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Research paper

Long Short-Term Memory Approach to Predict Battery SOC

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ABSTRACT

Estimating the 'State of Charge' (SOC) is a complex endeavour. Data-driven techniques for SOC estimation tend to offer higher prediction accuracy compared to traditional methods. With the progression of Artificial Intelligence (AI), machine learning has found extensive applications across various fields such as infotainment, driver assistance systems, and autonomous vehicles. This paper categorizes the machine learning techniques utilized in Battery Management System (BMS) applications and employs a modern supervised neural network approach to predict SOC. Accurate SOC estimation is crucial to prevent battery failures in critical situations, such as during heavy traffic or when traveling with limited access to charging stations. Long Short-Term Memory (LSTM) networks are particularly adept at classifying, processing, and predicting based on time series data. These models are capable of capturing and retaining features over time, making them suitable for this study. The model's predicted SOC closely matches the true SOC, and the SOC prediction error remains nearly zero even with a large sample of input data.

1. INTRODUCTION

The ongoing transition in the automotive industry from Internal Combustion (IC) engines to electric mobility necessitates electric vehicles with mileage reliability comparable to that of IC engines. (Li, Z., Huang, J., Liaw, B.Y., et al., 2017). This can be accomplished by utilizing batteries with high power and energy density. However, opting for a battery pack with the highest capacity would increase the weight of the Electric Vehicle (EV), thereby impacting its overall performance. Thus, there is a trade-off between battery capacity and EV mileage (Landi, B.J., Ganter, M.J, et al., 2009). Lithium-ion battery packs fulfill the requirements of EVs and Hybrid Electric Vehicles (HEVs), yet their durability, safety, and lifespan remain concerns from a functionality standpoint. SOC, temperature, and the charge/discharge cycle number serve as essential parameters to evaluate the lifetime of lithium-ion batteries (Li, J., Cheng, et al., 2018). The battery management system (BMS) plays the major role in

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controlling and monitoring in all aspects of battery operations in an EV (Lim, D.J., Ahn, et al., 2016). A Battery Management System (BMS) is a single functional module that basically deals with balancing cells, monitoring cell temperature, estimating battery pack state of health, and State of Charge (SOC), which typically consists of a specific type and number of cells (e.g.; Nissan Leaf has 192 cells while the Tesla Model S consists of 7,104 cells). SOC is the most critical of parameters that, in a sense, might let EV drivers predict how much distance could be traveled based on the remaining battery capacity. The absence of accurate estimation of SOC causes battery failure when an electric vehicle is subjected to heavy traffic conditions or traveling to areas with very poor access to charge stations.

Estimation of SOC is a difficult and rather complicated task as it is a non-linear function dependent on temperature and current. SOC estimation methods are further divided into four subcategories : direct measurement, model-based, book-keeping estimation, and computer intelligence-based methods (Xiong, R., Cao et al., 2017). Data-driven approaches have a much higher prediction performance as they've been based on data science and machine learning algorithms than traditional techniques for SOC estimation (Lim, D.J., Ahn, et al., 2016). Because of the advancement in artificial intelligence (AI), machine learning is now already in use in almost all its possible application areas, especially in infotainment, driver assistance, and driverless vehicles. Because of its exceptional learning capabilities, artificial intelligence is dominating businesses (Xiong, R., Cao, J, et al., 2017). In order to accurately estimate SOC, researchers are working to integrate AI into battery management systems. For an EV application, this promotes the development of an effective prediction technique that is appropriate, accurate, adaptable, and able to precisely estimate SOC (Pai, S., Sindhu, M.R, et al., 2019). Regression AI approaches fall into four categories: neural networks, support vector machines (SVM), decision trees, and linear regression (Huria et al., 2013). For linear data, the first two methods work well. The work focuses on employing Artificial Neural Networks (ANN) and SVM models for accurate SOC prediction because batteries have non-linear features (Tejaswini P., Sivraj P., 2020).

While these packs of batteries present several barriers against electric vehicles, they should be monitored for their state of health in normal or abnormal conditions throughout the runtime. Another battery cell monitoring is the status and operation indications of that battery (Bliss G Carkhuff et.al., 2018). Moreover, voltage, current, and temperature controls should be highly observed as the battery cells are protected from over-current and over-voltage influences (Thomas Morstyn et al., 2015 ; Huazhen Fang et al., 2016). Feature extraction and data-driven methods have been used to generate data which can analyze the consumption pattern for electric vehicles and predict future status of the battery (Ravi S et al., 2013 ; Guangzhong Dong et al., 2017). This is the voltage, current, and temperature recording for the battery cells which are done using different sensors and data-acquisition systems (Tingting Dong et al., 2008 ; RM Williams et al., 1983). Protect electric car batteries from both overcurrent or overvoltage when charging or discharging, whether on the road or on the grid. So that it will be well protected and it will extend its life cycle, battery management in different modes is essential (Huazhen Fang et al., 2016 ; Quan O et al., 2018). The physical properties make the accessibility to internal parameters of the battery very difficult. Lithium-ion batteries are highly nonlinear due to certain time-variant factors, and accurate models are required by BMS to handle such behaviors and predict its internal properties and states. Different theories have been proposed by many scholars to infer SOC, SOH, RUL, SOP, and SOF. Though much research is being done to improve battery performance but still, battery modeling doesn't assure accuracy. (Prashant S et al., 201 9; Dickson et al., 2015).

Electric motors and associated accessories in EVs are powered by battery cells connected in series. These cells operate under distinct conditions than the battery's charging and discharging processes. Every cell may have a different voltage and current than the others, which could cause certain cells to be overcharged or undercharged. Because of the deformation of the battery's anode, cathode, and separator, these might lead to early damage to certain cells and occasionally internal short circuits.

Balance of the cells allows them to achieve effective energy distribution and cell voltage levels with regard to overcoming such a problem in EVs (Xin Cao et al., 2017; Ming Liu et al., 2017). Thus, it requires an efficient battery power management control (PMC) to ensure maximization of consumption while minimizing losses and distributing the cell energy between electric vehicle batteries. An efficient BMS can reduce the number of charges and discharges of a battery over the lifespan of that battery. Thus, the PMC brings to the fore numerous electrical gadgets and patents, which is, currently, one of the most significant subjects in industrial and automotive research.

When the battery is in the discharging mode, it may be exposed to under-current and under-voltage. While in the charging mode, the battery may be exposed to over-current and over-voltage, and consequently, its temperature will increase rapidly (Xuning Feng et al., 2018). Therefore, the battery protection is indispensable in BMS and plays a crucial role. In the past few years, many accidents have been witnessed and have led to life and financial losses. These issues prompted the battery manufacturers to develop solutions for temperature control and heat management that guarantee operations in the permissible and tolerable ranges of the cells and prevent from thermal runaway and internal short circuit (Xuning F et al., 2016 ; Jianan Z et al.,2018). In order to implement BMS in EV, a combination of hardware and software is always needed. With the development of the wireless charging of EVs over the sparse charging stations in the smart network, communication and networking as one of the subsections of BMS will affect the overall battery performance (Vaka R et al., 2018). Machine learning (ML) is a broad topic with a large variety of applications. A comprehensive classification of ML is presented in (Shree K S et al., 2019), which describes the different techniques of machine learning. This paper provides an appropriate classification of machine learning techniques that have been implemented in BMS applications. It also applies modern supervised neural network approach to predict SOC.

2. OVERVIEW OF MACHINE LEARNING APPROACHES

Fig 1 shows the use of machine learning approaches in BMS applications. In this classification, the machine learning methods are divided into three main groups ; (A) supervised learning, (B) unsupervised learning, and (C) reinforcement learning.

2.1 Supervised Learning

1) Artificial Neural Networks (ANN) : Biological neural networks serve as the foundation for the ANN idea (Ardeshiri Rouhi R et al., 2020). Activation functions, like Sigmoid functions, are employed in ANNs to connect their nodes and add up their weights. Back-propagation, a stochastic gradient descent technique, is typically used to train the ANN neural nodes. The ANN class is further subdivided into two groups:

- **Classic Neural Networks :** Wavelet neural networks (WNN), feed forward neural networks (FFNN), radial basis functions (RBFN), and extreme learning machines (ELM) are all included in this subgroup (Ardeshiri Rouhi R et al., 2020).
- **Modern Neural Networks :** They are usually called deep neural networks. Since they have multiple layers, these networks gradually extract more and more information from the input. The main types of deep learning methodology, which are referred to as deep NNs, are recurrent neural networks (RNNs), convolutional neural networks (CNNs), and advanced versions of them, such as long short-term memory networks (LSTM). Lately, researchers have also started looking into the current trends of combining deep learning techniques for more effectiveness (Ardeshiri Rouhi R et al., 2020; Hasim S et al., 2014).

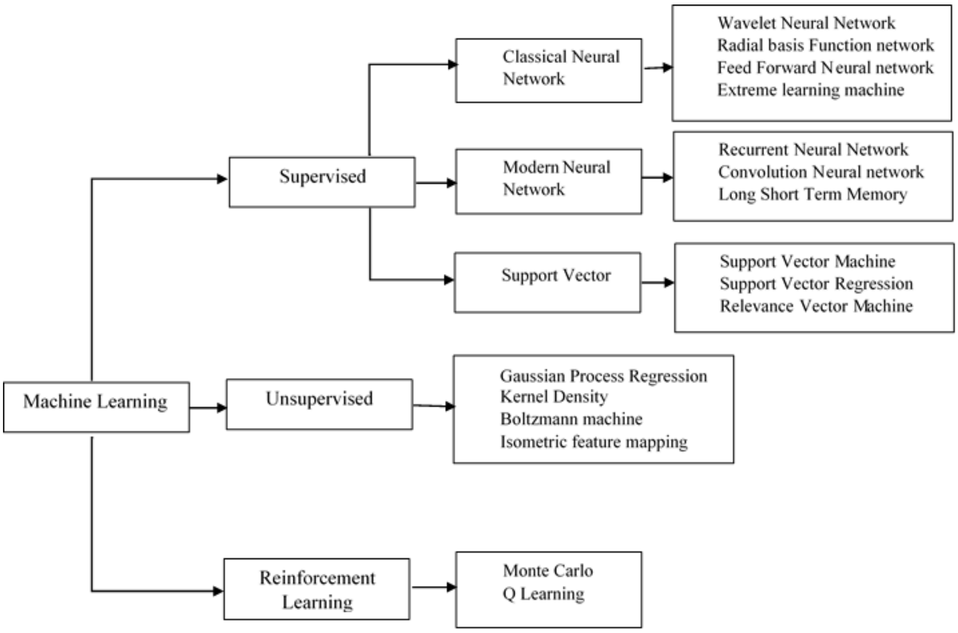


Fig1. Machine Learning in BMS Applications

2) Support Vector Machine (SVM): Support Vector Machines are supervised learning models with their own learning algorithms for data analysis in both classification and regression (Harris Drucker.,et .al.,1997). It has been borrowed from kernel regression and has been found suitable for very many linear and nonlinear regression applications such as support vector regression and relevance vector machine (Ardeshiri Rouhi R. et al., 2020 ; Hasim S et al., 2014).

2.2 Unsupervised Learning

The two main goals of this group which are used in different applications are clustering the data into groups by similarity and dimensionality reduction to compress the data while maintaining its structure and usefulness data. This group includes Gaussian process regression (GPR), kernel density, Boltzmann machine, and isometric feature mapping (ISOMAP) (Man C et al., 2019 ; Yuecheng Li et al., 2019).

2.3 Reinforcement Learning

This form of machine learning is called reinforcement learning. An agent learns to behave in this environment by taking actions and finding out what happens as a result of those actions (Leslie P K., et.al. 1996). The RL main tasks involve policy, reward function, value function, and a possible model of the environment which is useful for decision making for a problem. In the past years, this area has seen many improvements brought by researches (Man C et al., 2019 ; Yuecheng Li et al., 2019), such as Monte Carlo and Q-Learning methods, among others.

3. EMERGING TRENDS

Researchers in (Sagar S et al., 2023) mainly focus on the study of battery management system to enhance the power performances of electric vehicles by controlling key parameters like current, voltage, temperature, and SOC (State of Charge). A secondary loop cooling scheme is used for the battery thermal management system in (X. Kuang et al., 2020), and based on this, a phased control strategy for adjusting the compressor speed according to the battery temperature interval is proposed. This study (Yixin Wet al. 2024)established a control-oriented BTMS model with adequate precision. A fast charging-cooling joint control strategy for the battery pack was proposed, and a thermal management strategy suitable for diverse requirements was optimized using a MOO algorithm.

This article (Romain M et al., 2021) reports the results of an experimental ageing campaign of batteries in fast charging conditions in order to fill existing knowledge gaps. One novelty comes from the comparison of three commercial 18650 lithium-ion cells, which represent different electrode materials and different internal designs for cells oriented more towards energy or more towards power applications. These strategies present several contributions to the design of energy storage systems for electric vehicles, including the choice of a cell, design of thermal management systems, and design of optimised fast charging protocols. With the assembly of more than 200 three-electrode test cells, researchers in (Johannes Sieg et al., 2022) could reveal that the fast-charging capability of the investigated type of lithium-ion pouch cell was not reduced by aged electrode material, but by electrolyte consumption in particular.

4. METHODOLOGY

It is frequently used as the basic framework for recurrent neural network (RNN) systems in speech recognition, natural language processing, or other uses of sequences. However, such networks do not possess the capabilities of long-short term memory (LSTM). The RNN structure is more straightforward than LSTM, comprising an input section, hidden-state components, and an output section. Because it has a greater number of memory cells and gates, an LSTM framework is able to selectively retain or forget particular pieces of information across extended spans of time. The architecture of an LSTM (see Fig 2) can also be understood as a series of such recurring "blocks" or "cells," each of which contains a group of connected nodes.

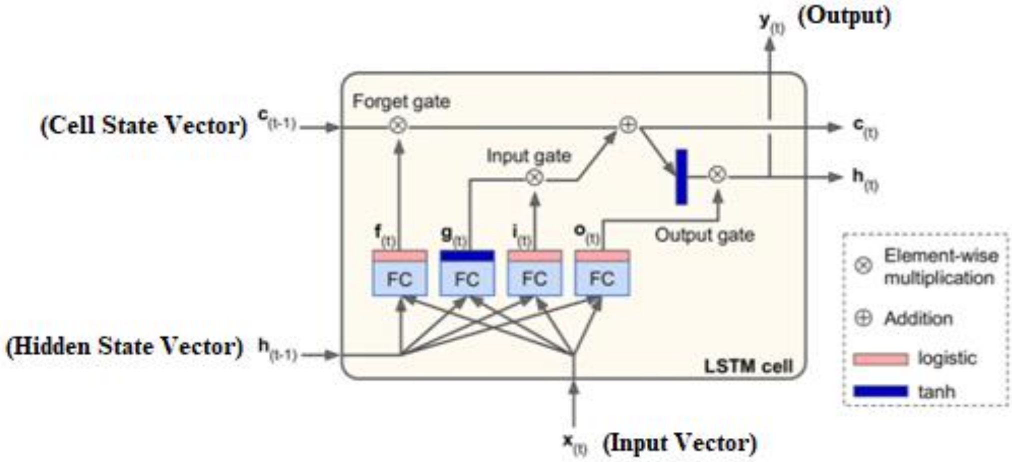


Fig 2 LSTM Architecture

The current observation or token in the series is represented by the input vector x_t, which is fed into the LSTM at each time step. Hidden state vector h_t, represents the current “memory” of the network and this hidden state is initialized to a vector of zeros at the beginning of the sequence. Long-term data is stored throughout the sequence by the LSTM through the maintenance of a cell state vector called c_t. At the start of the series, a vector of zeros is used to initialize the cell state. To regulate the information flow throughout the network, LSTM employs three different kinds of gates:

- **Forget Gate:** It receives two inputs; the current input, x_t, and the prior hidden state, h_{t-1}. It then outputs a vector of values, ranging from 0 to 1, indicating how much of the previous cell state should be retained and how much should be "forgotten." The LSTM may "erase" or "remember" specific data from the previous time step.

- **Input Gate:** This gate receives the current input, x_t, and the previous hidden state, h_{t-1}. It then outputs a vector of values, ranging from 0 to 1, indicating how much of the current input should be added to the cell state. The LSTM may "add" or "discard" new information to the cell state in a selective manner.
- **Output Gate:** This gate receives the current input (x_t), the previous hidden state (h_{t-1}), and the current cell state (c_t). It then produces a vector of values (between 0 and 1) that indicate the percentage of the current cell state that should be output as the current hidden state (h_t). When calculating the output, the LSTM can "focus" or "ignore" specific portions of the cell state.

The network's prediction or encoding of the current input is represented by a vector, y_t, which is output by the LSTM at each time step. The LSTM is ideally suited for tasks that require modelling long-term dependencies or sequences because of its ability to selectively "remember" or "forget" information over time due to the combination of its cell state, hidden state, and gates. For training the LSTM model, the input data sequence is applied to the LSTM cell. The LSTM (Long short term memory) model is then trained using the keras optimizer “Adam”. The activation functions are selected as “SELU” (Scaled Exponential linear unit). The model loss function is “Huber” and metrics such as “MSE”, “MAE” and “MAPE” are described during the execution of program written in python.

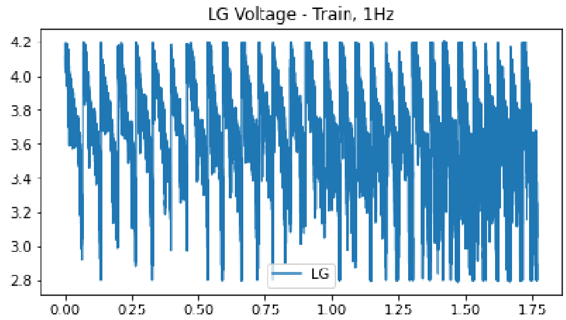
5. RESULTS AND DISCUSSION

For creating the machine learning model LG18650HG2 Li-ion battery data was obtained from https://data.mendley.com/datasheets/cp34733x7xv/3. The data sheet is read using command instructions and parameters from the datasheet including, “charge”, “temp”, “discharge cycles” are obtained. LG train, test stats are obtained from the data sheet which includes time-stamp of “voltage”, “current”, “temperature”, “power”, “capacity”, “voltage average”, “current average”, “power average” detailing their count, mean, min, std, 25%, 50%, 75% and max values (Table 1).

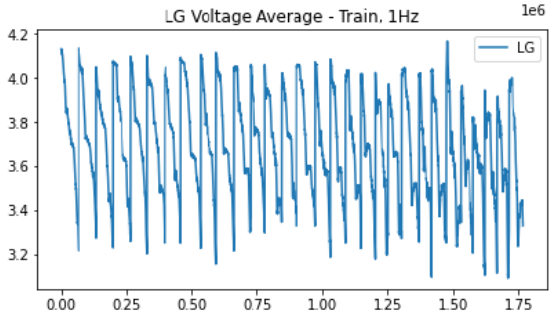
Table 1. Time stamp of various parameters used to train the model

Time Stamp	Count	Mean	Std	Min	25%	50%	75%	Max
Voltage	1766953	3.66610	0.262907	2.788130	3.495400	3.672890	3.861010	4.209560
Current	1766953	-1.32756	2.560378	-18.098280	-2.55154	-0.94246	-0.097060	6.004720
Temperature	1766953	7.85238	12.53895	-9.884900	-0.31548	9.359110	23.976150	26.289630
Power	1766953	-4.57294	8.942017	-50.875355	-9.20468	-3.438450	-0.385844	25.184354
Capacity	1766953	0.48665	0.268261	0.000000	0.269442	0.474609	0.717070	0.978041
Voltage Average	1766953	3.70079	0.227465	3.094400	3.521779	3.695029	3.890524	4.168740
Current Average	1766953	-1.28926	0.720794	-3.711826	-1.71516	-1.16092	-0.764838	1.225048
Power Average	1766953 .	-4.49477	2.448886	-11.434436	-5.98558	-4.12078	-2.685925	5.168611

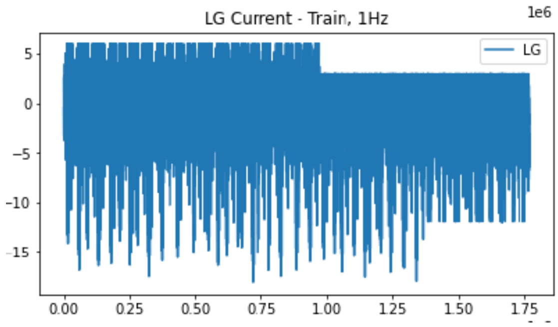
Table 1 represents the dataset with a count of 1766953.0 values which is used to train the model. The mean, std, min, 25%, 50%, 75% and max valus of these data are obtained for the training model. Various parameters (voltage, current, temperature, etc) are plotted for the same as represented in fig 3.



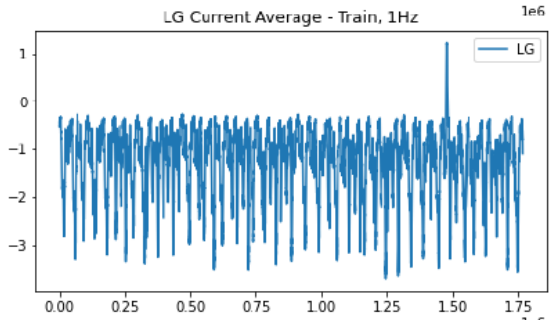
(a)



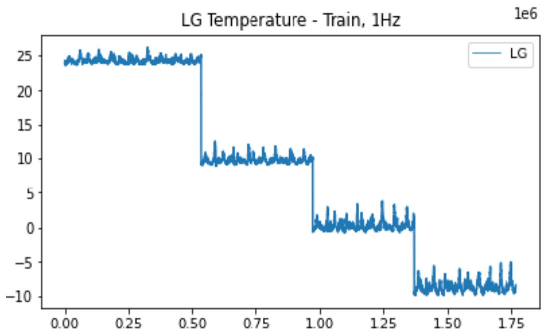
(b)



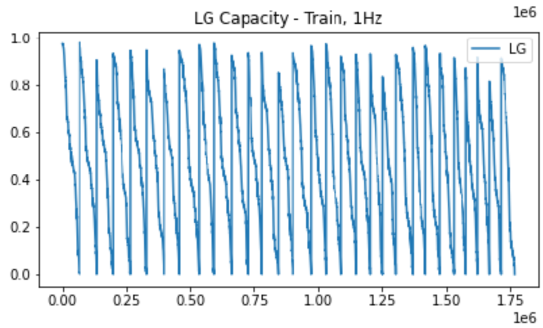
(c)



(d)



(e)



(f)

Fig 3. Plots of (a) Voltage (b) Average Voltage (c) Current (d) Average Current (e) Temperature (f) Capacity for training dataset

Fig 3(a) represents the variation in voltage value over the entire range of dataset with a min value of 2.78 and a maximum value of 4.2. Fig 3 (b) represents the average voltage with min value as 3.09 and max value as 4.16. Fig 3(c) and (d) represent current and average current for the training dataset with min and max values as -18.09, -3.71 and 6.0, 1.22 respectively. The temperature and capacity plots are shown in fig 3 (e) and (f) respectively with mean values of 7.85 and 0.486. Table II below shows the dataset which is used to test the model.

Table 2 represents the dataset with a count of 104286.0 values which is used to test the model. The time-stamp parameters are plotted for test dataset as shown in Fig. 3.

Table 2. Time stamp of various parameters used to test the model

Time Stamp	Count	Mean	Std	Min	25%	50%	75%	Max
Voltage	1042865	3.677300	0.261296	2.786280	3.496750	3.688530	3.884600	4.200460
Current	1042865	-1.099719	2.359092	-18.07018	-2.19552	-0.62575	-0.08428	6.00217
Temperature	1042865	6.917488	12.07144	-10.09522	-0.42063	9.14879	23.76583	26.81543
Power	1042865	-3.778445	8.247301	-50.86696	-7.92974	-2.31815	-0.32107	25.181295
Capacity	1042865	0.483628	0.267320	0.000000	0.258047	0.493902	0.713217	0.955909
Voltage Average	1042865	3.704194	0.229102	3.049703	3.523453	3.715520	3.899700	4.110379
Current Average	1042865	-1.097604	0.727766	-3.810302	-1.33660	-0.88870	-0.52397	-0.309855
Power Average	1042865	-3.823480	2.438030	-11.88619	-4.54066	3.073495	-1.88738	-1.233941

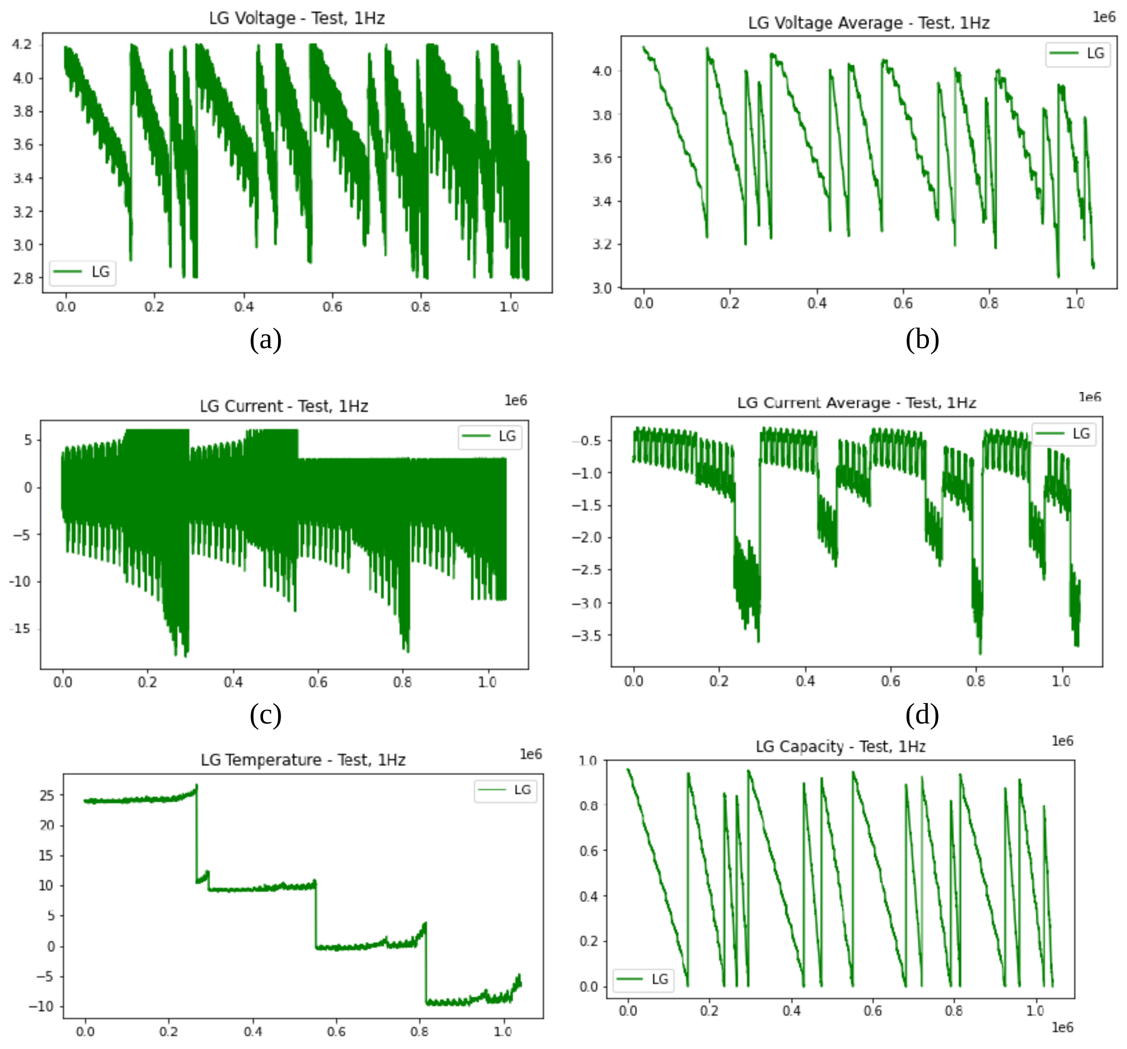


Fig 4. Plots of (a) Voltage (b) Average Voltage (c) Current (d) Average Current (e) Temperature (f) Capacity for Test dataset

Fig.4 (a) represents the variation in voltage value over the entire range of dataset with a min value of 2.78 and a maximum value of 4.2. Fig. 4 (b) represents the average voltage with min value as 3.04 and max value as 4.11. Fig. 4(c) and (d) represent current and average current for the training dataset with min and max values as -18.07, -3.81 and 6.0, -0.309 respectively. The temperature and capacity plots are shown in Fig. 4 (e) and (f) respectively with mean values of 12.07 and 0.267.

Fig.5 represents the train dataset without normalization. To train the model the input parameters must be defined in terms of "0" and "1" therefore normalization is applied to the train dataset and the plot is represented in Fig. 6.

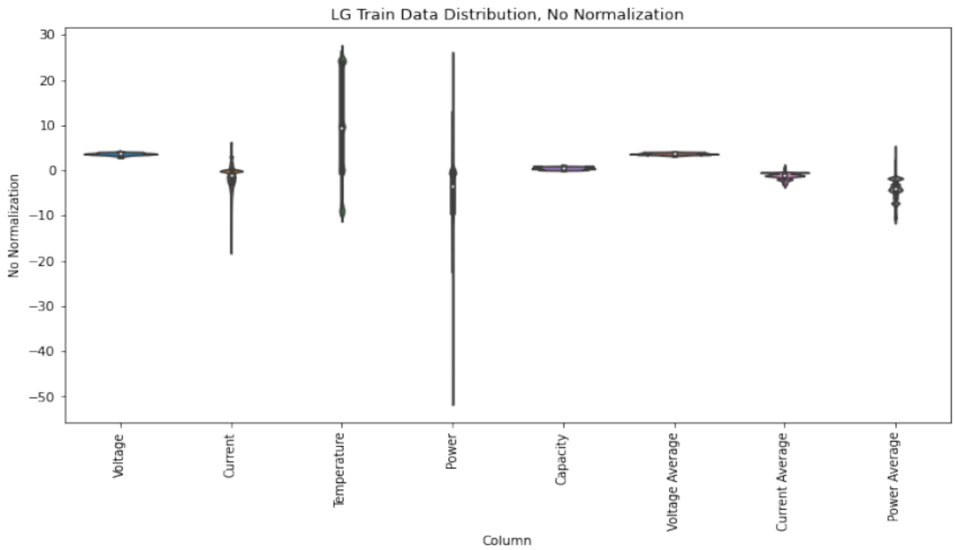


Fig 5. Train data distribution with no normalization

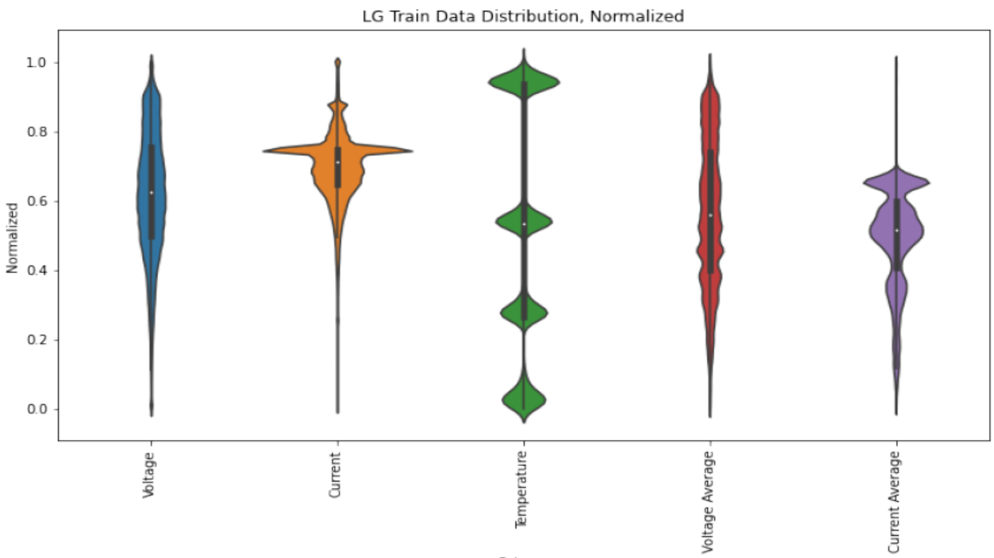


Fig 6. Train data distribution with normalization

After normalization a pair plot is obtained for train dataset involving voltage, current and temperature as shown in Fig. 7.

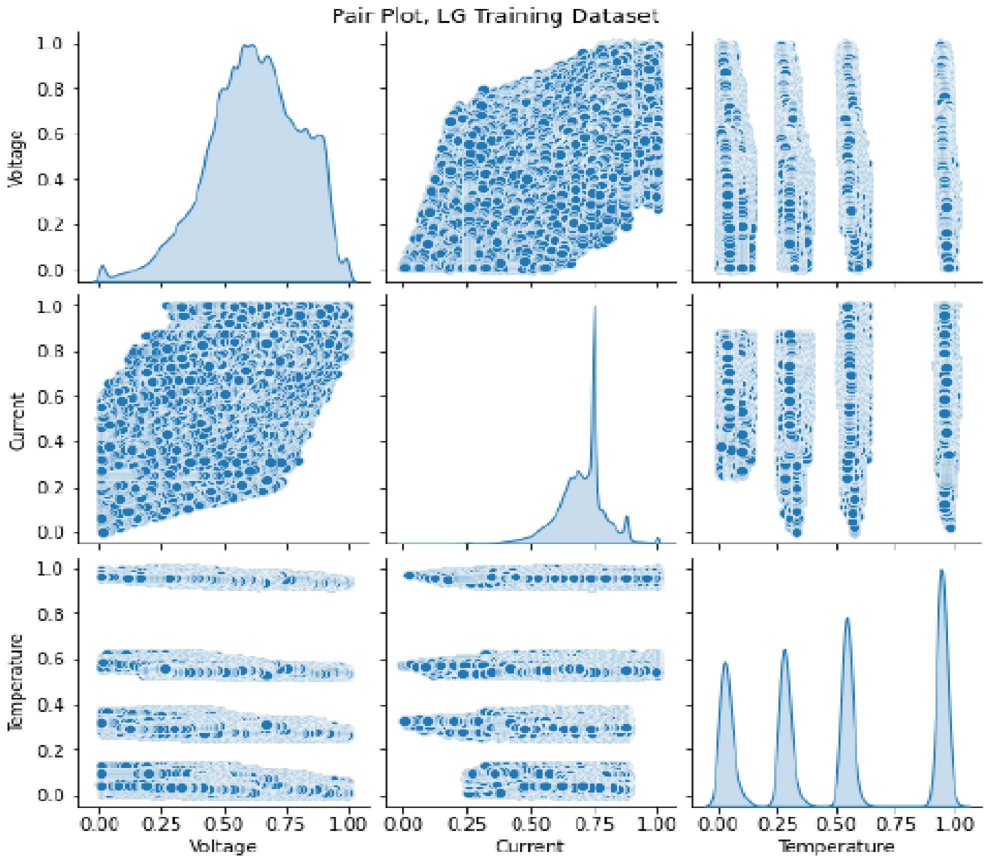


Fig 7. Pair plot for LG training dataset

Table. 3 Metrics and model loss function

Sr, No	Loss	MSE	MAE	MAPE	RMSE	Val_loss	Val_mse	Val_mape	Val_rmse	Epoch
95	0.000428	0.000855	0.013767	259.842468	0.029246	0.001555	0.036195	700.750793	0.055768	95
96	0.000443	0.000886	0.014863	256.820770	0.029761	0.001423	0.000068	708.750793	0.053340	96
97	0.000464	0.000927	0.014530	249.468979	0.030453	0.002421	0.047037	718.532898	0.069584	97
98	0,000512	0.001025	0.014094	266.529449	0.032015	0.001920	0.037644	716,537109	0.061967	98
99	0.000423	0.000846	0.013897	253.4972693	0.029083	0.001423	0.032937	697.973389	0.053349	99

After 99 epochs it can be seen that the model loss function has stabilised as shown in Table 3. The values of "MSE", "MAE" are similar too. Fig 8 shows a plot of training v/s validation loss. It is clear from the plot that as number of epochs increase the validation loss reduces.

Predicted value of SOC is close to the true value of SOC which is shown in fig 9 (a) whereas fig 9 (b) represents the predicted error distribution over the entire range of count. For a larger count of input data (1750) the predicted error (SOC) is close to "0". Hence we can say that the amount of predicted error (SOC) is quite negligible.

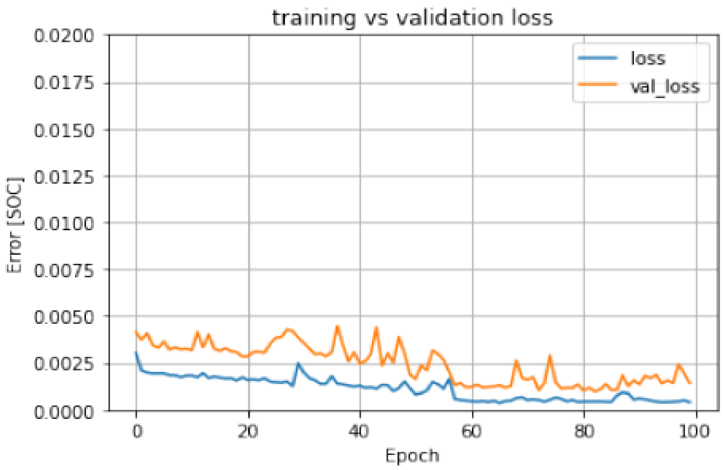
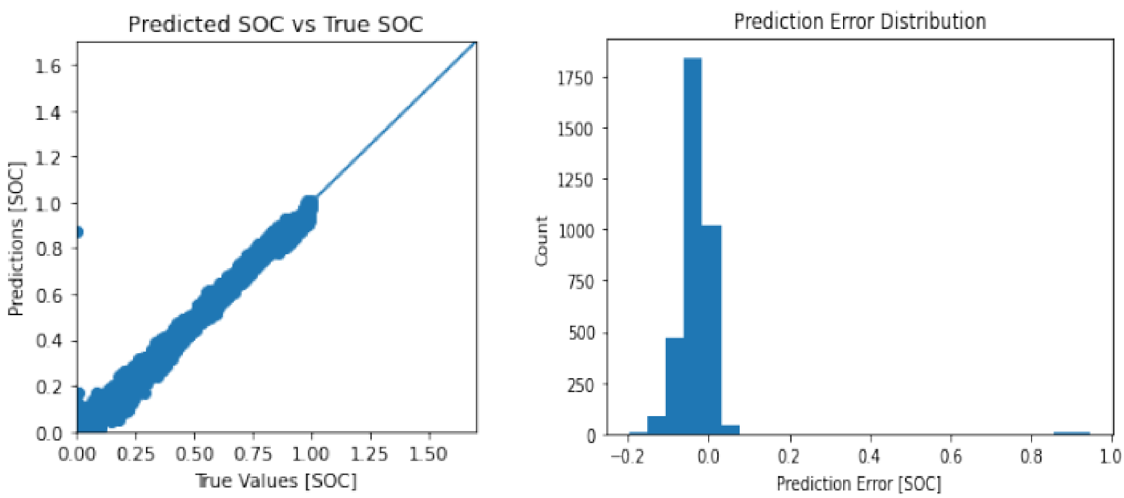


Fig 8. Training v/s validation loss



(a) (b)

Fig 9 (a) Predicted SOC v/s True SOC. (b) Prediction error distribution

6. CONCLUSION

As EVs face many challenges due to the battery packs, it is necessary that battery conditions should be monitored in normal and abnormal conditions during run-time Given the physical properties of battery, there is a challenge to access its internal parameters. Also, lithium-ion batteries, possess nonlinear behaviour's owing to some time-variant parameters. Thus, accurate models are needed in BMS to address these behaviour's and to estimate the battery internal parameters and states. Now-a-days, AI is ruling industries due to its extraordinary learning capabilities. Researchers are aiming to make use of AI in battery management systems for accurate estimation of SOC. This encourages developers to determine an efficient prediction strategy that is best suited, accurate, adaptive and is capable of estimating SOC precisely for an EV application

Dr. Philip kollmeyer performed various tests on a brand new 3Ah LG HG2 cell at McMaster university, Hamilton, Canada and the data collected during the test was made available on https://data.mendley.com/datasheets/cp34733x7xv/3. which is used by researchers worldwide for designing SOC estimator using different approaches. We have used the Long short term Memory

(LSTM) to predict SOC which is compared with True SOC. Long short-term memory (LSTM) networks, a variant of Recurrent Neural Networks (RNNs), excel at learning sequence dependencies in prediction tasks. Unlike typical feedforward neural networks, LSTMs incorporate feedback connections. They are widely used in generative models, particularly in natural language processing. Moreover, LSTM networks are highly effective for tasks involving classification, processing, and prediction of time series data. These models can capture and retain features over extended periods, making them ideal for this study.

SOC plays a very important role in BMS and is a key indicator towards the state of charge. A fully charged battery has an SOC of 1 while a completely discharged battery has a SOC of 0. Predicting battery SOC with high accuracy assures avoiding many problems such as overcharging or discharging during a long journey. The main goal of SOC measurement *is to determine how much energy a battery still has at specific time and conditions* with acceptable accuracy. Experimental results show that our models achieved high accuracy in predicting SOC, with the error in the predicted SOC being nearly zero, even for large input data samples.

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