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Original scientific paper

Heuristic Adaptive Dynamic Programming-based Energy Optimization Strategies for Hybrid Electric Vehicles

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Abstract: This study suggests a more accurate series-parallel hybrid electric vehicle (HEV) energy management control technique based on heuristic adaptive dynamic programming (HADP). This article provides a solution to the energy management problem of Electric Vehicle using the Stimulant Dependent Heuristic Adaptive Dynamic Programming (SDHADP) algorithm. The reinforced Q learning model along with the three-layer feed-forward neural network with backpropagation is detailed with the necessary diagrams and equations. The approach to connecting the battery of a BEV to a residential system is novel and innovative. The experimental results highlight the importance and effectiveness of the SDHADP algorithm using an electric vehicle. This is done with the help of a BV feed-forward neural network with back-propagation. In the model, which is in charge of controlling the system based on the training given by the BV network, Markov decision theory was adopted by scholars as a paradigm for posing and solving planning problems in the face of uncertainty and is in charge of the battery management system.The suggested technique uses online learning control methods to improve upon the efficiency of the traditional Q-learning method by more than 4.55% under the specified real-world driving circumstances.

Keywords: electric vehicles; energy management system; SDHADP algorithm; machine learning; neural network

1 INTRODUCTION

In the ongoing effort to lessen transportation's overall energy footprint, electrification has emerged as a crucial strategy. When it comes to the family of electrified cars, HEVs play a noteworthy role. Unlike conventional automobiles and battery electric vehicles (BEVs), hybrid electric vehicles have a larger complexity and take use of running multiple propulsion systems to fulfill the load on the road [1-3]. Energy management, which seeks to define the most acceptable power split between the many on-board multi-source energy systems, is a crucial component of HEV functioning. Energy management strategies (EMSs) are responsible for real-time evaluation of the optimal power ratio between internal combustion engines (ICEs) and electric motor-generators (EMGs), regarding the required drive power and the available energy in the battery consumption and emissions. Batteries are the primary source of energy for electric vehicles. A high voltage (HV) battery pack, traction motor, engine, and generator are the standard components of the dual propulsion system. Customers get to enjoy the benefits of driving a true electric vehicle (EV) thanks to the HV battery pack and the motor. A high voltage (HV) battery pack will be charged by the engine when its state of charge (SOC) drops below a certain threshold, and the engine may also be used to supplement the HV battery pack's power output in order to handle peak demand. HEVs are more difficult to run than standard automobiles and BEVs because they may utilize many powertrain components simultaneously [4]. The energy management strategy is the set of controls used to optimize the efficiency of these parts. Battery electric vehicles (BEVs) are another name for them. The BEV stores power in a single battery. The BEV can go in any direction, forwards or backwards, thanks to its battery. In appearance, the BEV is indistinguishable from the mechanical cars now on the market. Both the power source and the driving system of a BEV are fundamentally different from those of gasoline or diesel-powered automobiles. In today's world, the gasoline tank is the battery, and the engine is the electric motor [5]. The electric energy stored in a battery is the lifeblood of an EV or HEV. Lithium-ion batteries are used in most electric and hybrid electric cars because they are powerful, have a high energy density, and last a long time. Heat is produced by Li-ion batteries both during charging and usage. To learn how various materials charge and discharge, one can consult the respective manufacturer's technical datasheet. In this project, we are creating a machine-learning algorithm that links the BEV to a smart home system during its idle period. The cost of power is factored into the BEV's price. It charges during off-peak hours and releases electricity to the home grid during peak hours. This optimization issue cannot be handled using dynamic programming as the system is nonlinear. Power needs and consumption levels might change over time. In areas where the price of power is greater during peak hours and cheaper during off-peak hours, this technique can be highly beneficial. By avoiding power use at peak times and charging the BRV battery during off-peak times, the system saves money for the customer [6]. The machine learning system learns about the appropriate usage of batteries depending on the existing power tariffs and the household load. Hybrid electric vehicles (HEVs) are equipped with several power sources, allowing for flexible driving modes and configurations. They're better than regular cars in cutting gas costs while still satisfying commuter needs. It is vital to establish a sensible and efficient energy management strategy (EMS) given the complexity of HEVs' powertrains and power allocation. Here is how the rest of the paper is structured. The HEV model and the energy management issue are introduced in Section 2. A DHP-based energy management control technique is designed in Section 3. In Section 4, we use simulated comparisons with other current EMSs to verify the efficacy and benefit of the proposed EMS of HEVs. The conclusion is the last part.

2 LITERATURE REVIEW

The research looked at the issues of battery swap stations, such as allocation and stocking. The Markov Decision Process was the basis of the model. Battery deterioration was also evaluated in the study. The battery charging, draining, and swapping out method worked well in order to calculate the kinetic energy and power management of battery-powered vehicles on a trajectory [7-9]. The results of the experiments show that two discrete variables, one representing the vehicle's operation and the other the power distribution, may be used for co-optimization using dynamic programming. Energy costs can be cut by between 5.3% and 24.0%. To illustrate the issues with energy management in BEVs, a dual-engine system is analyzed that is fuelled by Li-ion batteries and supplementary power units. The system featured dynamic programming and a map-based component to split power between the battery and the motor. There was a 1.9 percent drop in gasoline use. Hybrid electric cars may make the most of reduced component sizes and increased power thanks to an energy management system that incorporates a dimensional optimization framework. To do this, the system employs the dynamic programming technique. An efficiency of 31.3 percent was achieved by the system optimizing gas mileage with a dynamic programming approach [10, 11]. Scheduling algorithms for electric car charging can be enhanced by using data-driven tools and machine learning technology for learning and prediction. Recent studies on optimization-based tactics have centered on how to incorporate modeling and simulation expertise to provide more realistic optimization outcomes. In this work, we look at two different dynamic programming techniques. However, the stochastic dynamic programming algorithm approach yields a control that depends on a particular state [12-14], while the deterministic dynamic algorithm solves the optimization problem by sequentially calculating each state at each time step in a backward order. This work makes two key advances compared to previous approaches. First, a DHP-based control method for HEVs is presented [15], which takes use of the DHP's pinpoint accuracy to dynamically adjust the network weights in response to driving data in order to achieve optimal control and lower energy usage. The next step is to fine-tune the action network's underlying structure. By increasing the number of nodes in the hidden layer, the grid can better accommodate the control variables, and the network's weights can converge more quickly.

3 PROPOSED SYSTEM

One of the HADP foundational structures, Heuristic Adaptive Dynamic Programming (HADP) combines reinforcement learning, the DP optimization principle, and the neural network approximation function to achieve more accuracy with a somewhat more complicated structure. In this regard, the DHP energy management strategy (EMS) is built by the backpropagation neural network (BPNN) as an Action networking and two Critic networks approximating the control policy and the resulting gradient of value function about the state variable. The battery management system consists of the residential load. During peak times, the electricity consumption is very high, especially at night time. The load on the power grid increases. This article finds out a solution to the problem of maintenance of load demand on the grid using the battery of BEV.

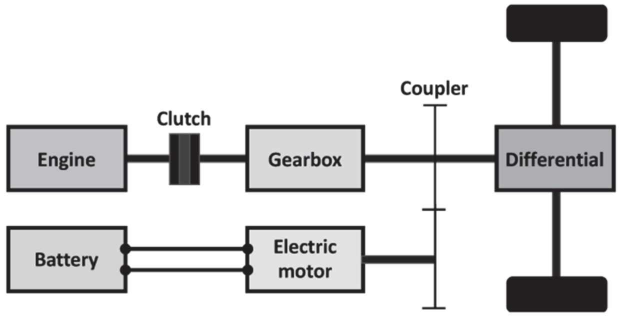

Figure 1 Process flow of the proposed system

Fig. 1 depicts the process flow of the proposed system. The system consists of the battery system and the corresponding residential and BEV loads. The BEV load is used once the battery is fully charged. At this time the battery supplies the power to the residential to meet the residential load at peak hours during high electricity costs. The battery system plays two important roles. In the first place, it saves cost by not using electricity directly from the power grid thereby saving cost and reducing the domestic load on the power grid. During the off-peak hours, the battery system is charged back when the domestic and residential load is low. The optimal battery usage pattern is to be found based on the electricity charges and domestic and residential loads. The study uses some assumptions: First the BEV is operated daily. When the BEV is operational the battery cannot be used to satisfy the residential load and during the operational process, the BEV is fully charged. The residential use of the battery happens during high peak hours when the cost of electricity from the grid is high and during low peak hours, the residential load is met directly from the power grid. When the power consumption is directly from the power grid the battery is assumed to be in the charging state. The state from charging to discharging changes when the power consumption is not met directly from the power grid. In the BEV system, the charging of the battery is depicted as

$$C_{T+1} = C_T - C_T n\left(C_T\right) + 1\ [\mathrm{h}],\ C_T > 0 \tag{1}$$

C_{T+1} (kWh) gives the batteries residual energy during the period T. The energy output from the battery is given by C_τ (kW) in time τ. The efficiency of energy conversion is given by $n(C_T)$. The time step is given by 1 h. Consider $n(C_\tau)$ = 1 is the efficiency for the optimal case of the battery. In the system, the discharging of the battery is depicted as:

$$C_{T+1} = C_T - C_T n\left(C_T\right) \times 1\ [\mathrm{h}],\ C_T < 0 \tag{2}$$

The idle cycle of the battery is given by $C_\tau = 0$. The load demand at time τ is given by L_τ. The output of the power grid at time τ is given by G_τ. The equation balancing the load is given b.

$$L_T = C_T + G_T \tag{3}$$

Considering equations 1, 2 and 3, the optimization for the system is given as

$$\begin{aligned} &\text{Min} P_T = \sum E_T \times G_T \\ &C_{\min} \le C_T \le C_{\max} \end{aligned} \tag{4}$$

The E_τ denotes the electricity rate. The function of the performance index is given by P_τ.

$$x_{T+1} = f\left(x_T\right) = \begin{pmatrix} \left(C_T + C_{2T}\right) - u_T \\ C_{2T} - u_T \end{pmatrix} \tag{5}$$

The application of Q learning to the battery management problem of BEV. An approach based on reinforced learning (RL) is proposed. $J^*_{(xk)}$ the optimal cost and the optimal control policy $PI^*_{(xk)}$ are defined as

$$J^*_{(xk)} = \min_u \left(Q^*\left(x_k, u\right)\right) \tag{6}$$

$$PI^*_{(xk)} = \arg\min_u \left(Q^*\left(x_k, u\right)\right) \tag{7}$$

Now the updated equation becomes:

$$Q\left(x_k, u\right) < -Q\left(x_k, u\right) + \alpha\left(g_k + r\min Q\right)\left(x_{k+1}, u\right) - Q\left(x_k, u\right) \tag{8}$$

Based on the state of the system x_k, the criteria is to select a minimum Q value for the control u_k. Based on the action of the UK, the state changes from to x_{k+1} with as the reward. The updating of the Q function $Q\left(x_k, u_k\right)$ takes place. Eq. (8) gives the standard framework of the RL learning algorithm. The new proposed algorithm for battery management is based on Eq. (8) for battery management is based on eEq. (8).

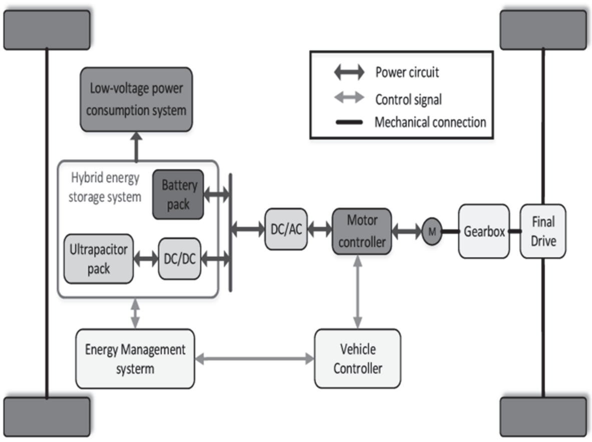

Figure 2 Architecture of Battery Management System with Q Learning

Convergence is very important for Q learning and RL systems. When Q learning is applied to problems like the BEV Battery Management system, the algorithm takes a lot of time to converge. It depends directly on the properties and dimensions. In case the dimensions are large, the convergence time increases proportionally. Fig. 2 shows the working architecture of the battery management system. The proposed B-Select algorithm is a self-learning algorithm. The realization can be performed in many different methods. The primary goal and objective of the B-Select algorithm is to connect to the BV network and approximate the performance index in dynamic programming systems by making use of the model of the control between the BV network and the residential system. The self-learning algorithm based on inputs, experience and training identifies the optimal performance index and optimal control for the system. In this article, the authors use the Stimulant Dependent Heuristic Adaptive Dynamic Programming (SDHADP). Fig. 2 contains the structure diagram of SDHADP. The output of the BV network is V_T.

3.1 Pseudo Code for BEV Control

$Q\left(x_k, u_k\right)$ ← Initialize

Steps repeated n times $n = 1, 2, 3, \ldots, n$

Step 1: Update all utilised parameter values u_k at stage $x_k Q\left(x_k, u_k\right)$

Step 2: Shift state $k + 1$ ← reward $g\left(x_k, u_k\right)$

Step 3: Update model on observation → Reward $g\left(x_k, u_k\right)$ State x_{k+1}

Step 4: Update Q using model actions

$Q\left(x_k, u\right) < -Q\left(x_k, u\right) + a\left(\left(g_k + r\min Q\right)\left(x_{k+1}, u\right) - Q\left(x_k, u\right)\right)$

Step 5: Assign $x_k < x_{k+1}$

Step 6:

$Q\left(x_k, u\right) < -Q\left(x_k, u\right) + \alpha\left(\left(g_k + r\min Q\right)\left(x_{k+1}, u\right) - Q\left(x_k, u\right)\right)$

Penalty $x_k < -x_k < g\left(x_k, u\right) - \alpha\left(g_k + Q\left(x_{k+1}, u\right)\right)$

The SDHADP scheme has the advantage that it does not require a mathematical model. The BV network is a three-layer feed-forward neural network with backpropagation. The network is self-learning and assumes the optimal values for performance index and model control from previous experience. The model is based on reinforced learning that has an agent to control the network unless optimal objectives are not achieved. The Q learning model framework is implemented in the system. The working is that for all assumptions correctly made by the system, a reward is provided and for all assumptions made wrong a penalty is given to the system by the agent. Here the motivation principle is used so that the machine learns to maximize the reward and lower the penalty. Fig. 3 shows the 3-layer feed-forward neural network with backpropagation. The three layers are the input layer, the hidden layer and the output layer. There are 5 hidden layers. The inputs consist of g_t, x_t, c_t and u_t values. The hidden layer further breaks up the input into smaller units trying out all permutations and combinations to speed up the computation. The output unit gives the probability of the optimal performance index and optimal control for the network. The model in the SDHADP is used to approximate the control.

Based on the operating mode of the battery, the operating mode of the battery is divided into three operation control modes. The model in the structure performs as the selection system based on the performance index for the system. This process simplifies the operation mechanism of the battery and does not influence the optimization principle.

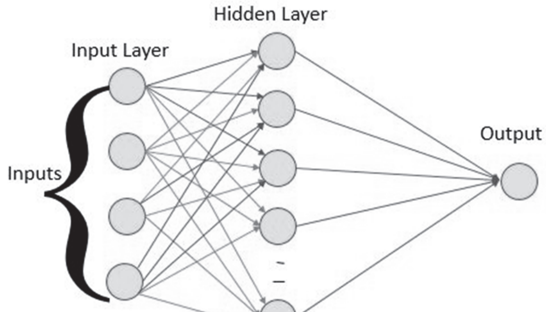

Figure 3 BV Network

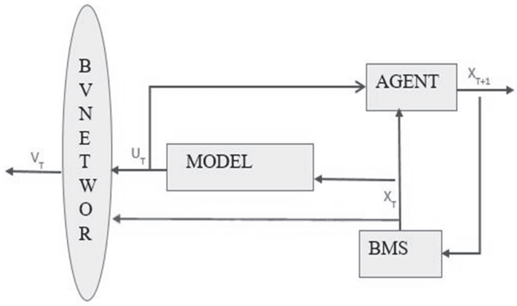

Figure 4 Stimulant Dependent Heuristic Adaptive Dynamic Programming (SDHADP) Structure

In the SDHADP system, the objective is to reduce the error. This is achieved by,

$$\|E\| = \sum\nolimits_T \frac{1}{2} x\left(v_T - u_T - r v_{T+1}\right)^2 \tag{9}$$

The developed system consists of two main parts, a BV network and a model for controlling. The BV network is a 3 three-layer feed-forward neural network with backpropagation. The error propagates backward and the weights are corrected to eliminate the error. The gradient descent function is used to come out of the loop error repeating. The training process of the BV network is as follows:

Step 1: Given the BV network (D1) collect the random data, states and available actions.
Step 2: Get the optimal V_t.
Step 3: Train the model framework (D2) using the control optimization process.
Step 4: The weights of D1 and D2 are the same.
Step 5: Repeat steps 3 to 5 till the error is negligible.
Step 6: Pick D1 as the trained BV network and D2 as the trained model framework.

The model module defines the actions of the battery based on the values of the utilization value parameter U_t. The model framework initiates the charging function when the value of U_t is greater than zero. The discharge function is initiated when the value of Ut is less than zero and the charging of the battery is performed when the value of U_t is greater than zero. Fig, 5 shows the working of the model framework. This is performed after the training of the BV network. The function that optimizes the requirement of the BV network and the model framework is selected

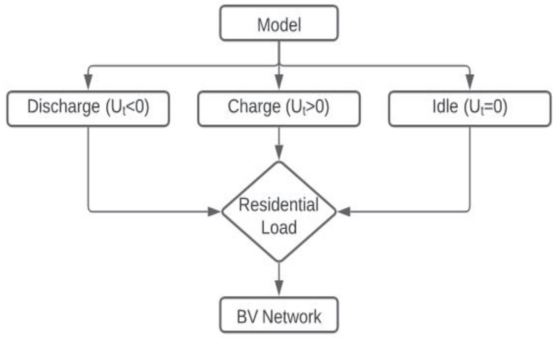

Figure 5 Function of the model framework

4 EXPERIMENTAL ANALYSIS

To highlight the effectiveness of the proposed SDHADP algorithm the experiments are conducted with the BEV and the residential environment. The initial condition followed in the experiments is that the BEV is to be fully charged when applied to the BEV. The battery is connected to the residential load when BEV is idle and the residential system has more load demands from the grid. The control used in our experiment is that the battery is used in the BEV from morning 6 to evening 6. For the rest 12 hours the battery is used in the residential system for load demands.

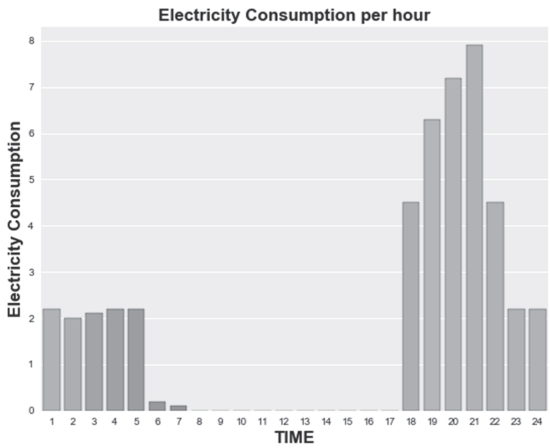

Figure 6 Electricity Consumption in Volt

Fig. 6 shows the average electricity consumption or demand for one month, 24 hours a day. The load demand and consumption are considered continuous functions for 24 hours and seven days a week. The outcomes of our dynamic programming method are examined alongside those of two straightforward scheduling approaches. The first tactic involves making an efort to constantly charge the battery whenever the BEV is connected, regardless of the financial or logistical implications of doing so or the requirements of the individual. The second technique suggests selecting the acts that will be charged at random. Simulations are used to evaluate these strategies, using, on the one hand, a database of measured data collected from a real fleet of cars, and, on the other hand, the data on the price of petrol as well as the hourly price of electricity, taking into consideration that the price of electricity is higher at peak hours. These variables are taken into acount when running the simulations. Both the red, orange, and blue arrows depict hypothetically the two best routes for the same journey, but they begin in a variety of charge states. Take note that the price of electricity is tied to each time step and that this price is subject to change. Each triangle within a column indicates the Q value that is connected to one of the potential states, ranging from N0 (an empty battery) to NN (a battery that has been fully charged) in a given time step. In the middle of the graph is an illustration of a moment when there is no connection because the car is moving. During this time when no decisions can be made, the red arrows point to a drop or discharge in the level of charge that has been accumulated. Depending on how the Q learning model works, there may be a fee for this option if the battery does not have enough power for the trip. Fig. 7 suggests that, on average, the battery is fully charged at midnight. As the initial condition states that the charged battery is connected to the BEV. The battery is ready for use at midnight for the BEV that connects the battery for optimal use from morning 6 to evening 6. It is clear from the figure that the battery is discharged to meet the high load demands of the residential system during peak evening hours from 6 to 10 p.m. The load demand on the grid is very high, and in some countries, the electricity charge is high during peak hours.

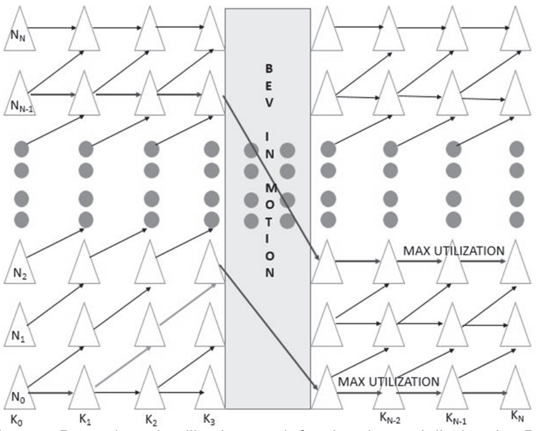

Figure 7 Dynamic path utilization graph for charging and discharging BEV battery

The trials are reliant on a database that was collected for a fleet of cars and includes information on the use of conventional vehicles. The information on each user of a BEV is described by all of the driving activities they engage in, such as the distance driven, the speed at which they go, and the amount of time it takes for them to connect. As a result of these activities, the amount of energy that is used will be computed for each time slot t to build a driving profile for each specific BEV user according to the input set. With an app on a mobile device, you can record these inputs in the real world. We tested three different policies: dynamic programming, always charging, and random decisions, for a total of five vehicles over 60 days during the summer and rainy seasons. Using the methodology described, dynamic programming is the answer to the problem. In addition, dynamic programming necessitates having access, either through historical records or through forecasts, to the pricing of energy and gas, the initial state of charge of the vehicle, and the journeys performed during the period being optimised. The remaining policies are heuristics that serve as results for the baseline. The Always Charge heuristic refers to a naive charging behaviour that is uncontrolled and occurs when BEV drivers charge their vehicles whenever and wherever it is possible, so long as the vehicle's battery is not completely depleted. There is no consideration given to the amount of energy that is required or the cost of the electricity. The Random Decisions policy is a simple set of rules that uses a random number generator to decide how the battery should be charged. For these tests, we will assume that the car is a plug-in hybrid BEV with a gasoline engine that can be turned on if the batteries run out while the car is moving. It is necessary to define two experiment parameters: the number of bins (B) that will be used to discrete the state of charge, and the time slot that will be utilised for decision-making (k). Tab. 1 illustrates the average gain of 5 cars using the dynamic programming model over the basic B = 10 bins scheme, in both seasons (summer and rainy) on the training set, with varying time intervals (k = 10, 30, and 60) and different numbers of bins in the discretisation of the state of charge. We can recognise a linear pattern between the average gain and the increase in the number of bins that were used for discretisation, and this tendency holds for both the dry and wet seasons. When we take a look at the coefficient of variation, which is calculated by dividing the standard deviation by the mean and indicates the amount of relative variability to the mean, we see that the results are not too spread out. It demonstrates a correlation between the amount of time that has passed and the amount of money that has been spent on the vehicle's operational charging. It demonstrates that the outcomes of DP are quite sensitive to the selection of this parameter, with effectiveness being dramatically reduced for intervals of 30 and 60 minutes as compared to intervals of 10 minutes.

Table 1 Average gain for 5 BEV tested during the training phase

Season	K Minutes	Mean		
		10 Bins	30 Bins	60 Bins
Summer	10	1.73	2.28	3.12
	30	4.73	5.32	5.89
	60	0.81	0.97	1.04
Rainy	10	1.41	2.32	3.97
	30	5.12	5.73	6.24
	60	0.69	0.81	0.93

This is to be expected because a shorter amount of time allows for a greater degree of flexibility in the decision-making process. Both the amount of time needed to compute dynamic programming and the size of the datasets grow at a linear rate proportional to the number of bins that are employed. According to the findings that were presented earlier, using B = 10 bins appears to be an acceptable compromise. This is because the benefits of increasing the number of bins are relatively modest while doing so significantly increases the amount of computational work required by the methods that were investigated.

5 CONCLUSION

This article investigates the use of BEV batteries as a means of resolving the issue of maintaining the grid's load demand. The SDHADP algorithm is used to solve the issue of power management in BEVs. The essay examines the structure of the environment with a dynamic approach. The major components of the design are the BPNN-based speed prediction model, the HDP-based speed planning design, and the DHP-based EMS. A MATLAB/Simulink-based simulation confirmed the performance of the suggested control approach. All of the diagrams and equations required to understand the reinforced *Q* learning model and the three-layer feed-forward neural network with backpropagation are included. Connecting a BEV's battery to a home's electrical system is a fresh and original idea. The concept has the potential to lessen one's monthly power bill and, more importantly, to lessen the grid's peak load demand. The experimental findings verify that a suitable dynamic solution to the issue of energy management in BEV can be found using the SDHADP algorithm. To further enhance the efficacy of energy consumption optimization, we want to build an energy management strategy in future research (by increasing the state input in the network).

REFERENCES

[1] Mirko, G., Dragan, S,, Vladimir, P., Slavko, M., & Aleksandar, M. (2017). Electric Vehicle Conversion: Optimisation of Parameters in the Design Process. *Tehnički vjesnik*, *24*(4), 1213-1219. https://doi.org/10.17559/TV-20160613131757

[2] Venkatasatish, R. & Dhanamjayulu, C. (2022). Reinforcement learning based energy management systems and hydrogen refuelling stations for fuel cell electric vehicles: An overview. *International Journal of Hydrogen Energy*, *64*(47), 27646-27670. https://doi.org/10.1016/j.ijhydene.2022.06.088

[3] Fu, Z., Wang, H., Tao, W., Ji, B., Dong, Y., & Song, Y. (2022). Energy Management Strategy for Fuel Cell/Battery/Ultracapacitor Hybrid Electric Vehicles Using Deep Reinforcement Learning With Action Trimming. *In IEEE transactions on vehicular technology*, *71*(7), 7171-7185. https://doi.org/10.1109/TVT.2022.3168870

[4] Liu, X., Guo, H., Cheng, X., Du, J., & Ma, J. (2022). A Robust Design of the Model-Free-Adaptive-Control-Based Energy Management for Plug-In Hybrid Electric Vehicle. *Energies*, *15*, 7467. https://doi.org/10.3390/en15207467

[5] Jeoung, H., Lee, W., & Park, D. (Eds.). (2022). Data-Driven Analysis of the Correlation of Future Information and Costates for PMP-based Energy Management Strategy of Hybrid Electric Vehicle. *Int. J. of Precis. Eng. and Manuf.-Green Tech*, *9*, 873-883. https://doi.org/10.1007/s40684-021-00400-0

[6] Reza, B., Mohammad, I., & Saman, S. (2016). Investigation of Energy Usage and Emissions on Plug-In and Hybrid Electric Vehicles. *Tehnički vjesnik*, *243*(3), 899-906. https://doi.org/10.17559/TV-20140928112417

[7] Kim, Y., Figueroa Santos, M., Prakash, N., Baek, S., Siegel, J., B., & Rizzo, D. M. (2020). Co-optimization of speed trajectory and power management for a fuel-cell/battery electric vehicle, *Applied Energy*, *260*, 114254. https://doi.org/10.1016/j.apenergy.2019.114254

[8] Bai, Y., Li, J., He, H., Santos, R. C. D., & Yang, Q. (2020). Optimal Design of a Hybrid Energy Storage System in a Plug-In Hybrid Electric Vehicle for Battery Lifetime Improvement. *IEEE Access*, *8*, 142148-142158. http://dx.doi.org/10.1109/ACCESS.2020.3013596

[9] Hu, J., Li, J., Hu, Z., Xu, L., & Ouyang, M. (2021). Power distribution strategy of a dual-engine system for heavy-duty hybrid electric vehicles using dynamic programming. *Energy*, *215*, 118851. https://doi.org/10.1016/j.energy.2020.118851

[10] Shahriar, S., Al-Ali, A., R., Osman, A., H., Dhou, S., & Nijim, M. (2021). Prediction of EV Charging Behavior Using Machine Learning. *IEEE Access*, *9*, 111576-111586. http://dx.doi.org/10.1109/ACCESS.2021.3103119

[11] Hu, X., Li, S., E., & Yang, Y. (2016). Advanced Machine Learning Approach for Lithium-Ion Battery State Estimation in Electric Vehicles. *IEEE Trans. Transp. Electrific*, *2*(2), 140–149. https://doi.org/10.1109/TTE.2015.2512237

[12] Xu, M., Wang, R., Zhao, P., & Wang, X. (2019). Fast charging optimization for lithium-ion batteries based on dynamic programming algorithm and electrochemical-thermal-capacity fade coupled model. *Journal of Power Sources*, *438*, 227015. https://doi.org/10.1016/j.jpowsour.2019.227015

[13] Lee, H., Kang, C., Park, Y., I., Kim, N., & Cha, S. W. (2020). Online Data-Driven Energy Management of a Hybrid Electric Vehicle Using Model-Based Q-Learning. *IEEE Access*, *8*, 84444–84454. https://doi.org/10.1109/ACCESS.2020.2992062

[14] Xu, B., Zhou, Q., Shi, J., & Li, S. (2022). Hierarchical Q-learning network for online simultaneous optimization of energy efficiency and battery life of the battery/ultracapacitor electric vehicle. *Journal of Energy Storage*, *46*, 103925. https://doi.org/10.1016/j.est.2021.103925

[15] Shufen, W. & Yanwu, C. (2023). Effect of Battery Pack Connection on Vehicle Ride Comfort. *Technical Gazette*, *30*(2), 584-589. https://doi.org/10.17559/TV-20221109024651

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