces was made more efficient by Li Y and Wu Y. et al. [19,20] by pre-training the actor-Critic network and integrating the inclination and congestion information. Lian R. and colleagues [21] developed a better approach for including expert knowledge in DDPG for energy management. This structure was developed with the hopes of facilitating quicker learning and improving efficiency while using less gas.

The following are the contributions that the innovations made to the article based on the motivations: We intend to improve the fuel efficiency of HEVs by taking into account current traffic conditions in real-time via an in-vehicle vision sensor. This information includes things like the condition of the traffic light and the flow of road traffic. Interestingly, previous studies on EMS have ignored the importance of onboard visual systems. A cutting-edge reinforcement-learning-based energy management system has been created for extended electric-tracked vehicle range hybridization. With the goal of deriving an energy-efficient strategy and realizing faster training speed and lower energy consumption than the conventional DQL-based policy, a deep learning algorithm that employs a new iterative algorithm to update the weights of the nodes in the neural network has been proposed. The network nodes' weights are updated via a novel optimization technique in this method. Using the picture data, the real-time deep learning-based object identification algorithm known as YOLO is applied to identify traffic signals and the number of cars in the immediate area. The DRL agent receives the discovered data and processes it. The outcomes of the experiments reveal that the traffic data identified by YOLO is possible to increase fuel efficiency without adding any additional costs associated with the hardware.

The remainder of the paper is prepared in the following fashion: In Section II, the works related to energy consumption are presented to the reader. In Section III, the algorithm for solving the proposed model and the deep earning is discussed. In Section IV, along with an analysis of the performance obtained from the proposed system. Section V is where we draw a conclusion to the article and explore the way forward.

2. Related Works

To classify EMSs, regulation and optimized-based algorithms are the most used options [22, 23]. These two classes can be used as broad categories for EMSs. However, while rule-based methods are frequently devoid of sophisticated and technically hard algorithms, they are often more compute-demanding for use in real-time software and need ultra-precise adjustment [25,26]. [27] Optimization-based enterprise management systems, backed by analytical and numerical methods, have been found to affect the reduction of cost functions in studies significantly. Dynamic programming (DP) is a method for selecting a vehicle's most optimal control strategy by analyzing its whole operating cycle to identify all possible work-state combinations and minimize fuel consumption and emissions [28]. However, the technique cannot be employed for real-time applications because of the massive computational expense and the prerequisite for comprehensive preview knowledge of future routes; instead, it can only be used to offer criteria for analyzing various EMSs. After then, many researchers devoted attention to studying actual optimization algorithms [29,36], the Equivalent Consume Risk reduction Strategy [31], and the model control strategy [32]. These are just a few examples. It is difficult to maximize energy allocations using the conventional EMSs described above since doing so requires the processing of enormous volumes of information in real time, which makes it challenging. As a result, learning-based EMSs, in particular, approaches based on deep reinforcement learning, are the subject of a significant amount of research.

The artificial neural networks (ANN) predictor used data from the previous driving cycle as well as other data collected as input variables. Following that, the anticipated future velocity sequence was fed into a Model Predictive Control (MPC) algorithm. The journey details, including road conditions and the path traveled by automobile, were relayed via the communication device. The intelligent EMS was created by Zhang et al. [33]. This EMS, in conjunction with the chaining neural network velocity prediction mode, builds up future driving cycles with the goal of minimizing fuel usage.

Complete, deep transfer reinforcement learning (DTRL) is a viable approach that might make it easier to construct DRL-based control agents; however, it is not being investigated in HEV EMSs at the moment. As part of this study, we look at adapting DRL-based EMSs to other HEVs and provide a novel DTRL framework for HEV energy management. The DTRL framework is founded upon a deep deterministic policy gradient DRL model, which is continuous in nature (DDPG). This model aims for improved generalization and steers clear of the discretization mistake [34]. We show that it is possible to increase the learning efficiency of one kind of HEV by transferring information from another type of HEV with a powertrain structure that is very different from the first HEV.

In addition, the state variable quantity used in reinforcement learning algorithms is distinct, which indicates that there is a restricted range of possible values for those variables. The "curse of dimensionality" issue will arise after the thickness of the discrete points reaches a certain threshold [35]. Research in the energy management field based on deep reinforcement learning and in which the states are set continuously, has been presented as a solution to this problem. In the paper referred to as [20], a continuous control method for managing energy on a series-parallel plug-in hybrid electric bus was published. This technique was based on deep reinforcement learning. An extensive number of driving cycles were generated from the traffic simulation and used to train the smart energy agent. Deep RL network updates were made using the stochastic gradient descent (SGD) method. The suggested method performed significantly better than the usual reinforcement learning strategy, as the experiments and simulations show.

Further deep learning method for hybrid electric vehicle power corporate governance is described in reference [37]. In the research, the neural networks were updated using a different steepest descent method called Adam, incorporating reweighted measurement. The research used this technique. In the first place, prior research has frequently used gradient descent techniques to minimize the loss function and update the weights of the nodes during the training of neural networks. Current optimization approaches hamper the efficacy of deep RL-based resource management controls because they need a high number of training cycles and frequently fall into the trap of local optimization. It is required to use a novel optimization strategy to investigate better ways to update the neural network nodes and implement the deep reinforcement learning-based energy management control.

3. Methodology

A straightforward diagrammatic representation of our approach is shown in Figure 1, which was created with the goal of making the suggested EMS more comprehensible. As shown in Figure 1, the DRL agent receives two different types of observations. These observations include the intrinsic vehicle states of speed, acceleration, and state of charge of the battery, as well as the external visual observation acquired through a camera. The DRL algorithm takes the environmental observations it gets at each time step into consideration before deciding how the power should be dispersed between the machine and the motor. After then, the DRL agent receives feedback on the HEV's overall energy usage, which is the direct result of the decision that it made.

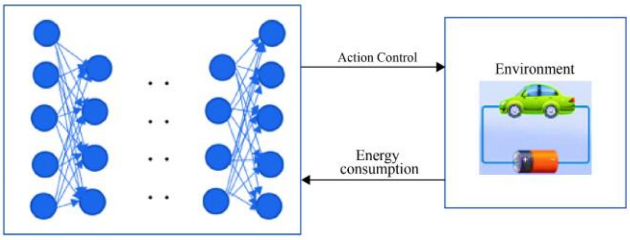

Fig. 1 Deep reinforcement learning

Table 1. Parameters of electric vehicle

Parameters	Value
Maximum efficiency	56kw
Maximum efficiency	49kw
Maximum efficiency	81kw
Most possible traction	468Nm
Potential	1.2kwh
planetary gearbox	2.4
Transmission gear ratio	3.992
control bulge	1338kg
Wheelbase Diameter of the Drive Train	0.312m
the coefficient of air resistance	0.32
Presentational Zone	$2.32m^2$
Inertia of Rolling	0.021

3.1. Powertrain Modelling

EMS studies have shown that the longitudinal dynamics of a vehicle—both the vehicle's and the engine's—have a noteworthy impact on the quantity of energy consumed by the vehicle. This discussion centres on a hypothetical vehicle with mass M and speed v. In order for the vehicle to go forward, it must combat a variety of obstacles, including rolling resistance, vertical resistance, air drag, and vehicle inertia. The equation for vehicle dynamics may be used to determine the propulsive force, denoted by the letter F_{tr}:

$$F_{tr} = cr_f M g_c cos\theta + 0.5 cr_d A_f v^2 \lambda + M g sin\theta + M \frac{dv}{dt} \quad (1)$$

Where cr_f Is the constant of the resistance coefficient between the wheel and the roadway, g_c is the gravitational velocity, is the road angle, is the air density, cr_d is the coefficient of drag, and A_f is the vehicle's frontal sectors. Table I provides a summary of the most important electric vehicle specifications, all of which have been taken directly from the relevant literature.

As a result, the tension that is operating on the tire, symbolized by the letter T_t, and the power that is needed to drive the engine of the vehicle, denoted by the letter P_{tr}, may be computed as follows:

$$\begin{cases} T_t = F_{tr} r \\ P_{tr} = F_{tr} v \end{cases} \quad (2)$$

It can be written as

$$\begin{cases} T_t = (cr_f M g_c cos\theta + 0.5 cr_d A_f v^2 \lambda + M g sin\theta + M \frac{dv}{dt}) r \\ P_{tr} = (cr_f M g_c cos\theta + 0.5 cr_d A_f v^2 \lambda + M g sin\theta + M \frac{dv}{dt}) v \end{cases} \quad (3)$$

r denotes the radius of the tire. The effective internal impedance battery model contains a battery open-circuit voltage source as well as an internal controller in its construction. The equations of the battery model that relate to the calculations that need to be done may be summarized as follows:

$$\begin{cases} I_b = \frac{v_o - \sqrt{v^2 - 4 r p_b}}{2r} \\ SOC = SOC_i - \frac{1}{c_b} \int_0^n I_b dt \end{cases} \quad (4)$$

$$SOC = SOC_i - \frac{1}{c_b} \int_0^n \frac{v_o - \sqrt{v^2 - 4 r p_b}}{2r} dt \quad (5)$$

The battery current is defined as I_b and SOC_i is the initial or the starting value of SOC. v_o defines the open circuit voltage, r is the resistance value, p_b is the power output of the battery, and c_b denotes the battery capacity.

The typical driving speed and the typical turning speed of cars are calculated by,

$$\begin{cases} v_a = \frac{v_a + v_b}{2} \\ \omega = \frac{v_a - v_b}{v_t} \end{cases} \quad (6)$$

v_t represents the vehicle tread. Figure 2 shows the velocity distributions for the Comma.ai Highway Driving Cycle (CHDC)

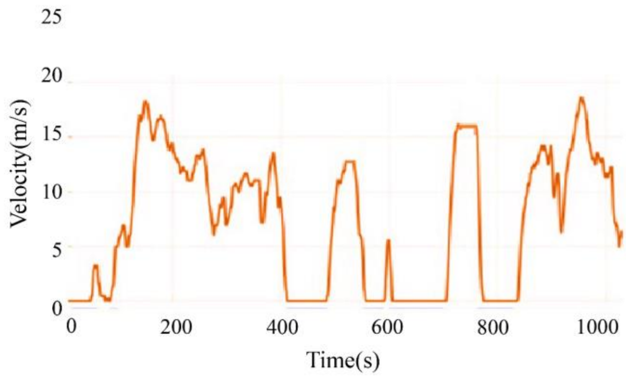

Fig. 2 Velocity distributions for the comma.ai highway driving cycle

3.2. Image Processing

After being inspired by the exceptional performance shown on picture classification and detection, Convolutional networks were shown to effortlessly generate results in several computer vision tasks, including object recognition. This research provides methods for detecting traffic signals and counting cars by employing the state-of-the-art, real-time object recognition system You Only Look Once (YOLO), which has been proven to be accurate and rapid in object identification. We utilize YOLOv3, the most recent version, to enhance the precision of CNN models. Figure 10 is a schematic depicting the CNN architecture. As a network based on feature learning, 75 convolutions are its primary tool.

The YOLO sensor is capable of detecting vehicles, red lights, and green lights. Examining vehicle detection data can help estimate the total number of autos. Traffic density is a key metric for evaluating the condition of a network's traffic flows and may be used by a variety of applications. We utilize the vehicle enumeration number determined by the visual system because the volume of traffic ahead of the controlled electric vehicles may be thought of as a quantity of density. Figure 3 shows the suggested method's framework. It is made up of three parts: the input picture, the YOLO network's structure, and YOLO's detections. The Darknet 53, which consists of 53 layers, is employed as the feature extractor in YOLO, making it a fully convolutional network.

3.3. Energy Management Algorithm

An EMS powered by a hybrid of deep neural networks and traditional reinforcement learning is created. Since the suggested EMS is an end-to-end control approach, it makes choices based exclusively on the system's current state. This is a deep Q-network, a type of deep reinforcement neural network (DRN). Value function calculation, DRL algorithm design, and an online learning application based on DRN algorithms are shown here. Algorithm for Managing Energy Our proposed management system is grounded in these three pillars: deep learning incessant estimate, necessary traction energy, and secondary energy.

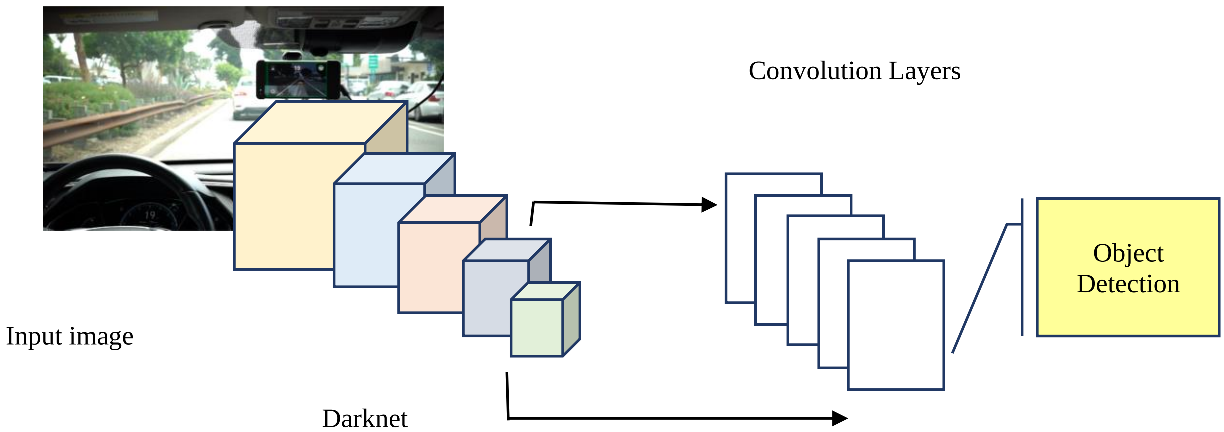

Fig. 3 The proposed method of YOLO's framework

Algorithm for the Prediction and Control of Energy Use

1. *Notation:*
    a. Air Conditioning - A_c
    b. Traction – Tr
    c. Alert – Al
    d. predicted sequence triplets – pst
    e. time – t , Dst – D
    f. Full comfort -FC, HalfComfort -HC,
2. *Input*: Battery Level and a History of Triplets
3. *Output*:A_c, Half, Tr or Al
4. *While* Not at Ddo
5. *nextpst*(a,by and t)
    a. Predicted t to D
    b. *Calculate*FC, HC and T.energies to D
6. *if*Tr.Energy ≥ SoC, *then*
    a. Raise Severe A
7. *else if* HC≥ *then* SoC
    a. Raise Tr Only
8. *else if*FC ≥ SoC *then*
    a. *Raise*HC Only
9. *end if*
10. *end while*

The electric vehicle control technique may be expressed mathematically as an endless horizon dynamic optimization problem, as shown below.

$$W = \sum_{k=0}^{\infty} \Upsilon^k r(k) \quad (7)$$

where $r(k)$ represents the instantaneous reward experienced by at time k, and (0, 1) is a discount factor that guarantees the countless sum of cost function conjunction. The ideal value, denoted by $O^*(St_k, Ac_k)$, is the highest possible cumulative reward that may be earned by doing the action Ac_kwhile in state St_k. Here is how the Bellman Equation determines $O^*(St_k, Ac_k)$:

$$O^*(St_k, Ac_k) = Er[r + \Upsilon \max_{x_{k+1}} O^*(St_{k+1}, Ac_{k+1}|St_k, Ac_k] \quad (8)$$

As indicated in Equation 11, we apply the Q-learning approach to update the value estimation.

$$O_{k+1}(St_k, Ac_k) = O_k(St_k, Ac_k) + \eta(r_{k+1} + \Upsilon \max_{x_{k+1}} O_k(St_{k+1}, Ac_{k+1}) - O_k(St_k, Ac_k)) \quad (9)$$

The activation function for the hidden layers is the rectified linear unit (ReLU), and the linear layer is utilized to get the action value for the output layer. Using the maximum Q-value action with probability $1 - \epsilon$ and a random action with probabilityϵ, the ϵ-greedy strategy picks actions in an effort to strike a balance between exploration and exploitation. By using the neural network's forward calculation capabilities, we can estimate the Q-value for every control operation. Equation 10 defines the loss function to be the square root of the mean error between the desired Q-value and the neural network's predicted output.

$$TQ = r + \Upsilon \max_{x_{k+1}} O(St_{k+1}, Ac_{k+1}, \theta^-) \quad (10)$$

$$Loss(L) = Er[(TQ - O(St_k, Ac_k))^2] \quad (11)$$

$r + \Upsilon \max_{x_{k+1}} O(St_{k+1}, Ac_{k+1}, \theta^-)$ define the output of the deep neural network. θ^- Obtained from the previous epoch.

4. Experimental Setup

Simulation tests are conducted in MATLAB and the ADVISOR co-simulation environment to measure the efficacy of the proposed DRL-based approach. The driving cycle is employed in the learning process after an initial evaluation of the offline learning application. The ADVISOR is used to create a simulation model of the electric vehicle in question. Meanwhile, Table 2 summarises the DRL-based algorithm's hyperparameters employed in the simulations.

Table 2. Parameters of the experimental set-up

Hyperparameter	Value
Batch size	64
Memory	1000
Factor	0.98
Lr (Learning Rate)	0.00001
Starting Exploration value	1
Terminal Exploration value	0.23
Replay	200

4.1. Dataset

The comma.ai team has released comma2k19, a dataset consisting of more than 33 hours of traffic data from the 280 freeway in California. This equates to 2019 individual segments, each of which is 1 minute long, over a 20-kilometre stretch of Interstate 8 between San Jose and San Francisco in California. A completely replicable and scalable dataset, comma2k19, is at your disposal. The information was gathered with the use of comma EONs, which, in addition to the usual smartphone sensors like camera, GPS, and temperature, also have a 9-axis inertial measurement unit.

Fig. 4 Sample image from the dataset

Figure 4 illustrates the onboard computer capable of seeing. Roadside records from the city of Guiyang's endemic dataset repository provide the basis for this study's data collection. The information is gathered along Changing South Road along the route to the Chinese Academy of Sciences Guizhou Technology Innovation Park.

To evaluate the model's efficacy, we employ a pair of datasets comprised of data gathered from Chinese roads and a Comma.ai driving dataset. The city driving elements, such as traffic signals and pedestrians, are not covered because the dataset only contains highway driving scenarios. We incorporate a city driving cycle into our research to make it more comprehensive. Roadside records from the city of Guiyang's endemic dataset repository provide the basis for this study's data collection. Acceleration and camera-captured images are among the data acquired.

5. Performance Evaluation

In this study, we assess the energy models' capability to bring about traction and comfort. We run two different tests: When the driver wants to relax, he or she cranks up the air conditioner to a temperature of 20 degrees and a humidity level of 55 percent. The halfway comfortable setting provides a temperature and humidity level of 25 degrees, which is preferable to the outdoor circumstances of 400 degrees and 82% humidity. Figure 4 and 5 displays the estimated and forecasted energy usage for travel periods under full comfort, half comfort, and traction-only driving conditions. Distances, estimated times, and forecasted timings are all derived from data collected along Route 2. We demonstrate that in the convenience scenario, energy is completely utilized at the point where its value reaches the SoC value within the predicted period.

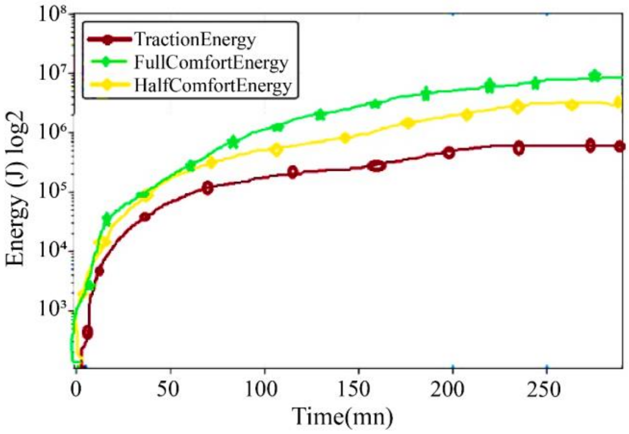

Fig. 5 Estimated and forecasted energy usage for travel periods under full comfort, half comfort, and traction-only driving conditions

What this signifies is that the anticipated energy is adequate for a basic average complexity automobile calculation to allow for comfortable driving to the destination. However, the energy is insufficient to allow for a pleasant drive to the location in reality and through our estimated time, where many parameters are considered. Insufficient time has elapsed by the time its value reaches the SoC. As a result, the battery will run dry long before the intended location is reached. We demonstrate that the estimated and expected timeframes are achievable using the predicted energy for the 50% comfort driving scenario. However, its precise worth varies greatly across the two journeys. It seems to reason that more power will be used for the anticipated time calculation as opposed to the estimated time calculation. Similarly, standard driving mode (traction alone) provides adequate energy to reach the destination for both travel durations. Yet again, the anticipated travel uses more energy since it more closely mimics the actual traffic congestion circumstances.

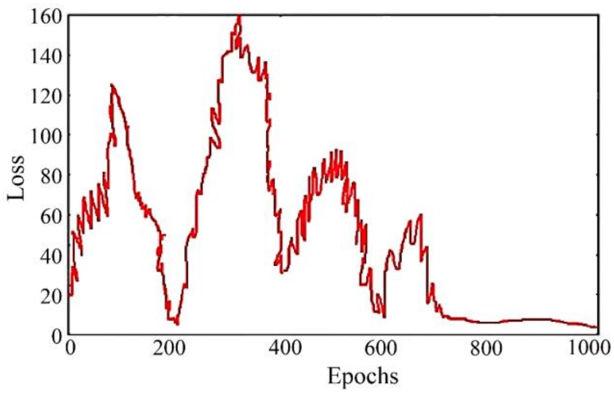

Fig. 6 Training losses of the proposed method

Using the driving cycle depicted in Fig. 2 as input, we train the proposed neural network and verify the efficacy of the planned deep reinforcement learning algorithm by comparing it to the benchmark technique DP and the conventional deep Q learning method with Adam optimizer. The number of training episodes is set to 20. Training loss variations for the deep Q learning using RMSE and the Adam are depicted in Fig. 6. Both losses tend to decrease as the number of training steps increases, indicating that the neural networks are becoming closer and closer to ideal. In addition, the suggested method's loss curve quickly approaches zero, demonstrating the novel algorithm's efficiency.

Figures 7 and 8 show the different route predictions using the proposed methodology.

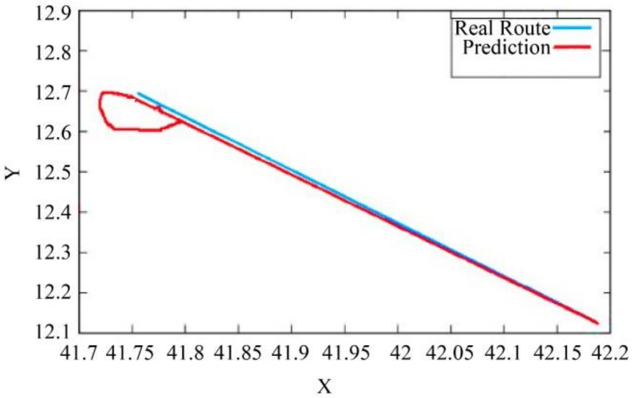

Fig. 7 Predicted route 1

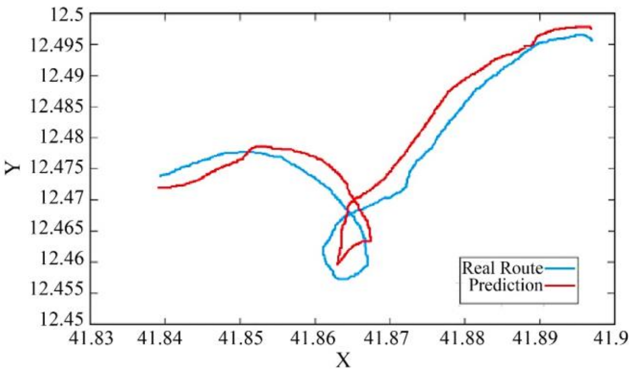

Fig. 8 Predicted route 2

The average Root Mean squared error for each neural network design is displayed in Figure 9 below, as mentioned in Table III. The optimum RMSE value is equivalent to 0.015 when using a neural network of 8 neurons (8 layers, 90 hidden neurons, and two dense layers), significantly improving the prediction's efficiency while requiring little processing time.

Table 3. Neural network setup

Configuration	Epochs	Iteration per each epoch
1	100	3000
2	100	3000
3	200	4000
4	600	6000
5	1000	70000

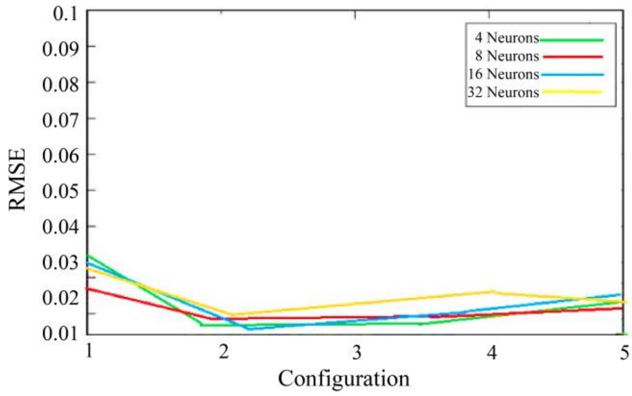

Fig. 9 Root Mean squared error for each neural network design

The average loss clearly lowers rapidly throughout training, as shown in Figures 10 and 11. The cumulative reward for a single epoch is shown as a line (Figure 8) along the training timeline. The track's main upward direction can be seen despite the fluctuating curvature.

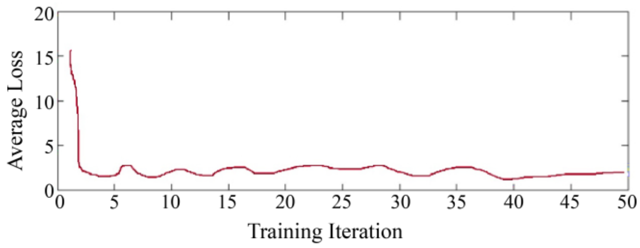

Fig. 10 Average loss through training

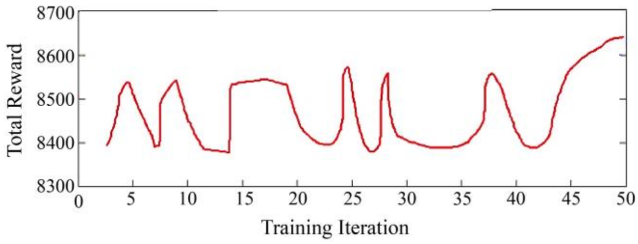

Fig. 11 The cumulative reward for a single epoch

During training, the overall prize might decline rather dramatically at times. This is because the algorithm incurs a heavy penalty whenever it makes a decision that causes a breach of the SOC constraint.

6. Conclusion

To reduce the amount of fuel that an electric vehicle has to use, an Energy Management System has been designed in this article. This system incorporates a computer vision system, a form of deep reinforcement learning, and an active noise algorithm. In addition, comparative research of the exploration technique is carried out using a variety of action noise. The simulation findings reveal that the approach based on vision-based deep reinforcement learning is superior to the original agent in terms of its ability to obtain the best fuel optimality in the urban driving cycle. While this is happening, the vision-based energy management system that includes information on the traffic density is superior to the original agent in a driving cycle on the highway. The enhancement is accomplished by the addition of more information about the atmosphere that is updated in real-time. Finally, the authors demonstrate how the development cycle length may be cut down by sharing information among various types of energy management systems. Because of the information that was transferred, the generalization performance with regard to vicissitudes in the characteristics of the vehicle has been enhanced, and the fuel economy has been preserved. We also explore the knowledge transfer between two vehicles with powertrains that are pretty different from one another and have control variables that are distinct from one another. Surprisingly, there have also been reports of improved results.

To better address the challenge of energy management, it is intended that future studies will provide a novel approach to sample selection and training. This action will be taken in response to the previously mentioned issue of insufficient sample selection during the algorithm's planning phase. In addition, future studies will focus on the structural analysis of neural networks used for deep reinforcement learning. It is anticipated that the performance will be confirmed by the use of real automobiles as well as the hardware-in-the-loop test.

References

[1] Wisdom Enang, and Chris Bannister, "Modelling and Control of Hybrid Electric Vehicles (A Comprehensive Review)," *Renewable and Sustainable Energy Reviews*, vol. 74, pp. 1210–1239, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[2] Clara Marina Martinez et al., "Energy Management in Plug-In Hybrid Electric Vehicles: Recent Progress and a Connected Vehicles Perspective," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 6, pp. 4534–4549, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[3] M.F. M. Sabri, K.A. Danapalasingam, and M.F. Rahmat, "A Review on Hybrid Electric Vehicles Architecture and Energy Management Strategies," *Renewable and Sustainable Energy Reviews*, vol. 53, pp. 1433–1442, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[4] Pei Zhang, Fuwu Yan, and Changqing Du, "A Comprehensive Analysis of Energy Management Strategies for Hybrid Electric Vehicles Based on Bibliometrics," *Renewable and Sustainable Energy Reviews*, vol. 48, pp. 88–104, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[5] Niklas Rotering, and Marija Ilic, "Optimal Charge Control of Plug-In Hybrid Electric Vehicles in Deregulated Electricity Markets," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1021–1029, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[6] Oliver Bohlen, Julia Kowal, and Dirk Uwe Sauer, "Ageing Behaviour of Electrochemical Double Layer Capacitors: Part I. Experimental Study and Ageing Model," *Journal of Power Sources*, vol. 172, no. 1, pp. 468-475, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[7] Bote Zhao et al., "A Comprehensive Review of Li4ti5o12-Based Electrodes for Lithium-Ion Batteries: the Latest Advancements and Future Perspectives," *Materials Science and Engineering: R: Reports*, vol. 98, pp. 1-71, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[8] Raphael Wegmann et al., "Optimized Operation of Hybrid Battery Systems for Electric Vehicles Using Deterministic and Stochastic Dynamic Programming," *Journal of Energy Storage*, vol. 14, pp. 22-38, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[9] Jan Becker et al., "Dimensioning and Optimization of Hybrid Li-Ion Battery Systems for Evs," *World Electric Vehicle Journal*, vol. 9, no. 2, p. 19, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[10] Thomas Nemeth et al., "Optimized Operation of a Hybrid Energy Storage System with LTO Batteries for High Power Electrified Vehicles," *2019 IEEE Transportation Electrification Conference and Expo, IEEE*, pp. 1–6, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[11] Markus Lelie et al., "Battery Management System Hardware Concepts: An Overview," *Applied Sciences*, vol. 8, no. 4, p. 534, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[12] YongZhi Zhang et al., "Validation and Verification of a Hybrid Method for Remaining Useful Life Prediction of Lithium-Ion Batteries," *Journal of Cleaner Production*, vol. 212, pp. 240-249, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[13] M.S. Hossain Lipu et al., "Data-Driven State of Charge Estimation of Lithium-Ion Batteries: Algorithms, Implementation Factors, Limitations and Future Trends," *Journal of Cleaner Production*, vol. 277, p. 124110, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[14] Guodong Du et al., "Deep Reinforcement Learning Based Energy Management for a Hybrid Electric Vehicle," *Energy*, vol. 201, pp. 117591, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[15] Teng Liu et al., "Reinforcement Learning of Adaptive Energy Management with Transition Probability for a Hybrid Electric Tracked Vehicle," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 12, pp. 7837-7846. 2015. [CrossRef] [Google Scholar] [Publisher Link]

[16] Mevludin Glavic, "(Deep) Reinforcement Learning for Electric Power System Control and Related Problems: A Short Review and Perspectives," *Annual Reviews in Control*, vol. 48, pp. 22-35, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[17] Jingda Wu et al., "Continuous Reinforcement Learning of Energy Management with Deep Q Network for a Power Split Hybrid Electric Bus," *Applied Energy*, vol. 222, pp. 799-811, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[18] Huachun Tan et al., "Energy Management of Hybrid Electric Bus Based on Deep Reinforcement Learning in Continuous State and Action Space," *Energy Conversion and Management*, vol. 195, pp. 548-560, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[19] Yuecheng Li et al., "Energy Management for a Power-Split Hybrid Electric Bus Via Deep Reinforcement Learning with Terrain Information," *Applied Energy*, vol. 255, pp. 113762, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[20] Yuankai Wu 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*, vol. 247, pp. 454–466, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[21] Renzong Lian et al., "Rule-Interposing Deep Reinforcement Learning Based Energy Management Strategy for a Power-Split Hybrid Electric Vehicle," *Energy*, vol. 197, pp. 117297, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[22] Clara Marina Martínez et al., "Energy Management in Plug-in Hybrid Electric Vehicles: Recent Progress and a Connected Vehicles Perspective," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 6, pp. 4534- 4549, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[23] Sidun Fang et al., "Optimal Hierarchical Management of Shipboard Multibattery Energy Storage System Using a Data-Driven Degradation Model," *IEEE Transactions on Transportation Electrification*, vol. 5, no. 4, pp. 1306-1318, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[24] Zhao Xiu-Chun, and Guo Ge, "Survey on Energy Management Strategies for Hybrid Electric Vehicles," *Acta Automatica Sinica*, vol. 3, pp. 321-334. 2016. [CrossRef] [Google Scholar] [Publisher Link]

[25] Jiankun Peng, Hongwen He, and Rui Xiong, "Rule Based Energy Management Strategy for a Series–Parallel Plug-In Hybrid Electric Bus Optimized by Dynamic Programming," *Applied Energy*, vol. 185, pp. 1633-1643, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[26] S. G. Li et al., "Energy and Battery Management of a Plug-In Series Hybrid Electric Vehicle Using Fuzzy Logic," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 8, pp. 3571–3585, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[27] Saman Ahmadi et al., "Improving Fuel Economy and Performance of a Fuel-Cell Hybrid Electric Vehicle (Fuel-Cell, Battery, and Ultra-Capacitor) Using Optimized Energy Management Strategy," *Energy Conversion and Management*, vol. 160, pp. 74-84, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[28] Daming Zhou et al., "A Comparative Study of Extremum Seeking Methods Applied to Online Energy Management Strategy of Fuel Cell Hybrid Electric Vehicles," *Energy Conversion and Management*, vol. 151, pp. 778-790, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[29] Jihun Han, Youngjin Park, and Dongsuk Kum, "Optimal Adaptation of Equivalent Factor of Equivalent Consumption Minimization Strategy for Fuel Cell Hybrid Electric Vehicles under Active State Inequality Constraints," *Journal of Power Sources*, vol. 267, pp. 491-502. 2014. [CrossRef] [Google Scholar] [Publisher Link]

[30] S. Manoj, and S. Pradeep Kumar, "Deep Learning-Based State-of-Charge Assessment Model for Hybrid Electric Vehicles Energy Management Systems," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 10, no. 1, pp. 209-218, 2023. [CrossRef] [Publisher Link]

[31] Pinak Tulpule, Vincenzo Marano, and Giorgio Rizzoni, "Energy Management for Plug-In Hybrid Electric Vehicles Using Equivalent Consumption Minimi-Zation Strategy," *International Journal of Electric and Hybrid Vehicles*, vol. 2, no. 4, pp. 329-350, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[32] Yanjun Huang et al., "Model Predictive Control Power Management Strategies for HEVs: A Review," *Jounal of Power Sources*, vol. 341, pp. 91-106, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[33] Fengqi Zhang, Junqiang Xi, and Reza Langari, "Real-Time Energy Management Strategy based on Velocity Forecasts Using V2V and V2I Communications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 2, pp. 416-430, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[34] Timothy P. Lillicrap et al., "Continuous Control with Deep Reinforcement Learning," *arXiv preprint arXiv:1509.02971*, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[35] Ziming Yan, and Yan Xu, "Data-Driven Load Frequency Control for Stochastic Power Systems: A Deep Reinforcement Learning Method with Continuous Action Search," *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 1653-1656, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[36] Namwook Kim, Jongryeol Jeong, and Chunhua Zheng, "Adaptive Energy Management Strategy for Plug-in Hybrid Electric Vehicles with Pontryagin's Minimum Principle Based on Daily Driving Patterns," *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 6, no. 3, pp. 539-548, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[37] Roman Liessner et al., "Deep Reinforcement Learning for Advanced Energy Management of Hybrid Electric Vehicles," *The 10th International Conference on Agents and Artificial Intelligence*, vol. 2, pp. 61-72, 2018. [CrossRef] [Google Scholar] [Publisher Link]