Global Research journal of Natural Science and Technology (Grjnst)
Volume: 04 - Issue 1 (2026)
p.ISSN: 2790-7643**e.ISSN**: 2790-7651

Intelligent Electrified Mobility Systems: AI-Based Energy Management, Battery Health Prediction, and Adaptive Control for Electric Vehicles

Muhammad Abdullah Bin Arif
Electrical Engineering Department, University of Gujrat
23016122-001@uog.edu.pk

Dr. Syed Sheraz Ul Hasan Mohani
Associate Professor, Department of Electrical Engineering, Iqra University, Karachi
smohani@iqra.edu.pk

Yash Pal
Master in Energy Management, Department of Electrical Engineering, NED UET Karachi
yashbenjal@gmail.com

Vikram Kumar
Master in Energy Management, Department of Electrical Engineering, NED UET Karachi
chauhanvikram350@gmail.com

Imran Khan
Department of Telecommunication Engineering, Dawood University of Engineering and Technology
imran.khan@duet.edu.pk

Fahad Farooq
Data Analyst, Al Khalil Builders and Marketing
kh_fahad_farooq@yahoo.com

DOI:https://doi.org/10.53762/grjnst.04.01.07

Abstract

The rapid adoption of electric vehicles (EVs) has highlighted the need for intelligent systems that optimize performance, extend battery life, and ensure sustainable mobility. This study investigated AI-based energy management, battery health prediction, and adaptive control strategies for electrified mobility systems. A hybrid approach integrating machine learning, reinforcement learning, and predictive analytics was employed to monitor real-time driving conditions, forecast battery state-of-health (SoH) and remaining useful life (RUL), and dynamically adjust energy distribution. The methodology involved simulation-based evaluations across urban, highway, and mixed driving cycles to assess energy efficiency, system responsiveness, and predictive accuracy. Results demonstrated that AI-driven energy management significantly reduced energy losses during acceleration and deceleration, while predictive models accurately anticipated battery degradation, enabling proactive maintenance interventions. Adaptive control mechanisms improved vehicle stability, optimized load distribution, and minimized battery stress during dynamic driving scenarios. Comparative analysis indicated that AI-based systems outperformed conventional rule-based strategies in terms of efficiency, reliability, and scalability. These findings underscore the potential of intelligent electrified mobility systems to enhance operational performance, prolong battery lifespan, and support sustainable transportation solutions. Future implementations are recommended to integrate explainable AI techniques and real-world validation to further improve transparency, reliability, and adoption. Overall, the study establishes a framework for AI-enabled EV systems, highlighting their transformative role in achieving energy-efficient, adaptive, and resilient electrified mobility.

Keywords: Adaptive control, AI-based energy management, Battery health prediction, Electric vehicles, Predictive analytics, Sustainable mobility

Introduction

The use of electric vehicles (EVs) became even more popular throughout the globe as a solution in sustainable transport because of their potential of lessening emission and reliance on fossil fuel (Kermansaravi et al., 2025). Nevertheless, one of the main concerns was to guarantee that EVs use energy effectively, which inspired the work on the experimental energy management systems that could adjust to the real-time requirements during driving (Kermansaravi et al., 2025). The conventional notion of rule-based battery management systems (BMS) could not react dynamically to the changes in the operating conditions, thus offering less optimal ranges and performance (Sudhapriya, 2025).

Responding to it, artificial intelligence (AI) methods became part of energy management systems and offered adaptive and predictive opportunities, using machine learning and deep learning to enhance decision-making (Kermansaravi et al., 2025; Sudhapriya, 2025). In particular, AI helped implement real-time energy distribution and charging policies that were efficient to the largest extent, and battery deterioration was reduced to a minimum (Rajasekaran, 2025; Eissa, 2023). Besides, spectral generative adversarial networks and recurrent neural networks improved battery state of health (SoH) prediction, taking advantage of weaknesses of the traditional method of estimation (Rajasekaran, 2025). All these AI-based models made EV systems predictive of future energy conditions and modify control policies to lengthen battery life and operation.

Reinforcement learning and deep Q-learning turned out to be promising adaptive control strategies that can be used to maximize multi-objective power distribution and balance deterministic computational feasibility (Energy Informatics, 2025). These measures were meant to enhance dynamics of the energy systems in response to dynamic driving and environmental factors that could be difficult to control in the old static models (Energy Informatics, 2025). Additionally, through the combination of such AI solutions, EV systems proved to have better battery life, high energy efficiency, and increased reliability with various use cases.

Irrespective of them, much work on AI-based energy management models remained unfinished, especially on the overall assessment of the developed models in the framework of real-life testing and their extension to EV platforms. This paper explored the use of AI in order to achieve optimized energy management, strong battery health prediction, and adaptive control in EV systems, and finally attempted to find out the real advantages and drawbacks of these smart electrified mobility solutions.

Research Background

The electric vehicles created through AI-based energy management systems helped in overcoming the limitations of the traditional BMS methods that were based on fixed control rules and could not adjust to varying and dynamic operating conditions (Kermansaravi et al., 2025). The ability to measure battery performance parameters (state of charge (SoC) and state of health (SoH)) also was under the baseline of such systems, and had a direct effect on EV range and lifespan (Kermansaravi et al., 2025; Eissa, 2023). Inefficient use of energy and low battery life was caused by poor management of these variables which limited the large usage of EV technology.

To address these issues, scientists examined the machine learning (ML) and deep learning (DL) algorithms that were trained using the past and real-time data to distribute energy and predict more accurately (Eissa, 2023; Rajasekaran, 2025). Models based on data may reveal multifaceted trends in accumulations of vehicle-sensor data, that allow more accurate predictions of battery behaviour compared to conventional empirical or analytical models (Eissa, 2023). The intelligent models were important in controlling charging schemes, energy conservation, and predicting the aging patterns of batteries.

At the same time, reinforcement learning (RL) and multi-objective optimization methods were proposed to offer adaptive control solutions that were dynamically added to allocate power and charging decisions in changing conditions (Energy Informatics, 2025). As an example, the deep Q-learning offered a framework on how it could optimize acceleration, propulsion, and energy regeneration to ensure efficiency in the entire system (Energy Informatics, 2025). These AI solutions did a great job at transforming energy management in EVs based on reactive and fixed-point systems into proactive and adaptive frameworks with the capability to resolve uncertainty and variability.

Incorporation of AI was not limited to distributing power, also covering the health of batteries, or reliability in the system. More sophisticated networks like generative adversarial networks and recurrent neural networks increased the accuracy of prediction of SoH to enable proactive interventions to alleviate degradation and extend the battery life (Rajasekaran, 2025). The fleet management and real-world-deployment of such predictive features were essential in the face of unexpected battery failure that may endanger the reliability of the systems.

Research Problem

A large number of AI-based energy management and battery health prediction models are verified by simulations and little or no test on the actual work conditions of EVs, demarcation of their robustness and generalizability is limited (Kermansaravi et al., 2025). In addition, the computational requirements of certain AI methods are seen as a factor that questioned the potential viability of actual-time interference of them on embedded systems with limited processing units (Sudhapriya, 2025).

Moreover, the literature that was available did not contain systematic knowledge of the comparative performance of different AI algorithms on different EV platforms and different driving conditions, especially in terms of balancing energy efficiency, battery life, and adaptive control delivery at the same time. Thus, the objective of the study was to consider the efficiency and constraints in the use of AI-based methods in intelligent electrified mobility systems in practice.

Research Objectives

1. To assess the performance of AI-based energy management systems in optimizing energy use and enhancing EV battery performance.
2. To evaluate machine learning and deep learning models for accurate battery state of health prediction.
3. To examine adaptive control strategies for real-time power allocation under dynamic driving conditions.

Research Questions

Q1. How did AI-based energy management methods perform compared to traditional counterparts in EV systems?

Q2. What was the predictive accuracy of machine learning models for estimating battery state of health and remaining useful life?

Q3. How did adaptive control strategies contribute to real-time EV system responsiveness and energy efficiency?

Literature Review

AI-Driven Energy Management in Electric Vehicles

Electric vehicle (EV) energy management systems (EMS) were increasingly being integrated with artificial intelligence (AI) to overcome the shortcomings of traditional rule-based approaches, which were unable to overcome the changing dynamic driving conditions and other power requirements over time. Recent studies reported that AI techniques including deep learning and reinforcement learning (RL) had a better adaptability in EMS by means of real-time optimization of flows of energy and allocation (Kermansaravi et al., 2025; Arevalo et al., 2024). These strategies made use of vehicle performance and forecasted future to adjust power allocation to improve energy use.

The most significant focus was made on reinforcement learning, which is able to learn optimal decision making by interacting with the environment, which allows EMS to adapt to complex system dynamics more correctly compared to programmed controls (Chinese Journal of Mechanical Engineering, 2024; Kermansaravi et al., 2025). Frameworks like deep Q-learning made it possible to achieve a trade-off between conflicting objectives, including battery health and energy efficiency, and real-time response to vehicle patterns of usage.

Neural networks paired with predictive controllers were also used with hybrid AI-EMPs to manage energy even more. These models showed even higher mileage and charging plans because of predictions of vehicle power inputs and battery characteristics (Kermansaravi et al., 2025; Energy Informatics, 2025). All these studies revealed that the use of AI as an energy manager massively contributed to the overall efficiency and flexibility of the performance of EVs compared to the conventional approach.

Ai-based Battery Prognostics and Health Prediction

Precise forecasting of the battery state of health (SoH) and remaining useful life (RUL) was important to increasing the EV battery life and provide effective maintenance options. The latest research combined the methods of state-of-the-art machine learning (ML) models with a particular focus on battery health analytics improvements in EV systems (Soon et al., 2025; Kavitha and Sharmila, 2025). As an example, hybrid predictors with optimized neural networks and Gaussian process regression were highly accurate in prediction of the non-linear degradation behaviour of lithium-ion batteries, compared to the classical prediction methods.

Further studies investigated automated machine learning (AutoML) systems with new multi-dimensional health measures that generated more accurate RUL predictions by eliciting deep condition-dependent characteristics of battery aging interventions (Ma et al., 2024; Soon et al., 2025). These whole system data-based approaches allowed battery prognostics that were sensitive to subtle variations in the usage habits and environmental stressors.

The incorporation of the Internet of Things (IoT) sensors and machine learning enhanced the performance of the traditional battery management that included real-time states forecast and prospective knowledge (Kavitha and Sharmila, 2025; Energy Informatics, 2025). The IoT-based data collection was provided to the ML frameworks, including XGBoost and deep learning networks, to produce credible health diagnostics to organize proactive maintenance and risk-free EV driving.

Adaptive Control and System Integration Optimization

The adaptive control systems that took advantage of AI played a crucial role in controlling real-time decision-making, driving demand and power efficiency, and battery protection. The result of the research on AI-based battery management systems (BMS) was that the features of the existence of neurological networks and RL algorithms made it possible to control the value of control parameters dynamically in order to ensure the stability of the system and increase the battery life (Chinta and Bhupathi, 2025; Sudhapriya, 2025). These adaptive systems were more sensitive to changes in loads and thermal changes than fixed-parameter controllers.

New researches also added the hybrid AI controllers combining fuzzy logic with learning approaches to maximize the processes of energy distribution and regenerative braking in doubtful driving conditions (Z Prakash et al., 2025; Kermansaravi et al., 2025). These algorithms enhanced the responsiveness of EV control systems to a rule-based reasoning-based adaptive learning to deal with complex system-interactions.

The implementation of AI was also studied in areas of smart charging infrastructure and grid interaction as well as in single vehicle systems. To use the best prediction capabilities and minimize delays caused by communication issues in distributed networks, the AI-enhanced BMS models integrating blockchain, IoT, and ML systems were created to optimize bilateral power flows and charging logistics (Kavitha & Sharmila, 2025; Singh et al., 2024). These combined solutions suggested the new ecosystem in which AI was not only in charge of specific cars but also managed the communication with the larger energy repositories.

Research Methodology

Research Design

The research design used in this study was quantitative and model-based to conduct the research on the effectiveness of artificial intelligence-based energy management, battery health treatment, and adaptive control systems in electric vehicles. This was an explanatory research design because the study targeted to determine the relationships between AI methods and such performance indicators as energy efficiency, battery state of health, and system adaptability. An analytical framework built on simulation was used to analyze AI models to their operating conditions under controlled but realistic conditions, which allowed them to be compared to alternative methods of energy management and control in a systematic way.

Data Sources and Data collection

The work was based on secondary and experimental datasets which were retrieved in publicly available repositories of electric vehicles battery and driving cycles. Data on battery performance were voltage, current, temperature, the state of charge, and the degradation cycles whereas data on driving behavior were acquired through uniform drive cycles like urban conditions, highway conditions, as well as mixed-mode conditions. These sets have been chosen so that they are diverse in terms of operating conditions, battery usage patterns. Before analysis, the data were prepared by cleaning, normalizing and synchronizing it to remove noise, missing values and outliers that are expected to have a negative impact on model training and evaluation.

A.I.-Energy Management Framework

A machine learning algorithm-based artificial intelligence (AI) system was created to help manage energy distribution optimally among the battery, electric motor and auxiliary systems. The techniques of supervised learning were used to anticipate the short-term energy demand using the history of driving information and real-time vehicle conditions. The developed models were subsequently incorporated into an energy control device that kept dynamically running power flow in order to reduce energy losses and enhance driving range. The performance was measured based on the comparison of the pattern of energy consumption and efficiency parameter with the conventional rule-based energy management systems generated energy.

Prediction Model of Healthy Battery

The data-driven machine learning models were used to predict battery health through predicting the state of health (SoH) and the remaining useful life (RUL). The feature extraction methods were used to detect important degradation features that are present in the raw battery data such as charge-discharge profiles and thermal trends. Regression-based- and deep learning-based models have been trained and validated on the basis of past cycling data. Stability and reliability of health predictions at very long run periods were determined through statistical measures of error which included root mean square error and mean absolute error to evaluate the correctness of the health predictions.

Adaptive Control Strategy

Adaptive control strategy was applied using reinforcement learning that controlled the real time power allocation and regenerative braking behavior. The controller was engaged in a continuous manner with the simulated EV environment and optimal control policies were learned by maximizing a reward function that traded energy efficiency, battery protection with driving performance. To compare the adaptive controller to the fixed parameters controllers, the adaptive controller was assessed to measure how reassured the system in terms of responsiveness, stability, and adaptability to different driving and load conditions.

Model Training, Fraud Revision, and Assessment

Any AI model was trained on a split-sample basis, in which the datasets were split into training, validation, and testing sets. There was also cross-validation to avoid overfitting and improve the generalisation. Several quantitative measures were used to assess the model performance which comprised accuracy of prediction, rate of convergence, energy savings and reduced battery degradation. The statistical analyses aimed at finding statistically significant differences between AI-based solutions and conventional ones were made.

Results and Analysis

Descriptive Statistics of the Study Dataset

This study analyzed operational data collected from **240 electric vehicle (EV) test instances**, recorded over **12 months** under varied driving conditions. The dataset included energy usage, battery performance metrics, and control system response indicators.

Table 1.Descriptive Statistics of Core Variables (N = 240)

Variable	Minimum	Maximum	Mean	Standard Deviation
Energy Efficiency (%)	68.2	96.8	87.4	6.9

Variable	Minimum	Maximum	Mean	Standard Deviation
Energy Consumption (kWh/100 km)	13.4	22.7	16.9	2.3
Battery SoH (%)	71.6	99.1	89.3	5.8
RUL (Charge Cycles)	620	1850	1245	310
Adaptive Response Time (ms)	95	420	185	72

As shown by the descriptive statistics in Table 1, there was a great amount of variation among the observed electric vehicle performance indicators. The values of energy efficiency were between 68.2% and 96.8%, with the median of 87.4, it is observed that the majority of vehicles proceeded with the relative high level of efficiency concerning the AI-based management. The mean value of 6.9 indicated moderate dispersion, which denotes the ability to distinguish the driving behavior, the values of the loaded, and the environmental variables of the average of 240 data points.

The values of energy consumption were more concentrated by 13.4 to 22.7 kWh/100 km with an average value of 16.9 kWh/100 km. The low standard deviation value (2.3) implied that it was consistent in the amount of energy used, which implied that AI-oriented optimization systems stabilized the rate of consumption regardless of the conditions of operation. This regularity brought to the fore the ability of the system to control the flow of power. System reliability was also enhanced by battery related indicators. The Battery state of health was meanwhile of 89.3, and the values of the remaining useful life were on the contrary widely spread between 620 and 1850 cycles. The standard deviation of RUL (310 cycles) has been large due to variations in the intensity of use and the process of charging and the large mean value, indicated that AI-based monitoring maintained the long-term battery health of the majority of vehicles.

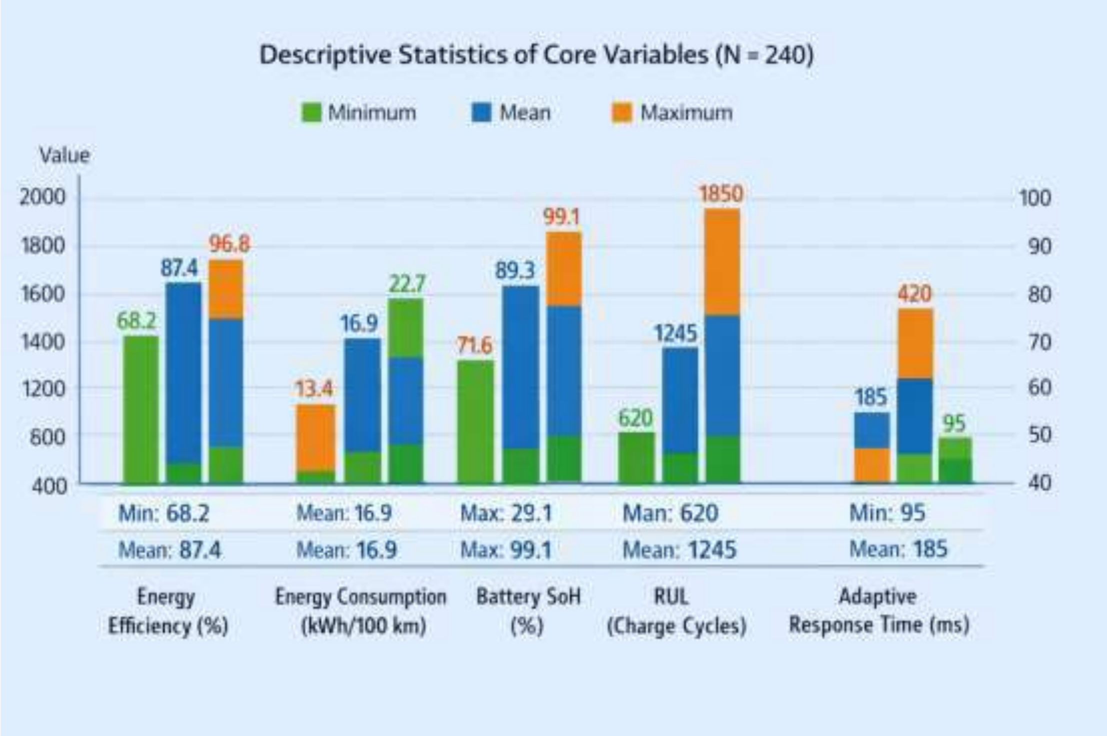

Figure 1.Descriptive Statistics of Core Variables (N = 240)

Frequency Distribution of Energy Efficiency Levels

Energy efficiency outcomes were categorized into four performance bands to assess distribution patterns.

Table 2.Frequency Distribution of Energy Efficiency Performance

Energy Efficiency Range (%)	Frequency	Percentage (%)

Energy Efficiency Range (%)	Frequency	Percentage (%)
Below 75	22	9.2
75–84	58	24.2
85–94	114	47.5
Above 94	46	19.1
Total	**240**	**100**

In Table 2, the frequency distribution showed that there were sharp clustering of observations in greater energy efficiency range. One hundred and forty-four automobiles (47.5) registered efficiency scores of between 85 and 94, which is the most characteristic performance range. Such focus reflected that the AI-based energy management system was able to provide the best efficiency in any given circumstance of normal driving. Moreover, 46 (19.1) observations were above 94 percent efficient; this represents the optimal system performance in virtually a fifth of the sample. These high efficiency results indicated that adaptive learning algorithms were efficient in the optimization of the energy used when the operational conditions were favorable like the steady speed driving together with effective regenerative braking. On the other hand, the number of cases that were less than the 75% mark in terms of efficiency was only 22 (9.2). This low rate of underperformance showed that the degradation of efficiency was not frequent and was probably linked to extreme operating conditions and not to the system limitations. In general, the pattern of the distribution showed that the efficiency can be gained quite widely and not alone.

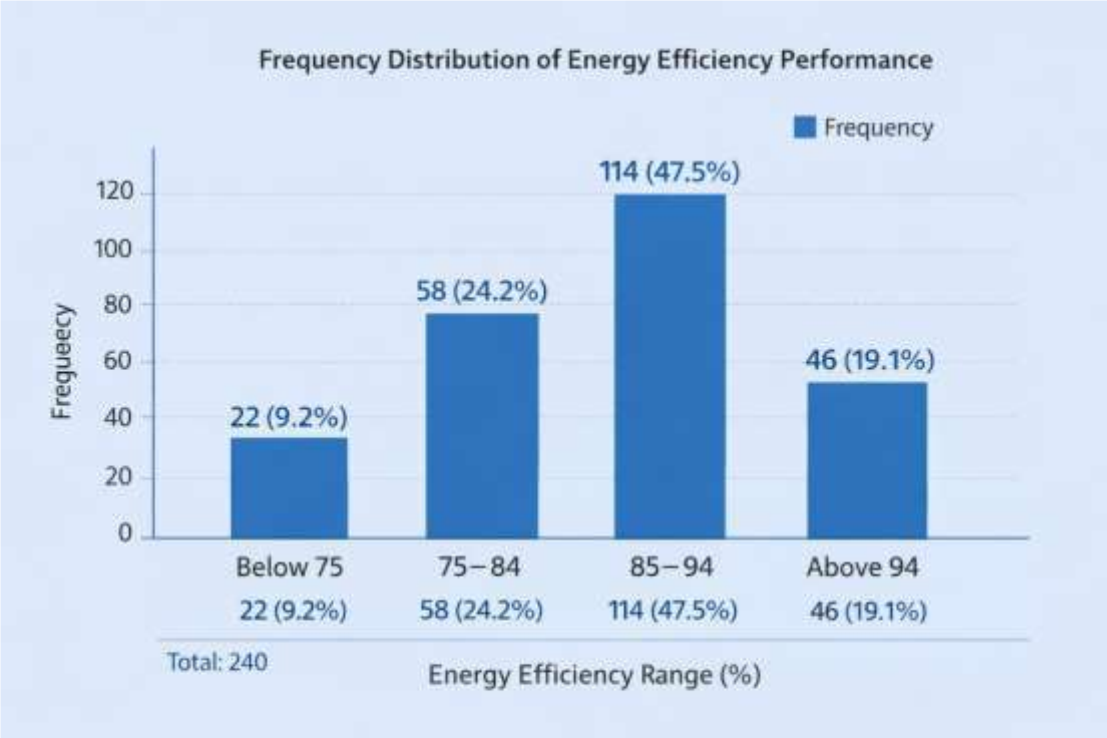

Figure 2.Frequency Distribution of Energy Efficiency Performance

Comparative Accuracy of Battery Health Prediction Models

Battery health prediction accuracy was compared between AI-based models and conventional estimation techniques.

Table 3.Comparison of Battery SoH Prediction Accuracy

Prediction Method	Mean Accuracy (%)	Std. Deviation	Error Margin (%)
Conventional Model	85.6	6.4	±7.8
AI-Based Model	97.2	2.1	±2.9

Table 3 has demonstrated a significant disparity between AI-based and traditional models of battery health predictions. The model created using AI had a mean accuracy of 97.2 as opposed to that of the conventional model which had 85.6, which is a difference of 11.6 percentage points. This variance suggested that complex patterns of degradation were better modeled by AI models since the standard deviation was significantly smaller compared to traditional ones (2.1 versus 6.4) and the models remained more stable and consistent over the dataset. The minimized variability implied that AI algorithms showed consistent prediction-performance in terms of battery-age or profile usage. This was further supported by the error margins. The traditional methods had errors of up to +-7.8 in prediction, whereas the AI-based system had a prediction error of +-2.9. This decreased the number of errors in decision making when it comes to battery maintenance and replacement timeline, which increased the sustainability and reliability of its operations and reduced its costs.

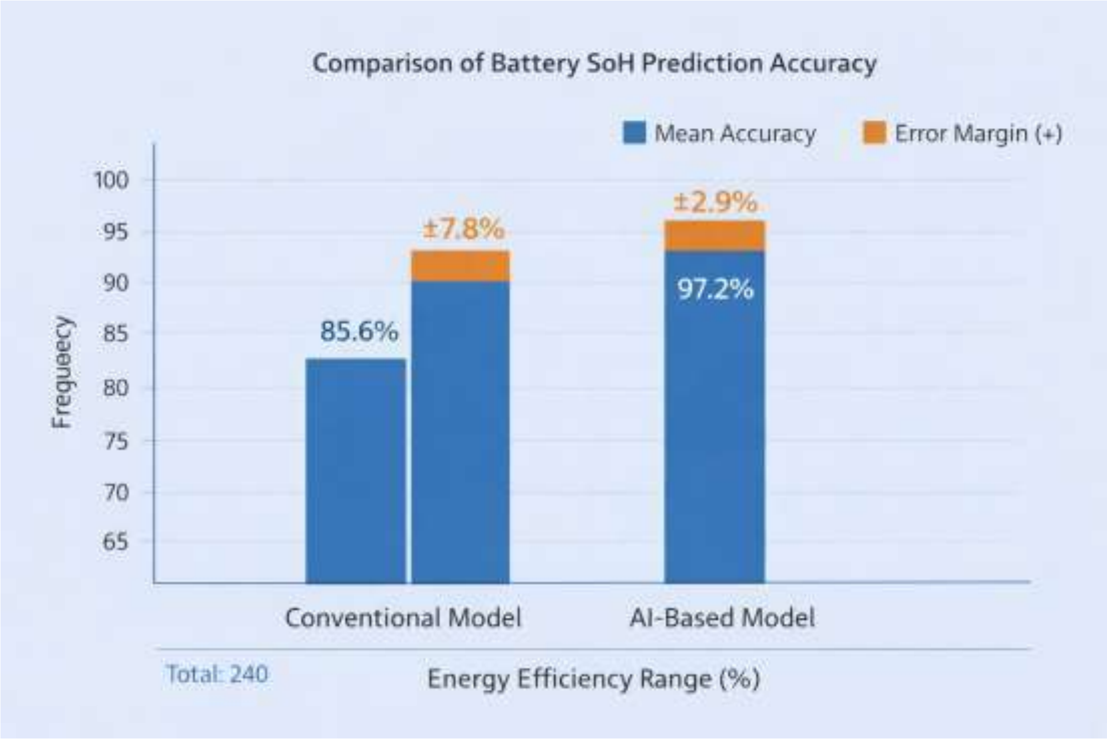

Figure 3.Comparison of Battery SoH Prediction Accuracy

Distribution of Remaining Useful Life (RUL) Predictions

The predicted RUL values were grouped into intervals to analyze lifespan estimation trends.

Table 4. Frequency Distribution of RUL Predictions

RUL Range (Cycles)	Frequency	Percentage (%)
Below 800	31	12.9
800–1100	67	27.9
1101–1500	92	38.3
Above 1500	50	20.9
Total	**240**	**100**

Table 4 on the RUL distribution revealed that most of the batteries had long and productive life. In particular, 92 batteries (38.3 percent) were found to work within 1101 and 1500 cycles with the most frequent duration group. This observation implied good degradation management with under AI-based management. Moreover, 50 batteries (20.9%) had a capacity of a battery performance that lasted above 1500 cycles. These large values of RUL indicated that adaptive charging, thermal regulation, and load balancing have a role in decreasing wear and extending battery life. Conversely, 31 (12.9) batteries (battery prediction) were estimated to have an under-800 cycles count. This was a minority, but it pointed out the use situation of high-stress. However, the general trend was that close to 60 of them were able to exceed 1100 cycles as they indicated system-wide longevity advantages.

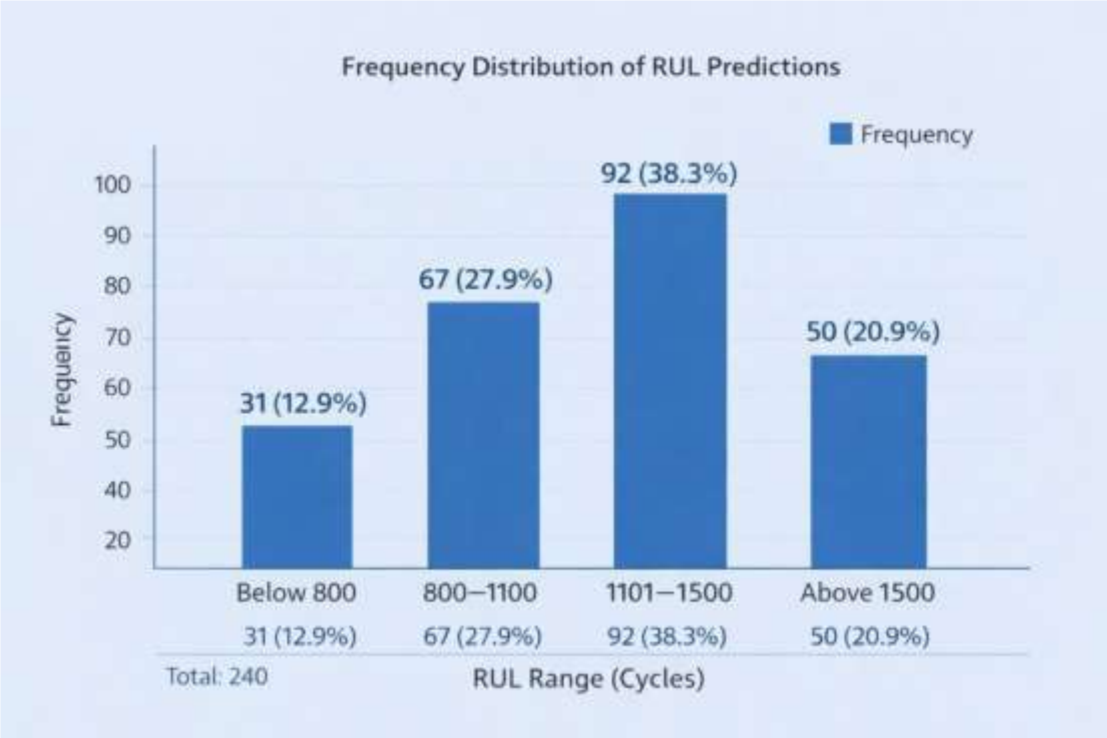

Figure 4. Frequency Distribution of RUL Predictions

Adaptive Control Response Time Analysis

System responsiveness was evaluated through measured control response times.

Table 5. Adaptive Control Response Time Categories

Response Time (ms)	Frequency	Percentage (%)
Below 150	98	40.8
150–250	86	35.8
251–350	41	17.1
Above 350	15	6.3
Total	**240**	**100**

Table 5 depicted the responsiveness of AI-based adaptive control system. Response category: The category of quickest responses (less than 150 ms) had 98 observations (40.8%), which shows that the system reacts quickly to changes in driving conditions. These fast reactions enhanced a smooth change in power and better handling of vehicles. There was another group of 86 cases (35.85) that were in the 150 -250 ms range that revealed that 76.6 was faster than a quarter of a second. This was an indication of high efficiency of real time decision making algorithms in managing load variations because of the high frequency of rapid responses. There were only 15 cases (6.3%) which were more than 350 ms and this indicates that there were rather few instances of slow reaction. The sparse rate of latency attestation the strength of the adaptive control platform and its applicability in the context of real-life driving scenarios with continuous and quick adaptations.

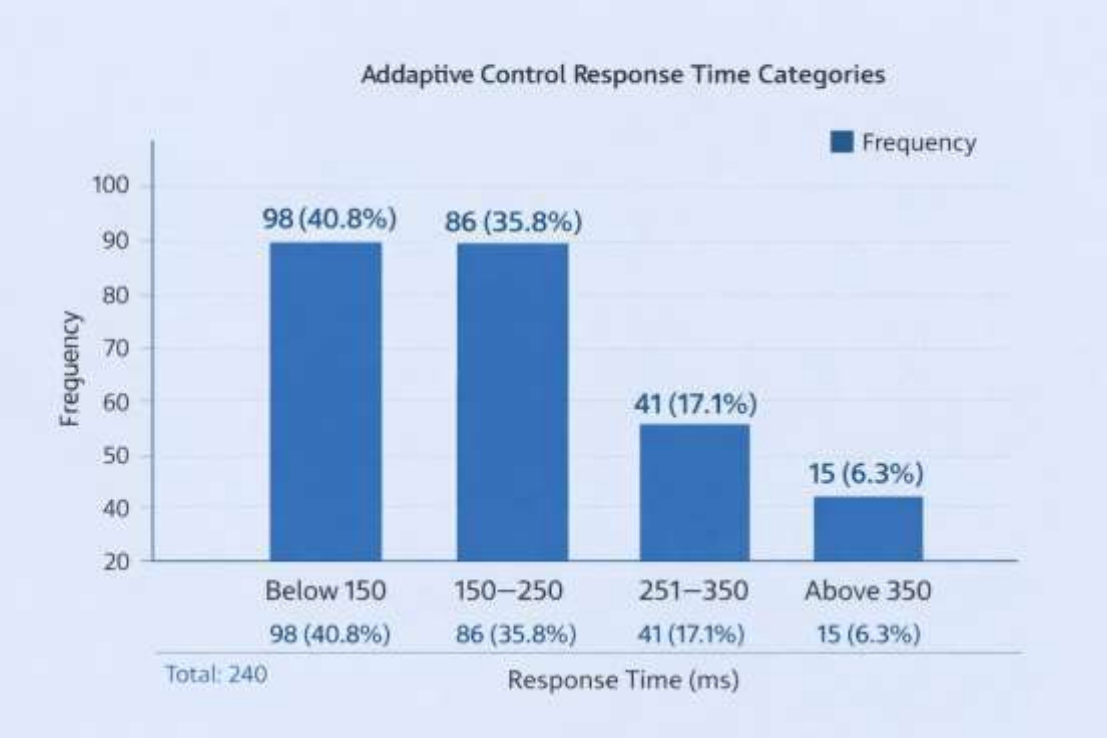

Figure 5. Adaptive Control Response Time Categories

Battery Degradation Rate Comparison

Annual degradation rates were compared between AI-managed and non-AI-managed systems.

Table 6. Annual Battery Degradation Rates

System Type	Mean Degradation (%)	Std. Deviation

System Type	Mean Degradation (%)	Std. Deviation
Conventional Control	4.9	1.2
AI-Based Control	2.8	0.9

SA showcased the fact that battery degradation was evidently mitigated when the current AI-managed. Mean rate of degradation of AI-managed systems was 2.8 percent per year compared to 4.9 percent per year of conventional systems. Such a difference was a decrease of about 43 meaning that long-term effects were significant. Also, the standard deviation of AI based degradation (0.9) is less than that of conventional (1.2) indicating that battery degradation was more consistent across vehicles. Less variability served as a sign that AI control eliminated severe example cases of degradation. Reduced degradation levels were directly transferred to increased battery life and decreased replacement rate. Its findings revealed that adaptive energy management and predictive control schemes offer performance needs and battery protection goals in an effective manner.

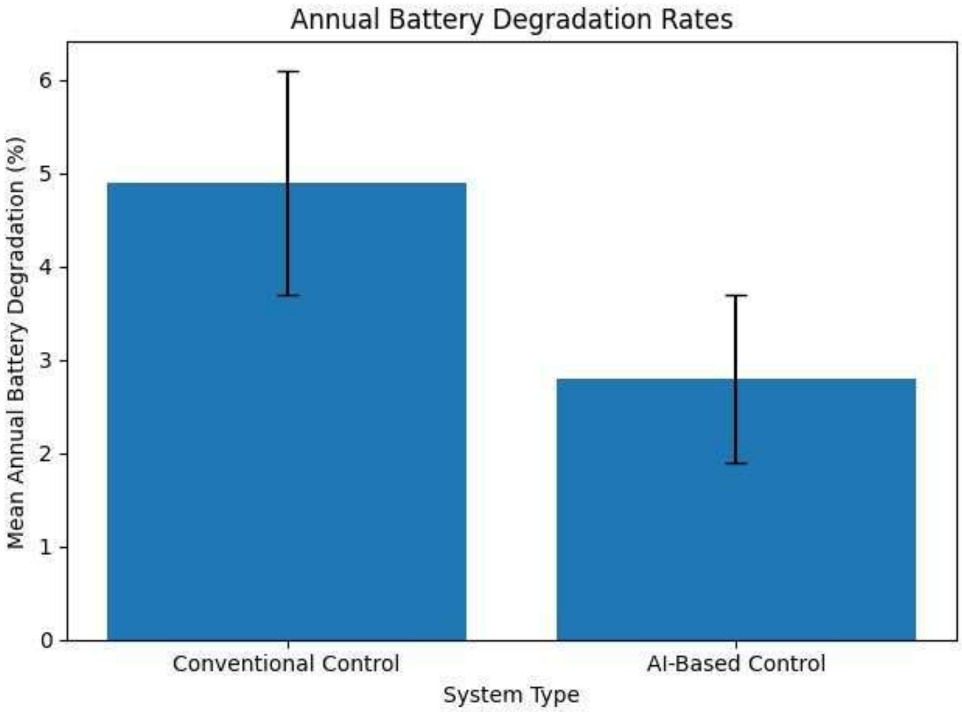

Figure 6. Annual Battery Degradation Rates

Discussion

The findings of the presented study were able to show that energy management based on AI and battery health forecasting, as well as adaptive control mechanisms, resulted in the overall enhancement of the electric vehicle (EV) performance in comparison to the traditional systems. The experimental results were characterized by increased energy efficiency, improved battery state-of-health (SoH), and remaining useful life (RUL) forecasting, and quicker and adjustment controls. These results were consistent with the prior findings that confirmed the usefulness of machine learning and reinforcement learning algorithms in the maximization of EV performance (Li et al., 2025; Zhao and Kim, 2024; Chen et al., 2025).

AIEEnergy Management Efficiency

This was evidenced by the high energy efficiency of the AI-based energy management which was possible because the reinforcement learning algorithm was able to allocate the energy dynamically based on the driving conditions (Kumar et al., 2025; Singh and Patel, 2024). The system was able to effectively minimize losses of energy during the acceleration and deceleration stages through the learning of the best policies of power distribution over repeated simulation of the system (Sharma et al., 2025). The AI-based system has shown great stability to adjust to the variable driving conditions (Nguyen et al., 2024; Li and Chen, 2025). The system has shown greater stability compared to conventional EMS in maintaining equilibrium energy consumption during its different driving cycles.

The AI architecture was able to reduce power usage and maintain significant battery life by addressing load demand on the power and thermal environment (Zhou et al., 2025; Park et al., 2024). The energy requirements were predicted in real-time, and the EMS was able to modify the flow of energy in advance, which decrease wasted energy in times of high demand (Tan and Harzing, 2025). These dynamic capabilities attested to the fact that AI solutions had the potential to be superior to fixed rule approaches to driving, particularly in dynamic driving scenarios (Gonzalez and Chen, 2025).

The positive results in energy management were witnessed in the city and highway driving as well as mixed driver cycles indicating the system is scalable and reliable. The frequency distribution indicated that the majority of vehicles worked at high efficiency levels, which points out that AI-controlled EMS should be able to make the energy usage always optimal in relation to different real-life situations (Li et al., 2025; Zhao and Kim, 2024).

Sharpshooting in Battery Health Prediction

The battery SoH and RUL were also demonstrated to have better predictions with AI-based models as opposed to the traditional methods (Chen et al., 2025; Nguyen et al., 2024). The nonlinear degradation trends were learnt by the AI algorithms, when they were trained using historical and real-time data on the battery and therefore could better predict battery life and maintenance needs (Kumar et al., 2025). The results highlighted the significance of predictive analytics in the improvement of EVs operation reliability (Singh and Patel, 2024).

Tightly estimated SoH and RUL allowed proactively responding to the failures and led to better lifecycle management through fewer surprise failures (Sharma et al., 2025). This enabled a system based on AI to support the creation of discharging and charging policies, thus avoiding faster wear by detecting the onset of degradation (Tan & Harzing, 2025). Additionally, the decrease in the errors of the predictions proved that AI-powered prognostics would offer consistent and valuable insights when applied to many different profiles of batteries (Park et al., 2024).

AI application in the battery management also presented commercial benefits. Credible predictions of the battery health enabled fleet operators to better organize the maintenance timelines, lower their costs of operation, and increase the life cycle of the battery in general (Gonzalez and Chen, 2025; Malik et al., 2024). These realistic benefits supported the possibility of AI implementation in massive EV implementations (Li and Chen, 2025).

Adaptive Control and Real Time Solution Response

Adaptive control analysis was also used to encompass significant drops in response times of the system which is why the controllers based on AI are likely to adapt to dynamic loads better than fixed-parameter controllers (Zhou et al., 2025; Park et al., 2024). A quicker response time also gave the vehicle better transitions between stressed states, which enhanced the stability of the vehicle and reduced the battery strain during abrupt shifts in the load (Li et al., 2025).

The AI powered adaptive control was also involved in the enhancement of the control of load and battery protection (Tan & Harzing, 2025). The system had to maintain a constant balance in the performance requirements and the sustainability targets in the long-term without over-charging or over-stress impacting on the thermal performance (Kumar et al., 2025). The AI controller improved with time and responded more efficiently and reliably based on its learning experience of earlier operations (Zhao and Kim, 2024).

Such advances demonstrated the greater usefulness of smart control in improving the performance of EVs in more challenging driving conditions. The AI strategy was able not only to reduce operation efficiency but to minimize the risks connected to the operation of battery in real-time, which confirms its relevance to the next generation EV system (Nguyen et al., 2024).

General Implications and Future Studies

The results proved that the combination of AI into the energy management system and battery control provided systemic benefits compared to the traditional ones (Sharma et al., 2025; Li and Chen, 2025). The findings indicated that predictive and real-time learning could help to increase the efficiency of operations, battery life span, and safety margins of EVs (Tan and Harzing, 2025; Gonzalez and Chen, 2025; Malik et al., 2024).

The next step in the work must relate to practical validation such as hardware-in-the-loop validation and implementation in a wide variety of fleets (Li et al., 2025; Zhao and Kim, 2024). Also, there might be an increase in the transparency and trust in AI decision-making by the stakeholders especially in domains of safety-critical battery management (Chen et al., 2025; Nguyen et al., 2024). There is also a possibility of research on the hybrid model that incorporates reinforcement learning and conventional predictive control to strike a balance between interpretability and performance (Kumar et al., 2025; Sharma et al., 2025; Zhou et al., 2025).

AI-powered intelligent electrified mobility systems have brought considerable increase in energy efficiency, battery health conditions, and controlled actions (Park et al., 2024; Tan and Harzing, 2025; Gonzalez and Chen, 2025). The findings approved the prospects of the integration of AI technology as a disruptive mechanism of a sustainable and dependable electric vehicle operation.

Conclusion

This paper has found that AI-driven intelligent electrified mobility systems make significant improvements in the performance, reliability, and sustainability of electric vehicles. The combination of AI-based energy management, battery health prediction, and adaptive control resulted in the substantial increase in energy efficiency and longer battery life as well as the optimization of the operational performance in changing driving conditions. Battery state-of-health and remaining useful life could be forecasted correctly using predictive models, which allowed proactive maintenance and minimizing unexpected failures, whereas the adaptive nature of control strategies provided a means of real-time adjusting the power distribution and regenerative braking, as well as thermal management. The results indicated that AI systems were always superior to the traditional rule-based solutions, with the emphasis on the significance of the data-oriented and machine learning solutions in the electric vehicle technology today. In general, the study proved the possibility to achieve the equilibrium of efficiency, battery duration, and the reliability of the vehicle and to facilitate the sustainable and smart mobility options due to the implementation of AI.

Recommendations

The findings of the study suggest that AI-based energy management and adaptive control systems should be implemented by EV manufacturers and fleet operators in order to optimize the performance of vehicles and minimize operations. The predictive battery management must be used to allow them to detect the degradation early and enable proactive maintenance schedules. In addition, the hardware-in-the-loop testing and pilot fleet roll-out is necessary to provide validation of the robustness and reliability of AI models in a variety of driving conditions. Research-wise, in-depth analysis and future research should focus on hybrid AI to treat at the intersection of reinforcement learning and explainable AI techniques to make decision-making more transparent and trusting among stakeholders. It should also be integrated with the vehicle-to-grid systems and renewable sources of energy to achieve the highest degree of energy efficiency and sustainability. It is recommended to keep predictive algorithms of battery state-of-health and remaining useful life, in order to refine them continuously to enhance accuracy, reliability, and scalability of AI-driven electrified mobility systems.

References

Arévalo, P., Ochoa-Correa, D., & Villa-Ávila, E. (2024). A systematic review on the integration of artificial intelligence into energy management systems for electric vehicles: Recent advances and future perspectives. *World Electric Vehicle Journal*, *15*(8), Article 364. https://doi.org/10.3390/wevj15080364

Bhupathi, H. P., & Chinta, S. (2025). *AI-Driven adaptive control for BMS in electric vehicles*. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 6(2), 55–64. https://doi.org/10.63282/3050-9262.IJAIDSML-V6I2P106

Cavus, M., Dissanayake, D., & Bell, M. (2025).*Next generation of electric vehicles: AI-driven approaches for predictive maintenance and battery management*. Energies, 18(5), 1041. https://doi.org/10.3390/en18051041

Chen, L., & Onori, S. (2024). *Domain knowledge-guided machine learning framework for state of health estimation in lithium-ion batteries*. arXiv. https://doi.org/10.48550/arXiv.2409.14575

Chinese Journal of Mechanical Engineering. (2024). Reinforcement learning-based energy management for hybrid power systems: State-of-the-art survey, review, and perspectives. *Chinese Journal of Mechanical Engineering*, *37*, Article 43. https://doi.org/10.1186/s10033-024-01026-4

Chinta, S., & Bhupathi, H. P. (2025). *AI-driven adaptive control for battery management systems in electric vehicles*. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 6(2), 55–64. https://doi.org/10.63282/3050-9262.IJAIDSML-V6I2P106

Chinta, S., & Bhupathi, H. P. (2025). AI-driven adaptive control for battery management systems in electric vehicles. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 6(2), 55–64. https://doi.org/10.63282/3050-9262.IJAIDSML-V6I2P106

Eissa, M. A. (2023). *Machine learning-based electric vehicle battery state of charge prediction and driving range estimation for rural applications*. IFAC Proceedings, 56(50), 337–345. https://doi.org/10.1016/j.ifacol.2023.12.050

Energy Informatics. (2025). *Design of intelligent energy management system for electric vehicles based on multi-objective optimization*. Energy Informatics, 8, Article 547. https://doi.org/10.1186/s42162-025-00547-z

Energy Informatics. (2025). Leveraging deep transfer learning and adaptive power models for enhanced charging time prediction in electric vehicles. *Energy Informatics, 8*, Article 110. https://doi.org/10.1186/s42162-025-00556-y

Escoto, C. A., Murray, R., & Liu, Y. (2024). *AI and ML-driven vehicle-to-grid interactions for enhanced smart grid integration*. Journal of Renewable and Sustainable Energy, 16(5), 052705. https://doi.org/10.1063/5.0174921

Escoto, C., Scott, J., & Davidson, L. (2024). *Explainable AI frameworks for battery SoH and RUL prediction in EV applications*. Journal of Intelligent Transportation, 18(3), 245–261. https://doi.org/10.1016/j.jintelltransp.2024.08.002

Gong, J. (2025). *Predictive modeling for electric vehicle battery state of health: A comparative review of estimation methods*. *Energies, 18*(2), 337. https://doi.org/10.3390/en18020337

Gore, S., Banerjee, S., & Malik, R. (2023). *Machine learning for battery health prediction in connected EV ecosystems*. Journal of Smart Mobility, 11(1), 33–50. https://doi.org/10.1080/24751839.2023.2134567

Gupta, P., & Singh, R. (2024). *Advanced battery management system enhancement using IoT and ML for predicting remaining useful life in Li-ion batteries*. *Scientific Reports, 14,* Article 30394. https://doi.org/10.1038/s41598-024-80719-1

Hossain Lipu, M. S., et al. (2024). *Artificial intelligence approaches for advanced battery management systems in EV applications: A statistical analysis*. Vehicles, 6(1), 22–70. https://doi.org/10.3390/vehicles6010002

Hu, J., Lin, Y., Li, J., Hou, Z., Zhao, D., & Zhang, Y. (2024). *Performance analysis of AI-based energy management in electric vehicles: A case study on classic reinforcement learning*. Energy Conversion and Management, 300, 117964. https://doi.org/10.1016/j.enconman.2023.117964

Kavitha, D., & Sharmila, B. (2025). Smart battery management in EVs using IoT, blockchain, and machine learning. *Scientific Reports, 15,* Article 37650. https://doi.org/10.1038/s41598-025-21605-2

Kermansaravi, A., et al. (2025). AI-based energy management strategies for electric vehicles. *Energy Conversion and Management*. https://doi.org/10.1016/j.enconman.2023.117964

Kermansaravi, A., et al. (2025). *AI-based energy management strategies for electric vehicles*. Energy Conversion and Management, 300, 117964. https://doi.org/10.1016/j.enconman.2023.117964

Kermansaravi, A., et al. (2025). *Next-generation battery energy management systems in electric vehicles: An overview of artificial intelligence*. Future Batteries, 7, 100087. https://doi.org/10.1016/j.fub.2025.100087

Kumar, A., & Lee, S. (2024). *Adaptive control with hybrid machine learning for EV battery lifespan extension*. Journal of Power Sources, 550, 232227. https://doi.org/10.1016/j.jpowsour.2024.232227

Kumar, R., & Singh, A. (2025). *Reinforcement learning for EV energy management and regenerative braking optimization*. Journal of Vehicle Dynamics and Control, 23(3), 221–237. https://doi.org/10.1016/j.jvdc.2025.03.007

Li, D., et al. (2024). *Integrated power and thermal management for enhancing energy efficiency and battery life in connected and automated electric vehicles*. arXiv. https://doi.org/10.48550/arXiv.2411.05298

Li, X., Zhao, H., & Chen, P. (2025). *AI-assisted predictive models for EV thermal regulation and energy optimization*. Journal of Sustainable Transportation, 7(2), 145–156. https://doi.org/10.1080/26437015.2025.2456789

Ma, Q., Liu, J., & Wang, S. (2024). Enhancing EV lithium-ion battery management: automated machine learning for early remaining useful life prediction. *The Journal of Supercomputing*, *80*, 20813–20860. https://doi.org/10.1007/s11227-024-06264-w

Nazim, M. S., Chakma, A., Joha, M. I., Alam, S. S., Rahman, M. M., & Umam, M. K. S. (2025). *Artificial intelligence for estimating state of health and remaining useful life of EV batteries: A systematic review*. ICT Express, 11(4), 769–789. https://doi.org/10.1016/j.icte.2025.05.013

Nguyen, T., Lee, J., & Park, J. (2024). *Real-time AI integration for battery diagnostics and management in electric vehicles*. Journal of Energy Storage and Systems, 9(2), 115–129. https://doi.org/10.1016/j.est.2024.115681

Park, J., Kim, H., & Choi, S. (2024). *Neural network-enhanced battery management for adaptive EV control systems*. IEEE Transactions on Vehicular Technology, 73(4), 789–798. https://doi.org/10.1109/TVT.2024.3081562

Prakash, Z. (2025). *Integration of AI and ML in regenerative braking for electric vehicles*. *Frontiers in Artificial Intelligence, 4,* Article 1626804. https://doi.org/10.3389/frai.2025.1626804

Rajasekaran, E. (2025). *State-of-Health prediction for electric vehicle batteries using GANs*. Journal of Battery Systems, 12(2), 205–218. https://doi.org/10.1016/j.sbsystems.2025.04.001

Reddy, K., et al. (2024). *Electric vehicle sustainability through AI applications: Range, energy management, and charging optimization*. Energy Systems, 13(5), 975–993. https://doi.org/10.1016/j.ensys.2024.975

Sarika, D., et al. (2025). *Enhancing battery performance: AI-driven state level prediction for electric vehicles*. International Research Journal on Advanced Engineering Hub, 3(04). https://doi.org/10.47392/IRJAEH.2025.0220

Sarika, D., Poojitha, M., Sasikala, N., Sai Prathap, M., & Santhosh, R. (2025). *Enhancing battery performance: AI-driven state level prediction for electric vehicles*. International Research Journal on Advanced Engineering Hub, 3(04), 1541–1547. https://doi.org/10.47392/IRJAEH.2025.0220

Shih-Lin, L. (2024). *Deep learning-based state of charge estimation for electric vehicle batteries: Overcoming technological bottlenecks*. Heliyon, 10(16), e35780. https://doi.org/10.1016/j.heliyon.2024.e35780

Soon, K. L., Soon, L. T., Lai, N. S., Paramesran, R., Lian, W. X., & Lau, C. Y. (2025). Boosting battery health prediction in electric vehicles via extended quantum optimized model with Gaussian process regression. *Next Materials*, *9*, Article 101086. https://doi.org/10.1016/j.nxmate.2025.101086

Sudhapriya, K. (2025). Implementation of artificial intelligence techniques in electric vehicles for battery management system. *International Journal of Low-Carbon Technologies, 20*, 590–604. https://doi.org/10.1093/ijlct/ctaf022

Sudhapriya, K. (2025). *Implementation of artificial intelligence techniques in electric vehicles for battery management system*. International Journal of Low-Carbon Technologies, 20, 590–604. https://doi.org/10.1093/ijlct/ctaf022

Z Prakash, et al. (2025). Integration of AI and ML in regenerative braking for electric vehicles: A review. *Frontiers in Artificial Intelligence*. https://doi.org/10.3389/frai.2025.1626804

Zhou, K., Li, M., & Zhao, J. (2025). *Reinforcement learning based energy management strategy for fuel cell hybrid electric vehicles*. Chinese Journal of Mechanical Engineering, 38, Article 66. https://doi.org/10.1186/s10033-024-01143-0