BATTERY PARAMETER ESTIMATION OF LITHIUM-ION BATTERIES USING TEMPORAL CONVOLUTIONAL NETWORK

A Project Report

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Under the guidance of
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DECLARATION

I, the undersigned hereby declare that the project report "BATTERY PARAMETER ESTIMATION OF LITHIUM-ION BATTERIES USING TEMPORAL CONVOLUTIONAL NETWORK", submitted for partial fulfillment of the requirements for the award of the degree of Master of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me, under the supervision of Dr. Fousia M Shamsudeen. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to the ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed as the basis for the award of any degree, diploma or similar title of any other University.

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C E R T I F I C A T E

This is to certify that, this report titled ***BATTERY PARAMETER ESTIMATION OF LITHIUM-ION BATTERIES USING TEMPORAL CONVOLUTIONAL NETWORK*** is a bonafide record of the **Project** presented by **ANSALNAKHAN N (TKM21MEAI02)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, **M.Tech in Mechanical Engineering (Artificial Intelligence)** in **APJ Abdul Kalam Technological University** .

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Abstract

For electric vehicles, lithium-ion (Li-ion) batteries serve as the primary energy source. Accurately estimating and predicting the state of health (SOH) and remaining useful life (RUL) of lithium-ion batteries play an increasingly crucial role in intelligent battery health management systems. Additionally, it serves as a battery failure early warning system. Model-based and data-driven approaches can be broadly classified as the two types of approaches that have been documented in recent years for SOH estimation and RUL assessment of lithium-ion batteries. Among these, data-driven techniques can produce more accurate predictions. This work focuses on developing a deep learning model for battery parameter estimation in electric vehicles. A Temporal Convolutional Network (TCN) model is proposed for SOH monitoring and RUL assessment in Lithium-ion batteries before the failure of the battery. Three analytical indices: RMSE, MAE and R SQUARE are chosen to evaluate the prediction results numerically. The proposed model is experimented and tested using NASA lithium-ion battery health dataset. The prediction results of both SOH and RUL showed good accuracy of 99% indicating that the proposed model has high robustness and good performance.

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Chapter 1

Introduction

The modern, expanding economy makes extensive use of lithium-ion battery technology in a variety of sectors, including transportation, home appliances, communications, aircraft, and others. One of the key parts of electric vehicles is the energy storage system which is expected to enter the present transportation sector as a result of the steadily rising environmental pollution and oil prices. Up until now, electric cars and consumer devices have traditionally used lithium ion batteries as their primary power source. They provide many advantages, such as a long life cycle and a very high power density, making them the best choice for the energy storage system [6, 7].

However, since it is a battery, its performance gradually reduces, increasing the likelihood of certain disasters (such as battery explosions in EVs and cell phones). Further research are required to precisely monitor the battery's condition and, thereby, ensuring its life span in order to boost the authenticity of the entire energy system [8]. The safety of Li-ion batteries must therefore be ensured by a battery management system, which consist of three crucial factors: state of charge (SOC), remaining useful life (RUL), and state of health (SOH). These three factors are related to the charge of the batteries and their ageing, respectively. Furthermore, regular repairs would be unnecessary with precise battery RUL and SOH estimates.

Due to the significance of SOH and RUL to the battery system operation, numerous researches on remaining useful life assessment and state of health monitoring have been conducted. Based on how their concepts and structures differ, there are two categories that can be applied to current models: model based techniques and data driven methods. The relevant models can be derived from the battery's numerous electrochemical processes, and the SOH and RUL can be predicted using information like as internal resistance, voltage, and current. Model-based methods are the name given to these strategies. One of the main model types, along with pseudo two dimensional models and single particle models, is electrochemical models based on the physical principles. Due to the intricasy of the battery's intrinsic reaction, measurement data frequently contain noise.

In light of this, processing data by a particle filter [25] increases the accuracy of the results. It has also been possible to predict battery life using a technique based on the second order central difference particle filter. The difficulty of the partial differential equations that these algorithms must solve, however, increases the strain on the battery management system. Along with electrochemical models, analogous circuit models are typically used to explain the correlation between state of health and the measured variables. The analogous circuit model extracts characteristics from the voltage during the charging and discharging process., and then model between the parameters and the SOH is made using the least squares method or the Gaussian process regression technique [26]. Yet another limitation of model-based methodologies is that it is hard to correctly represent battery's attenuation process due to the influence of objective elements, and therefore model lacks accuracy and resilience.

Data-driven methodologies have benefited from machine learning's speedy development. Data-driven methodologies don't need a particular physical model. Rather, they employ machine learning approaches to build pertinent models using a vast amount of battery measured history data. As a result, these techniques are more resilient and adaptive and have greater application potential. Data-driven strategies are built on the basis of selection and processing of the data where it is important to identify relationships between parameters and SOH. Neural networks, support vector regression,, autoregressive moving average models, and support vector machines are typical examples of data driven approaches. Although these methods by themselves successfully estimate a Li-ion battery's RUL and SOH, their accuracy is still insufficient for all stages of the life cycle.

This work focuses on developing a deep learning model for the battery parameter estimation in electric vehicles. A Temporal Convolutional Network (TCN) model is proposed for monitoring the State of Health (SOH) and predicting the Remaining Useful Life (RUL) in Lithium-ion batteries before the failure of the battery.

The other sections of this work are written as follows: Chapter 2 displays a review of the literature. Chapter 3 is about the background study. The methodology of the proposed model is described in Chapter 4. The performance evaluation metrics used here is explained in chapter 5. The experimental study and findings of the suggested method are presented in Chapter 6. Finally, a conclusion is given.

Chapter 2

Literature Review

Zraibi et al. [1] proposed a CNN-LSTM-DNN hybrid method, which is a combination of Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and Deep Neural Networks (DNN), for estimating the battery's remaining useful life (RUL) and improving prediction accuracy while maintaining an acceptable execution time. The suggested hybrid estimation approach's superiority is demonstrated through a comparison against several ML estimation techniques. Three statistical indicators are chosen to evaluate the prediction results numerically: the MAE, R2, and RMSE. The model performance is validated by using two datasets of various lithium-ion batteries from NASA and CALCE. The model shows good accuracy indicating that this method is reliable for RUL prediction.

For the remaining useful life prediction of lithium ion batteries, Liqun et al. [2] proposed a sequence decomposition via deep learning integrated strategy. Principal component analysis and complementary ensemble empirical mode decomposition are used to isolate local variations and overall degradation trend from the battery ageing data. The fully connected layers and long and short term memory neural network are created as a transfer learning model. Based on offline training data, the model's hyperparameter optimization and fine-tuning strategy is created. Three publicly accessible LIB datasets with various degradation properties are used for experimental analysis. The experimental results show that this approach can produce precise, flexible, and reliable prediction for RUL estimation.

Cheng et al. [3] presented an empirical mode decomposition (EMD) method combined with back propagation long-short-term memory (B-LSTM) neural network (NN) for estimating SOH and RUL of lithium ion batteries. BLSTM NNs with many-to-one structure use readily available battery parameters such as current and voltage to estimate SOH. The EMD method is used to process SOH data in order to lessen the influence of capacity regeneration and other circumstances, after which the one-to-one structure's backpropagation occurs and RUL prediction is carried out by neural network. Test results were validated using the CALCE lithium ion battery dataset. Model prediction results for different types of batteries give good accuracy, proving that this combined model has high durability and good applicability.

Ren et. al [4] proposed a new LIB RUL prediction method based on improved convolutional neural network and long short term memory, named as Auto-CNN LSTM. This approach utilizes deep CNN and LSTM to extract more deeper information from limited data. To enhance the training of CNN and LSTM, an autoencoder is used to expand the dimensions of the data. Additionally, a filter is applied to ensure a stable and uninterrupted output. Real world experiments carried out on this method demonstrate its superior performance when compared to other traditional methods.

A deep learning based prediction system called ADLSTM-MC, that combines the attributes of Monte Carlo simulation and adaptive dropout long short-term memory (ADLSTM), was proposed by Zheming et al. [5]. Two datasets of LiFePO4/graphite and LiNi0.8Co-0.15Al0.05O2 graphite batteries with various discharge cut off voltages and charging and discharge rates are taken to assess the performance of the suggested technique. While existing models typically require between 40 percent and 70 percent of the degradation data, the ADLSTM-MC technique is demonstrated to accurately accomplish early prediction with only 25 percent of the complete degradation data. Mean absolute error (MAE) and root mean square error (RMSE) of the proposed capacity prediction model are less than 0.033 and 0.027, respectively, and the R2 ranges from 0.957 to 0.982.

Steffen et al. [15] proposed State of health estimation of lithium-ion batteries with a temporal convolutional neural network using partial load profiles. The study presents a temporal convolutional neural network (TCN) model that processes raw sensor data without requiring feature engineering or extensive preprocessing steps. The dataset used is open battery data from NASA PCoE.The generalized aging model estimates the SOH with an overall root mean squared error of 1.0%. The study also investigates the influence of partial load cycles from different SOC ranges on SOH estimation performance for LCO based battery cells. This model is capable of on-board operations and can be adopted and transferred to battery management system (BMS) applications.

Chapter 3

Background Study

3.1 Electric cars and Lithium-ion Battery

Electric cars rely on rechargeable lithium-ion batteries to power their electric motors. These batteries consist of thousands of individual cells that work together to provide energy to the car. Lithium-ion batteries are able to be repeatedly charged and discharged due to the composition of their electrodes and electrolytes [16]. However, over time, this process can cause the battery to degrade and lose its capacity, which reduces the car's range and increases the time needed between charges. Despite this, the latest predictions suggest that a single lithium-ion battery for an electric vehicle can last between 10 to 20 years before needing to be replaced.

3.1.1 Lithium-ion Battery Cell Design

A typical lithium-ion battery cell design consists of four main components: the cathode, the anode, the electrolyte, and the separator as shown in figure 3.1 [17, 18].

The cathode is the positive electrode of the cell and is typically made of a metal oxide material, such as lithium cobalt oxide ($LiCoO2$), lithium nickel manganese cobalt oxide ($LiNiMnCoO2$), or lithium iron phosphate ($LiFePO4$). The cathode material determines the energy density and voltage of the battery.

The anode is the negative electrode of the cell and is typically made of graphite or silicon-based materials. During charging, lithium ions are extracted from the cathode and inserted into the anode. During discharging, the opposite occurs, and lithium ions flow back from the anode to the cathode.

The electrolyte is a non-conductive solution that facilitates the flow of lithium ions between the cathode and anode during charge and discharge. The electrolyte is typically made of a lithium salt, such as lithium hexafluorophosphate ($LiPF6$), dissolved in an organic solvent.

The separator is a thin, porous layer that prevents the cathode and anode from touching each other and causing a short circuit. The separator is typically made of a polymer material, such as polyethylene or polypropylene.

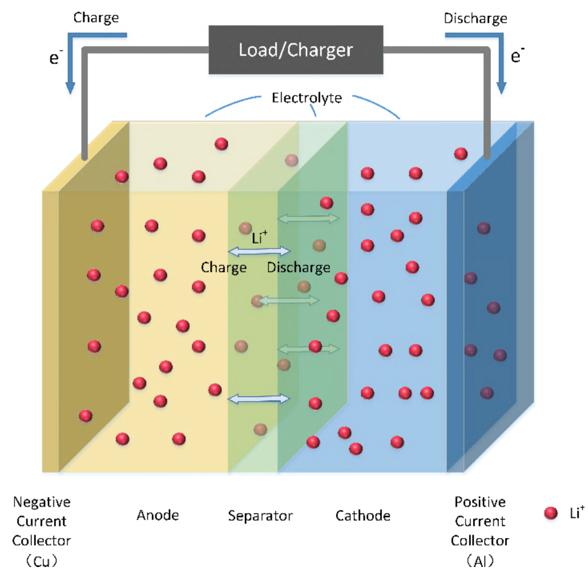

Figure 3.1: Lithium-ion Battery Cell Design

The design of a lithium-ion battery cell is critical for optimizing the performance, safety, and lifespan of the battery. The design factors that can influence the performance of the cell include the electrode materials, electrolyte composition, separator thickness, and cell geometry. Battery manufacturers optimize these factors to achieve the desired energy density, power density, and cycle life of the battery while minimizing safety risks.

3.1.2 Advantages of Li-ion Battery

- High energy density: Lithium-ion batteries have a high energy density, which means they can store more energy per unit weight or volume than other types of batteries.

- Low self-discharge rate and fast charging: Lithium-ion batteries have a low self-discharge rate, meaning they can retain their charge for a longer period of time than other batteries. They can be charged quickly, sometimes in as little as 30 minutes, depending on the charger and battery capacity

- Long lifespan and Environmnt friendly: Lithium-ion batteries have a longer lifespan than other types of batteries, and can last for several years with proper care and maintenance. They are less harmful to the environment than other types of batteries.

3.1.3 Types of Li-ion Batteries

Lithium-ion batteries are used in various applications such as mobile devices, laptops, electric vehicles, and renewable energy storage systems. In electric vehicles, they are used to power the electric motor and provide the necessary energy for driving. The type and size of the lithium-ion battery used in an electric vehicle depend on factors such as the vehicle's range, weight, and cost [19], [20]. Generally, high-capacity lithium-ion batteries are used in electric vehicles to provide a longer driving range, while smaller batteries are used in hybrid vehicles to supplement the internal combustion engine.

There are primarily five types of lithium-ion batteries used in electric vehicles:

- Lithium Cobalt Oxide (LiCoO2): This is the most common type of lithium-ion battery used in electric vehicles. It has a high energy density but is relatively expensive and has a shorter lifespan.

- Lithium Manganese Oxide (LiMn2O4): This type of lithium-ion battery has a longer lifespan and is less expensive compared to LiCoO2. However, it has a lower energy density and is less stable.

- Lithium Nickel Cobalt Aluminum Oxide (LiNiCoAlO2): Also known as NCA, this type of lithium-ion battery has a high energy density and a longer lifespan compared to LiCoO2. However, it is expensive and has a lower thermal stability.

- Lithium Iron Phosphate (LiFePO4): This type of lithium-ion battery is safer and has a longer lifespan compared to other types of lithium-ion batteries. However, it has a lower energy density and is heavier, making it less suitable for electric vehicles that require a lighter battery.

- Lithium Nickel Manganese Cobalt Oxide:- It has two major advantages as compared to the other batteries. The first one is its high specific energy, which makes it desirable in electric powertrains, electric vehicles, and electric bikes. The other is its low cost. It is moderate in terms of specific power, safety, lifespan, and performance when compared to the other lithium ion batteries. It can be optimized to either have high specific power or high specific energy.

3.2 Available Lithium-ion Battery Datasets

3.2.1 NASA Data Repository

The NASA Lithium-Ion Battery Dataset [9] is a collection of data from experiments conducted by NASA's Power Systems and Energy Storage Group to study the performance and health of lithium-ion batteries used in space applications. The dataset includes data from several tests performed on different types of lithium-ion batteries under various operating conditions and environments.

The data includes measurements of the battery's voltage, current, temperature, and capacity over time, as well as metadata such as the battery chemistry, manufacturing date, and cell type. The dataset also includes information about the battery's health, such as the state of charge, state of health, and cycle life.

This dataset is publicly available and is intended to be used by researchers and engineers to develop and validate models for predicting the performance and health of lithium-ion batteries in space applications. The dataset can also be used for other applications, such as developing battery management systems for electric vehicles and other terrestrial applications.

3.2.2 CALCE Battery Research Group

The CALCE (Center for Advanced Life Cycle Engineering) Battery Dataset [21] is a collection of data on the performance and aging of commercial lithium-ion batteries used in various applications, including consumer electronics, electric vehicles, and stationary energy storage systems. The dataset was created by the CALCE Electronic Products and Systems Center at the University of Maryland.

The dataset includes data from accelerated aging tests, in which the batteries were subjected to various environmental conditions and operating profiles to simulate the effects of long-term use. The data includes measurements of the battery's capacity, internal resistance, voltage, and temperature over time, as well as metadata such as the manufacturer, model, chemistry, and cell configuration.

The CALCE Battery Dataset is intended to be used by researchers and engineers to develop and validate models for predicting the performance and aging of lithium-ion batteries in different applications. The dataset can also be used for other purposes, such as developing battery management systems, optimizing battery designs, and evaluating the reliability and safety of batteries in different environments.

The different types of lithium ion battery dataset available in CALCE are INR 18650-20R Battery, A123 Battery, CS2 Battery and CX2 Battery. INR 18650-20R Battery and A123 Battery datasets are mainly used for the State Of Charge estimation [23] and CS2 Battery and CX2 Battery dataset is used for State Of Health and Useful Life estimation [1],[24].

3.2.3 Toyota Research Institute

The Toyota Research Institute (TRI) Battery Dataset [22] is a collection of data on the performance and aging of lithium-ion batteries used in hybrid and electric vehicles. The dataset was created by the Toyota Research Institute, which is a subsidiary of Toyota Motor Corporation focused on research and development of advanced technologies.

The dataset includes data from several experiments conducted on commercially available lithium-ion batteries used in Toyota hybrid and electric vehicles. The data includes measurements of the battery's voltage, current, temperature, and capacity over time, as well as metadata such as the battery chemistry, manufacturing date, and cell type.

This dataset contains 124 commercial Lithium ion batteries that have been cycled to failure. The A123 System was used to create the lithium ion phosphate/graphite cells. This dataset is mainly used for State of Health and Remaining Useful Life estimation.

Chapter 4

Methodology

4.1 Objective(s)

To develop a deep learning model

- To effectively estimate the State of health of li-ion batteries used in electric vehicles.
- To Predict the remaining useful life of li-ion batteries before the failure of the battery

4.2 Proposed Model

4.2.1 Definition of SOH and RUL

SOH indicates the battery's overall health and its ability to provide power. State of health (SOH) of lithium ion batteries refers to the current health condition of the battery in relation to its original state. It is expressed as a percentage of the battery's original capacity that remains after repeated charge and discharge cycles.

$$SOH = \frac{C_t}{C_0} \times 100 \tag{4.1}$$

Where Ct is the battery capacity at the t-th cycle or the current capacity and
Co is the inital battery capacity

The remaining useful life (RUL) of a battery is the number of cycles remaining to get to the failure threshold or to reach the end of life of the battery. It represent the useful life left on the battery at a particular time of operation.

$$RUL(t) = t - t_{eol} \tag{4.2}$$

where t is the cycle number of the current capacity and
teol is the cycle number when the battery reaches failure threshold

4.2.2 Dataset Used

The battery health dataset utilized in this study was originally presented by the prognostic CoE at NASA Ames and acquired through experimentation on lithium ion batteries [9].

The selected batteries for the experimental analysis were B0005, B0006, B0007, and B0018, which all have a rated capacity of 2.0 Ah and underwent cyclic charge and discharge at a temperature of 24 degrees Celsius. During the charging process, the batteries were subjected to a constant current of 1.5A until the voltage reached 4.2V, followed by constant voltage charging until the current dropped to 20mA. For the discharge phase, the batteries were subjected to a constant current of 2A until the voltage dropped to 2.7V, 2.5V, and 2.2V, respectively. To ensure the safety performance of the system, it is generally recommended to reduce the capacity to 70% - 80% of the nominal capacity as a life limit [14]. In NASA's dataset, the end-of-life (EOL) is defined as 30% of the rated capacity, which equals 1.4Ah. The capacity degradation curves of the four batteries is shown in the figure 4.1.

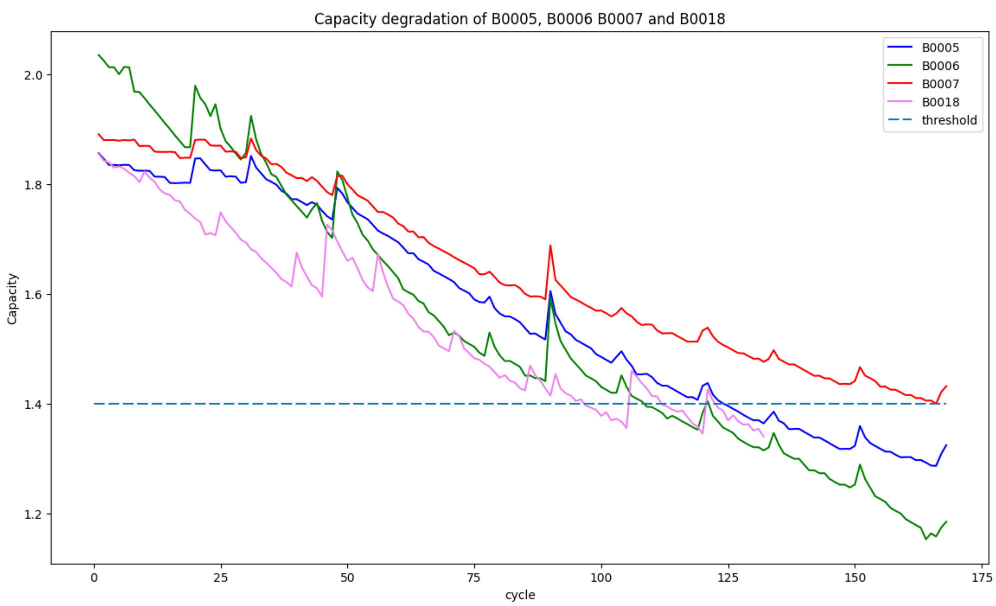

Figure 4.1: Capacity degradation of B0005, B0006, B0007 and B0018 battery

The capacity decay paths of the battery cell depicted in Figure 3.1 exhibit remarkable similarity when subjected to the same discharge rate. However, the decay path diverges significantly at varying discharge rates, mainly due to a variety of uncertain factors of battery aging. In large-scale systems that utilize numerous lithium-ion batteries, like electric vehicles, inconsistent battery performance can severely compromise the safety performance of the entire system. This emphasizes the importance of having efficient monitoring of the state of health and prediction of the remaining useful life for lithium-ion batteries.

It is also observed a common trend of local capacity regeneration phenomenon among different lithium-ion battery capacity sequences. Therefore, it is crucial to enhance the model's capability to capture this phenomenon under varying operating conditions and battery cells. This is the key factor in improving the model's ability to accurately monitor the state-of-health (SOH). As shown in Figure 3.1, the capacity attenuation slope of the battery at end-of-life (EOL) differs across various operating conditions. This implies that the model must possess the ability to forecast long-term behavior for achieving high accuracy in remaining useful life (RUL) prediction.

Dataset Preparation

The training and testing is done on all four datasets B0005, B0006, B0007, and B0018 individually. The dataset is formatted to be compatible with TensorFlow during the training phase by creating two structures that correspond to the expected input and output. For the input data, the relevant characteristics of the dataset are filtered, which are:

- Battery Capacity
- Voltage at load
- Current at load
- Temperature
- Voltage measured
- Current measured
- Time
- Cycle

For the output data, the SOH and RUL of the battery is calculated.

4.2.3 Proposed Methodology

Traditional CNN's are designed for processing 2 dimensional data. They can process 1 dimensional data, but Temporal Convolutional Networks(TCN) are specifically designed to process 1 dimensional sequential data [10]. TCN are useful for time series data because they can capture both local and long-range temporal dependencies within the data. They can learn to identify patterns in data that are indicative of future trends, which allows them to make accurate predictions. They works by applying a convolutional filter to the time series data. The filter slides over the data, with each step capturing a local feature of the data. The output of the convolution layer is passed through a series of non-linear activation functions and pooling layers, which compresses the information and capture increasingly complex features of the data. The TCN model is created by incorporating dilated convolution, residual connection, and dropout technology [12] onto a causal convolution network.

Causal Convolution Network

A 1D causal convolution is a linear operation that applies a filter to the input sequence in a causal way, meaning that the output at any given time step depends only on the current and previous input values. This is important for time series data since we typically want to predict future values based on past values. The 1D causal convolution operates on the input sequence, sliding a filter of a fixed width (usually referred to as kernel size) over the sequence one step at a time, and computing the dot product between the filter and the input values at each step. This produces a new sequence of values, which can be further processed by subsequent layers.

Dilated Convolution

To account for all the historical capacity sequence information, using a causal convolution model can result in a deep network. To address the issues of slow training speed and high memory usage caused by network depth, two solutions have been proposed. The first solution is the use of dilated convolution technique [13], and the second is the incorporation of skip connections. Dilated convolution is a modification to the standard convolution operation, in which the filter is applied over a wider area of the input sequence by skipping some of the input values. This allows the receptive field of a convolutional layer to be increased without increasing the number of parameters. This skipping is achieved by adding gaps (dilation) between the filter elements, which controls the effective receptive field of the filter. In a TCN, dilated convolution can be used to increase the receptive field of the network, allowing to capture long term dependencies in time series data. Dilated convolution allows the network to process input sequences at different temporal resolutions, which can be useful for modeling complex temporal patterns.

Residual Connection

To some degree, deep neural networks can achieve better predictive performance due to their greater expressive ability. In addition to dilated convolution, another approach to addressing the problems caused by network depth is the use of skip connections. This is crucial to our model's ability to capture local regeneration and to achieve faster performance than commonly used hybrid models. The skip connection technique is inspired by the residual network (ResNet) [11].

Residual connections are a technique in deep neural networks that allows information to bypass certain layers in the network, allowing the network to learn more complex representations of the data. Residual connections are a way to help overcome the problem of vanishing gradients in deep neural networks. By adding residual connections, the gradients can be backpropagated more easily through the network, which can help improve training and prevent overfitting. In a residual connection, the output from a previous layer is added to the output of the current layer before the activation function is applied. This allows the network to learn to make small adjustments to the output from the previous layer, rather than having to learn the entire output from scratch. In a TCN, residual connections can be used to improve the performance of the network by allowing information from earlier layer to be preserved and combined with information from later layers.

4.2.4 Overall Workflow of the model

The overall framework of the SOH estimation and RUL prediction of lithium-ion battery integrated with all algorithms is given in Figure 4.2. From the battery dataset, the relevant features capacity, voltage at load, battery terminal voltage, current at load, battery terminal current, battery temperature, cycle and time are filtered and given as input to the network. The TCN network is created by incorporating dilated convolution, residual connection, and dropout technology onto a causal convolution network. Before giving the eight independent input features directly to the TCN model, first the eight features are given to a convolutional layer. The eight independent features are flattened and then reshaped. The reshaped output

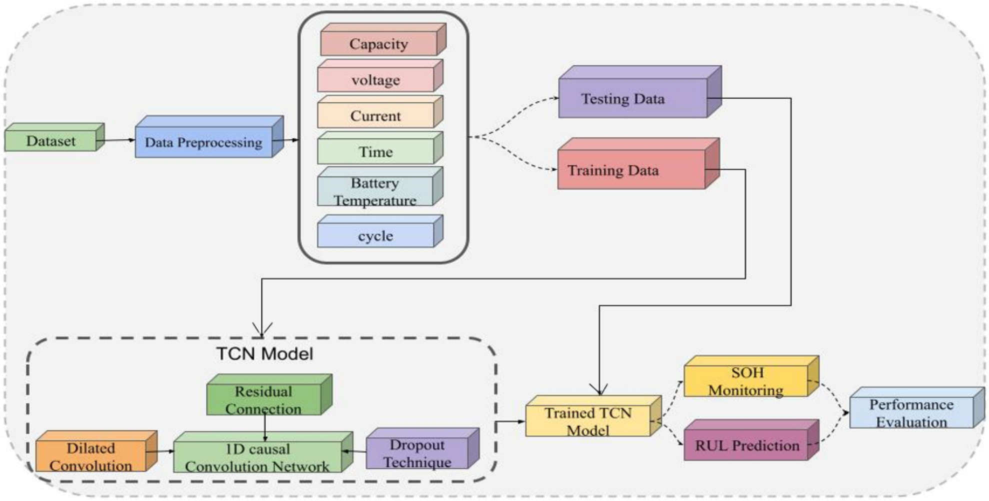

Figure 4.2: Framework of the SOH estimation and the RUL prediction model

is the mixed representation of the eight input features. This mixed feature vector is given as input to the TCN model. It then applies an initial convolutional layer with a kernel size of 1*1. This is followed by a specified number of stacks of residual blocks, each of which contains multiple dilated convolution layers with the specified dilation rate, kernel size and padding as well as batch normalization, ReLu activation and dropout. The output of the final residual block is then globally averaged and the resultant feature vector is fed into a dense output layer with a linear activation function to produce the final output.

The Model Architecture of the trained TCN model is shown in Figure 4.3
The basic parameters of the TCN model used are configured as follows:
Number of iterations:- 200
Size of the kernel: 3×1
number of stacks = 1
number of filters = 32
Dilation factor: [1, 2]
dropout rate = 0.2
Optimizer: adam

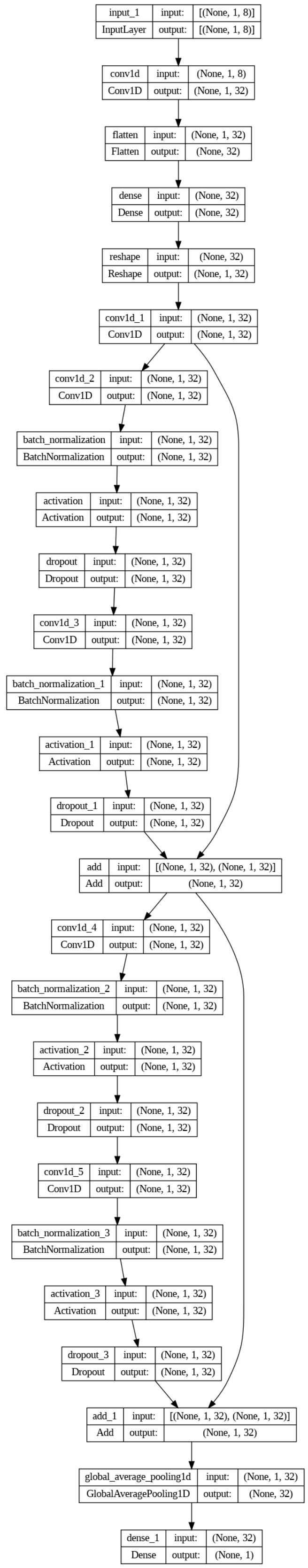

Figure 4.3: Architecture of the trained TCN model

Chapter 5

Performance Evaluation Metrics

The following standard metrics are used to measure the performance of TCN model in SOH and RUL estimation.

1. **Root Mean Square Error(RMSE):** It is the root of the mean of the square of the error. Root Mean Square Error is defined as the standard deviation from the prediction error.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{N}} \tag{5.1}$$

2. **Mean Absolute Error(MAE):** The Mean Absolute Error measures the average magnitude of the forecasting errors without taking into account their direction.

$$\text{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{5.2}$$

3. **R Squared:** R-squared (R2) is a statistical measure that represents the proportion of the variance for a dependent variable that is predictable by an independent variable or variables in a regression model.

$$R^2 = 1 - \frac{RSS}{TSS} \tag{5.3}$$

where R squared is the coefficient of determination
RSS is Residual Sum Of Squares
TSS is Total Sum Of Squares

$$RSS = \sum_{i=1}^{n} (y_i - f(x_i))^2 \tag{5.4}$$

$$\text{TSS} = \sum_{i=1}^{n} (y_i - \bar{y})^2 \tag{5.5}$$

Chapter 6

Results and Discussions

The primary purpose of monitoring the State of Health (SOH) in the experiment is to proactively maintain the battery. Therefore, selecting the appropriate starting point based on the actual usage scenario can provide a better indication of the model's reliability. On the other hand, predicting the Remaining Useful Life (RUL) is more focused on replacing the battery in practice, which makes accurately predicting the failure point more critical. In this scenario, there are four datasets - B0005, B0006, B0007, and B0018. B0005, B0006, and B0007 contain a total of 168 cycles each, while B0018 contains a total of 132 cycles. The dataset is divided into training and testing sets in a 70-30 ratio, with 70% reserved for training and 30% reserved for testing. Therefore, for B0005, B0006, and B0007 batteries, the first 118 cycles are designated as the training set, and the remaining cycles are known as the prediction set. For B0018, the first 83 cycles are considered as the training set, and the remaining cycles are referred to as the prediction set.The Python 3.10 language was used to write the experimental analysis models in this article, and the experiments were conducted on a laptop. The computer used for the experiments had an i5-7300 CPU and a NIVIDA 1050Ti GPU.

6.1 State of Health Estimation

To evaluate the performance of the model, we need to compare the predicted state of health (SOH) values with the actual SOH values of the batteries. Figure 6.1(a) shows the actual SOH of the B0005 battery. To effectively monitor the State of Health (SOH), the model should have minimal error in forcasting the upcomming SOH value. That is, the actual SOH values and predicted SOH values in the testing data should be similar. Figure 6.1(b) shows the the comparison of the actual SOH and the predicted SOH of the testing data. The graph indicates that the model accurately captures the data pattern and predicts SOH similar to actual SOH. The SOH prediction graph of B0005 battery is shown in figure 6.1(c). The RMSE, MAE and R Square values obtained are 0.00081, 0.00058 and 0.9995 respectively.

Figure 6.2 shows the prediction results of B0006 battery. The actual SOH of the B0006 battery is shown in figure 6.2(a). Figure 6.2(b) illustrates the comparison of actual SOH and predicted SOH of the testing set. The graph shows that the model correctly captures the data pattern and predicts the SOH values. The SOH prediction graph of B0006 battery is shown in figure 6.2(c). The obtained RMSE, MAE and R Square values are 0.00027, 0.00066 and 0.9997 respectively.

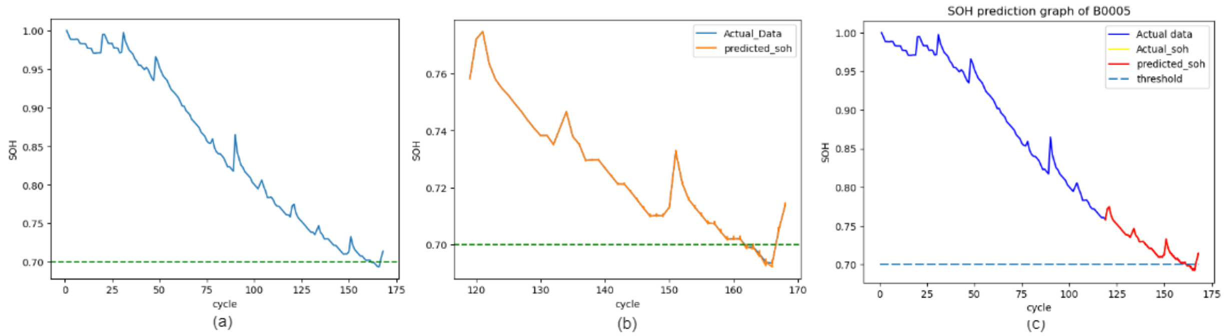

Figure 6.1: SOH prediction results of B0005

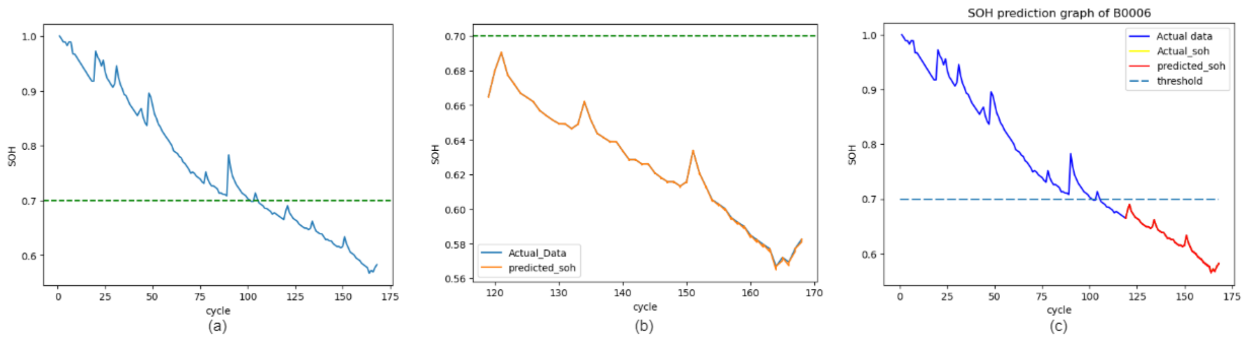

Figure 6.2: SOH prediction results of B0006

The third lithium ion battery is B0007. The prediction results of B0007 battery is shown in figure 6.3. Figure 6.3(b) illustrating the graph of comparing actual SOH and predicted SOH shows that the model have very minimal error in forcasting the upcomming SOH value. Figure 6.3(c) indicates the SOH prediction graph of B0007. The RMSE, MAE and R Square values obtained are 0.00057, 0.00022 and 0.9998 respectively.

B0018 is the fourth Li-ion battery that exhibits significant fluctuation and oscillation during capacity decline and has less cycles than the previous batteries shown in Fig 6.4. Figure 6.4(b) indicates that the model accurately captures the data pattern and predicts SOH similar to actual SOH. The RMSE, MAE and R Square values achieved are 0.00046, 0.00044 and 0.9998 respectively.

All the figures indicate that the predicted curve of the proposed model closely aligns with the actual state of health (SOH) curves. Therefore, the TCN model exhibits a high degree of accuracy in estimating the SOH values of these batteries. Table 6.1 summarises the performance evaluation of the SOH estimation of batteries B0005, B0006, B0007, and B0018. It shows that the for a TCN model, RMSE and MAE values are very less and have achieved the best R Square.

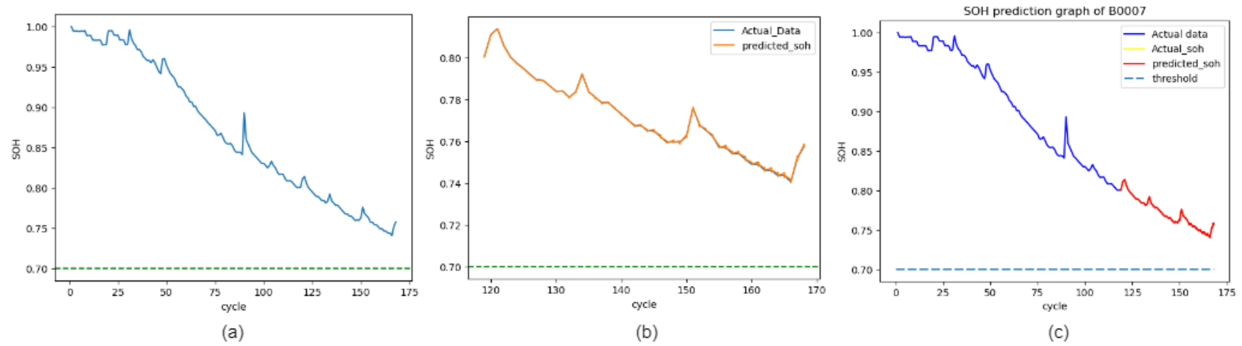

Figure 6.3: SOH prediction results of B0007

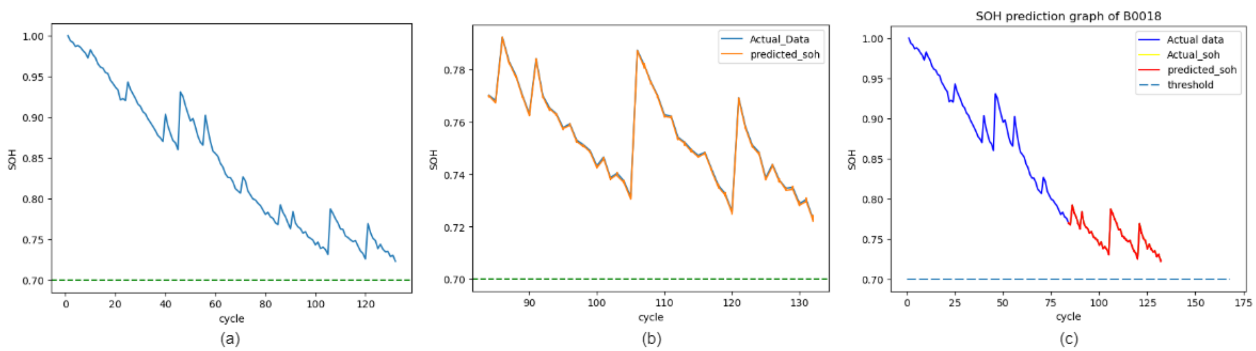

Figure 6.4: SOH prediction results of B0018

6.2 Remaining Useful Life Estimation

To evaluate the performance of the model, we need to compare the predicted RUL values with the actual capacity values of the batteries. In order to keep track of how much longer a battery will last, it's important for the model to make accurate predictions. Figure 6.5(a) displays the actual capacity of the B0005 battery. Figure 6.5(b) compares the predicted RUL values to the actual capacity, indicating how well the model works. The graph shows that the model is able to accurately predict the RUL values and matches the actual capacity. The RUL prediction graph for B0005 battery is depicted in Figure 6.5(c), and the RMSE, MAE, and R Square values obtained are 0.00016, 0.00048, and 0.9998 respectively.

Figure 6.6 displays the RUL prediction outcomes of the B0006 battery. Figure 6.6(a) represents the actual capacity of the B0006 battery. Figure 6.6(b) illustrates the comparison between the predicted RUL and actual capacity of the testing set. The graph shows that the model accurately identifies the data pattern and predicts the RUL values. Figure 6.6(c) demonstrates the RUL prediction graph of B0006 battery. The obtained RMSE, MAE, and R Square values are 0.00013, 0.00054, and 0.9998 respectively.

The RUL prediction results of the B0007 battery are demonstrated in Figure 6.7. Figure 6.7(b) displays the graph comparing the actual capacity and predicted RUL, indicating that

Table 6.1: Performance evaluation of SOH estimation of B0005, B0006, B0007 and B0018 battery

Battery ID	**RMSE**	**MAE**	**R SQUARE**
B0005	**0.00081**	**0.00058**	**0.9995**
B0006	**0.00027**	**0.00066**	**0.9997**
B0007	**0.00057**	**0.00022**	**0.9998**
B0018	**0.00046**	**0.00044**	**0.9998**

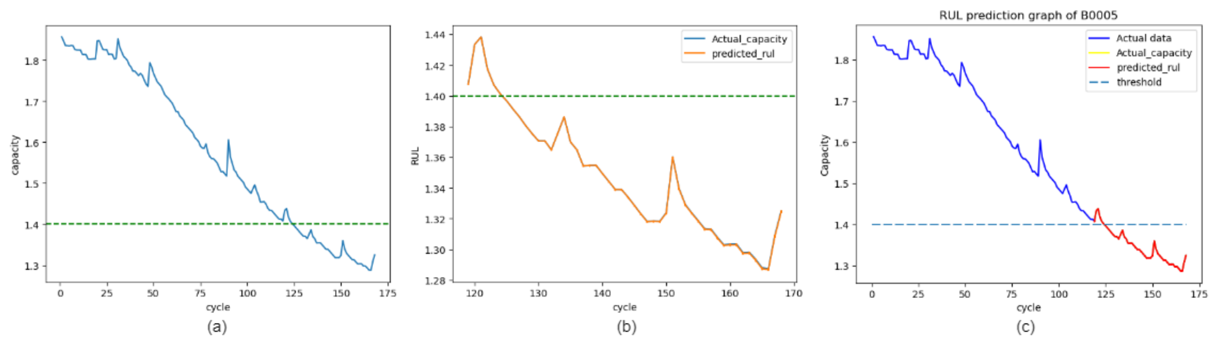

Figure 6.5: RUL prediction results of B0005

the model has an insignificant error in predicting the upcoming RUL value. Figure 6.7(c) shows the RUL prediction graph of B0007. The obtained RMSE, MAE, and R Square values are 0.00048, 0.00038, and 0.9997, respectively.

Figure 6.8 shows the RUL prediction results of B0018 battery. Figure 6.8(b) indicates that the model accurately captures the data pattern and predicts RUL similar to actual capacity. The RMSE, MAE, and R Square values obtained are 0.00028, 0.00065, and 0.9995 respectively.

All of the figures indicate that the predicted curve of the proposed TCN model is very close to the actual capacity curves. As a result, the TCN model is very accurate in estimating the RUL values of these batteries. Table 6.2 provides a summary of the performance evaluation of the RUL estimation of batteries B0005, B0006, B0007, and B0018. The table illustrates that the RMSE and MAE values achieved for the TCN model is minimal, and the best R Square values have been obtained.

Table 6.2: Performance evaluation of RUL estimation of B0005, B0006, B0007 and B0018 battery

Battery ID	**RMSE**	**MAE**	**R SQUARE**
B0005	**0.00016**	**0.00048**	**0.9998**
B0006	**0.00013**	**0.00054**	**0.9998**
B0007	**0.00048**	**0.00038**	**0.9997**
B0018	**0.00028**	**0.00065**	**0.9987**

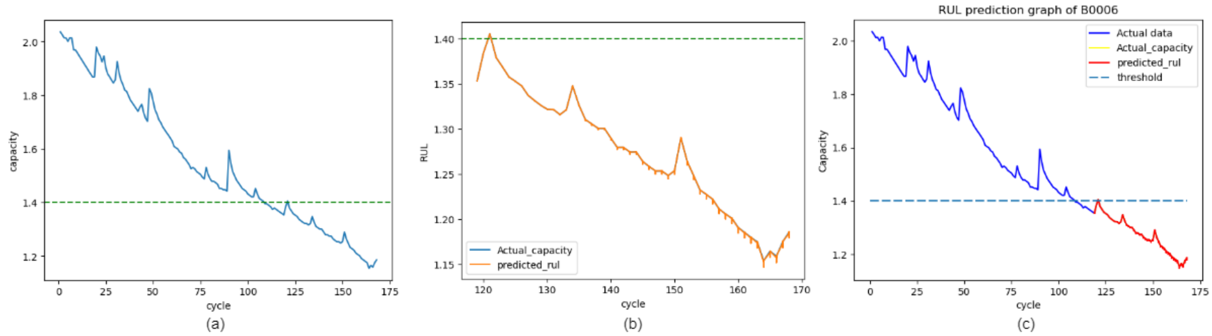

Figure 6.6: RUL prediction results of B0006

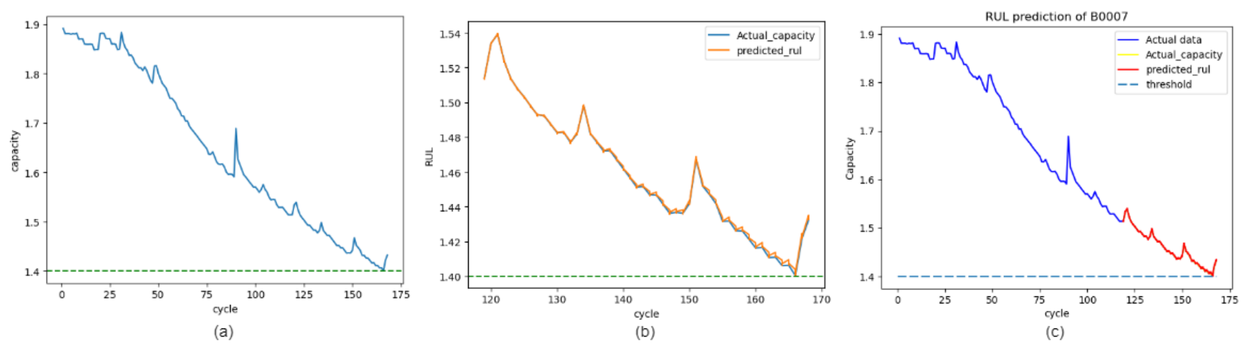

Figure 6.7: RUL prediction results of B0007

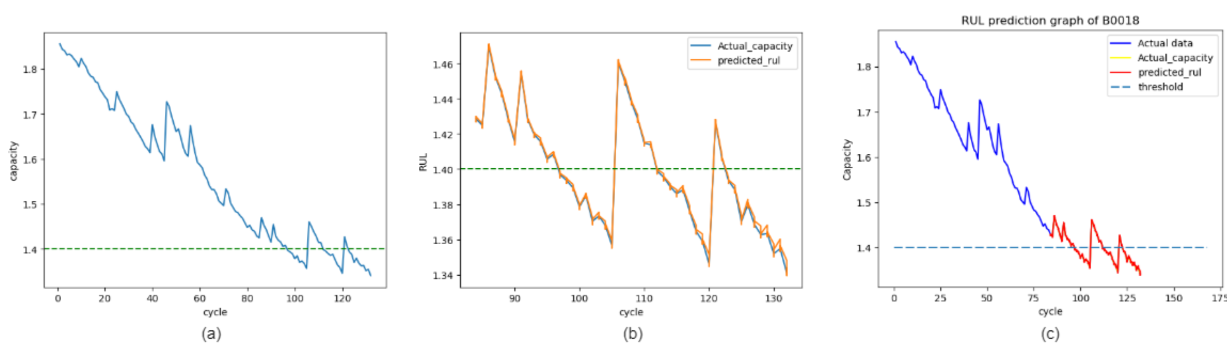

Figure 6.8: RUL prediction results of B0018

Chapter 7

Conclusion

Over the past few years, there has been growing interest in the prognostic and health management (PHM) of lithium-ion batteries. A crucial aspect of PHM is monitoring the state of health (SOH) and predicting the remaining useful life (RUL) of the batteries. Monitoring the SOH helps to extend the battery's lifespan, while accurately predicting the RUL is crucial for ensuring system safety. Therefore, it is necessary to implement measures that enable effective predictions for both SOH and RUL. The proposed study introduces a Temporal Convolutional Network (TCN) model, which is well-suited for estimating the state of health and predicting the remaining useful life of batteries. To enhance the model's sensitivity to local regeneration phenomena, the techniques of Dilated Convolution and residual connection are employed. The proposed model has been experimentally validated on NASA Battery Health dataset. The experimental results of SOH and RUL estimation demonstrate a good prediction results with an average R Square of 0.9998 and RMSE of 0.00057 respectively. The findings demonstrate that the proposed model can produce a reliable and accurate SOH and RUL prediction and this can be used as a tool in real time scenario.

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