Estimating Battery State of Health using Machine Learning

Ameera Arif
Department of Computer Science
Lahore University of Management Sciences
Lahore, Pakistan
https://orcid.org/0000-0001-9976-4593

Muhammad Hassaan
Department of Computer Science
Lahore University of Management Sciences
Lahore, Pakistan
https://orcid.org/0000-0003-2891-2119

Mujahid Abdullah
Department of Computer Science
Lahore University of Management Sciences
Lahore, Pakistan
https://orcid.org/0000-0002-8485-1165

Ahmad Nadeem
Department of Computer Science
Lahore University of Management Sciences
Lahore, Pakistan
https://orcid.org/0000-0003-1049-3892

Naveed Arshad
Department of Computer Science
Lahore University of Management Sciences
Lahore, Pakistan
naveedarshad@lums.edu.pk

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***Abstract*—The share of energy consumption in the transportation sector is projected to increase at an annual average rate of 1.4% up to 2040. This is primarily due to a transition towards electric vehicles (EVs) from internal combustion engine- based modes of transportation. Batteries are the most crucial component in EVs, constituting a significant share of the price of the vehicle. With usage, batteries degrade, thereby, limiting their ability to store energy which adversely impacts the driving range offered by EVs. Therefore, the need is to study the deterioration of batteries in electric means of transportation. We have created data-driven models to monitor battery health, predict the deterioration in batteries and give insights to the EV owners to make better decisions. The dataset used in this study is published by Sandia National Labs (SNL). It is a result of experiments performed on NMC cells. We present a comparison of three models - multiple linear regression, support vector regression, and artificial neural network for battery health monitoring with mean average percentage error (MAPE) of 1.99, 0.74, and 0.72 respectively.**

Keywords—Electric Vehicles, Battery degradation, Green Energy, State of Health, NMC cell, data-driven models, Artificial neural network (ANN).

I. INTRODUCTION

With increasing population and expanding economies around the globe, the energy consumption in transport sector is expected to increase rapidly. The US Energy Information Administration quotes that the transport sector consumes almost 25% of the energy in the world [1]. This bulk usage of energy is primarily through internal combustion engines (ICEs), using gasoline as a fuel, which is linked to climatic adversities and severe health issues. Subsequently, we have electric cars whose sales have soared in 2020 and reached 3 million units, which is 40% more than the sales in 2019. It is expected that, by the year 2030 the number of electric cars on roads will be 300 million which will account for almost 60% of all car sales [2]. This boost in sales of EVs will yield several advantages with the foremost being utilization of environment- friendly and renewable sources of energy such as solar and wind to cater the needs of transportation segment instead of emission-prone hydrocarbons. The operational cost of EVs is also quite low in comparison to ICE-based vehicles and this cost differential is expected to increase with rising fuel prices [3].

However, one advantage of ICE vehicles over EVs is convenient storage and reliable provisioning of gasoline. Fossil fuels are easier to store in a vehicle's fuel tank while the energy storage in batteries of EVs is not only costly but also has a higher charging time compared with gasoline refueling and this storage capacity degrades over time [4]. The degradation is due to chemical changes in the battery chemistry and operating temperatures which requires a battery thermal management system [5], [6]. Batteries work as a result of an electro-chemical reaction which sends power to terminals. The chemical reaction slows down in cold weather. Batteries also deteriorate faster at higher charging or discharging rates but with non-linear trends. Additionally, the use of fast DC chargers accelerates the process of battery degradation [7]. As the battery deteriorates, the cells in the battery experience reduction in energy storage capacity. The capacity of the cells to store energy is called State of Health (SOH). It is a measurement of its health and performance as compared to a fresh battery. It is hugely affected by charge/discharge rate, number of cycles, and temperature. Generally, a battery is considered towards the end of its life if it is unable to conserve 80% of its total energy capacity [8]. It is very important to monitor and interpret the safe usage of batteries so that their life can be prolonged.

This study provides a comparison of various machine learning models to predict battery SOH using cycle index, temperature, and charge/discharge rate. The data is a collection of experiments performed on NMC based 18650 cells [9]. The upcoming section II explains an overview of previous work done while section III gives details of the methodologies used. The underlying experiments are present in section IV in the form of a case study followed by discussion of results in V. The paper concludes with a summary in section VI.

II. Literature Review

Battery storage systems are crucial for all types of electric vehicles whether hybrid, plug-in hybrid, or all-electric ones. The most used batteries are lithium-ion based as they have high energy efficiency, good performance and low self-discharge [10]. Others are nickel-metal hydride, lead-acid and super-capacitors. These are also energy efficient but vary in terms of performance, life cycle, and ease of access. To prolong the lifetime of batteries, we study battery deterioration patterns and the factors that affect it. Xu et al. [11] assess the battery health loss of lithium-ion batteries due to their operating profiles. The proposed model is based on battery aging tests and basic theories of degradation profiles (like the Arrhenius relationship and SEI formation) which are tested in real-world scenarios of electric market.

Safari et al. put forward detailed insight on the reduction of LFP cell performance during non-destructive electrochemical techniques [12]. The capacity retention impacts aging which is in turn affected by temperature, and this is measured in this paper where results show that capacity fade increases at higher temperatures. Another test was the impedance test which measures the ability to deliver the same capacity in a defined potential window irrespective of the C-rate used to cycle the cell. It was observed that cell impedance is not affected within a year of aging but reduces to 60% after a year. Under the same temperature, the cells which were under cycled lost more capacity and it was concluded that lithium was the main source of capacity fade. The same ECS journal published interesting research [13] on $LiFePO_4$ cells where experiments on electrodes of the cell using X-Ray show reconstruction of redox reaction. Similar experiments were performed at low and high temperatures on similar cells for capacity recovery, electrochemical impedance, and capacity analysis in [14]. But another addition was that they disassembled the batteries in order to perform material analysis. It was concluded that lithium was yet again the reason for battery aging.

Alan Millner, a renowned scientist in the domain of energy systems presents a new model [15] based on crack propagation for lithium-ion batteries degradation. Theoretically, lithium- ion batteries are modeled with respect to cycling and time via diverse procedures. These theories are then characterized to develop an equivalent circuit to predict characteristics for any temperature, charge/discharge rate, consumed cycles etc. It is concluded that battery life can be conserved for PHEV if the state of charge and deep cycles are maintained at <60% while the temperature is kept lower than 30 degrees. A unique inference technique to judge the 'what-ifs' of degradation modes is put forward in [16] where each electrode's behavior is judged separately. In [17] the writers present a comprehensive approach for 18650 cells based on calendar and cycle aging tests for an aging model where capacity loss and resistance are measured. Fernandez et al. [18] present capacity fade and aging models for electric vehicles by performing tests on lithium-ion batteries. The model proposes battery degradation in terms of temperature and depth of discharge.

Lyu and Gao [19] propose a model for state of health estimation based on repetitive experiments. The capacity degradation is defined as an increase in ohmic resistance of the battery and is called HI. The relationship between HI and capacity degradation is termed linear hence a linear state space model with an added Kalman filter is proposed which gives an average error of 2.12% under variable conditions. An estimation of SOC and SOH is proposed in [20] to identify parameters for lithium NMC battery of the first order RC model. The deterioration of this model is determined for different battery aging levels. The SOC and SOH results are judged by using a large dataset. Two simple theoretical models are proposed in [21] to estimate the state of health of lithium-ion batteries. These are the battery VO+ model and charge capacity model. Another unique idea is presented in [22] where the internal resistance in a vehicle is identified to monitor state of health which is done by getting signals for the vehicle during normal functioning. The internal resistance generates a degradation index which is validated using measured data. The results are promising with low effort and robust calculations.

Moving a step ahead, Kaur et al. apply deep learning models [23] to estimate the capacity for lithium-ion batteries in EVs. It is concluded that long short-term memory (LSTM) performs best among feed-forward neural network (FNN), LSTM, and convolutional neural network (CNN) with an average RMSE of 0.0426 as compared to 0.0447 of FNN and 0.0527 of CNN. He et al. [4] propose another SOH estimation method using LSTM with Bayesian optimization with a maximum relative error of 0.2%. Preger et al. [24] present insights on 18650 NMC, NCA and LFP cells belonging to the same dataset to assess the effect of temperature, discharge current and depth of discharge which impact battery degradation. To this end, this paper presents novel research in the field of machine learning specifically on SNL data. The paper by Preger et al. only gives an analysis of the factors on battery degradation as compared to our paper which presents SOH estimation models with high accuracy. This research has been successful in achieving state-of-the-art accuracy by applying data refinement techniques, followed by data training using three different machine learning models.

III. Methodology

The deterioration of the health of lithium-ion batteries is predictable because it is affected by various external factors. When considering external factors, the impact of temperature and usage pattern impact the health of batteries [25]. The prediction of SOH of a battery using machine learning models is proposed in the following sections. We use three distinct models: multiple linear regression (MLR), support vector machine (SVM), and artificial neural network (ANN).

A. Multiple Linear Regression (MLR)

Using multiple variables to predict a numerical outcome depending on a linear model is called Multiple Linear Regression (MLR). The variable to be predicted is referred to as the dependent variable, and the variables to predict the value of dependent variables is known as independent or explanatory variables [26]. MLR is a basic model used to capture only linear relations between variables and will be used as a baseline model to judge the performance of the other two models.

$$Y = \beta_o + \sum_{i=1}^{n} \beta_i X_i + \in \quad (1)$$

In equation 见上方, Y is the response variable, X_i is for predictors, n is the number of predictor variables, β is the coefficient interpreted as the average effect on Y of one unit increase in X, holding all other predictors fixed. ∈ is the error term.

B. Support Vector Regression (SVR)

SVR is a supervised learning algorithm for predicting numerical values and is a variant of Support Vector Machine. Its basic concept is to find the best fit non-linear curve with minimal error. It works by locating a hyperplane in an N-dimensional space to distinguish between data points, where N is the number of features [27]. SVR requires the tweaking of gamma and cost hyperparameters, which regulate the model's complexity. It allows non-linear modeling which helps the handling of complex data patterns.

C. Artificial Neural Network (ANN)

Lastly, ANN is used which is a computational learning algorithm, based on a network of functions to manipulate the data and translate it into desired output [28], [29]. ANN can have several hidden layers with various neurons in each layer. The number of layers, number of neurons, activation functions, and learning rates for each attribute are adjusted to obtain the best possible combination between overfitting and underfitting. Adding too many layers or neurons to create a complex model does not guarantee better results on unseen data [30]. Initially, each node in an ANN is assigned a numerical weight at random, which is then tweaked by backpropagation [31], [32].

D. Evaluation Method

There are several metrics for evaluating the performance of such models. Mean Error (ME), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are the most commonly used error measures. ME calculates the average difference between actual and predicted values. It is prone to negating overestimation and underestimation. As a result, it may produce a deceptive sign of improved model performance. MAE addresses this issue by taking the absolute value of estimations into consideration. However, it does not show the severity of that inaccuracy in relation to the actual value [33]. MAPE addresses the above-mentioned shortcomings and is thus viewed as a better metric for evaluation of the three models employed in this study. The formula for calculating MAPE is shown in equation below [34].

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - P_t}{A_t} \right| \quad (2)$$

where n is the number of test samples, A represents the actual value and P is the value predicted by the model.

IV. CASE STUDY

The data set used in this study is derived from results published by Sandia National Labs (SNL) in "Degradation of Commercial Lithium Cells as a Function of Chemistry and Cycling Conditions" [9]. The experiments were performed on NMC based 18650 Li-Ion cells that deteriorated to 80% of the original capacity. The whole aging tests examined the impact of temperature and discharge current on the battery health of these cells while the charge rate remained constant throughoutthe experiment.

Several experiments were performed with charge/discharge rate and temperature as variables. Following factors are recorded in each experiment- minimum and maximum current, minimum and maximum voltage, maximum charge, discharge capacity, and energy against the total time consumed for each cycle. Charge energy is the dependent variable, and it is filtered for the maximum and minimum value at 80% SOH to focus on the first life [35] of the cells. The values are derived from the manufacturer data sheet [36]. Out of all the attributes presentedin the SNL data set, the following are selected:

- Charge Energy (measured in Watt Hours, Wh)
- Cycle Index (number of cycles of charging)
- Discharge Rate (measured in coulombs, C)
- Temperature (measured in Celsius, °C)

The histogram of the dependent variable i.e., charge energy is visualized by the bar plot in figure 1. The maximum energy that a cell can retain is 10.92 Wh. This figure shows that the charge energy during experiments is usually between 8.7 and 11Wh which is evident from the left skewness of the histogram.

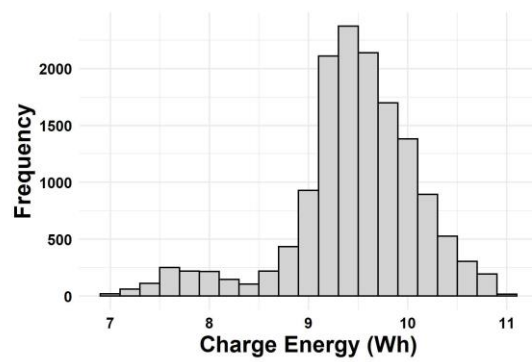

Fig. 1. Histogram of Charge Energy

Figure 2 shows the distribution of charge energy relative to the three independent variables i.e., temperature, discharge rate, and cycle index. The charge energy for 15 °C shows that it is relatively lower than the other two temperature variations recorded in the dataset. The boxplots for discharge rate however show a non-linear relation. As the discharge rate increases the charge energy also increases, but there is a drop after 2 °C.

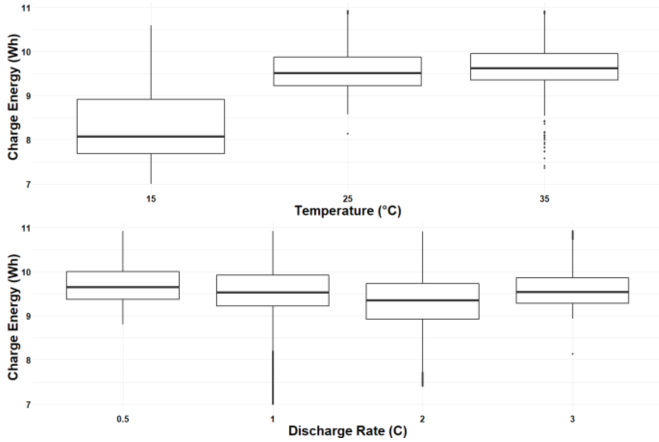

Fig. 2. Charge Energy Distribution

In figure 3 the decrease in charge energy with the increase in consumed cycles of a battery pack is shown. The trend, however, is dependent on the temperature and is more prominent at lower temperatures.

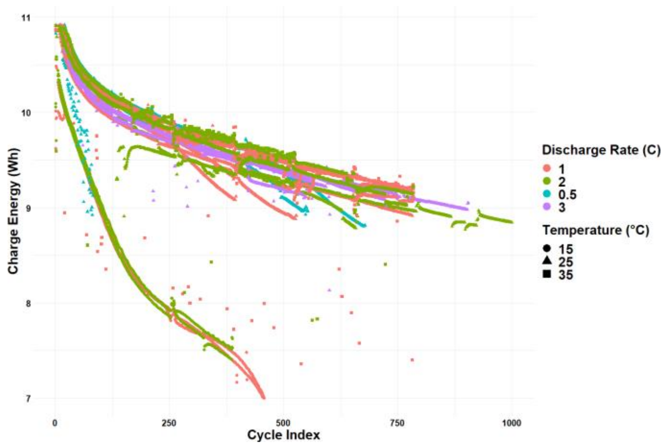

Fig. 3. Charge Energy Against Cycle Index

The mathematical representation of MLR used is shown below. Here $Charge\ Energy$ is the response variable, β_i is the co-efficient for $Temperature$ which can have 3 possible values depending on the temperature, while β_j denotes the coefficient for $Discharge\ Rate$ which can have 4 possible values. β_3 is constant as $Cycle\ Index$ is a numerical variable.

$$Charge\ Energy = \beta_o + \beta_i\ Temperature + \beta_j\ Discharge\ Rate + \beta_3\ Cycle\ Index \quad (3)$$

Table I shows the values of β coefficients for their respective variables. A change of 1 unit in a particular variable result in a change of charge energy by the value denoted by the β coefficient. The β coefficient of temperature at 25◦C (1.52) denotes that if there is a 25◦C change in temperature, the charge energy would increase by 1.52Wh on average, whereas the intercept value represents that a fresh cell at 0◦C will have charge energy of 8.70 Wh. In figure 5, the prediction of trained data by MLR can be seen in the first scatter plot.

TABLE I. GRADIENT COEFFICIENTS FOR MLR

Coefficient	*Value*
β_0	8.70
Temperature 15°C	0
Temperature 25°C	1.52
Temperature 35°C	1.66
Discharge Rate 0.5C	$4.60e^{-02}$
Discharge Rate 1C	0
Discharge Rate 2C	$7.53e^{-02}$
Discharge Rate 3C	$7.06e^{-02}$
Cycle Index	$-1.79e^{-03}$

The second model adopted in this study is SVR which results in a 7-dimensional hyper-plane depending on 7 features of the input data. The design model uses epsilon regression and radial basis kernel to decipher the non-linearities of data. The cost and gamma values are 1 and 0.14 respectively. Figure 5 shows the predicted values of trained data by SVR.

The architecture of the ANN model used in this study is shown in figure 4. There are 3 hidden layers with 2,3,2 neurons respectively to process the input data. The weights assigned to each neuron are also shown in figure 4, however, this is not significant information as the assigned weights are incomprehensible. For this reason, ANNs are treated as black box.

Table II shows the performance of the three models using the three-error metrics discussed above. According to ME, MLR has the smallest value. However, MAPE shows that ANN outperforms both MLR and SVM. This is due to the ability of ANN to learn non-linear relationships between variables.

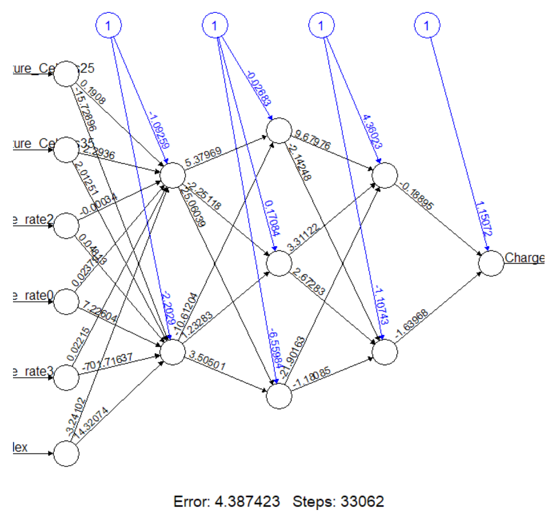

Fig. 4. ANN Model.

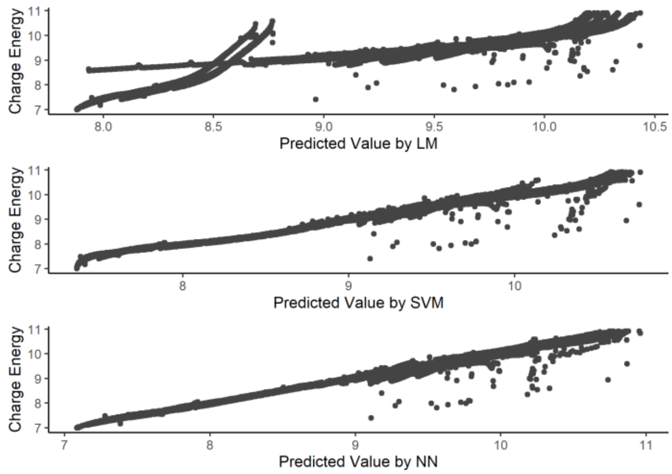

Fig. 5. Actual Values vs Predicted Values for Train Data.

Even though the performance of SVR is not as good as that of ANN, it does improve on MLR due to its non-linear nature. However, good performance on training data is not a rational way to judge the performance of a model. Hence the next section will discuss model prediction on test data which shows if the model is overfitting or underfitting on unseen data.

TABLE II. Error Metrics for Regression Models on Trained Data

Error Parameter	MLR	SVR	ANN
ME	$-3.74e^{-14}$	$-1.83e^{-3}$	$2.60e^{-6}$
MAE	0.18	0.06	0.06
MAPE	1.93	0.70	0.68

V. Results & Discussion

Figure 6 shows the predicted values and the actual values for each model for test data. The scatter plots show that ANN has the most linear output in comparison to other two models. MLR deviates from linearity at about 8.5Wh on predicted values. However, ANN also shows low variation with respect to SVR. This superiority in performance is evident from the table III, which shows that MAPE for ANN is 0.72. This is less than MLR and SVM which have MAPE of 1.99 and 0.74 respectively. It shows that ANN neither underfits nor overfits as MAPE for the test data is quite close to the train data.

The models discussed in this paper can be further used to create helpful tools for EV drivers to better understand the deterioration of their vehicles' battery as it is the most expensive component. With better battery deterioration models, drivers can be more cautious of their driving as the models will be able to predict the battery deterioration depending on the external conditions and the discharge intensity by the driver's driving pattern. Such models can be used for optimal battery utilization in electric vehicles.

The models presented in this study are a starting point for future work. Several other factors such as voltage, current, and usage patterns need to be discussed to create more robust models. Other than machine learning, mathematical modeling can also be used to build sophisticated models.

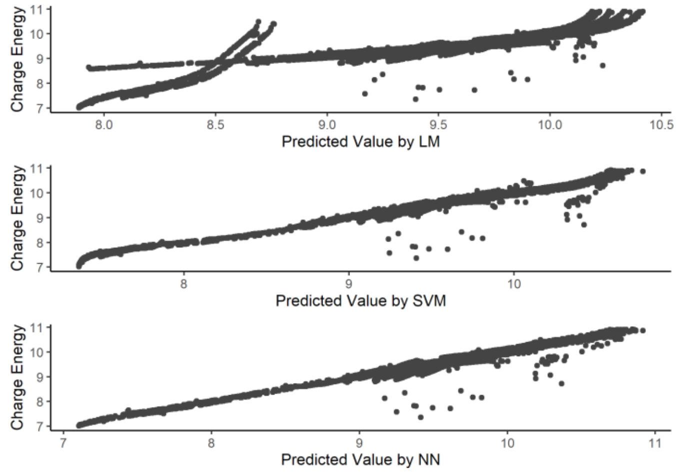

Fig. 6. Density Plot of Predicted Values for Test Data.

TABLE III. Error Metrics for Regression Models

Error Parameter	MLR	SVR	ANN
ME	$-9.22e^{-3}$	$-2.49e^{-3}$	$-7.85e^{-4}$
MAE	0.18	0.07	0.0.07
MAPE	1.99	0.74	0.72

VI. Conclusion

Using temperature, discharge rate, and cycle index, three models are designed to predict charge energy. These can be used to measure the deterioration of batteries in electric vehicles as the transportation sector is one of the highest energy consumers. The ANN model has superior performance on both train and test data which shows the need for a non-linear model and a complex architecture to understand the data. The prediction can be improved by more sophisticated modeling and better input parameters, such as usage behavior data. The models designed in this paper are based on experimental data. Real-life data can be collected to improve the utility of the trained models.

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