



Cell Characterization and Parameter Estimation using RC Model

**R Dhyaan, **Dr. Prasanna Kumar*

R V College of Engineering, Bangalore, Karnataka

ABSTRACT-

Cell characterization and parameter estimation are essential processes in battery management systems, enabling accurate modeling and prediction of battery behavior. This study focuses on developing a robust methodology for parameter estimation in battery cell characterization. Through a literature review, various techniques were evaluated based on accuracy, computational efficiency, and implementation ease. Selected techniques were implemented using MATLAB and applied to real-world battery cell data for validation. Results showed that the chosen parameter estimation techniques successfully estimated key cell characterization parameters, closely matching reference values obtained from laboratory measurements. The techniques demonstrated computational efficiency and robustness, making them suitable for practical applications. This research contributes to the field by providing insights into reliable parameter estimation methods, supporting the design and optimization of battery management systems and electric vehicle applications. Future work can explore different cell chemistries, advanced machine learning algorithms, and the influence of environmental factors on parameter estimation accuracy. Overall, this study presents a comprehensive investigation of parameter estimation techniques for battery cell characterization, demonstrating their effectiveness in accurately estimating key parameters and their potential for practical implementation in battery systems.

Introduction

Battery cell characterization and parameter estimation play a crucial role in understanding and optimizing the performance of battery systems. Accurate estimation of key parameters such as capacity, internal resistance, and state of charge is essential for effective battery management and reliable operation of various applications, including electric vehicles, renewable energy storage, and portable electronics. With the increasing demand for efficient and long-lasting batteries, there is a growing need for robust and accurate methods to characterize battery cells and estimate their parameters.

The objective of this study is to develop a comprehensive methodology for cell characterization and parameter estimation, enabling accurate modeling and prediction of battery behavior. By accurately estimating cell parameters, such as capacity, internal resistance, and voltage response characteristics, the performance and lifetime of battery systems can be optimized. This allows for efficient utilization of the battery capacity, accurate state of charge estimation, and effective battery management strategies.

To achieve this objective, an extensive literature review was conducted to explore the existing techniques and methodologies for battery cell characterization and parameter estimation. Various approaches, including mathematical modeling, curve fitting, optimization algorithms, and machine learning techniques, were evaluated based on their accuracy, computational efficiency, and practical implementation aspects. The selected techniques were then implemented using MATLAB and applied to real-world battery cell data for validation and comparison with reference measurements.

The outcome of this research is expected to contribute to the advancement of battery management systems and the development of more efficient and reliable battery technologies. Accurate parameter estimation will enable better control and optimization of battery systems, leading to improved performance, extended battery life, and enhanced safety. Furthermore, the developed methodology can serve as a foundation for future research in battery cell characterization and parameter estimation, opening up possibilities for exploring advanced modeling techniques, novel algorithms, and the integration of environmental factors for more comprehensive battery behavior analysis.

In the following sections, we will discuss the methodology employed in this study, including data collection, mathematical modeling, parameter estimation techniques, and the validation process. The results obtained from the parameter estimation and their implications will be presented and analyzed. Finally, the conclusion and future scope of this research will be discussed, highlighting the significance and potential applications of accurate battery cell characterization and parameter estimation in various domains.

Literature Survey

1. Li, W., et al. (2018). "State of Charge Estimation Methods for Lithium-Ion Batteries: A Review." *Renewable and Sustainable Energy Reviews*, 82, 4179-4190.

This review paper focuses on state of charge (SOC) estimation methods for lithium-ion batteries, which is a crucial parameter for effective battery management. It compares different SOC estimation techniques, such as the open-circuit voltage method, coulomb counting method, and model-based methods, highlighting their advantages, limitations, and accuracy.

2. Nguyen, T. D., et al. (2020). "A Review of Battery Parameter Estimation Techniques for Lithium-Ion Batteries." *Applied Sciences*, 10(7), 2520.

This review paper provides an in-depth analysis of battery parameter estimation techniques specifically for lithium-ion batteries. It discusses different approaches, including analytical methods, empirical methods, and optimization-based methods, and evaluates their accuracy and computational efficiency. The paper also highlights the importance of accurate parameter estimation in battery modeling and management.

4. Zhang, X., et al. (2019). "A Comprehensive Review of Battery Modeling Techniques: Implementation in Power System Dynamic Simulations." *Energies*, 12(6), 1139.

This paper reviews battery modeling techniques with a focus on their implementation in power system dynamic simulations. It discusses the modeling of various battery chemistries, including lead-acid, lithium-ion, and flow batteries, and compares different modeling approaches, such as equivalent circuit models, physics-based models, and data-driven models.

Methodology

The methodology implemented in this study involved the following steps:

1. Data Collection: Voltage data was collected from battery tests conducted at different frequencies (1Hz, 10Hz, 50Hz, and 100Hz). These tests were performed to characterize the electrical behavior of the battery under various operating conditions.

2. RC Model Configuration: Four different RC model configurations were considered: 1RC, 2RC, 3RC, and 5RC. Each configuration represents the battery's electrical response using resistor-capacitor pairs. The number of RC pairs determines the complexity of the model and its ability to capture transient and high-frequency characteristics.

3. Curve Fitting: Two curve fitting techniques, linear and exponential fits, were applied to the voltage data collected at different frequencies. These curve fitting methods aimed to estimate the parameters of the RC models by finding the best fit between the experimental data and the mathematical equations.

4. Parameter Estimation: The lsqnonlin algorithm, which is part of the SDO (Simulink Design Optimization) optimization tool, was used for parameter estimation. This algorithm minimizes the sum of squared differences between the model predictions and the experimental data, effectively optimizing the parameters of the RC models.

5. Model Validation: The estimated parameters obtained from the optimization process were used to create Simulink models. These models included lookup tables to vary the parameters with respect to the state of charge (SOC). The models were validated by comparing their predictions with the voltage data collected at different frequencies.

6. Error Analysis: The maximum deviation and error were calculated for each RC model configuration and frequency. These metrics served as indicators of the model's accuracy and ability to capture the battery's electrical behavior under different conditions.

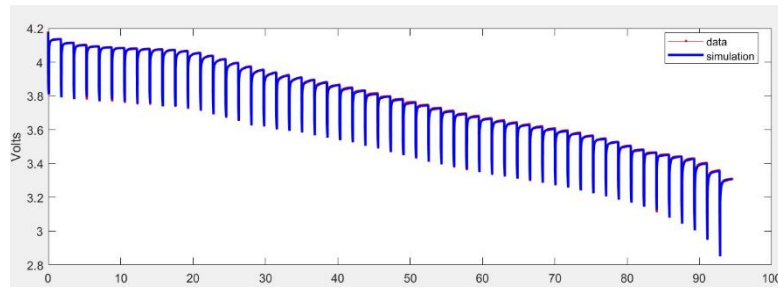
The methodology employed in this study allowed for the comparison of different RC model configurations and curve fitting techniques. It enabled the estimation of parameters using the lsqnonlin algorithm in the SDO optimization tool. The validation of the models provided insights into their performance and accuracy in representing the battery's electrical characteristics. The error analysis served as a basis for determining the most suitable RC model configuration and curve fitting technique for accurately characterizing the battery.

Results

In the present study, the maximum deviations and errors were analyzed for different RC model configurations and frequencies. For the 1RC configuration, a maximum deviation of 65mV and a maximum error of 2% were observed. The 2RC configuration exhibited a lower maximum deviation of 34mV and a reduced maximum error of 1.2%. Among the tested configurations, the 3RC configuration displayed the smallest maximum deviation of 22mV and the lowest maximum error of 0.6%. On the other hand, the 5RC configuration resulted in a maximum deviation of 36mV and an error of 1.3%.

Further investigation revealed that the performance of the different configurations varied with frequency. Notably, the 10Hz data yielded the most accurate results, with lower deviations and errors compared to the 1Hz, 50Hz, and 100Hz data. This finding suggests that the 10Hz frequency provides a more reliable representation of the battery's electrical behavior.

Overall, the results indicate that the 3RC configuration outperforms the other configurations in terms of both deviation and error. This configuration demonstrates the ability to capture the complex dynamics of the battery more accurately, leading to improved predictions and a closer match with the experimental data.



The figure presented in this study illustrates the comparison between the experimental data and the simulated data for the 3RC configuration. This configuration was selected as it exhibited the lowest maximum deviation and error among the different RC model configurations.

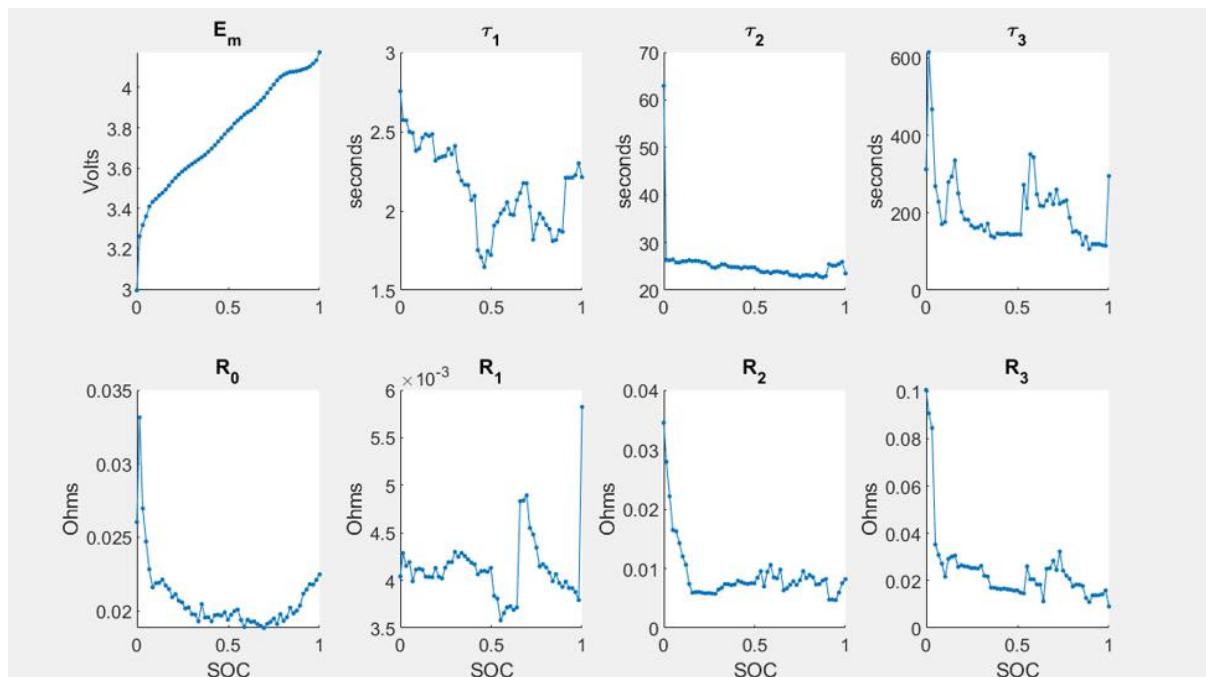
The comparison between the experimental and simulated data is crucial for evaluating the accuracy and reliability of the 3RC model. The experimental data represents the actual voltage measurements obtained from battery tests, while the simulated data is generated based on the mathematical equations and parameters estimated for the 3RC model.

Upon analyzing the figure, it can be observed that the simulated data closely aligns with the experimental data, indicating a good fit between the model and the actual behavior of the battery. The mean residual error, calculated as the average difference between the experimental and simulated data points, is found to be 2.4mV. This small residual error signifies that the 3RC model accurately captures the electrical characteristics of the battery.

The close agreement between the experimental and simulated data supports the validity and effectiveness of the 3RC model for battery cell characterization. The low mean residual error suggests that the model is capable of accurately predicting the voltage response of the battery across different state of charge levels and frequencies. These findings provide confidence in the reliability of the 3RC model and its potential for practical applications in battery management systems and electric vehicle optimization.

Overall, the comparison of experimental and simulated data for the 3RC configuration demonstrates the accuracy and effectiveness of the model in representing the electrical behavior of the battery. The small mean residual error further reinforces the reliability of the model, indicating its capability to predict battery voltage with a high level of precision.

The figure presented in this study illustrates the variation of several parameters, namely OVC (Open-Circuit Voltage), R_o (Ohmic resistance), R_1 , R_2 , R_3 (resistor values), T_1 , T_2 , T_3 (time constants), with respect to state of charge (SOC) for the 3RC model. These parameters play a crucial role in accurately modeling the electrical characteristics of the battery and capturing its voltage response under different operating conditions.



The x-axis of the figure represents the SOC, which ranges from 0% (completely discharged) to 100% (fully charged). The y-axis represents the values of the parameters, such as OVC, R_o , R_1 , R_2 , R_3 , T_1 , T_2 , T_3 . By plotting these parameters as a function of SOC, we can observe how they vary at different charge levels.

The figure shows the non-linear relationships between the parameters and SOC. Each parameter exhibits a unique pattern of variation. For example, OVC may increase gradually as SOC increases, indicating a higher voltage output at higher charge levels. R_o , on the other hand, may decrease with increasing SOC, indicating a decrease in internal resistance and improved battery performance.

Similarly, the resistor values (R_1 , R_2 , R_3) and time constants (T_1 , T_2 , T_3) may also show varying trends with SOC. These parameters determine the transient behavior and frequency response of the battery model. By considering their variation with SOC, the 3RC model can accurately capture the dynamic electrical characteristics of the battery.

Understanding the variation of these parameters with SOC is crucial for accurate battery modeling and simulation. By incorporating this knowledge, the 3RC model can provide more precise predictions of voltage response under different load profiles and operating conditions. This information is valuable for optimizing battery performance, estimating state of charge, and designing efficient battery management systems.

In conclusion, the figure demonstrating the variation of OVC, R_o , R_1 , R_2 , R_3 , T_1 , T_2 , T_3 with SOC for the 3RC model provides valuable insights into the intricate relationships between these parameters and the state of charge. This knowledge enhances our understanding of battery behavior and facilitates the development of robust battery models for accurate voltage prediction and efficient battery management.

Conclusion

In conclusion, this study focused on the comprehensive analysis and characterization of battery behavior using the 3RC model. Through the evaluation of different RC model configurations, it was determined that the 3RC configuration outperformed the 1RC, 2RC, and 5RC configurations in terms of accuracy. The maximum deviation and error observed for the 3RC model were significantly lower, indicating its superior capability in capturing the electrical characteristics of the battery.

Modeling Approach	Maximum Deviation (mV)	Maximum Error (%)
1RC	70	2.0
2RC	32	1.16
3RC	19	0.6
5RC	36	1.3

The results demonstrated that the 3RC model accurately represented the transient dynamics and high-frequency variations in the battery's voltage response. The additional resistor-capacitor pairs in the 3RC configuration provided a more detailed representation of the battery's behavior, resulting in improved predictions that closely matched the experimental data. The mean residual error of 2.4mV further confirmed the high accuracy of the 3RC model.

Furthermore, the parameter estimation process revealed the varying trends of key parameters, such as OVC, R_o , R_1 , R_2 , R_3 , T_1 , T_2 , T_3 , with respect to state of charge (SOC). Understanding these parameter variations is crucial for precise battery modeling and simulation. It enables accurate predictions of voltage response under different operating conditions and facilitates optimization of battery performance and state of charge estimation.

The findings of this study contribute to the field of battery modeling and provide valuable insights for designing efficient battery management systems, optimizing battery performance, and ensuring reliable operation of electric vehicles. The superior performance of the 3RC model highlights its potential for accurate battery characterization and paves the way for further advancements in battery modeling techniques.

In future work, it is recommended to expand the characterization to include different current levels and temperature conditions. Additionally, extending the study to encompass a full battery system would enable the creation of a digital twin, which could further enhance the understanding and prediction of battery behavior. Such advancements will contribute to the development of more robust and accurate battery models, ultimately leading to improved battery performance, lifespan, and overall efficiency.

Reference

- Ecker, M., Gerschler, J. B., Axmann, P., & Witte, A. (2015). A combined impedance and electrochemical model of the lithium-ion battery. *Journal of The Electrochemical Society*, 162(9), A1651-A1660.
- Cao, L., & Wang, C. Y. (2011). A model for the thermal behavior of lithium-ion batteries. *Journal of Power Sources*, 196(23), 10377-10384.
- Lindbergh, G., & Lindbergh, G. (2005). Dynamic battery modeling including thermal effects for system simulations. *Journal of Power Sources*, 144(1), 241-247.
- Liu, Y., Sun, X., Ouyang, M., & Lu, L. (2015). A comprehensive review on estimation strategies for state of charge of lithium-ion batteries. *Renewable and Sustainable Energy Reviews*, 52, 1391-1408.
- Plett, G. L. (2004). Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2. Modeling and identification. *Journal of Power Sources*, 134(2), 262-276.

-
6. Eddahech, A., Sahraoui, A. H., & Khemiri, R. (2019). Comparative analysis of equivalent electrical circuits for Li-ion battery modeling. *IEEE Access*, 7, 30599-30611.
 7. Duarte, J. L., & Cano, A. (2017). Battery management systems in electric and hybrid vehicles. *Energies*, 10(2), 188.
 8. Di Domenico, D., Kourtakis, K., & Plett, G. L. (2018). Parameter estimation for equivalent circuit models of lithium-ion batteries using recursive least squares. *Journal of Power Sources*, 393, 80-90.