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RESEARCH ARTICLE

A Machine Learning-Based Real-Time Remaining Useful Life Estimation and Fair Pricing Strategy for Electric Vehicle Battery Swapping Stations

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ABSTRACT The increasing adoption of electric vehicles (EVs) has led to the widespread implementation of battery swapping stations. However, ensuring fairness in battery pricing remains a significant challenge since variations in battery health and performance among swapped batteries can result in user dissatisfaction and operational inefficiencies. This paper introduces a novel approach to enhance fairness in battery swapping by integrating a machine learning-based real-time prediction model with a pricing strategy based on remaining useful life (RUL) estimation to address this issue. The proposed solution comprises a real-time RUL estimation system and a dynamic pricing mechanism that ensures fair pricing based on battery health and performance. This integrated approach aims to improve user satisfaction and the operational efficiency of swapping stations. The paper evaluates various machine learning algorithms for real-time RUL estimation regarding accuracy, computation time, and memory usage. The results suggest that XGBoost provides the most suitable balance between accuracy and efficiency, making it an effective solution for real-world applications. Comparative analysis shows that the XGBoost model outperforms the second-best method (Random Forest) with a lower error (3.50 vs 3.79) while maintaining competitive computational efficiency (9.75 vs 8.52 seconds) and memory usage (2.12 vs 2.32 MB) when solving a typical numerical case study problem. The proposed approach has the potential to accelerate the adoption of electric vehicles and contribute to sustainability goals by promoting efficient battery utilization and fair pricing mechanisms.

INDEX TERMS Battery swapping station, electric vehicle, machine learning, remaining useful life, XGBoost.

I. INTRODUCTION

Due to the depletion of fossil fuels and their adverse environmental effects, electric vehicles are emerging as a cleaner and more sustainable transportation alternative and have received increasing attention in recent years [1], [2]. Electric vehicles are rapidly expanding their market share. They are beginning to replace traditional internal combustion engine vehicles, as demonstrated by Figure 1, which shows a significant increase in the number of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) between 2014 and 2023 [3].

Battery technology is critical to optimizing the performance and longevity of electric vehicles. [4]. Batteries, as the most essential components of electric vehicles, directly affect the vehicle's range, charging time, and overall performance. Therefore, the continuous development of battery technology allows electric vehicles to stand out as a competitive option.

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No matter how advanced the current battery systems are, long charging times are still a significant disadvantage for electric vehicles. This disadvantage can negatively affect users' tendency to prefer electric vehicles. Long waiting times reduce the potential users' interest in electric vehicles, becoming a factor that limits their widespread use.

Battery swapping stations have emerged as a promising solution to address the challenges of long charging times and enhance user convenience [5], [6].

Battery swapping stations allow users to quickly replace their discharged batteries with fully charged ones [7]. They allow users to perform battery changes in just a few minutes without waiting for traditional long charging times [8], [9].

Pricing mechanisms in battery swapping stations are crucial in ensuring cost-effectiveness and user acceptance [10]. The current literature focuses on fixed pricing, subscription models, and user-based pricing [11], [12]. Fixed pricing models provide a straightforward approach but may lack flexibility, while subscription models can offer predictability but may not cater to varying usage patterns [13], [14]. The fixed pricing model provides battery swapping for a fixed fee, while the subscription model involves battery usage over a specified period.

Various approaches have been proposed to optimize battery-swapping processes, focusing on cost reduction, efficient battery allocation, and accurate state-of-health (SOH) estimation [15]. One approach is based on the radial basis function neural network with the war strategy optimization algorithm to minimize overall swapping costs while considering factors such as energy consumption and travel time [16]. Furthermore, user-centric battery allocation models have been introduced to enhance battery-swapping efficiency by prioritizing battery exchanges based on SOH and state of charge (SOC), ensuring rapid and fair distribution of batteries while maximizing system benefits [17]. The study focuses on overcoming operational challenges in cold environments to estimate battery SOH using only charging data [18]. These models provide high-accuracy predictions, contributing to the reliable and safe operation of battery-swapping stations.

However, these models often fail to consider dynamic factors like the battery's remaining useful life (RUL), hindering the pricing process from being fair and transparent. As such, one of the key downsides of the battery swapping stations. The most crucial problem is the lack of a fair method for battery replacement considering their RUL [19]. Battery swapping stations may randomly disadvantage some users since different RULs vary. Therefore, a fair assessment of the battery's health is essential during replacement. For example, replacing an old one with a reduced RUL with a newer one with a longer RUL creates unfairness in terms of the cost imposed on the user. Such injustices may make it difficult for users to adopt the battery replacement system and, therefore, limit the effectiveness of the systems.

Recent studies have highlighted the importance of data-driven approaches for RUL estimation, leveraging machine learning techniques to enhance prediction accuracy

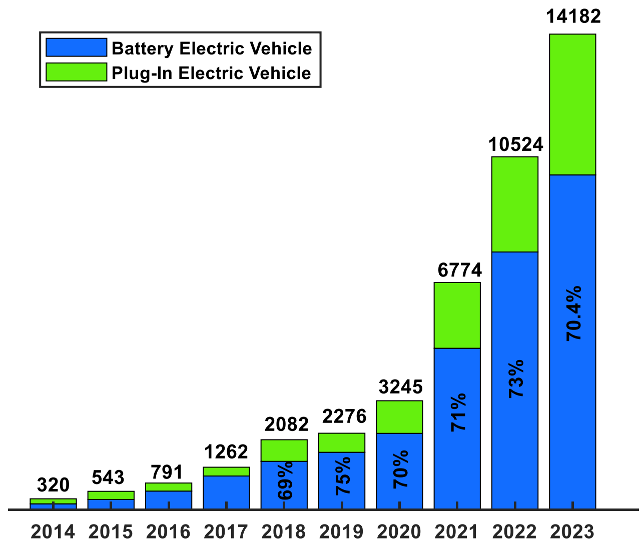

FIGURE 1. Increase in the number of BEV and PHEV vehicles between 2014-2023 [3].

and reliability [20], [21], [22]. To prevent these inequalities, a need for systems that evaluate battery performance and estimate the RUL arises. The RUL estimation is vital because battery performance naturally degrades over time, and various factors affect this deterioration. These factors include charge-discharge cycles, temperature changes, and usage habits [23], [24], [25]. Therefore, RUL estimation is critical for users to understand the actual value of their batteries and experience a fair replacement process.

This study addresses an area that has not been previously studied in the literature and introduces a strategy based on RUL estimation to increase the efficiency of battery-swapping stations to ensure fairness to users. This strategy consists of two main components: real-time RUL estimation and fair pricing. As the first component, an XGBoost-based approach is proposed to apply the RUL estimation. XGBoost has been successfully applied in various fields, including healthcare, finance, and energy systems, proving its effectiveness in handling large-scale datasets with high accuracy and efficiency [26], [27], [28]. XGBoost is a powerful tool, especially for analyzing battery health data, thanks to its ability to effectively model complex and nonlinear relationships. XGBoost's scalability makes it well-suited for handling larger datasets and more complex feature sets due to its efficient parallel processing and optimization techniques [26]. Due to its parallel processing capability and efficient handling of sparse data, XGBoost remains robust even as dataset size and feature complexity increase, making it suitable for real-world battery-swapping applications. One of the main contributions of this study is demonstrating the real-time application potential of using XGBoost-based RUL estimation which will allow users to evaluate the battery status instantly. The second component is developing a fair pricing mechanism for battery swapping. Dynamic evaluation of factors such as battery health measurements, discharge time, voltage behaviour, and charging characteristics required and pricing should be based not only on the remaining capacity but also on the performance characteristics of the battery. In this context, the heat map created to visualize the relationships between RUL and other variables allows the determination of the variables to be considered in the pricing process. The developed strategy will ensure that users experience a more equitable battery swapping process and thus support the adoption of electric vehicles. As such, the proposal will encourage the widespread use of electric vehicles and significantly contribute to the development of battery swapping systems by providing a guiding basis for future research and applications. The dataset utilized in this research encompasses a diverse range of battery usage scenarios, closely mirroring real-world operating conditions to ensure practical applicability. However, it is important to acknowledge potential limitations, such as regional or operational biases, which may affect the generalizability of the findings to broader contexts. The assumptions and presumptions made in this study are expressed as follows:

- It is assumed that the necessary design has been implemented to ensure that the electric vehicle's battery is quickly exchanged at the battery swapping stations.
- It is assumed that the electric vehicle records data on battery performance and that the station can access this data.
- It is also assumed that the battery swapping station has the appropriate technical infrastructure and the necessary equipment to support all battery swapping processes.

These assumptions constitute the essential elements supporting the applicability and effectiveness of the proposed system. The main contributions of this paper to the research field are:

- This study presents an innovative strategy that combines real-time RUL estimation with a fair pricing mechanism. The relationships between RUL and variables allow the determination of suitable and essential variables to be considered in the pricing process.
- The performance of various machine learning algorithms for real-time RUL estimation is evaluated based on critical metrics of computation time and memory usage.
- An essential contribution of this study is that XGBoost is used for real-time battery exchange applications for the first time for real-time battery exchange applications. Compared to other methods in the literature, the XGBoost algorithm yields the best results in the current study.

The remainder of the paper is organized as follows: Section II discusses the importance of XGBoost for RUL estimation of batteries, pricing approaches, existing methods, and their limitations. Section III introduces the model development process, a description of the dataset used, relationship analysis with a heat map, and the developed fair pricing mechanism. Section IV discusses in detail the two components of the proposed approach and Section V evaluates the performance of the proposed strategy. Finally, Section VI summarizes the study's key findings and introduces suggestions for future work.

II. BATTERY RUL ESTIMATION

RUL is the estimated time a battery can maintain its functionality from its current state [29]. Estimating RUL is critical in monitoring battery health and optimizing maintenance strategies. Estimating RUL for electric vehicle batteries helps prevent unexpected failures by determining when batteries need to be replaced, thus improving user experience and reducing operational costs [30], [31], [32].

Existing methods are built on physical modelling, statistical analysis, machine learning, and hybrid techniques according to their basic approaches and implementation procedures [33]. Physical modelling is based on understanding batteries' chemical and electrical behaviour [34]. The accuracy of physical methods varies depending on the system's complexity and the model's assumptions. Physical model-based RUL estimation methods can be challenging to develop and implement, as they require complex mathematical models to represent the system dynamics accurately and often lead to high computational costs. Statistical methods can estimate RUL using historical data analysis and regression techniques [35]. Statistical-based methods are limited to linear relationships and are inadequate in modelling complex, nonlinear relationships because they rely on certain assumptions.

Machine learning techniques have significantly progressed in battery RUL estimation in recent years. These methods can discover complex relationships by learning from large data sets [36]. Machine learning-based systems combine data mining and statistical modelling techniques to analyze batteries' past performance data and learn from it to predict their future behavior [37]. Machine learning algorithms are highly effective in revealing complex relationships regarding battery health and performance, mainly due to their ability to deal with large and complex data sets [38]. Some studies and methods used for RUL estimation between 2020 and 2024 are listed in Table 1.

Supervised learning is one of the most widely used forms of machine learning and has often been preferred for RUL estimation [39]. This traditional method relies on the persistence of the estimated model using training data labelled with past data. For example, the support vector machines (SVM) method has been used to calculate the distribution of batteries based on past data [37], [38]. However, the success of supervised learning methods depends on the quality and quantity of training data. It is also essential to carefully tune the hyperparameters to prevent over-learning (over-fitting) of the model.

Deep learning also plays a vital role in RUL estimation [42], [43]. Since deep learning techniques work effectively on large datasets, they offer an advantage in handling battery health data's high dimensionality and complexity of battery health data. Artificial neural networks (ANN) and recurrent neural networks (RNN) have demonstrated strong performance on RUL data [41], [42]. These methods can learn complex patterns based on dynamic data such as battery discharge cycles, temperature variations, and voltage behaviour. However, the computational requirements of these methods are high, which can lead to limitations in real-time applications.

Machine learning-based systems hold significant importance in research due to their potential to provide high accuracy and reliability in estimating the RUL of batteries. These systems can deeply analyze the relationships between various variables related to battery health by learning complex interactions within the data. In particular, gradient boosting-based algorithms stand out in this process for their ability to enhance prediction performance [46].

Despite the significant advancements in RUL estimation methods over recent years, existing approaches face several limitations. EMD-based hybrid models suffer from mode-mixing problems and high computational complexity. While deep learning approaches, including LSTM variants, show promising results, they require extensive training data and computational resources, making real-time implementation challenging for battery swapping stations. Gaussian process regression methods struggle with scalability when dealing with large datasets and exhibit high computational complexity during the training phase. Ensemble learning approaches improve prediction accuracy but at the cost of increased model complexity and training time. The transformer-based model and capsule network architecture require significant computational resources and careful hyperparameter tuning, which can be impractical for real-time applications. Particle filter-based approaches face challenges in parameter optimization and may suffer from particle degeneracy. Traditional regression methods lack the capability to capture complex non-linear relationships in battery degradation patterns. While integrated frameworks and hybrid models attempt to address these limitations, they often result in complex architectures that are difficult to implement and maintain in practical applications.

Considering the above limitations, this study proposes an RUL estimation method based on the XGBoost algorithm and validates its effectiveness for a real-time battery swapping station. The XGBoost algorithm is distinguished by its advantages, including fast computation time, high accuracy, and efficient memory usage [47]. Its capability to model complex and non-linear relationships makes it a powerful tool for analyzing battery health data. Additionally, XGBoost's hyperparameter tuning options optimize the model's performance. With these features, XGBoost is a critical solution for improving RUL estimation in battery-swapping processes.

Unlike previous studies in the literature, this research considers the accuracy of the calculated RUL values and the computation speed and RAM usage of the methods employed. In this context, detailed evaluations of computation speed and memory usage enable the use of lower-cost microcontrollers. Thus, it aims to reduce the costs of battery swapping stations and increase their feasibility.

TABLE 1. Methods used for RUL estimation.

Ref.	Year	Method
[48]	2020	Empirical Mode Decomposition (EMD)+Deep Neural Networks (DNN)+Long Short-Time Memory (LSTM)
[49]	2020	Hybrid Extreme Learning Machine (ELM) And Random Vector Functional Link (RVFL) Ensemble Learning Network
[50]	2020	Dual Gaussian Process Regression (GPR)
[51]	2021	LSTM, GPR, EMD
[52]	2021	Dempster-Shafer Theory (DST) and the Support Vector Regression-Particle Filter (SVR-PF)
[53]	2021	Multivariable Linear Regression (MLR)
[54]	2022	Denoising Transformer (Detransformer)
[55]	2022	Gaussian-Process-Regression (GPR)
[56]	2023	Multi-Dimensional İnput Fusion Model (GM-LSTM)
[57]	2023	Hybrid Deep Learning Model
[58]	2023	Capsule Network Architecture
[59]	2023	Expectation Maximization-Unscented Particle Filter
[60]	2023	Integrated Data-Driven Framework
[61]	2024	Tuned Random Forest
[62]	2024	Hyperparameter-Tuned Long Short-Term Memory (LSTM)

III. XGBOOST MODEL AND THE REQUIRED DATASET

A. DATASET FOR THE RUL ESTIMATION

The dataset used in this study is obtained from the Kaggle platform titled "Battery Remaining Useful Life (RUL)" [63]. It is designed to predict the RUL of electric vehicle batteries and includes 14 NMC-LCO 18650 batteries. These batteries have a nominal capacity of 2.8 Ah tested at 25°C for 1,000 cycles using a CC-CV charging rate (C/2) and a discharging rate (1.5C). The dataset contains various performance metrics collected during each battery's charge/discharge cycles. These features are used to model the electrical behaviour of the batteries and enable RUL predictions. The data used for RUL estimation includes:

- Discharge Time: Indicates how long the battery can supply energy during each charge-discharge cycle. A decrease in this duration over time signals a drop in battery capacity.
- Time at 4.15V: Reflects how long it takes for the voltage to reach 4.15V during charging, which is directly related to the battery's charging performance. Longer times indicate capacity loss.
- Time Constant Current: Provides information on how long the battery operates at a constant current level, which is crucial for monitoring performance and estimating RUL.
- Decrement 3.6-3.4V: The time taken for the voltage to drop from 3.6V to 3.4V indicates how quickly energy is consumed and highlights capacity degradation.
- Maximum Voltage Discharge: Represents the maximum energy delivery capability of the battery. A decrease in this value over time suggests the battery is nearing the end of its useful life.

- Minimum Voltage Charge: Indicates the minimum capacity at which the battery can be charged. Lower values point to advancing capacity loss.
- Charging Time: The time needed for the battery to charge fully provides essential insights into capacity reduction and the extent of the battery.

These parameters are used to evaluate the battery's wear and performance loss over time for RUL estimation. In the proposed strategy, vehicles arriving at the battery swapping station continuously share this data, and the RUL values of the batteries are used to determine whether a replacement is needed.

B. XGBOOST

XGBoost is a fast and flexible algorithm capable of achieving high accuracy rates, especially on large and complex datasets. Known as an improved version of Gradient Boosting, the XGBoost method is mainly used for classification and regression problems in the literature [64]. XGBoost is built on Boosting, one of the ensemble learning techniques [64]. Boosting aims to create a robust model for weak learners. In the Boosting approach, successive models are constructed where each model corrects the errors made by the previous one. XGBoost takes these core principles and introduces a faster and more efficient algorithm. Its success is built on two key elements:

- Gradient Boosting: Gradient Boosting is a technique that iteratively improves model prediction accuracy by progressing through a loss function. Each new model focuses on correcting the errors of the previous one. XGBoost operates based on Gradient Boosting but also uses second-order derivatives. This allows it to consider the slope of the loss function and the curvature, enabling more precise updates [65].
- Regularization: To prevent overfitting, XGBoost incorporates L1 (Lasso) and L2 (Ridge) regularization terms [66]. This helps the model maintain its generalization capability without becoming overly complex.

XGBoost builds decision trees sequentially. The first tree produces initial predictions for the dataset. Each subsequent tree is then created to reduce the errors in the projections of the previous tree. Each new tree estimates the residuals, which are the differences between the target variable and the current predictions of the model. At the end of this process, all trees are combined to form the final model. XGBoost focuses on minimizing the loss function when adding new trees. The loss function represents the difference between predicted and actual values. Minimizing this loss ensures that the model makes more accurate predictions.

XGBoost prevents overfitting using L1 (absolute value) and L2 (squared) regularization. These regularization terms control the complexity of the model, making it more straightforward and generalizable. While classical Gradient Boosting only uses the first derivative of the loss function, XGBoost takes both the first and second derivatives into account. This allows for more precise updates and accelerates the optimization process.

IV. PROPOSED STRATEGY

This section introduces the two main components of the proposed strategy. XGBoost-based real-time RUL aims to make more informed decisions during the swapping processes by quickly and accurately predicting batteries' RUL using the XGBoost algorithm. The RUL-based pricing decisions implement pricing algorithms based on the predicted RUL data, creating a fair and dynamic pricing mechanism for the battery-swapping process. Figure 2 presents the flowchart of the proposed strategy and shows that the strategy determines whether a battery swap will take place based on the RUL values of the EV battery and the batteries available at the station, along with the associated costs to be calculated. After calculating the RUL value of the EV battery, this value is compared with the RUL values of the batteries available at the station. This comparison forms the basis of the decision-making process:

- If the RUL value of the EV battery is equal to that of the battery at the station, the swap can be performed without any additional charge.
- If the RUL value of the EV battery is higher than that of the battery at the station, it indicates that the vehicle's battery is in better condition. In that case, the station must compensate the customer for the difference in battery quality. This ensures a fair transaction and encourages users to opt for battery swapping.
- If the RUL value of the EV battery is lower than that of the battery at the station, the customer must pay a fee to receive a better battery.

In some cases, the RUL value of the EV battery may fall below the threshold value set by the station. The station may reject the battery swap request in such cases. This helps maintain a minimum quality level for the batteries at the station and prevents excessively degraded batteries from being included in the system.

When price adjustments are necessary (either compensation to the customer by the station or a fee charged to the customer), the price is calculated based on the RUL difference. This cost can be proportional to the RUL difference. As a result of these calculations, the final decision is made. If the necessary conditions are met and any payment processes (if applicable) are completed, the battery-swapping process will be approved. Otherwise, the swap will be rejected, and the customer will be informed.

A. XG-BOOST BASED REAL-TIME RUL ESTIMATION PROCEDURE

Employing the XGBoost regression method for RUL prediction consists of data preparation, model training, performance evaluation, and result recording. The dataset containing key variables affecting battery life should be loaded during the data preparation phase. The dataset is then divided into training (80%) and test (20%) subsets to evaluate the model's generalization capability.

The accuracy is defined by the mean square error (MSE) in which minor prediction errors do not significantly impact, but more significant prediction errors carry more weight. The goal is to minimize MSE, expressed by

$$MSE = \frac{1}{n}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \quad (1)$$

where y_i represents the actual value, $\hat{y}_i$ represents the predicted value, and N denotes the number of data points.

The model predicts each tree, and the error between these predictions and the actual values is calculated. The prediction errors in the output of each tree determine the errors. XGBoost updates the model parameters using the gradient of the error values. The gradient indicates how and how much to change to reduce the prediction errors of the current model. In each iteration, the gradient of the MSE is computed, and this information guides how the model will be updated. XGBoost enhances the model's performance by iteratively adding new trees. Each new tree attempts to correct the prediction errors of the previous trees, thus training each added tree to reduce the MSE. This process incorporates regularization terms to prevent overfitting while increasing the model's overall accuracy.

XGBoost is controlled by hyperparameters such as learning rate, maximum depth, and the number of trees. These parameters affect the model's complexity and learning speed. Using a low learning rate with more trees generally provides better generalization performance and minimizes the MSE more effectively.

In this study, hyperparameter tuning was conducted to enhance the performance of XGBoost. This includes optimizing the important parameters in the model's learning process that can significantly impact the model's overall performance. The Random Search method was employed for hyperparameter tuning. Random Search determines the best-performing hyperparameter combinations by making random trials within a specific hyperparameter range. The advantage of this method is its ability to explore a wide hyperparameter range in a shorter time, thereby offering the possibility of obtaining more effective results.

During the process of determining the optimal hyperparameters, k-fold cross-validation was applied. This technique tests the model on different subsets of the data to evaluate its overall performance. This reduces the risk of overfitting and achieves more generalizable results. To ensure the XGBoost model performs optimally, a learning rate of 0.30, a maximum depth of 10, and the number of trees set at 500 were determined. These parameters impact the model's learning speed and complexity, enhancing prediction accuracy. Throughout the training process, RUL predictions were successfully learned within nonlinear patterns.

At the end of the training process, the model's predictions are evaluated on the test data, and the MSE is calculated. The low value of this MSE measures the model's success. A low MSE indicates that the model fits the data well and that its predictions are reliable.

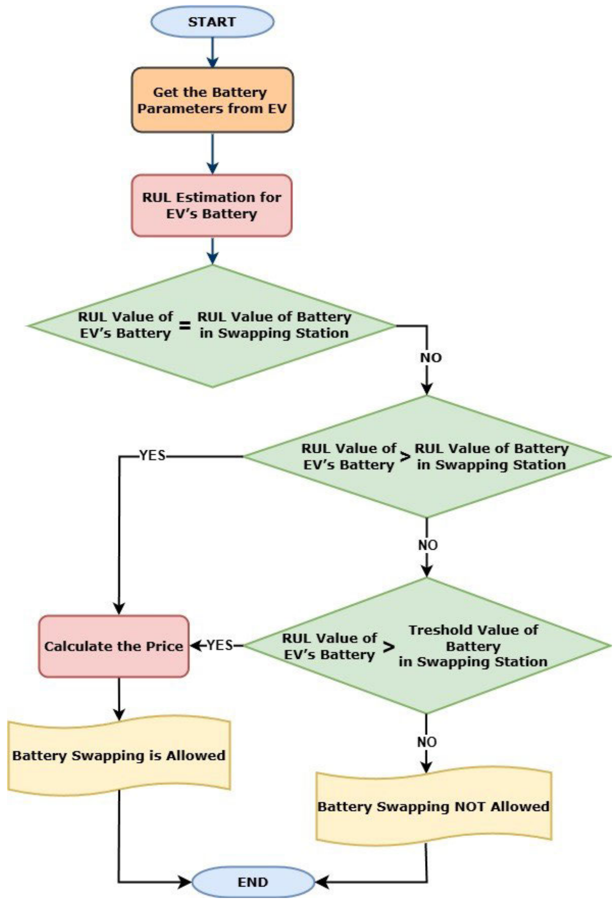

FIGURE 2. Flowchart of the proposed method.

B. RUL-BASED BATTERY PRICING PROCESS

A heat map should be created, as shown in Figure 3, to visualize the relationship between the data used in this study and the RUL values. The heat map visualizes the correlation between the RUL of electric vehicle batteries and various variables. Positive correlations (values close to +1) indicate that the two variables move in the same direction, while negative correlations (values close to −1) indicate that they move in opposite directions.

A correlation coefficient of –1 between Cycle Index and RUL indicates that as the number of cycles increases, the battery RUL significantly decreases. This finding confirms that batteries tend to degrade as the cycle count increases throughout their lifespan. A low positive correlation of 0.01 between Discharge Time and RUL suggests that discharge duration has little effect on RUL. The correlation coefficient between Time at 4.15V and RUL is 0.18, indicating a positive but limited effect. The correlation between Constant Current and RUL is 0.04, indicating a weak influence.

The correlation between 3.6V-3.4V Decrement Time and RUL is 0.01, which indicates a very weak interaction and suggests that this variable has almost no effect on RUL. On the other hand, the correlation coefficient between Maximum Voltage Discharge and RUL is 0.78, indicating a strong positive relationship between these two variables. The correlation of –0.76 between Minimum Voltage Charge and RUL indicates that low charging voltages negatively impact the lifespan of the battery. Charging at low voltages can adversely affect the health of the battery. There is a very weak positive relationship (0.02) between Charging Time and RUL, suggesting that the effect of charging duration on the remaining lifespan of the battery is minimal.

The correlation map in Figure 2 shows that variables, such as Cycle Index and Maximum Voltage Discharge, significantly impact RUL, while other variables (such as constant current duration or charging time) have much less influence. Therefore, the developed battery pricing process considers each variable's effect on RUL. Thus, each component should be weighted according to the correlation coefficients provided in Figure 3 and included in the pricing calculation, as

$$Cost = Base_{cost} + (RUL_{station} - RUL_{vehicle})\, constant + \sum_{i=1}^{n} ((X_{(i,vehicle)} - X_{(i,station)}) \cdot W_i) \quad (2)$$

where $X_{i,vehicle}$, represents the value of the i^{th} variable associated with the vehicle's battery; this variable could be a feature such as discharge time. On the other hand, $X_{i,station}$, denotes the value of the i^{th} variable associated with the battery at the station. W_i indicates the degree of the relationship of the i^{th} variable with RUL and can take on a positive or negative value.

The formula's variable representing the base price denotes the standard battery replacement fee. The difference multiplier indicates the charging factor that will be applied per unit of RUL difference; for example, an additional fee of \$10 may be added for a difference of 100 units.

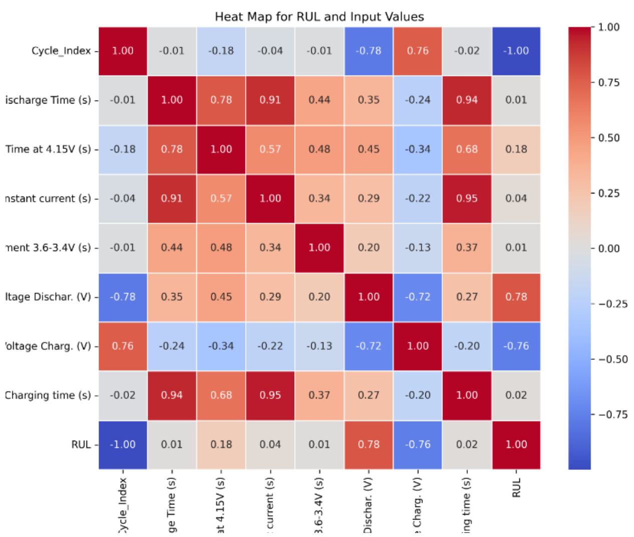

FIGURE 3. **Heatmap for electric vehicle RUL and input values.**

V. PERFORMANCE EVALUATION

The performance metrics of the developed XGBoost model on the training and testing datasets are discussed first in this section to examine the model's prediction accuracy and generalization capability. Subsequently, the performance and effectiveness of the proposed strategy is evaluated through numerical analyses.

A. PREDICTION MODEL

In this section, the RUL prediction performance of the proposed XGBoost-based model is compared with five alternative methods reported in the literature (including Lasso [67], [68], Random Forest [69], [70], Gradient Boosting [46], Kernel Ridge [71], [72], and Decision Tree [73]) to demonstrate its suitable and superior estimation performance. This comprehensive comparison details the effectiveness and superiority of the proposed model in terms of prediction accuracy and generalization capability. The root mean square error (RMSE) and sum of squared errors (SSE) error metrics have been calculated during each model's training and testing processes to determine the performance differences among these methods. Training metrics indicate the model's performance during the learning process, while test metrics reveal how effective the model is against new and unseen data.

Total error training is an important indicator for assessing the overall success of the model by reflecting the total error made in both training and test sets. Additionally, relative error training indicates the obtained error rate and normalizes the model's performance, allowing for comparisons between different models. The runtime (in seconds) is also considered to understand the effectiveness and efficiency of the model's training process, indicating the total time spent on model training. Finally, the RAM capacity used reflects the amount of memory consumed during the model's training process, which is crucial for evaluating the model's memory efficiency and hardware requirements.

Table 2 compares the RMSE and SSE of different RUL prediction models during their training and testing processes, demonstrating the performance of each algorithm. According to the results, significant differences exist in the performance of the models used for RUL prediction. XGBoost exhibits the best performance with an RMSE of 0.56 and an SSE of 3782.65 on the training dataset, and it achieves an RMSE of 3.50 and an SSE of 36812.98 on the test dataset. These results indicate that XGBoost has a high prediction accuracy, providing a substantial advantage in practical applications.

The total error values presented in Table 3 are critical for evaluating the overall performance of the RUL prediction models. Total error represents the sum of the differences between the predicted values by the model and the actual values, reflecting the model's overall performance and error accumulation. According to the data in Table 2, the XGBoost model exhibits the lowest error, with a total error of only 932.39 units on the training dataset. The total error value on the test dataset is determined to be 6,309.58. This indicates that XGBoost's reliable predictions provide the best

TABLE 2. RMSE and SSE values of RUL estimation models.

Methods	RMSE Train	RMSE Test	SSE Train	SSE Test
Lasso	7.05	7.39	599466.56	164361.23
Random_Forest	1.37	3.79	22568.77	43218.40
Gradient_Boosting	6.72	7.58	544105.00	173146.01
Kernel_Ridge	12.16	14.31	1780573.20	617100.81
Decision_Tree	3.64	5.78	159452.23	100576.75
XGBoost	0.56	3.50	3782.65	36812.98

application results. This model's performance is also consistent with the low RMSE and SSE values in Table 2. Notably, a positive relationship exists between RMSE and total error values; lower RMSE values correspond to lower total error values.

When examining the total error values of other models, it is notable that they are significantly higher than those of XGBoost. The high error values of this model are further supported by the elevated RMSE and SSE values in Table 2. XGBoost proves to be a reliable option for RUL prediction by exhibiting the best performance in both total error and RMSE.

Table 4 presents the relative error values of various machine-learning models for predicting the RUL of electric vehicle batteries and shows that the XGBoost model stands out with the least relative error values of 0.0001 on the training set and 0.0038 on the test set. The results in Table 4 corroborate the findings in Tables 2 and 3. For instance, XGBoost's status as having the lowest RMSE and total error values and the lowest relative error demonstrates that it performs best overall.

Table 5 displays the running times of the machine learning models used for RUL prediction of electric vehicle batteries. Training time is a crucial parameter that indicates how long a model takes for training and prediction processes, providing critical insights into the model's efficiency. When assessed alongside the results in Table 2, the impact of training times on model performance can be observed more clearly.

The Decision Tree model stands out with the shortest training time of 2.5208 seconds, which provides an advantage for applications seeking faster predictions. However, the Decision Tree's RMSE (5.78) and total error (10.6777) values lag behind those of more complex models. Therefore, the speed of this model does not necessarily translate to better performance. The XGBoost model showcases impressive performance with a training time of 9.7533 seconds, providing an effective solution given the size and complexity of the dataset. With an RMSE of 3.50 and a total error of 6.3096, XGBoost emerges as a model capable of making fast and accurate predictions. Therefore, XGBoost stands out as a strong option not only in terms of training time but also for its predicted performance.

Table 6 displays the RAM usage capacity values of the RUL estimation models. Lasso regression and XGBoost exhibit the least memory usage at 2.07 MB and 2.12 MB,

TABLE 3. Total error values of RUL estimation models.

Methods	Total Error Train	Total Error Test
Lasso	53753.65	14007.21
Random_Forest	9025.12	6396.52
Gradient_Boosting	53352.99	15021.17
Kernel_Ridge	79313.53	21868.84
Decision_Tree	29141.42	10677.77
XGBoost	932.39	6309.58

TABLE 4. Average relative error values of RUL estimation models.

Methods	Relative Error Train	Relative Error Test
Lasso	0.0080	0.0085
Random_Forest	0.0013	0.0039
Gradient_Boosting	0.0080	0.0091
Kernel_Ridge	0.0118	0.0132
Decision_Tree	0.0044	0.0065
XGBoost	0.0001	0.0038

TABLE 5. Running times of RUL models.

Methods	Time (second)
Lasso	6.6075
Random_Forest	30.5232
Gradient_Boosting	14.0304
Kernel_Ridge	42.2754
Decision_Tree	2.5208
XGBoost	9.7533

respectively, reflecting the advantages of being lightweight models.

Since training time and RAM usage are critical indicators of a model's practical applicability, it is essential to consider the training time and RAM capacity alongside prediction performance. Table 7 presents the results of the Friedman Ranking. This ranking reflects the models' overall effectiveness in prediction accuracy, error rates, and efficiency in training time, and memory usage. The results show that XGBoost is the most reliable model overall, demonstrating superior prediction accuracy and lower error rates.

B. BATTERY PRICING STRATEGY

In this section, the proposed RUL-based pricing strategy has been evaluated based on the dataset used in the study. In the proposed approach, variables strongly influencing RUL, such as Cycle Index and Maximum Voltage Discharge, contribute more significantly to pricing. In contrast, the contribution of variables with weaker effects, such as constant current time or

TABLE 6. RAM usage values of estimation models.

Methods	RAM Usage (MB)
Lasso	2.07
Random_Forest	5.07
Gradient_Boosting	5.09
Kernel_Ridge	3.13
Decision_Tree	5.06
XGBoost	2.12

charging time, is limited. As visually illustrated in Figure 3, the calculated correlation values of the variables concerning RUL can be substituted into Equation 3, allowing the equation to be rearranged as

$$\begin{aligned} Cost = {} & Base_{cost} + (RUL_{station} - RUL_{vehicle})\ constant \\ & + \left(X_{dechargetime,vehicle} - X_{dechargetime,station}\right) 0,01 \\ & + \left(X_{4.15Vtime,vehicle} - X_{4.15Vtime,station}\right) 0,18 \\ & + \left(X_{statecurrenttime,vehicle} - X_{statecurrenttime,station}\right) 0,04 \\ & + \left(X_{3.6-3.4Vtime,vehicle} - X_{3.6-3.4Vtime,station}\right) 0,01 \\ & + \left(X_{\max dechargevoltage,vehicle} \right. \\ & \left. - X_{\max dechargevoltage,station}\right) 0,78 \\ & + \left(X_{\min dechargevoltage,vehicle} \right. \\ & \left. - X_{\min dechargevoltage,station}\right) (-0,76) \end{aligned} \tag{3}$$

The proposed RUL-based dynamic pricing model has been compared with a fixed pricing strategy for the evaluation in two different scenarios. The considered scenarios compare two distinct vehicle-to-station battery pairs with identical RUL differences but varying performance characteristics. Scenario 1 features a more significant discharge time difference and a slightly smaller maximum discharge voltage, leading to higher costs. Conversely, Scenario 2 demonstrates reduced performance differences, resulting in lower costs. Both scenarios share the same RUL difference, highlighting the impact of additional variables on pricing under the proposed model. The proposed model incorporates multiple variables affecting battery health, including RUL, discharge time, voltage parameters, and their correlations with RUL; however, the fixed pricing strategy only uses a constant unit cost per RUL difference (e.g., \$0.1) without accounting for additional variables.

Table 8 illustrates the cost outcomes for the two scenarios using the fixed pricing model, where the total cost is calculated solely based on the RUL difference between the station and vehicle batteries. In both Scenario 1 and 2, the RUL difference is the same (200 units), leading to identical costs of \$20 for each scenario. The fixed pricing model simplifies the calculation by ignoring critical performance variables, such as discharge time and voltage differences, which affect the battery's health and performance. As a result, the cost remains constant across both scenarios, regardless of the underlying performance variations, resulting

TABLE 7. Friedman ranking test results.

Methods	Rankings
XGBoost	1
Random Forest	2
Decision Tree	3
Lasso Regression	4
Gradient Boosting	5
Kernel Ridge	6

TABLE 8. Cost comparison under fixed pricing model.

Variable	Scenario 1	Scenario 2	Explanation
RUL Difference	800 (station) – 600 (vehicle) = 200 units	900 (station) – 700 (vehicle) = 200 units	Fixed cost calculated as: RUL Difference × \$0.1/unit.
Other Variable	Ignored	Ignored	Fixed pricing overlooks performance indicators, leading to simplified and potentially unfair results.
Total Cost	\$20	\$20	Costs remain identical for both scenarios as no other factors are considered.

in unfair pricing that doesn't reflect the actual battery condition.

Table 9 compares the total costs of two scenarios based on the variation in crucial battery performance variables such as RUL difference, discharge time, 4.15V time, maximum discharge voltage, and minimum discharge voltage. In Scenario 1, the battery at the station has a higher RUL value than the vehicle battery (200 units of RUL difference), along with a more extensive discharge time difference of 0.3 units, resulting in a higher total cost of \$24.12. Conversely, Scenario 2 shows a similar RUL difference (200 units) but with a far smaller discharge time (0.2 units) and maximum discharge voltage (−0.04), which reduces the total cost to \$22.74. Although both scenarios have similar values for 4.15V time and minimum discharge voltage, the differences in performance parameters in Scenario 1 lead to higher costs.

This study shows that the proposed model adjusts pricing according to battery performance, costing \$24.12 and \$22.74 in different scenarios while the fixed pricing model remains static at \$20 in both scenarios because of ignoring the RUL. This comparison between the proposed and fixed pricing models highlights critical differences in variables considered, fairness, complexity, and cost variance across scenarios. The fixed pricing model that only considers the RUL difference results in a less fair pricing structure, as users with high-quality batteries are penalized, while users with degraded batteries might be rewarded. The proposed model, while more complex and requiring additional computation and data collection, offers a more precise pricing strategy.

With the proposed approach, battery pricing is not only based on the RUL value but also considers other critical

TABLE 9. Cost comparison based on battery performance variables in different scenarios.

Variable	Scenario 1	Scenario 2	Explanation
RUL Difference	800 (station) – 600 (vehicle) = 200 units	900 (station) – 700 (vehicle) = 200 units	Base costs remain constant due to identical RUL differences.
Discharge Time	5.5 (station) – 5.2 (vehicle) = 0.3 units	5.0 (station) – 4.8 (vehicle) = 0.2 units	Larger differences in Scenario 1 increase the cost.
4.15V Time	2.0 (station) – 1.8 (vehicle) = 0.2 units	1.7 (station) – 1.5 (vehicle) = 0.2 units	A similar impact on both scenarios.
Maximum Discharge Voltage	4.12 (station) – 4.15 (vehicle) = –0.03	4.14 (station) – 4.18 (vehicle) = –0.04	Slightly larger performance differences in Scenario 2 reduce the cost more.
Minimum Discharge Voltage	3.52 (station) – 3.50 (vehicle) = –0.02	3.50 (station) – 3.48 (vehicle) = –0.02	Negligible impact on both scenarios.
Total Cost	$24.12	$22.74	Scenario 1 incurs higher costs due to greater performance differences.

variables that directly affect the battery's performance, resulting in a more fair and balanced pricing structure. In particular, the significant role of variables with high correlation coefficients in pricing allows for a more accurate battery health assessment. Thus, the proposed model offers an adaptable pricing structure based on each battery's lifespan and performance indicators, providing a solution that better meets users' needs.

VI. CONCLUSION

This paper has proposed a dynamic pricing strategy for battery prices in battery swapping stations for electric vehicles. The price is determined according to the correlation and weighting of essential parameters on the RUL value, such as Cycle Index and Maximum Discharge Voltage. Through numerical studies, it is shown that the proposed strategy provides a pricing structure that more fairly evaluates the lifespan and performance of batteries. Various machine learning models have also been comprehensively evaluated to enable real-time RUL estimation. The numerical results indicate that among the tested models, XGBoost demonstrates the overall best performance in terms of accuracy and computation speed with a test RMSE of 3.50, a computational time of 9.75 seconds, and RAM usage of 2.12 MB, outperforming the second-best method (Random Forest) which achieves a test RMSE of 3.79, computational time of 8.52 seconds and RAM usage of 2.32 MB. Integrating this machine learning tool with the proposed pricing strategy makes the proposal highly applicable in real-world scenarios.

The dataset utilized in this research encompasses a diverse range of battery usage scenarios, closely mirroring real-world operating conditions to ensure practical applicability. However, it is important to acknowledge potential limitations, such as regional or operational biases, which may affect the generalizability of the findings to broader contexts. During the preprocessing phase, missing data was handled using mean and median imputation techniques, to ensure that the dataset remains consistent and complete for model training, thus maintaining the integrity of the analysis. These preprocessing steps enhanced the dataset's reliability, ultimately supporting the robustness of the proposed model's performance.

This study paves the way for more equitable and efficient battery-swapping operations, offering a promising model for future developments in electric vehicle infrastructure and further advancing the application of machine learning in real-world solutions.

Future studies may aim to further enhance prediction accuracy by combining the strengths of multiple algorithms through hybrid models. Furthermore, future work can also focus on hyperparameter tuning to further optimize model performance. Additionally, the scalability of the solution can be further evaluated for more extensive real-world settings, considering the increased complexity and data volumes associated with extensive battery-swapping stations. Additionally, using advanced feature engineering techniques, such as deep learning, could lead to further performance improvements. This work has been conducted under specific data sets and conditions. Testing the proposed models with different data sets for various battery types, technologies, and environments is crucial.

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