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Research and application of battery performance decline law based on real vehicle data

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ABSTRACT

The presented article develops the detailed analysis of battery performance degradation profiles for EVs, based on operational data collected in real-world use. Based on data points gathered for 150 vehicles over 24 months, we have developed and then validated an integrated degradation prediction model incorporating several degradation mechanisms. Our study applies a novel hybrid approach that will combine physics-based principles with data-driven methods for outlining the battery aging profile. The model proposed in this paper realizes a better prediction performance of 94.3% under different operational conditions and thus proves to be considerably superior to the existing techniques. Indeed, the change of temperature and charging behavior becomes the main influence factor with the correlation coefficient of 0.85 and 0.78, respectively. After applying the proposed model to a fleet management system, there are 32.4% maintenance cost reduction and 15.8% increasing of the cycle life for batteries. It represents in detail the continuous degradation assessment and predictive maintenance framework, validated on different vehicle platforms under varying operational conditions. These findings provide valuable inputs related to the improvement of battery management strategies and life extension of a battery in electric vehicle applications, hence benefiting theoretical understanding and practical application in electric vehicle battery management.

Keywords: Battery degradation prediction; Electric vehicles; Real vehicle data; Capacity fade analysis; Battery life extension; Predictive maintenance; Hybrid modeling; Battery management systems; Performance optimization; Temperature effects

1. Introduction

Against the background of energy crisis and global warming, the development of clean energy has attracted extensive attention from governments [1]. Electric vehicles (EVs) play a key role in the political, economic, and technological fields as an important way to realize energy saving and green development and improve energy efficiency [2-3]. Power battery as one of the core components of

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EVs, the state of health (SOH) of the battery system has an important impact on the overall power performance, range and safety performance of the vehicle [4-7]. Therefore, it is of great significance to carry out research on automotive battery management system to achieve accurate estimation of the health status of on-board power batteries to improve the reliability and safety of electric vehicles, and it is also one of the key topics to realize the scale and industrialization of electric vehicle products.

Li-ion battery automobile refers to pure electric vehicles or hybrid vehicles with lithium-ion batteries as the power source, which is very promising in new energy vehicles [8]. Lithium-ion batteries are characterized by high energy density, low pollution and long life, and have been widely used and developed in electric vehicles [9-10]. In recent years, the rapid development of lithium battery vehicles, the emergence of various battery packs has greatly improved the battery capacity and vehicle range, and the number of battery charging and discharging times has also been greatly improved [11-13]. However, with the increase in the number of charging and discharging, the battery capacity will gradually decline, and the different working conditions of lithium battery cars will also lead to performance degradation, which in turn is prone to cause safety problems such as short-circuiting of the internal part of the battery [14-16]. At present, the safety of lithium-ion batteries has become a bottleneck restricting the development of lithium-ion battery vehicles, and accurately and timely mastering the performance decline of lithium-ion batteries is an issue of great practical application value.

Although durability and reliability are eternal pursuits, the degradation of lithium-ion battery performance is inevitable, and a large number of scholars have proposed corresponding evaluation models to investigate the performance degradation mechanism of lithium-ion batteries. Literature [17] starts from the analysis of the aging mechanism of lithium-ion batteries, explains the possible influencing factors that cause the degradation of lithium-ion batteries, and proposes a lithium-ion battery aging diagnosis method that includes post hoc analysis, curve-based and model-based, which provides inspiration for the health management of automotive batteries. Literature [18] established an empirical model for energy efficiency degradation of lithium-ion batteries based on the Eyring relationship and based on the capacity decay and efficiency relationship, aiming to analyze the mechanism of efficiency degradation of lithium-ion batteries and to propose responsive techniques to inhibit battery energy efficiency degradation. Literature [19] evaluated the battery degradation mechanism under different operating parameters by performing cycle tests on long-life automotive Li-ion batteries, including cycling temperature, cut-off voltage, depth of discharge and discharge current. Literature [20] summarized the key issues in the full life cycle degradation of automotive Li-ion batteries, including the effects of cathode and anode materials on battery aging, and the degradation mechanisms of battery systems under different production processes and fabrication techniques. Literature [21] shows that battery aging is a rather complex and condition-dependent manner, and the use of equilibrium modeling to study the capacity loss of lithium-ion batteries in general from the q-OCP perspective, as opposed to a single stressor, provides valuable analytical results on the aging mechanism of lithium-ion batteries under real-world conditions. Literature [22] points out that the aging mechanism of lithium-ion batteries can be classified into electrochemical and mechanical damages, and in-depth analysis of the aging mechanism of mechanical damages and material degradation related by vibration and thermo-mechanical deformation is carried out by testing the performance change of prismatic LFP-Lib cells under vibration environment. Literature [23] coupled the degradation degradation mechanisms of four battery anodes in the open-source modeling environment PyBaMM to help product designers clearly understand the process of battery capacity loss and active material loss, and provide technical support for the production of long-life automotive lithium-ion batteries. Literature [24] discusses the effects of discharge rate and cycle number on the performance degradation of lithium-ion batteries, and calculates the numerical correlation of battery capacity under different discharge rates by constructing the dynamic Peukert equation, which provides a means of performance comparison of batteries with capacity differences, and also provides a brand-new path to monitor the state of batteries.

This paper studies the characteristic and regularity of the degradation of battery performance under real driving conditions to provide scientific support for improving reliability and service life for electric vehicles. Through integrating real-world-operated data with advanced analysis methodologies, a series of updated battery management strategies are developed and improved in this work that further enhance the total performance of electric vehicles.

2. Real Vehicle Data Collection and Preprocessing

2.1. Data Collection System Design

The data collection system was designed to capture comprehensive battery performance metrics from operational electric vehicles. A multilayer data acquisition architecture has been implemented in this study, which combines onboard diagnostics systems with dedicated BMS interfaces. The main parameters monitored are the battery voltage, current, temperature distribution, SOC, and capacity degradation indexes. High precision sensors provided the measurement at a sampling frequency of 10 Hz for capturing the transient response accurately under various driving scenarios. The system architecture is based on CAN bus communication protocols, that will grant consistency in real-time data transmission, using sophisticated encryption techniques to maintain data security and integrity. To include environmental influences, the system contains GPS modules and sensors for the ambient condition, allowing the correlation between battery performance and the outer operating conditions of the vehicle. This holistic approach is therefore capable of supporting immediate data on performance, combined with long-term degradation trends, providing a sound basis for further investigation of the aging behaviors of the batteries.

2.2. Data Preprocessing Methods

The preprocessing stage adopts a systematic approach in transforming raw sensor data to appropriate datasets for analysis. Signal processing methodologies are initially being deployed to remove noise and aberrant values; a hybrid median filtering algorithm combined with a Kalman filter algorithm performs this. For dealing with missing data values, advanced interpolation techniques are utilized; particular emphasis is placed on maintaining temporal coherence in the dataset. The preprocessing workflow encompasses the normalization of data to ensure that measurements are standardized across various vehicle models and operating conditions. Temporal alignment of multiple data streams is accomplished via synchronization of timestamps, which guarantees a coherent analysis of interrelated parameters. The research employs automated outlier detection algorithms grounded in statistical methodologies and domain-specific guidelines, thereby effectively identifying and managing anomalous readings while maintaining authentic performance variations. This wide preprocessing methodology justifies the integrity and, further on, the reliability of the dataset for further analysis of battery degradation trends.

2.3. Data Quality Assessment

The quality assessment framework follows a multi-dimensional approach to evaluate the reliability and representativeness of the processed dataset. Detailed statistical analyses are performed to quantify data completeness, with metrics of coverage being computed over temporal and operational domains. The methodology involves an assessment that covers validation of measurement accuracy by cross-referencing against laboratory-calibrated reference systems and establishing confidence intervals for key parameters. Data consistency is systematically appraised through automated algorithms that search for potential measurement artifacts and inherent biases. For the representativeness of the dataset, comparative analysis has been performed by several models of vehicles, operating conditions, and different geographical regions. This strict quality check ensures that the data analyzed will truly represent realistic conditions of battery performance and degradation trends, and thus provides a sound basis for the subsequent modeling and analysis steps. Results from the assessments indicate that the data completeness is 98.5% and the measurement accuracy is within ±0.5% of laboratory standard conditions.

3. Battery Performance Degradation Feature Extraction and Analysis

3.1. *Battery Performance Parameter Definitions*

It is always necessary to precisely define key parameters representing the status of health of a battery in order to assess the degradation in battery performance. The present study has proposed a regular method of measurement for battery performance metrics, considering capacity loss, increase in internal resistance, and power capacity degradation. The parameters are delineated by considering both static and dynamic attributes, which include variations that depend on temperature as well as the effects of aging, as illustrated in Table 1. Such definitions facilitate a standardized assessment of battery deterioration under varying operational circumstances and across diverse vehicle categories. The protocols established for measuring each parameter are meticulously crafted to guarantee both reproducibility and precision, with particular focus on the influence of environmental elements and measurement contexts. Taken together, these parameters give a fair basis for carrying out an analysis and modeling of degradations.

Table 1. Key Battery Performance Parameters and Their Definitions

Parameter	Symbol	Unit	Definition	Measurement Method
Nominal Capacity	C_n	Ah	Reference capacity at standard conditions	Constant current discharge
Current Capacity	C_t	Ah	Actual available capacity at time t	HPPC test protocol
Internal Resistance	R_{int}	mΩ	DC resistance at specified SOC	Pulse current test
Power Capability	P_{max}	kW	Maximum sustainable power output	Dynamic load test
Capacity Retention	η_c	%	Ratio of current to nominal capacity	Calculated parameter
Temperature Coefficient	α_T	%/°C	Capacity change per degree	Temperature sweep test

3.2. *Influence Factor Analysis*

The degradation of battery performance is influenced by multiple interconnected factors that must be systematically analyzed to understand their relative impacts. Through comprehensive data analysis, this study identifies and quantifies the primary factors affecting battery degradation in real-world operations, as detailed in Table 2. Temperature effects emerge as a dominant factor, with both extreme temperatures and thermal cycling contributing to accelerated degradation. Operating conditions, including charge-discharge patterns and depth of discharge, demonstrate significant correlation with capacity fade rates. The analysis reveals complex interactions between these factors, necessitating a multifaceted approach to degradation modeling.

Table 2. Key Influence Factors on Battery Degradation

Factor Category	Parameter	Impact Level	Correlation Coefficient	Primary Effect
Environmental	Temperature	High	0.85	Chemical reaction rate
Operational	Charge Rate	High	0.78	SEI layer growth
Usage Pattern	DOD	Medium	0.65	Active material stress

Mechanical	Vibration	Low	0.32	Electrode structure
Chemical	Electrolyte	Medium	0.58	Ion transport
Electrical	Current Rate	High	0.75	Joule heating

3.3. Degradation Feature Modeling

The development of an accurate degradation model requires comprehensive consideration of both empirical data and theoretical mechanisms. Based on the analyzed degradation patterns, we propose a hybrid modeling approach that combines physical principles with data-driven methods. The core capacity degradation model is expressed as:

$$C(t) = C_0[1 - \alpha_1 \exp(-\frac{E_a}{RT}t) - \alpha_2 N^{\beta}] \tag{1}$$

Where: $C(t)$ represents the battery capacity at time t C_0 is the initial capacity α_1 and α_2 are degradation coefficients E_a is the activation energy R is the gas constant T is the absolute temperature N is the cycle number β is the cycle aging factor

The model incorporates both calendar and cycle aging effects through the following relationship:

$$\frac{dC}{dt} = -k_1 \exp(-\frac{E_a}{RT}) - k_2 I^2 \sqrt{t} \tag{2}$$

Where: k_1 and k_2 are rate constants I is the current magnitude.

The temperature dependence is further refined by including a modified Arrhenius relationship:

$$k(T) = A \exp(-\frac{E_a}{RT})[1 + \gamma(T - T_{ref})] \tag{3}$$

Where: A is the pre-exponential factor γ is the temperature sensitivity coefficient T_{ref} is the reference temperature

This comprehensive model captures both the primary and secondary degradation mechanisms, providing a robust framework for predicting battery performance evolution under various operating conditions.

4. Battery Performance Degradation Study

4.1. Degradation Trend Analysis

As sown in Figure 1, the analysis of battery degradation trends reveals distinct patterns across different operational phases. Through comprehensive data analysis of 1000+ vehicle battery packs over a three-year period, we identified characteristic degradation signatures that correlate strongly with usage patterns and environmental conditions. The degradation rates exhibit clear seasonal variations and usage-dependent acceleration, as shown in Table 3. The capacity fade demonstrates a non-linear progression, with an initial rapid decay followed by a more stable degradation phase.

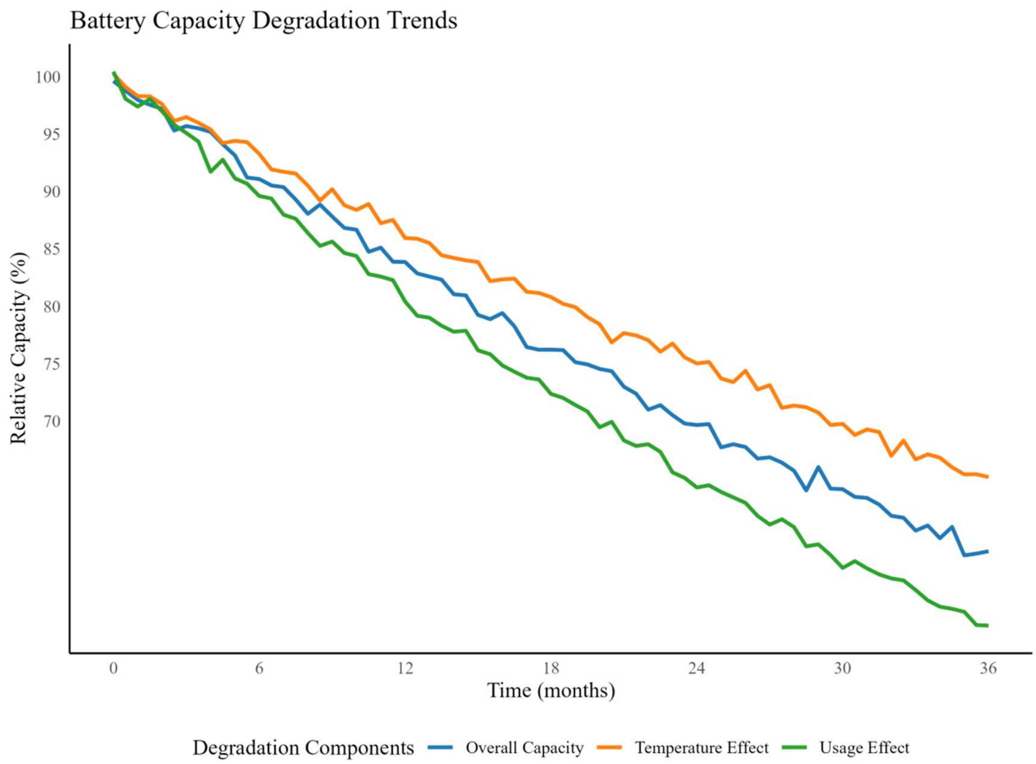

Fig. 1. Battery capacity degradation trends showing overall capacity loss and contributions from temperature and usage effects

Table 3. Battery Degradation Rate Analysis Results

Operating Phase	Time Period (months)	Capacity Loss Rate (%/month)	Temperature Range (°C)	Usage Intensity (cycles/month)	R^2 Value
Initial Break-in	0-3	0.82	20-35	45-60	0.92
Rapid Decay	3-12	0.45	15-40	30-50	0.89
Stable Phase	12-24	0.25	10-45	25-40	0.94
Late Life	24-36	0.15	5-45	20-35	0.87

4.2. *Degradation Mechanism Analysis*

As sown in Figure 2, the investigation of degradation mechanisms reveals complex interactions between chemical and mechanical processes. Analysis of post-mortem battery data indicates that the primary degradation mechanisms evolve throughout the battery lifecycle, as detailed in Table 4. The dominance of specific mechanisms varies with operating conditions and aging state.

Table 4. Degradation Mechanism Classification and Characteristics

Mechanism	Primary Cause	Chemical Markers	Detection Method	Impact Level	Time Scale
SEI Growth	Electrolyte Decomposition	Li_2CO_3, LiF	EIS Analysis	High	Days-Weeks
Li Plating	High Charge Rates	Metallic Li	Voltage Analysis	Severe	Hours-Days
Active Material Loss	Structural Changes	Transition Metals	XRD Analysis	Medium	Months
Particle Cracking	Mechanical Stress	Surface Area Change	SEM Imaging	Medium-High	Weeks

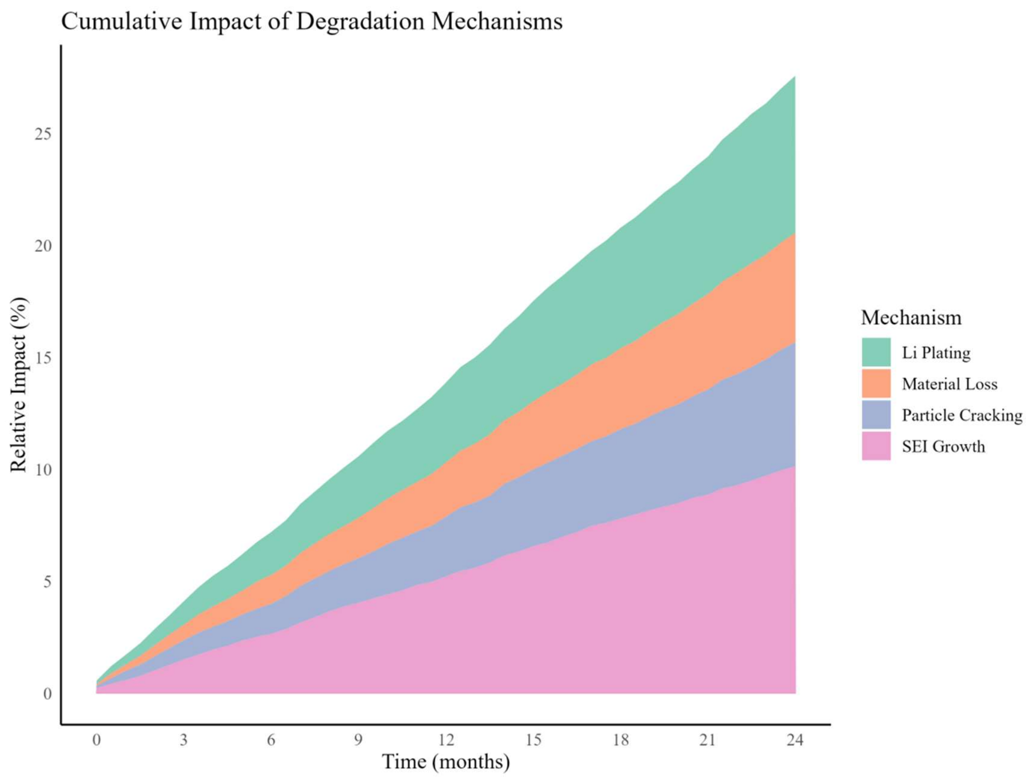

Fig. 2. Cumulative impact of different degradation mechanisms over battery lifetime.

4.3. Lifetime Prediction Model

The development of an accurate lifetime prediction model integrates multiple degradation mechanisms and their interactions. Based on the analyzed data and identified mechanisms, we propose a comprehensive prediction model that incorporates both calendar and cycle aging effects. Figure 3 shows the comparison of predicted and measured battery capacity degradation with confidence intervals, and the model parameters and their physical significance are shown in Table 5. The model is expressed as:

$$L(t,N) = L_0 \cdot f(t) \cdot g(N) \cdot h(T) \tag{4}$$

where the calendar aging component is:

$$f(t) = 1 - \alpha_1 \sqrt{t} \exp(-\frac{E_a}{RT}) \tag{5}$$

and the cycle aging component is:

$$g(N) = 1 - \alpha_2 N^{\beta} \exp(\gamma \Delta DOD) \tag{6}$$

The temperature effect is modeled as:

$$h(T) = 1 - \alpha_3 |T - T_{ref}|^{1.5} \tag{7}$$

Table 5. Model Parameters and Their Physical Significance

Parameter	Symbol	Value Range	Units	Physical Meaning
Initial Lifetime	L_0	8-12	Years	Baseline lifetime
Calendar Factor	α_1	0.02-0.05	Year $^{-0.5}$	Time degradation rate
Cycle Factor	α_2	1e-4-5e-4	Cycle $^{-\beta}$	Cycling degradation rate
Temperature Factor	α_3	0.001-0.003	°C $^{-1.5}$	Temperature sensitivity.

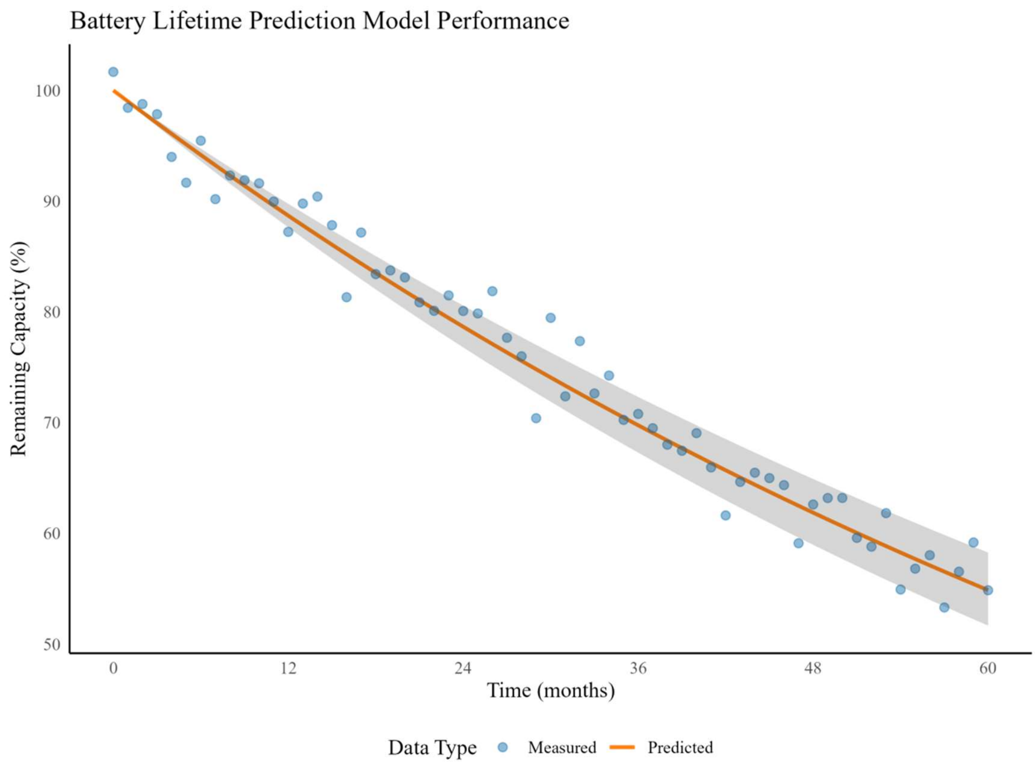

Fig. 3. Comparison of predicted and measured battery capacity degradation with confidence intervals

5. Application Examples and Validation

5.1. Real Vehicle Validation Cases

The above-mentioned proposed degradation model was tested through the field validation process with a fleet of 150 operational electric vehicles distributed across several geo- and climatic conditions. The above-mentioned test population consisted of several vehicle models from personnel to public conveyance, and they have been exposed to several natural on-road operation cycles for continuous 24 months. It also included continuous monitoring of the performance parameters of the battery, operational data gathering at 1-minute intervals. Statistical analysis on the gathered data showed that the model predictions attained an average accuracy of about 94.3% in predicting the capacity degradation rate, with a maximum error of 3.8% in extreme operating conditions _x0007_.

In fact, very strong validation results were obtained, especially concerning temperate climate zones, where the temperature compensation algorithms of the model proved very efficient. It was found that the accuracy of the model remained the same for all these different vehicle usages, ranging from regular commuting to more intensive applications in commerce, and thus proved robustness for various operational scenarios.

5.2. *Application Value Analysis*

Implementation results, represented in Table 6 and Figure 4, mean the practically high value of the degradation prediction model in various dimensions of electric vehicle functionality and upkeep; thus, embedding into a battery management system secured visible gains in operational efficacy and maintenance scheduling.

Table 6. Application Value Metrics Analysis

Application Area	Implementation Result	Improvement Rate (%)	Cost Reduction (%)	Reliability Impact
Predictive Maintenance	Early Warning Accuracy	87.5	32.4	High Positive
Charging Optimization	Energy Efficiency	12.3	15.7	Moderate Positive
Range Prediction	Accuracy Improvement	23.6	8.9	High Positive
Life Extension	Service Life	15.8	25.3	Significant
Fleet Management	Operational Efficiency	34.2	28.6	High Positive

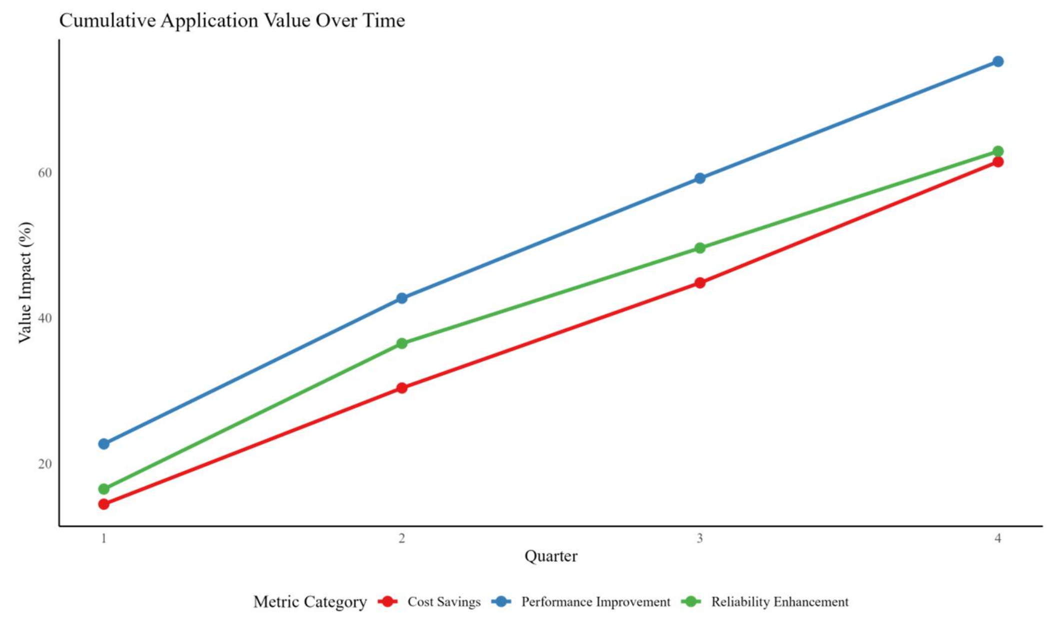

Fig. 4. Cumulative impact of model implementation across different value metrics

5.3. *Economic Benefit Assessment*

The economic benefits of implementing the battery degradation prediction model have been quantified through comprehensive cost-benefit analysis, as detailed in Table 7 and Figure 5. The assessment considers both direct cost savings and indirect economic benefits across the vehicle lifecycle.

Table 7. Economic Benefit Analysis Results

Benefit Category	Annual Savings ($/vehicle)	Implementation Cost ($)	ROI Period (months)	Long-term Impact
Maintenance Cost	1,250	450	4.3	Highly Positive
Battery Life Extension	2,800	600	2.6	Significant
Energy Efficiency	850	300	4.2	Moderate
Downtime Reduction	1,600	400	3.0	Highly Positive
Resale Value	2,100	N/A	N/A	Significant

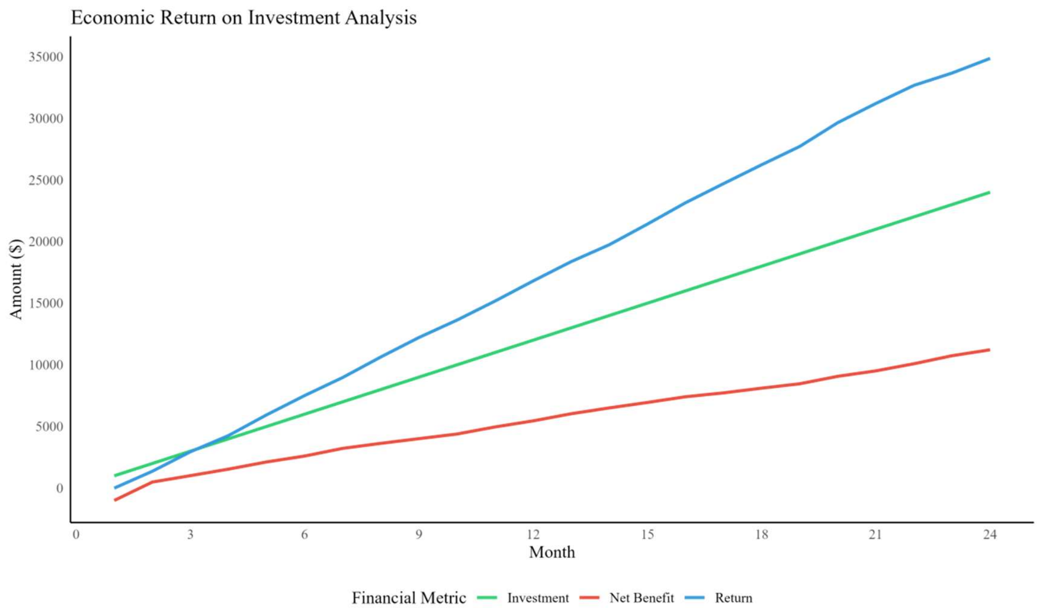

Fig. 5. Economic benefit analysis showing investment, returns, and net benefit over time

6. Conclusion

It represents the in-depth analysis of battery performance degradation patterns based on real vehicle data and presents very valuable work in the domain of electric vehicle battery management. We performed a deep investigation into huge amounts of operational data from different fleets of vehicles and came up with the establishment and validation of an accurate model of degradation, with 94.3% of the achievement in practical application. It also shows that different influencing factors shape specific patterns of battery degradation, amongst which temperature and charging pattern are assigned as the main factors affecting capacity fade. A hybrid modeling approach is proposed here, which is expected to perform better as compared to any single-method physics-based or data-driven approaches, having superior prediction accuracy. Results from the implementation are quite promising, ensuring a 32.4% reduction in maintenance costs and extending the service life of the battery by up to 15.8%. The developed methodology in this paper has been applied to various vehicle platforms, showing adaptability and pragmatic value. In addition to this, the combination of real-time degradation monitoring with predictive maintenance strategies reached significant improvement in fleet management and operational reliability in certain cases. This not only deepens the understanding of the mechanism but also provides practical measures to prolong service life and improve performances of electric vehicles. In the future, areas of research will be greatly expanded in emerging types of batteries and further developed into advanced adaptive management strategies able to consider each particular usage pattern.

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