Proc. of Int. Conf. on Math.Adv. and Appl., 2(1) (2025), 108-112



Proceedings of
International Conference on
Mathematical Advances and Applications

ISBN 978-605-69387-8-8

SOC Estimation for Lithium-Ion Batteries Using ANN: Enhancing Battery Performance and Efficiency

Mehmet Akif KAÇAR[1], Zeynep ÖZTÜRKGİL[1], Abdülsamed ÇELİK[1], Musa TERKEŞ[1] and Alpaslan DEMİRCİ[1]

[1]*Department of Electrical Engineering, Faculty of Electrical and Electronics, Yıldız Technical University, İstanbul, Türkiye*

Article Info

Keywords: *State of Charge, Artificial Neural Networks, Coulomb Counting, Estimation, Oxford aging dataset.*
2010 AMS: *93A99, 68T07*
Received:17.06.2025
Accepted:20.10.2025
Available online:22.10.2025

Abstract

Accurate estimation of the state of charge (SoC) is critical for optimizing the performance, safety, and lifespan of lithium-ion batteries, which are widely used in electric vehicles (EVs) and portable electronic devices. The development of reliable models for SoC estimation is essential for enhancing the efficiency of battery management systems. In this study, an artificial neural network (ANN)-based model has been developed using SoC data obtained from analytical methods as labels for estimating the SoC in lithium-ion batteries. The model uses voltage (V) and charge (q) data from battery cells as input, and its accuracy is evaluated using performance metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE). The results show that the model provides high accuracy in SoC estimation and offers an effective solution to issues such as charge-discharge imbalances. During the training process, continuous improvement in MSE values has been observed due to adaptive learning mechanisms that enhance the model's accuracy. In the future, the integration of heuristic optimization techniques and further development using diverse datasets under different environmental conditions are planned to improve the model's accuracy.

1. Introduction

1.1. Literature Review

With the rapid advancement of technology and population growth, environmental pollution has led to a significant shift from fossil fuel-powered vehicles to electric vehicles (EVs) [1, 2]. As EVs become more widespread, the importance of the batteries that supply energy to them increases. Consequently, improvements in battery lifespan and efficiency are essential [3]. Despite high installation costs, lithium-ion batteries are preferred for EVs due to their superior efficiency compared to other battery types [4]. Batteries are subject to aging, performance degradation, and risks like combustion and explosion. To ensure their safe operation, they must be used within defined "safe operating ranges", managed through Battery Management Systems (BMS) [5, 6]. In BMSs, accurate state of charge (SoC) estimation is critical for system efficiency. Accurate SoC information plays a vital role in optimizing battery lifespan, safety, and performance [7]. Battery cells are not identical due to factors like internal resistance, leading to imbalances and different voltage levels [8]. BMSs use active or passive balancing methods to address these issues [9]. Passive balancing discharges cells with excess energy, while active balancing transfers energy from higher-energy cells to lower-energy ones [1, 10]. SoC estimation is crucial for controlling this balance. Due to the complexity of lithium-ion batteries' chemical energy storage, SoC estimation is a challenging process [11]. A variety of methods, including analytical approaches, heuristic techniques, and ANNs, have been proposed for SoC estimation, with ongoing research aimed at enhancing their accuracy, reliability, and practical applicability [12, 13].

Email addresses and ORCID numbers: akif.kacar@std.yildiz.edu.tr, 0000-0001-8720-7642 (A. Kaçar), zeynep.ozturkgil@std.yildiz.edu.tr, 0000-0003-0169-8765 (Z.Öztürkgil), abdülsamed.celik@std.yildiz.edu.tr, 0009-0001-0831-486X (A.Çelik) musa.terkes@yildiz.edu.tr, 0000-0002-4411-411X (M.Terkes), ademirci@yildiz.edu.tr, 0000-0002-1038-7224 (A.Demirci),
Cite as: A. Kacar, Z. Öztürkgil, A. Çelik, M.Terkes, A.Demirci *SOC Estimation for Lithium-Ion Batteries Using ANN: Enhancing Battery Performance and Efficiency*, Proc. of 7Int. Conf. on Math. Adv. and Appl., 2(1) (2025), 108-112.

1.2. Motivation and Contributions

The rising number of EV fleets and the demand for energy-efficient technologies have highlighted the crucial role of the BMS, particularly lithium-ion batteries, in ensuring the performance and safety of these vehicles. Accurate estimation of the SoC is fundamental for managing battery health, enhancing lifespan, and preventing potential safety hazards such as overcharging or discharging. However, the complexity of battery behavior and the limitations of conventional methods, such as voltage-based and current-based approaches, make accurate SoC estimation a challenging task. ANN have emerged as a promising solution due to their ability to model nonlinear relationships and handle the complexities of battery dynamics, thus offering a more reliable and efficient approach for SoC estimation. This study addresses the challenges in SoC estimation by developing an ANN-based model that utilizes voltage (V) and charge (Q) data from lithium-ion batteries to predict SoC. The model's performance is evaluated using well-established metrics, including MAE and MSE, to assess its accuracy and reliability. Using the Oxford Battery Degradation Dataset and adaptive learning mechanisms, the proposed model shows steady improvements in estimation accuracy, making it a reliable solution for battery management systems. The primary contribution of this work lies in its development of a high-precision ANN model capable of addressing critical issues such as charge-discharge imbalance, and its potential for future optimization through heuristic algorithms and integration with diverse datasets to further enhance its applicability in real-world scenarios.

2. Methodology

2.1. Explanation of the Oxford Battery Degradation Dataset

2.1.1. Battery Model

In this study, Kokam SLPB533459H4 lithium-ion pouch cells with a capacity of 740 mAh were used to investigate battery performance and aging [14]. Kokam is a well-known manufacturer of lithium-ion cells, and these cells are commonly used in energy storage systems due to their high efficiency. The performance of lithium-ion batteries is influenced by environmental conditions, charge/discharge cycles, and the chemical reactions occurring over time. Understanding the aging behavior of these batteries is crucial for improving battery management systems (BMS). The tested cells were subjected to 1-C (740 mA) charge/discharge profiles and pseudo-OCV (Open-Circuit Voltage) cycles at lower current levels. The tests were conducted in a thermal chamber at 40°C [14]. The primary objective of this work is to understand the aging process of the cells over time and use this information to improve battery management practices.

2.1.2. Data Acquisition

The data were obtained through long-term cycling tests of the cells conducted at Oxford University by the Howey Research Group. The batteries were tested using the Bio-Logic MPG-205 multi-channel battery testing system, which allows parallel data collection from up to 8 cells. The tests included both 1-C and pseudo-OCV charge/discharge cycles. The charge profile was applied using a constant current-constant voltage (CC-CV) method, and a discharge cycle based on the Urban Artemis driving profile was performed after each charge cycle. These tests were conducted to simulate typical urban driving conditions [14]. During each cycle, time (t, in seconds), voltage (v, in Volts), charge (q, in mAh), and temperature (T, in degrees Celsius) data were recorded. The 1-C charge/discharge cycle represents a full charge and discharge of the battery at its nominal capacity, while the pseudo-OCV cycle involved discharging at a lower current (40 mA) to measure the open-circuit voltage [14]. The data obtained from the tests were recorded every 100 cycles to monitor the battery's performance and degradation over time.

2.1.3. Data Preprocessing

Data preprocessing is a crucial step for ensuring accurate modeling and analysis. The data, stored in MATLAB binary (.mat) files, were cleaned by removing missing or inconsistent values and ensuring proper formatting. These preprocessed data were then used for modeling and analysis, including regression models and machine learning algorithms, to predict battery aging and optimize its management. Data quality and cleanliness are essential for reliable results.

2.2. Obtain Target Variable for the Proposed ANN Model

The y label or target variable (SoC) for the proposed ANN model was obtained using the Coulomb counting based analytical methods: current-based, voltage-based, and hybrid methods. This approach focused on a supervised learning model that would learn from the label. The voltage-based method relies on modeling and analyzing the relationship between open-circuit voltage (OCV) and SoC [15]. However, to accurately measure the OCV, the battery must be rested for a certain period. This introduces potential errors in OCV measurements, especially during real-time assessments, limiting the practical efficiency of the voltage-based method due to OCV-SoC modeling errors and measurement uncertainties [16]. On the other hand, the Coulomb counting method, which accumulates the currents entering and leaving the battery over time, is commonly used for SoC estimation [17]. In this study, analytical regression methods, such as Coulomb counting, were utilized to derive the SoC values for the proposed ANN model. The first stage is as shown in 2.1.

$$\mathrm{SoC}(t) = \mathrm{SoC}(t_0) + \frac{Q_t}{C_n} \tag{2.1}$$

In 2.1, represents the initial $SoC(t_0)$ of the battery, C_n is the nominal capacity, and Q_t is the total amount of charge flowing in the battery-load interaction. Q_t is the integral of the battery's charge/discharge current over the operating period. In this case, the state of charge is expressed as in 2.2 [18].

$$\mathrm{SoC}(t) = \mathrm{SoC}(t_0) + \frac{1}{C_n}\int_0^t I(t)\,dt \tag{2.2}$$

The battery's capacity is affected by temperature. If the nominal capacity at the reference temperature T_0 is C_n, the nominal capacity expression can be written as given in 2.3, depending on the temperature change and the temperature coefficient. Additionally, since Q_t data is already available in the Oxford dataset, the SoC is represented as shown in 2.3.

$$\mathrm{SoC}(t) = \mathrm{SoC}(t_0) + \frac{Q_t}{C_n(1+\alpha(T-T_0))} \tag{2.3}$$

Here, represents the current temperature of the battery (°C), and a is the temperature coefficient. The SoC values, which serve as the output of the ANN model created using the Oxford dataset, are calculated using 2.3. The temperature coefficient a is assumed to be 0.005. However, the accuracy of this method is directly dependent on the initial SoC value and measurement errors. In the literature, the Coulomb counting method is highlighted as an important reference point for verifying the accuracy of SoC estimations obtained from other methods [16, 19].

2.3. Proposed ANN Model

One of the frequently used ML-based methods for SoC estimations is ANNs [20]. ANNs are computational models inspired by the biological mechanisms of the human brain, consisting of processing units called neurons and weighted connections between these units. These weighted connections form the fundamental structure of the network. After completing the neuronal structure, the system becomes functional through recall and training algorithms [21]. ANNs consist of three main layers: the input layer, the output layer, and the hidden layer. The input layer receives data and signals from the external environment, the output layer generates the final output, and the hidden layer, which is located between the input and output layers, supports the system's information processing capabilities by representing the strength of connections between neurons [22]. This method relies on training an ANN model to understand nonlinear relationships and complex battery behaviors using data such as current, voltage, and temperature for SoC estimation [23]. Studies have highlighted that ANN-based models offer lower error rates due to their ability to model nonlinear battery behaviors, making them more reliable for SoC estimation compared to analytical methods [24, 25]. However, the accuracy of ANN-based methods depends on the size and quality of the dataset. Using large datasets to achieve high accuracy can significantly extend training times. Furthermore, ANN models may get stuck in local minima during training, leading to incorrect predictions [26]. To overcome these challenges, heuristic algorithms, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), are increasingly being used to optimize hyperparameters, improve accuracy, and accelerate training processes. These methods allow the model to better learn nonlinear relationships and adapt to the dataset [27]. Optimization algorithms are particularly effective in determining hyperparameters such as learning rate, number of hidden layers, and number of neurons, aiming to achieve maximum accuracy in ANN models. Recent studies have shown that PSO-optimized ANN models offer up to a 20% lower error rate compared to traditional methods [25]. The designed ANN consists of two hidden layers with 64 and 32 neurons, respectively. The model uses voltage (V) and charge (Q) data from the "Oxford Battery Degradation" dataset [14] as input. The output of the model is the SoC values, calculated using 2.3. The Levenberg-Marquardt algorithm was used to optimize the cost functions during the training process.

2.4. Model Verification and Performance Metrics

The model's performance was evaluated using two metrics: Mean Squared Error (MSE) and Mean Absolute Error (MAE). MAE measures the average absolute differences between predicted and observed values, indicating how far predictions deviate from actual results. A lower MAE reflects better accuracy, especially when there are no large errors, providing a clear measure of the model's average error. MSE calculates the average of the squared differences between predicted and actual values. By amplifying the effect of larger errors, it allows for a more detailed evaluation of the model's accuracy. MSE penalizes large deviations more heavily, helping the model minimize larger errors effectively. A lower MSE indicates that the model's predictions are closer to the true values and better at reducing significant errors. In conclusion, the equations for MAE and MSE are given as in 2.4 and 2.5.

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2.4}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2.5}$$

The ANN model was developed by utilizing the initial cycles of all cells in the dataset, with the model using voltage (V) and charge (Q) data as inputs for SoC estimation. The results for the model's outputs are presented in Table 1. Additionally, Fig.2.1 shows the estimated and actual SoC values on the same graph. Fig.2.2 shows the variation of the MSE metric during the model's training process. The training results of the ANN model are summarized in terms of the MAE and MSE for each individual cell. The MAE values across the cells range from 0.000017845 to 0.00014742, which indicates a close alignment between the estimated and actual values. Lower MAE values suggest a higher degree of accuracy in the model's estimations. The MSE values, which are slightly higher than the corresponding MAE values, range from 0.000001957 to 0.00090276. Since the MSE penalizes larger errors more heavily, it reflects the model's sensitivity to any significant deviations in predictions. In general, the model performs consistently well across all cells, with most MSE values being relatively low, suggesting the model's effectiveness in accurately predicting the SoC. Cell 1 shows the highest MSE value, which indicates some level of discrepancy between estimated and actual SoC values, but still within an acceptable range. On the other hand, Cell 8 exhibits the lowest MSE, reflecting excellent estimative accuracy. The ANN model shows promising performance in SoC estimation with minimal errors, validating its potential for battery management.

Table 1: MODEL PERFORMANCE RESULTS

Cell	MAE	MSE
1	0.0000228	0.00090276
2	0.00014742	0.00001373
3	0.00011283	0.00027723
4	0.000032558	0.000020781
5	0.000019419	0.0007085
6	0.000042164	0.0000056581
7	0.000017845	0.00059533
8	0.000028869	0.000001957

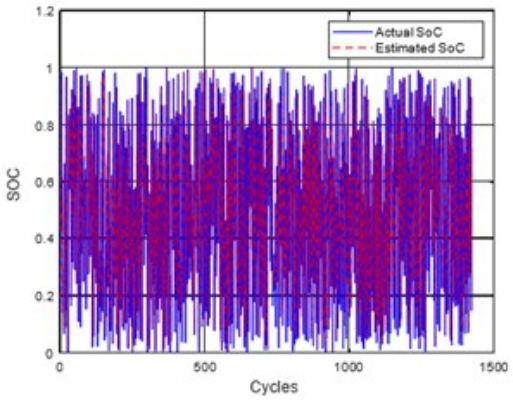


Figure 2.1: Estimated and actual SoC for the Cell 1

As shown in Fig. 2.1, even Cell 1, with the worst SoC estimation performance, demonstrates high accuracy between actual and estimated SoC values. The analysis used the Oxford dataset and Coulomb counting SoC values, divided into 60% training, 20% validation, and 20% testing. The results highlight that high accuracy can be achieved with simple, cost-effective techniques. As shown in Fig. 2.2, the training performance rapidly converges after 100 epochs, with steady improvements in accuracy, typical of adaptive learning algorithms. This indicates that the model successfully learns nonlinear system behaviors and was trained with appropriate optimization. The training performance improvement confirms the model's potential for high-accuracy SoC estimations in BMS.

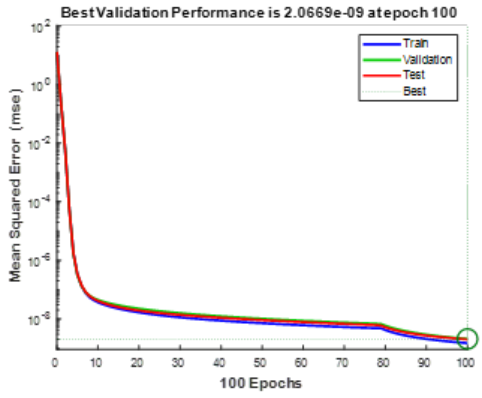


Figure 2.2: Model performance over 100 epochs

3. Conclusion

This study presents an ANN-based model for estimating the SoC of lithium-ion batteries, demonstrating its potential to enhance BMS performance. The model uses voltage and charge data as inputs, with Coulomb counting providing SoC labels for training. The results show accurate SoC estimations with low MAE and MSE values across various battery cells, addressing charge-discharge imbalances and improving battery health monitoring. Adaptive learning with the Levenberg-Marquardt algorithm further improves accuracy, as seen in the steady reduction of MSE during training. Further optimization with heuristic algorithms like GA or PSO could enhance performance, and the model's generalizability could be improved by testing with diverse datasets under different conditions. Future work will explore optimization, hybrid ML approaches, and real-world datasets to enhance the model's robustness, supporting better battery management in EVs and portable devices.

Article Information

Acknowledgements: The authors would like to express their sincere thanks to the editor and the anonymous reviewers for their helpful comments and suggestions.

Author's Contributions: All authors contributed equally to the writing of this paper. All authors read and approved the final manuscript. (or The article has a single author. The author has read and approved the final manuscript.)

Conflict of Interest Disclosure: No potential conflict of interest was declared by the author.

Copyright Statement: Authors own the copyright of their work published in the journal and their work is published under the CC BY-NC 4.0 license.

Supporting/Supporting Organizations: Supporting Organizations: This research was funded by the TÜBİTAK 2209-A Research Project Support Program for Undergraduate Students (Project No: 1919B012414887). No additional financial support was received from any public, private, or non-profit institutions.

Ethical Approval and Participant Consent: It is declared that during the preparation process of this study, scientific and ethical principles were followed and all the studies benefited from are stated in the bibliography.

Plagiarism Statement: This article was scanned by the plagiarism program. No plagiarism detected.

Availability of Data and Materials: Not applicable.

References

[1] R. Inan, M. Güçkıran, Y. E. Altınışık, S. Tek, and M. Potuk, "The real-time implementation of a battery management system designed with an improved passive balancing method for electric vehicles," The Journal of the Faculty of Engineering and Architecture, Gazi University, vol. 38, no. 3, pp. 1757–1768, Jan. 2023, doi: 10.17341/gazimmfd.938914.

[2] S. Paltacı, S. Yalçın, and A. Genç, "Design and implementation of a relay-switching battery management system for electric vehicles," Int. J. 3D Print. Technol. Digit. Ind., vol. 7, no. 2, pp. 243–251, 2023, doi: 10.46519/ij3dptdi.1324753.

[3] T. Aykut, S. Çetin, A. Mandacı, and S. Güner, "Design of a battery management system with active balancing topology," Mediterranean Journal of Engineering, vol. 2, no. 1, pp. 35–48, 2024.

[4] M. Yılmaz, E. Çınar, and A. Yazıcı, "A literature review on autonomous battery management systems in electric vehicles," EMO Science Journal, vol. 14, no. 2, pp. 7–22, 2024.

[5] M. A. Özcan, "Design of a battery managament system for electric forklift," Istanbul Okan University Graduate School, 2023. [Online]. Available: https://tez.yok.gov.tr/UlusalTezMerkezi/tezSorguSonucYeni.jsp

[6] A. F. Challoob, N. A. Bin Rahmat, V. K. A. Ramachandaramurthy, and A. J. Humaidi, "Energy and battery management systems for electrical vehicles: A comprehensive review & recommendations," Energy Explor. & Exploit., vol. 42, no. 1, pp. 341–372, 2024, doi: 10.1177/01445987231211943.

[7] O. Demirci, S. Taskin, E. Schaltz, and B. Acar Demirci, "Review of battery state estimation methods for electric vehicles - Part I: SOC estimation," J. Energy Storage, vol. 87, p. 111435, 2024, doi: https://doi.org/10.1016/j.est.2024.111435.

[8] R. Menak, T. Karadağ, M. Altuğ, and N. Tan, "A review study on battery management systems in electric vehicles," Gazi Univ. J. Sci. Part A Eng. Innov., vol. 8, no. 2, pp. 234–275, 2021.

[9] T. Duraisamy and D. Kaliyaperumal, "Machine Learning-Based Optimal Cell Balancing Mechanism for Electric Vehicle Battery Management System," IEEE Access, vol. 9, pp. 132846–132861, 2021, doi: 10.1109/ACCESS.2021.3115255.

[10] H. Kaymaz and Y. Hançar, "Cell balancing methods for battery management systems in electric vehicles," Journal of Intelligent Transportation Systems and Applications, vol. 4, no. 1, pp. 59–73, 2021, doi: 10.51513/jitsa.897126.

[11] M. Danko, J. Adamec, M. Taraba, and P. Drgona, "Overview of batteries State of Charge estimation methods," Transp. Res. Procedia, vol. 40, pp. 186–192, 2019, doi: https://doi.org/10.1016/j.trpro.2019.07.029.

[12] X. Tang, B. Liu, and F. Gao, "State of Charge Estimation of LiFePO4 Battery Based on a Gain-classifier Observer," Energy Procedia, vol. 105, pp. 2071–2076, 2017, doi: https://doi.org/10.1016/j.egypro.2017.03.585.

[13] C. Fleischer, W. Waag, Z. Bai, and D. U. Sauer, "Adaptive On-line State-of-available-power Prediction of Lithium-ion Batteries," J. Power Electron., vol. 13, no. 4, pp. 516–527, Jul. 2013, doi: 10.6113/JPE.2013.13.4.516.

[14] C. Birkl, "Oxford Battery Degradation Dataset 1." University of Oxford, 2017.

[15] K. Movassagh, A. Raihan, B. Balasingam, and K. Pattipati, "A Critical Look at Coulomb Counting Approach for State of Charge Estimation in Batteries," Energies, vol. 14, no. 14, 2021, doi: 10.3390/en14144074.

[16] B. Balasingam, M. Ahmed, and K. Pattipati, "Battery Management Systems—Challenges and Some Solutions," Energies, vol. 13, no. 11, 2020, doi: 10.3390/en13112825.

[17] G. Fathoni, S. A. Widayat, P. A. Topan, A. Jalil, A. I. Cahyadi, and O. Wahyunggoro, "Comparison of State-of-Charge (SOC) estimation performance based on three popular methods: Coulomb counting, open circuit voltage, and Kalman filter," in 2017 2nd International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT), 2017, pp. 70–74. doi: 10.1109/ICACOMIT.2017.8253389.

[18] K. S. Ng, C.-S. Moo, Y.-P. Chen, and Y.-C. Hsieh, "Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries," Appl. Energy, vol. 86, no. 9, pp. 1506–1511, 2009, doi: https://doi.org/10.1016/j.apenergy.2008.11.021.

[19] K.-S. Ng, Y.-F. Huang, C.-S. Moo, and Y.-C. Hsieh, "An enhanced coulomb counting method for estimating state-of-charge and state-of-health of lead-acid batteries," in INTELEC 2009 - 31st International Telecommunications Energy Conference, 2009, pp. 1–5. doi: 10.1109/INTLEC.2009.5351796.

[20] M. Kurucan, M. Özbaltan, Z. Yetgin, and A. Alkaya, "Applications of artificial neural network based battery management systems: A literature review," Renew. Sustain. Energy Rev., vol. 192, p. 114262, 2024, doi: https://doi.org/10.1016/j.rser.2023.114262.

[21] S. Shanmuganathan, "Artificial Neural Network Modelling: An Introduction," in Artificial Neural Network Modelling, S. Shanmuganathan and S. Samarasinghe, Eds., Cham: Springer International Publishing, 2016, pp. 1–14. doi: 10.1007/978-3-319-28495-8_1.

[22] Y. Wu and J. Feng, "Development and Application of Artificial Neural Network," Wirel. Pers. Commun., vol. 102, no. 2, pp. 1645–1656, 2018, doi: 10.1007/s11277-017-5224-x.

[23] S. El Fallah, J. Kharbach, Z. Hammouch, A. Rezzouk, and M. Ouazzani Jamil, "State of charge estimation of an electric vehicle's battery using Deep Neural Networks: Simulation and experimental results," J. Energy Storage, vol. 62, p. 106904, 2023, doi: https://doi.org/10.1016/j.est.2023.106904.

[24] A. Manoharan, D. Sooriamoorthy, K. M. Begam, and V. R. Aparow, "Electric vehicle battery pack state of charge estimation using parallel artificial neural networks," J. Energy Storage, vol. 72, p. 108333, 2023, doi: https://doi.org/10.1016/j.est.2023.108333.

[25] M. H. Zafar et al., "Hybrid deep learning model for efficient state of charge estimation of Li-ion batteries in electric vehicles," Energy, vol. 282, p. 128317, 2023, doi: https://doi.org/10.1016/j.energy.2023.128317.

[26] A. Manoharan, K. M. Begam, D. Sooriamoorthy, and V. R. Aparow, "Study on Artificial Neural Network Optimization for Electric Vehicle Battery State of Charge estimation," in 2023 9th International Conference on Computer and Communication Engineering (ICCCE), 2023, pp. 334–339. doi: 10.1109/ICCCE58854.2023.10246092.

[27] M. H. R. Miranda, F. L. Silva, M. A. M. Lourenço, J. J. Eckert, and L. C. A. Silva, "Particle swarm optimization of Elman neural network applied to battery state of charge and state of health estimation," Energy, vol. 285, p. 129503, 2023, doi: https://doi.org/10.1016/j.energy.2023.129503.