Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Electric Vehicle Battery Charging Estimation by ANN and Fuzzy Logic

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Citation: *Mr. Sagar Subhash Chikurdekar, et al. (2025), Electric Vehicle Battery charging estimation by ANN and Fuzzy Logic, Journal of Information Systems Engineering and Management, 10(42s),*

ARTICLE INFO

Received: 30 Dec 2024

Revised: 19 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

The state of charge (STOC) of lithium-ion batteries (LTIB) poses a significant challenge in the implementation and advancement of battery management systems, necessitating precise measurement of the battery capacity utilized in electric vehicle (EV) development, thereby emerging as a straightforward issue. Efficient regulation of battery energy, to mitigate dangers associated with overcharging and over-discharging, is feasible only with an accurate calculation of the STOCH, which supports several situations and constraints. In the STOCH esteem analysis, it is imperative to account for the influence of diverse components on the operational cycle of lithium-ion batteries, such as cell aging and cell imbalance, by employing various sophisticated similar circuit models of the batteries. Fitting assessment computations are employed to quantify and improve the precision of STOCH evaluations. The batteries and battery management systems (BMTS) are essential components of electric vehicles (EVs). The STOCH admiration, denoting the excess limit or capacity in the batteries, also constitutes the central border of the BMTS. This approach use a perpetual battery to control the STOCH value via an Arduino UNO microcontroller. Additionally, we will examine the battery display using a simulation of an associate degree Arduino regulator utilizing a MATLAB Simulink model. In MATLAB, an associate degree ANN model is to be developed for the detection of the battery's prudent STOCH.

Keywords: fuzzy logic control, Artificial Neural Networks (ANN), MATLAB Simulink

1. INTRODUCTION

The global use of energy assets is seeing a significant increase. This and conventional energy sources, such as fossil fuels (petroleum, coal, and natural gas), have proven increasingly difficult to harness. Recently, electric vehicles (EVs) have been swiftly produced due to escalating air pollution and depleting fossil fuels. The battery, being a crucial component of electric vehicles (EVs), significantly impacts their performance, including driving range, acceleration capabilities, and lifespan. Metal particle batteries are currently being used across a wide spectrum of energy-storage applications, from kilowatt-hour energy-type batteries in camera systems to multi-megawatt batteries for network-dependent services. This tendency has introduced a set of requirements in high-voltage and high-energy applications that depend heavily on precise (STOCH) assessment. precise The STOCH assessment enhances the protection of battery packs against overcharging and discharging. Inaccurate calculation of STOCH may lead to a diminished power-yield potential, thereby significantly reducing the overall energy of the board structure. STOCH is defined by the current battery constraints and is often presented as a magnitude of a reference restriction. The preferable STOCH reference shall be either the evaluated limit of an alternative battery or the maximum capacity of the current battery. Two techniques are planned for the STOCH assessment of metal particle batteries. The STOCH examination presents some challenges regarding battery utilization. The STOCH of a battery, which denotes its remaining capacity, can serve as a critical constraint for a bearing process. The STOCH serves as a critical boundary that reflects battery performance; thus, an accurate assessment of the STOCH cannot only

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e-ISSN: 2468-4376
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safeguard the battery and prevent excessive discharge but also facilitate the development of cost-effective management processes for energy conservation. A battery serves as a potential energy source, and such artificial energy cannot be readily obtained. The issue complicates the measuring of the STOCH of a battery. The precise measurement of the STOCH remains profoundly enigmatic and cannot be maintained, given the limitations of battery types and the continual exposure involved. Various instances of poor precision and accountability in the evaluation of the STOCH sector are extensively discussed.

2. BACKGROUND

Batteries have significantly benefited from mechanical advancements, allowing enough power density for use in electric cars. Compared to previous battery technologies, lithium-ion (Li-Ion) batteries provide several advantages, including enhanced energy and power density as well as an extended lifespan. In India, lithium particle batteries are extensively utilized for energy capacity due to their lower cost, while lithium-ion batteries are significantly more expensive. One of the primary constraints affecting the usable capacity of a battery is the STOCH. There are primarily two principal approaches employed in STOCH assurance: the estimation of battery open circuit voltage (OCV) and the incorporation of a continuous flow of charge into and out of the battery pack, referred to as Coulomb Counting (CC). In all scenarios, the driving circumstances in electric cars render the proper determination of STOCH fairly challenging using the aforementioned typical approaches. Recently, several scientists and organizations have been endeavoring to enhance the precision of STOCH measurement. The primary function of the BMTS is to monitor and control the battery's . Due to the susceptibility of cell technology to counterfeiting, an error in computation might potentially result in cell damage or a fire. Conversely, a precise assessment will yield benefits like extended battery life, enhanced performance, and greater vehicle efficiency. Despite extensive research on STOCH assessment, there is a paucity of studies examining ways to assess the correctness of STOCH evaluation for real battery systems. The predominant solutions for enhancing the precision of STOCH test duration assessments, as indicated in the reports and specialized releases, are more applicable to a virtual testing environment than to a physical framework.

3. THEORETICAL STUDY

3.1 BMTS

BMTS comprises several sensors, actuators, regulators, and signal lines, as seen in Figure 1. The primary function of a Battery Management System (BMS) is to guarantee the safe and efficient utilization of energy within the battery while delivering precise condition information to the vehicle's energy management system. It must be capable of delivering suitable mediations for the battery structure, given its operation under an unknown condition. The primary function of the control circuit is to assess the (STOCH), SOH, SOP, and SOL of batteries through sophisticated calculations utilizing estimations of battery current, voltage, and temperature derived from basic signals.

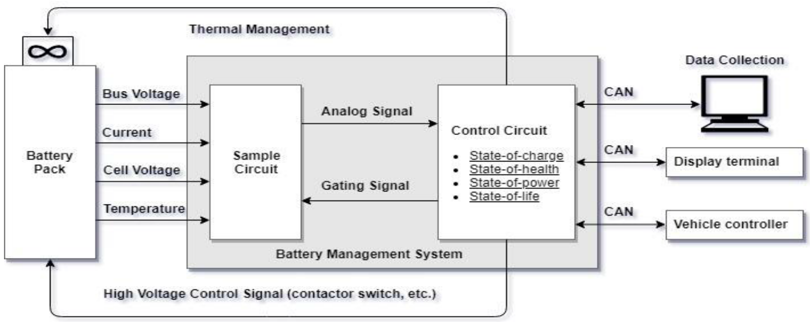

Figure 1. Battery Management System

3.2 Artificial NNA Based Methods:

The BP brain network is the most recognized form in simulated brain architectures. The BP brain network is employed in STOCH assessment owing to its superior capabilities in nonlinear planning, self-association, and self-

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learning. ANNA employs a numerical computation methodology for complex NNA characteristics or equivalent interactions. The NNA possesses the capability to manage information and elucidate relationships among diverse initial complicated factors. The link between the target and information is nonlinear and intricately intertwined in STOCH assessment. A BP NNA utilizes NNA computations to address a non-linear framework and features a simpler geometric structure than conventional NNA methods. This BP NNA is capable of measuring battery STOCH, as seen in Figure 2.

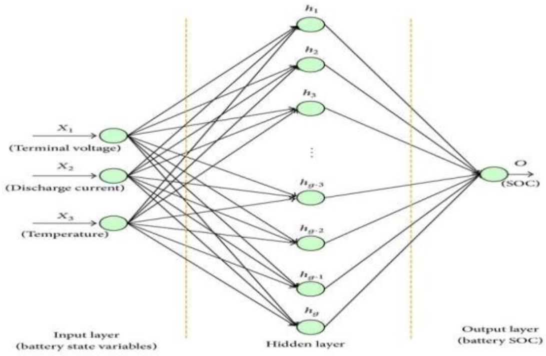

Figure 2. BP NNA for a battery

3.3 Elman NNA

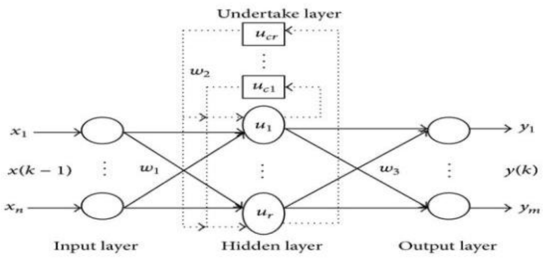

Figure 3. The topology structure of Elman neural network

Elman NNA is a feedback neural network architecture that incorporates a backpropagation neural network hidden layer together with an additional layer that functions as a delay operator, serving the purpose of memory. This configuration enables the network system to adapt to time-varying dynamic characteristics while maintaining robust global stability. Figure 3 illustrates the construction of the Elman Neural Network Architecture.

4. Hardware Connection:

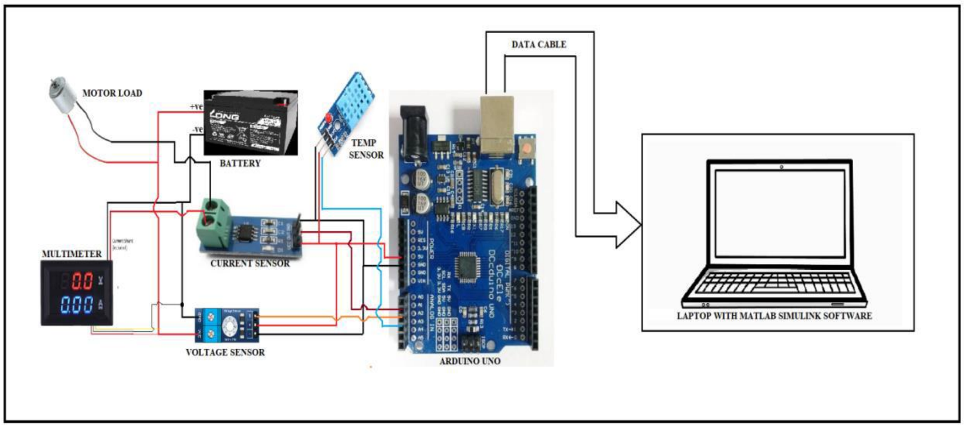

Figure 4. Connection diagram of hardware components

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The diagram depicts an embedded system with an Arduino Uno microcontroller connected to many sensors, a display unit, a Bluetooth module, and a computer interface for data monitoring. The system includes a gas sensor, a temperature and humidity sensor (DHT11/DHT22), and a pulse sensor to acquire real-time environmental and health data. An OLED display serves for local visualization, while wireless transmission to a computer system is enabled via the Bluetooth module (HC-05/HC-06). A power source and batteries enable the system to operate independently. This configuration is utilized in environmental surveillance, health assessment, and IoT-facilitated remote data acquisition.

4.1 Arduino UNO R3

The Arduino UNO R3 is powered by the ATmega328P, an 8-bit microprocessor from the AVR family. It features digital and analog I/O pins for connecting various expansion boards, breadboards, or other circuitry. The board has serial connection ports, including USB, which is utilized for programming via a computer. Arduino microcontrollers are often programmed in a language derived from C and C++.

4.2 Voltage Sensor

The module operates based on the strain theory of the obstruction point, reducing the input voltage at the red terminal to one-fifth of the original voltage. The maximum input voltage for the module must not surpass 25V (5V × 5) in a 5V system or 16.5V (3.3V × 5) in a 3.3V system, given that the Arduino's analog input maximum voltage is 5V. The Arduino AVR chip features a 10-bit ADC, resulting in a resolution of 0.00489V (5V/1023), which establishes the lowest input voltage at 0.02445V (0.00489V × 5). The Voltage Sensor functions as a voltage divider utilizing two resistors of 30kΩ and 7.5kΩ to provide a 5:1 voltage reduction ratio. The design (Figure 5) illustrates the Voltage Sensor Module, which possesses a maximum input voltage threshold of 25V.

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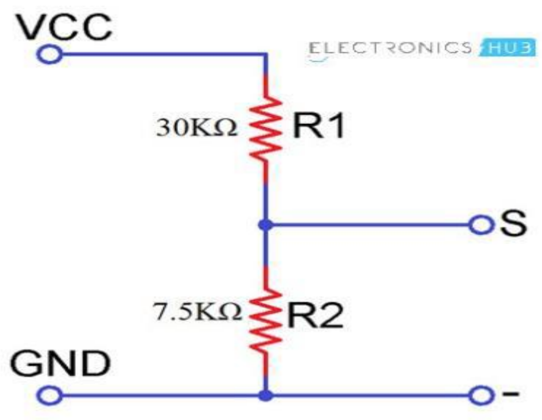

Figure 5. Schematic diagram of voltage sensor

4.3 Current Sensor: ACS712 5A

The ACS712 Current Sensor, developed by Allegro MicroSystems, is designed for accurate measurement of both direct and alternating currents. It operates based on the Hall Effect, utilizing a copper strip internally linked between the IP+ and IP- pins. When current flows through this strip, it generates a magnetic field that is detected by the Hall Effect sensor. The sensor outputs an analog voltage that corresponds to the detected AC or DC current. The ACS712 integrated circuit is housed in an 8-lead SOIC package, with its pinout illustrated in Figure 6 and the current sensor module depicted in Figure 7.

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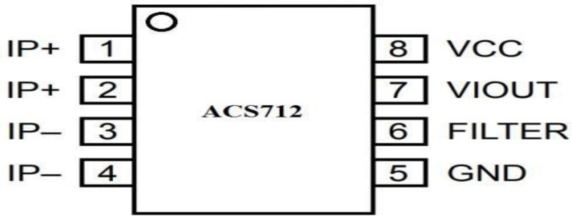

Figure 6.Pin Diagram of Current Sensor

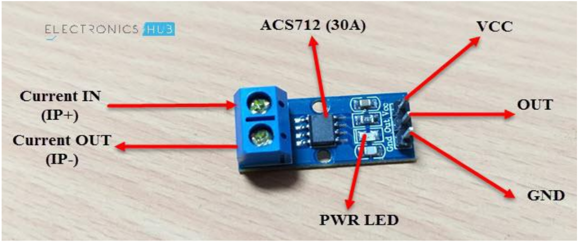

Figure 7.Current sensor

Current sensor calibration:

Vcc=5V

Qov=0.5*Vcc

Sensitivity=0.185

Vin=5/1024*analog read(Vin)

Voltage=Vin-Qov+0.012

Current = voltage/sensitivity

4.4 Temperature sensor

The LM35 is a temperature sensor that provides an analog output signal directly proportional to the measured temperature in degrees Celsius. It provides centigrade measurements without any external calibration. With a sensitivity of 10mV/°C, the output voltage increases with rising temperature. The three-terminal sensor is capable of measuring temperatures ranging from -55°C - 150°C. Unlike a thermistor, the LM35 delivers more precise temperature measurements.

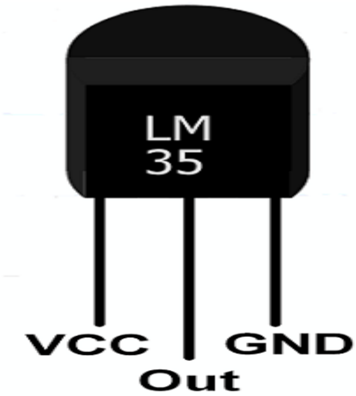

Figure 8 pin diagram of LM35 temperature sensor

5. MATLABST Model

The simulation model for the aggregation of battery data has been developed using MATLABST simulation. This model is seen in Figure 9. The specs and description of the model blocks are provided below.

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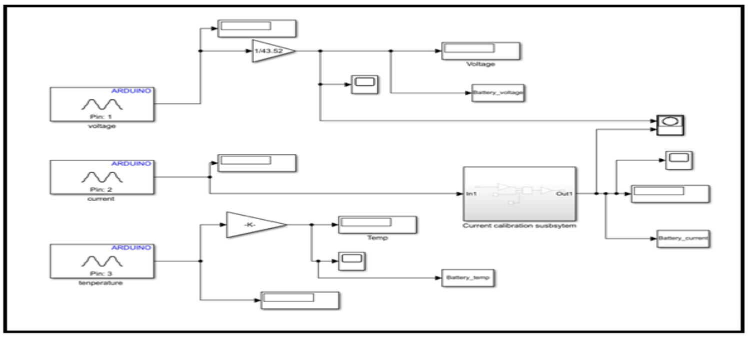

Figure 9. Simulation model for measurement of battery V, I, T

5.1 Complete Simulation Model

The simulation model emulates real-time battery voltage, current, and STOCH performance, juxtaposing the results of battery STOCH with the simulated outcomes delineated in this work. An EV battery simulation is performed, succeeded by a comparison examination between the EV battery and a real-time battery.

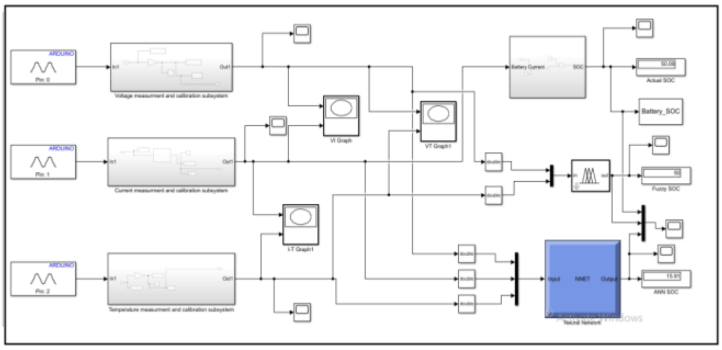

Figure 10. MATLABST Simulation of complete system

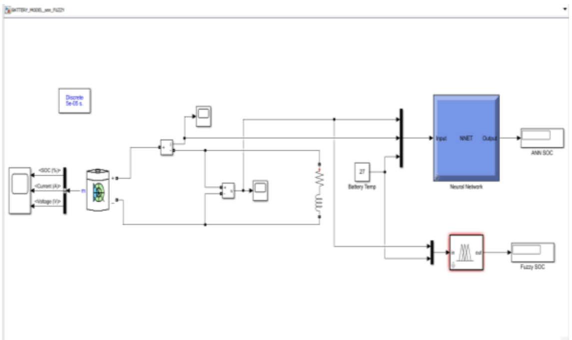

Figure 11. MATLABST Simulation of Battery

6. RESULT

Results

	Samples	MSE	R
Training:	67	9.03004e-2	9.99944e-1
Validation:	14	2.55616e-1	9.99875e-1
Testing:	14	1.21844e-1	9.99919e-1

Figure 12. Training performance parameter for NNA for STOCH estimation

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Figure 10 illustrates the ANN training procedure, in which 70% (67 of 95 samples) of the dataset was employed for training. The remaining 30% (28 samples) was employed for validation and testing. Upon the successful completion of training, the Mean Square Error (MSE) for all datasets reached its minimal value. Figure 11 illustrates the training performance characteristics of the Neural Network Algorithm (NNA). The training procedure encompassed 92 epochs with the backpropagation method, achieving optimal validation performance of 0.25562 at epoch 86.

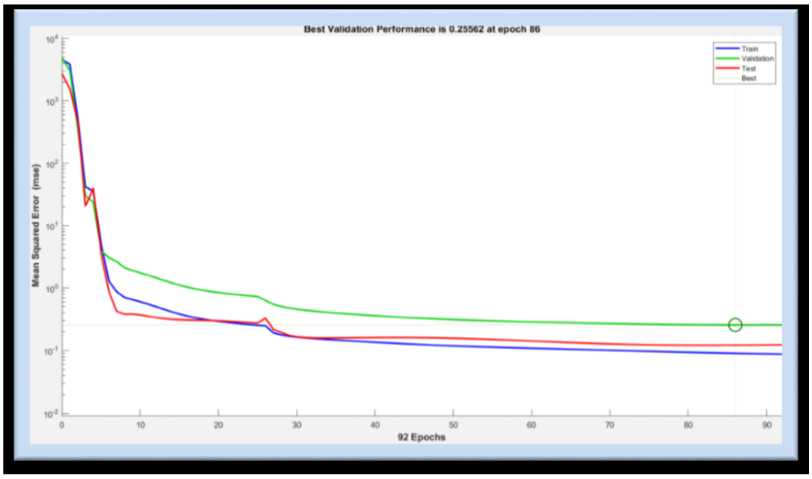

Figure 13. NNA training

Figure.13 shows the regression window in NNA training. Regression R value measure the correlation between outputs and targets. An R value of one means a close relationship, zero means a random relationship. The overall regression value is 0.99995.

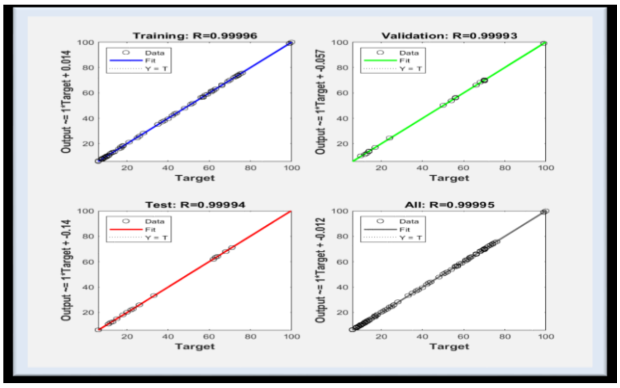

Figure 14 NNA Training Regression

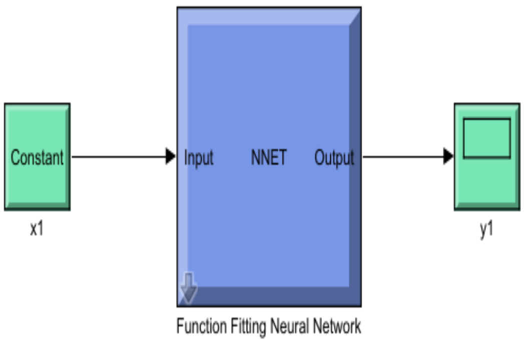

Figure 15. NNA Simulink Model

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The Levenberg-Marquardt back-propagation method, often known as trainlm, was employed to train the back-propagation neural network (BPNNA) model due to its efficiency in achieving quick convergence for function approximation problems. The hyperbolic tangent (Tanh) function, defined as f(x) = (1 - exp(-2x)) / (1 + exp(-2x)), was employed as the activation function for the hidden layer to address the non-linearity of the data. The output layer utilized a purelin (pure linear) activation function to guarantee a linear correspondence between the hidden layer output and the final output. The network architecture comprised a solitary hidden layer with 10 neurons. The training performance was evaluated using the mean square error (MSE) criterion, resulting in a value of 0.0877, indicating an acceptable degree of accuracy. The model achieved convergence after 92 iterations, with the final reported gradient being 0.126. The regression value attained was 0.99995, signifying an almost perfect correlation between the goal and expected outputs.

6.1.1Battery system parameter analysis

6.1.1 Battery parameter analysis

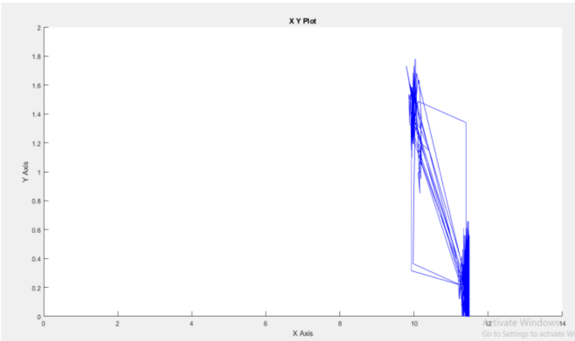

Figure 16. Battery voltage verses battery current (V-I) Characteristics of real time battery

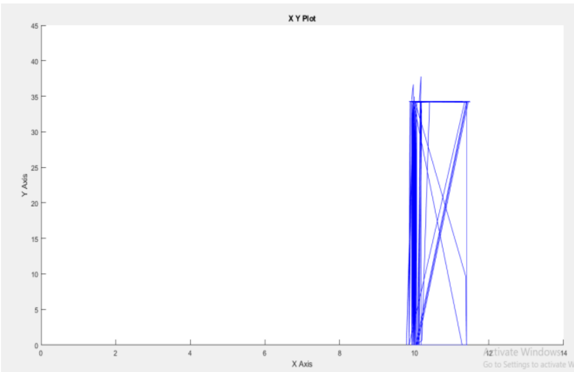

Figure 17. Battery voltage verses battery temperature (V-T) characteristics of real time battery

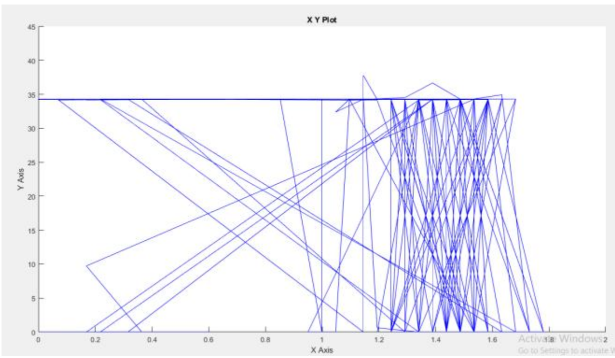

Figure 18. Battery current verses battery temperature (I-T) characteristics of real time battery

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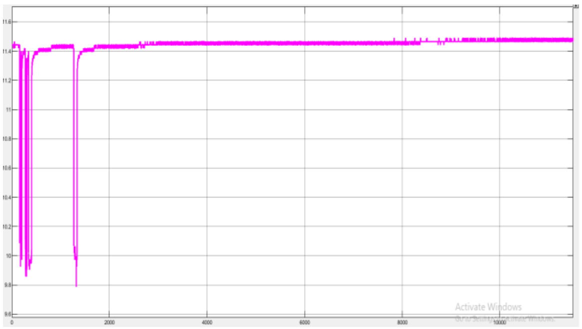

Figure 19. Battery output voltage verses simulation time curve of lithium ion battery

In this work, a brain network has been constructed from battery pack current, voltage, and temperature readings. The data set for training has been received from the equipment model. The battery is connected directly to MATLAB Simulink through an Arduino with pin numbers allotted being referred to in the Simulink model. This connectivity is facilitated through the Simulink Support Package for Arduino hardware. The real voltage and current discharge waveforms are shown in Figures 17 and 18.

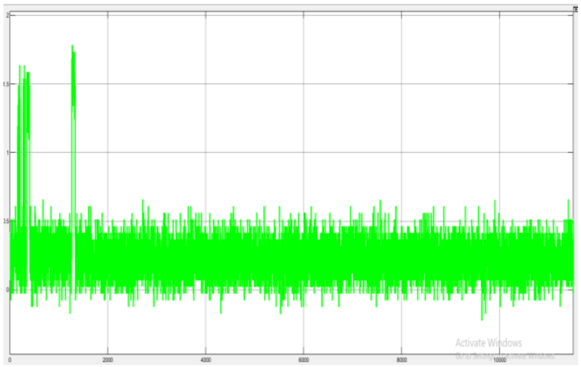

Figure 20. Battery output current verses simulation time curve of lithium ion battery

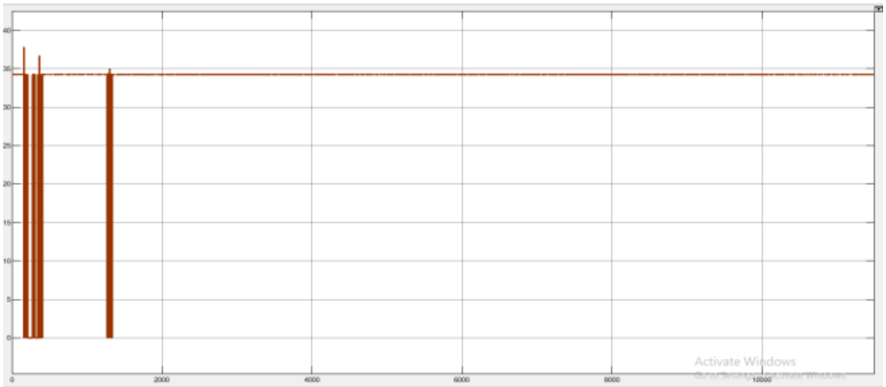

Figure 21. Battery body temperature verses simulation time curve of lithium ion battery

6.2 STOCH Calibration results

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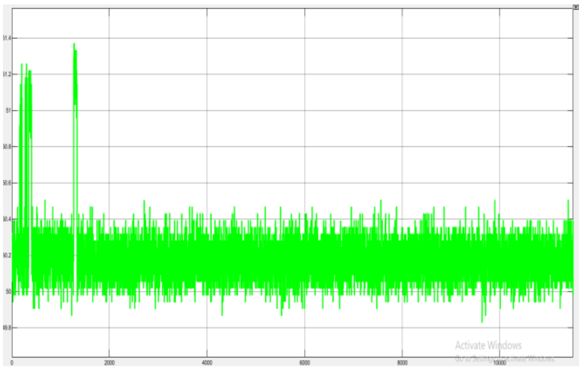

Figure 22. STOCH calibration using conventional formula

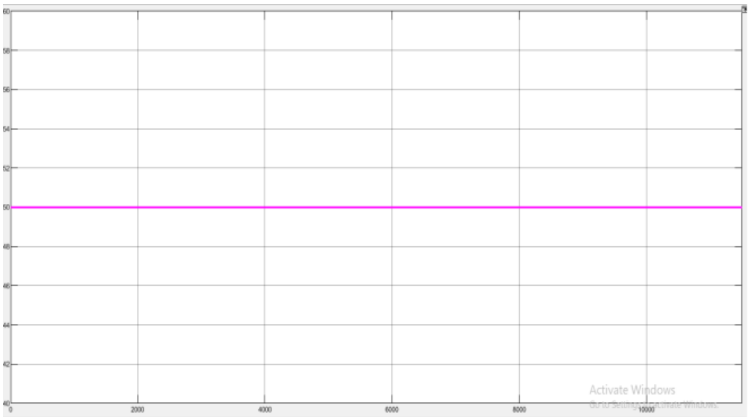

Figure 23. STOCH calibration using Fuzzy Logic controller

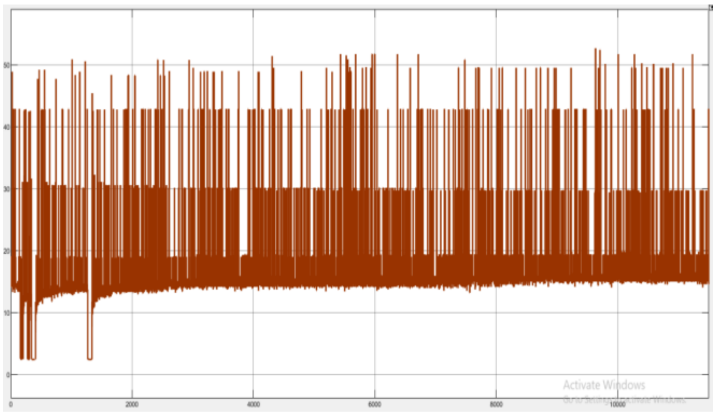

Figure 24.STOCH calibration using Artificial Neural Network

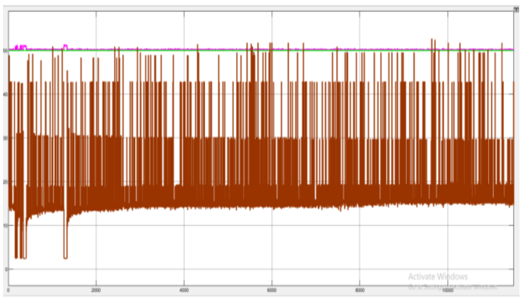

Figure 25. STOCH calibration graph for conventional formula, fuzzy logic controller and artificial neural network

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7. CONCLUSION:

The accurate assessment of STOCH is the primary issue with battery board systems. This suggestion introduced battery STOCH evaluation methodologies and chose a main strategy based on a simulated brain network for STOCH evaluation. The OCV approach employs the intricate link between OCV and STOCH. The extended discharge period of batteries impacts their utilization across many applications. The CC approach directly calculates STOCH from the interplay of modern, computationally resilient elements. The foundational STOCH and hence the aggregation of detector faults diminishes the rationality of the CCM. The EIS approach will immediately reflect the alterations of the internal boundaries within the battery. The EIS methodology is responsive to STOCH types; nevertheless, the intricacy of web-based EIS calculation constrains its online applicability. Model-based methods are far more precise and stable than alternative approaches; nevertheless, they are also considerably more computationally intensive. Furthermore, its appearance is closely associated with the structured battery model. Methods based mostly on artificial neural networks are not challenging to execute online following the preparation of disconnected data. This job examines mostly ANN-based algorithms to determine the charge state of an electric battery. It is noted that artificial neural networks (ANN) are utilized for the real-time assessment of charge conditions in lithium-ion batteries used in electric vehicles (EVs). The downy principle approach is not cost-effective for this type of STOCH alignment, which relies on two information sources: battery voltage and internal battery temperature. The conventional equation-based STOCH approach principally depends only on battery current.

ABBREVIATIONS

State of charge – STOCH

MATLAB software – MATLABST

Neural Network algorithms – NNA

lithium-ion batteries – LTIB

battery management systems – BMTS

state of health- SOH

state of power availability –SOP

state of life - SOL

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Journal of Information Systems Engineering and Management
2025, 10(42s)
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https://www.jisem-journal.com/
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