Investigation of Evolutionary Intelligence Techniques for The State of Charge Estimation of Rechargeable Batteries in Electric Vehicles (EVs)

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Abstract*– The increase in pollution caused a shift in the industry from combustion engines toward Electrically powered vehicles. The electrification of vehicles; has an enormous impact on the research of batteries and battery management systems. The batteries go through various tests to verify their reliability and their ability to perform in a satisfactory matter, with it being the most suitable battery for the vehicle. Furthermore, the battery management system is the system responsible for overseeing various parameters, with the most important parameter being the state of charge (SOC) of the battery. SOC can be estimated using various techniques, but this paper focuses on simulating the battery using an intelligent technique, with the SOC being estimated using a neural network and compared with the SOC estimation using an extended Kalman filter. The neural network estimation method; produced valid results with high accuracy in comparison to the estimated extended Kalman filter method, and the values were closer to the real values of the SOC.

Keywords—State of charge (SOC), Open circuit voltage (OCV), Extended Kalman filter, Neural network.

I. Introduction

Electric vehicles (EVs) and plug-in hybrid electric vehicles are the center of attraction to all car manufacturers to be able to reach the goal of zero carbon emissions. The current combustion engines emit a large amount of Nitrogen Oxide and Carbon Monoxide from the burning of fuel. That resulted in a total of 24% of carbon emissions being produced by modern combustion engine cars. All the governments are now pushing for electric cars as a method of protecting the environment and marketing it as the future of automotive. The development of a better generation of EVs or plug-in hybrid cars that are more efficient and more powerful is essential to be able to attract the customers of the current combustion engine cars. The development of more efficient and powerful cars is related to the research and development of the battery and the Battery Management System (BMS).

The author in [1] stated that the Battery management system is a system that consists of different electronic components, and various functions and features that are essential to ensure the efficient operation of both the system and the battery. The system is also responsible for overseeing the safety and reliability of the battery by supervising all the operating parameters of the battery such as voltage, current, and temperature by collecting their information using the sensors in the battery. Not to mention, it will ensure that the battery is charging efficiently and prevent overcharge and discharge of the battery or any major anomalies, which ensures that the battery is safe to be used. It is also responsible for estimating the battery states such as state of charge (SOC) and ensuring that it remains in its specified window, state of energy (SOE), state of health (SOH), and informing the user of any changes in its state, and state of power (SOP). The BMS ensures that the battery is operating in the safest and most efficient viable way without any risk of damage to the battery. It is also responsible for protecting the battery against high currents, and large temperature changes that can highly affect the SOC and SOH. One of the most vital estimations needed for the BMS system is the SOC, which is defined in [1] as the amount of remaining capacity that can be used before the need for recharging. SoC can be influenced by several factors like current rate, temperature, battery degeneration, uncertainties about the battery, and external disturbance. Moreover, one of the problems that arise with the battery is aging, which can affect the total capacity of the battery that can be delivered during its lifespan.

Nowadays, one of the most used batteries is the lithium-ion battery, they are used in portable devices and electric vehicles due to their various characteristics which made it one of the most used batteries in the industry. The attraction toward lithium-Ion batteries is due to numerous factors and characteristics of the battery such as high-power density, high cell voltage, lifespan, and low discharge rate. On the other hand, the battery has some chemical factors that can affect the battery such as a reduction in the battery`s lifespan caused by over-charging and over-discharging the battery or operating the battery outside of its designated temperature ranges. Based on the author in [3] All the previously mentioned drawbacks increased the need for the BMS. The main purpose of the research is the study of the battery and the intelligence technique that could be used for the estimation of the battery, in addition to simulation of the SOC using one of the evolutionary intelligent techniques, and extended Kalman filter. The results of both methods will be compared to the true SOC result to decide which method have the higher accuracy in results.

II. SOC ESTIMATION TECHNIQUES:

Based on the author in [5] The estimation of SOC can be done using several methods, due to the variety in methods they are classified according to the methodology of the estimation. There are several ways of classification of methodology that could vary from one literature to the other. Due to the diversity in literature, only four categories will be mentioned, because those are the most commonly mentioned categories in literature. The first category is the direct measurement method, which uses the battery`s physical property in the measurement. The second category is the book-keeping method, which uses the discharge current as input and calculates the SOC by integrating the discharging current. The third category is the adaptive systems, which are self-designed and can adjust the SOC values based on the different discharge conditions, and the category that contains evolutionary intelligent estimation techniques. The fourth and last category is the hybrid methods, which are hybrid models that use different SOC estimation methods, to have the highest accuracy and performance.

Table 1: Classification of SOC estimating mathematical methods

Categories	Methods
Direct measurement	1. Open Circuit Voltage (OCV) Method 2. Terminal Voltage Method 3. Impedance Method 4. Impedance Spectroscopy Method
Book-keeping methods	1. Coulomb Counting Method 2. Modified Coulomb Counting Method
Adaptive systems	1. Artificial neural network 2. Fuzzy network 3. Genetic algorithm 4. Particle swarm 5. Kalman filter

The two estimation methods that the papers will focus on and will be used in the simulation are the extended Kalman filter and neural network. Kalman filter was explained by the author in [6] as an asset of mathematical equations that are implemented as a predictor when certain conditions are met.

There is more than one version of the Kalman filter which is considered as a newly improved version of the original form of the Kalman filter like extended Kalman filter, unscented Kalman filter, and sigma Kalman filter that generates more accurate results. The original Kalman filter was formulated around 1960 and it was used at discrete points in time. The process is to define the progress of the state from k-1 to k. Kalman filter takes the previously estimated results from the sensors, and it tries to eliminate all of the noises while overcoming the existence of any insufficient data, and the current inputs to generate the output. It uses a two-step process, with the first process being the prediction step, and the second step is the correction step. The prediction step takes the estimated values of the current state, and by using the physical model of the system, it estimates its future value. The second step is the correction step, in this step the filter compares the predicted value to the actual value, and it calculates the measurement residual or the error rate. The error rate is then used in the next calculation to influence the results and get the most accurate results during the repetition of the process. The different variations of Kalman filter were created to address the problems that the standard Kalman filter could not solve. Each variation is vulnerable to certain situations, as the standard Kalman filter is used for linear systems. New variations of Kalman filter were created for dealing with non-linear systems. The most used variations for non-linear systems is the extended Kalman filter, the system is valid for non-linear systems. The Extended Kalman filter takes a non-linear system and linearize the system. As in the standard Kalman filter, the extended Kalman filter follows the same process as the standard Kalman filter, but with the addition of linearization as the first step. The linearization of the system has the potential of making the error propagate through the linearization process. In order to avoid the same problems in the extended Kalman filter,

The other method of estimation used is the artificial neural network, which is a computational system that is based on the biological nervous system, it is one of the intelligence techniques that can be applied for solving non-linear problems. The system consists of three layers, the input layer which receives the data and the inputs parameters, and the second layer consists of interconnected processing elements called neurons, that function together to transmit information from the input and solve the proposed problem. After solving the problems, the data is then transmitted to the final layer, which is the output layer that generates the final results. Each neuron in the system has weight, threshold value, and activation function. The weight affects the signal intensity at the connection based on if it has a positive or negative weight. The threshold is used to transmit the signal only if they have a threshold above which a signal previously had. Lastly, the activation function is the weighted sum of the summing unit, and the output is generated based on the signal from this activation value. One of the main advantages of the network is that in case one of the cells is damaged, the other cells can perform normally and make up for the absence of this cell.

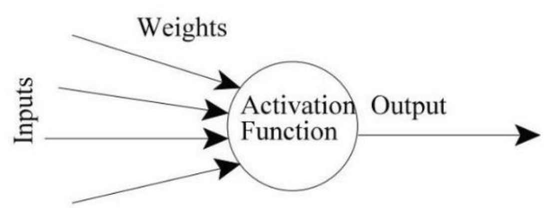


Fig 1: neural network neuron

There are two main types of neural network topologies, feedforward neural network, and feedback neural network. The feedforward neural network does not have any feedback loops, with each neuron sending the data to the next neuron, without receiving any data back. It has a fixed input and output, with every neuron receiving its data from the neuron on its left, the inputs are multiplied by the weight of each connection, and the output has the weight of each connection it can obtain. The feedforward network is usually used when the outcome of the network is already defined and known. On the other hand, the feedback neural networks, are considered memory systems, the system uses the feedback to compare the output result of the network and the output desired to be achieved. The difference between the two outputs is feedback to the system to modify the network and achieve the desired results. On the other hand, the system has its own problems such as there are no specific rules for the designing of a network, and the results produced are highly dependent on the training provided to the network, with some cases where it is impossible to provide any type of training for the system.

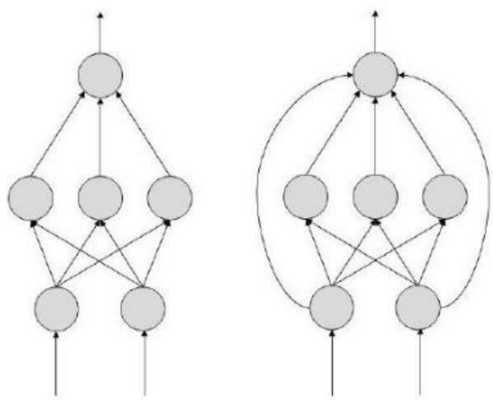


Fig 2: feed-forward neural network

III. Battery Data

The battery and the battery data used in the simulation were provided by McMaster University [11]. The battery was an LG 18650H2 battery with a nominal voltage of 3.6 volts and a nominal capacity of 3 Ah. The battery data was provided after being evaluated and simulated under different conditions such as the discharge and charge rate and temperatures. The different temperatures were simulated using a temperature chamber, but to simplify the estimation process, all of the temperatures were neglected except for the 25°C room temperature. One of the first data provided by the university about the battery is the discharge capacity versus the temperature and C-rate.

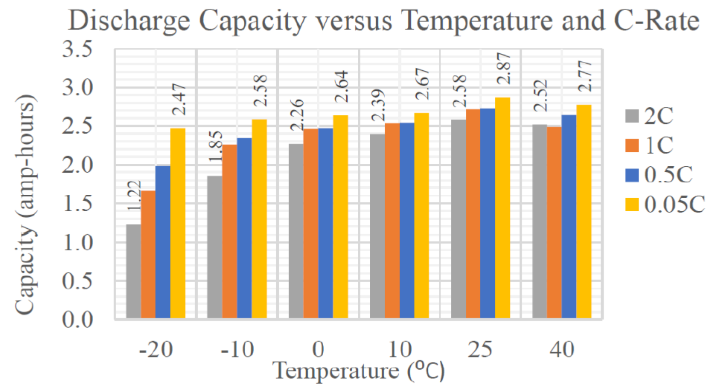


Fig 3:Discharge capacity versus temperature [11]

As previously mentioned, all of the temperatures will be neglected except the 25°C temperature, but the graph represents the effect of temperature on the capacity of the battery as the higher the temperature of the battery the faster the chemicals inside the battery react, on the other hand, the decrease in battery can increase the internal resistance of the battery, which increases the effort the battery requires to be charged and discharged. Furthermore, as shown in the above graph it is shown that when the battery is discharged with 2C rate (a discharge time of 30min) it is shown that the battery capacity is reduced in comparison to the other C rates, with the higher capacity occurring at the lowest C rate which is 0.05C. The decrease in capacity occurs due to the losses that occur during the discharge period, which can be represented as a form of heat.

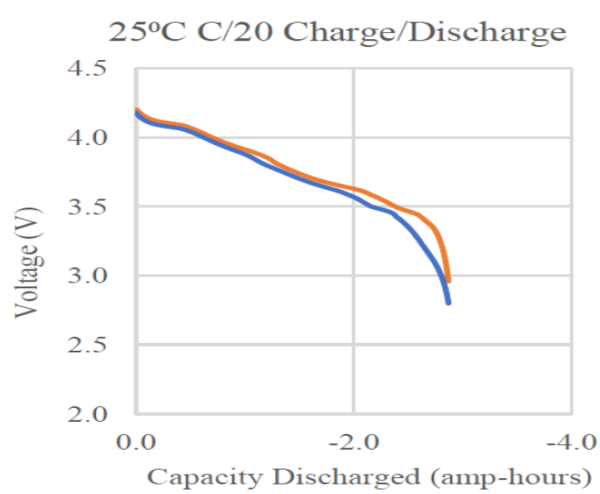
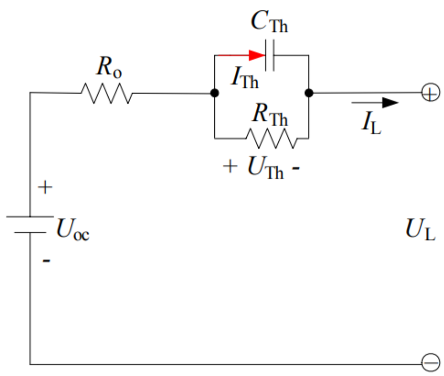


Fig 4: Charge/Discharge Voltage Vs C-Rate at different Temperatures [11]



The above graph (Fig. 4) shows the charge (orange line), and discharge (blue) voltage using the C-rate of 0.05C which takes around 20 hours to discharge and charge at room temperature. The graph clearly shows the changes in the voltage during the charge and discharge, and the capacity discharged from the battery, and it states that when the capacity decreases, the voltage will also decrease, and vice versa while the charging of the battery.

IV. BATTERY SIMULATION

Fig 5: Battery's equivalent circuit

The battery simulations are used to analyze how the battery will function in real life, and it provides the ability to verify that the used SOC estimation is valid. The need to verify the battery function and the reliability of the SOC estimation is essential to verify that the battery is suitable for the electric vehicle, and provide the required results, whether it is high performance or long-distance use of the vehicle and the battery. It can also provide insight into how exactly the battery will function and helps in the verification that the charge and discharge use of the battery is the compatible rate; and that the battery is not being overcharged or discharged so that it will not affect the vehicle`s battery or create problems and risks for the user. The simulation data is usually based on the empirical representation of the battery, which represents the battery as electric circuits, and the most commonly used model is the Thevenin model, the model is used in representing the battery and calculating the parameters of the battery. On the other hand, most of the simulations are done

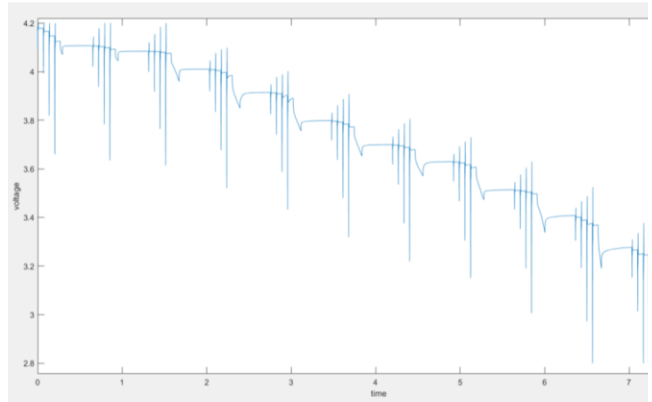


Fig 5: HPPC test voltage

by using real batteries and importing the data extracted from the battery to simulate it in any simulation application. The battery data is imported from real examples that went through various tests, to ensure the accuracy of the data and to verify that this is the exact battery that is suitable for the vehicle. There are several applications that can be used for the simulation of the battery such as ANYS, COMSOL Multiphysics, and MATLAB. MATLAB is considered one of the strongest simulation tools due to its various toolbox, and the flexibility of the system in simulating various applications. Moreover, the existence of Simulink that is user friendly, and has several libraries that can be used in the simulations, also one of the most important libraries is the SimPowerSystems library that has electrical components that can represent any electrical system and calculate it as a normal circuit. Furthermore, the ability to import diverse types of data makes it one of the most suitable software for simulating the battery system and the SOC estimation method. Not to mention, that the Simulink libraries already contain block that simulates essential SOC estimation methods such as extended Kalman filter, fuzzy logic, and Neural network, which make it easier for the user to use any of the previously mentioned methods if the data is suitable, and the user have sufficient knowledge.

A. characterization simulations:

The simulation of the battery in this research was done using the battery data gathered from McMaster University and supplied by MATHWORKS as lookup tables that can be easily imported to MATLAB. The battery data provided can give an insight into several aspects of the battery such as the HPPC test, OCV, and the drive cycle of the battery such as UDDS, HWFET, LA92, AND USA06.

The Hybrid pulse characterization test is one of the most important tests that use discharge and charge pulses to represent the battery`s dynamic power over the battery`s maximum usable voltage. The HPPC test was one of the tests that were done on the real-life battery, so the data provided about the HPPC test have high accuracy and can be represented easily using the lookup table provided.

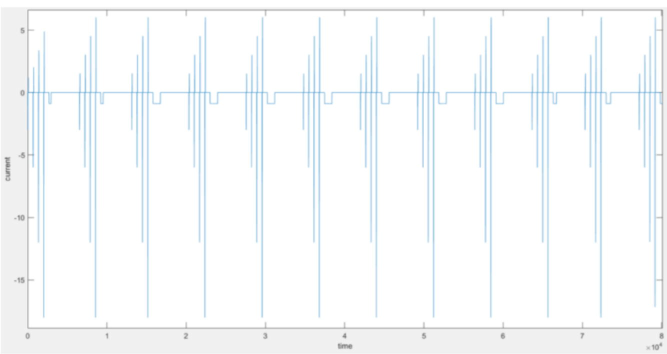


Fig 6: HPPC test current

As shown in the previous Figs, the maximum useable voltage is shown by charging and discharging the battery with pulses, with the current value dropping to almost -20A during the regenerating process and rising as high as 5A in the discharge process, and during the rest period the current remains at zero. Moreover, the SOC is being depleted during the test from 100% to 0% with each pulse depleting the battery by around 10%.

The second important simulation, which helps in analyzing the changes of the electronic energy in electrode materials is the OCV- SOC graph. It is an essential factor in estimating important parameters for the battery management system such as the SOC using the OCV method, and the SOH. While the OCV-SOC curve is considered stable, it can change according to the charge and discharge rate of the battery, battery temperature, cell variations, and cycle life of the battery. One of the problems that arise during the estimation of the battery SOC using OCV is that the flat area of the OCV-SOC curve for lithium-ion power battery enlarges the measurement errors of OCV.

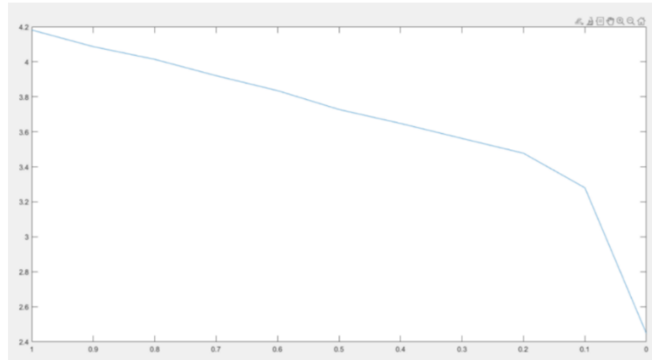


Fig 7: Battery OCV-SOC

B. SOC simulation:

The second part of the project, and the most important part is the implementation of a SOC estimation method. There are several types of intelligent methods that can be applied for SOC estimation such as neural network, particle swarm, genetic algorithm, and fuzzy logic. Each of the previously mentioned methods were evaluated to be able to reach the best possible result. The simulation was done using Feedforward neural network, while the other methods were experimented on to try and achieve the SOC estimation, several problems were faced which made the neural network the most suitable estimation method. Furthermore, an extended Kalman filter was added to the simulation to compare both results and to deduce which system is better and whether the intelligent systems have higher accuracy than the common method of estimation. The simulation was done on Simulink by importing the battery data supplied by McMaster University and MATHWORKS. The main benefit of the data supplied; is that they are provided in a format that makes it easy for the data to be tested, trained, and validated, which makes it suitable to be used with the neural network. The reason for choosing the feedforward neural network is that as previously mentioned the desired results are already known, which makes the feedforward neural network the most suitable option.

The model used in the simulation was proposed by MATHWORKS. The most important aspect of the model is the simplicity in using the blocks and the highly efficient results achieved. The model is simple due to its high reliability on having the battery data provided from McMaster University and having a constant temperature of 25°C, which removes the battery temperature effect from the process. The gathered data helped in reducing the number of blocks needed to achieve the same amount of data The data also provides real-life SOC value, which is labeled as true SOC that can be used in the comparison process, and determine which system has the higher accuracy between neural network and extended Kalman filter. The data is imported to the Simulink model using the nniput block, which takes the values of the battery without testing, training, and verification from the workspace and uses it as the input of the neural network block, and the de-normalize block. The neural network block uses a live-script code to implement the neural network, the code used is a standardized code that could be used with several applications provided by MATHWORKS, with the first part of the code dedicated to testing, training, and validating the data to be able to be used in the neural network. The second route for the nninput data is the de-normalize blocks that are used for separating the voltage, current, and temperature data to be suitable for the extended Kalman filter. Inside the de-normalize block, the values of the voltage, current, and temperature will be imported using Goto block and from block in MATLAB, to be connected to a scope, which shows the inputs and the results of simulation.

The result of the simulation shows that both the neural network and the extended Kalman filter can produce satisfactory results when compared to the true SOC value of the battery based on testing. Furthermore, the simulation validates the theory that intelligence techniques can produce high accurate results, because based on the simulation above, and comparing to the results of the extended Kalman filter its shows that at the beginning both of the methods started with similar values, but as soon as the discharge occurs the neural network was the faster method to produce SOC similar to the real SOC, and have higher accuracy than extended Kalman filter. Moreover, during the periods of 0.5 to 1.5 and 3 to 3.5 it shows that there is a substantial percentage of error in the extended Kalman filter method, on the other hand, the neural network maintains a smaller percentage of error and values closer to the real SOC during the entire time of the simulation. Based on the simulation above, it shows that the main problem in using an extended Kalman filter is the reduction of the accuracy of the SOC during the discharge period; and that it takes more time to be able to fix the percentage of error, unlike neural network method.

Conclusion

In conclusion, the main purpose of the research is the simulation of an intelligent SOC estimation method of a battery. Furthermore, the simulation of various aspects of the battery that will give us a priceless insight about various characteristics of the battery was made such as the HPPC test, which gives an insight into the dynamic power of the battery maximum usable voltage, OCV-SOC curve which can be used in the estimation of the SOC, and the different drive cycles of the battery, which provide an insight about the different driving styles and how it can consume the battery. The second step was the simulation of the SOC estimation technique. There were various intelligent SOC estimation methods that could be applied, but due to the limitations and various problems faced, the neural network was chosen as the most suitable method of SOC estimation. The main attraction of using the artificial neural network is the availability of suitable data; and the ability to have a simpler model. In addition to the neural network, simulation of the extended Kalman filter was made as a comparison between an intelligent method and a statistical method to see which has the higher accuracy in results. Based on simulation results it shows that neural network has higher accuracy in estimation, generating results closer to the true value; and that an extended Kalman filter can have an instability problem during the discharge, which can affect the accuracy of the results. Even though the system produced satisfying results that show that a neural network is a reliable, and suitable technique of estimation, an artificial neural network system can be improved by making it more suitable for more data types that require training, which is considered one of the drawbacks of neural network and have standard rules for designing the system to improve the results and make it more standardized and easier to use.

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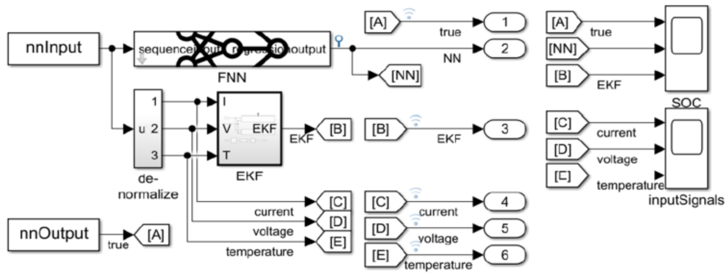

Fig 8: Simulink model

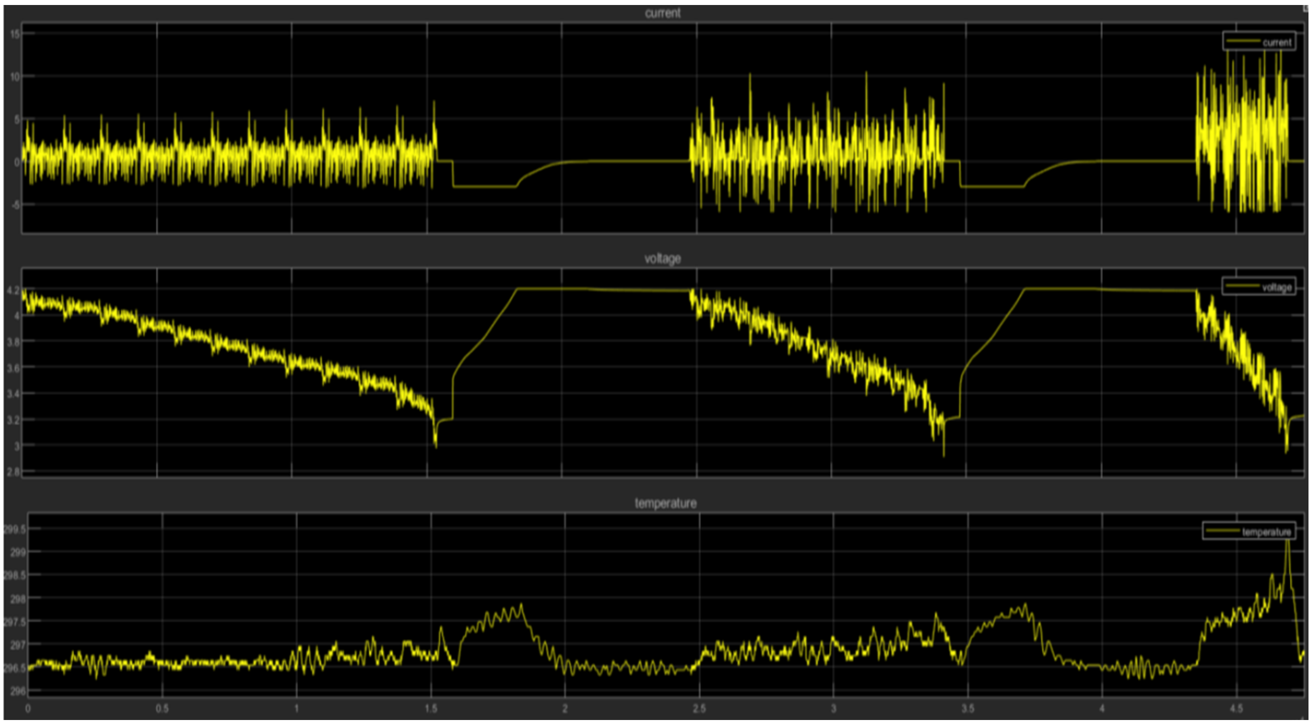

Fig 9: Battery SOC simulation inputs

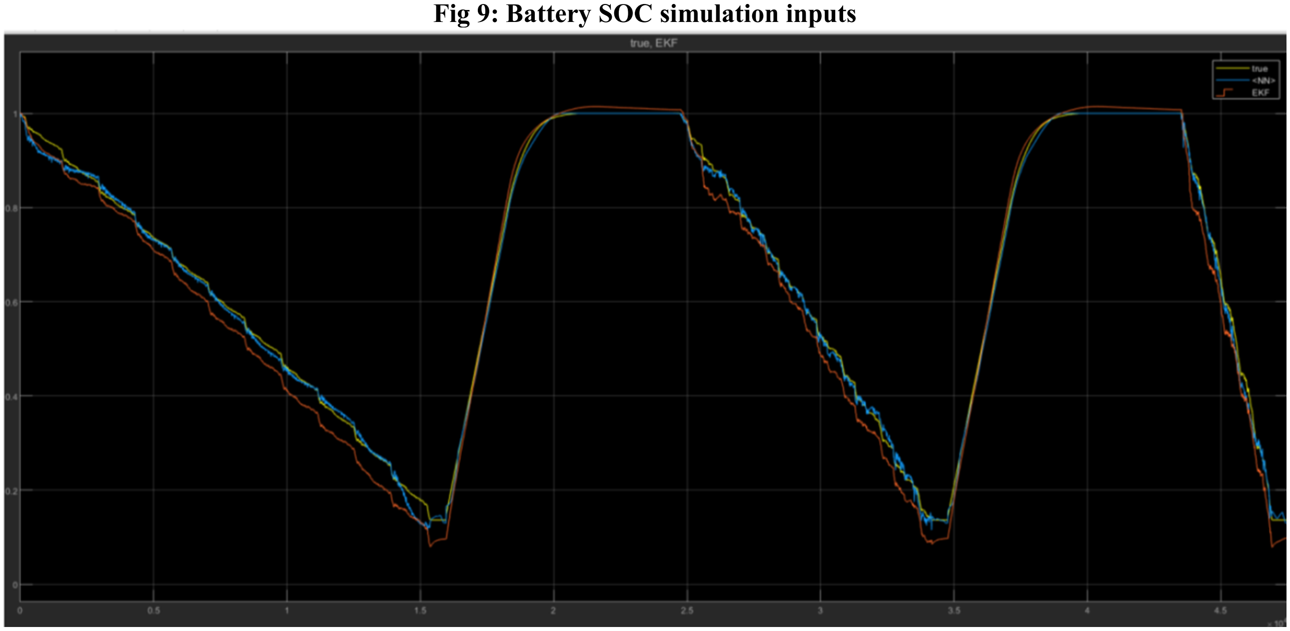

Fig 10:Simulation result