Machine Learning Based SoC Estimation For Lithium-Ion Battery In Electric Vehicle

1st Dr.K. Sundararaju
Department of Electrical and Electronics Engineering
M. Kumarasamy College of Engineering
Karur, Tamilnadu, India
sunkrr@gmail.com

2nd Jagadeesh S
Department of Electrical and Electronics Engineering
M. Kumarasamy College of Engineering
Karur, Tamilnadu, India
sjagadeeshjaga053@gmail.com

3rd Madhumithra N
Department of Electrical and Electronics Engineering
M. Kumarasamy College of Engineering
Karur, Tamilnadu, India
nmadhumithranatarajan@gmail.com

4th Manikandan K
Department of Electrical and Electronics Engineering
M. Kumarasamy College of Engineering
Karur, Tamilnadu, India
manimani7415@gmail.com

***Abstract*— The primary energy source for an electric vehicle is the battery. The operating condition of a battery is determined by its charging and discharging capability. Battery health estimation and control play a significant part in the safe operation and long-life of batteries in electric vehicles. A battery's State of Charge can be used to estimate battery health (SoC). The proposed system comprises of Multistage Converters with an ARIMA Model based on machine learning. The charging device comprises a multistage converter for quick charging by minimizing oscillations. The method is used in this design to anticipate the battery's life span and calculate the SOC (State of Charge). A lithium-ion battery's battery management system must be able to predict the State of Charge (SOC). In order to simultaneously and independently read cell current and voltage, this research offers the Autoregressive Integrated Moving Average (ARIMA) model. Through experimental use of the parameters corresponding to known C-rates, the battery parameters for an unidentified advanced C-rate are determined.**

Keywords— State of Charge, ARIMA Model, Lithium-Ion Battery, Electric Vehicle

I. INTRODUCTION

An electric vehicle (EV) which consists of electric motor instead of internal combustion engine which operates on battery. Unlike traditional cars that utilise gasoline or diesel engines, electrical vehicles employ an electrical motor that drive power from a battery or an electric cell. A battery is a collection of one or more cells that produce a flow of electrons in an electric circuit via a reaction. All batteries include three fundamental components: the anode (the "-" side), the cathode (the "+" side), and a few relatively suitable components (a substance that with chemicals reacts with the anode and cathode). The availability of batteries has become a vital part of modern electric vehicle. The battery is the most common type of storage power supply used in electric cars. Modern electric vehicles and PHEVs employ lithium-ion batteries, however the BMS plays the vital part in the electric vehicle. State of Charge (SoC) and State of Health are evaluated by the battery's square vital indicators (SoH). These characteristics square measure crucial for battery protection, battery life span expansion, and user operation safety. State of charge (SOC) may be used to evaluate battery systems for electric cars (EVs). Due to its rapid charging, high energy density, and long lifespan, lithium-ion batteries have been the subject of in-depth research into SOC estimation. SOC estimate is used by battery management systems (BMS) to keep the battery within a secure operational window, to implement management strategies, and ultimately to extend battery life. The ARIMA model is used for the main technique. ARIMA is an acronym that stands for "Autoregressive Integrated Moving Average." A well-liked statistical analytical tool and prediction model from the 1970s is the Autoregressive Integrated Moving Average (ARIMA) model. This is a statistical prediction model that extrapolates into the longer-term supported fitted values of previous data sequences. A good choice of error covariance allows the Kalman filter, a linear state estimator, to overcome state estimation mistakes. Complex nonlinear systems like lithium-ion batteries can have their state estimated using the extended Kalman filter approach[8].

II. PROPOSED SYSTEM

The proposed system is based on the State of Charge estimation technique and the Lithium-Ion battery life prediction.

Fig. 1. depicts a block schematic of the SoC estimating method.

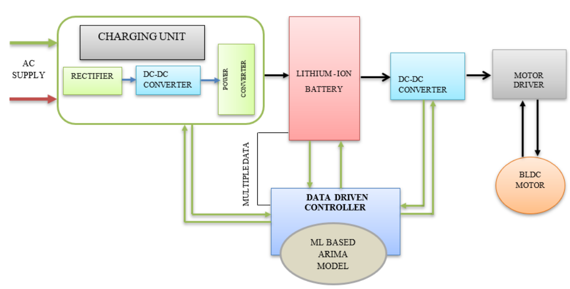

Fig. 1. Block digram for SOC estimation process

It is more efficient and accurate than the existing system. It is made up of Multistage Converters and a Machine Learning Based ARIMA Model. In order to prevent oscillations, the charging apparatus incorporates a multistage converter. The current model is composed of a

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single-stage converter with an Extended Kalman Filter, Column Counting, and an ANN-based algorithm.

III. SIMULINK AND RESULT

The simulation model illustrates SoC estimation using an ARIMA model based on machine learning.

The charging equipment is used to recharge the lithium-ion battery. The charging device is made up of a multistage converter for conversions. It is divided into three phases. The Rectifier makes up the initial step. The Rectifier transforms an alternating current supply to a direct current supply. The following stage, or second stage, consists of a DC to DC converter for voltage stabilisation in order to eliminate fluctuations in the subsequent process. The oscillation that occurs while charging and the subsequent procedure is eliminated by employing this type of multistage converter.

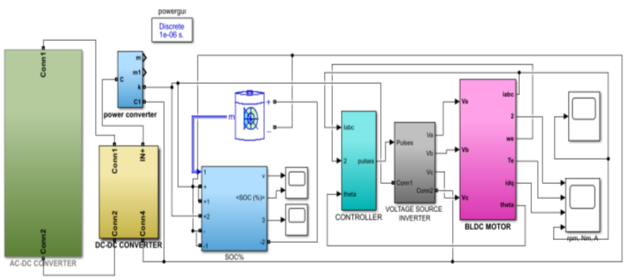

Fig. 2. Simulink Model

The Kalman Filter is employed in prediction and error correction. It makes predictions about voltage and current values and compares them with predetermined values. When the real value differs from the predetermined value, the filter will either increase or decrease it. It was then handed over to the controller for begining the controlling procedure.

The controller will detect when the charge reaches its maximum level. In this case, the controller for forecasting the State of Charge is an ARIMA model built on machine learning. The configuration of parameters such as current, voltage, and temperature is required for the estimate approach.

In order to predict the charging circumstances, these values are then compared with the measured parametric values. The lifetime will be predicted by forecasting and estimating the SOC (State Of Charge) conditions.

After charging, the Lithium-Ion battery will be connected to the Voltage Inverter through the Positive and Negative terminals. The Voltage Inverter transforms a single phase supply to three phase supply.

The converted three-phase supply is fed into the BLDC motor, and the motor is driven in a closed loop by monitoring current and voltage and sensing rotor position. The controller also controls the motor performance.

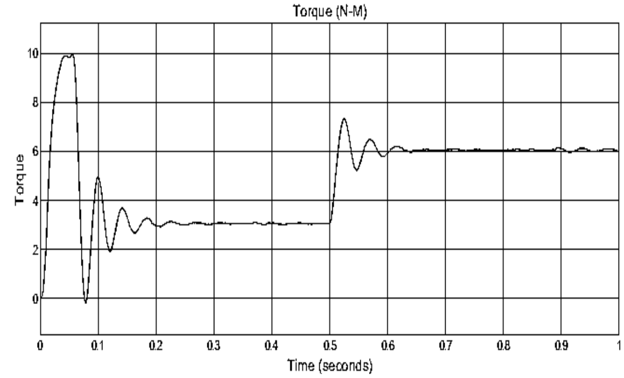

Fig. 3. Characteristics curve of Torque vs Time for BLDC

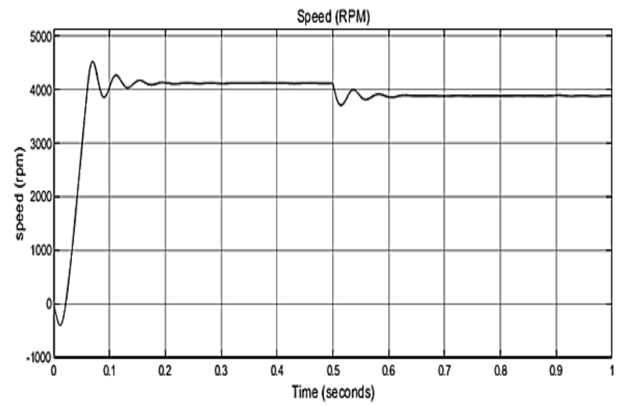

Fig. 4. Characteristics curve of Speed (rpm) vs Time for BLDC

Fig. 3. above illustrates the outcome of the simulation using the Characteristics curve of Torque vs Time for BLDC. Fig. 4. above illustrates the outcome of the simulation using the Characteristics curve of Speed (rpm) vs Time for BLDC. Starting torque is required to start the engine from a standstill. When the starting torque is raised, the RPM of the motor increases as well. In this case, torque is proportional to RPM. When the motor reaches the motion state, it keeps the torque and RPM constant.

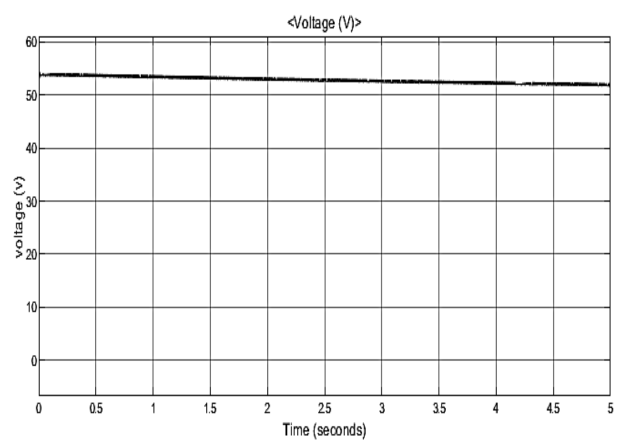

Fig. 5. Voltage vs. Time Characteristic Curve

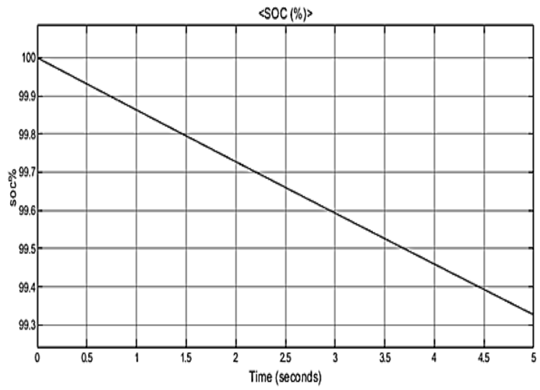

Fig. 6. Characteristics curve of SoC vs Time

The simulation result utilising the battery voltage is shown in Fig. 5.

Fig. 6. above illustrates the SoC's characteristics as a function of time

Depending on the time, the SOC decreases in the discharging state and increases in the charging state. For the SOC estimate, the voltage and current use a single common point that serves as a fixed value and is maintained by the ARIMA method. It continues to behave moderately in the first state. The SOC eventually drops when the voltage drops in specific situations. At a certain point, both increases.

IV. ARIMA ALGORITHM MODEL AND RESULT

Time-series forecasting algorithm known as ARIMA (Autoregressive Integrated Moving Average) can be utilized to estimate a battery's state of charge (SOC). ARIMA may be a good choice for SOC estimation for the following reasons:

Capture of temporal dependencies: Because a battery's SOC is influenced by its previous voltage and current values, ARIMA models can capture temporal dependencies in the data, which is important for SOC estimation. Additionally, ARIMA models are capable of capturing data trends and seasonality.

Good for predictions in the short term: Because the accuracy of the SOC estimate decreases as the prediction horizon expands, short-term predictions made by ARIMA models are crucial for SOC estimation.

Resilient to noise: Because battery voltage data can be noisy and may have missing values due to issues with data logging, ARIMA models are able to deal with missing values and are resistant to noise in the data.

Interpretable: For SOC estimation, ARIMA models are crucial because they make it possible for engineers to gain insight into the behavior of the battery and identify any issues. ARIMA models are relatively simple to interpret and comprehend.

Steps to be followed for writing the algorithm :

Step 1: Compile historical data on battery voltage
Step 2: Preprocess the data to eliminate any anomalies or noise (This step is not shown in the flowchart as it may vary depending on the data)
Step 3: Divide the data into training and testing sets
Step 4: Fit an ARIMA model to the training data
Step 5: Using the test data, validate the ARIMA model
Step 6: Use the fitted ARIMA model to predict the battery voltage for the following time step.

(Note: The blue colour indicates the actual value and the orange colour indicates the predicted value)

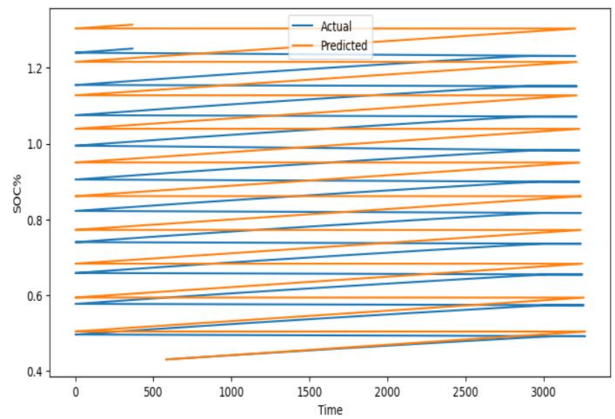

Fig. 7. Actual and Predicted curve of SoC vs Time

Fig 7. Shows the actual and predicted value of SoC and Time.

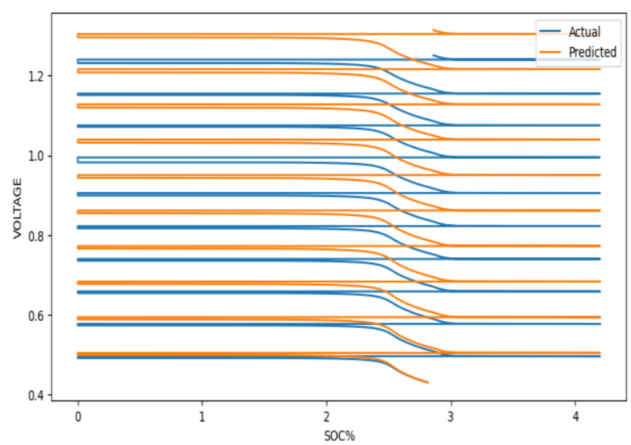

Fig. 8. Actual and Predicted curve of Voltage vs SoC

Fig 8. Shows the actual and predicted value of Voltage and SoC.

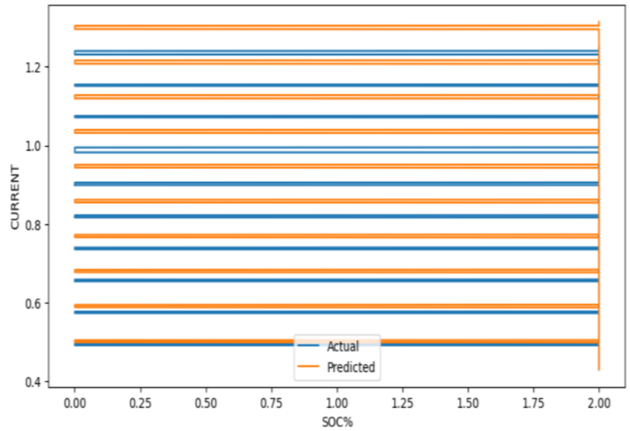

Fig. 9. Actual and Predicted curve of Current vs SoC

Fig 9. Shows the actual and predicted value of Current and SoC.

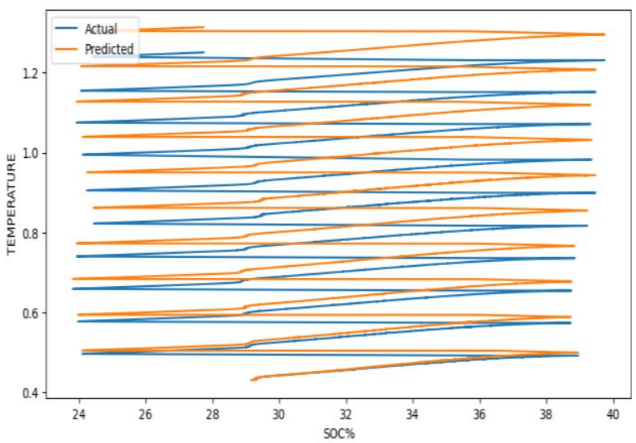

Fig. 10. Actual and Predicted curve of Temperature vs SoC

Fig 10. Shows the actual and predicted value of Temperature and SoC.

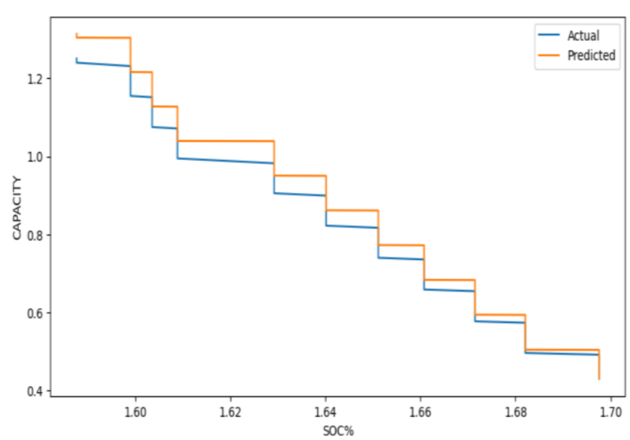

Fig 11. Actual and Predicted curve of Capacity vs SoC

Fig 11. Shows the actual and predicted value of Capacity and SoC.

V. CONCLUSION

The State of Charge (SOC) of the battery is an important factor to consider while predicting the battery's life. As a result, precise SOC evaluation not only avoids overcharging or discharging and enhances battery life, but also enables the application to utilise acceptable management approaches to fulfil the energy savings objective.

Oscillation and losses are minimized by using Multistage Converters. Instead of employing an ANN-based approach, the ARIMA Model can be used to control the estimation of SOC (State of Charge).

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