Research Plan

1. Rationale

In line with its push towards sustainability and the lowering of carbon emissions outlined in the Singapore Green Plan 2030, Singapore has launched concerted efforts to transition its vehicle population to cleaner energy, in particular, electric vehicles (EVs) [1]. Worldwide, nearly 10% of global car sales were electric in 2021 [2]. The biggest concern about the promotion of EVs is the Li-Ion battery, which provides a higher charge density over conventional acid lead batteries. Furthermore, they are more resilient to constant charging and discharging, decreasing the degradation of the battery over multiple use cycles. A battery is recommended to be replaced when its state of health (SOH) degrades to its end-of-life (EOL) capacity threshold since the usable capacity is expected to decrease at a more rapid rate after exceeding EOL [3]. SOH prediction also extends the battery lifespan by adopting an ageing-level-based charging strategy to vary the charge current according to a cell's health status [4]. Thus, it is crucial to be able to predict the SOH of Li-Ion batteries for battery energy management and maintenance.

There are mainly two methods to evaluate the SOH of batteries. The first method is to estimate SOH by extracting health indicators (HI) from the equivalent circuit or electrochemical models [5] [6]. The second method is to apply machine learning (ML) to predict battery SOH without knowing the exact battery model [3] [7]. However, for SOH estimation methods based on HI extraction, accurate approximation of the SOH degradation process is difficult due to the complexity of the battery system and the uncertainty of working conditions in real life. On the other hand, ML-based prediction methods address the drawbacks of model-based methods since they are modeless and data-driven. While some ML-based methods have achieved high accuracy and efficiency, the models are generally hard to train due to the complexity of their frameworks and modela parameters which can hardly be interpreted from battery electrochemistry and are expensive for embedded devices with limited storage space and computational power. Therefore, we aim to create a simple and efficient ML model to predict SOH,

2. Engineering Goals and Expected Outcomes

This project aims to propose a simple and efficient ML-based method for the SOH prediction of Li-Ion batteries. This project will propose a method based on popular ML models including long short-term memory (LSTM) and gated recurrent unit (GRU) to train the offline datasets and apply the method to the online prediction of SOH of batteries. Our focus will be on the ML architecture and algorithm of the SOH prediction framework. Our framework will be data-driven so that it will not be affected by the battery system working conditions, and also be accurate and efficient in SOH prediction.

3. Procedures

Our project will be conducted according to the following procedures:

a) Study all the pieces of literature that are relevant to our project and do preliminary research for the measurement of the state of health (SOH) of the battery.
b) Attempt related Python libraries and build the basic neural network
c) Pre-process the data collected and extract useful information from the datasets.
d) Discuss and propose a suitable framework for the SOH prediction
e) Build the model using Python
f) Train and evaluate the performance of the model
g) Adjust the relevant parameters and compare the results to choose the best results
h) Analyse the evaluation results and compare different models
i) Account for the significance of different results and the reasons for the difference

4. Risk and Safety

In line with the Covid-19 situation, and the usage of computers, our project will have the following risks and we have given the safety precautions accordingly:

a) Spread of Covid-19: The appropriate Safe Management Measures as recommended by the government of Singapore were adhered to in the course of undertaking this project – masks were worn, meetings were conducted online whenever possible, a safe distance of at least one metre apart was maintained between individuals while physically conducting experiments in the lab.
b) Long screen time for the data computation: Students should take a break and look away at least every 30 minutes. They should pay attention to their posture throughout the day, whether sitting or standing, to reduce some of the strains of screen time.

5. Data Analysis

Given the sample data set from the previous research, we will carry out experiments to test different ML models on the sample data to find out a better algorithm for predicting the SOH of the battery cell. Long-short term memory (LSTM) and Gated Recurrent Unit (GRU) will be used in our framework, according to the literature reviews and our preliminary testing.

We will then quantitatively evaluate the accuracy of SOH prediction from the two models, by using the loss function mean average error (MAE) and root mean square error (RMSD), to find the best model in the estimation of the SOH of the batteries. MAE and RMSD will be crucial in evaluating the performance of our two models, and we will compare them based on the two values.

6. Bibliography of References

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