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Dimensionality reduced deep learning-based state of health estimation of Lithium-Ion batteries using standard dataset

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ABSTRACT

Lithium-Ion batteries are used in everyday DC equipment's, electric vehicle technology, and microgrid technology. The necessity to verify the battery's state is crucial for the dependent apps to continue operating without interruption due to advancements in battery technology & adaption. This study uses dimension decreases in input attributes along with deep learning methods to determine the state of health of lithium-Ion batteries (LIB). principal component analysis (PCA), a deep learning technique, is combined with recurrent neural networks (RNN) to reduce dimensionality. For the purpose of evaluating the effectiveness of the dimensionality reduction used in the data, the state of health (SOH) estimate using the RNN with and without PCA is compared. The use of PCA-powered RNNs using mean square error (MSE) as the loss function throughout the training and testing stages of state-of-health (SOH) estimation showed great performance in terms of loss. This was seen during the training and testing processes' respective testing and validation phases.

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1. INTRODUCTION

In recent years, lithium-Ion batteries or LIB have dominated the electrical storage sector. The condition of the battery must be examined to ensure uninterrupted operation of the devices that rely on batteries for power. The LIB is more prevalent on the market for electric vehicles. For either routine maintenance or replacement, each application requires information on the battery's condition. By carefully calculating the state of charge (SOC), that stands for the amount of energy stored in the batteries, while maintaining track of the SOH, which represents the general condition and degree of degradation of the batteries, it is possible to implement into practice efficient methods which improve the operational life expectancy of the batteries. The single particle model is a simplified battery electrochemical model that is used in this study to track changes in lithium-ion content with varied loaded currents and calculate the number of recyclable lithium-ions at various aging degrees. In order to ensure both operational speed and optimization accuracy, the model's parameters are determined using a hybrid technique called the hybrid coyote optimization technique and the grey wolf optimizer. With mean absolute percentage errors for battery capacity below 2% and SOC prediction below 1.8%, the suggested technique exhibits great accuracy and resilience. SOC forecast time is less than 2 seconds during federal urban driving cycles [1].

For the purpose of assessing the state of health (SOH) of batteries, the unscented particle filter (UPF) algorithm integrates recent measurements to predict the battery health and expresses uncertainty. A UPF-based estimator accomplishes accurate SOH evaluation with less than 5% maximum estimation error and exhibits robustness across multiple lithium-ion battery types by collecting an online health indicator (HI) from measurable parameters and using it in a state-space model [2]. In order to accurately estimate the SOC and SOH of batteries in electric vehicles, a dual extended Kalman filter (EKF) and a fractional-order model (FOM) are used [3]. In order to overcome the difficulty of the batteries' complex aging mechanism, a novel method for precisely predicting the remaining useful life (RUL) and determining the state-of-health (SOH) of energy storage systems using LIB has been developed [4]. This method establishes a support vector regression-based battery SOH state-space model and makes use of a particle filter to estimate impedance degradation parameters. In order to improve accuracy and explore the connection between internal parameters and battery states, a joint extended Kalman filter-recursive-least squares method has been proposed [5] for state-of-charge estimation. This method estimates the SOH of lithium-ion batteries. Particle swarm optimization-least square support vector regression is used after parameter identification to produce reliable and accurate SOH estimation with good generalizability. The suggested method for state-of-health determination has undergone experimental tests on lithium iron phosphate batteries at various aging stages, and the results show that it is highly accurate and suitable. The remaining usable life (RUL) of a battery, for instance, can be predicted using a long short-term memory (LSTM) network based on capacity degradation [6]. A convolutional neural network and a long short-term memory unit are combined to provide a deep learning method for online capacity estimate of lithium-ion batteries.

The suggested algorithm achieves accurate capacity estimation with an absolute error of fewer than 0.021 Ampere-hour and 0.11 Ampere-hour for two battery types, enabling quick online capacity estimation. Partial charging voltage and current data are used in the proposed algorithm without wide pre-processing, leading to simpler training preparation and lower computational intensity [7]. Calculations that simulate various battery types are used in model-based SOH estimates. Data-driven approaches train machine learning algorithms using real-time data from these calculations. By contrasting the factors comprising advantages, estimation error, and downsides of each estimating method, an examination of such methods is given in the literature [8]. In order to calculate ECM parameters as well as battery SOC using dual time scales, a multi-scale extended Kalman filter relying on the first-order equivalent-circuit model (ECM) is used [9]. This emphasizes the significance of optimizing the excitation current for precise parameter and state estimation.

The study illustrates the effect of excitation current selection on estimation accuracy using Cramer-Rao bound analysis while taking voltage noise, current amplitude, and frequency into account. It then offers recommendations for creating battery current profiles that produce better SOC and SOH estimation performance. In order to estimate the SOC and SOH of power batteries used in electric vehicles accurately, the article [10] offers a hierarchical estimation model that takes into consideration the current rate. The proposed method significantly improves SOC and SOH estimation accuracy through the use of a fractional-order model, data-driven parameter identification, along with a multiscale dual extended Kalman filter (DEKF). It outperforms conventional DEKF addresses by 35.8% to 36.5% for SOC estimation as well as 34.8% to 43.1% for SOH estimation under various current conditions.

In order to improve the performance of battery management systems in LIB used in diverse applications, the study [11] suggests a co-estimation method for SOC and SOH based on fractional-order calculus. The plan comprises a dual fractional-order extended Kalman filter for simultaneous estimate of SOC and SOH, as well as a fractional-order equivalent circuit model parameterized utilizing a hybrid genetic algorithm/particle swarm optimization technique. The usefulness of the proposed approach in battery management tasks is validated by experimental results showing that it can estimate SOC and SOH having maximum steady-state errors of less than 1% and is resilient to battery aging. For estimating SOC and SOH, there is significant interest in artificial intelligence and machine learning (ML), including feed forward neural network (FNN), recurrent neural network (RNN), support vector machine (SVM) and radial basis function (RBF) and Hamming networks. Comparative analysis of these approaches takes into account elements like input and output quality, test conditions, battery types, as well as accuracy, placing emphasis on the significance of multiple training iterations, similar network structures, and identical data for accurate comparisons between estimation techniques [12]. Accurate capacity prediction of batteries in ESS is critical for safe operations, and this paper offers a deep learning-based battery management system (BMS) that estimates battery health and capacity using multiple channel charging profiles (MCCPs) [13]. Deep domain adversarial network (DDAN) is a model that includes a deep feature generator, dense bidirectional gated recurrent unit, as well as unsupervised feature alignment metrics to improve feature learning and knowledge transfer, and it has been shown to be effective in SOH estimation on a battery dataset [14]. In real-time simulations and hardware tests, a successful approach to forecast battery aging & estimating battery health.

The research project develops and implements mathematical models on a standalone hardware platform to determine an optimal machine learning-based method for SOH and RUL estimation, taking into account factors such as SOC, discharge voltage transfer features, internal resistance, and capacity. According to experimental findings, although a long short-term memory neural network efficiently predicts battery RUL with an accuracy of 10 cycles, a deep neural network predicts SOH with an acceptable error rate of 5%. The suggested method provides an ideal answer for estimating battery life by showcasing multiple machine learning models on a real hardware platform [15]. Auto-regression nested sequence (ARNS), described in literature [16], is a novel data-driven approach that effectively aggregates channel- and cycle-level information whereas including relaxation impacts for peak prediction. When applied to NASA and CALCE datasets, ARNS outperforms existing methods, especially during peak periods spanning multiple SOH states and cycles. Indirect health indicators (IHIs), which reflect battery capacity loss, can be extracted from voltage, current, and temperature curves throughout the charging and discharging processes, according to literature [17]. High estimation accuracy is achieved by selecting the significant IHIs using (PCA) and using them as inputs for SOH estimation using gaussian process regression (GPR). The development of a unique SOH [18] estimate method is based on the battery pack's behavior in active charge balancing (ACB), and has a positive correlation with SOH. We outperform state-of-the-art methods by leveraging this metric and other cell parameter to train a Random Forest (RF) regression estimator, which leads to accurate SOH estimate with 1.94% accuracy for capacity as well as 4.28% accuracy for resistance. A lithium-ion battery (LIB) online SOH monitoring technique is presented in article [19] that makes use of the battery's charge-discharge characteristic in real time.

The proposed method demonstrates accurate real-time prediction of LIB SOH using NASA experimental data, with strengthened accuracy due to the use of techniques such as complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), logistic regression based on sliding time window (LR-STW), Kalman filter (KF), and radial basis function neural network (RBFNN), as well as (PCA) to analyze the relationship between the charge-discharge feature and SOH. 124 commercial lithium iron phosphate/graphite cells with varied cycle lifetimes were cycled under fast-charging conditions, and a comprehensive dataset was created [20]. The potential of combining intentional data generation with data-driven modeling to comprehend complex dynamical systems is demonstrated by predictive models that achieve a 9.1% test error for quantitatively predicting cycle life as well as a 4.9% test error for classifying cycle life into two groups via using machine-learning tools to discharge voltage curves from early cycles. The changing pattern of the charging current during the constant-voltage (CV) phase serves as the foundation for developing an approach to detect battery SOH [21]. By establishing a measurable link between the normalized battery capacity and the current's time constant, an accurate estimation of SOH becomes achievable. The time constant of the CV charging current is acknowledged as a dependable indicator associated with battery aging. The proposed approach may successfully show the SOH of several batteries under a 2.5% error bound, according to experimental results.

The idea of effective battery capacitance is first mentioned in literature [22] as a way to forecast the SOH of certain cells. A linear relationship among maximum effective capacitance and SOH is found and validated using data from several Toyota Prius battery packs. The maximum effective capacitance is determined through a voltage versus charge curve analysis and acts as a signal for end-of-life or catastrophic failure of battery modules. A innovative method for predicting long-term remaining usable life (RUL) and estimating short-term (SOH) online is presented in literature [23] by combining particle filtering (PF) and a degradation model based on Brownian motion (BM). The review paper [24] discusses the viability and economics of data-driven methods for estimating battery health in practical applications by utilizing developments in "Big Data" analytics using statistical/computational tools. The authors classify these techniques according to the models and algorithms that underlie them, talk about their benefits and drawbacks, and explore the difficulties of managing the real-time battery health. This review intends to advance data-driven battery health estimate and forecasting across all technology readiness levels by offering insights into commercial technology decisions and research goals. An adaptable health estimation model is presented in the literature [25], which demonstrates the effectiveness of a Bayesian non-parametric approach employing Gaussian process regression for gauging capacity degradation across diverse usage scenarios. The author effectively anticipates long-term capacity fading using this technique on the NASA randomized battery usage dataset, attaining an optimal normalized root MSE of 4.3% alongside accurate computation of predictive uncertainty. Various literatures that discuss on the different battery performance evaluation and different chemical composition, novel methods for performance evaluation are considered [25]-[43].

Though the SOH implementation for batteries is used to build machine learning algorithms in the prior research, dimensionality reduction of the input characteristics using techniques for feature extraction is not addressed. In order to achieve the SOH estimation using the SVM implementation, this article uses the PCA-based feature extraction method. The implementation process is covered in section 2. Section 3 includes a description of the results and discussion, followed by the conclusion and references.

2. DIMENSIONALITY REDUCED RNN-BASED SOH ESTIMATION

The variables are prepared for PCA analysis to determine the total number of primary components to be used for SOH estimate. The dimensionality reduction method utilized in machine learning applications is

(PCA). By encapsulating every variable in a small number of variables, principal components (PC) can condense a sizable number of variables. All variables are linearly combined to create the principal components (PC), which are then generated. The SVM decision-making algorithm receives its input from the PCs.

A collection of experimental data called the NASA dataset for LIB can be used to calculate a battery's SOH. SOH stands for the battery's lifetime energy storage and delivery capacity. This dataset, which was produced by the NASA Ames research center and the jet propulsion laboratory, contains measurements of several lithium-ion battery properties made across a number of charge and discharge cycles. The dataset contains data on the voltage, current, temperature, capacity, and impedance of the batteries. It also includes information about the battery's structure and content, as well as the testing environment. Different testing techniques, such as accelerated aging and real-world cycling, were used to gather the results. As shown in Table 1, the dataset contains variables that were noticed during the charging and discharging cycles. The experiment is done on the data acquisition test bed using the lithium-ion battery's charging and discharging cycles. Rechargeable batteries in the 18650 size that are readily available on the market are employed. Table 2 lists the characteristics noticed for the impedance operation.

Models and algorithms are created using the dataset, which comprises all the variables gleaned from the charge-discharge cycles, in order to anticipate battery performance and calculate the battery's remaining usable life. LIB can be designed better and used more effectively in a variety of applications with the help of these models. After performing a PCA-based dimensionality reduction on the dataset, the data-driven SOH estimation is implemented using a recurrent neural network. To compare the outcomes of PCA extracted and non-PCA implementation, model loss is obtained for both. Figure 1 shows the block diagram for the SOH estimate using PCA and RNN.

Table 1. Data structure for charge, discharge operations

Attribute	Attribute explanation	Unit
Voltage_measured	Battery terminal voltage	Volts
Current_measured	Battery output current	Amps
Temperature_measured	Battery temperature	Degree Centigrade
Current_charge	Current measured at the charger	Amps
Voltage_charge	Voltage measured at the charger	Volts
Time	Time vector for the cycle	Secs
Capacity (Only for Discharge operation)	Battery capacity (Ahr) for discharge till 2.7V	Ahr

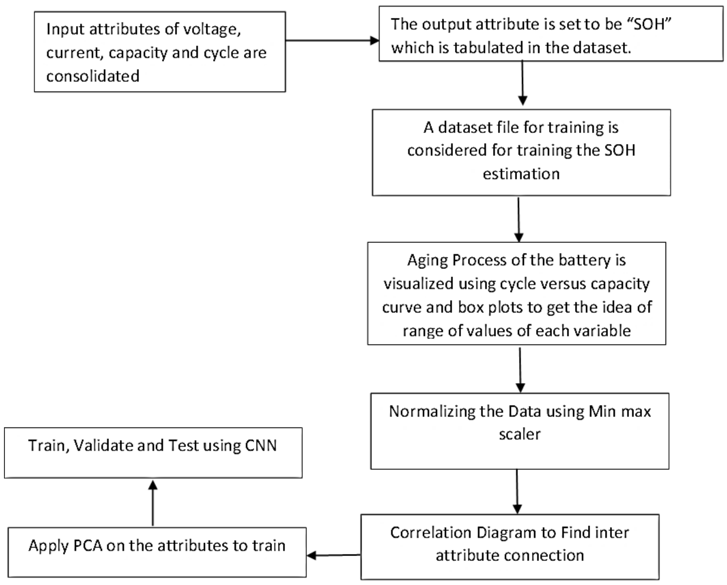


Figure 1. Dimensionality reduced SOH estimation using RNN

The block diagram shows how the specified CSV files are used to read the dataset. For the implementation of SOH estimation, the attributes are divided into input and output. Following the application of PCA, the data has been normalized utilizing the min-max scaler normalization method and trained on the RNN network having the following structure. To carry out the dimensionality-reduced SOH estimation utilizing RNN, Python-based code has been created. The MSE is used as the objective for convergence in the training and testing of SOH estimation using RNN. To appreciate the effectiveness of the approach, the comparative MSE convergence of the RNN without PCA and RNN with PCA is derived.

Table 2. Data structure for impedance operations

Attribute	Attribute explanation	Unit
Sense_current	Current in sense branch	Amps
Battery_current	Current in battery branch	Amps
Current_ratio	The ratio of the above currents	NIL
Battery_impedance	Battery impedance (Ohms) computed from raw data	Ohms
Rectified_impedance	Calibrated and smoothed battery impedance (Ohms)	Ohms
Re	Estimated electrolyte resistance (Ohms)	Ohms
Rct	Estimated charge transfer resistance (Ohms)	Ohms

3. RESULTS AND DISCUSSION

Figure 2 shows the box plots for the attributes: Figure 2(a): capacity, Figure 2(b): voltage measured, Figure 2(c): current measured, Figure 2(d): temperature measured, Figure 2(e): current load, and Figure 2(f): voltage load. Using a box plot, the input attributes are represented in order to determine their range of values. Figure 2 illustrates the attributes of the battery charging procedure alongside the span of values encompassing these characteristics.

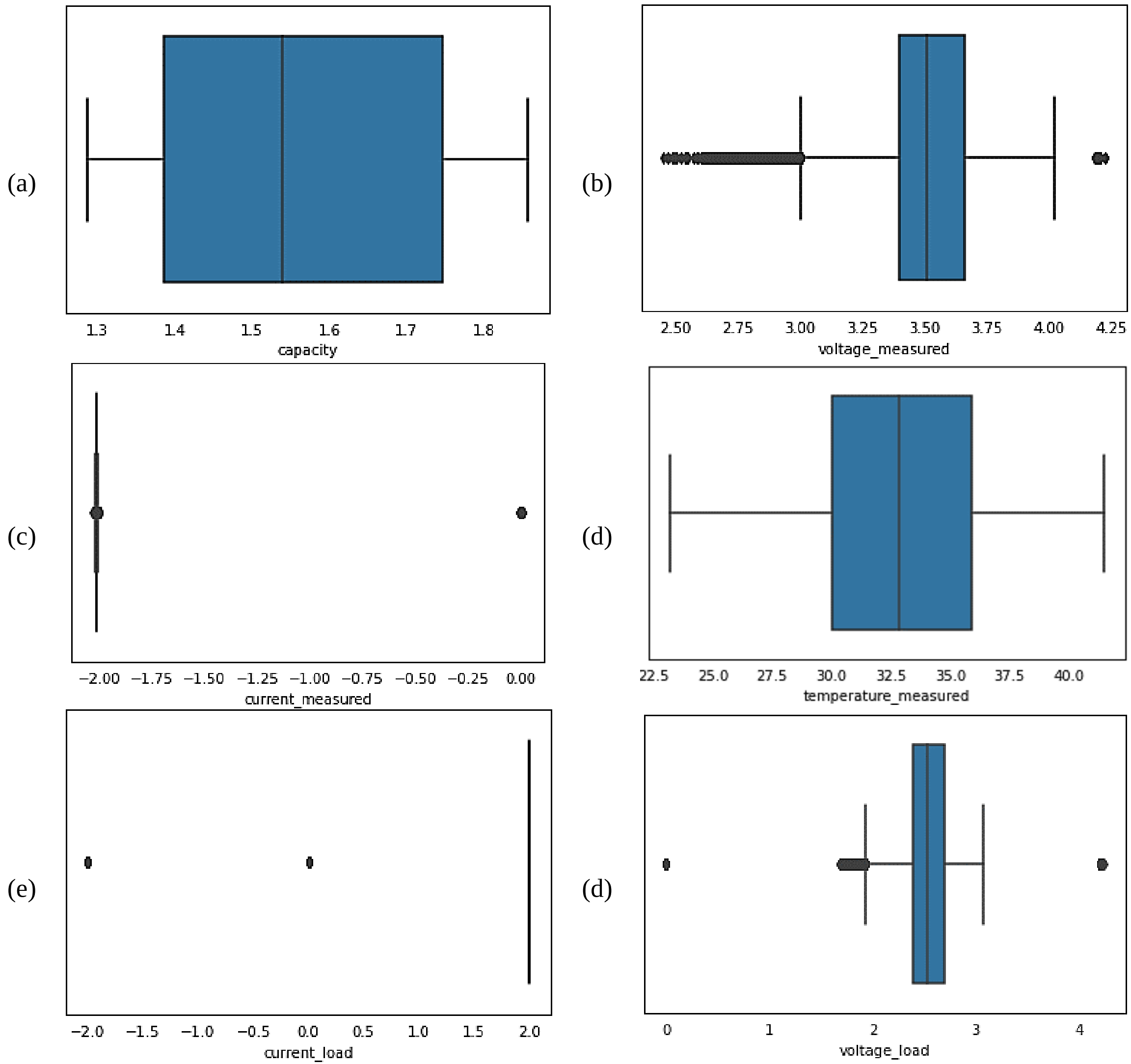


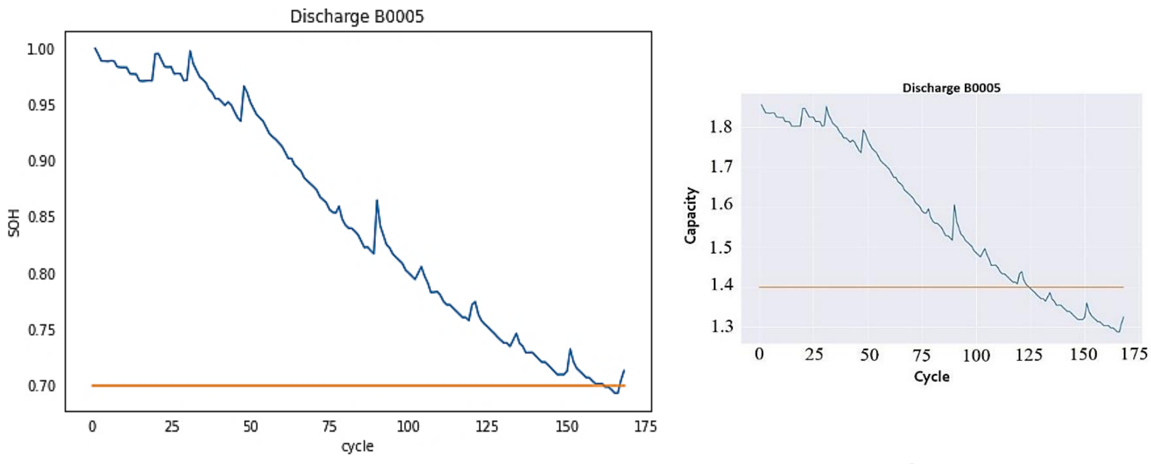
Figure 2. Box plots for the attributes of (a) capacity, (b) voltage measured, (c) current measured, (d) temperature measured, (e) current load, and (f) voltage load

To understand the battery's capacity profiling, the graph analyzes the data for SOH versus cycle. Figures 3(a) and 3(b) show the SOH versus cycle profile and the capacity versus cycle, respectively. Figures 3(a) and 3(b) exhibit the instantaneous SOH and capacity values along with the average SOH and capacity values. The Figure 3 clearly shows how the capacity and SOH have declined.

For efficient memory usage in SOH prediction training and testing, the attributes for SOH estimation must be feature minimized. The correlation diagram provides information about how closely the attributes are related; the higher the correlation, the less frequently an attribute is used. Although there is a higher correlation among all the distinctive factors, the ambient temperature has a larger correlation. For PCA analysis, all seven attributes are kept in place. Since PCA is used to extract variance from characteristics, it is calculated as a linear combination of attributes, and as a result, the implementation of PCA shows a reduction in dimensionality. Different percentage variances are contributed by the principal components (PCs). However, the first and second PCs, PC1 and PC2, are the principal variations that account for the majority of the variance in the characteristics. Figure 4(a) shows the PC graph, whereas Figure 4(b) shows the correlation graph between the qualities. Table 3 shows the PCs and their proportional contribution to reflecting the variance of the characteristics. It is evident from the chart that the top three or four PCs' contributions account for the majority of the differences in all the parameters.

To create the model loss versus epoch graphs, the RNN technique is used in conjunction with the original attributes and the extracted PCs, which may be all of them or only three or four of them. To compare the training convergence and testing model loss vs the epochs, the model loss graph with the train and test operation on the dataset is obtained. Model loss in machine learning is a metric indicating how effectively a model can forecast the target variable given a specific set of input data. The difference between the projected value and the actual value is used to calculate it. Figure 5 shows the model loss responses for the various instances addressed. Figures 5(a) and 5(b) show that the model loss response is identical when the whole set of characteristics and all PCs are used for the SOH estimation. While the model loss while employing 4 PCs and 3 PCs is comparable, as shown in Figures 5(c) and 5(d), respectively.

When using 4 Pcs for the SOH estimation, the root mean square of 0.1379859619348809 was achieved. When the characteristics are employed directly, the SOH estimation achieved using PCA and RNN essentially yields equal values of model loss. As a result, when dimensionality is reduced using PCA, the model loss values are close to those obtained when PCA is not used. As a result, as compared to an implementation that does not use PCA, the SOH estimation approach uses less RAM.

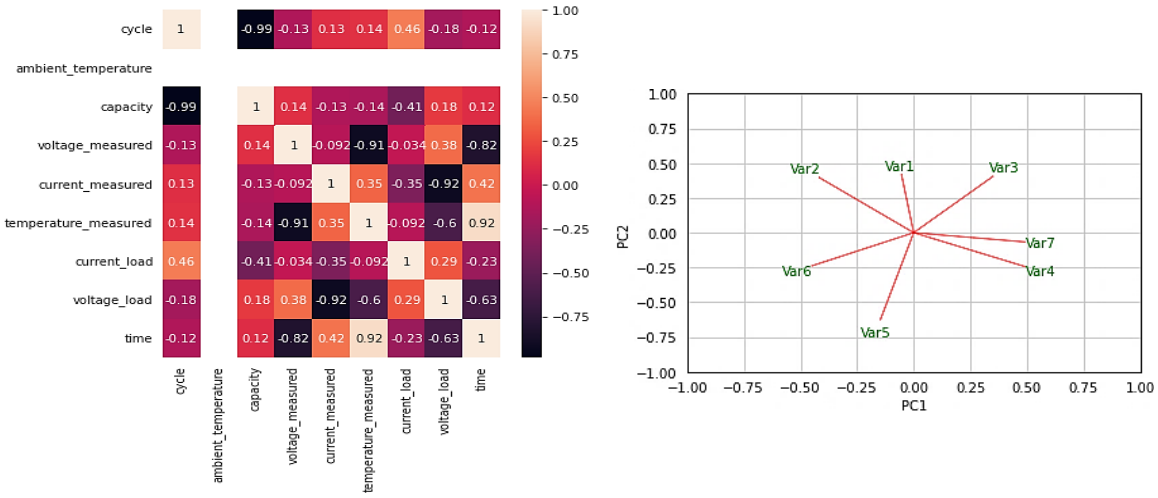


(a) (b)

Figure 3. Profiling of SOH and capacity: (a) SOH versus cycle and (b) capacity versus cycle

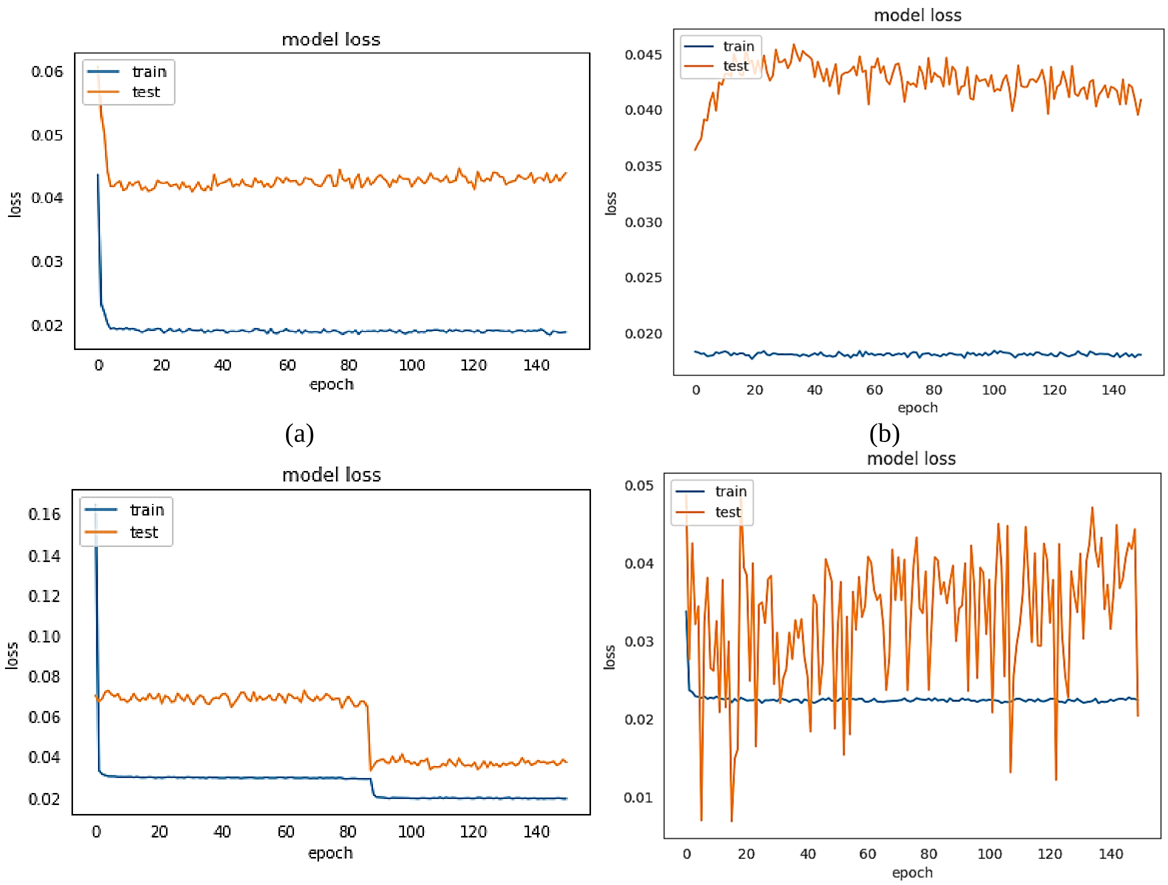
Table 3. PC contribution

PC number	Eigen value	Percentage
0	4.172993	59.614191
1	1.350306	19.290089
2	0.910773	13.011049
3	0.385525	5.507497
4	0.138061	1.972299
5	0.026477	0.378236
6	0.015865	0.226640



(a) (b)

Figure 4. PCA implementation: (a) correlation diagram and (b) principal components (PCs)



(a) (b) (c) (d)

Figure 5. Model loss response: (a) without PCA, (b) with all PCs, (c) with 3 PCs, and (d) with 4 PCs

4. CONCLUSION

The NASA dataset, a common dataset, is utilized in the machine learning context for SOH estimation. The PCA is used to apply the dimensionality reduction technique to the input attributes. Using the PCs acquired via PCA, the RNN from the Deep Learning technique is utilized to estimate the SOH. The model losses were provided by the implementation to be quite close to those when all attributes are utilized. Even when dimensionality reduction using PCA is used, the performance of the SOH estimation is still in a good range. The algorithm's RMSE results show that the PCA with RNN algorithm has increased memory economy while preserving performance equivalence to the non-PCA implementation.

REFERENCES

[1] X. Sun, Q. Chen, L. Zheng, and J. Yang, "Joint Estimation of State-of-Health and State-of-Charge for Lithium-Ion Battery Based on Electrochemical Model Optimized by Neural Network," *IEEE Journal of Emerging and Selected Topics in Industrial Electronics*, vol. 4, no. 1, pp. 168–177, 2022, doi: 10.1109/jestie.2022.3148031.

[2] D. Liu, X. Yin, Y. Song, W. Liu, and Y. Peng, "An on-line state of health estimation of lithium-ion battery using unscented particle filter," *IEEE Access*, vol. 6, pp. 40990–41001, 2018, doi: 10.1109/ACCESS.2018.2854224.

[3] L. Ling and Y. Wei, "State-of-Charge and State-of-Health Estimation for Lithium-Ion Batteries Based on Dual Fractional-Order Extended Kalman Filter and Online Parameter Identification," *IEEE Access*, vol. 9, pp. 47588–47602, 2021, doi: 10.1109/ACCESS.2021.3068813.

[4] J. Wei, G. Dong, and Z. Chen, "Remaining Useful Life Prediction and State of Health Diagnosis for Lithium-Ion Batteries Using Particle Filter and Support Vector Regression," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 7, pp. 5634–5643, 2018, doi: 10.1109/TIE.2017.2782224.

[5] D. Yang, Y. Wang, R. Pan, R. Chen, and Z. Chen, "State-of-health estimation for the lithium-ion battery based on support vector regression," *Applied Energy*, vol. 227, pp. 273–283, 2018, doi: 10.1016/j.apenergy.2017.08.096.

[6] K. Park, Y. Choi, W. J. Choi, H. Y. Ryu, and H. Kim, "LSTM-Based Battery Remaining Useful Life Prediction with Multi-Channel Charging Profiles," *IEEE Access*, vol. 8, pp. 20786–20798, 2020, doi: 10.1109/ACCESS.2020.2968939.

[7] Q. Xue, J. Li, Z. Chen, Y. Zhang, Y. Liu, and J. Shen, "Online Capacity Estimation of Lithium-Ion Batteries Based on Deep Convolutional Time Memory Network and Partial Charging Profiles," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 1, pp. 444–457, 2023, doi: 10.1109/TVT.2022.3205439.

[8] D. N. T. How, M. A. Hannan, M. S. Hossain Lipu, and P. J. Ker, "State of Charge Estimation for Lithium-Ion Batteries Using Model-Based and Data-Driven Methods: A Review," *IEEE Access*, vol. 7, pp. 136116–136136, 2019, doi: 10.1109/ACCESS.2019.2942213.

[9] Z. Song, X. Wu, X. Li, J. Sun, H. F. Hofmann, and J. Hou, "Current Profile Optimization for Combined State of Charge and State of Health Estimation of Lithium Ion Battery Based on Cramer-Rao Bound Analysis," *IEEE Transactions on Power Electronics*, vol. 34, no. 7, pp. 7067–7078, 2019, doi: 10.1109/TPEL.2018.2877294.

[10] P. Xu, X. Hu, B. Liu, T. Ouyang, and N. Chen, "Hierarchical Estimation Model of State-of-Charge and State-of-Health for Power Batteries Considering Current Rate," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 9, pp. 6150–6159, 2022, doi: 10.1109/TII.2021.3131725.

[11] X. Hu, H. Yuan, C. Zou, Z. Li, and L. Zhang, "Co-Estimation of State of Charge and State of Health for Lithium-Ion Batteries Based on Fractional-Order Calculus," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 11, pp. 10319–10329, 2018, doi: 10.1109/TVT.2018.2865664.

[12] C. Vidal, P. Malysz, P. Kollmeyer, and A. Emadi, "Machine Learning Applied to Electrified Vehicle Battery State of Charge and State of Health Estimation: State-of-the-Art," *IEEE Access*, vol. 8, pp. 52796–52814, 2020, doi: 10.1109/ACCESS.2020.2980961.

[13] N. Khan, F. U. M. Ullah, Afnan, A. Ullah, M. Y. Lee, and S. W. Baik, "Batteries State of Health Estimation via Efficient Neural Networks with Multiple Channel Charging Profiles," *IEEE Access*, vol. 9, pp. 7797–7813, 2021, doi: 10.1109/ACCESS.2020.3047732.

[14] Z. Ye and J. Yu, "State-of-Health Estimation for Lithium-Ion Batteries Using Domain Adversarial Transfer Learning," *IEEE Transactions on Power Electronics*, vol. 37, no. 3, pp. 3528–3543, 2022, doi: 10.1109/TPEL.2021.3117788.

[15] P. Venugopal *et al.*, "Analysis of Optimal Machine Learning Approach for Battery Life Estimation of Li-Ion Cell," *IEEE Access*, vol. 9, pp. 159616–159626, 2021, doi: 10.1109/ACCESS.2021.3130994.

[16] T. Pham *et al.*, "ARNS: A Data-Driven Approach for SoH Estimation of Lithium-Ion Battery Using Nested Sequence Models With Considering Relaxation Effect," *IEEE Access*, vol. 10, pp. 117067–117083, 2022, doi: 10.1109/ACCESS.2022.3217478.

[17] D. Y. Reddy, B. Routh, A. Patra, and S. Mukhopadhyay, "Gaussian Process Regression based State of Health Estimation of Lithium-Ion Batteries using Indirect Battery Health Indicators," 2021, doi: 10.1109/ICPHM51084.2021.9486519.

[18] A. Lamprecht, M. Riesterer, and S. Steinhorst, "Random Forest Regression of Charge Balancing Data: A State of Health Estimation Method for Electric Vehicle Batteries," *2020 International Conference on Omni-Layer Intelligent Systems, COINS 2020*, 2020, doi: 10.1109/COINS49042.2020.9191421.

[19] L. Mao, H. Hu, J. Chen, J. Zhao, K. Qu, and L. Jiang, "Online State-of-Health Estimation Method for Lithium-Ion Battery Based on CEEMDAN for Feature Analysis and RBF Neural Network," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 11, no. 1, pp. 187–200, 2023, doi: 10.1109/JESTPE.2021.3106708.

[20] K. A. Severson *et al.*, "Data-driven prediction of battery cycle life before capacity degradation," *Nature Energy*, vol. 4, no. 5, pp. 383–391, 2019, doi: 10.1038/s41560-019-0356-8.

[21] J. Yang, B. Xia, W. Huang, Y. Fu, and C. Mi, "Online state-of-health estimation for lithium-ion batteries using constant-voltage charging current analysis," *Applied Energy*, vol. 212, pp. 1589–1600, 2018, doi: 10.1016/j.apenergy.2018.01.010.

[22] P. Leijen, D. A. Steyn-Ross, and N. Kularatna, "Use of Effective Capacitance Variation as a Measure of State-of-Health in a Series-Connected Automotive Battery Pack," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 3, pp. 1961–1968, 2018, doi: 10.1109/TVT.2017.2733002.

[23] G. Dong, Z. Chen, J. Wei, and Q. Ling, "Battery health prognosis using brownian motion modeling and particle filtering," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 11, pp. 8646–8655, 2018, doi: 10.1109/TIE.2018.2813964.

[24] Y. Li *et al.*, "Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review," *Renewable and Sustainable Energy Reviews*, vol. 113, 2019, doi: 10.1016/j.rser.2019.109254.

[25] R. R. Richardson, M. A. Osborne, and D. A. Howey, "Battery health prediction under generalized conditions using a Gaussian process transition model," *Journal of Energy Storage*, vol. 23, pp. 320–328, 2019, doi: 10.1016/j.est.2019.03.022.

[26] K. Omiloli, A. Awelewa, I. Samuel, O. Obiazi, and J. Katende, "State of charge estimation based on a modified extended Kalman filter," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 5, pp. 5054–5065, 2023, doi: 10.11591/ijece.v13i5.pp5054-5065.

[27] Y. Boujoudar *et al.*, "Fuzzy logic-based controller of the bidirectional direct current to direct current converter in microgrid," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 5, pp. 4789–4797, 2023, doi: 10.11591/ijece.v13i5.pp4789-4797.

[28] N. K. Trung and N. T. Diep, "Online parameter identification for equivalent circuit model of lithium-ion battery," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 31, no. 1, pp. 151–159, 2023, doi: 10.11591/ijeecs.v31.i1.pp151-159.

[29] I. Boumedra, A. Diani, K. El Khadiri, A. Tahiri, M. O. Jamil, and H. Qjidaa, "High efficiency multi power source control constant current/constant voltage charger lithium-ion battery based on the buck converter," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 1, pp. 207–217, 2023, doi: 10.11591/ijece.v13i1.pp207-217.

[30] Z. E. Dallalbashi, S. Alhayalir, M. J. Mnati, and A. A. A. Alhayali, "Low-cost battery monitoring circuit for a photovoltaic system based on LoRa/LoRaWAN network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 2, pp. 669–677, 2023, doi: 10.11591/ijeecs.v29.i2.pp669-677.

[31] C. O. Omeje and C. U. Eya, "A comparative braking scheme in auto-electric drive systems with permanent magnet synchronous machine," *International Journal of Applied Power Engineering*, vol. 11, no. 4, pp. 251–263, 2022, doi: 10.11591/ijape.v11.i4.pp251-263.

[32] R. Ranom, R. S. Bacho, and S. N. A. S. A. Jamal, "The effect of electrolyte parameter variation upon the performance of lithium iron phosphate (LiFePO4)," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 28, no. 1, pp. 58–66, 2022, doi: 10.11591/ijeecs.v28.i1.pp58-66.

[33] H. Arshada, S. A. Zulkiflia, and M. H. Khan, "Adaptive filter algorithms for state of charge estimation methods: A comprehensive review," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 26, no. 3, pp. 1360–1367, 2022, doi: 10.11591/ijeecs.v26.i3.pp1360-1367.

[34] I. Chaoufi, O. Abdelkhalek, and B. Gasbaoui, "State of charge estimation of lithium-ion batteries using adaptive neuro fuzzy inference system," *IAES International Journal of Artificial Intelligence*, vol. 11, no. 2, pp. 473–484, 2022, doi: 10.11591/ijai.v11.i2.pp473-484.

[35] C. N. Van and T. N. Vinh, "State of charge estimation for lithium-ion batteries connected in series using two sigma point Kalman filters," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 2, pp. 1334–1349, 2022, doi: 10.11591/ijece.v12i2.pp1334-1349.

[36] K. Yamaguchi and K. Iida, "Auto tuning of frequency on wireless power transfer for an electric vehicle," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 2, pp. 1147–1152, 2022, doi: 10.11591/ijece.v12i2.pp1147-1152.

[37] M. Lagraoui, A. Nejmi, H. Rayhane, and A. Taouni, "Estimation of lithium-ion battery state-of-charge using an extended kalman filter," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 4, pp. 1759–1768, 2021, doi: 10.11591/eei.v10i4.3082.

[38] J. Khalfi, N. Boumaaz, A. Soulmani, and E. M. Laadissi, "An electric circuit model for a lithium-ion battery cell based on automotive drive cycles measurements," *International Journal of Electrical and Computer Engineering*, vol. 11, no. 4, pp. 2798–2810, 2021, doi: 10.11591/ijece.v11i4.pp2798-2810.

[39] M. A. Nazri *et al.*, "Fabrication and characterization of printed zinc batteries," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 3, pp. 1173–1182, 2021, doi: 10.11591/eei.v10i3.2858.

[40] M. Elmarghichi, M. Bouzi, and N. Ettalabi, "Online parameter estimation of a lithium-ion battery based on sunflower optimization algorithm," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 3, pp. 1505–1513, 2021, doi: 10.11591/eei.v10i3.2637.

[41] S. R. Salkuti, "Electrochemical batteries for smart grid applications," *International Journal of Electrical and Computer Engineering*, vol. 11, no. 3, pp. 1849–1856, 2021, doi: 10.11591/ijece.v11i3.pp1849-1856.

[42] A. M. Alsabari, M. K. Hassan, A. Cs, and R. Zafira, "Modeling and validation of lithium-ion battery with initial state of charge estimation," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 3, pp. 1317–1331, 2021, doi: 10.11591/ijeecs.v21.i3.pp1317-1331.

[43] B. V. Rajanna and M. K. Kumar, "Comparison of one and two time constant models for lithium ion battery," *International Journal of Electrical and Computer Engineering*, vol. 10, no. 1, pp. 670–680, 2020, doi: 10.11591/ijece.v10i1.pp670-680.

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