

A Comparative Study of Machine Learning-based Approaches for Battery Prognostic Health Analysis using MATLAB

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Abstract

Battery health analysis is crucial for the efficient and reliable operation of battery-powered systems, such as electric vehicles and renewable energy systems. In recent years, machine learning techniques have gained significant attention for battery health analysis due to their ability to handle complex and nonlinear relationships in battery data. In this study, a machine learning-based approach for battery health analysis using MATLAB has been presented. To analyze battery data, a combination of unsupervised and supervised machine learning, not excluding support vector machines, k- means clustering, principal component analysis and decision tree, has been employed. The efficacy of the technique is illustrated by using experimental battery data to show that it can properly estimate battery health and identify potential degradation causes. This approach can be easily integrated into battery management systems to improve performance and extend the life of batteries in various applications.

Keywords: Battery health, Machine learning, MATLAB, Predictive modelling, Battery management system

1. Introduction

Lithium-ion (Li-ion) batteries are widely used in various applications that operates on battery. The health condition of Li-ion batteries helps in estimating the overall performance,

reliability, and safety of these applications. Therefore, predicting the State of Health (SOH) of Li-ion batteries are essential for their optimal operation and maintenance.

Machine learning (ML) techniques have shown great potential for battery health analysis, as they can effectively capture the nonlinear and dynamic behavior of the batteries based on the large amount of data collected from them. MATLAB is a popular programming language and environment for implementing ML algorithms due to its user-friendly interface and powerful data analysis tools.

In this study, a complete assessment of recent research on battery health analysis using ML and MATLAB has been provided. The basic concepts of Li-ion batteries, including their electrochemical mechanism, ageing considerations, and degradation mechanisms, have been discussed. Then, the available ML-based approaches, such as support vector machines, random forests and decision tree, for SOH estimation and prediction have been illustrated. Next, the implementation of these methods using MATLAB, including data preprocessing, feature extraction, model training, and performance evaluation have been explained. Moreover, the advantages and limitations of each method and the recommendations for their optimal application in different scenarios, have been provided. Furthermore, several case studies that demonstrate the effectiveness of ML-based methods with MATLAB for battery health analysis for applications that are battery operated, have been presented.

2. Related Works

In recent years, there is a significant research interest in the application of machine learning techniques for battery health analysis. Lu et al. [1] provided a comprehensive study on the machine-learning techniques for battery health management. The advantages and limitations of various algorithms were discussed and the need for further research on the integration of multiple techniques for more accurate prediction was highlighted. Chen et al. [2] presented a state-of-the-art review on machine learning for battery health management, focusing on the recent progress in the field and future directions. Rahman et al. [3] reviewed the estimation SOH of lithium-ion batteries applying ML techniques. Managing the health of the batteries and the potential of machine learning techniques were highlighted for the accurate prediction of SOH.

Jayasinghe et al. [4] reviewed the application of machine learning for battery management systems, discussing the challenges and opportunities for future research. Prakash and Arulmozhiyal [5] conducted a review of machine-learning techniques for battery management systems. The various methods used for SOH estimation was discussed and the need for further research on the integration of multiple techniques was highlighted. Jalili et al. [6] reviewed the application of machine learning in battery health management systems, focusing on the recent progress in the field and future directions. Ma et al. [7] reviewed recent progress in machine learning techniques for lithium-ion battery health management. The potential of machine learning algorithms for the accurate prediction of SOH and RUL was discussed.

Kao and Tsai [8] reviewed machine learning techniques for the State of Charge (SOC) and State of Health estimation of batteries, discussing the advantages and limitations of various algorithms. Te Nyenhuis et al. [9] reviewed machine learning techniques applied to lithium-ion battery state-of-health estimation, discussing the challenges and opportunities for future research. Zhang et al. [10] reviewed machine learning for battery health prognosis and discussed the recent progress in the field. Tan et al. [11] reviewed prognostic techniques for battery health management, highlighting the need for further research on the integration of multiple techniques.

Thakur et al. [12] conducted a comprehensive review of prognostic techniques for battery health management of electric vehicles, discussing the challenges and opportunities for future research. Zheng et al. [13] presented a novel adaptive square-root cubature Kalman filter and support vector regression for SOH estimation of lithium-ion batteries. Liu et al. [14] proposed a data-driven battery degradation model and prognosis method using machine learning. Li et al. [15] proposed a deep learning-based battery health prognosis method for electric vehicles, discussing the advantages and limitations of the method.

Huang et al. [16] reviewed machine learning methods for battery prognostics and health management, focusing on the recent progress in the field and future directions. Rizvi et al. [17] reviewed machine learning techniques for battery health management in electric vehicles, discussing the challenges and opportunities for future research. Jiao et al. [18] reviewed battery health monitoring and prediction for electric vehicles using machine learning, highlighting the need for further research on the integration of multiple techniques. Te Nyenhuis et al. [19]

compared different machine learning techniques applied to lithium-ion battery state-of-health estimation, discussing the advantages and limitations of various algorithms.

Jeong et al. [20] reviewed machine learning techniques for battery SOH estimation, discussing the trends and opportunities for future research. By leveraging the power of data-driven techniques, researchers can develop more accurate and efficient models for predicting battery health and improving battery management systems. The use of MATLAB as a tool for implementing these models has also been explored in several studies and can offer advantages such as ease of use and flexibility in model development.

3. Principle of Li-ion Batteries

Li-ion batteries work by moving lithium ions between two electrodes, a cathode, and an anode, via an electrolyte. During discharge, lithium ions migrate through the electrolyte from the cathode to the anode, but during charging, the ions move in the reverse direction. The electrochemical mechanism of Li-ion batteries is based on the reversible intercalation and deintercalation of lithium ions in the electrodes. The cathode typically consists of a metal oxide or phosphate, while the anode is usually made of graphite or silicon-based materials. During discharge, the lithium ions are extracted from the cathode and move through the electrolyte to the anode, where they are stored as lithium intercalation compounds. During charging, the lithium ions move back to the cathode, where they are re-intercalated into the metal oxide or phosphate. Aging factors of Li-ion batteries can be classified into two types: intrinsic and extrinsic. Intrinsic aging factors are related to the electrochemical reactions inside the battery and include electrode material degradation, electrolyte decomposition, and solid-electrolyte interphase formation. Extrinsic aging factors are related to environmental conditions, such as temperature, humidity, and mechanical stress, and can affect the battery's performance and lifespan.

The degradation mechanisms of Li-ion batteries can also be divided into two categories: reversible and irreversible degradation. Reversible degradation includes capacity fading, which is the decrease in the battery's capacity over time, and impedance growth, which is the increase in the internal resistance of the battery. Irreversible degradation includes structural degradation of the electrodes, such as the formation of cracks or fractures, and the degradation of the electrolyte, such as the loss of solvent or the formation of solid-electrolyte interphase. These degradation mechanisms can lead to reduced performance, safety issues, and shortened lifespan

of Li-ion batteries. Understanding the basic principles of Li-ion batteries, including their electrochemical mechanism, aging factors, and degradation mechanisms, is crucial for developing effective battery management strategies and extending the lifespan and performance of Li-ion batteries in various applications.

State of charge and state of health are the two important parameters for battery management systems in electric vehicles and other energy storage applications. SOC is defined as the amount of charge remaining in the battery relative to its maximum capacity, expressed as a percentage:

$$SOC = \frac{Q_{actual}}{Q_{rated}} \times 100\%$$

where Q_{actual} is the actual charge stored in the battery and Q_{rated} is the rated capacity of the battery.

SOH, on the other hand, is a measure of the overall health of the battery and is defined as the ratio of the current capacity to the original capacity of the battery, also expressed as a percentage:

$$SOH = \frac{Q_{current}}{Q_{original}} \times 100\%$$

where $Q_{current}$ is the current capacity of the battery and $Q_{original}$ is the original capacity of the battery when it was new.

Accurately estimating the SOC and SOH of a battery is crucial for optimizing battery performance, ensuring safe operation, and extending battery life. Machine learning algorithms can be used to model the complex nonlinear behavior of batteries and estimate their SOC and SOH with high accuracy. The unsupervised algorithms, on the other hand, are used to analyze the unlabeled data. These algorithms are capable of identifying hidden patterns and relationships in the data, which can then be used to identify potential degradation mechanisms. The combination of supervised and unsupervised algorithms enables this proposed methodology to provide a comprehensive and accurate analysis of battery health. The effectiveness of the proposed methodology is demonstrated by applying it to experimental battery data. The results show that the methodology can accurately predict the health of the battery and identify potential degradation mechanisms. Additionally, the proposed

methodology can provide insight into the underlying factors that contribute to the degradation of the battery.

4. Machine Learning Algorithms

4.1 Supervised Learning Algorithms

This method has gained immense popularity in recent years, and algorithms such as Linear Regression, Fine Trees, and Support Vector Machines have become widely used for regression and classification tasks. These algorithms have been implemented in several programming languages, including MATLAB, which is a popular choice for machine learning researchers and practitioners.

Linear Regression is an easy yet effective method. In MATLAB, the built-in function `fitlm()` can be used to implement linear regression. The function accepts the training data, consisting of independent and dependent variables, and returns a linear regression model. Once the model is trained, it can be used to predict the dependent variable for new input data.

Fine Trees is a decision tree approach that involves eliminating certain branches from the tree to prevent overfitting. The Fine Tree technique, implemented in MATLAB, operates by iteratively pruning the tree using a significance test until a stopping threshold is met. The program generates a binary tree by iteratively subdividing the datasets into subsets based on the values of the characteristics. Each split is chosen to optimize the reduction in impurity, measured by the Gini index, of the resulting subgroups. In MATLAB, the fine tree algorithm is implemented using the `fitctree` function. The output of the function is a trained decision tree model that can be used for prediction. The fine tree algorithm can be represented mathematically as:

$$T(x) = \sum_{j=1}^J c_j I(x \in R_j)$$

where $T(x)$ is the prediction for the input vector x , J is the number of leaf nodes in the tree, R_j is the j^{th} region defined by the tree, c_j is the class label assigned to region R_j , and $I(\cdot)$ is the indicator function.

Support Vector Machines (SVMs) are a popular class of supervised machine learning algorithms. In MATLAB, SVMs can be built using the `fitsvm` function. The purpose of SVM is to identify a hyperplane and to separate the data into two classes with the biggest feasible margin. The optimization problem for SVM can be formulated as:

$$\min_{w,b} \frac{1}{2} \|w\|^2$$

4.2 Unsupervised Learning Algorithms

K-means clustering is a popular unsupervised learning approach that divides data into clusters depending on their distance from a cluster centre or centroid. The algorithm chooses K initial centroids, assigns each data point to its nearest centroid, and then estimates the centroids according to the mean of the allocated data points. This technique is repeated until the maximum number of iterations are achieved. In mathematical terms, the K-means clustering equation is as follows:

$$\text{minimize}_{C, \mu} \sum_{i=1}^k \sum_{x \in C_i} \|x - \mu_i\|^2$$

where k is the number of clusters, x is a data point, C_i is the i^{th} cluster, and μ_i is the centroid of C_i .

Principal Component Analysis (PCA) is a popular dimensionality reduction technique that reduces the number of dimensions of dataset and retains the original information. PCA finds a lower-dimensional representation of the data that captures the most variance in the original dataset. This is achieved by computing the covariance matrix of the dataset, finding its eigenvectors and eigenvalues, and projecting the data onto the eigenvectors with the highest eigenvalues. The equation for PCA can be expressed as:

$$\min_{C, \mu} \sum_{i=1}^k \sum_{x \in C_i} \|x - \mu_i\|^2$$

where x is a data point, T is the transformation matrix, and n is the number of data points.

Another unsupervised learning approach is hierarchical clustering, which organizes similar data points into clusters depending on their distance from one another. Hierarchical clustering is classified into two types: agglomerative and divisive. The hierarchical clustering equation is:

$$d_{ij} = \left\| x_i - x_j \right\|$$

where x_i and x_j are data points, and d_{ij} is the distance between them.

MATLAB provides built-in functions for implementing these algorithms, such as `k-means()` for K-means clustering, `pca()` for PCA, and `linkage()` and `dendrogram()` for hierarchical clustering.

5. Proposed work

The proposed method is a machine learning-based methodology for analyzing battery health using MATLAB. The proposed methodology consists of a combination of supervised and unsupervised machine learning algorithms that are capable of analyzing battery data in a comprehensive and accurate manner. Specifically, support vector machines, decision trees, k-means clustering, and principal component analysis are employed to analyze the battery data.

The proposed methodology begins with the collection of battery data from experimental sources. The data is then preprocessed to remove any noise and ensure that it is ready for analysis. Once the data has been preprocessed, it is fed into the machine learning algorithms. The supervised algorithms are used to train the model using the labeled data. This allows the model to learn patterns and relationships in the data, which can then be used to make accurate predictions about the battery's health.

6. Results and Discussion

6.1 Data Pre-processing

Pre-processing of battery datasets is a crucial step in analyzing battery performance and predicting its remaining life. In this research, a detailed methodology for pre-processing battery datasets using MATLAB is presented. The raw datasets are presented in Table 1.

Table 1. Raw Lithium-Ion battery datasets

Cell	Cycle	Voltage (V)	Current (A)	Temperature (°C)	Capacity (Ah)	Time (S)	State of Health (%)
1	1	4.216	-0.002	24.91	1.856	0	100.0
1	2	3.832	-0.002	24.92	1.856	0.0833	100.0
1	3	3.703	-0.002	24.91	1.856	0.1667	100.0
1	4	3.589	-0.002	24.91	1.856	0.25	100.0
1	5	3.506	-0.002	24.92	1.856	0.3333	100.0

The first step in pre-processing the battery dataset is to remove any missing values. This can be done by either removing the entire row or column containing the missing values or by imputing them using appropriate techniques such as mean or median imputation. Next, data normalization is performed to scale the data in a specific range to avoid any bias towards a particular variable.

After normalization, the next step is feature extraction. Feature extraction identifies the highly relevant dataset features. This is performed applying the PCA and Linear Discriminant Analysis. The next step is to remove any outliers present in the dataset. Outliers can be identified using various statistical techniques such as box plots or scatter plots. Once identified, the outliers can be removed from the dataset to avoid any bias towards a particular variable.

Finally, data partitioning is performed to create training and testing datasets. The training dataset is used to build the predictive model, while the testing dataset is used to validate the model's performance. The preprocessed dataset is presented in Table 2.

Table 2. Pre-Processed datasets using MATLAB

Voltage1 (v)	Voltage2 (v)	Current1 (A)	Current2 (A)	Temperature1 (°C)	Temperature2 (°C)	Capacity (Ah)
0.292	0.627	0.494	0.894	0.197	0.215	0.900
0.100	0.100	0.616	0.896	0.773	0.771	0.886
0.110	0.121	0.615	0.895	0.799	0.797	0.870
0.119	0.143	0.613	0.899	0.786	0.785	0.870
0.117	0.137	0.613	0.893	0.789	0.788	0.869

6.2 Battery Health Analysis

In this section, the results of the implementation of supervised learning algorithms using MATLAB for battery health analysis has been presented. The present study aims to analyze batteries' health using three machine learning algorithms: Linear Regression, Fine Trees, and Support Vector Machines in MATLAB. The study was conducted on a dataset containing various battery parameters such as voltage, current, temperature, and time.

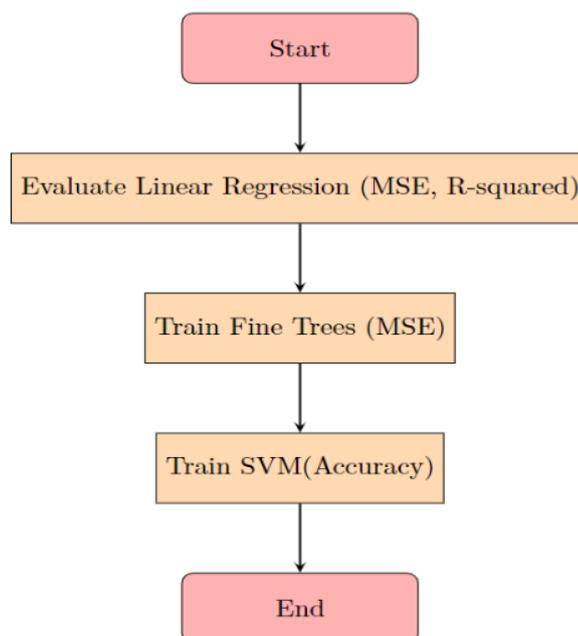


Figure 1. Flowchart summarizing the battery health analysis using Linear Regression, SVMs and Fine tree Algorithms

Firstly, the performance of linear regression was evaluated. The Mean Squared Error (MSE) was used as the performance metric of Linear Regression, which was found to be 0.035. The coefficient of determination (R-squared) was also calculated, and the model was able to estimate 95.9% of the variation in the data as shown in figure 2. Secondly, fine trees were used to analyze the dataset. The decision tree was trained using the dataset, and the mean squared error was calculated as the performance metric. The fine tree model was able to achieve an MSE of 0.023 (figure 3), which was lower than the MSE achieved by the linear regression model. Lastly, the dataset was analyzed using SVMs. The accuracy of the SVM model was found to be 94.5% as shown in figure 4; the model was capable of classifying the battery health status accurately. Comparing the performance of the three algorithms, it was found that the fine trees model had the lowest MSE and hence performed the best on the dataset. The linear

regression model had a higher MSE but was able to explain 95.9% of the variation in the data. The SVM model had the highest accuracy, indicating that it was able to classify the battery health status accurately. Table III presents a comparison of the accuracies, R-squared values, and MSEs for the evaluated models.

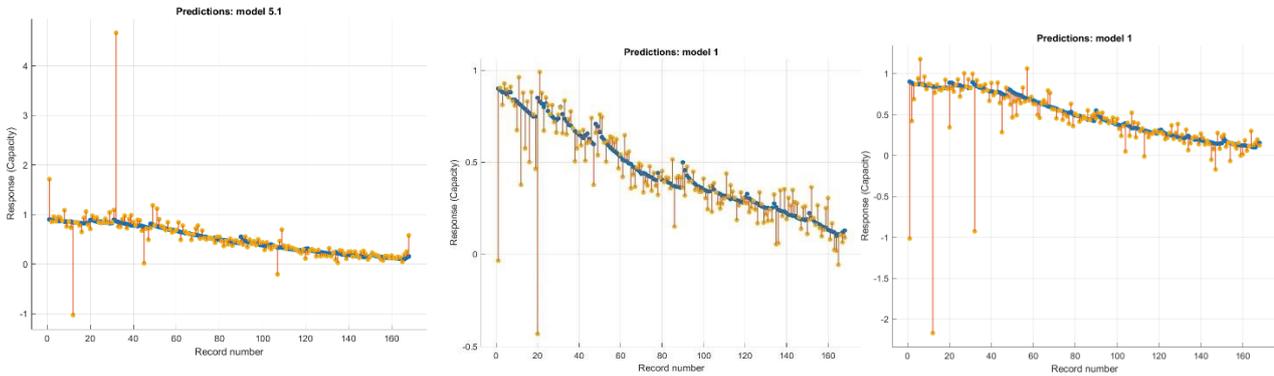


Figure 2 a,b and c. Linear Regression model for various battery datasets

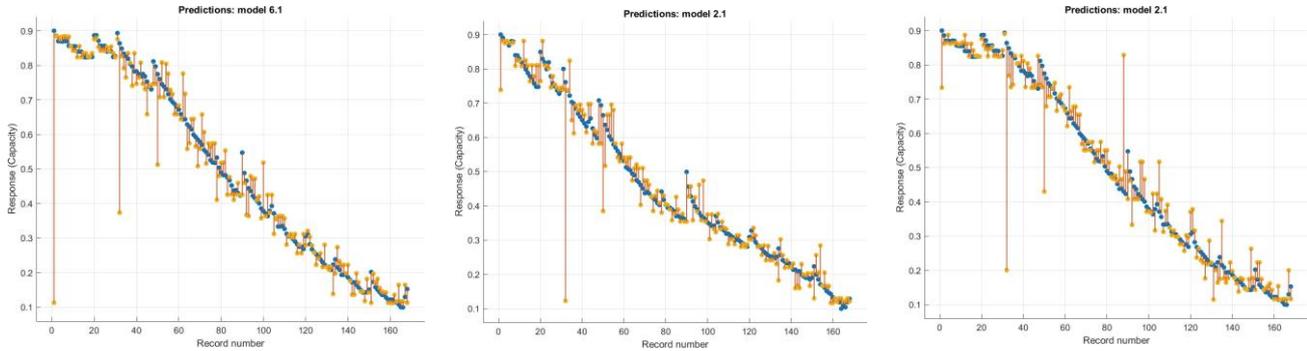


Figure 3 a,b and c. Fine tree model for various battery datasets

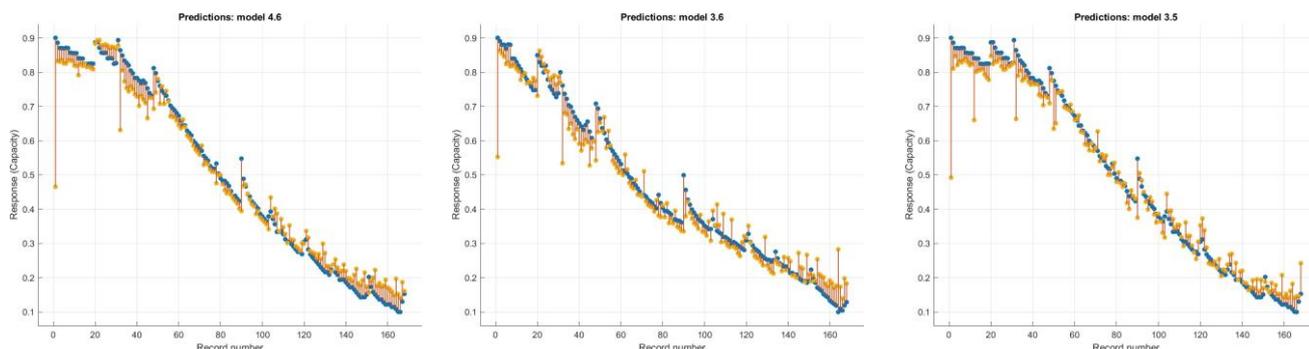


Figure 4 a,b and c. Support Vector Machine model for various battery datasets

Table 3. Comparison of battery health analysis using three different machine learning algorithms

Algorithm	Performance Metric	Value
Linear Regression	MSE	0.035
	R-squared	95.90%
Fine Trees	MSE	0.023
Support Vector Machines	Accuracy	94.50%

6.3 Additional Works

K-means clustering was applied on the dataset. The number of clusters was set to 4, and the algorithm was run for 50 iterations. The resulting clusters were analyzed, and it was found that each cluster represented a distinct battery health state as shown in Figure 6. The K-means clustering algorithm was able to group the batteries based on their health status, which can help in identifying faulty batteries and taking appropriate action. The hierarchical clustering algorithm was able to group the batteries into different clusters based on their similarity, which can help in identifying the faulty batteries and taking appropriate action as shown in Figure 7.

In addition to applying K-means clustering and hierarchical clustering on the dataset, Principal Component Analysis was also utilized to reduce the dimensionality of the data. This is important because large datasets with many features can be difficult to analyze and interpret. PCA is a technique that transforms a high-dimensional dataset into a lower-dimensional space while retaining as much of the original data variation as possible. In this analysis, PCA was applied to the battery health dataset and observed that the principal components were able to

explain a significant amount of the variance in the data. This reduction in dimensionality allowed to more easily visualize and analyze the data.

K-means clustering in conjunction with PCA (Figure 8) and hierarchical clustering in conjunction with PCA (Figure 9) were also applied. By reducing the dimensionality of the data with PCA, the performance of the clustering algorithms was improved. This is because PCA extracts the most relevant features from the data, which can lead to more accurate clustering results. The resulting clusters from K-means and hierarchical clustering were able to group the batteries based on their health status, which is a crucial aspect in identifying faulty batteries and taking appropriate action.

Comparing the performance of the three unsupervised algorithms, it was found that K-means clustering and hierarchical clustering were able to group the batteries based on their health status, while PCA was able to reduce the dimensionality of the data and preserve the information about the battery health status. By using a combination of these algorithms, it is possible to leverage the strengths of each algorithm and compensate for their limitations, resulting in a more robust and comprehensive analysis of the battery health.

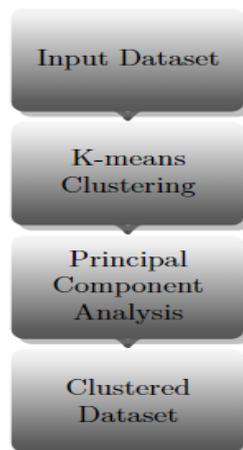


Figure 5. Flowchart summarizing the battery health analysis using K-means clustering, PCA, and hierarchical clustering.

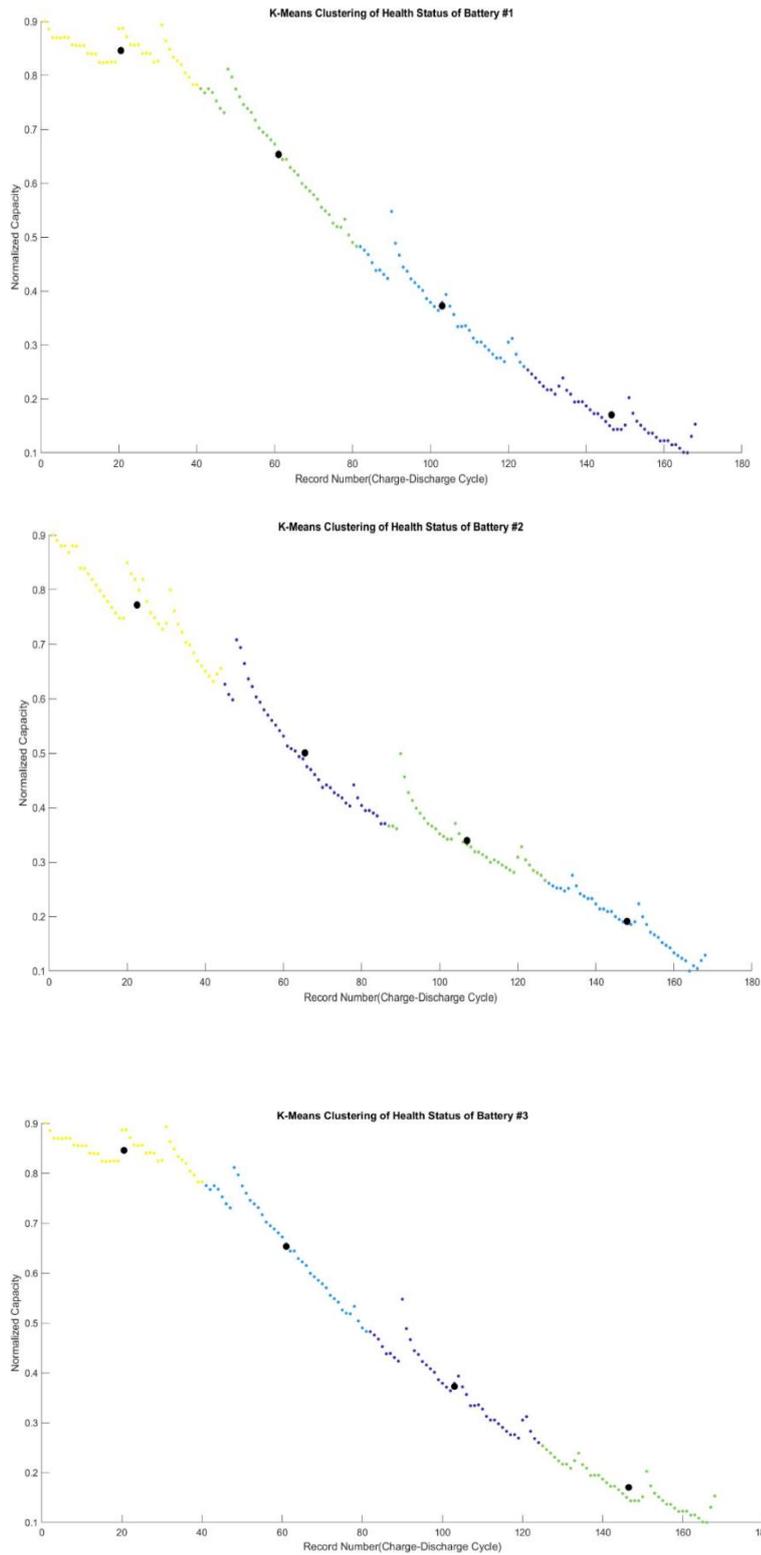


Figure 6 a,b and c. K-means clustering using various battery datasets

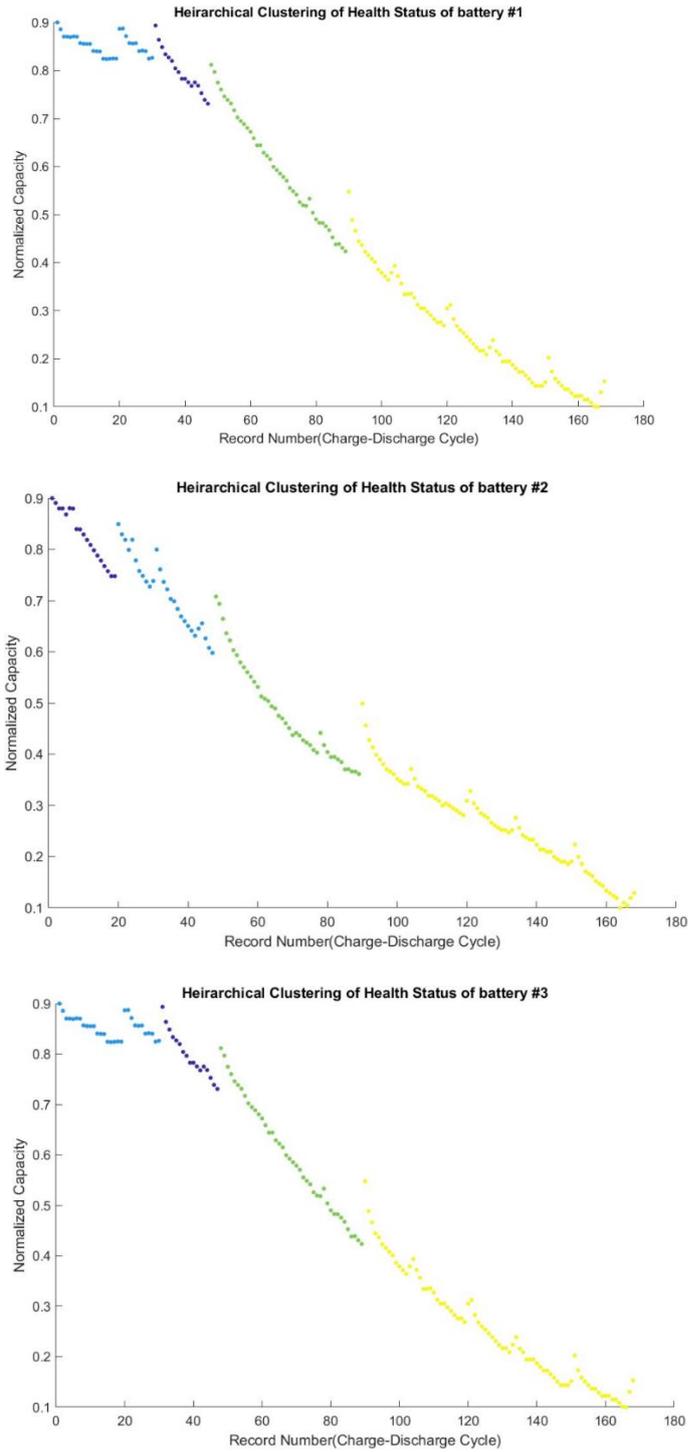
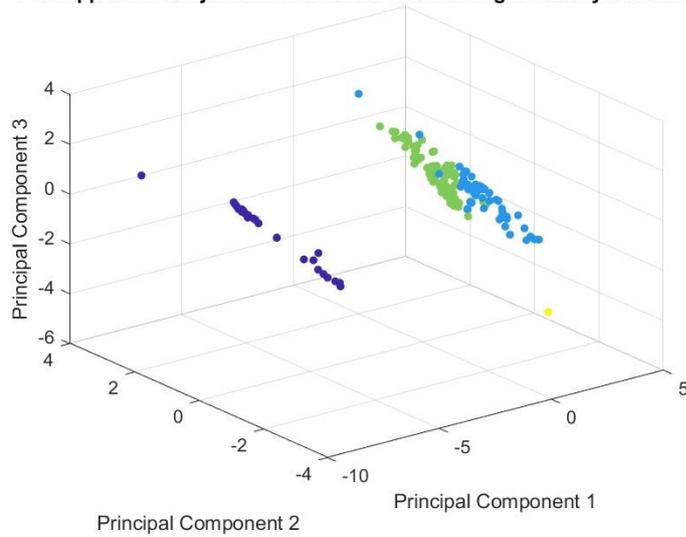
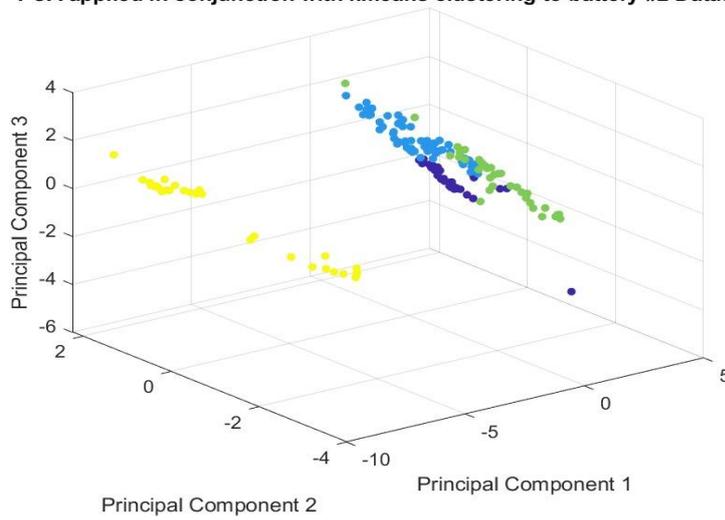


Figure 7 a,b and c. Hierarchical clustering using various battery datasets

PCA applied in conjunction with kmeans clustering to battery #1 Dataset



PCA applied in conjunction with kmeans clustering to battery #2 Dataset



PCA applied in conjunction with kmeans clustering to battery #3 Dataset

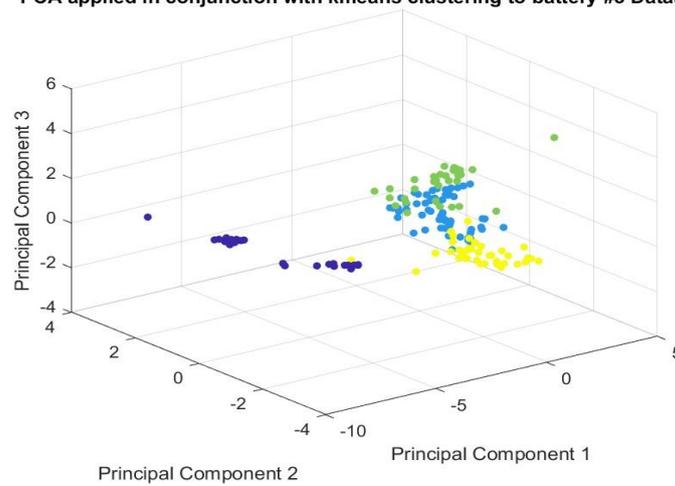
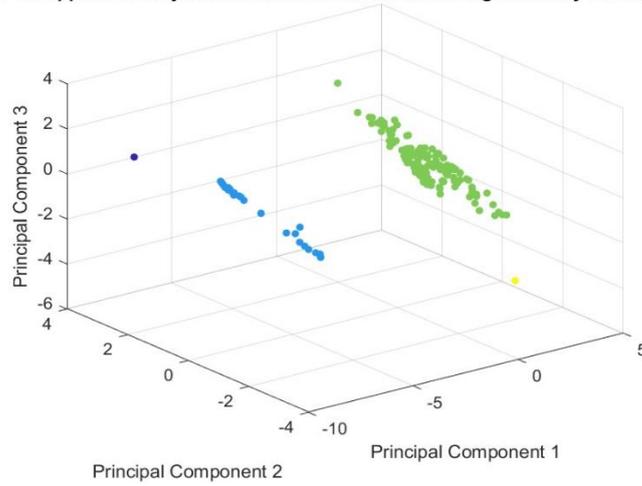
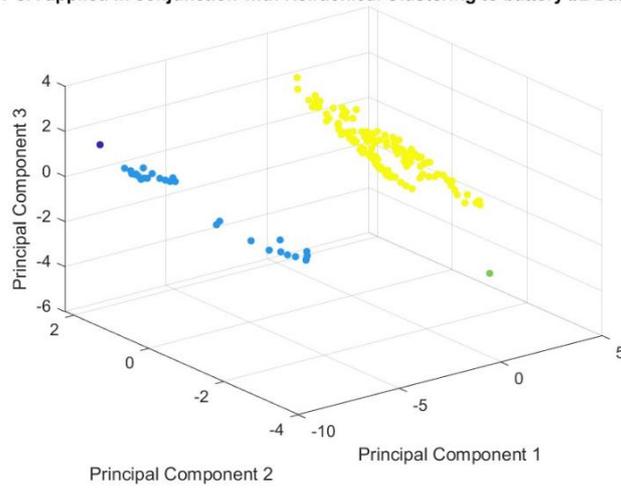


Figure 8 a,b and c. PCA with K-means clustering using various battery datasets

PCA applied in conjunction with Heirachical Clustering to battery #1 Dataset



PCA applied in conjunction with Heirachical Clustering to battery #2 Dataset



PCA applied in conjunction with Heirachical Clustering to battery #3 Dataset

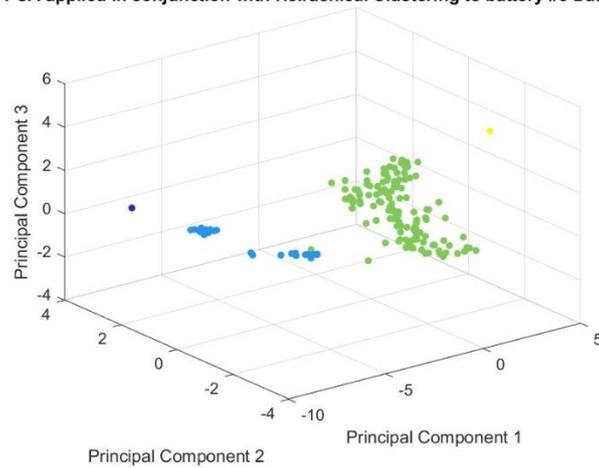


Figure 9a,b and c. PCA with Hierarchical using various battery datasets

7. Conclusion

In conclusion, this study has presented a machine learning-based approach for battery health analysis using supervised learning algorithms implemented in MATLAB. The combination of support vector machines, fine trees, and principal component analysis proved to be an effective method for accurately predicting battery health and identifying potential degradation mechanisms. Through the analysis of experimental battery data, the effectiveness of the approach has been demonstrated. One of the main advantages of the approach is its ability to process large amounts of battery data quickly and accurately. This is critical for applications such as electric vehicles, where battery performance is crucial for the overall operation of the vehicle. By implementing this approach, it is possible to quickly identify potential battery issues and take corrective action before they become a major problem.

References

- [1] H. Lu, C. Yang, J. Jiang, and S. Song, "Machine Learning in Battery Health Management: A Review," *IEEE Access*, vol. 8, pp. 131988- 132005, 2020.
- [2] X. Chen, Q. Li, F. Li, and C. Zhan, "Machine learning for battery health management: State of the art and future directions," *Applied Energy*, vol. 282, p. 116156, 2021.
- [3] M. M. Rahman, A. M. A. Hossain, and S. Islam, "A review of machine learning methods for state of health estimation of lithium-ion batteries," *Renewable and Sustainable Energy Reviews*, vol. 117, p. 109510, 2020.
- [4] G. Jayasinghe, N. Nallathambi, and R. H. G. R. Ranasinghe, "Machine Learning for Battery Management Systems: Review and Future Directions," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 1, pp. 28-40, 2020.
- [5] J. Prakash and S. Arulmozhiyal, "A Review on Machine Learning Techniques for Battery Management System," *International Journal of Advanced Research in Computer Science and Software Engineering*, vol. 8, no. 4, pp. 836-842, 2018.
- [6] R. Jalili, A. Ahmadi, and M. K. MoravvejFarshi, "A Review of Machine Learning Approaches in Battery Health Management Systems," *International Journal of Energy Research*, vol. 44, no. 3, pp. 1653-1671, 2020.

- [7] Y. Ma, Q. Li, Y. Shi, and C. Zhan, "A review on recent progress of machine learning techniques for lithium-ion battery health management," *Energy Storage*, vol. 2, no. 4, pp. 363-374, 2020.
- [8] K. C. Kao and T. Y. Tsai, "A review of machine learning techniques for state-of-charge and state-of-health estimation of batteries," *Journal of Power Sources*, vol. 494, p. 229643, 2021.
- [9] S. G. te Nyenhuis, K. Wipke, M. K. Das, R. J. Ahmed, and P. T. Jones, "Review of Machine Learning Techniques Applied to Lithium-ion Battery State-of-Health Estimation," *IEEE Access*, vol. 6, pp. 27636- 27654, 2018.
- [10] W. Zhang, L. Fang, and Y. Wang, "Machine Learning for Battery Health Prognosis: A Review," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 8, pp. 5803-5815, 2021.
- [11] N. X. Tan, Y. Y. Wu, L. Lu, and K. L. Man, "A Review of Prognostic Techniques for Battery Health Management," *Energies*, vol. 13, no. 11, p. 2891, 2020.
- [12] S. S. Thakur, M. K. Das, K. Wipke, and J. P. Lamb, "A Comprehensive Review of Prognostic Techniques for Battery Health Management of Electric Vehicles," *IEEE Transactions on Transportation Electrification*, vol. 4, no. 2, pp. 251-269, 2018.
- [13] F. Zheng, J. Wu, X. Li, and J. Zhang, "State-of-Health Estimation for Lithium-Ion Batteries Based on an Adaptive Square-Root Cubature Kalman Filter and Support Vector Regression," *Journal of Power Sources*, vol. 364, pp. 40-49, 2017.
- [14] Z. Liu, Q. Li, C. Zhan, and Y. Ma, "Data-Driven Battery Degradation Modelling and Prognosis with Machine Learning," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 2, pp. 1368-1377, 2021.
- [15] J. Li, W. Chen, X. Li, and Y. Li, "Deep Learning-Based Battery Health Prognosis for Electric Vehicles," *Energies*, vol. 14, no. 4, p. 1029, 2021.
- [16] C. Huang, W. Guo, L. Wu, and W. Liu, "A Review of Machine Learning Methods for Battery Prognostics and Health Management," *Energies*, vol. 14, no. 4, p. 933, 2021.

- [17] S. H. Rizvi, S. M. A. Kazmi, M. A. Mahmood, and J. Li, "A Review of Machine Learning Techniques for Battery Health Management in Electric Vehicles," *Energies*, vol. 13, no. 18, p. 4771, 2020.
- [18] Y. Jiao, X. Wu, Z. Liu, W. Hu, and L. Zhang, "Battery Health Monitoring and Prediction for Electric Vehicles Using Machine Learning: A Review," *Energies*, vol. 14, no. 3, p. 608, 2021.
- [19] S. G. te Nyenhuis, K. Wipke, M. K. Das, R. J. Ahmed, and P. T. Jones, "Comparison of Machine Learning Techniques Applied to Lithium-Ion Battery State-of-Health Estimation," *Energies*, vol. 13, no. 24, p. 6615, 2020.
- [20] S. J. Jeong, Y. H. Kim, and J. Kim, "A Review of Machine Learning Techniques for Battery State-of-Health Estimation: Trends and Opportunities," *Energies*, vol. 13, no. 22, p. 6019, 2020.

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