A Project Report

On

AI-ML based optimization of battery's thermal management in EVs

BY

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Birla Institute of Technology and Science-Pilani,

Hyderabad Campus

Certificate

This is to certify that the project report entitled "**AI-ML based optimization of battery's thermal management in EVs**" submitted by Mr/Ms. V S ABHINAV RAHUL GANDRAKOTA (ID No. 2019A8PS1354H) in partial fulfillment of the requirements of the course EEE/ECE/INSTR F376/F377, Study Project Course, embodies the work done by him under my supervision and guidance.

Date: 12/12/2022 **(Dr. Harish V Dixit)**

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ABSTRACT

Redox Flow Batteries have risen in popularity in recent years as a large-scale energy storage solution. Efficiency of the battery storage system relies on minimizing power loss, which in turn is dependent on predicting VRFB stack temperature and keeping it within a safe limit so as to prevent thermal precipitation. We have predicted variation of stack temperature with time duration of a practical 1kW 6kWh VRFB system dataset under four different operating current levels (40, 45, 50, and 60A) keeping a constant electrolyte flow rate of 180 ml/sec. In this report, we have used both Polynomial Regression and LSTM methods to accurately predict the stack temperature of the battery during charging and discharging profiles. The prediction accuracy of the algorithm has been tested using regression metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Correlation Coefficient (R2). The algorithm performance and the parameter performance graphs have also been plotted for visualization of results.

CONTENTS

INTRODUCTION

In recent years, there has been a massive transition from traditional fossil fuel sources to renewable energy sources for electricity generation. However, although these renewable energy sources have the advantage of being low carbon energy sources, there are a number of challenges. Firstly, they are relatively inflexible in terms of the fact that you cannot simply increase power supply on demand. They are also intermittent in nature, and often out of alignment with electricity demand, thus requiring excess capacity to stabilize supply. Sometimes there can even be an excess of supply, more than the grid can handle, leading to wasted electricity. All the above mentioned problems call for an efficient high capacity energy storage system to help balance the supply and demand issues.

One such energy storage solution is a Redox Flow battery. In this battery, the amount of energy stored is related to the amount of liquid electrolyte which is often contained in the external tanks. This electrolyte is then pumped through a battery stack where power can be put into or taken out of the fluids by changing their oxidation states. This design makes them quite flexible and modular. If you need more energy you can increase the size of the tanks and if you need more power you can increase the number of stacks. Also because the electrolyte is a liquid, the system tends to be more durable, safe, and has a longer lifetime.

Now, there are different types of redox flow batteries based on their chemistry. The ones that have been commercialized so far are Zn/Br systems, Fe/Cr systems and All Vanadium systems. The ideal characteristics to look for when choosing a RFB are high reactivity for more efficiency, and a large stable voltage window. Out of these, the most optimal system would be the Vanadium Redox Flow Battery (VRFB).

In VRFB, both the anolyte and catholyte are made up of Vanadium electrolytes, which is possible due to the fact that Vanadium has 4 useful oxidation states. Here, the V4+/V5+ redox couples are used for the positive electrode and the V2+/V3+ redox couples are used for the negative electrode. The electrolyte solution is composed of Sulfuric Acid. The advantage of this system is therefore high theoretical lifetimes since crossover effects are not irreversible considering that Vanadium is used on both sides and can thus be rebalanced. There are also limited unwanted hydrogen evolution side reactions at the anode leading to higher stability. Also, the high relative reactivity of the redox couples means that expensive catalysts aren't required.

In the case of using VRFB's for large scale energy storage, we need the system to be power efficient. In order to enhance energy and power performance, a novel cell design was introduced by Al-Yasiri et al.. Thermal modeling is another critical factor in building a battery management system. A thermal model of VRFB was initially presented by Tang et al. which was based on thermodynamic equations and mass transfer theory. This is necessary as V2+/V3+ precipitation occurs at temperatures below 5°C and V5+ precipitation occurs at temperatures above 40°C, which can lead to membrane degradation and hence a decrease in battery efficiency. Thus controlling battery temperature is an important aspect in the VRFB design for effective and safe operation.

Before we can optimize the battery temperatures, we must first be able to predict the VRFB stack temperatures accurately. In this paper, prediction of temperatures during charging and discharging was done using both Polynomial Regression and LSTM methods under different operating current levels and a fixed flow rate.

IMPLEMENTATION

The experimental data for charging and discharging profiles for 4 different stack currents (40A, 45A, 50A, 60A) was used to predict variation of VRFB stack temperatures with time for a flow rate of 180 ml/sec.

Polynomial Regression:

We first read all the csv files and renamed the columns for the 4 discharging datasets as they did not have any column names. We transformed the data into a dataframe containing one feature, namely 'Hours'. Then we split the dataset into a 80:20 split for training and testing respectively and randomly shuffled the data.

We created polynomial regression models for degrees 0-9 and implemented it on the dataset. We used gradient descent to update the weights at each iteration.

The MSE error was calculated every 5000 iterations and the model was run for a total of 50000 iterations.

The final MAE, RMSE and R2 errors were calculated and tabulated for each of the polynomial functions of degrees 0-9.

LSTM:

We read all the csv files and renamed the columns for the 4 discharging datasets as they did not have any column names just like in the Polynomial Regression Model. We used the 'train_test_split' function within

Scikit-learn to split the dataset 70:30 for training and testing respectively. We did not shuffle the data in this case as LSTM's need sequential data for performing time series prediction.

We reshaped the training and testing temperature data and performed Min-Max scaling using the 'MinMaxScaler' function within Scikit-learn so as to bring all temperature values within the range [0,1]. Min-Max scaling is performed when it is required to capture small variance in features and also for sparse data where the zero value needs to be preserved.

We then used the 'TimeseriesGenerator' module within Tensorflow to generate a time series with number of features as 1 and number of inputs as 5. Essentially this means that the model will use 5 values from the data to predict the 6th value in the data.

We then created an LSTM model having 100 hidden layers which takes an input of shape (5,1) and uses a ReLU activation function at the output layer finally giving an output of size 1. The Adam optimizer with a learning rate of 0.001, $\beta 1 = 0.9$, $\beta 2 = 0.999$, $\epsilon = 10\text{-}8$ was used with no weight decay. MSE error was used as the loss function.

The model was then trained on the training dataset for 50 epochs and the loss per epoch was plotted.

We then used the model for prediction over the length of the entire dataset and the predicted values were stored in an array before being rescaled to the original size. The array was added later as an extra column within the dataset.

The final MSE, RMSE and R2 errors were calculated and tabulated. We then plotted the algorithm performance and the parameter performance graphs.

RESULTS

To analyze the accuracy of the model, we use 3 different error metrics, namely: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Correlation Coefficient (R^2).

Polynomial Regression:

Table for Performance in case of charging:

Degree 0:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	1.000000054188	1.000000055486	1.000000058641	1.000000055149
R^2	-1.0837693e-07	-1.1097319e-07	-1.1728365e-07	-1.1029845e-07
MAE	0.79636311893	0.801527965507	0.806643076407	0.795542684259

Degree 1:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.261820765328	0.233474973369	0.303533285157	0.336275377946
R^2	0.931449886842	0.945489436810	0.907867544801	0.886918870187
MAE	0.206475791043	0.169643727601	0.217558073105	0.266074783454

Degree 2:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.205557362438	0.216289308930	0.258262037772	0.267785789811
R^2	0.957746170747	0.953218934842	0.933300719845	0.928290770774
MAE	0.145260037388	0.140918640798	0.169225480306	0.187461635800

Degree 3:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.196662257413	0.213183008453	0.249401050146	0.261860366255
R^2	0.961323956508	0.954553004906	0.937799116185	0.931429148584
MAE	0.130870066568	0.132380416088	0.161851338266	0.186646266834

Degree 4:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.195386430623	0.212057479148	0.251763094276	0.255061900489
R^2	0.961824142728	0.955031625537	0.936615344360	0.934943426918
MAE	0.127657159399	0.132614100533	0.165729052243	0.177712556956

Degree 5:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.195184030533	0.212900356460	0.246154103094	0.257549830532
R^2	0.961903194224	0.954673438219	0.939408157529	0.933668084792
MAE	0.127820553596	0.132176174674	0.156943206516	0.180971194849

Degree 6:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.195586122389	0.212631674367	0.249128205431	0.258178498011
R^2	0.961746068728	0.954787771055	0.937935137258	0.933343863164
MAE	0.128729361668	0.132075218875	0.161732632856	0.181767308904

Degree 7:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.196579219502	0.215318387015	0.246001621343	0.260355095727
R^2	0.961356610459	0.953637992213	0.939483202296	0.932215224128
MAE	0.130672156915	0.132803716934	0.156690198196	0.184498457729

Degree 8:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.196859206887	0.213491271545	0.253044708111	0.257538233717
R^2	0.961246452663	0.954421476973	0.935968375696	0.933674058173
MAE	0.131220560208	0.132506748650	0.167142818279	0.180123947075

Degree 9:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.194320664266	0.213420250161	0.167293886478	0.257324587811
R^2	0.962239479438	0.954451796820	0.935895413791	0.933784056507
MAE	0.126203424178	0.132271059049	0.167293886478	0.180724456040

Table for Performance in case of discharging:

Degree 0:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	1.000000058204	1.000000055225	1.000000057462	1.000000055997
R^2	-1.1640934e-07	-1.1045065e-07	-1.1492491e-07	-1.11995420e-07

MAE	0.770008808551	0.787162693602	0.792983024100	0.770988459230

Degree 1:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.303247155681	0.272996827443	0.312423058118	0.341918538934
R^2	0.908041162571	0.925472732205	0.902391832755	0.883091712732
MAE	0.241062627177	0.204512212672	0.222127963916	0.266723442306

Degree 2:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.227309483468	0.206544400886	0.255822700034	0.256984260024
R^2	0.948330398725	0.957339410462	0.934554746146	0.933959090099
MAE	0.164821701865	0.146087555100	0.164012651553	0.178320681513

Degree 3:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.205645552810	0.193170974883	0.250050009910	0.248064133493

R^2	0.957709906609	0.962684974462	0.937474992543	0.938464185673
MAE	0.135642152051	0.133084776897	0.160891533394	0.176436525171

Degree 4:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.206233199757	0.196277573161	0.253933664239	0.249087312706
R^2	0.957467867317	0.961475114273	0.935517694166	0.937955510648
MAE	0.137017529412	0.135538296143	0.165743781008	0.177457883947

Degree 5:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.207617533551	0.188109565125	0.252404796675	0.243459959915
R^2	0.956894959762	0.964614791508	0.936291818615	0.940727247918
MAE	0.138723584089	0.126613644975	0.164449738500	0.169574898223

Degree 6:-

Error Metric	Current

	40A	45A	50A	60A
RMSE	0.204035295128	0.192962434206	0.248973038305	0.249053722833
R^2	0.958369598341	0.962765498985	0.938012426196	0.937972243142
MAE	0.135149941818	0.132223665531	0.158905892604	0.177484027333

Degree 7:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.206231810842	0.187112701449	0.248591052542	0.250033653187
R^2	0.957468440196	0.964988836956	0.938202488595	0.937483172273
MAE	0.137107114912	0.126192688492	0.158658594923	0.178427523078

Degree 8:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.205996579914	0.186913950680	0.250532524627	0.249762565095
R^2	0.957565409063	0.965063175040	0.937233454103	0.937618661076
MAE	0.136121614675	0.125216421621	0.161687860071	0.178169665331

Degree 9:-

Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.206375854836	0.193461336996	0.253160743382	0.251233872041
R^2	0.957409006540	0.962572711087	0.935909638010	0.936881541539
MAE	0.137476199601	0.131813741665	0.164886502307	0.179716391834

LSTM:

Table for Performance in case of charging:

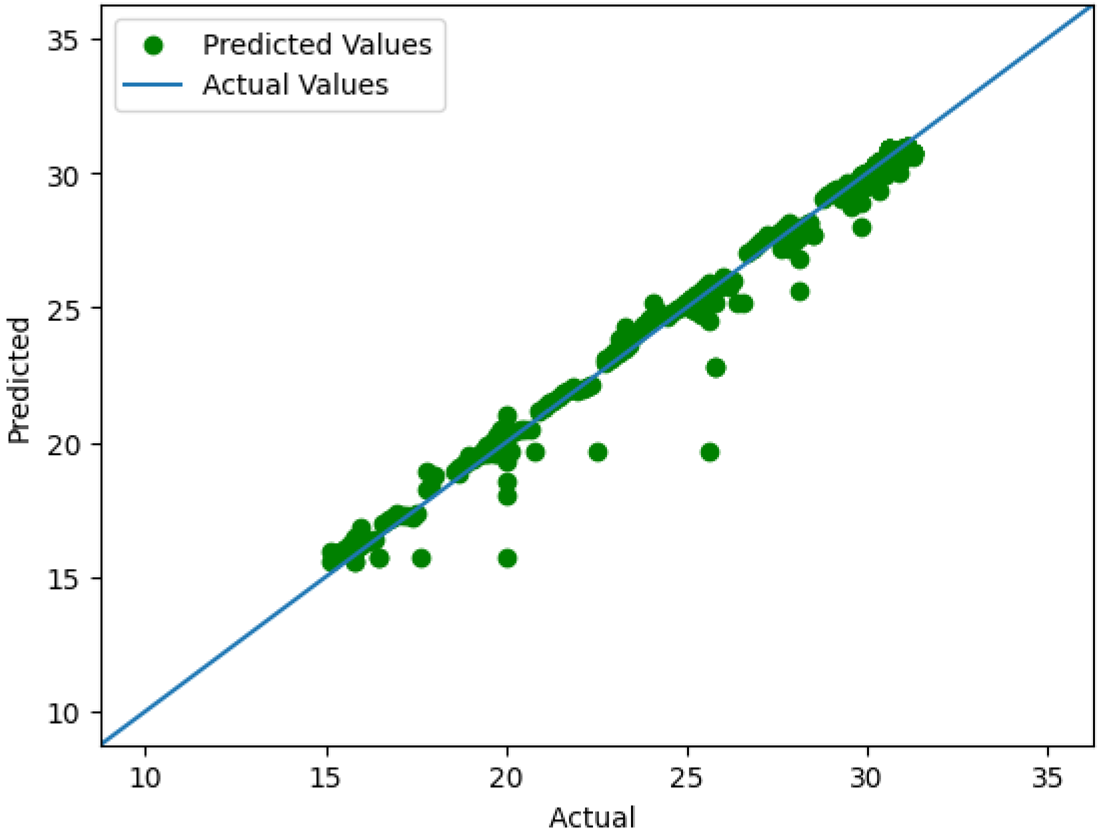
Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.342742386503	0.502422332494	0.527558536624	0.961910117138
R^2	0.993120516077	0.990662777835	0.989705123731	0.987888394547
MAE	0.173379036838	0.291018920655	0.346041830620	0.370003210320

Table for Performance in case of discharging:

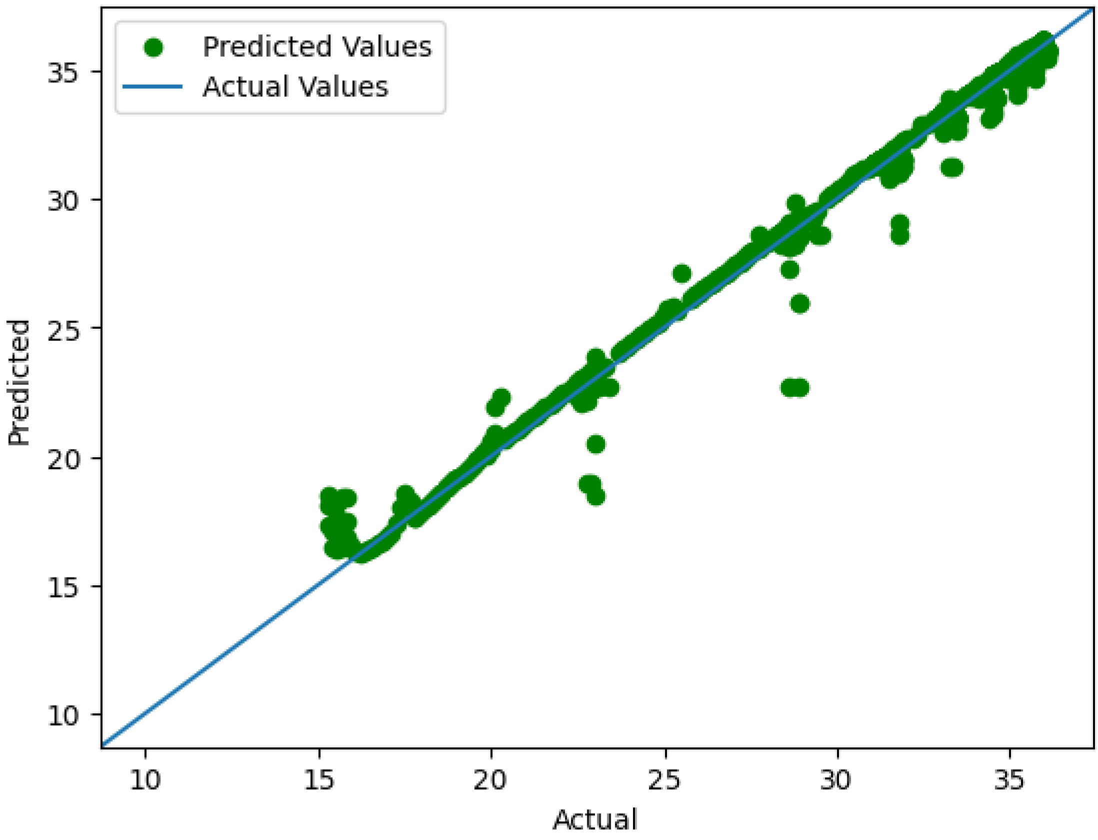
Error Metric	Current			
	40A	45A	50A	60A
RMSE	0.309661595769	0.407636375878	0.562765759471	0.776349582986
R^2	0.995161027621	0.994857159205	0.992715938415	0.993098315006
MAE	0.246384419321	0.207762836428	0.173442373104	0.175605433060

__Algorithm Performance Graphs:__

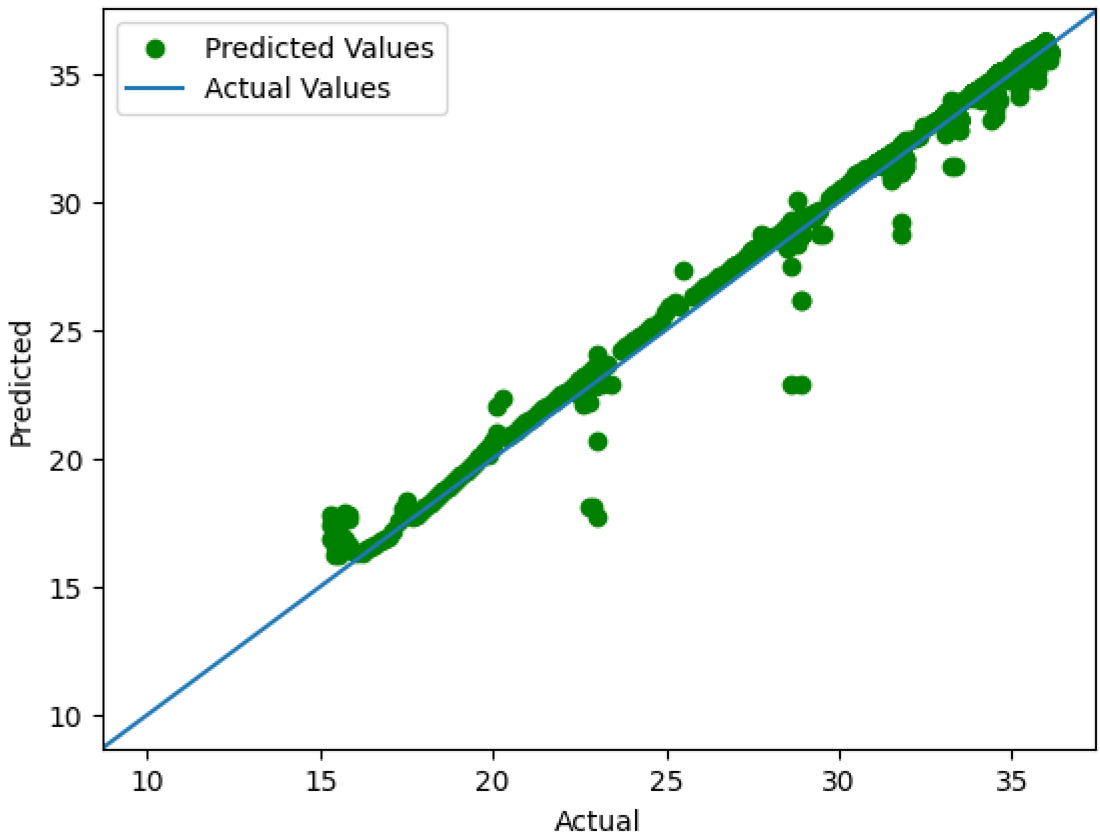
1) 40A Charging:-



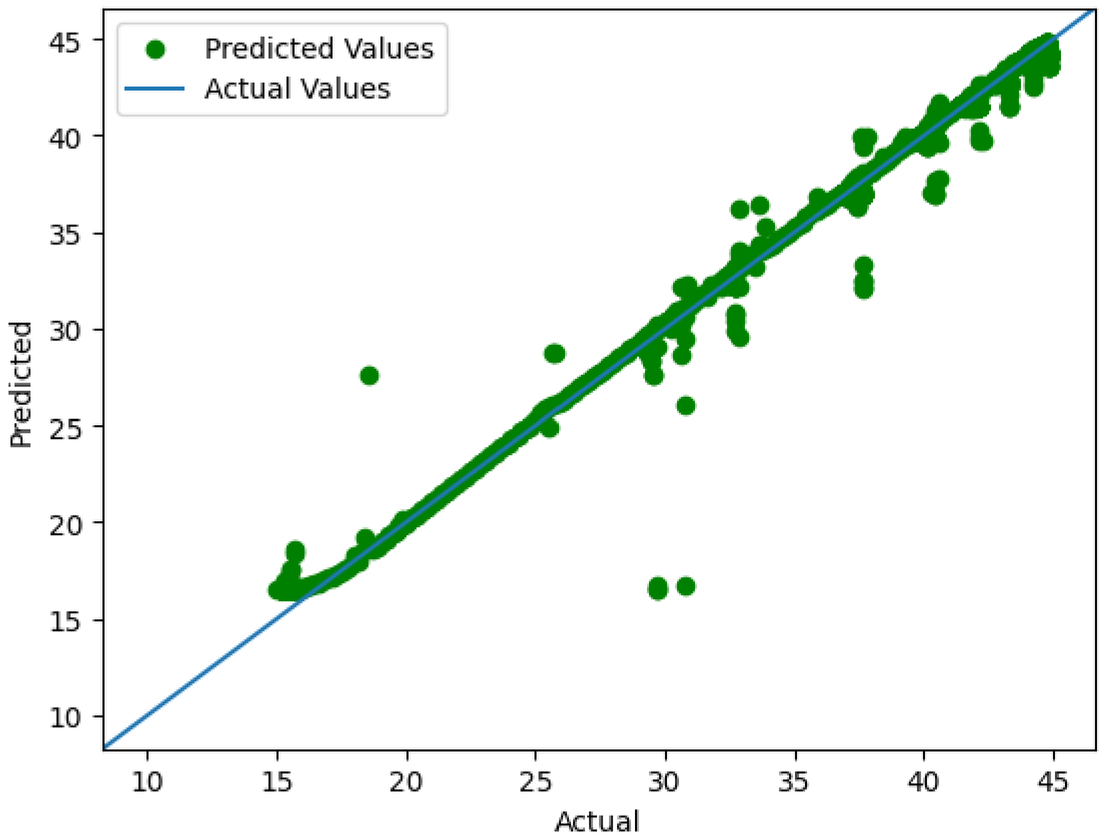
2) 45A Charging:-



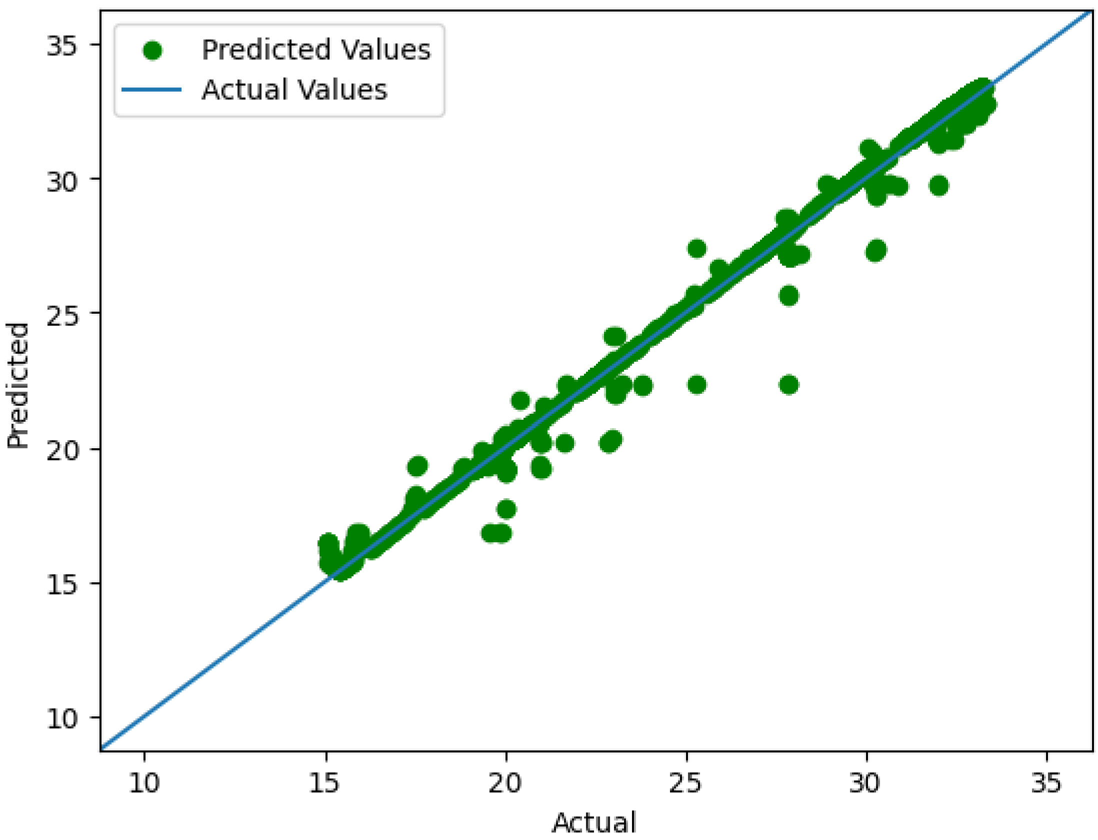
3) 50A Charging:-



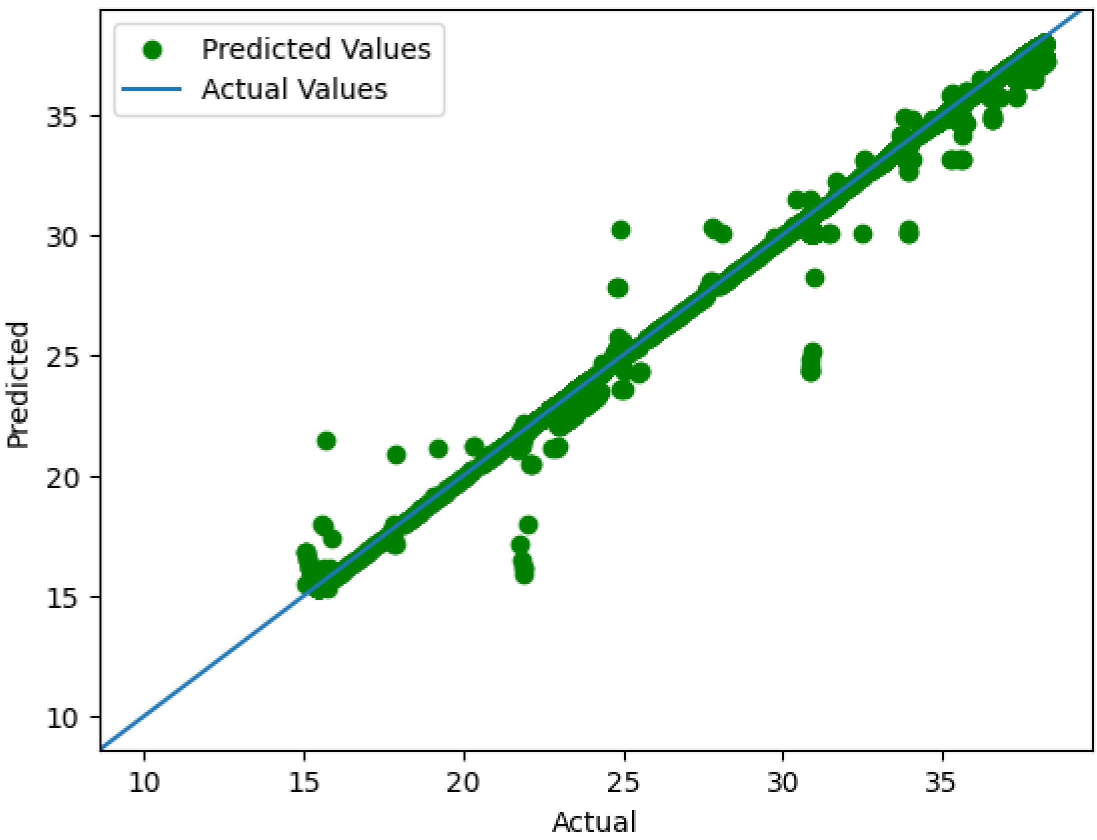
4) 60A Charging:-



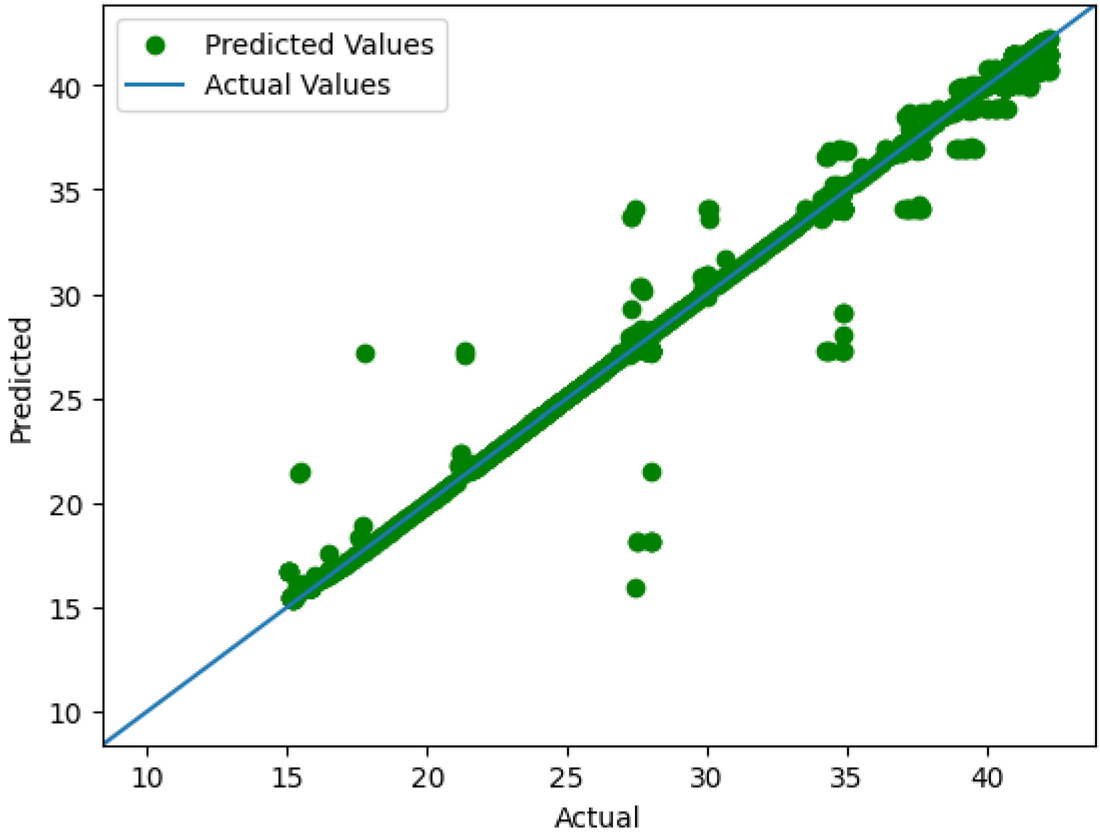
5) 40A Discharging:-



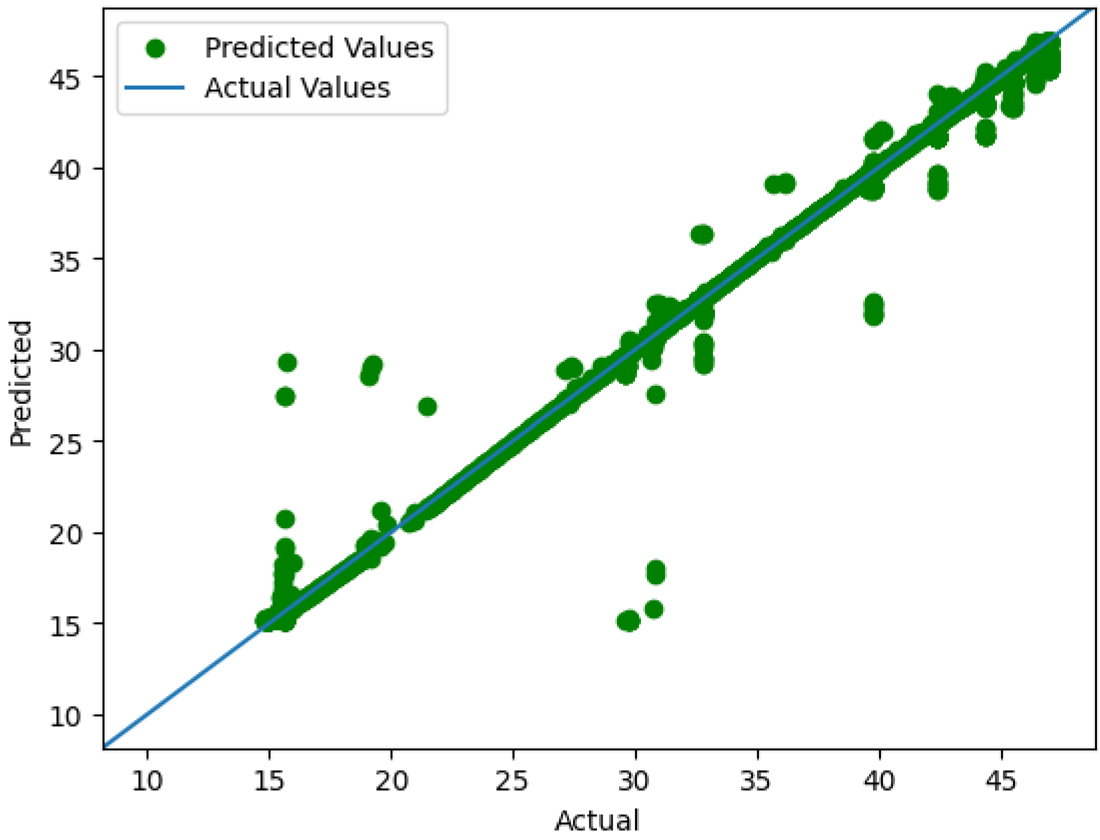
6) 45A Discharging:-



7) 50A Discharging:-



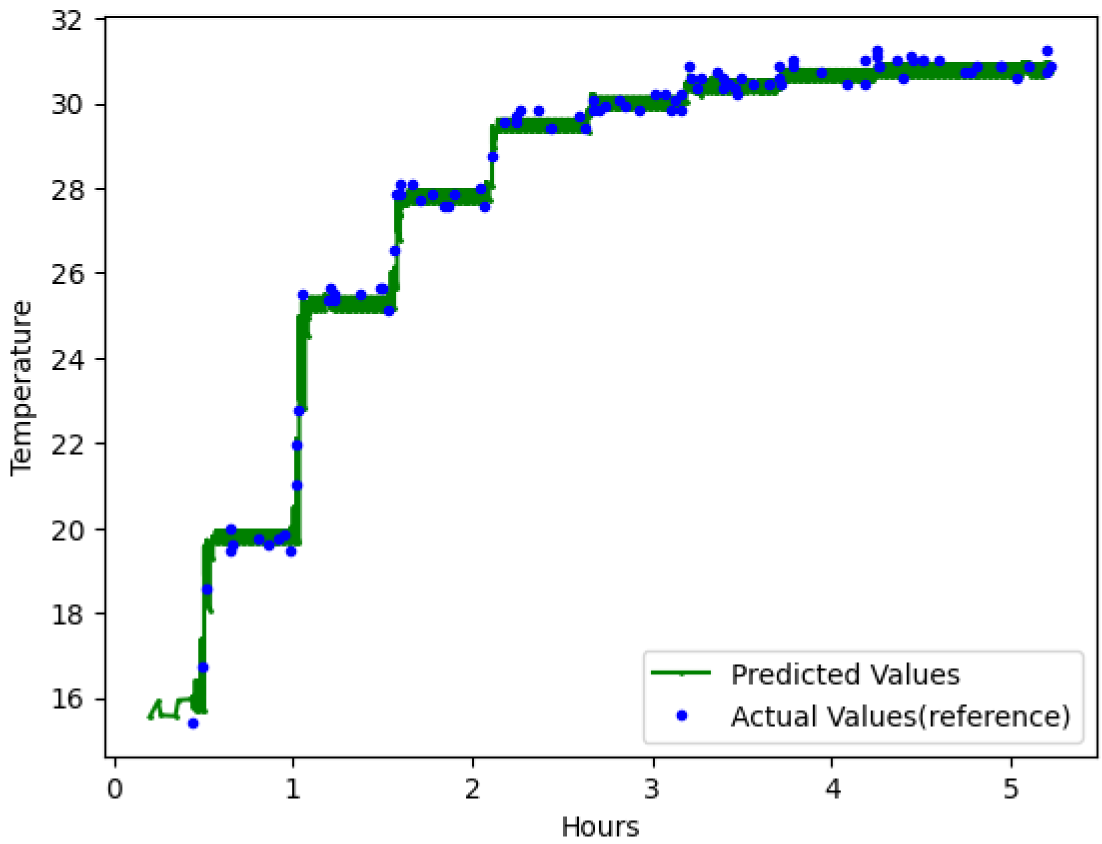
8) 60A Discharging:-



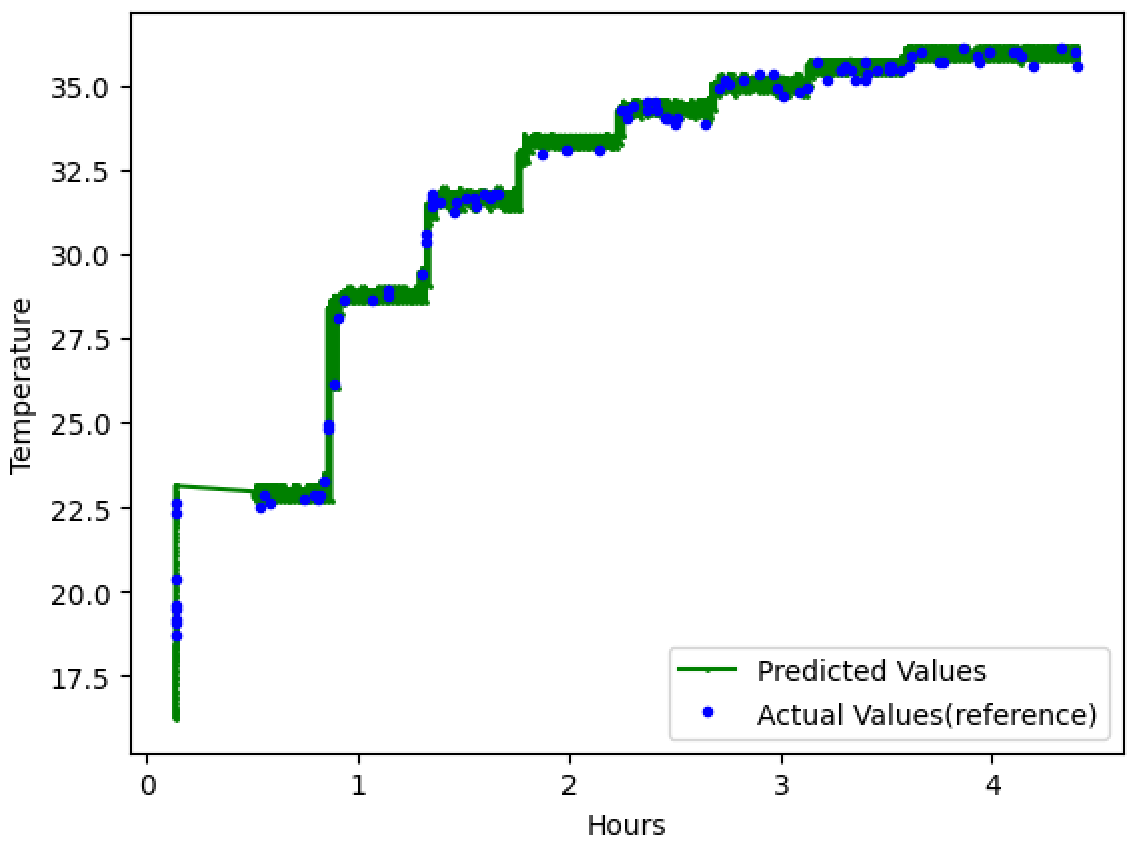
Parameter Performance Graphs:

For the actual values, we have taken only 100 points for charging and 150 points for discharging randomly so as to make the visualization of actual and predicted points more distinct.

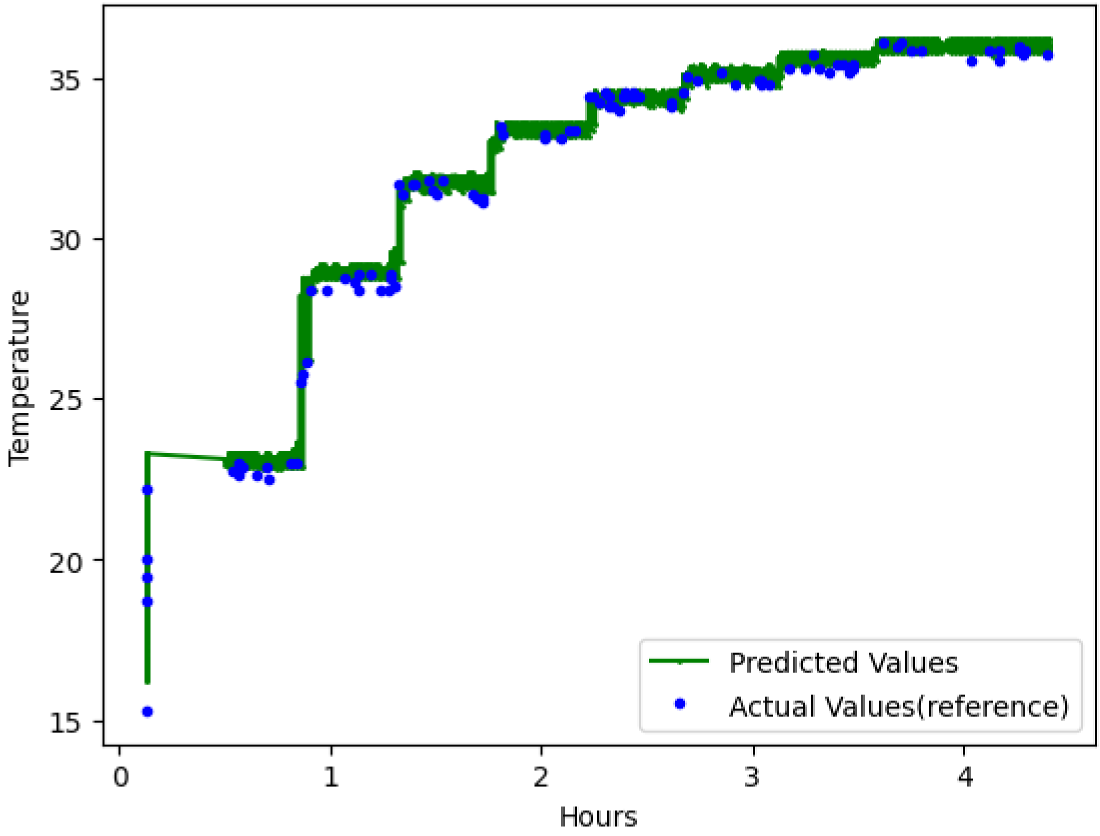
1) 40A Charging:-



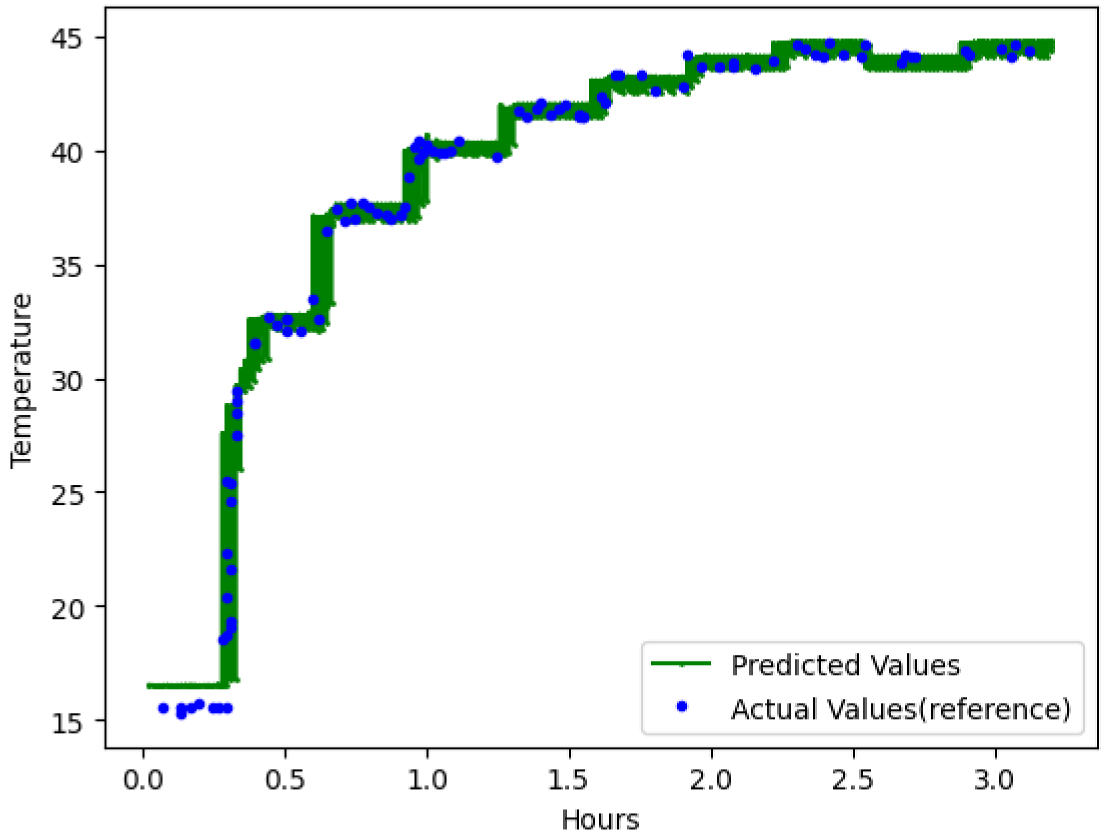
2) 45A Charging:-



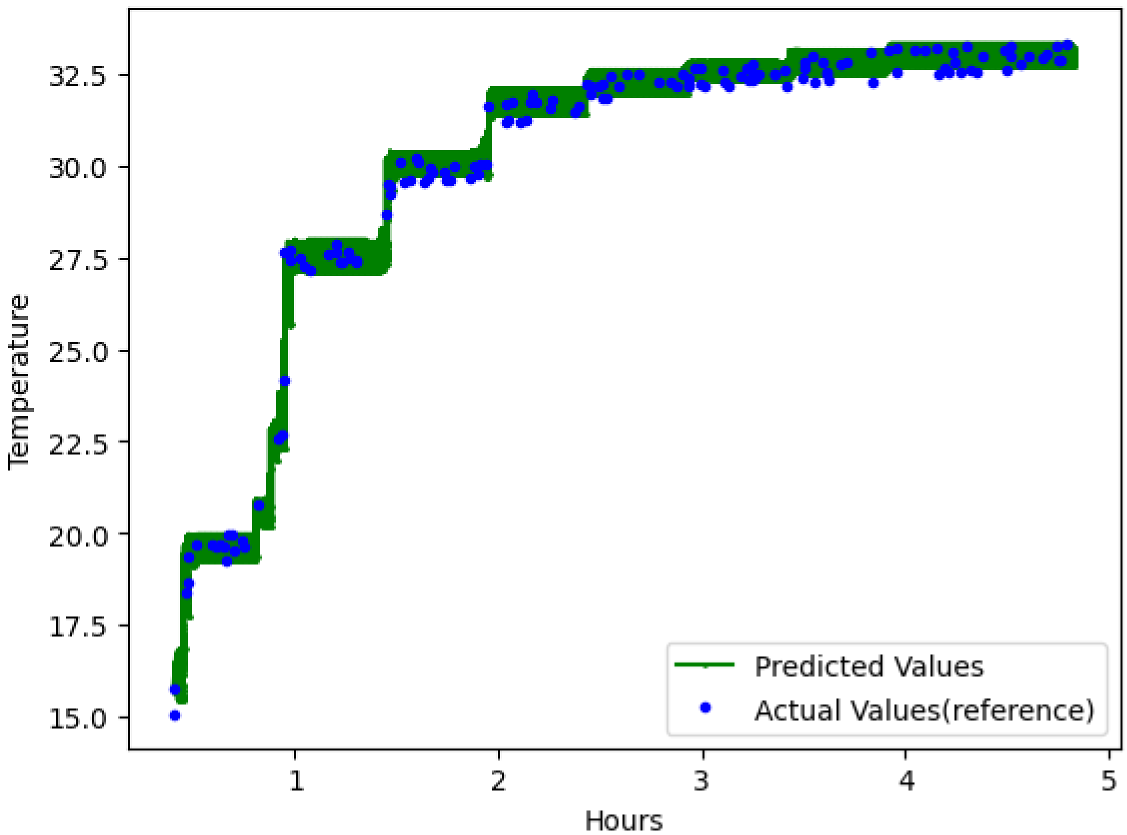
3) 50A Charging:-



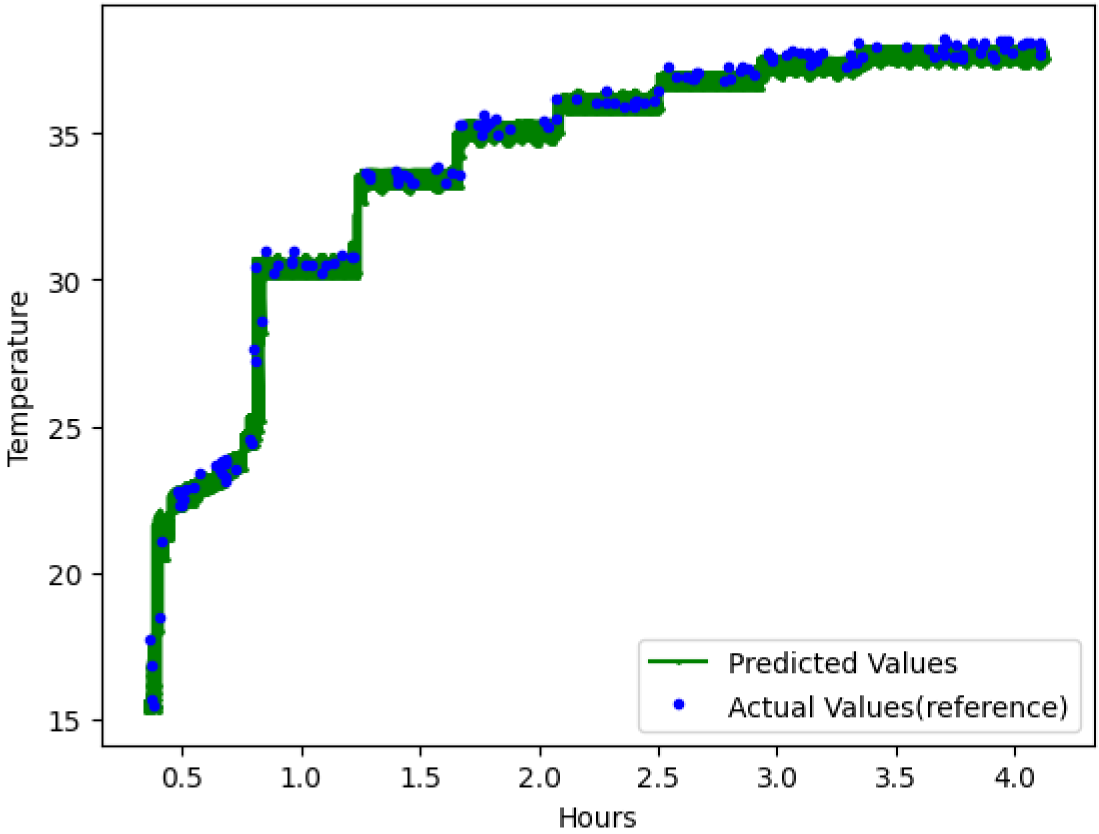
4) 60A Charging:-



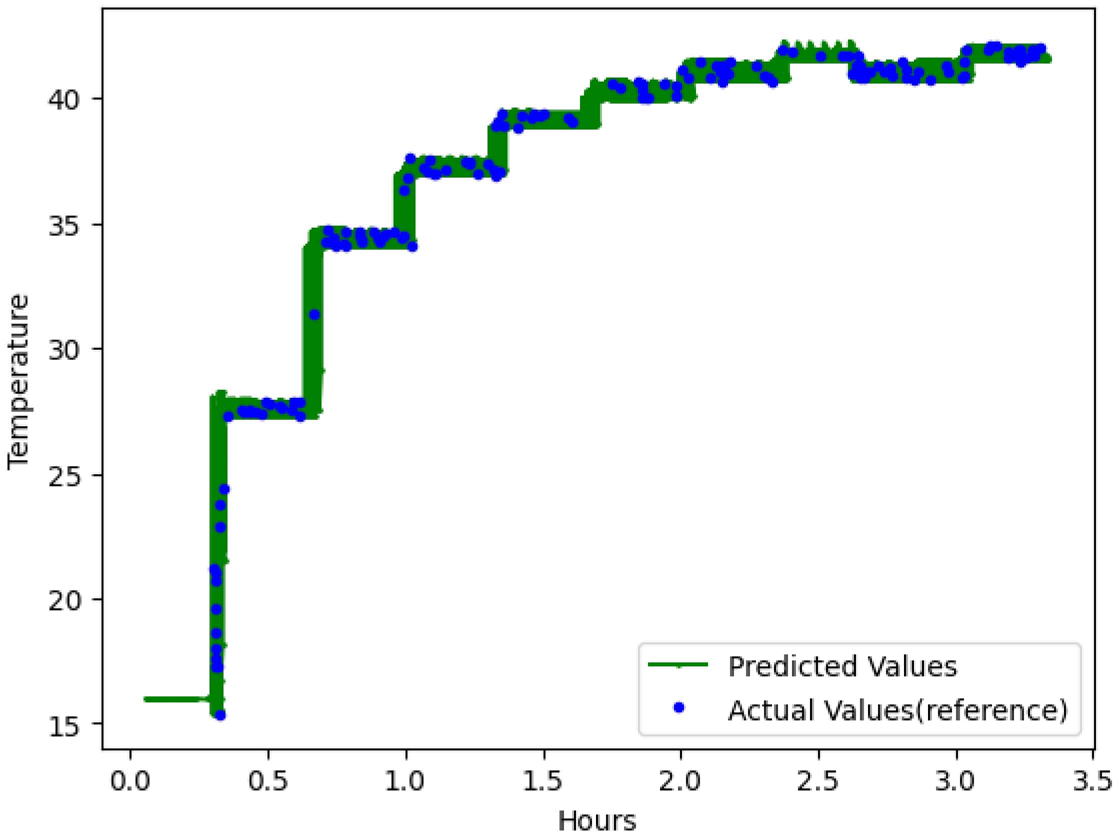
5) 40A Discharging:-



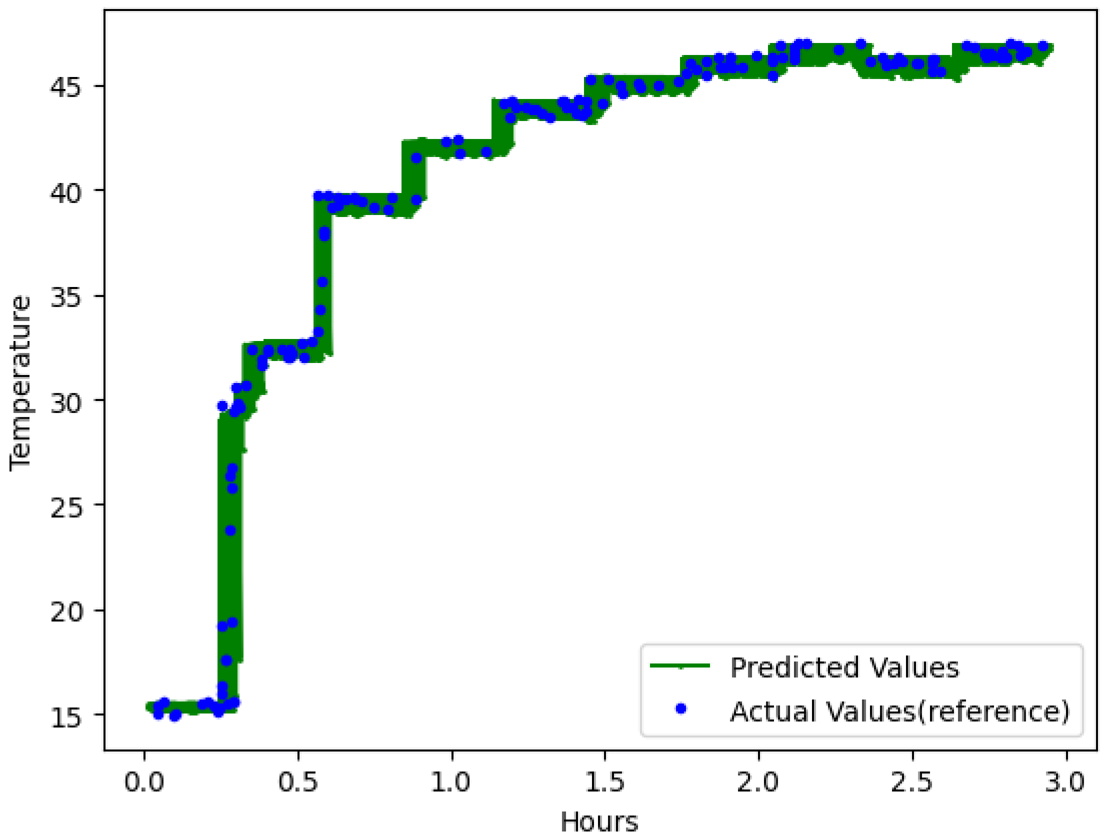
6) 45A Discharging:-



7) 50A Discharging:-



8) 60A Discharging:-



CONCLUSION

Upon training the Polynomial Regression model on the datasets and calculating R^2 error, we observed that the best degree polynomial function for each of the datasets w.r.t R^2 error are as follows:

1) 40A Charging = Degree 9 (0.962239479438)
2) 45A Charging = Degree 4 (0.955031625537)
3) 50A Charging = Degree 7 (0.939483202296)
4) 60A Charging = Degree 4 (0.934943426918)
5) 40A Discharging = Degree 6 (0.958369598341)
6) 45A Discharging = Degree 8 (0.965063175040)
7) 50A Discharging = Degree 7 (0.938202488595)
8) 60A Discharging = Degree 5 (0.940727247918)

In the case of LSTM, the best case R^2 error that we achieved was **0.995161027621** (40A Discharging dataset).

The results indicate that the LSTM model performs far better overall as compared to the Polynomial Regression model for predicting the VRFB stack temperature.

In the future, we plan on further optimizing the temperature with respect to flow rate using these algorithms.

REFERENCES

[1] Bhattacharjee A, Saha H. Development of an efficient thermal management system for Vanadium Redox Flow Battery under different charge-discharge conditions, Appl Energy 2018:1182-92

[2] Skyllas-Kazacos M, Rychcik M, Robins RG, Fane AG, Green MA. New All-vanadium redox flow cell. J Electrochem Soc 1986;133:1057–8.

[3] Zheng Q, Li X, Cheng Y, Ning G, Xing F, Zhang H. Development and perspective in vanadium flow battery modelling. Appl Energy 2014;132:254–66.

[4] Al-Yasiri M, Park J. A novel cell design of vanadium redox flow batteries for en-hancing energy and power performance. Appl Energy 2018;222:530–9.

[5] Bhattacharjee A, Roy A, Banerjee N, Patra S, Saha H. Precision dynamic equivalent circuit model of a Vanadium Redox Flow Battery and determination of circuit parameters for its optimal performance in renewable energy applications. J Power Sources 2018;396:506–18.

[6] Tang A, Ting S, Bao J, Skyllas-Kazacos M. Thermal modelling and simulation of the all-vanadium redox flow battery. J Power Sources 2012;203:165–76

[7] Zheng Q, Zhang H, Xing F, Ma X, Li X. Ning G, A three-dimensional model for thermal analysis in a vanadium flow Battery. Appl Energy 2014:1675–85

[8] Ra N, Bhattacharjee A. Prediction of vanadium redox flow battery storage system power loss under different operating conditions: Machine learning based approach. Int J Energy Res. 2022;1‐13.

[9] Hochreiter, Sepp & Schmidhuber, Jürgen. (1997). Long Short-term Memory. Neural computation. 9. 1735-80. 10.1162/neco.1997.9.8.1735

[10] F. Karim, S. Majumdar, H. Darabi, and S. Chen, "Lstm fully convolutional networks for time series classification," IEEE access, vol. 6, pp. 1662–1669, 2017.

[11] https://arxiv.org/pdf/2003.05672.pdf

[12] Ostertagova, Eva. (2012). Modelling Using Polynomial Regression. Procedia Engineering. 48. 500–506. 10.1016/j.proeng.2012.09.545.