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Degradation Abatement in Hybrid Electric Vehicles using Data-Driven Technique

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Abstract

Electrified transportation is considered one of the most feasible technological solutions to address the growing climate change challenges in the electric transportation sector. However, the batteries used in electric vehicles (EVs) and hybrid electric vehicles (HEVs) have limited life. The degradation of the battery is accelerated by the operating conditions of the vehicle, which further reduces its life and increases the reliability and economic concerns for the vehicle's operation. This paper provides a technique to minimize the degradation of the battery used in HEVs called a prognostic-based control framework. A data-driven method is used to predict the degradation path of the battery. Depending on the degradation, the control strategy of the system is reconfigured to reduce the degradation and increase the battery's operating life.

Keywords: Battery Degradation; Degradation Prediction; Degradation Abatement; Hybrid Electric Vehicles; Lithium-ion Battery

1. Introduction

Electric vehicles (EVs), whether battery electric vehicles (BEV) or hybrid electric vehicles (HEV), are considered next-generation transportation that uses alternative energy storage systems to replace or in conjunction with an internal combustion engine. In an HEV, multiple power-generating sources supply power to the vehicle. Batteries are currently

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the most preferred ESS for energy storage in EVs because of their high energy density, small size, and reliability (Song et al., 2014). The average cost of a battery for an electric vehicle (EV) accounts for around 30% of the total cost as of 2020 (Lu et al., 2022; Hoang et al., 2022; Barré et al., 2013). This high cost raises concerns regarding the economic viability of EVs, highlighting the need for reduced degradation costs to drive the adoption of electrified transportation.

Recently, most EVs utilize lithium-ion batteries as their power source. These batteries undergo a complex degradation process during the actual operation of the EV. The operating conditions like temperature, charging current, discharging current, and depth of discharge (DoD) accelerate the degradation (Timilsina et al., 2023; Gumrukcu et al., 2022). Battery degradation takes place gradually over a period of time due to driving conditions, as mentioned, which has three significant impacts on the vehicle. Firstly, it reduces the vehicle's driving range due to a decrease in capacity. Secondly, it lowers the charging/discharging efficiency due to an increase in resistance. Lastly, it requires battery replacement once the capacity drops below the degradation limit (Smith et al., 2010). Also, in EV applications, the battery's lifespan is shorter compared to other components, as its reliability is maintained until it reaches 80% of its original capacity leading to the faster replacement of the battery (Liu et al., 2019).

Due to the presence of multiple sources in HEV, energy management (EM) is necessary, whose goal is to optimally allocate the power between these sources (Onori et al., 2012). While allocating the power, the main objective of the EM is to reduce the fuel consumption by the vehicle (Song et al., 2014). While doing so, the EM does not look at the degradation of the battery that can increase the vehicle's operating cost in the long run. Hence, in HEV, it can be stated that the degradation of the battery depends on the strategy of the EM (Tang et al., 2015; Song et al., 2014), as EM does not consider any of the degradation aspects. Hence a comprehensive control strategy is required.

A proper control strategy requires accurate degradation forecasting. In recent years, advancements have been made in predicting degradation paths through the use of various models, which can be classified into three main categories: model-based, data-driven, and hybrid approaches, as detailed in the literature (Hoang et al., 2022; Lu et al., 2022; Severson et al., 2019). The degradation path of batteries is estimated using a range of statistical models, as illustrated in (Severson et al., 2019). However, operating conditions have a significant impact on the degradation processes in the case of HEVs, as their operating conditions can be highly variable. So, the statistical models that do not consider future operating conditions may not be effective in predicting the degradation path.

The study (Hoang et al.,2022) uses Markov's chain model to predict the degradation path of the battery. However, the use of Markov Chain models for future predictions can be hindered by several limitations, such as assuming that the future state is only determined by the present state and ignoring other factors, believing that the data-generating system is static, and having a tendency to overfit data and produce unreliable results when faced with new data. Additionally, Markov Chain models have difficulty modeling complex non-linear relationships, which can result in incorrect predictions. The need to compute the transition matrix also slows the computational process.

In recent years, there has been a significant enhancement in model-free/data-driven algorithms, like neural networks. These algorithms offer a range of benefits, including their ability to model complex non-linear relationships between inputs and outputs, resulting in their suitability for a variety of applications. Furthermore, they have the capability to generalize from training data to new, unseen data, making them practical for real-world scenarios. Additionally, neural networks can automatically extract relevant features from input data, reducing the requirement for manual feature engineering. They are also well-suited for big data applications, as they can handle large amounts of data. Finally, they are able to learn from unstructured data, such as images, audio, and text, broadening the range of problems they can be used to solve (Hecht-Nielsen, 1992). Hence, in this paper, instead of Markov's chain model, a more advanced learning algorithm, i.e., a neural network (NN) (data-driven method), is used to predict the degradation path of the battery.

1.1. Contributions

In this paper, a new method for mitigating degradation in HEVs is proposed, named "prognostic-based control framework (PBCF)". This framework utilizes a NN to model the degradation of the battery over time. By predicting the degradation path of the battery, the rate of degradation can be calculated and can be fed into the EM system. The degradation rate cost is then incorporated into the EM's objective function, which is used to determine the power allocation between the engine and the battery. By doing so, the proposed method ensures that the operation of the vehicle is not compromised while accounting for the battery's degradation.

The integration of degradation forecasting (DF) into the real-time control and management of HEVs is a recently adopted concept. In particular, the integration of DF with real-time EM is a novel approach. The idea behind this integration is to use predictions about the future degradation of the battery to inform and improve the real-time decision-making of the EM system. This helps to ensure that the HEV operates efficiently while taking into account the future degradation of the battery, resulting in a more optimized and sustainable performance over time.

1.2. Paper Architecture

A detailed explanation of the powertrain model employed in this study is given in the next section. This is followed by a description of the hierarchical control architecture that directs the model's behavior. In the following section, the degradation modeling and forecasting model is addressed in more detail, showing how it fits within the suggested framework. After this, a prognostic-based control method is presented and assessed using numerical simulations. Finally, the paper concludes with a summary of the results and recommendations for further research in this field.

2. Hybrid Electric Vehicle Architecture

HEV provides a better driving experience with a quiet and clean environment while reducing operating costs compared to traditional gas-powered vehicles. The significant advancements in power electronics technology have made HEVs more dependable and efficient. These vehicles typically use an Internal Combustion Engine (ICE) and an electric motor to drive the powertrain. The way in which the ICE and motor contribute to a vehicle's transmission can classify HEVs into different architectures, including series, parallel, series-parallel, and complex HEVs.

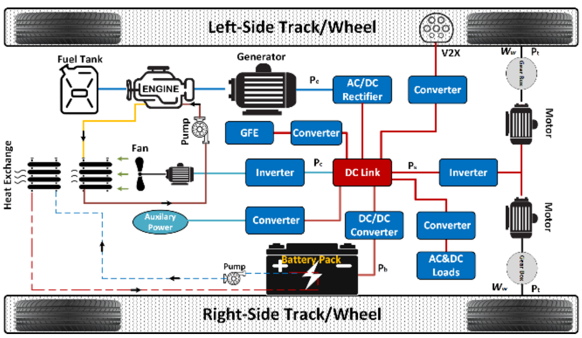

Fig. 1. Series HEV architecture

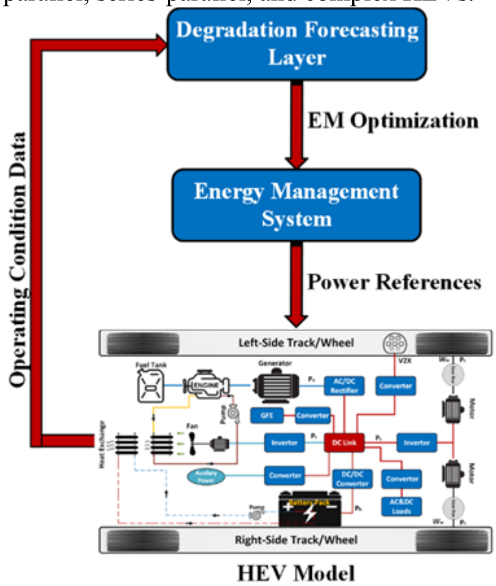

Fig. 2. Multi-level control architecture

In this study, a series HEV is selected because of its flexibility in control compared to other HEV architectures. These advantages include a straightforward design with reduced control complexity, high fuel efficiency as it primarily utilizes its electric motor for propulsion, decreased engine wear and tear as the internal combustion engine is only used to recharge the batteries, and the highest level of control flexibility (Hoang et al., 2023). Figure 1 shows the powertrain model used in this study. This model consists of a $600V$ DC bus powered by an ICE and an energy storage system (ESS), i.e., a battery. The implementation of power electronics converters as an interface between the energy sources and the loads enables a clean separation of the two. This design is economically viable due to recent advancements in power electronics technology and a decrease in the cost of power electronic devices.

The decoupling of energy sources and loads from the bus makes the implementation of an electric motor more straightforward, as it relaxes the issues related to power split in HEVs. This design provides greater flexibility in controlling the electric motors and resolves various constraints related to propulsion loads and the ICE. Additionally, the design of the model enables the vehicle to participate in the vehicle-to-grid (V2G) mode and the vehicle-to-vehicle (V2V) mode. There is a V2X outlet provided in the design, which facilitates the exchange of energy for this purpose. This enhances the functionality of the vehicle and increases its versatility.

3. Multi-Level Control Architecture

The adoption of computational devices in vehicles has significantly increased over the past few years. The reduction in cost and the improvement of their capabilities have made it possible to deploy a wide range of computational devices in vehicles. Different controllers, i.e., electronic control units (ECUs), are becoming computationally powerful and affordable. The integration of these devices has made it possible to optimize vehicle performance and improve fuel efficiency (Hoang et al., 2023). One of the key advantages of using computational devices in vehicles is the ability to perform optimization and forecasting functionalities. These functionalities allow for implementing complex algorithms and strategies that enable vehicles to operate more efficiently.

The development of such technology has motivated to use different controllers in several fields (Arsalan et al. 2020) . This concept can be used in vehicles, which is implemented in this study, as shown in figure 2. The first layer is EM, which is required due to the presence of multiple power-generating sources in the vehicle. EM decides the amount of power to be delivered by each source to the vehicle while satisfying certain constraints. The EM obtains and analyzes information from both the vehicle and the operator in order to generate optimal set points that are sent to the actuators and then executed to operate the vehicle.

So, in comparison to conventional ICE vehicles, EM provides an additional layer of decision-making that determines the optimal power split across the onboard energy sources. Also, hybrid vehicle architectures have different optimization criteria for EM. Hence, EM implements different strategies depending on the architecture of the powertrain. So, for the series HEV as shown in figure 1, the optimization of EM can be broadly defined as

$$\min \sum_{s\in\dot{S}}^{n} f_s(P_s(t_k)) \tag{1}$$

$$P_s(t_k) = \text{Ƥ} \tag{2}$$

where the discrete domain includes a time instant represented by t_k, and a set of energy sources denoted by $\dot{S}$. At time t_k, P_s indicates the power generated by source $\dot{S}$. The constraints set of $P_s(t_k)$ is denoted by Ƥ. To simplify the presentation, the notation of t_k is neglected.

The primary goal of EM's optimization problem is to minimize fuel costs, but the degradation of other electrical components presents a challenge and increases the overall cost of vehicle operations. This is especially true for batteries, which are one of the most expensive components of a vehicle, as discussed earlier. Hence, it is imperative to acknowledge that the vehicle's operating cost is not solely determined by fuel expenses. The cost associated with the degradation of components must also be incorporated into the optimization process to achieve long-term cost reduction.

However, incorporating appropriate degradation costs into the optimization process can be challenging. Some works have adopted a simplistic approach of adding a constant value to the total cost function, as represented by (1). However, this approach fails to account for the fact that component degradation is influenced by various factors, such as its current condition and operating conditions. In other words, the rate at which a component degrades may vary significantly depending on the environment it operates in, as well as its current state. Therefore, it is necessary to develop more nuanced and accurate models that account for these factors when estimating degradation costs. The model for degradation prediction is explained in detail in the following section 4.

The maximum amount of energy/power that can be generated from any energy source is not infinite but rather has a specific upper limit. Therefore, one of the significant constraints when optimizing EM is the lower and upper generation limits. (3) and (4) represent these constraints for (2) and must be taken into consideration during the optimization process. The powertrain's main objective is to ensure that the energy generated is supplied to the loads. This means that the total amount of energy generated should be sufficient to meet the total energy demands of the loads, as well as any losses that may occur during the energy transfer process. To ensure that this requirement is met, a constraint represented by (5) is formed, which must be taken into consideration when optimizing EM.

$$\underline{P_{bat}} \leq P_{bat} \leq \overline{P_{bat}} \tag{3}$$

$$\underline{P_{ICE}} \leq P_{ICE} \leq \overline{P_{ICE}} \tag{4}$$

$$P_{bat} + P_{ICE} = P_{ACload} + P_{DCload} + P_{\Pr opulsion} + P_{V2X} + P_{Loss} \tag{5}$$

where, P_{bat} and P_{ICE} are the power generated by the sources battery and engine, respectively. Also, P_{ACload} and P_{DCload} represent the power demanded by the AC and DC loads of the vehicle. $P_{Propulsion}$ denotes the power demanded by the powertrain for the propulsion of the vehicle. Similarly, P_{V2X} is the power consumed or supplied by the vehicle for the V2G or V2V operation. Lastly, P_{Loss} denotes all the losses that occur in the vehicle.

Each source has its internal constraints that represent (3). The internal constraints for the engine and battery are represented by (6) and (7), which represent the ramp rate limits when adjusting their generation. And for the battery, the state of charge (SoC) has to be maintained. Therefore, (8) and (9) denote the battery SoC constraints, where $\delta T = t_{k-1} - t_k$.

$$\left| P_{ICE}(t_{k+1}) - P_{ICE}(t_k) \right| = rr_{ICE} \tag{6}$$

$$\left| P_{bat}(t_{k+1}) - P_{bat}(t_k) \right| = rr_{bat} \tag{7}$$

$$\underline{SoC_{bat}} \leq SoC_{bat} \leq \overline{SoC_{bat}} \tag{8}$$

$$SoC_{bat}(t_{k+1}) = SoC_{bat}(t_k) - \frac{\delta T i_{bat}}{Q_{nom}} \tag{9}$$

4. Degradation Modeling and Prediction

Artificial neural networks (ANNs) have become a popular tool for modeling complex systems and making predictions based on data. This algorithm is designed to mathematically mimic the neural activity of the brain through a network of interconnected neurons. The NN's internal structure consists of a large number of these neurons, as shown by circles in figure 3, which shows a simplified NN.

NNs are created to learn from data and then make predictions based on that learning. Neurons are the center of a neural network, the fundamental computing units that process input data and generate output. Weighted connections link neurons to one another, creating a network of interconnected nodes. Each neuron in the network gets information from one or more other neurons, processes that information, and then transmits the outcome to one or more other neurons.

To predict the degradation paths of the component, a degradation model based on NN is constructed. The degradation of the component is impacted by its working conditions. For example, the degradation path of the battery is impacted by the working temperature, charging and discharging cycles, and the depth of discharge (Timilsina et al., 2023). In the study (Hoang et al., 2022), Markov's chain-based model is used to predict the degradation path. However, there are several drawbacks of Markov Chain models, as discussed in section 1; therefore, in this study, a backpropagation NN (BPNN) is used.

The most promising choice among existing battery technologies applicable to EVs is lithium-ion (Li-ion) batteries, which are also now regarded as the best option for developing future-generation EVs. Li-ion batteries are emerging as the best fit for EVs as they have a higher energy density than any other battery technologies, higher power density, good high-temperature performance, and, most importantly, are lighter and smaller than other batteries (Timilsina et al., 2023). Due to the lack of publicly available battery pack data of an HEV or EV, a $2.9Ah$ Panasonic $18650PF$ cell's different test data conducted in a lab at the University of Wisconsin-Madison is used to predict the degradation path of the battery (Kollmeyer, 2018). This cell data is scaled up to the battery pack of $73\ kWh$ to increase the accuracy of the study.

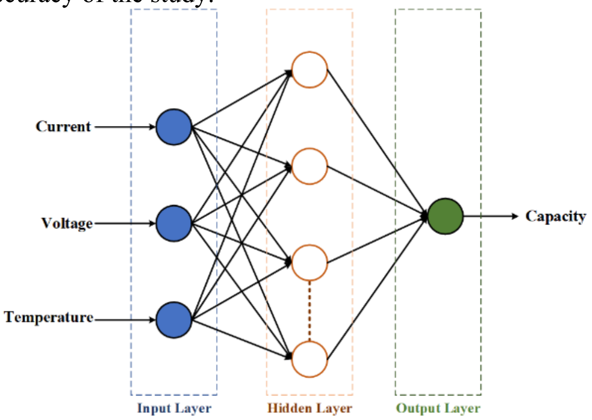

Fig. 3. A simple Neural Network with three inputs and one output

This study uses a three-layer backpropagation neural network architecture consisting of an input layer, a hidden layer, and an output layer to predict battery capacity loss. Before feeding the data to the model, they are pre-processed, and the necessary features are extracted: voltage, current, temperature, and capacity. The neural network's input layer accepts three inputs, namely current, voltage, and temperature, while the output layer predicts the capacity of the battery. The number of hidden layers is one, and the number of neurons is ten. The following sets of data denote the separation of data into training, testing, and validating data.

$$\delta_{train} = [(x_1, Y_1), (x_2, Y_2), (x_3, Y_3) .... (x_N, Y_N)] \tag{10}$$

$$\delta_{test} = [(x_{n+1}, Y_{n+1}), (x_{n+2}, Y_{n+2}), (x_{n+3}, Y_{n+3}) .... (x_s, Y_s)] \tag{11}$$

$$\delta_{validation} = [(x_{s+1}, Y_{s+1}), (x_{s+2}, Y_{s+2}), (x_{s+3}, Y_{s+3}) .... (x_t, Y_t)] \tag{12}$$

where x and Y represent the data extracted from the raw data. x is the input to the NN and has three variables voltage, current, and temperature as $x_i = (V_i, i_i, T_i)$. Similarly, Y is the output from the network which represents the capacity of the battery. The δ_{train} is used to train the NN whereas δ_{test} and $\delta_{validation}$ are used to test and validate the model developed using train data sets. Now, the main objective is to minimize the estimation error $J(\theta)$ and the difference between the actual capacity and the estimated capacity from the NN denoted by $f(x_i; \theta)$

$$J(\theta) = \frac{1}{2} \sum_{i=1}^{n} (f(x_i, \theta) - Y_i)^2 \tag{13}$$

$$\hat{\theta} = \arg\min_{\theta} J(\theta) \tag{14}$$

There are different numerical algorithms that can be employed to optimize θ , including Levenberg-Marquardt (LM), Adaptive Moment Estimation (Adam), Adagrad, Broyden-Fletcher-Goldfarb-Shanno (BFGS) and Stochastic Gradient Descent (SGD) (Hecht-Nielsen, 1992). Here, LM algorithm is used, and this algorithm is based on the following partial derivative formula.

$$\theta : \theta - \alpha \frac{\partial J(\theta)}{\partial \theta} \tag{15}$$

where, α is the learning rate and at the beginning initial value of θ is assigned and updated after each iteration until its convergence. To minimize the estimated error in (13) employing the gradient w.r.t the network weights θ, a backpropagation algorithm is used. The main objective of this study is not to develop new learning algorithms for the NN, but rather to utilize existing algorithms to determine the capacity loss. To achieve this, accurate data is collected to serve as the input and output to the network. For this, battery aging data obtained from laboratory at University of Wisconsin-Madison is used, as previously mentioned

5. Proposed Control Strategy

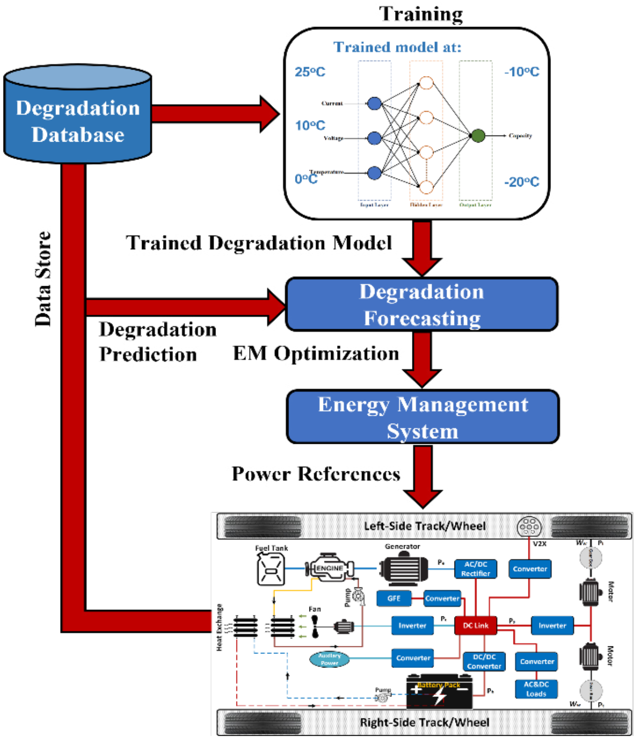

Fig. 4. Prognostic-based control framework.

The preceding sections explained the role of EM in HEV and the method of predicting the degradation path via the degradation forecasting layer. The placement of these two layers and their communication with HEV is shown in figure 2. Now, this section presents, in detail, a technique for integrating these two layers to minimize the overall operating cost of the vehicle. In this research, an approach is proposed to incorporate the impact of degradation on the cost function of EM. The idea is to consider the degradation of vehicle components as an additional cost that needs to be factored into the optimization process. In order to assess the degradation of a component's capacity over time, it is necessary to measure the change in capacity of the component over the predicted degradation period. The degradation of a component s can be predicted from an initial time t_0 to a final time t_k as a new parameter $\Delta P_S(t_k)$ which can be obtained from the degradation prediction model.

$$\Delta_S(t_k) = \Delta P_s(t_k) \tag{16}$$

With this information on capacity loss, a cost can be calculated, which is added to the objective function of the EM. If ρ_s is the total initial cost of each capacity unit of the component s, the following degradation rate cost can be calculated and sent into the EM.

$$f_s^d(P_s) = \rho_s \Delta_s P_s \tag{17}$$

$$f(x) = 0.00052x^2 + 0.0152x + 0.65 \tag{18}$$

Hence, in this proposed approach, the penalized degradation rate cost is calculated by the DF layer and then fed into the EM layer. As previously mentioned, this degradation cost is incorporated into the objective function of the EM layer. Based on the newly formed objective function, the EM layer will reconfigure the power allocation between the engine and battery to minimize the capacity loss of the battery, as shown in figures 5 and 6. The power allocation by the EM without PBCF is shown in Figure 5, with the majority of the power coming from the battery and the engine supplying the rest of the insufficient power to meet the vehicle's demand. In contrast, figure 6 displays the power allocation of the EM when PBCF is implemented. This figure shows that the engine is also supplying power, reducing the burden on the battery to supply the demanded power. Also, the battery charges frequently under PBCF, which maintains its SoC, as seen in the figure.

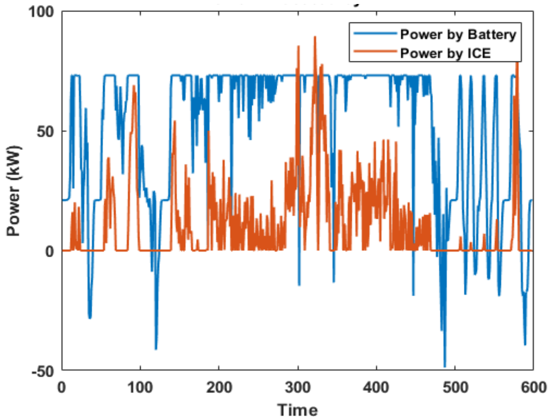

Fig. 5. Power allocation by EM without PBCF

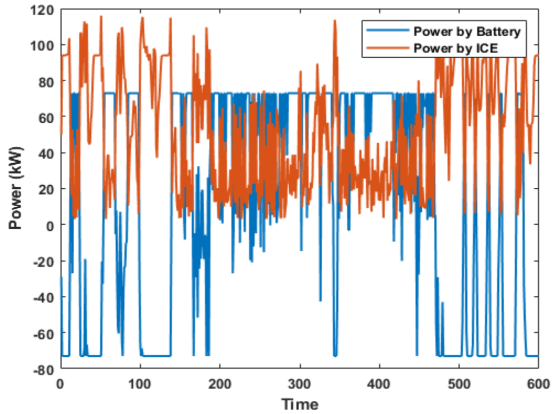

Fig. 6. Power allocation by EM with PBCF

6. Results and Discussion

The proposed framework is validated by conducting a numerical simulation on an HEV powertrain model, as shown in figure 1. In this model, there are two sources that provide power to the DC bus, one ICE of 180 kW and another a battery pack of 73 kWh. Different loads are categorized as AC and DC loads, and compared to all the loads, the propulsion load is the highest, which demands more power. For the propulsion load in this paper, a US06 drive cycle is used and operated multiple times to predict the capacity loss of the battery under this cycle. The minimum and maximum SoC of the battery is changed between 40% and 90% for the normal operation of the battery pack.

A BPNN is implemented to predict the battery's degradation path, as described in section 4. Following model training, the model was validated and tested, resulting in an R-square value of 0.9858 and a mean square error (MSE) of 0.0142. Using this trained NN model, the degradation path was predicted for a new data set that was not used during training, testing, or validation. The NN output was then compared to the actual data, as shown in figure 5, and the predicted path closely followed the actual path with an MSE of 0.0163.

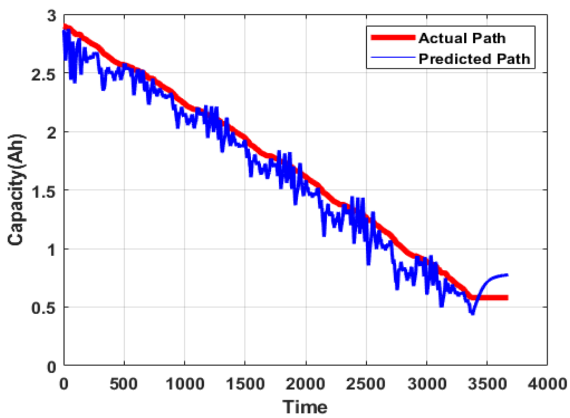

Fig. 7. Prediction of capacity fade using proposed NN

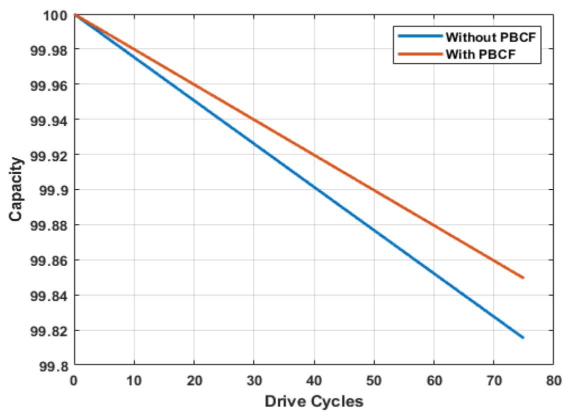

Fig. 8. Battery degradation abatement with PBCF

The degradation forecasting layer predicts the degradation of the battery after running for 75 drive cycles. From the simulation, the degradation path of the battery is reduced after applying the proposed strategy i.e., PBCF, which can be seen in figure 5. The vehicle with PBCF employed has less degradation compared to the vehicle without PBCF.

This reduces the degradation costs of the battery used in HEV. The average cost of the battery is $151 for each kWh as of 2022 (Bloomberg, 2022). With the numerical simulation, the proposed strategy reduces the degradation from 0.185% to 0.151%, and the battery degradation cost is reduced from $101.17 to $82.29, which is reduced by 18.66% after running the vehicle for 75 drive cycles.

7. Conclusion

The use of a DF layer, in addition to EM in an HEV, can increase the operating life of the battery and decrease the overall operating cost of the vehicle. In this paper, this is verified by using a PBCF for HEV. An HEV model is run for multiple drive cycles to predict the degradation path of the battery, which is calculated by the DF layer. Depending upon the degradation path, a degradation rate cost is calculated and included in the objective function of EM. This reallocates the power between the sources of the HEV so that the degradation is minimized and the overall operating cost is reduced. A numerical simulation is used to validate this control strategy.

Acknowledgment

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References

Song Z, Hofmann H, Li J, Hou J, Han X, Ouyang M. Energy management strategies comparison for electric vehicles with hybrid energy storage system. Applied Energy. 2014 Dec 1;134:321-31.

Lu J, Xiong R, Tian J, Wang C, Hsu CW, Tsou NT, Sun F, Li J. Battery degradation prediction against uncertain future conditions with recurrent neural network enabled deep learning. Energy Storage Materials. 2022 May 4.

Onori S, Spagnol P, Marano V, Guezennec Y, Rizzoni G. A new life estimation method for lithium-ion batteries in plug-in hybrid electric vehicles applications. International Journal of Power Electronics. 2012 Jan 1;4(3):302-19.

Hoang PH, Ozkan G, Badr P, Timilsina L, Edrington C. A Prognostic Based Control Framework for Hybrid Electric Vehicles. SAE Technical Paper; 2022 Mar 29.

Gumrukcu E, Arsalan A, Muriithi G, Joglekar C, Aboulebdeh A, Zehir MA, Papari B, Monti A. Impact of Cyber-attacks on EV Charging Coordination: The Case of Single Point of Failure. In2022 4th Global Power, Energy and Communication Conference (GPECOM) 2022 Jun 14 (pp. 506-511). IEEE.

Tang L, Rizzoni G, Onori S. Energy management strategy for HEVs including battery life optimization. IEEE Transactions on Transportation Electrification. 2015 Aug 21;1(3):211-22.

Barré A, Deguilhem B, Grolleau S, Gérard M, Suard F, Riu D. A review on lithium-ion battery ageing mechanisms and estimations for automotive applications. Journal of Power Sources. 2013 Nov 1;241:680-9.

Smith K, Markel T, Kim GH, Pesaran A. Design of electric drive vehicle batteries for long life and low cost. InAccelerated Stress Testing and Reliability (ASTR), IEE Workshop on 2010 Oct 6 (pp. 6-8).

Arsalan A, Ahmad J, Tahir M, Mazumder SK. Distributed Control and Power Management of Islanded DC Nanogrids with Applications to Rural Electrification. In2020 IEEE Energy Conversion Congress and Exposition (ECCE) 2020 Oct 11 (pp. 4662-4667). IEEE.

Liu C, Wang Y, Chen Z. Degradation model and cycle life prediction for lithium-ion battery used in hybrid energy storage system. Energy. 2019 Jan 1;166:796-806.

Severson KA, Attia PM, Jin N, Perkins N, Jiang B, Yang Z, Chen MH, Aykol M, Herring PK, Fraggedakis D, Bazant MZ. Data-driven prediction of battery cycle life before capacity degradation. Nature Energy. 2019 May;4(5):383-91.

Hecht-Nielsen R. Theory of the backpropagation neural network. InNeural networks for perception 1992 Jan 1 (pp. 65-93). Academic Press.

Timilsina L, Badr PR, Hoang PH, Ozkan G, Papari B, Edrington CS. Battery Degradation in Electric and Hybrid Electric Vehicles: A Survey Study. IEEE Access. 2023 Apr 27.

Hoang PH, Ozkan G, Badr PR, Timilsina L, Papari B, Edrington CS. Integrating degradation forecasting into distribution grids' advanced distribution management systems. International Journal of Electrical Power & Energy Systems. 2023 Aug 1;150:109071.

Kollmeyer P. Panasonic 18650pf li-ion battery data. Mendeley Data. 2018 Jun;1(2018)

Bloomberg New Energy Finance. "Lithium-ion Battery Pack Prices Rise for First Time to an Average of $151/kWh." BNEF, 6 Dec 2022, https://about.bnef.com/blog/lithium-ion-battery-pack-prices-rise-for-first-time-to-an-average-of-151-kwh/.