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An Online Data-driven Remaining Useful Life Estimation of Lithium-ion Battery for Early Warning of Battery Failure

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Abstract

The lithium-ion battery industry has grown into one of the largest segments in the portable battery industry for consumer portable applications. The performance of these applications depends heavily on the timely maintenance of Li-ion batteries. However, the diverse aging process, huge battery variability, and dynamic operating environment of lithium batteries have brought great challenges to users in predicting the remaining service life of lithium batteries. Therefore, this project aims to create a model that can use data-driven fuzzy systems to predict the remaining life of lithium batteries. When the battery life is about to run out, an early warning will be sent to the user to remind the user to replace it in time. The battery will experience countless charge and discharge cycles under certain environmental factors, and the relevant data of the battery will be recorded every five minutes until the battery is damaged. The principle of prediction is to input the data set into the model and transfer the change trend of the data. Compute forecast results. The model considers four factors that affect battery remaining life prediction, namely, charge capacity, discharge capacity, and state of health (SOH) as input features, and remaining useful life (RUL) data as training output data. According to the relationship between the input features and the output data, and according to the constraints, the output results are restricted and adjusted during the fuzzy reasoning process, and finally the appropriate output data is obtained. The developed system is expected to help users schedule the optimal replacement of lithium-ion batteries when service is coming to an end. And we encapsulate the whole program into a graphical user interface (GUI), through the GUI, users can operate more conveniently, and can see the calculation results of the lithium battery data more intuitively. Therefore, it is more convenient for users to use this program for the remaining useful life of lithium batteries.

Keywords: [Lithium battery，fuzzy logic，RUL，GUI]

1 Introduction

In this Internet era, people's lives do not turn on computers, mobile phones, etc. electronic devices. As the amount of devices used increases, battery life is of concern. Lithium batteries are the most common because of their low cost, high energy density, and long lifespan. However, Their capacity and power will change over time, and if handled improperly, it will bring the risk of fire or explosion.

Curiously, despite the prevalence of electronic devices, the domain lacks applications that specifically focus on predicting the Remaining Useful Life (RUL) of lithium batteries. Existing tools like OMNI CALCULATOR and ALL ABOUT CIRCUITS primarily provide calculators for generic battery life estimation, often sidestepping the critical trend analysis required for assessing battery health. This oversight can lead to substantial prediction inaccuracies, especially considering that formula-based calculations may fall short of ensuring precision.

To address these limitations and achieve more reliable predictions, adopting a holistic methodology becomes imperative—one that harnesses historical data and trends to perform accurate analyses. This is where the incorporation of fuzzy logic algorithms becomes invaluable, presenting a robust avenue for enhancing the accuracy and reliability of battery life predictions.

To fulfill our objectives, we have outlined three pivotal aims:

1. Development of a GUI-based prediction system that accurately estimates the remaining useful life of a lithium battery, specifically tailored to the characteristics of the CS2 model.

2. Enhancement of prediction accuracy by integrating an AI-based approach, featuring fuzzy logic and constraint modeling, into the system. This technique adeptly handles uncertainties, accommodates vague information, and addresses the intricate nonlinear relationships within the data, culminating in predictions of heightened precision.

3. Comprehensive evaluation of the performance of the developed system.

Our project's scope encompasses the following components:

Graphical User Interface (GUI): The GUI is meticulously crafted to predict the remaining service life (RUL) of the lithium battery model CS2. It offers an uncomplicated interface for data input and prediction outcomes, streamlined into a single primary interface. Elements such as user login interfaces are deliberately excluded from this scope.

Battery:Our project's focus is laser-targeted on predicting the remaining service life of the specific lithium battery model CS2. Given the unique characteristics inherent to distinct lithium battery models, employing data from other battery types would likely yield results deviating significantly from accuracy.

Charge and Discharge Cycle Data Condition Requirement: The prediction system necessitates adhering to specific charge and discharge cycle data conditions to ensure robust and standardized input data. These conditions encompass a steady current rate of 0.5C during charging until the voltage reaches 4.2V. This voltage threshold is then sustained throughout charging until the current falls below 0.05A. Furthermore, a discharge cutoff voltage of 2.7V is prescribed, contributing to dependable and consistent data inputs crucial for precise RUL prediction.

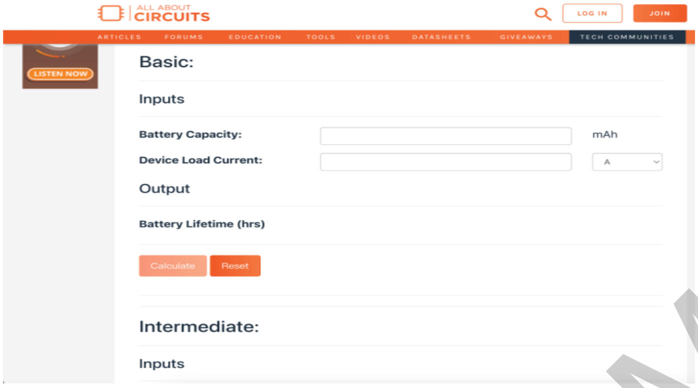

Figure 1 All about circuits website

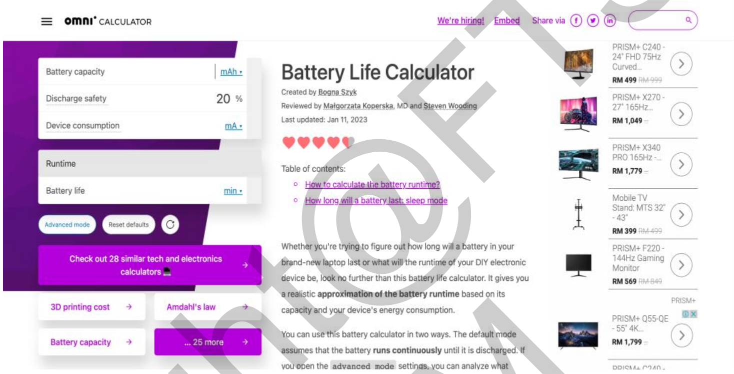

Figure 2 Omni calculator website

2 Methodology

In this project, we will adopt an agile methodology to develop a data-driven fuzzy logic-based GUI program for battery remaining useful life (RUL) prediction. Agile methods will allow us to implement this complex task incrementally in a flexible, iterative manner, ensuring that the final software product accurately meets user needs and system requirements.

In the requirements analysis stage, we conduct an in-depth analysis of system requirements by understanding the needs of users and the system. In this stage, the functions of the GUI interface, user interaction requirements and specific requirements of the fuzzy logic battery RUL prediction algorithm will be clarified.

We will then move to the data collection and preprocessing phase, guided by agile methods. The focus will be on developing a data collection module for a specific type of lithium battery to ensure that we can capture enough battery data and do the necessary preprocessing to use it as input to the fuzzy logic algorithm.

The development of the fuzzy logic part will follow. At this stage, we will carefully define a suitable fuzzy set based on multiple tests on the fuzzy set to ensure the accuracy and stability of the obtained prediction results. The parameter adjustment and optimization of fuzzy logic will continue in agile iterations to meet the actual needs of battery RUL prediction.

With the continuous improvement of the fuzzy logic part, we will focus on developing an intuitive and friendly GUI interface. We will design the interface based on the user's interface needs so that the user can easily enter data, view forecast results, and interact with the system.

In the continuous testing and user feedback phase, agile methods will allow us to test after each development phase and get user feedback in a timely manner. Internal testing and user acceptance will ensure that each stage functions properly and meets user expectations. We will make necessary revisions and adjustments based on feedback.

Through the above steps of agile method, we will successfully realize the development of GUI program based on data-driven fuzzy logic battery RUL prediction. This methodology will ensure that testing and tuning are done at each stage to ensure that the final software product can accurately and efficiently predict the remaining battery life, providing practical tools and methods for battery health management.

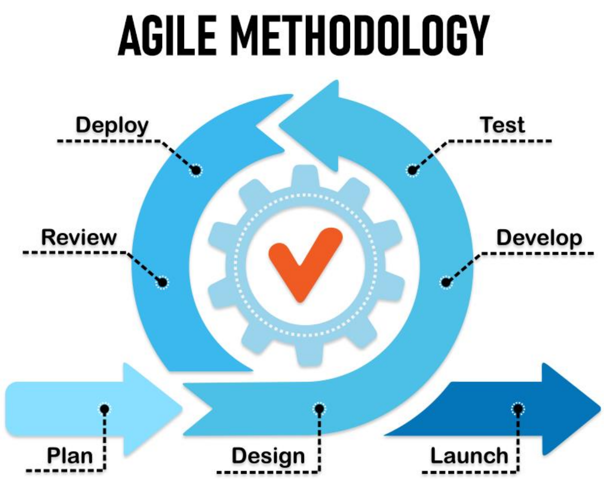

Figure 3 Agile methodology

3 Design And Implementation

We divide this program into three main parts: data preprocessing, fuzzy logic design, and GUI interface(Figure 4). First, in the data preprocessing stage, I carefully analyzed the original dataset and found that it contains thousands of data points. To better process these data, we first process the missing or outliers, and then convert them to record by cycle for further analysis. Through careful analysis of the different variables in the data set, we integrate the mean or maximum value of the data within the same loop, thereby clearly preparing the data file for use in the fuzzy logic section.

In the fuzzy logic design stage, our model considers four key factors affecting the prediction of battery remaining life, namely charge capacity, discharge capacity, and state of health (SOH), which are used as input features, while remaining useful life (RUL) data is used as training output. According to the relationship between input features and output data, combined with constraints, we restrict and adjust the output results during the fuzzy inference process to obtain the most suitable prediction output.

In GUI interface design, we are committed to providing users with a convenient parameter selection interface. Users can choose to input various parameters, and we will display data trend graphs and fuzzy rule graphs to provide users with more intuitive information. In addition, when the remaining service life of the battery is less than 20%, the system will issue a warning slogan to remind the user to replace the battery in time to avoid unnecessary trouble. We designed it to provide users with an intuitive and convenient tool to help them better manage their battery health.

In terms of data storage, we choose to use MATLAB's internal storage and generate MAT data files to store and deliver files. This method not only helps efficient data management, but also effectively promotes the smooth progress of data transmission. Through internal and MAT-file calls, we can achieve effective interaction between datasets and algorithms, providing a solid foundation for the functionality of the entire system.

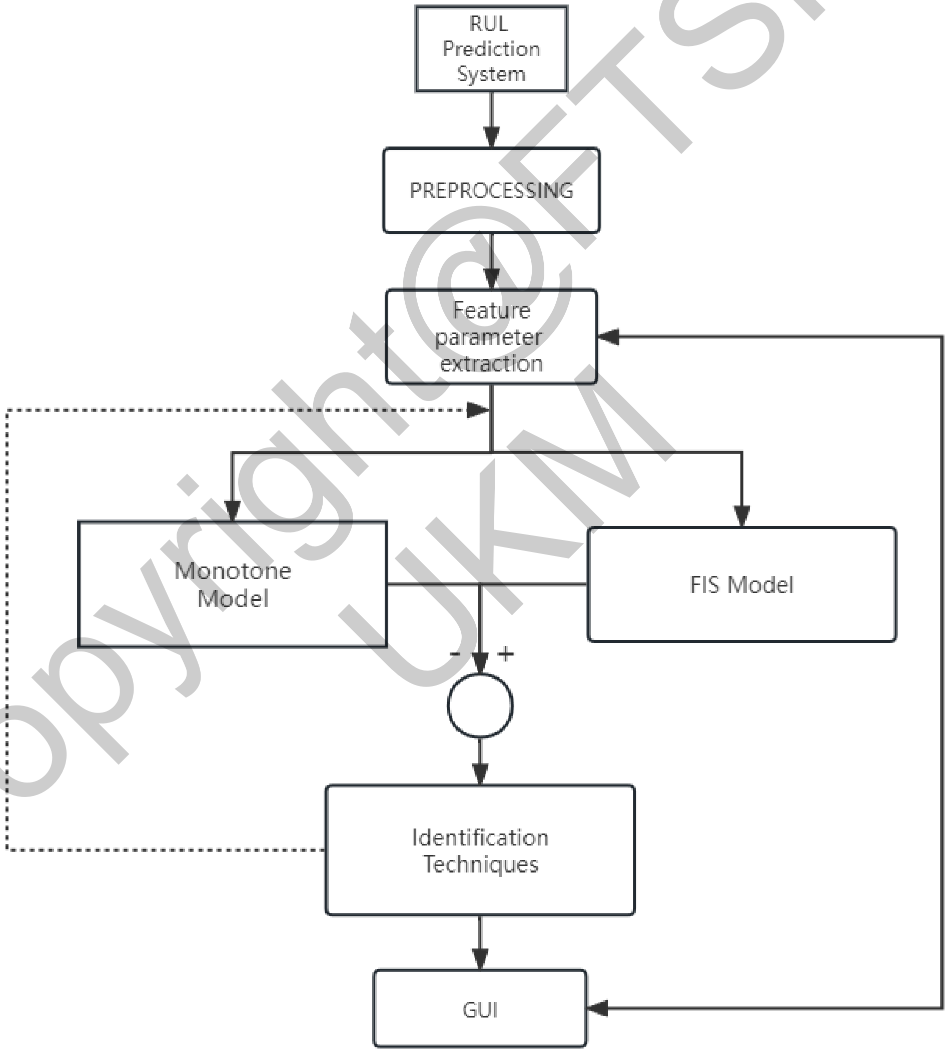

Figure 4 Main structure

4 Result

In the result after data preprocessing, we obtained a reduced dataset with only 50 rows of data, each row corresponding to a unique battery cycle (Figure 5). This carefully screened dataset aggregates representative data points for different variables at each cycle, consistently characterizing the battery's behavior over its useful life. And we store it as a new excel file so that users can directly view or get our processed dataset.

Observing the trend graph generated from this refined dataset, we can clearly see a monotonic trend. The presence of this monotonic trend indicates a significant consistent pattern in the data. The consistency of this pattern not only confirms the quality of our data preprocessing, but also lays a solid foundation for the fusion of datasets in our model training process.

In the fuzzy logic part, we took a series of steps to build the model accurately. First, we performed an elaborate fuzzy set definition on the data of the input variables, then we specified and parameterized a FIS model (Fuzzy Inference System). Next, we performed parameter identification based on the trends of the dataset and input data to form a set of fuzzy If-Then rules that best fit the data samples. These rules are the basis for model reasoning, enabling more accurate predictions by capturing ambiguous relationships among data.

Subsequently, we performed validation tests on the established model to ensure its performance on the test dataset. This validation process aims to confirm that the final model formulation is correct. We terminated the process once the results of the validation tests were satisfactory and it was determined that the built model could be used for further prediction tasks. However, if the validation test results are not as expected, we go back to the previous step and revisit and define the dataset to ensure that our model more accurately reflects the real situation. This iterative process continues until we achieve satisfactory model performance.

In the GUI design, we carefully designed two pages, namely the guide page (Figure 6) and the main page (Figure 7). The introductory page is mainly used to briefly introduce our program topic and its functions to provide users with an initial understanding. The main page contains three core sections, which are data selection, parameter selection and forecast result display.

In the data selection section, the user can select the required data file, and once the selection is completed, the corresponding data trend graph will be displayed on the interface. This interactive function can visually display the changing trend of the selected data, so that users can better understand the situation behind the data.

The parameter selection section allows users to set relevant parameters by themselves for model prediction. Users can adjust parameters as needed to obtain more accurate prediction results. In the prediction result display section, users can clearly view the best fuzzy rules corresponding to the data and the time when the prediction results are converted. In addition, we also provide some relevant data for evaluating the performance of the model, so that users can fully understand the accuracy and reliability of the model (Figure 8).

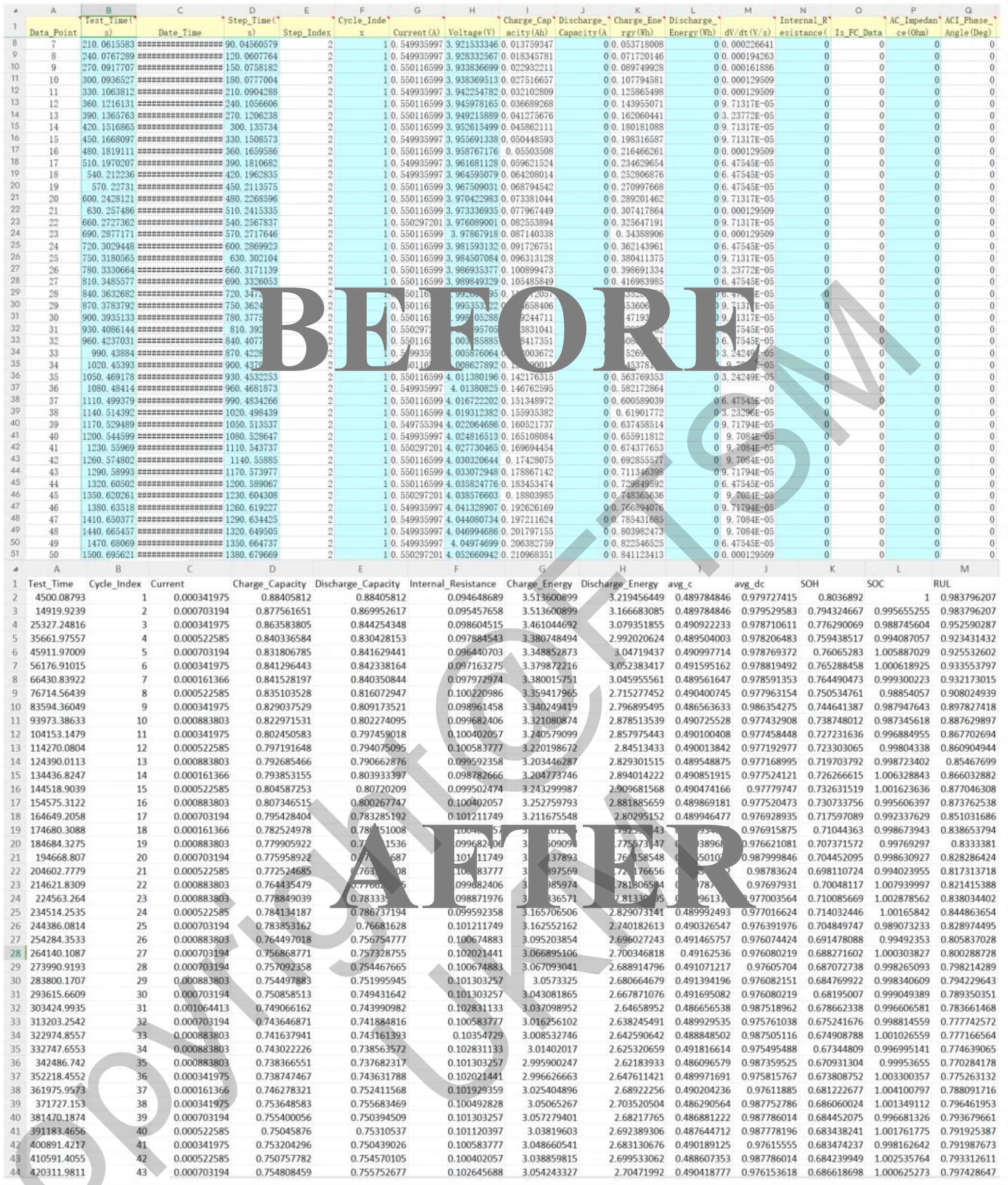

Figure 5 Data preprocessing comparison

Figure 6 Home interface

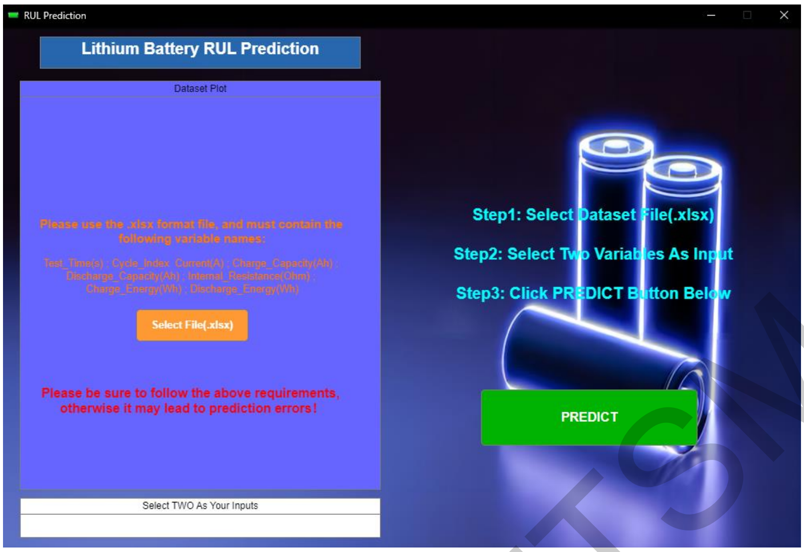

Figure 7 Main interface

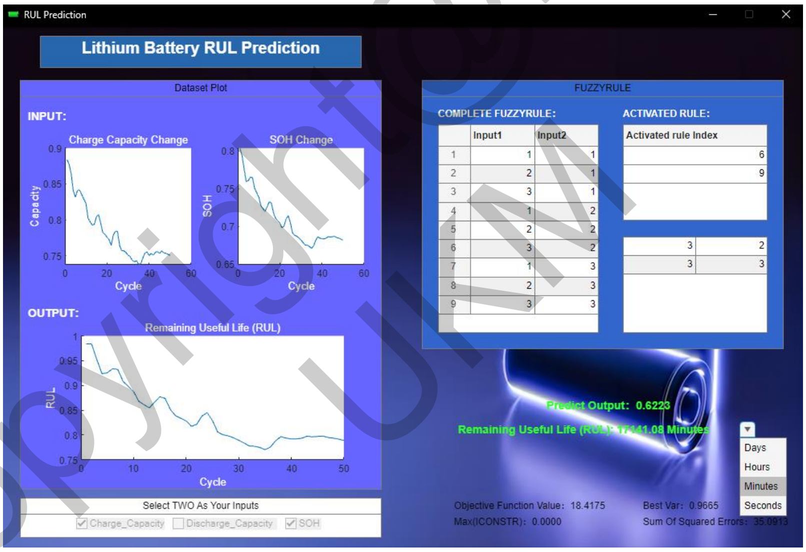

Figure 8 Predicted interface

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5 Conclusion

The project focuses on utilizing data-driven fuzzy logic for predicting the Remaining Useful Life (RUL) of lithium batteries, aiming to provide early warnings to users before battery depletion. The process involves requirement analysis, framework, and algorithm design.

Fuzzy logic methodology is employed for data analysis and prediction, addressing an existing gap in the online domain. The primary contributions encompass complex lithium battery data preprocessing, fuzzy logic-based prediction, and performance evaluation. Interaction with the algorithm is facilitated through a graphical user interface (GUI), overcoming challenges encountered during design and implementation. The test phase confirms the effectiveness of fuzzy logic in data analysis, processing, and prediction.

Strengths of the project include the novel use of data-driven fuzzy logic for RUL prediction, leading to a GUI-driven system. Fuzzy logic's compatibility with human-like computing thinking aids data analysis beyond traditional data definitions. However, limitations are observed. Complex data operations lead to consideration of only two parameters for prediction, limited battery models, and the requirement for monotonic data characteristics. These constraints affect system flexibility, imposing specific input data conditions on users during algorithm execution.

Enhancements can be made post-design. Increasing input parameters can improve prediction accuracy by incorporating more battery-affecting data. Expanding battery type selection beyond one model can enhance system versatility. Adapting data requirements to various formats and refining data preprocessing code can enhance operational performance. GUI design optimization can enhance aesthetics and potentially expand to a global web application for broader accessibility.

6 Appreciation

I am deeply grateful to my supervisor, Dr. Kerk Yi Wen, for her invaluable guidance and unwavering support throughout the design and development process of this project. Her expertise and insights in the field of fuzzy logic proved instrumental in shaping the successful execution of the fuzzy logic component of the project. Dr. Kerk Yi Wen not only provided me with a thorough understanding of fuzzy logic concepts but also patiently assisted me in overcoming challenges and clarifying doubts, ensuring that I could navigate through difficulties with confidence. Her dedicated mentorship played a pivotal role in the development of the project and greatly contributed to its successful completion.

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