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Impact of Vehicle-to-Grid (V2G) on Battery Degradation in a Plug-in Hybrid Electric Vehicle

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Abstract

Electric vehicles (EVs) are becoming increasingly recognized as an effective solution in the battle against climate change and reducing greenhouse gas emissions. Lithium-ion batteries have become the standard for energy storage in the automobile industry, widely used in EVs due to their superior characteristics compared to other batteries. The growing popularity of the Vehicle-to-grid (V2G) concept can be attributed to its surplus energy storage capacity, positive environmental impact, and the reliability and stability of the power grid. However, the increased utilization of the battery through these integrations can result in faster degradation and the need for replacement. As batteries are one of the most expensive components of EVs, the decision to deploy an EV in V2G operations may be uncertain due to the concerns of battery degradation from the owner's perspective. This paper examines the degradation of the battery employed in Plug-in Hybrid Electric Vehicles (PHEVs) for both V2G connection and its typical operating schedule. For assessing the degradation in driving scenarios, the US06 drive cycle is employed. On the other hand, for the V2G scenario, a 10 kW bidirectional charger is utilized. The charger discharges the battery up to 20 kWh in 2 hours or up to 60% state of charge (SoC) and subsequently charges it back to 90% SoC at a constant 1C rate. This V2G setup simulates the discharging and charging patterns typically observed in real-world scenarios and allows for evaluating battery performance and degradation under such conditions. Finally, an economic analysis is conducted by considering the capacity loss of the battery resulting from the V2G connection. This study considers the incentives obtained through the V2G connection, providing an assessment of the economic viability and potential benefits associated with utilizing the vehicle in V2G applications.

Introduction

Electrified vehicles are gaining popularity due to the fluctuating cost of non-renewable energy sources and their significant ecological consequences. The use of electrified vehicles, either full electric vehicles (EVs) or hybrid electric vehicles (HEVs), contributes to mitigating the environmental effects in contrast to conventional internal combustion engine (ICE) vehicles [1]. Among the various battery technologies suitable for EVs, lithium-ion (Li-ion) batteries stand out as the most promising and preferred option for the future generation of EVs [2]. Li-ion batteries offer several advantages that make them an excellent fit for EVs. They currently provide a higher energy density than any other battery technology, enabling longer driving ranges and improved performance. Additionally, Li-ion batteries exhibit a higher power density and perform admirably under high-temperature conditions. Most notably, they remain lighter and more compact than alternative battery types, contributing to enhanced overall vehicle efficiency and design [2].

Energy storage batteries have long served as a dependable system for utilities. However, the substantial cost of these batteries has posed a challenge in installing large-capacity systems for utility purposes. In recent years, the sales of EVs have witnessed rapid growth. Consequently, the idea of utilizing EV batteries to support the electrical grid has gained momentum. This emerging concept is known as Vehicle-to-Grid (V2G) technology, a smart charging approach that enables car batteries to contribute power back to the grid. Essentially, it leverages high-capacity batteries not only as a means to power EVs but also as backup storage units for the electrical grid [3, 4].

Apart from V2G, there is another noteworthy abbreviation linked to bi-directional charging - V2X. V2X, which stands for vehicle-to-everything, encompasses various use cases, including vehicle-to-home (V2H), vehicle-to-building (V2B), and vehicle-to-load (V2L) services[3]. These applications further extend the versatility and potential of utilizing EV batteries beyond just powering the vehicles.

V2G technology enables bi-directional charging, allowing for both charging the EV battery and sending back the stored energy from the car's battery to the power grid [5]. From the utility's perspective, V2G technology offers a range of significant advantages. V2G presents a flexible and dynamic energy storage system that supports the electrical grid in various ways. By collecting the energy storage capacity of several connected EVs, utilities can stabilize the grid during peak demand periods; meeting increased energy requirements. Conversely, surplus energy from the grid can be utilized to charge EV batteries during off-peak hours, effectively balancing energy supply and demand. Leveraging the vast distributed network of energy storage devices represented by EVs, V2G allows utilities to enhance grid resilience and reliability without the need for expensive additional energy storage facilities [6, 7]. Furthermore, EVs, with their substantial battery capacities, can serve as backup power sources for houses during emergencies when connected as V2H systems. Moreover, V2G technology facilitates the seamless integration of renewable energy sources into the grid, enabling EV batteries to store excess energy from renewables during peak production times and release it back to the grid when renewable generation is low, which can support the frequency balance and voltage balance of the grid [8, 9].

Participating in V2G connection programs offers EV owners a chance to capitalize on financial incentives. Through this approach, the owners can sell the energy from their EV batteries back to the grid during peak demand periods, while recharging their vehicles during off-peak times. This dual strategy not only has the potential to generate income but also contributes to stabilizing the grid. Notably, reports from [10] indicate that in California, USA, EV owners have earned annual amounts ranging from $650 to $1575, while in the UK, earnings have varied between $525 and $1575. Similarly, in Sweden, the reported earnings have spanned from $30 to $655 per year [10]. Furthermore, according to [11], a total savings of $793.28 was achieved over a span of 5 months through V2G operations with a 15 kW bidirectional charger installed on a Nissan LEAF. The study also suggests the potential for an annual savings of $1900, which could be further enhanced by utilizing a bidirectional charger with a higher power rating.

Nevertheless, these incentives fail to account for the battery's degradation cost. Since the battery is a critical component in Plug-in Hybrid Electric Vehicles (PHEVs), its degradation must be taken into consideration during V2G connection. Ignoring the degradation cost in V2G strategies may not accurately assess the true potential benefits of V2G implementation, considering that the battery pack represents a substantial cost within the vehicle. Therefore, it is crucial to incorporate battery degradation into proposed charging methodologies to achieve a genuine and reliable economic assessment.

Few researchers have considered approximate assumptions when modeling battery degradation in V2G applications. For instance, study [12] introduced a decentralized optimal scheduling approach for EVs with the aim of extending battery lifespan. To achieve this, this paper recommends maintaining State of Charge (SOC) levels between 20% to 85%. Another study [13] involves integrating renewable energy by coordinating the charge/discharge of EVs within specific predefined limits to mitigate battery degradation. This paper studied the impact of different charging and discharging currents on battery degradation. Nonetheless, there exists a research gap in terms of investigating the economic implications of EV operations within the context of both V2G functionality and regular usage, while also taking into account the associated battery degradation costs. In an effort to bridge this gap, a thorough techno-economic analysis of the V2G application, considering a comprehensive battery degradation model for both V2G and regular vehicle operation, is presented in this study.

Statement of Contribution

As previously stated, research on accurately predicting battery degradation during both vehicle operation and V2G connections is limited. To address this research gap comprehensively, this study embarks on the development of a data-driven degradation model using the Neural Network technique, enabling precise forecasts of battery degradation in EVs.

In addition to the model's creation, a realistic real-world scenario is formulated, encompassing vehicle operation for both standard driving and V2G connections. This scenario provides a robust foundation for testing and validating the degradation model's predictions under practical conditions. To evaluate the economic implications from the perspective of EV owners, a numerical simulation of the vehicle is conducted in MATLAB/Simulink, considering the battery degradation. Based on the findings of the numerical simulation, an economic analysis is conducted to determine whether the incentives obtained from V2G connections are beneficial enough from the battery degradation standpoint. Moreover, a comparison is made between the prediction of the End-of-Life (EOL) of the battery for standard EV applications and EV applications with V2G connections, shedding light on the potential impact of V2G operations on battery lifespan.

The remaining paper is segmented as follows: Section 3 explains the vehicle architecture considered in this study. Section 4 introduces the degradation modeling technique. The operating scenario of the vehicle is explained in detail in Section 5. Section 6 presents the finding from the simulation done in MATLAB/Simulink. Finally, Section 7 provides the paper's conclusion and suggests future research directions.

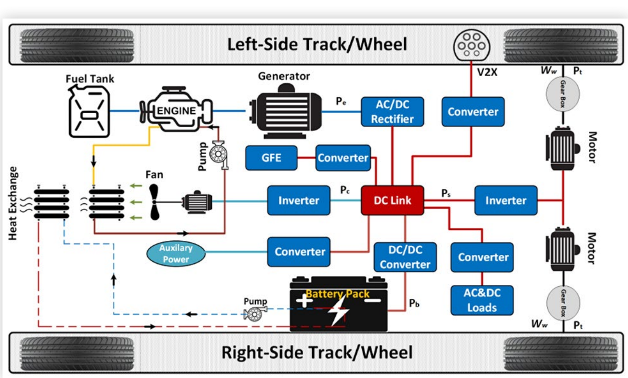
Architecture of Plug-in Hybrid Electric Vehicle

HEVs are gaining popularity as a sustainable transportation solution. They utilize multiple energy sources, with at least one delivering electrical power to an electric motor for propulsion. HEVs can be classified into various types based on their energy sources and power delivery architecture. The most common type combines an Internal Combustion Engine (ICE) with a battery to meet power demands. This paper focuses on the PHEV with series configuration among HEV architectures due to its simplicity and control flexibility.

In a series HEV, the ICE is not directly connected to the drivetrain but instead powers a generator, converting its output into electricity. This electricity is then used to charge the battery or drive the electric motor, which propels the vehicle's wheels. This configuration enables precise control of power to each wheel, simplifying traction control. Power electronics technology has significantly enhanced the efficiency and reliability of HEVs [14]. The series hybrid architecture offers numerous benefits, including improved fuel efficiency, reduced emissions, and enhanced control over power distribution to the wheels [2]. Moreover, the absence of a direct connection between the ICE and the drivetrain allows for more flexible control and simplifies traction control [15].

This section provides a concise overview of the electrical model. The model comprises a 600V (V_{DC}) bus that is powered by an ICE and battery. Figure 1 illustrates the architecture of the vehicle considered where the decoupling of energy sources and loads from the bus through the power electronics converters interface can be seen. Recent advances in power electronics and cost reduction of electronic devices have made this design economically viable. The decoupling of energy sources facilitates the implementation of Energy Management (EM) and alleviates power split issues in HEVs. Notably, this design relaxes constraints arising from propulsion loads and ICE dynamics in EM. This model enables vehicle-to-grid (V2G) and vehicle-to-vehicle (V2V) modes, incorporating a V2X outlet, which is the main focus of this study. The vehicle dimensions and dynamic parameters needed to calculate the reference power for a predefined drive cycle are taken from the study [16].

FIGURE 1 PHEV architecture considered for the study.



Degradation Modeling and Prediction

Battery safety and reliability are vital for EVs. Li-ion-based EV batteries experience aging and degradation over time, reducing capacity and driving range. Factors like battery states, driving behavior, charging conditions, and environmental conditions influence EV usage and energy consumption. Minimizing degradation through precise modeling and optimizing battery usage is crucial to maximizing EV lifetime value. Identifying factors contributing to degradation is challenging, hindering the establishment of a degradation model.

Battery lifecycle is shorter in automotive applications as the operation of vehicles beyond 80% of the initial capacity of the battery is considered unreliable [15]. Understanding the complex degradation mechanism is essential for economic viability and extending the battery life. Factors like temperature, discharging and charging currents, and DoD impact battery capacity and contribute to degradation differently [2, 17]. EV batteries face various stresses during operation due to these factors, and they should be considered while modeling or predicting the degradation path of the battery.

Artificial Neural Networks (ANNs) have gained popularity as a powerful tool for modeling complex systems and data-driven predictions. These algorithms mathematically imitate brain neural activity using interconnected neurons. NNs are designed to learn from data and make predictions accordingly. Neurons are at the core of the network, serving as fundamental computing units that process input data and produce output. Weighted connections link neurons, forming an interconnected network. Information is exchanged between neurons, processed, and transmitted to others [18]. Therefore, in this study, a degradation model based on NN is created to forecast the degradation path of the battery.

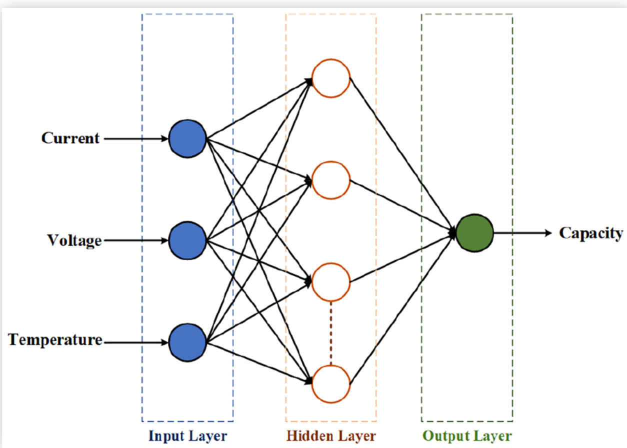
This study uses a three-layer neural network architecture to predict battery capacity loss. The architecture comprises an input layer, a hidden layer, and an output layer. Before being fed into the model, the data undergoes pre-processing, and essential features, including voltage, current, temperature, and capacity, are extracted. The input layer of the neural network accepts three specific inputs: current, voltage, and temperature. On the other hand, the output layer is responsible for predicting the battery's capacity. The hidden layer consists of 32 neurons, and the architecture has a single hidden layer. The activation function applied in this layer is the Rectified Linear Unit (ReLU) function. ReLU is commonly used in hidden layers as it enables the model to learn intricate non-linear relationships, contributing to enhanced predictive performance [18]. Finally, the output comprises a single neuron, as the regression task aims to predict the capacity loss of the battery. No activation function is specified for the output layer, ensuring that it produces raw output values, directly representing the predicted continuous output. The data is separated into distinct sets to facilitate training, testing, and validation, each serving its purpose in the predictive model as shown by (1).

$$\delta_{train} = \left[\left(x_1,\ Y_1\right),\ \left(x_2,\ Y_2\right),\ldots\ldots\ldots\ldots\ldots\left(x_n, Y_n\right)\right] \quad \text{(1a)}$$

$$\delta_{test} = \left[\left(x_{n+1}, Y_{n+1}\right),\ \left(x_{n+2}, Y_{n+2}\right),\ldots\ldots\ldots\ldots\ldots\left(x_s, Y_s\right)\right] \quad \text{(1b)}$$

$$\delta_{validation} = [\left(x_{s+1}, Y_{s+1}\right), \left(x_{s+2}, Y_{s+2}\right),\ldots\ldots\ldots\ldots\ldots\left(x_t, Y_t\right) \quad \text{(1c)}$$

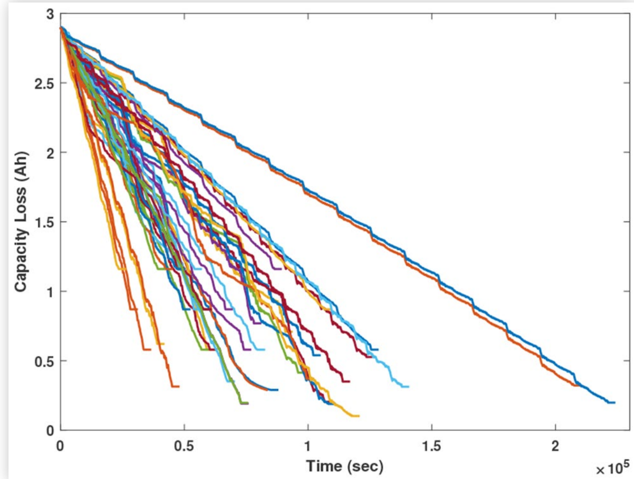
FIGURE 2 A simple neural network with three inputs and one output.



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.

The models are compiled using the mean squared error (MSE) as the loss function and the Adam optimizer. The MSE loss function measures the average squared difference between predicted and actual output values. During training, the models use the Adam optimizer, which is a popular optimization algorithm known for its effectiveness in updating the model's parameters based on the calculated gradients. Adam is an optimization algorithm that builds upon stochastic gradient descent (SGD) to handle non-convex problems efficiently. It offers faster convergence and requires fewer computational resources than other optimization methods. Particularly, Adam excels in scenarios with large datasets, as it maintains more accurate gradients over multiple iterations of learning. By integrating the benefits of two other stochastic gradient techniques, namely adaptive gradients and root mean square propagation, Adam presents a learning approach that optimizes various NNs.

FIGURE 3 Battery cell degradation dataset used to train the NNs.



To train the neural networks, enough historical aging data is needed. In this study, 2.9 *Ah* Panasonic 18650 PF cell lab test data from the University of Wisconsin-Madison is utilized due to the limited availability of publicly accessible battery pack data used in HEVs or EVs [19]. The cell data is scaled up to the battery pack of 73 *kWh* to enhance the study's accuracy. This dataset comprises multiple aging tests conducted at five distinct temperatures: 25°C, 10°C, 0°C, −10°C, and −20°C [19]. Each temperature setting includes ten unique aging datasets. Consequently, all these datasets were employed in the neural networks' training, testing, and validation process. During the pre-processing of this dataset, four specific parameters—voltage, current, temperature, and battery cell capacity—are extracted to train the neural network. The patterns of aging data for each test are illustrated in Fig. 3.

Each data point presented in Fig 3 is utilized in the training, testing, and validation processes, except for one specific dataset. The neural network's fitting during the training phase yields a Mean Absolute Error (MAE) of 0.0789, MSE of 0.0129, and R-square of 0.9743. Subsequently, this trained network is employed to predict the capacity loss of a battery cell that wasn't part of the training or testing phases. The fitting for this unseen data reveals an MAE of 0.08167, MSE of 0.0212, and an R-square of 0.9556.

Analysis of Operation of PHEV

The degradation of a vehicle's battery used for V2G operations can result from two distinct cases. Firstly, degradation may occur during regular vehicle operation, which includes driving and other typical functions. Secondly, there can be degradation specifically associated with the

V2G connection process depending upon the charging and discharging of the battery.

In the driving scenario, the simulation employs the US06 drive cycle as a representation of typical driving patterns. On the other hand, for the V2G connection, the vehicle is connected using a 10 kW bidirectional charger. During this V2G operation, the battery undergoes a discharge phase for 2 hours, followed by a recharge to a predefined SoC. By considering these two distinct scenarios, the simulation aims to predict the battery degradation in both regular vehicle usage and V2G operations, which are explained in detail in the following subsections.

Degradation under Driving Condition

To simulate a real-world scenario, a PHEV is considered, operating for the average national distance in the U.S., approximately 12,000 miles. To represent this in the simulation, the US06 drive cycle, which covers 8.01 miles, is chosen as a standard driving profile. For a typical day, the vehicle completes four US06 drive cycles, resulting in a total distance of 11,695 miles per year, closely approximating the national average.

In a PHEV, due to the presence of multiple power-generating sources, it demands an Energy Management (EM) system [20, 21]. The primary function of this EM system is to efficiently distribute power between these sources. In the specific vehicle we are considering, there are two power sources: the engine and the battery. The main objective of the EM system is to optimize power allocation between these sources, aiming to minimize overall fuel consumption [22]. As a result, the power supplied by the battery may differ from the total power demanded by the vehicle. Consequently, the degradation of the battery is influenced by the extent to which it contributes to supplying power in the vehicle's operation. For this study, we have adopted an EM system previously explored in the studies [15, 23]. A detailed explanation of this EM system and its functioning within the context of power allocation between the engine and the battery in the PHEV is provided as follows.

Energy Management

The general representation of Energy Management optimization can be described by (2), utilizing an optimization function aimed at minimizing fuel costs.

$$\min \sum_{s \in S} f_s\left(P_s\left(t_k\right)\right) \tag{2a}$$

$$P_s\left(t_k\right) \in \mathcal{P} \tag{2b}$$

where t_k is the time instant in the discrete domain, S is the set of indices of energy sources, and $P_s(t_k)$ is power generated by source s at t_k, $\mathbf{x}_k(t_k)$ is the set of states of system s, and $\mathcal{P}$ and $\mathcal{X}$ are correspondingly the constraints set of $P_s(t_k)$ and $\mathbf{x}_s(t_k)$. For the sake of presentation, t_k is omitted.

The power supplied by the ICE (P_{ICE}) determines the operational cost of the vehicle, specifically fuel consumption. This cost is minimized by the EM as depicted in (2a) and is represented in quadratic form, as shown in (3):

$$f_s\left(P_s\right) = c^F\left(\alpha_s\left(P_s\right)^2 + \beta_s P_s + \gamma_s\right), \alpha_s > 0 \tag{3}$$

where c^F (\$/gallon) is the cost of fuel. P_s represents the power supplies by the ICE. α_s represents the quadratic term in the cost function. It is a positive parameter (α_s > 0) that influences the curvature of the cost function. A higher value of α_s increases the weight of the quadratic term in the cost function, making the optimization process more sensitive to deviations from the desired reference powers. β_s represents the linear term in the cost function. It captures the impact of the reference powers (P_s) on the overall cost. The value of β_s determines the weight of the linear term in the cost function. It can be positive or negative, indicating the preference for a specific power split or penalizing deviations from the desired split. And finally, γ_s represents the constant term in the cost function. It represents any additional costs or benefits associated with the power split that is not captured by the quadratic or linear terms.

The EM optimization is formulated as a constrained optimization problem, taking into account various constraints. These constraints encompass the power limits of the vehicle's power sources, the total load demanded, and the SoC of the battery. To tackle this optimization problem effectively, the Sequential Quadratic Programming (SQP) algorithm is employed. SQP is an iterative approach specifically designed for solving nonlinear programming problems with constraints. Its main objective is to identify the minimum or maximum of the objective function while satisfying the defined constraints throughout the iterative process.

Besides these, there are several constraints that should be considered as stated in (2b) and are explained in detail. It is worth noting that every energy source has its generation capacity limits. Therefore, one of the constraints of (2b) is lower and upper generation limits as

$$\underline{P_{bat}} \le P_{bat} \le \overline{P_{bat}} \tag{4a}$$

$$\underline{P_{ICE}} \le P_{ICE} \le \overline{P_{ICE}} \tag{4b}$$

The main goal of the powertrain is to supply loads properly. The total generation should meet the total load and any losses. With the considered configuration, the following constraint (5) can be formed.

$$P_{bat} + P_{ICE} = P_{AC\,load} + P_{DC\,load} + P_{propulsion} + P_{V2X} + P_{loss} \tag{5}$$

where P_{bat} is power generated by the battery, P_{ICE} is power generated by the ICE, $P_{AC\,load}$ is AC load, $P_{DC\,load}$ is DC load, $P_{propulsion}$ is propulsion load, P_{V2X} is power used for V2X mode, and P_{loss} is the total loss.

Each system has its own internal constraints, as stated in (**??**). The components considered in this study are ICE and battery; hence following constraints are assumed for these power-generating sources.

$$|P_{ICE}(t_{k+1}) - P_{ICE}(t_k)| < rr_{ICE} \tag{6a}$$

$$|P_{bat}(t_{k+1}) - P_{bat}(t_k)| < rr_{bat} \tag{6b}$$

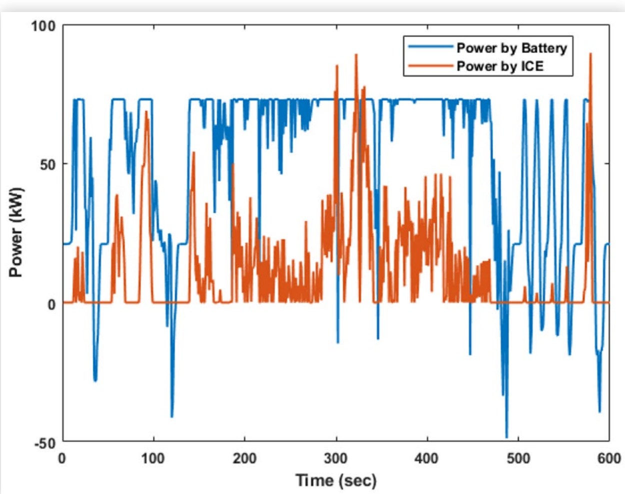
$$\underline{SoC_{bat}} \le SoC_{bat} \le \overline{SoC_{bat}} \tag{6c}$$

$$SOC_{bat}(t_{k+1}) = SOC_{bat}(t_k) - \frac{\delta T i_{bat}}{Q_{nom}} \tag{6d}$$

where $\delta T = t_{k+1} - t_k$. Constraints (6a) and (6b) are understood both the battery and the ICE have ramp rate limits when adjusting their generation. Constraints (6c) and (6d) are the battery's SoC constraints. Q_{norm} is the nominal capacity of the battery.

The primary aim of this EM system is to optimally allocate power among the power-generating sources, focusing on economic objectives while considering system constraints. To achieve economic efficiency, the EM system specifically targets fuel consumption and endeavors to minimize it by assigning a greater portion of power to the battery. The allocation of the power between the sources is shown in Figure 4. Now, the power supplied by the battery from this EM is used to calculate the degradation of the battery.

FIGURE 4 PHEV architecture considered for the study.



Degradation under V2G Connection

As previously mentioned, to implement a V2G connection, it is essential to have a bidirectional charger either at the substation or at home, depending on the specific application. V2G chargers typically come in different power ratings like 7 kW, 10 kW, and 15 kW, with 10 kW being a commonly used option in V2G setups [24]. One significant concern for EV owners is the impact of V2G on the vehicle's battery and whether it is a viable long-term solution. Normally, during cruising, an EV consumes power at around 20 kW and can draw well over 100 kW during acceleration [25]. However, when an EV is utilized for V2G, the battery experiences minimal stress, remains cool and does not drain quickly. Moreover, V2G services usually last for only short periods, typically two to four hours, resulting in relatively low and slow energy discharge. Considering an average EV's battery capacity of 60 kWh, which is six times larger than a typical 10 kWh home battery and approximately three times more energy than an average household uses in a day, the impact on the battery is less severe [25]. For instance, if a 10 kW bidirectional charger is used and the battery is discharged for just 2 hours, only 20 kWh of energy is extracted, which should not significantly affect the battery. Given these points, a simulation is conducted to analyze the impact of V2G on the battery of a PHEV.

The simulation for the V2G connection considered in this study is done for a relatively longer time due to the process of discharging and then charging the vehicle's battery. To model this, a normal working day profile is used, where the PHEV owner commutes to the office, parks the vehicle in a location with V2G capability, and later drives back home. Upon reaching the office and connecting the vehicle to the V2G port, the battery's SoC is checked. For the purpose of this study, it is assumed that the battery has an SoC of more than 80% at the time of connection. Subsequently, the vehicle's battery is discharged using a 10 kW bidirectional charger for 2 hours, depleting 20 kWh of energy. This discharge process operates at a 1 C-rate for 2 hours or until the battery's SoC reaches 60%, ensuring there is no significant degradation of the battery during the V2G operation.

After the discharge phase, the battery is then charged back at a 1 C-rate until it reaches 90% SoC. This total discharging and charging process takes approximately 4 hours in total, which is sufficient time for the V2G connection until the EV owner returns after their office hours. Overall, this simulation scenario allows for a realistic representation of a PHEV's daily operations and its involvement in V2G activities, considering both distances covered and the time required for charging and discharging operations. Similarly, the cost of degradation is calculated using (7), where 0.2 is a factor included as the battery can only be used from 100% to 80% in EV applications.

$$Cost\ of\ Degradation = Initial\ Cost * \frac{Capacity\ Loss}{0.2} \tag{7}$$

Numerical Simulations

This study analyzes the degradation of battery for V2G application using a PHEV with a powertrain depicted in Figure 1. The PHEV's internal combustion engine (ICE) has a capacity that can generate up to 180 kW, supplying the DC bus. The battery's capacity is 73 kWh. Among various loads in vehicle operations, the propulsion load is typically the most significant. Figure 5 shows a sample of the propulsion load for the US06 drive cycle used in this study.

To predict battery degradation, a trained neural network (NN) is employed as part of the degradation prediction model. This study utilizes the dataset from the University of Wisconsin-Madison to model battery degradation accurately. For the economic analysis section, the average cost of each kWh in 2023 is considered to be $151 [26].

To see the impact of battery degradation in a PHEV, the vehicle is simulated as outlined in Section 5. Initially, the vehicle is simulated to undergo two US06 drive cycles representing the distance covered from home to the office. For this operating scenario, the power supplied by the battery has to be calculated, which is allocated by the EM as discussed in Section 5.1.1, and the power allocation is shown in Figure 4. Depending upon the power supplied by the battery, the degradation of the battery is calculated.

Subsequently, the vehicle is connected for V2G operation. During the first two hours, the battery is discharged by 20 kWh using a 10 kW bidirectional charger. Following this, the battery is charged back until it reaches 90% SoC. The operation sequence is depicted in Figure 6, where the battery's initial SoC is set close to 90%. During the first 1200 seconds, the battery's SoC decreases due to the vehicle's operation under two US06 drive cycles. Between 1200 seconds and 8400 seconds, the battery is discharged by 20 kWh, leading to a SoC of 62.21%. Subsequently, the vehicle's battery is charged until it reaches 90% SoC again. When the battery reaches 90% SoC, the vehicle is driven for two more US06 drive cycles, causing its SoC to decrease from 90%, as shown in Figure 6. Again, for the next day, the simulation is started in the same way. Here, the simulation is conducted for seven days in MATLAB/Simulink, and the variation of SoC for these seven days is shown in Figure 7.

FIGURE 5 Sample of propulsion power for US06 drive cycle.

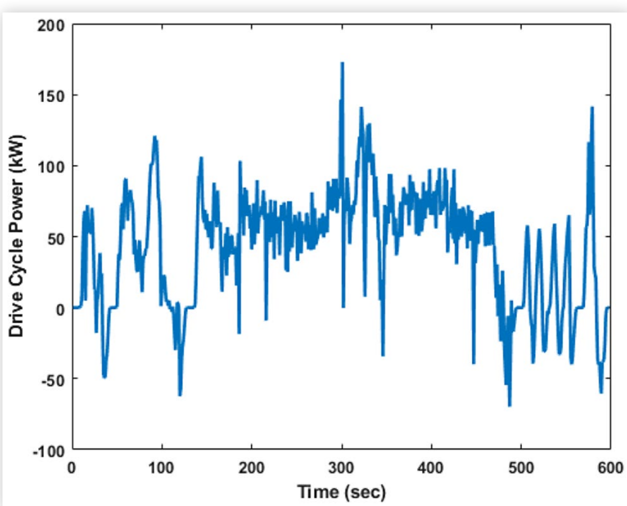


FIGURE 6 SoC of battery during the operation of a vehicle in a day.

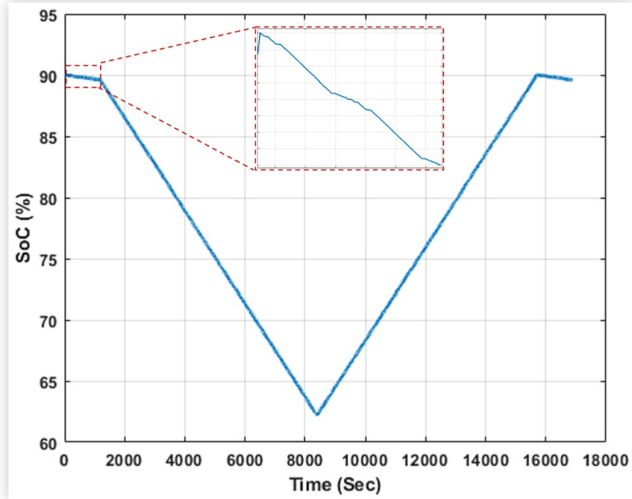


FIGURE 7 Variation of SoC of battery during the operation of the vehicle simulated for seven days.

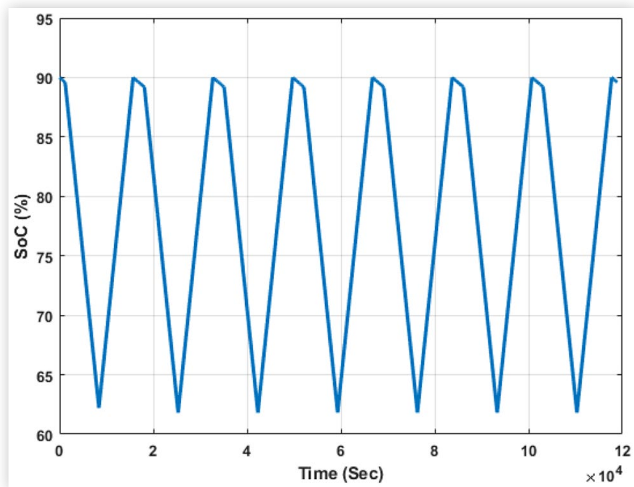


Figure 8 illustrates the degradation path of the battery, simulated over the course of a week. Throughout each day, as previously mentioned, the vehicle follows a specific pattern. It begins with operating for 2 US06 drive cycles, lasting approximately 20 minutes. Subsequently, it connects to a V2G system for about 4 hours, followed by another couple of US06 drive cycles operating for 20 minutes, as indicated by a zoomed portion inside the red box in Figure 8. This figure illustrates that the battery experiences higher degradation during the operation of the vehicle using the US06 drive cycle in comparison to the V2G connection. This discrepancy can be attributed

FIGURE 8 Degradation path of battery simulated for seven days.

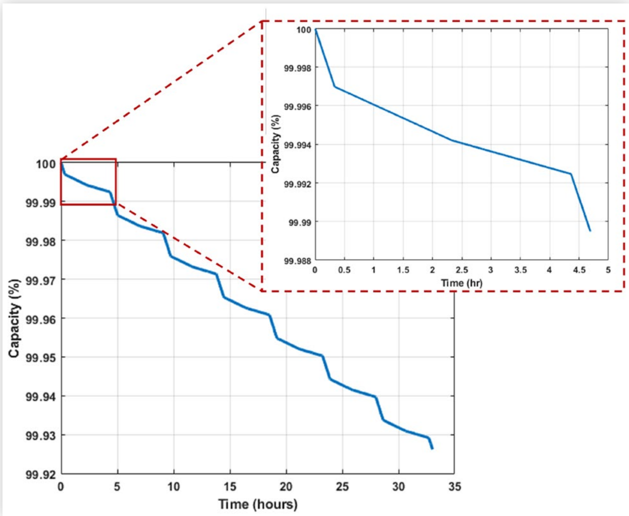
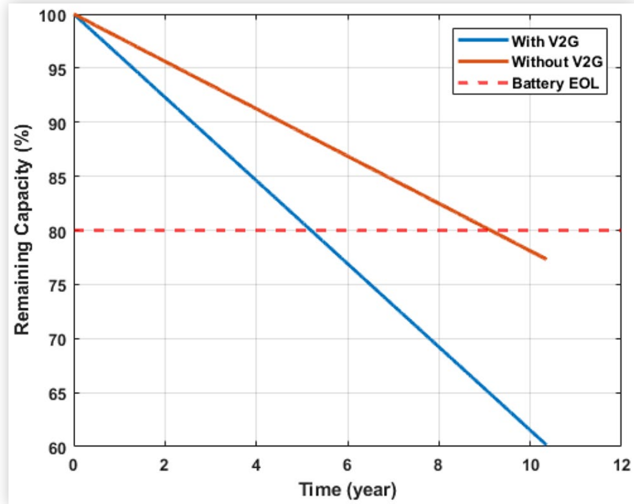


FIGURE 9 Degradation path of battery with and without V2G connection.



to the higher stress the battery undergoes while accelerating the vehicle during its operation, leading to increased degradation. In contrast, during the V2G connection, the battery experiences reduced stress as only 20 kWh of power is extracted at a slow rate for two hours each. As a result, the degradation is comparatively lower during this phase. Hence, the vehicle operates for approximately 4.7 hours each day, and the cumulative degradation path of the battery over the span of 7 days is depicted in Figure 8.

Economical Analysis

Table 1 presents both the capacity loss of the battery and the economic analysis for degradation. Over the course of a week, the vehicle without V2G connection experienced a capacity loss of 0.042%, while the vehicle with V2G connection encountered a slightly higher capacity loss of 0.0738%. When analyzing the data over a year, the vehicle without a V2G connection is projected to have a capacity loss of 2.184%, resulting in a degradation cost of \$1203.75. On the other hand, the vehicle with a V2G connection is expected to have a higher capacity loss of 3.83%, leading to a cost of \$2110.9 for degradation of the battery. Based on the data, the battery used in a vehicle without a V2G connection needs replacement after approximately 9 years, whereas the battery used in a vehicle with a V2G connection requires replacement after around 5 years. Figure 9 illustrates the battery degradation path for the vehicle under two conditions: with and without a V2G connection. This figure confirms the earlier discussed observation regarding the battery's EOL.

TABLE 1 Comparison of Degradation of Battery under Different Scenarios

	Without V2G	With V2G
Degradation in a Week	0.042%	0.0738%
Degradation in a Year	2.184%	3.83%
Cost of Degradation per year	\$1203.75	\$2110.9
Battery age until EOL	9.16 years	5.22 years

If the EV owner intends to sell the 20*kWh* of stored energy back to the utility, it must undergo a conversion process back to AC using an inverter. However, the inverter incurs an efficiency loss of around 10%. Consequently, the amount of energy available for the EV owner to sell to the utility at the point of connection is reduced to 18*kWh*. Conversely, while charging the battery, the conversion from AC power to DC is facilitated by a converter (rectifier) with an efficiency loss of approximately 10%. As a result, the EV owner needs to pay for 22*kWh* of AC power to effectively charge the battery with 20*kWh* of usable energy.

The opportunity for incentives arises when the EV owner can sell power/energy to the utility during peak hours when the selling rate is higher. To illustrate this, let's consider the rate provided by Pacific Gas and Electric Company (PG&E) for analysis purposes as provided in [27]. During peak hours, the buying rate set by the utility (selling price for EV owners) is 64 cents per kWh, while the selling rate for the utility (buying rate for EV owners) is 28 cents per kWh. Table 2 summarizes these buying and selling rates for the vehicle connected to V2G.

According to the data in Table 2, it can be inferred that by using a V2G connection over the course of a year, an EV owner can potentially save up to \$1956.4. This amount represents the savings generated by feeding 20 kWh of energy into the grid daily. The potential savings can be further increased by exchanging a higher amount of energy during a V2G connection.

If the EV owner opts for a V2G connection, they need to replace the battery after approximately 5.22 years of continuous operation. However, they will also receive an incentive of around \$10212 over that period. It's worth noting that this V2G arrangement will lead to battery

TABLE 2 Electricity buying and selling for during V2G connection

	Buying	Selling
Energy (kWh)	22	18
Rates	$0.28	$0.64
Cost for a day	$6.16	$11.52
Cost for a year	$2248.4	$4204.8
Saving	$1956.4	

degradation costs amounting to $4735, resulting in an overall net saving of $5477 after 5.22 years.

On the other hand, if the EV owner decides against a V2G connection, the battery would need replacement after 9.16 years, as projected from the battery's degradation path, without any incentives.

Conclusion

This study provides a comprehensive examination of battery degradation in a PHEV from two distinct perspectives. The first perspective involves analyzing battery degradation during the vehicle's regular operation by utilizing an EM to determine power delivery and subsequent capacity loss. The second focus of the study delves into battery degradation under V2G connection, with capacity loss being assessed using a data-driven approach via Neural Networks.

Subsequently, an economic analysis is undertaken through real-world scenario simulations. This analysis involves calculating total savings attainable through a V2G connection and estimating the battery's anticipated lifespan until a replacement is necessary. By furnishing EV owners with this extensive insight, the study empowers them to make well-informed choices regarding the adoption of V2G connections. While these connections offer appealing incentives, it's prudent to recognize that they might accelerate the battery replacement timeline.

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