Analysing Real Time Battery Condition Using Machine Learning For Electric Vehicles

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ABSTRACT
Batteries are essential electrochemical cells that deliver energy to a variety of electrical devices. These cells must be routinely maintained in order to operate properly. Battery management systems control charge and temperature, lowering possible safety, health, & property issues. To regulate battery performance, these systems use merit measures. Since current approaches over data-driven fault prediction produce good results on the specific processes on which they were trained, they frequently lack the ability to adapt to changes, To address this issue, this research presents a continuous learning neural network strategy that uses a data-driven approach to monitor these parameters. To estimate these values, the machine learning algorithm used in this work finds relevant characteristics from the discharge curves. The efficiency of the suggested technique was assessed using extensive simulations at various voltage as well as temperature levels.

KEYWORDS:
Electric vehicle; Battery; Machine Learning; parameters

1. Introduction

As people throughout the world become increasingly ecologically conscious and look for alternatives to conventional gas-powered vehicles, electric vehicles (EVs) rapidly growing in popularity. Some of the trends in the electric vehicle industry include increased range, more affordable prices, and the development of new battery technologies [1]. The range of EVs has been increasing steadily in recent years, with some models now capable of driving up to 400 miles on a single charge. As battery costs continue to decline, EV prices are becoming more competitive with traditional vehicles [2]. Additionally, new battery technologies are being created, such as lithium-sulfur batteries and solid-state batteries, which could significantly increase the range and performance of EVs. Another trend is the growth of electric SUVs and pickup trucks, which were previously not widely available in the market. Furthermore, the expansion of EV charging infrastructure is helping to alleviate range anxiety and make electric vehicles more accessible to drivers. Finally, there is a trend towards using renewable energy to power EVs, with more companies offering solar panels and home battery storage systems that can be used to charge electric vehicles.

In order to maintain maximum effectiveness and endurance, the functionality of the battery system is monitored and regulated as part of the intricate process known as electric vehicle battery management. Battery management system monitor the battery's voltage, temperature, and state of charge using a number of sensors and algorithms, and they modify the charging process as necessary. For the battery to be charged properly and efficiently, they can also adjust the regenerative braking system. One of the main challenges in electric vehicle battery management is balancing the need for high performance with the limitations of the battery technology. Battery management systems could aid in preventing problems that could shorten battery life or potentially pose safety risks, such like overcharging, undercharging, as well as excessive heating. By optimising the battery's energy utilisation and minimising power loss, effective battery management may also aid in extending an electric vehicle's range [3][4].

Battery management systems also can offer insightful information about the battery's usage, which can guide future battery research and development and boost overall vehicle efficiency. Overall, managing the batteries in electric vehicles is essential to maintaining their effectiveness, safety, and lifetime. The proportion of the battery's overall capacity that represents the quantity of energy that is now held within it. For the battery to last as long as possible and operate at its best, the SoC must be kept within safe yet ideal range. The battery's performance and longevity can be significantly impacted by overcharging or undercharging it. The battery might overheat from overcharging, which might result in damage and shorten the battery's lifespan. A battery that has been undercharged may have a shorter range and eventually becomes unresponsive or fails to maintain a charge.

Battery management monitor and analyse the battery's SoC and control its charging process to make sure the battery's charge gets to the right level using a variety of sensors and algorithms. By avoiding both overcharging and undercharging, this ensures that the battery is charged properly and efficiently. Battery management systems can also provide drivers with information about the battery's SoC, which can help them to plan their journeys and optimize their driving habits to maximize range [5]. By knowing the battery's SoC, drivers can adjust their driving speed and style to conserve energy and extend the battery's range.

Overall, the importance of state of charge in electric vehicle battery management cannot be overstated. Maintaining the battery's SoC within a safe and optimal range is essential for ensuring the battery's longevity and performance, as well as maximizing the vehicle's range and efficiency.

The remainder of the paper is organised as follows. The related studies concerning battery power management are covered in Section 2, and the suggested machine learning-based battery monitoring is illustrated in Section 3. The outcomes of the implementation are shown in Sections 4 and 5, and Section 6 wraps up the study.

2. Related works

Several of the strategies make use of machine learning tools like logistic regression and deep learning, while others use Bayesian inference and state-space modelling. Some techniques focus on using voltage and current measurements to estimate the state of health, while others use vibration data or discharge processes. There are also techniques that combine data-driven technology with physics-of-failure. The goal of these methods is to accurately estimate the health and battery's life to prevent unexpected failures and improve battery performance.

Yu et al [6] developed the adaptive Gaussian mixture model (AGMM) to detect changes in battery health during the course of an online session. The AGMM removes and adds components to model the current health state, and a Bayesian-inference based probability indicator is created. Banaei et al [7] proposed a technique to calculate a Li-Ion battery's state-of-health (SOH) using pulse width. The approach uses terminal current measurement to forecast voltage output and pulse width of a healthy battery. Online assessment of the observed and projected voltages reveals details about the battery's health, providing a tool to identify potential battery issues.

Lee et al [8] built a method to diagnose battery cell issues using deep neural network (DNN) state classifiers. Data on discharging from using battery cell at high temperatures was used by the DNN state classifier The experiment demonstrated that battery SOH measurement can detect the battery's state with accuracy. A enabled battery SOH was created by Hu et al. [9] employing a deep learning based indicator as well as prediction system. The association among sample entropy as well as capacity loss is recorded utilising advanced Bayesian predictive modelling techniques. Brief voltage sequence sampling entropy is employed as a reliable indication of capacity loss.

Xing et al [10] proposed a prognostics-based fusion approach that blends data-driven technology with physics-of-failure (PoF) by contrasting their distinct properties. The approach focuses on battery monitoring systems and aims to estimate condition and predict life. Li et al [11] predicted the SOH and batteries life using a multi prediction system using an average entropy and relevant vector machine (RVM). The RVM model incorporates a wavelet denoising technique to identify trend information and lessen uncertainty. Tang et al [12] developed a technique for keep tracking the health of batteries with a number of indications (MIs). Using single indicator (SI) dispersion, three health indicators are taken from the real operating circumstances of EVs to show the requirement of MIs.

Senthil Kumar et al [13] proposed an online database that may be used to manage, track, and log battery metrics including voltage, temperature, current, power and state of charge. An android app is used to display the info to the user. Chetan et al [14] developed a vibration-based health monitoring method that collects data on the vibration of batteries used in vehicles to realize the need for repair or replacement. A set of vibration sensors and a microcontroller for data acquisition are used to collect the data, It is then graphed to comprehend the sort of flaw or the stage of the battery's life is experiencing.

Weng et al [15] for the purpose of SOH monitoring, comprehensive model parametrization and adaption framework was created to address the V-Q curve identification issue. The model parameters are computed in real time by using the straightforward structure of the support vector regression representations with specified support vectors (SVs).

Zhou et al [16] have introduced a novel kind of symmetric and antisymmetric longitudinal linear ultrasonic motor. This motor's stator is made up of a combination of Langevin transducers, which translate axial displacement to perpendicular displacement and produce an oval driving foot trajectory. The motor is highly precise and has a straightforward build. A fuzzy logic approach has been put up by Ananto et al [17] for calculating average SOH in Li-Po batteries. This technology takes into account two battery metrics and modifies the SOH in accordance with battery ageing and ambient factors, boosting the result's precision. This technique is simple to include into the batteries used for electric vehicles.

Anbuky et al [18] have described a method for measuring the health of batteries that relies on constant online readings. A multi-source domain adaption network (MSDAN) for battery health has been created by Zhuang et al. The technique makes use of the multi-source transfer learning methodology to track the deterioration of battery health.

3. Proposed system

The current work introduces a continuous learning neural network monitoring technique shown in figure 1 that relies on data-driven analysis to estimate the parameters mentioned earlier. To distinguish crucial features from discharge curves, a machine learning approach is utilized.

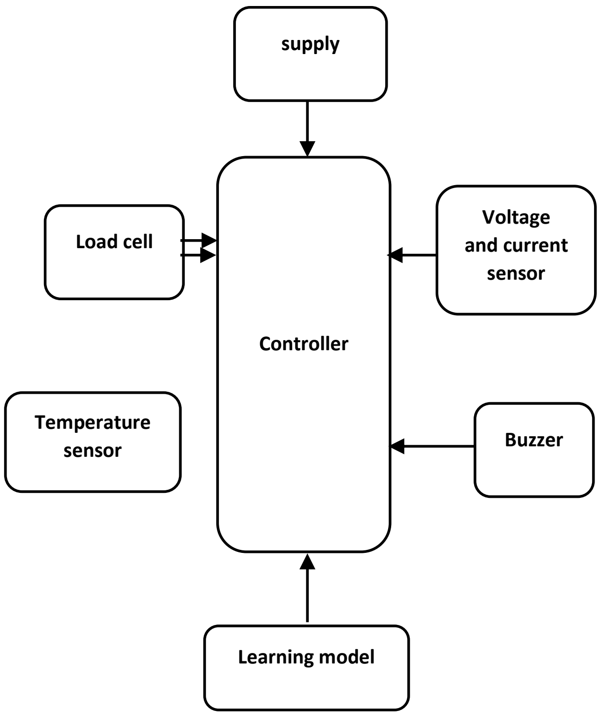

Fig. 1. Battery monitoring system

The use of artificial neural networks (ANNs) has been found to be highly adaptable for creating insight mappings based on prior data. ANNs consist of a variety of computational components that are connected via weighted connections, with layered feed-forward networks for an input-to-output mappings without dynamics or memory. These networks include an input, an output and several hidden layers that link the input to the output. The ANNs are trained for Wi and w0 by maximizing a cost function through the determination of ideal values. The deep learning has garnered significant interest, new methods have also been developed to increase the reliability of smaller networks, such as enabling lowered floating-point and integer arithmetic to achieve a specialized structure. In this study, a shallow intake neural network with one hidden layer of 15 units was chosen based on a research network tuning procedure, with the multiple units of an input and output being limited by variable numbers used for input and output. The Scaled Conjugate Gradients (SCG) is used for Training that does not require a user-selected or line search parameters and takes advantage of conjugate gradient optimization's strong convergence properties.

The training procedure for an Artificial Neural Network (ANN) used in battery SOC maintenance involves adapting insight mappings based on prior data. An ANN is a highly adaptable computational model consisting of a variety of straightforward computational components connected via weighted connections. The layered feed-forward networks, which do not include loops, are utilized to create input-to-output mappings that have no dynamics and no memory. The integral gain of ANN is represented by x = x1, x2, …, xM, where w0 represents a weight correction and bias, Wi indicates input xi weights and h(x) denotes an activation function. Typically, the hyperbolic tangent is used to perform a universal approximation. In a feed-forward network, an input, hidden and output layer, that are linking with an input to the output can be identified.

The ANN is used to train a cost function to determine the Wi and w0's ideal values. Although deep learning has garnered significant interest recently, new methods implemented for a network's reliability of smaller sizes. Hardware vendors have begun to enable lowered floating-point and arithmetic and provide small-scale, specialized architectures for reliable and scalable technology.

The control model used in battery SOC maintenance employs a shallow intake neural network (completely connected one hidden layer cross-perceptron). The choice of a hidden layer layout with 15 units is made possible by research network tuning procedure. The SCG approach is used for training, taking advantage of conjugate gradient optimization's strong convergence qualities and having the benefit of not needed a line search or parameters of user-selected.

4. Hardware implementation

The proposed system consist of temperature sensor, voltage, current and load sensor for continuous monitoring**.** The DH11 sensor is an electrical project-compatible digital temperature and humidity sensor. It is useful for battery-powered applications because to its tiny form size and little power consumption. The DH11 sensor measures the humidity ratio and temperature using a thermistor and a capacitive humidity sensor, respectively. It communicates with microcontrollers such as Arduino through a single-wire digital interface and provides accurate and reliable readings.

A current transformer is used to estimate an alternating current (AC) by producing a proportional AC current in its secondary winding. It is designed to isolate the measurement circuit from the high voltage or high current of the primary circuit. The current transformer consists of a primary winding that carries the current measurement and a secondary winding that is connected to the measuring instrument. When current flows through the primary winding, It causes a secondary winding current that is equivalent to that of the primary current. Power systems frequently employ current transformers for current monitoring and measurement.

An Arduino controller is a popular open-source microcontroller board that can be programmed to perform various tasks in electronic projects. It has a simple and easy-to-use programming language, making it accessible to beginners and experienced programmers alike. The Arduino board includes an Atmel AVR microcontroller, input/output pins, analog-to-digital converters, and other components that make it a versatile platform for developing electronic projects. The ability of Arduino boards to operate motors, sensors, displays and other parts makes them appropriate for a variety of applications.

An example of a transducer is a load cell, which measures weight or force by turning mechanical force in to electrical signal. It is frequently employed in scientific, commercial, and industrial settings where exact and precise weight measurements are needed. Whenever a force is given to the sensor element, the load cell measures how much it deforms or strains. A computer or programmable logic controller, for example, may read and analyse the electrical signal that is created by this deformation (PLC).

5. Results & discussion

A continuous learning algorithm developed in C language in the Arduino software is then transferred to the Arduino board using a B-type mini cable. A load cell is used to measure the load, and a microcontroller alone cannot regulate it. Therefore, a load driver, temperature sensor, a lithium-ion battery of 4 volts, a 2x16 liquid crystal display (LCD), a load cell, and other components are all linked to the Arduino board.

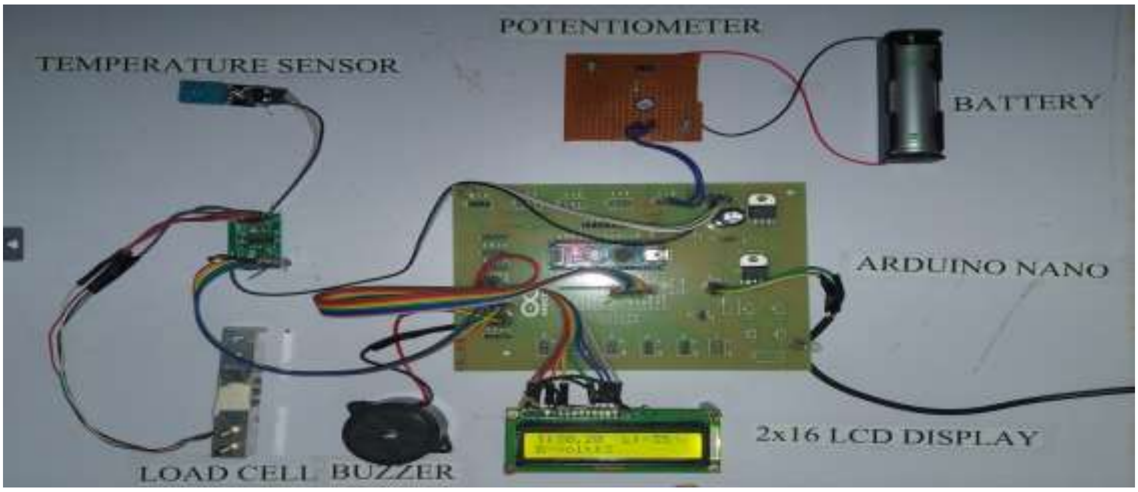

Fig.2: Displays the batterey's temperature, voltage and current at normal operating conditions.

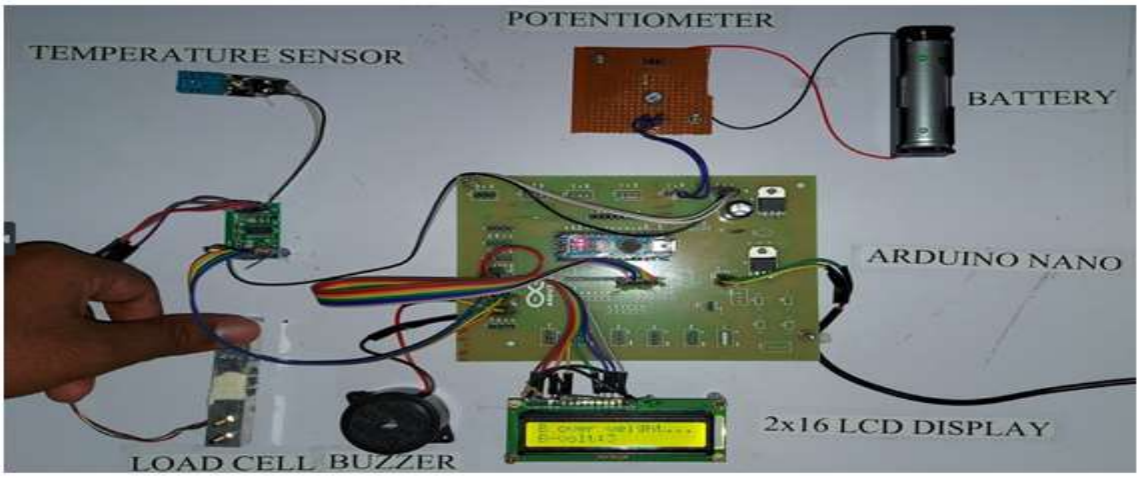

Fig. 3: indicates that the applied load on the battery cell has reached the threshold value assigned in the algorithm (1Kg), and the buzzer rings until the load is restored.

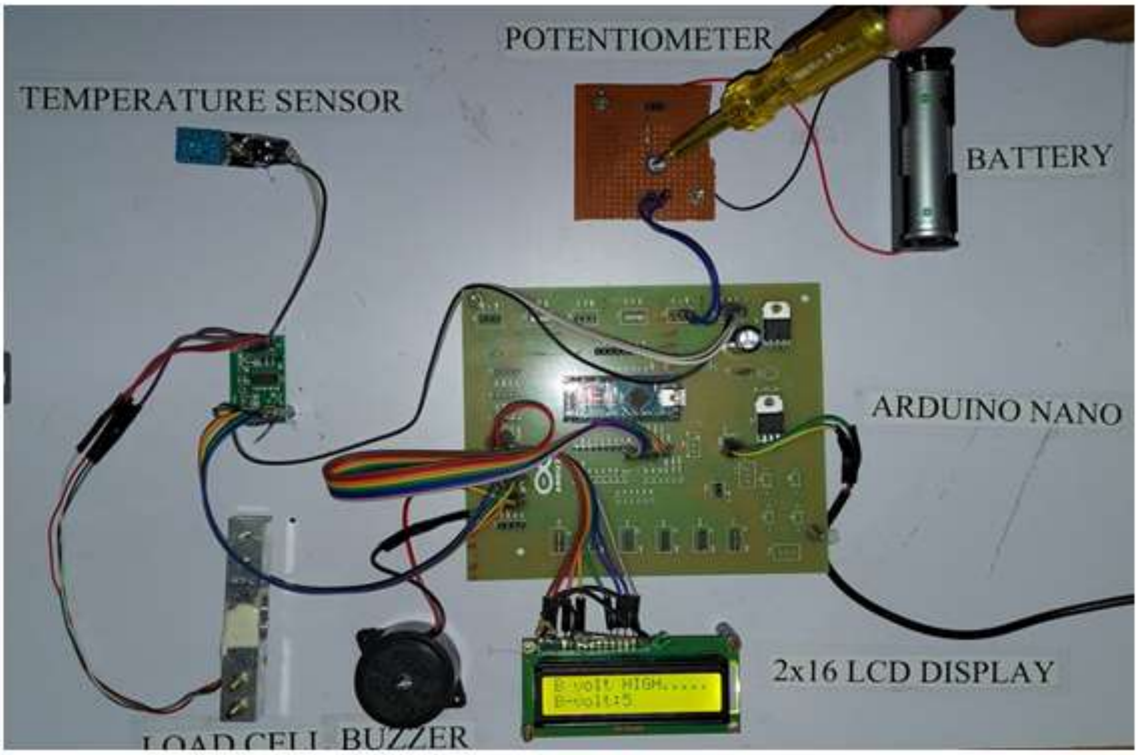

Fig. 4: Indicates that the voltage of the battery has reached the maximum threshold value assigned in the algorithm (5Volt), and the buzzer rings until the voltage is restored.

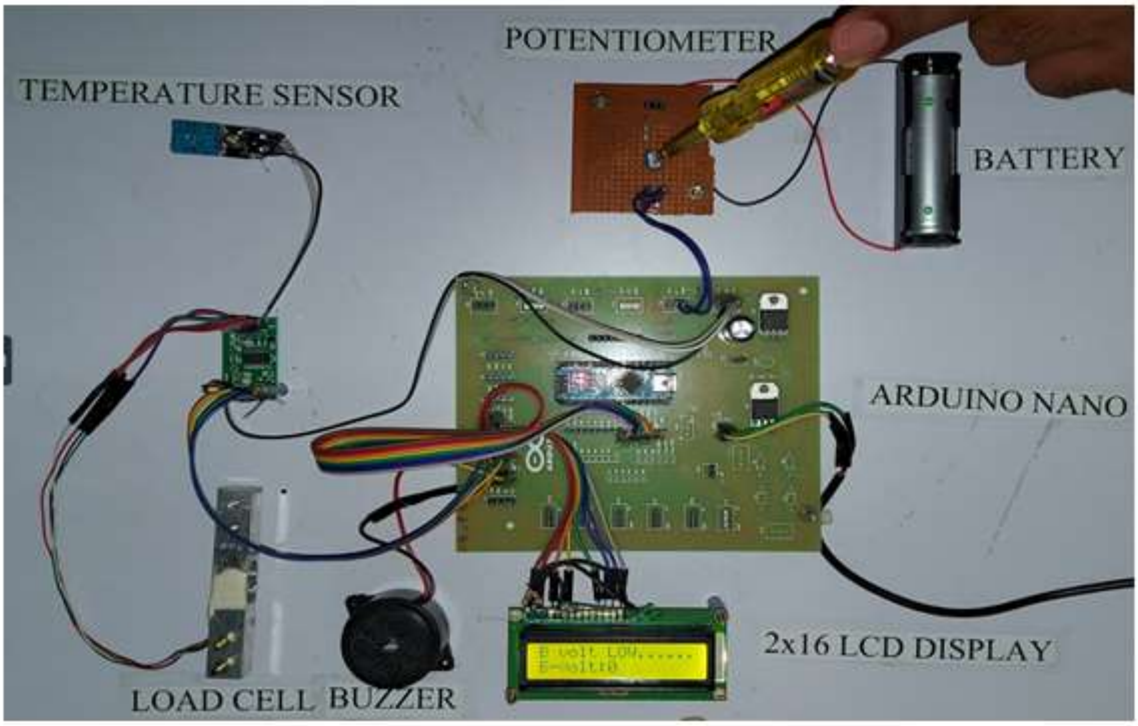

Fig. 5: indicates that the voltage of the battery cell has reached the minimum threshold value assigned in the algorithm (1Volt), and the buzzer rings until the voltage is restored.

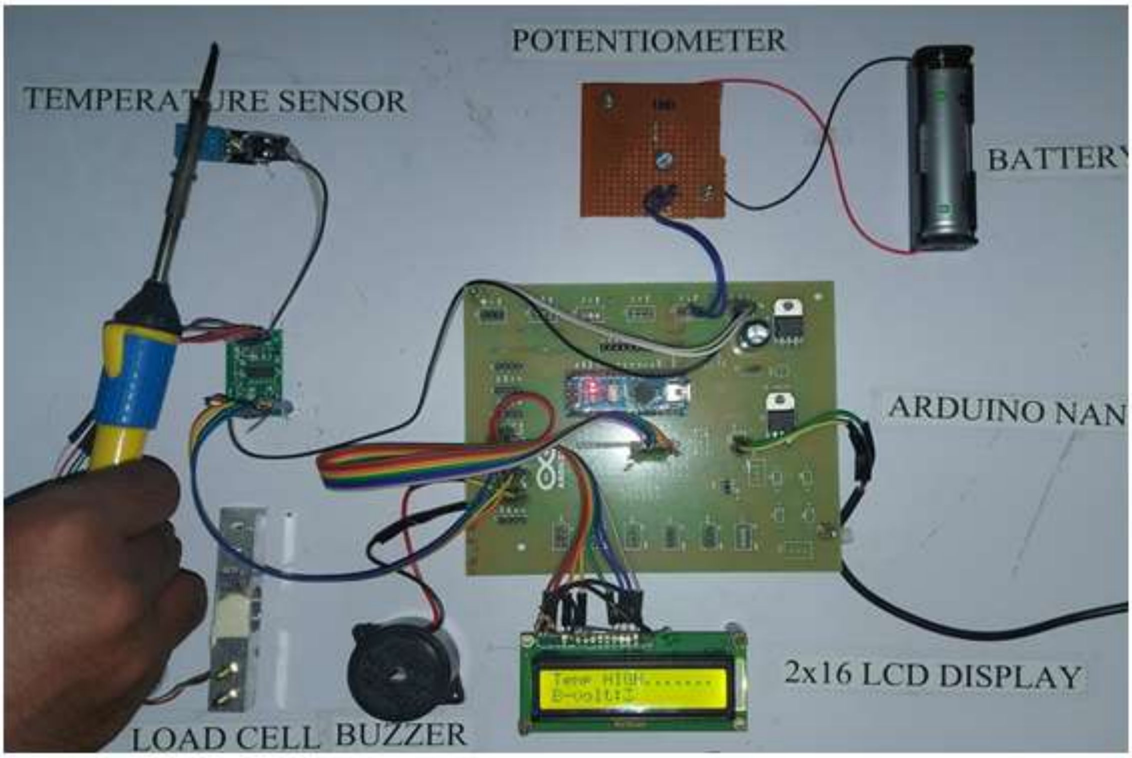

Fig. 6: Displays that the temperature of the battery cell has surpassed the algorithm's designated threshold temperature (37℃), resulting in the buzzer ringing until the temperature is restored.

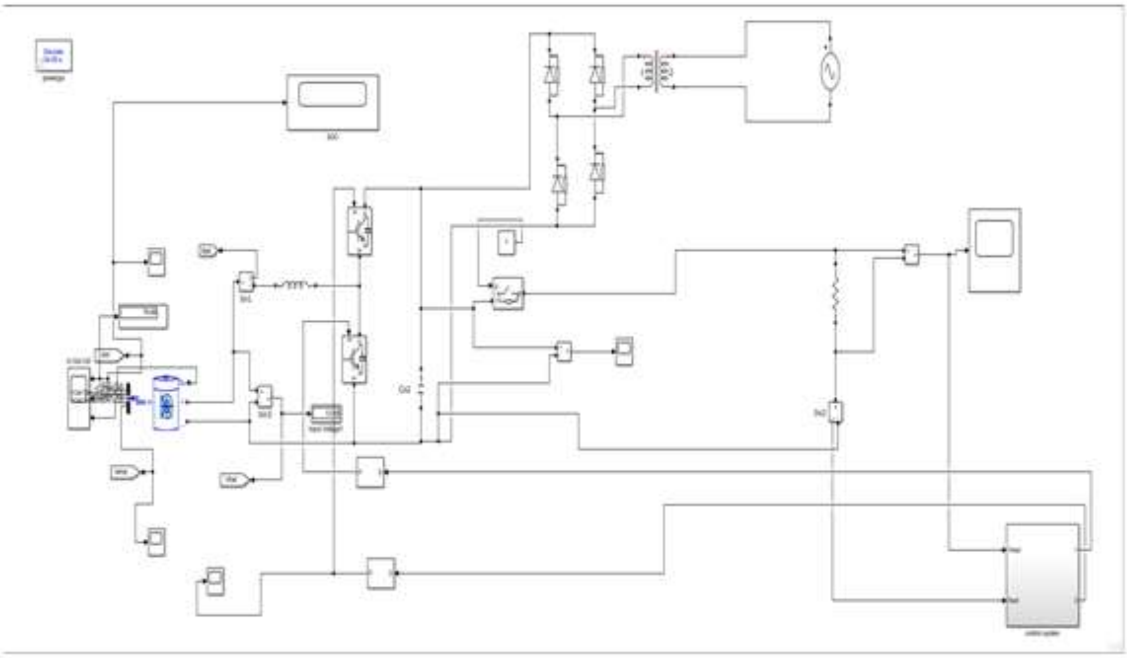

Fig.7: Overall Simulink model

If the current, temperature, or voltage reaches the assigned threshold value during simulation, the mosfet switch connected to the subsystem embedded with a machine learning algorithm will activate automatically, preventing the flow of voltage and current. In the case of the prototype, if the current, temperature, or voltage reaches the assigned threshold value, the buzzer connected to the Arduino board embedded with adaptive learning algorithms will sound, indicating that the engine is at a critical stage and prompting the user to turn it off.

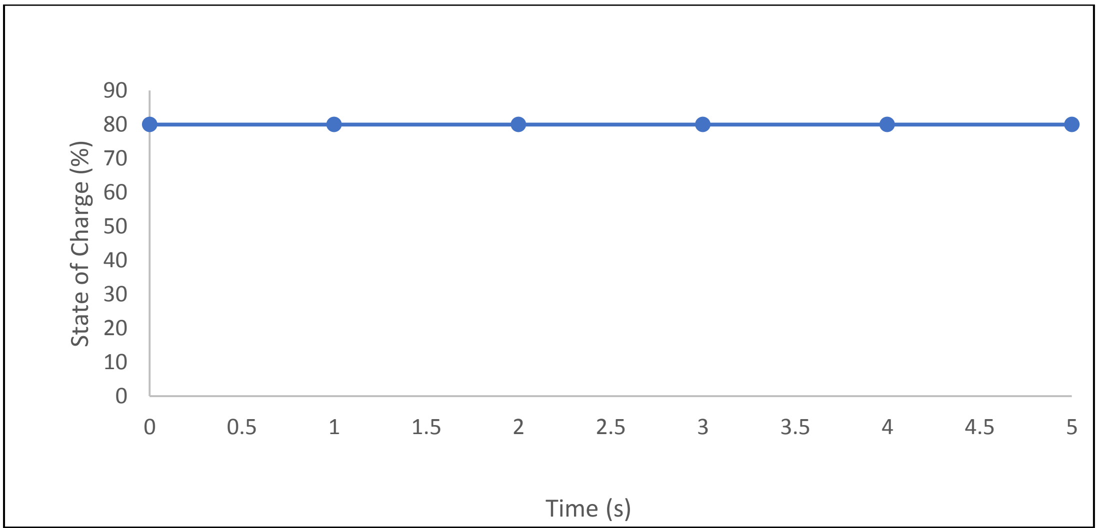

Fig.8: State of Charge

Figure. 8: shows the State of Charge plot of proposed battery control. When the SoC, voltage, and temperature all hit zero, the rest of the battery capacity is calculated as a percentage of the battery's maximum capacity. The current is measured for 5 seconds in X axis(time) and Y axis is the current observed, it indicates that the proposed control maintain constant voltage at 80 by triggering the charging and discharging switches.

Table 1 presents a summary of the Precision, F1 Score, Accuracy, and Specificity values achieved by the proposed algorithm (ANN) compared to other machine learning techniques like Support Vector Machine, Decision Tree, and Random Forest. The results indicate that the proposed algorithm outperforms the other methods as shown in Figure. 8 with the highest F1 Score, Accuracy, Precision, and Specificity values of 94.76, 94.84, 97.61, and 92.47, respectively.

Models	F1-Score	Accuracy	Precision	Specificity
RF	89.46%	84.43%	87.76%	78.18%
DT	92.92%	89.76%	92.13%	85.39%
SVM	90.38%	86.32%	89.06%	79.87%
ANN	94.76%	94.84%	97.61%	92.47%

Table 1: Performance Analysis of Precision, F1 Score, Accuracy and Specificity of the proposed method with Various Models.

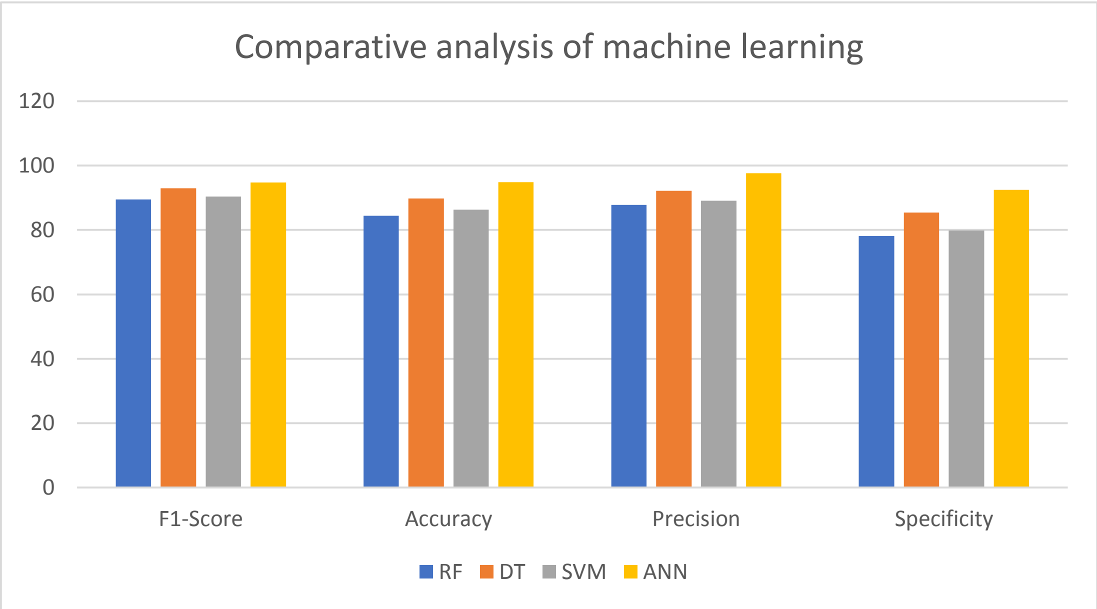

Fig.8: Performance analysis.

6. Conclusion

Detecting and monitoring battery health degradation is essential to ensure minimal equipment downtime and maximum productivity. However, developing a battery health management that can accurately track the battery health degradation throughout its entire lifespan is a major challenge. To address this challenge, this study presents a continuous learning approach for monitoring the SOH of batteries. An artificial neural network (ANN) is trained to learn the dynamic changes throughout its lifespan. The proposed approach offers guidance for developing a SOH management technique using an adaptive learning technique with minimal human involvement required.

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