Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 10, No. 4, November, Pp. 547-560

The application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) method in Estimating State of Charge (SOC) and State of Health (SOH) of lithium-ion batteries

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Article Info
Keywords:
Adaptive Neuro Fuzzy Inference System (ANFIS), Lithium Ion Battery, State of Charge (SOC), State of Health (SOH)

Article history:
Received: June 11, 2025
Accepted: September 12, 2025
Published: November 01, 2025

Cite:
S. Muslimin, E. Prihatini, N. L. Husni, and W. Caesandra, "The Application of the Adaptive Neuro Fuzzy Inference System (ANFIS) Method in Estimating State of Charge (SOC) and State of Health (SOH) of Lithium-Ion Batteries", *KINETIK*, vol. 10, no. 4, Nov. 2025.
https://doi.org/10.22219/kinetik.v10i4.2357

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Abstract
The increasing reliance on lithium-ion batteries (LIBs) for electric vehicles and portable electronics demands accurate monitoring of battery performance, particularly the State of Charge (SOC) and State of Health (SOH). Conventional estimation methods—such as Coulomb counting, Kalman filtering, and equivalent circuit modeling—face challenges under dynamic conditions due to drift and limited adaptability. Recent studies have explored machine learning and neuro-fuzzy approaches to enhance prediction accuracy, yet many lack integration of real-time hybrid learning or struggle with high estimation error in noisy data environments. This research aims to apply the Adaptive Neuro-Fuzzy Inference System (ANFIS) to estimate SOC and SOH using experimental data from a 48V lithium-ion battery. The novelty lies in combining voltage, current, and capacity data within a MATLAB-based ANFIS framework that employs a hybrid learning algorithm integrating backpropagation and Recursive Least Squares Estimation (RLSE). Training data for SOC estimation used charging voltage and current, while SOH estimation incorporated discharging data and capacity. Results show that ANFIS achieved high accuracy with RMSE of 0.1466 and MAE of 0.021 for SOC, and RMSE of 0.012 and MAE of 0.0017 for SOH. The estimated SOH was 33.61%, closely aligned with actual values. These findings confirm ANFIS as a robust and adaptive method for real-time battery diagnostics. Future work will explore multi-input hybrid models, the integration of IoT-based BMS telemetry, and testing across diverse battery chemistries to generalize the model's performance and extend its application in smart energy systems.

1. Introduction

The rapid economic development and the global shift toward electrification in transportation and renewable energy integration have led to the widespread adoption of lithium-ion batteries (LIBs) across various applications, ranging from portable electronic devices to electric vehicles [1], [2], [3]. LIBs are favored for their high energy density, long cycle life, low self-discharge rate, and environmental friendliness. However, to ensure optimal performance and safety, these systems depend heavily on a Battery Management System (BMS) [4]. The BMS plays a vital role in maintaining battery integrity by monitoring operational parameters, preventing overcharge/discharge, and estimating critical internal states such as the State of Charge (SOC) and State of Health (SOH) [5].

Despite its importance, the BMS continues to face challenges in accurately estimating SOC and SOH, especially under varying load and environmental conditions [6], [7]. SOC indicates the remaining usable capacity of a battery, whereas SOH reflects the long-term capability of the battery to store and deliver energy, serving as an indicator of aging and degradation [5]. A high SOH ensures reliable battery operation, while a declining SOH suggests reduced performance and shortened lifespan [8], [9]. Given the increasing use of embedded and non-removable batteries in modern systems, there is an urgent need for real-time, non-invasive, and intelligent estimation methods that can dynamically track battery conditions without physical intervention [10], [11].

A wide range of methods has been explored for SOC and SOH estimation, including Coulomb counting [12], Kalman filtering [13], electrochemical modeling [7], Ant Colony Optimization, and equivalent circuit models [6]. Although effective in ideal scenarios, these techniques often suffer from drift, parameter sensitivity, and limitations in adapting to diverse operational profiles [8], [14], [15]. In response, soft computing approaches—particularly Artificial Neural Networks (ANN) [10], [16], [17], [18], Fuzzy Logic (FL) [5], [19], and the Adaptive Neuro-Fuzzy Inference System (ANFIS)—have emerged as viable alternatives for their superior learning, generalization, and nonlinear mapping capabilities [19], [20], [21].

ANFIS uniquely combines the human-like reasoning ability of fuzzy inference systems with the adaptive learning strengths of neural networks [6], [21]. The fuzzy system component enables intuitive knowledge representation using

IF-THEN rules, while the neural network component performs optimization and adaptation [22]. ANFIS has been shown to be highly effective in handling system nonlinearity, uncertainty, and noisy input data—key characteristics of battery behavior under real-world usage [23], [24]. Studies demonstrate that while FL-based SOC estimation can achieve an average error of 2% [7], and ANN methods around 3% [8], ANFIS consistently outperforms with an error margin as low as 1.2% [17], making it a compelling solution for precision battery diagnostics.

Recent advancements further highlight the potential of hybrid ANFIS-based approaches, where it is combined with machine learning models or physics-informed estimators to enhance robustness and accuracy in SOC and SOH prediction [13], [25], [26], [27], [28]. For instance, Yu et al. [25] proposed a physics–machine learning fusion method that significantly outperformed standalone models in dynamic environments, while Demirci et al. [26] reviewed systematic SOC estimation frameworks tailored for electric vehicle applications. Other works have emphasized the incorporation of driving patterns, temperature effects, and battery degradation factors such as internal resistance and capacity fade into estimation frameworks [27], [28].

Nonetheless, significant research gaps remain. Many existing models lack generalizability across different battery chemistries, cannot reliably handle extreme degradation scenarios, or fail to incorporate real-time sensor feedback from modern BMS platforms [29], [30], [31]. The integration of ANFIS with streaming battery telemetry, edge AI, and IoT frameworks for SOH tracking is still underexplored [27], [28].

This study aims to develop, evaluate, and benchmark the application of ANFIS in estimating the SOC and SOH of lithium-ion batteries by utilizing empirical datasets and comparing the results with conventional approaches. ANFIS integrates fuzzy logic with neural network learning, enabling it to address the limitations of battery data and provide a flexible, adaptive, and accurate solution compared to traditional methods. To further demonstrate its effectiveness, the performance of ANFIS is directly compared with Ant Colony Optimization (ACO), an established optimization algorithm for complex problem-solving. This comparison highlights ANFIS's ability to combine intuitive learning and adaptive reasoning, thereby offering a more comprehensive framework for predictive diagnostics and failure analysis in intelligent battery management systems, with significant implications for electric vehicles.

2. Research Method

Figure 1 illustrates the flowchart of estimation using the ANFIS method. The estimation of SOC and SOH using the ANFIS method will be compared with the actual SOC and SOH values.

2.1 Training Data

The training data used in this research consisted of voltage, current, and actual SOC during battery charging for SOC estimation, while for SOH estimation, the training data included voltage, current, and actual capacity during battery discharging. The training data were used to train and test the ANFIS method in estimating SOC and SOH values.

2.2 Processing

The first process carried out after obtaining the actual data from the HMI is to input the data into Microsoft Excel, where voltage and current serve as input variables and actual SOC or actual capacity serves as output variables. Once the required data is ready, it can be directly input into the MATLAB application. The data processing flow is presented in Figure 2.

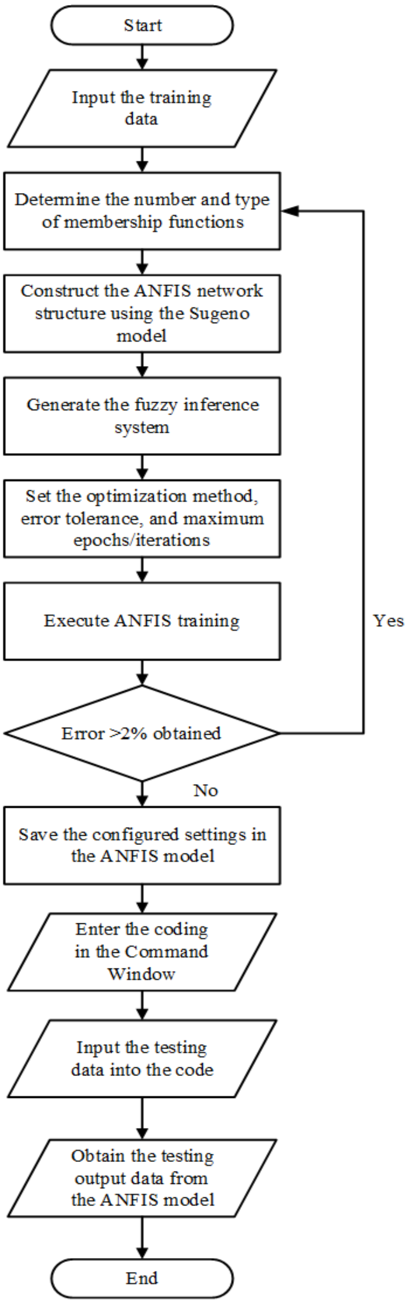

Figure 1. Flowchart ANFIS

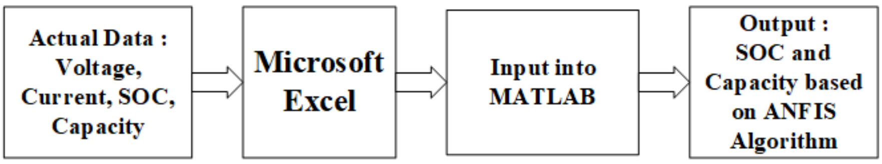

Figure. 2 Input Data Processing

This study used MATLAB toolbox ‘`anfisedit`’, which can be accessed by typing `anfisedit` in the Command Window. The prepared data were then loaded into the toolbox for ANFIS training after the toolbox is open. The next step involved determining the number of linguistic terms and selecting the type of membership function, using Generalized Bell (Gbell) with three linguistic terms for each input in the ANFIS training. Subsequently, the hybrid optimization method was selected, the error tolerance was set to 0, and the number of epochs was specified as 100 before clicking 'Train Now' to start the training process. After the training was completed, the settings were saved, and the process continued in the MATLAB Command Window for further coding

2.3 State of Charge (SOC)

State of Charge (SOC) is a parameter used to measure the percentage of remaining battery power [10]. Accurate SOC estimation is essential to ensure safety and optimize battery life [11]. SOC also provides real-time information about the battery's power status to the user [12], [13]. With this information, users can recharge the battery if the SOC is low or limit power usage if the SOC is high. These steps help avoid sudden power depletion and extend battery life. SOC can be calculated based on voltage information, such as actual voltage, maximum and minimum battery voltage based on the manufacturer's specifications. The SOC formula is expressed in Equation 1 [14]:

$$SOC = \frac{V_o - V_{min}}{V_{max} - V_{min}} \times 100\% \tag{1}$$

2.4 ANFIS Method Structure

In the first layer of the ANFIS structure, inputs are transformed into linguistic sets using membership functions, specifically the Generalized Bell (Gbell) function. In this case, each input has three linguistic sets: low, medium, and high. This means that the nodes in the first layer consist of six outputs, referred to as membership degrees. The second layer is the rule layer, where the inference system processes and determines the rules to be applied. For example, if the voltage is low and the current is low, then the SOC will also be low. This layer consists of nine rules. The third layer is the normalization layer, which ensures that the total output from the nine rules equals 1 or 100% by calculating the proportion or ratio of each rule's output to the total output of all rules. The fourth layer is the defuzzification layer, responsible for converting the fuzzy output into a crisp (concrete or precise) output. The fifth and final layer is the output layer, which sums up all the outputs from the previous layer, providing the final prediction for both SOC and SOH. The ANFIS structure used in this study is illustrated in Figure 3 and Figure 4.

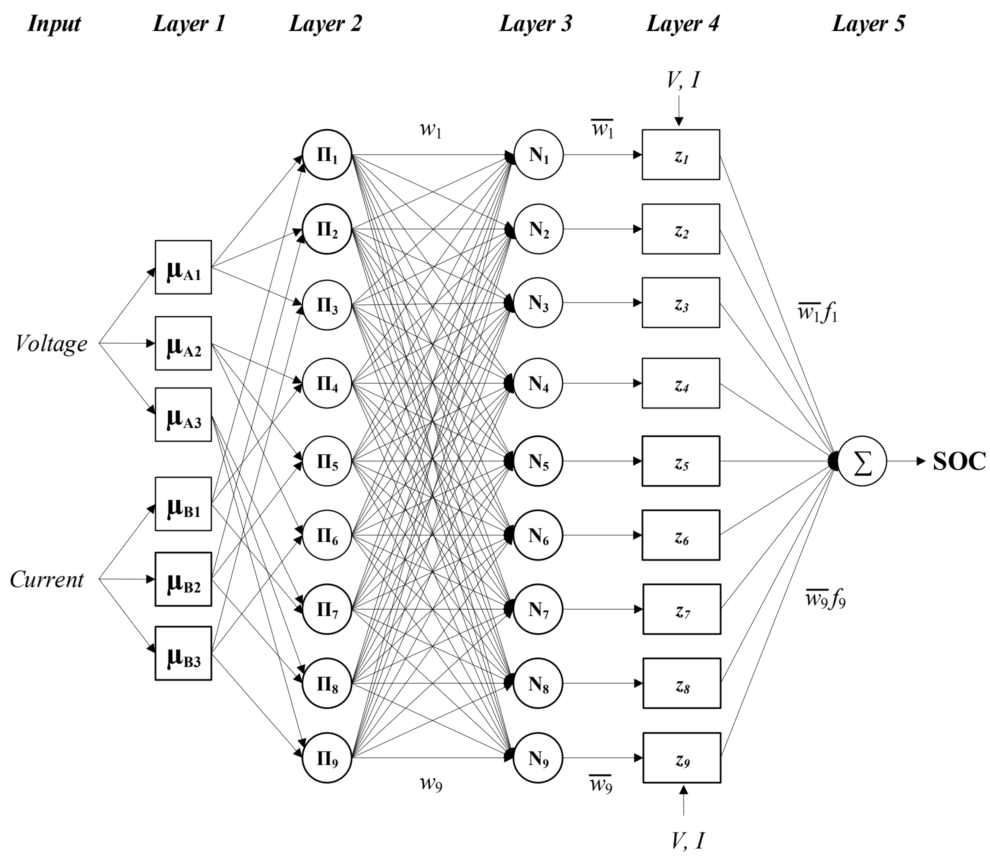

Figure 3. SOC ANFIS Structure

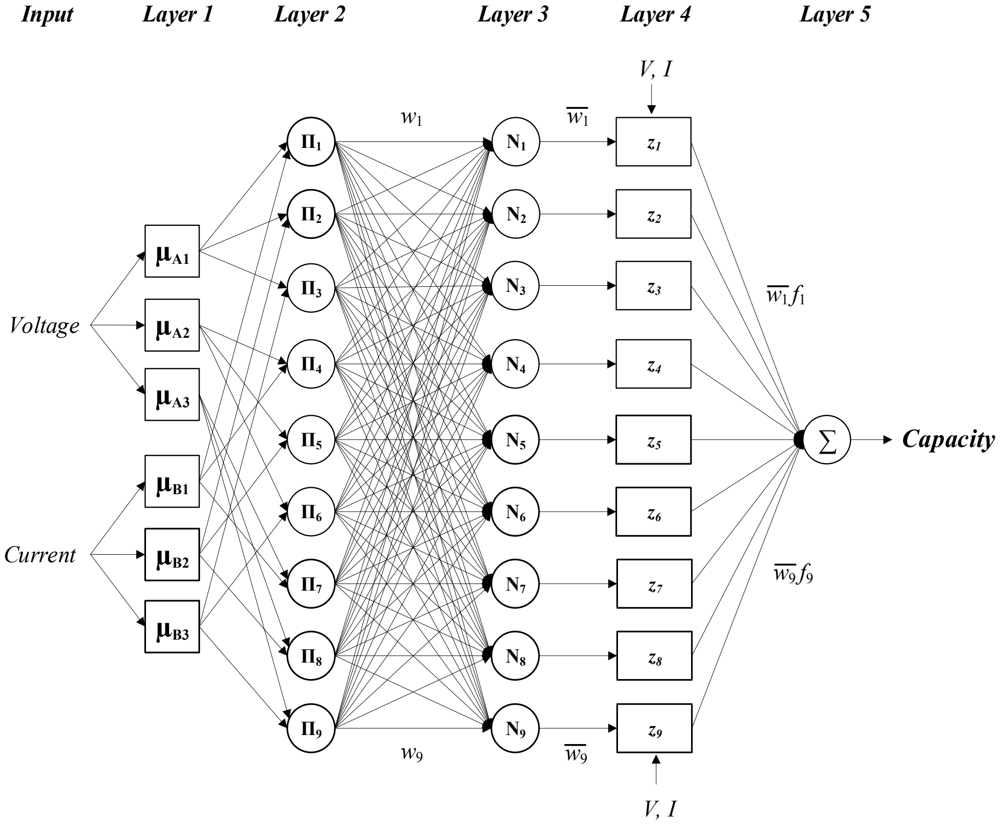

Figure 4. SOH ANFIS Structure

These figures depict the ANFIS structure used to estimate SOC and SOH, where both structures share the same layers and explanation, with two inputs consisting of voltage and current and nine rules. However, they differ in their outputs. The output of the ANFIS structure for SOC prediction is the SOC value, while the output of the ANFIS structure for SOH prediction is the capacity. Unlike SOC estimation, which uses charging data, SOH estimation uses discharging data. After determining the capacity, the SOH is calculated using the formula defined in Equation 2 [8]:

$$SOH = \frac{Q_{NOW}}{Q_{NEW}} \times 100\% \tag{2}$$

2.5 ANFIS Theorem

ANFIS is a system that combines fuzzy inference system concepts with neural network architecture [19]. The first-order Takagi-Sugeno-Kang (TSK) model is used in ANFIS due to its simplicity [20]. The neural network in ANFIS optimizes the fuzzy parameters in the fuzzy inference system [19]. In summary, ANFIS integrates fuzzy logic with artificial intelligence to make predictions or decisions based on data [21]. Below is the mechanism of the first-order TSK fuzzy inference with two inputs, x and y, and one output, f, along with the corresponding if-then fuzzy rule base [20], [21],

$$\text{Rule 1 : If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1$$
$$\text{Rule 2 : If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2$$

where A_1 and A_2 are the membership functions for input x, and B_1 and B_2 are the membership functions for input y (premise part), while p, q and r are the consequent parameters (consequent part), as shown in Figure 5 [20].

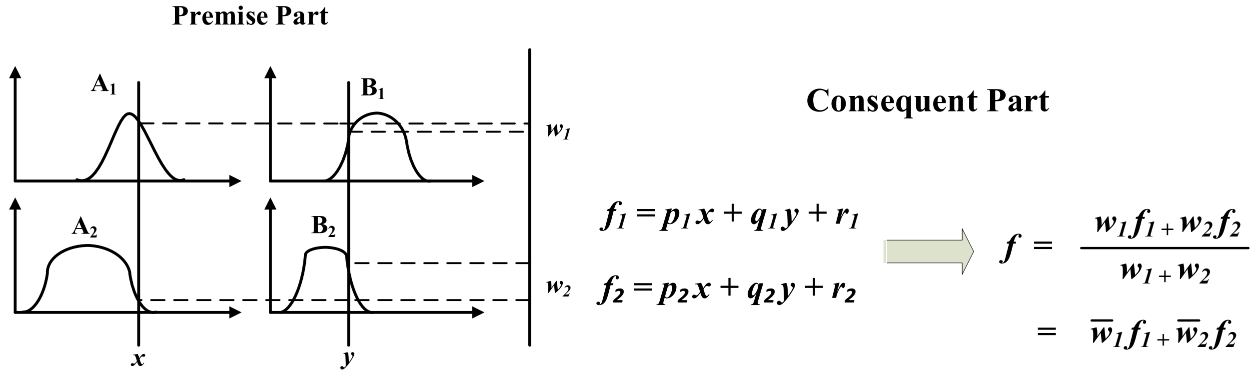

Figure 5. Fuzzy Inference System

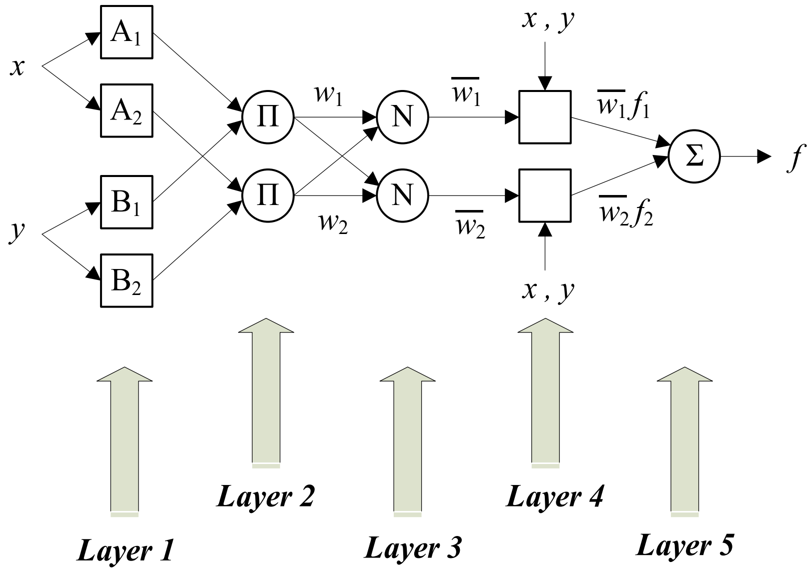

Figure 6. ANFIS Structure

ANFIS consists of five layers [22], as shown in Figure 6. The first and fourth layers contain adaptive nodes, while the other layers contain fixed nodes [6], [20], [21], [23].

A brief description of each layer is as follows:

Layer 1: Layer 1 is the fuzzification layer [24], which converts crisp numbers into fuzzy values using fuzzy sets. All nodes i in Layer 1 are adaptive nodes (parameters can change), with the node functions defined in Equations 3 and 4 [21], [23]:

$$O_{1,i} = \mu_{Ai}(x), \qquad i = 1,2 \tag{3}$$

$$O_{1,i} = \mu_{Bi-2}(y), \quad i = 3,4 \tag{4}$$

The membership function used is of the generalized bell (gbell) type, as expressed in Equation 5 [21], [23]:

$$\mu A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right| 2b_i} \tag{5}$$

Layer 2: Layer 2 is the rule layer [24], where all nodes in this layer are non-adaptive (parameters are fixed) and are labeled as "Prod." The function of these nodes is to multiply each incoming input. The node function is defined in Equation 6 [21], [23]:

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y) \quad i = 1,2 \tag{6}$$

Layer 3: Layer 3 or the normalization layer [24], consists of non-adaptive nodes labeled "Norm" and is responsible for computing the normalization before it is applied to Layer 4. The function of these nodes is to display the normalized firing strength, which is the ratio of the output of node i in the previous layer to the sum of all outputs in the previous layer, as defined in Equation 7 [21], [23].

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{7}$$

Layer 4: Layer 4 is the defuzzification layer [24]. It multiplies by functions involving the inputs (x and y) to produce output in crisp form. Each node in this layer is adaptive, with the node function defined in Equation 8 [21], [23]:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{8}$$

Layer 5: This layer contains a single fixed node labeled "Sum." The function of this layer is to sum the results from Layer 4. The node function is defined in Equation 9 [21], [23]:

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

2.6 Hybrid Learning Algorithm

The hybrid learning for the Adaptive Neuro Fuzzy Inference System (ANFIS) combines two learning methods: the forward pass and the backward pass.

In the forward pass, the premise parameters of ANFIS remain fixed, while the consequent parameters are adjusted using the Recursive Least Square Estimator (RLSE) based on the given input-output data. In other words, RLSE iteratively refines the consequent parameters to improve the model's accuracy in producing the desired output [21][25].

In the backward pass, the consequent parameters are kept constant, and the error between the adaptive network's output and the actual output is propagated back using gradient descent to adjust the premise parameters. This process, known as the backpropagation-error algorithm, involves each layer receiving error information from the previous layer and adjusting its premise parameters to improve overall prediction accuracy. One complete forward-backward learning cycle is called one epoch, as shown in Table 1 [21][25].

Table 1. Hybrid Learning Process of ANFIS

	Forward Pass	Backward Pass
Premise Parameters	Fixed	Gradient descent
Consequent Parameters	RLSE	Fixed
Signal	Node Output	Error Rate

2.7 Recursive Least Square Estimator (RSLE)

The RLSE method is used to incorporate data pairs into the calculation of matrix A, which is derived from signals received from the previous layer, along with the actual values of each input data and the corresponding output or target data (y)[25]. This allows RLSE to update parameters based on new incoming data, ensuring that the parameter outputs align with the available data. This process enables continuous parameter updates, thereby improving prediction capability and overall accuracy, as shown in Equation 10 [21][25]:

$$\theta = (A^T A)^{-1} A^T y \tag{10}$$

Explanation:

A	Data matrix
A^T	Transpose of matrix A
y	Desired output data
$(A^T A)^{-1}$	Multiplication of the inverse of matrix A and the inverse of the transpose of matrix A
$A^T y$	Multiplication of the transpose of matrix A and the output data

2.8 Root Mean Square Error (RMSE)

In evaluating the accuracy of predictions, it is important to compare predicted results with actual data. One common method for measuring prediction errors is Root Mean Square Error (RMSE). RMSE calculates the average of the squared differences between predicted values and the observed actual values [26]. A smaller RMSE value indicates higher prediction accuracy. RMSE is useful for identifying the error rate in predicting numerical data, providing insight into how well the model estimates the actual data. The RMSE formula is defined in Equation 11 [27]:

$$\sqrt{RMSE = \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \tag{11}$$

Explanation:
A_t = Actual data values
F_t = Predicted values
n = Number of data points
Σ = Sum of all values

2.9 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a method used to measure the accuracy of a prediction model [26]. Similar to Root Mean Square Error (RMSE), MAE evaluates how close the predictions are to the actual values, but with a simpler calculation formula [27]. MAE represents the average absolute difference between the actual and predicted values [26]. A smaller MAE value indicates higher prediction accuracy. The RMSE formula is defined in Equation 12 [27]:

$$MAE = \frac{\sum|Y' - Y|}{n} \tag{12}$$

Explanation:
Y' = Predicted Value
Y = Actual Value
n = Number of Data Points

3. Results and discussion

3.1 SOC Estimation

The testing in this research was conducted using the type of batteries listed in Table 2.

Table 2. Spesification of Lithium-ion Batteries

Battery Type	Capacity	Voltage Min	Voltage Max
Lithium Ion	30 Ah	37 V	54.75 V

The template is designed for, but not limited to six, as shown in Table 3. Table of SOC Estimation using the ANFIS Method.

Table 3. SOC Estimation Using the ANFIS Method

No	Time (s)	Voltage (V)	Current (A)	Actual SOC (%)	Estimation SOC with ANFIS (%)
39	78	48.689	7.565	65.8535	65.8133
40	80	48.71	7.765	65.9718	65.8965
…	…	…	…	…	…
131	262	50.621	3.069	76.7380	76.7810
132	264	50.642	3.071	76.8563	76.8941
133	266	50.663	3.068	76.9746	77.0078
134	268	50.684	3.067	77.0930	77.1208
135	270	50.705	3.070	77.2113	77.2327
136	272	50.726	3.070	77.3296	77.3450
137	274	50.747	3.068	77.4479	77.4577

Table 3 presents comparison between the actual SOC values and the estimated SOC values obtained using the ANFIS method.

In Figure 5, the graph compares the actual SOC (black line) with the SOC predicted using the ANFIS method (red line). The graph demonstrates that the ANFIS estimation closely aligns with the actual SOC, as the red line nearly overlaps the black line. For instance, at data point 137, where the voltage is 50.747 V, the actual SOC is recorded at 77.4479%, while the ANFIS-predicted SOC is 77.4577%. This minimal difference highlights the high accuracy of the ANFIS method in estimating the SOC.

In Figure 6, the SOC versus current graph indicates that the SOC estimation using the ANFIS method closely matches the actual SOC values. For instance, at data point 40, with a current of 7.765 A, the actual SOC is 65.9718%, while the ANFIS-estimated SOC is 65.8965%. This small difference highlights the accuracy of the ANFIS method in estimating SOC.

Figure 7 illustrates the relationship between SOC and time, where the ANFIS method provides SOC estimations that closely match the actual SOC values. For instance, at data point 132 when the time reaches 264 seconds, the actual SOC is 76.8563%, while the ANFIS-estimated SOC is 76.8941%. This minimal difference underscores the accuracy of the ANFIS method. The graph also indicates that SOC tends to increase over time, indicating that battery charging boosts SOC.

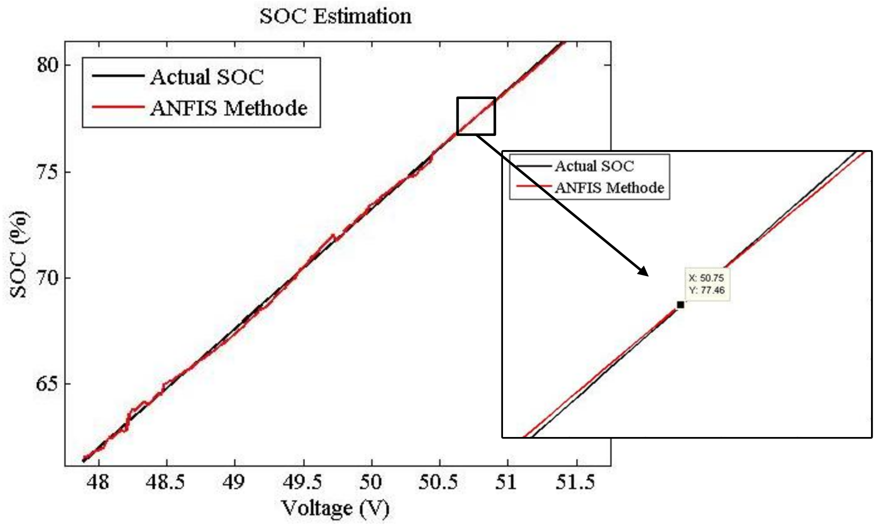

Figure 7. SOC Versus Voltage Chart

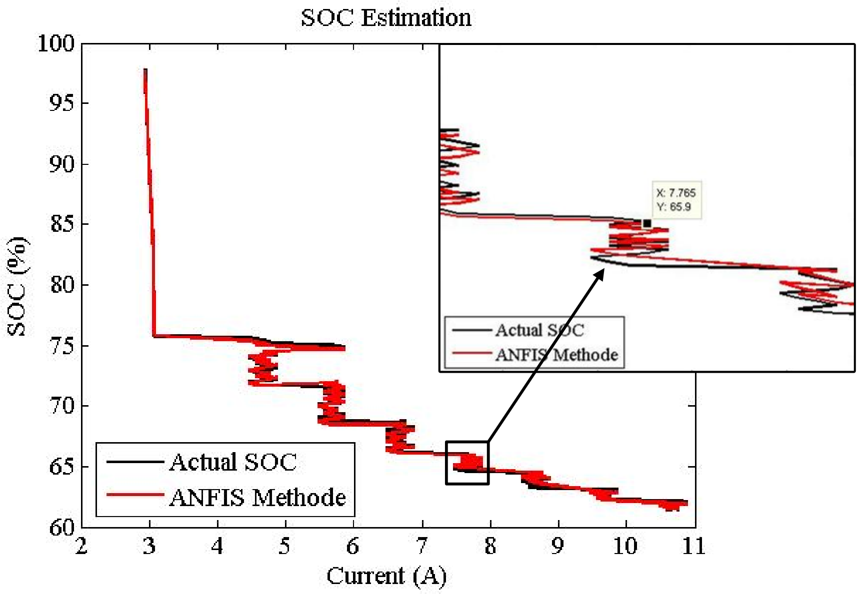

Figure 8. SOC Versus Current Chart

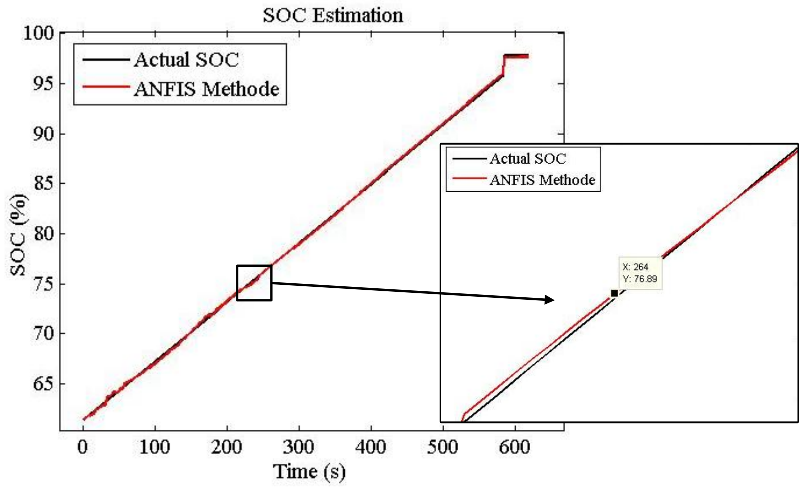

Figure 9. SOC Versus Time Chart

3.2 SOH Estimation

Before obtaining the SOH estimation, it is necessary to first estimate the battery capacity using the ANFIS method. Table 3 presents comparison between the actual capacity values with the estimated capacity values obtained using the ANFIS method.

Figure 8 shows the capacity versus voltage graph from the battery discharge process. The black line represents the actual capacity, while the red line indicates the capacity estimated using the ANFIS method. At data point 404, when the voltage reaches 47.1 V, the actual capacity is 17.07 Ah, while the ANFIS-estimated capacity is 17.077 Ah. The close match between the estimated and actual values demonstrates the high accuracy of the ANFIS method, as shown in Table 4.

Table 4. Capacity Estimation Using the ANFIS Method

No	Time (Minute)	Voltage (V)	Current (A)	Actual Capacity (Ah)	Estimation Capacity with ANFIS (Ah)
404	404	47.10	14.86	17.070	17.077
405	405	47.00	14.89	16.901	16.908
406	406	47.00	14.89	16.901	16.908
407	407	47.00	14.89	16.901	16.908
…	…	…	…	…	…
419	419	46.80	14.96	16.563	16.554
420	420	46.70	14.99	16.394	16.392
421	421	46.70	14.99	16.394	16.392
422	422	46.70	14.99	16.394	16.392
423	423	46.60	15.02	16.225	16.229

Figure 9 shows the capacity versus current graph from the battery discharge process. The graph also demonstrates that the ANFIS method provides estimations very close to the actual values. This is evident from data point 419, where the current is 14.96 A, the actual capacity is 16.563 Ah, and the ANFIS estimation is 16.554 Ah, indicating a very close match to the actual value.

Figure 10 shows the capacity versus time graph from the battery discharge process. Similar to the previous graphs, the black line represents the actual capacity, while the red line indicates the capacity estimation using the ANFIS method. The graph also illustrates that capacity decreases over time during the battery discharge process. Evidence of the ANFIS method's accuracy is reflected in the close match between the estimated and actual values at data point 423. At this point, when the time reaches 423 minutes, the actual capacity is 16.225 Ah, while the ANFIS estimation is 16.229 Ah, demonstrating the high accuracy of the ANFIS method.

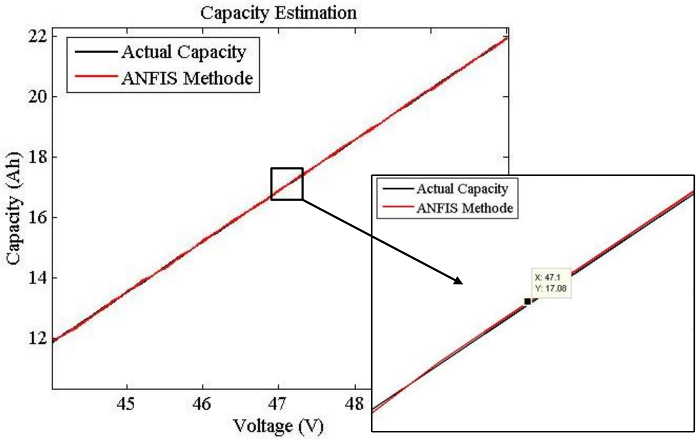

Figure 10. Capacity Versus Voltage Chart

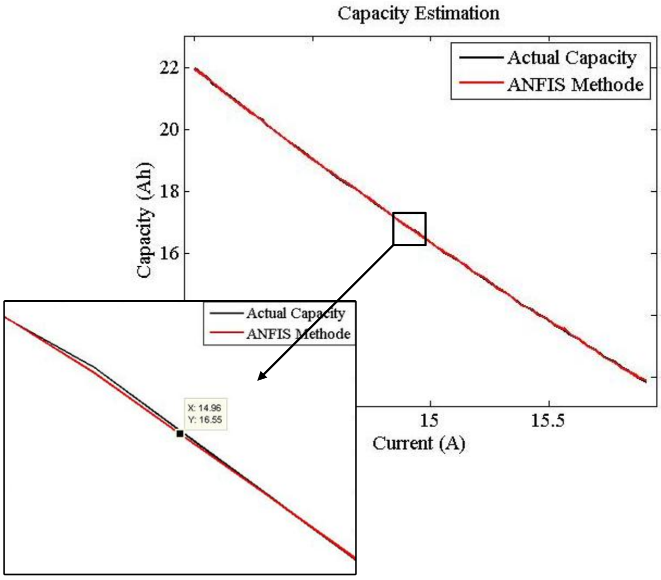

Figure 11. Capacity Versus Current Chart

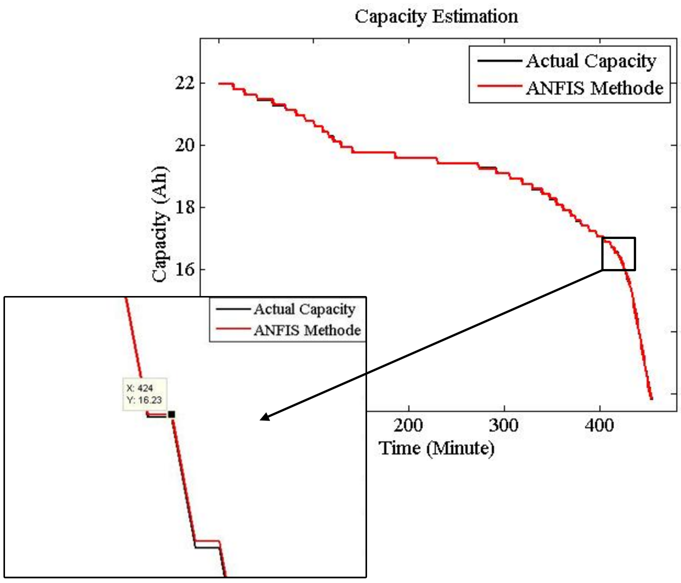

Figure 12. Capacity Versus Time Chart

After multiple charge and discharge cycles, the maximum voltage reached 50 V with a capacity of 21.969 Ah, while the minimum voltage was 44 V with a capacity of 11.887 Ah, as shown in Figures 11 and 12. Based on these values, the usable capacity of the battery is calculated to be 10.082 Ah. Therefore, the SOH estimation for the battery is:

$$SOH = \frac{10.082\ \text{Ah}}{30\ \text{Ah}} \times 100\% = 33.61\%$$

This study presents a comparison of data management using the Ant Colony Optimization (ACO) and ANFIS algorithms, showing the differences between the two algorithms. The variations in the results can be seen in Figures 13 and 14.

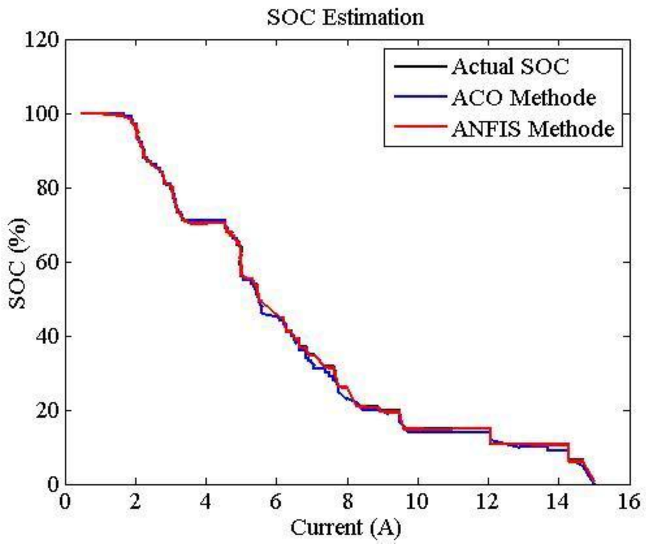

Figure 13. Comparison of SOC Estimation Using ACO and ANFIS Algorithms

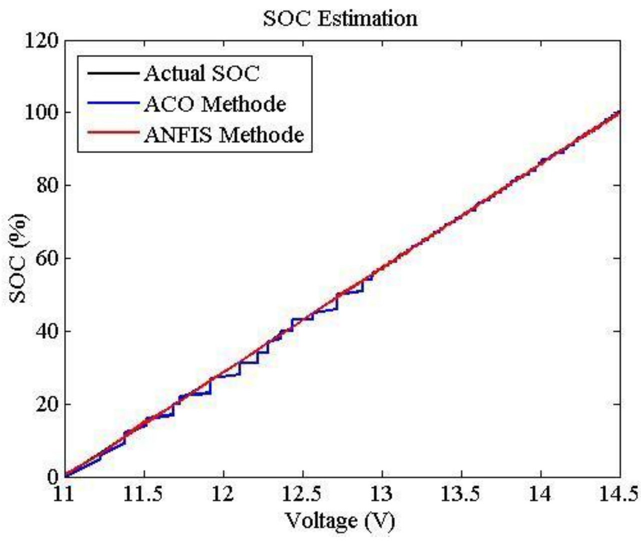

Figure 14. Comparison of SOC Estimation Using ACO and ANFIS Algorithms

The comparison between the ANFIS and Ant Colony Optimization (ACO) methods in estimating the State of Charge (SOC) of lithium-ion batteries, as presented in Figures 13 and 14, indicates that both approaches are capable of closely following the actual SOC curve. Nevertheless, the ANFIS method (red line) exhibits a more consistent alignment with the actual SOC (black line) across the entire current range. In contrast, the ACO method (blue line) demonstrates noticeable deviations at certain points, particularly in the mid-discharge region, which reduces its accuracy relative to ANFIS. These findings highlight that, although ACO provides reasonably accurate estimations, ANFIS achieves superior precision and reliability by integrating fuzzy logic with adaptive learning from empirical datasets. Consequently, ANFIS can be regarded as a more robust and comprehensive approach for implementation in intelligent battery management systems, where accurate SOC estimation is essential to improving diagnostics, predictive maintenance, and overall energy efficiency.

3.3 Data Analysis

The analysis of State of Charge (SOC) estimation using the Adaptive Neuro Fuzzy Inference System (ANFIS) method shows that the ANFIS model provides highly accurate SOC estimates, as evidenced by a Root Mean Square Error (RMSE) of 0.1466 and a Mean Absolute Error (MAE) of 0.021. For capacity estimation in determining State of Health (SOH), ANFIS results in an RMSE of 0.012 and an MAE of 0.0017. The low RMSE and MAE values indicate that the ANFIS model effectively aligns the estimated values with the actual data, resulting in minimal estimation errors and small deviations. These findings demonstrate that the ANFIS method provides highly accurate estimation, as shown in Table 5 and 6.

Table 5. RMSE and MAE Results for SOH and SOC Estimation Using ANFIS

ANFIS Method	RMSE	MAE
State of Charge (SOC)	0.1466	0.021
State of Health (SOH)	0.012	0.0017

Table 6. RMSE and MAE Results for SOH and SOC Estimation Using ACO

	RMSE	MAE
State of Charge (SOC)	0.32238	0.27

4. Conclusion

This study has demonstrated the effectiveness of the Adaptive Neuro-Fuzzy Inference System (ANFIS) in accurately estimating the State of Charge (SOC) and State of Health (SOH) of lithium-ion batteries using voltage, current, and capacity data. The ANFIS model, developed using the MATLAB toolbox `anfisedit` and optimized via a hybrid learning algorithm (combining backpropagation and Recursive Least Squares Estimation), shows strong capability in modeling nonlinear battery behavior under dynamic conditions. Experimental results revealed high estimation accuracy, with an RMSE of 0.1466 and MAE of 0.021 for SOC prediction, and an RMSE of 0.012 and MAE of 0.0017 for SOH (based on capacity degradation). The final SOH value was calculated at 33.61%, closely matching the actual measured capacity degradation. These results confirm the suitability of ANFIS for real-time, data-driven battery diagnostics. Compared to conventional estimation methods, ANFIS offers better adaptability, reduced sensitivity to sensor noise, and the ability to capture complex nonlinear relationships without explicit physical modeling. This makes ANFIS a promising approach for integration into smart Battery Management Systems (BMS). For future research, the ANFIS model can be further enhanced through the integration of additional parameters such as temperature, cycle count, and internal resistance. Moreover, the application of hybrid deep learning–fuzzy models and real-time deployment on embedded platforms or edge AI systems can expand the applicability of this method for advanced electric mobility and grid-scale storage systems.

Acknowledgement

The authors would like to acknowledge the Electrical Engineering Department, Politeknik Negeri Sriwijaya, for funding support through Contract No. 7650/PL6.2.1/SPK-A3/2024, and PPM Dit. APTV through Contract No. 278/PKS/D.D4/PPK.01.APTV/VII/2024 and No. 7320/PL.2.1/SPK/2024 under the Thematic Research Program A3. The authors also extend their sincere gratitude to Universiti Brunei Darussalam, for the role as a collaborative partner in this international research project.

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