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Neural Network Implementation for Battery Failure Detection in Electric Vehicles

S.Vijitha[1], Dheeraj Hebri[2], Sangeeta Singh[3], M. Manohara[4], Mohammad Ishrat[5], D Raja Joseph[6]

[1]Department of Computer Science and Engineering ,Vels Institute of Science, Technology & Advanced Studies, Chennai, Tamil Nadu 600117, India.
[2]Department of Master of Computer Application, Srinivas Institute of Technology, Mangaluru, Karnataka 574143, India,
[3]Department of Electrical Engineering, JSS Academy of Technical Education, Noida, Uttar Pradesh 201301, India.
[4]School of Engineering, Mohan Babu University, Tirupati, Andhra Pradesh 517102, India.
[5]Department of Computer Science and Engineering, KoneruLakshmaiah Education Foundation,Vaddeswaram, Guntur, Andhra Pradesh 522502, India.
[6]School of Aeronautical Sciences, Hindustan Institute of Technology and Science, Chennai, Tamil Nadu 603103, India.

E-mail : vijithas.se@velsuniv.ac.in, dheeraj.h7@gmail.com, sangeetasingh.eed@jssaten.ac.in, muppirimanohar@yahoo.com, ishratgzp@gmail.com, drajaj@hindustanuniv.ac.in

Abstract- Soil destruction and global warming have recently come to the forefront of discussion in industrialised nations as governments strive to accommodate the rising demands of their citizens. The demand for zero-emission electric cars has increased as a result of international competitiveness and technological advancements (EVs). Concerns about the high voltage of increasing numbers of electric cars are shared by an increasing number of individuals. Since the system of batteries may be at responsible for over 30% of EV accidents, it is vital to investigate how problems with LIBs are recognized. Many different kinds of problems make it hard to fix EV's LIB. Fast and precise diagnosis of battery pack problems is crucial for the immediate and ongoing safety of EV operation. Utilizing models of neural networks like multiple hidden layers (MLP) or nonlinear activation functions, this research provides a mechanism for identifying and fixing problems with electric vehicle batteries (RBF). To generate information for the BFD system, battery simulations are done in MATLAB. Accuracy may be improved by performing pre-processing steps on the information once it has been generated. After training, the two models are put to the test to see how well they perform. There are both positive and negative measures that may be used to determine which model is the best.

Keyword: Accuracy, Neural Network, Model, Electric Vehicle, Battery, and Fault.

I. INTRODUCTION

In an effort to help the transportation sector become more eco-friendly and productive in the face of dwindling energy resources and rising air pollution, LIB has advocated for electric vehicles on a global scale [1]. The effectiveness of electric vehicles is determined on their batteries. As a result of its high voltage, electrical power, energy density, extended cycle life, environmental protection, and low weight [2], LIB has affected the development of electric cars around the world. For voltage and capacity, the battery pack may use 100 or 1000 cells wired in parallel and serial configurations. Each cell or associated piece of equipment presents a serious threat to safety for a variety of reasons, including design flaws, manufacturing defects, misuse, battery ageing, and asymmetrical collapse. Without quickly identifying and fixing these issues, the safe haven enjoyed by EV operators could be jeopardized, and thermal runaway could occur in extreme cases. Voltage fluctuations are a reliable indicator of battery health, according to multiple scientific studies [3,]. Overvoltage and undervoltage are the most typical voltage fluctuations. When the voltage of a battery rises above a certain point, a closed circuit or high voltage may develop. Excessive battery drain or undervoltage might result in a short circuit or other catastrophic failure. To prevent thermal runaway, LIB requires precise voltage predictions, rapid detection of voltage anomalies, prompt issue diagnostics, and fault warnings. Numerous researchers are looking at the history of fault diagnostics. In this study, the battery issue is addressed using NN.

Article [4] describes the use of extended Kalman filtering (EKF) for soft SC fault diagnosis in EV dashboard systems. The EKF calculates the SOC of the problematic cell by continuously modifying a gain grid in response to voltage measurements. Without revealing the severity of the problem, resistance principles allow us to compare the estimated and estimated states of charge (SOC) of damaged cells. Soft SC tests measure the overall performance of a rechargeable battery pack by simulating a short circuit with varying resistance values in a single cell. The experimental data confirms the effectiveness of the small SC problem recognition method. Results show that the suggested soft SC fault detection and resistance estimation approach works reliably and effectively. In order to identify problems with voltage detectors in energy storage systems, the authors employ deep learning [5]. The most prevalent types of experimental failure were used to categorize the flaws introduced to experimental data for the creation of datasets. Deep Learning is used in our model for identifying faulty voltage sensors. After training and testing, Long Short-Term Memory (LSTM) is capable of dealing with time series on voltage sensor diagnostics, making it a useful reference for battery system sensor issues.

The model-based malfunction detection technique given in the study [6] makes advantage of the toggle switches of the RBS in both the training phase and the validation process. This method is categorized as a proactive error algorithm for identification since it modifies the design of the system in order to find and fix defects that are unable to be isolated by itself. Statistical analysis is performed on the residuals, also known as the differences between the sensor measurements and the prediction. One method that can be used to identify errors is called fuzzy clustering. The application of a filter known as Kalman with a set of multiple sigma points to reduce model uncertainty increases the sensitivity and durability of the fault detection method. A fault's peak-to-trough variation can also be evaluated with the use of the filter. In order to locate the next switch state that is practically doable, a policy evaluation that is based on continuously consecutive hypothesis testing has been developed and is now being researched. Modeling and empirically isolating further flaws both go quite well with the active technique that has been presented. A diagnostic methodology for LIB systems used in hybrid electrically powered aircraft is proposed in the study detailed in source [7], with a primary focus on short circuiting (SC) fault recognition and sensor failure recognition. Identifying if a short circuit has occurred in the LIB system is known as short circuiting (SC) fault recognition. The article describes the structural analysis technique used to create the bug-hunting software. This approach can be used to study how well various system defects can be detected and isolated in a digital setting, which is important in the field of augmented reality (AR). The LIB system's AR capabilities are improved as a result of the incorporation of a wide variety of devices that allow detection and diagnosis of issues considerably easier. If you select the right tests and generate the right residuals, you'll have a method known as failure detection and isolation (FDI). The LIB computer's diagnostic technique should be tested to ensure it can identify and distinguish between internal SC faults, external SC difficulties, and sensory failures.

For the goal of identifying battery faults, the journal [8] presents an entropy weighting method for estimating the risk components of each rechargeable. Next, the dimensions of the battery's flaws are compared using the acquired ratios. Use the real-world dataset generated from an energy storage device, as well as the public experimental datasets kept by MIT and Stanford, to verify the efficacy of the algorithms employed in this research. To begin, we choose a data extraction strategy that functions exceptionally well in engineering settings. The collected weight information from each indicator is then calculated using the entropy weight technique. The data is then used to determine what went wrong with the battery. A technique that can be utilized during the examination of an issue to lessen the subjective effect of dimension-based judgments is to calculate the battery's capacity based mostly on its energy rather than its actual dimensions. This method excels in failure identification for LIB systems because it does not necessitate complex training models or processes for adjusting hyper-parameters. The method of defect detection employed in this article [9] is a hybrid one. One of the reasons it's employed is because it's effective in fixing common problems with LIB packs, like faulty sensors and relays. To properly represent the continuous and discrete behaviors of the electrical pack, the required automata are built in accordance with hybrid system theory. Instead of using a centralized management system for the battery bank, a decentralized diagnostic architecture is adopted. This helps to reduce processing time and energy usage. Using a method called dual EKF, we can make educated guesses about the cell characteristics, terminal voltages, and state-of-charge. The distinguishability analysis can be performed because we know the current, voltage, and SOC. Both event observation and investigation into the distinguishability of the continuous dynamics are essential to the diagnostic process. Two batteries connected in series and parallel make up the battery pack, which is tested using the Federal Urban Driving Schedule operating cycle to confirm the diagnostic method's efficacy. The detrimental effects of state irregularity on time-series feature extraction, fusion, dimensional reduction by manifold learning, and outlier detection via clustering were mitigated by signal analysis, according to the study's authors. You can read all about it in their paper [10]. Real-world pre-fault performance data from vehicles with thermally runaway systems demonstrates that earlier observations are feasible and proves the longevity of the recommended method, in contrast to evaluations from actual battery controllers and earlier signal-based methods with single characteristics. This evidence also shows that the proposed approach can lead to early observations. Using an LSTM and a similar circuit model, the authors of Article [11] offer a novel method for identifying whether a battery has failed to perform properly. The reduction in computation time and the increase in diagnostic accuracy can be attributed to the combination of a prejudging model and the improved adaptive boosting technique. If implemented, the proposed technology could pave the way for a system that provides advance warning to users of thermal runaways caused by battery systems. The validation results lend credence to the idea that the suggested technique may accurately identify thermally fleeing cells and forecast battery cell breakdown.

This publication is broken up into four separate parts. In the first section, we discuss the development of electric vehicles, the present standing of the industry, and the most recent discoveries made about the identification of battery flaws. The methodology of the study as well as a flowchart detailing its procedures are included in the second section. The final section provides aid in picking the NN model that is most appropriate for a given situation by analyzing the various available possibilities. In the fourth and last portion of the study, which analyzes a wide variety of prospective models, the investigation is brought to a conclusion.

II. METHODOLOGY

The research process is broken out in great depth here. Modelling batteries is the first step in this investigation. SIMULINK in MATLAB is used to simulate the Li-ion battery. After this, a number of readings are taken, including those for current, voltage, SoH, and temperature. The issue is generated by adjusting the model's components. In both cases—a bad battery and a good one—the data is produced. The collected information on the battery life is three hundred. The next step is processing the data to get rid of any blanks and normalise everything to a number between 0 and 1. The information is split into "train" and "test" sets. The neural network (NN) model is fed its training data. RBF and MLP are used for the NN model. After collecting these metrics, the best model is selected. To ensure the model is functioning properly, test data is implemented. The battery's health may be classified with the aid of the NN model that was specifically developed for this purpose. Figure 1 shows how NN is used to identify battery faults.

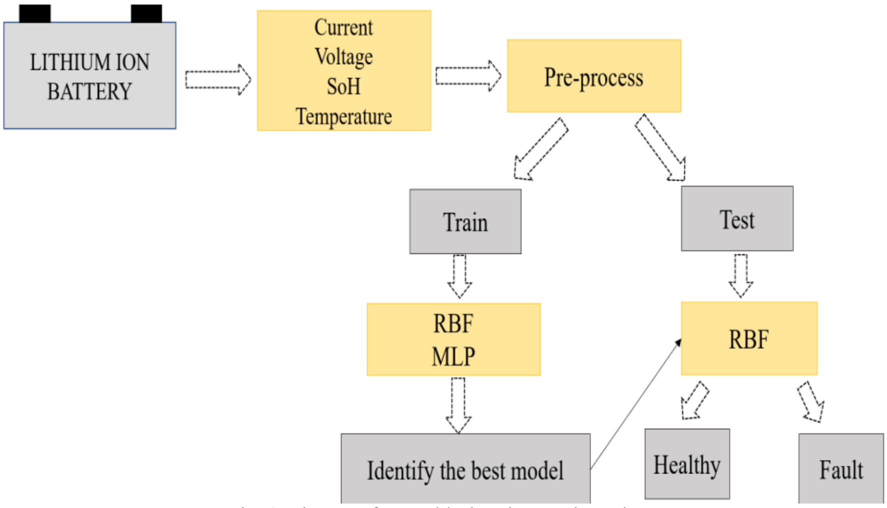


Fig. 1Using NN for troubleshooting EV batteries

A. *Data acquisition and processing*

We built a LIB model in MATLAB using Thevenin's first-order model as our starting point. An ohmic current source (U OC), a terminal impedance (R 0) equal to the series combined value of the resistances in the liquid and solid phases, and a polarization capacitor (C 1) make up the dipole device in this analogous model. The electrical components and defining elements that make up a circuit's subsystems are what give each subsystem its own features. Figure 2 presents a LIB model that is comparable to Thevenin's. Creating a circuit that faithfully depicts the battery's complicated behaviors and dependence on temperature, current, state of charge, and health is the first step in constructing a credible LIB model. Taking readings from cells within the same battery pack is essential before designing a controller due to the fact that these dependencies vary by battery type.

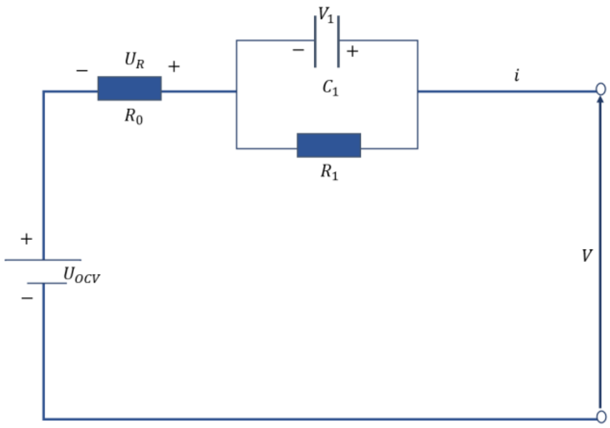


Fig. 2. Model of the LIB based on Thevenin's first order[12]

These equations determine model voltages and currents:

$$\dot{U}_{C1} = \frac{U_{C1}}{R_1 C_1} + \frac{i}{C_1}$$
$$V_t = U_{OC} + V_1 - R_0 i$$

whereV_t→Battery'svoltage, $\dot{U}_{C1}$→ Voltage drop at $R_1 C_1$ terminal's , and$i$→ Battery's current.

A basic thermal model determines the battery's ideal internal temperature. Researchers discovered that convection dominates cooling and internal resistance dominates heating. To construct a bigger battery, it is necessary to connect additional battery cell blocks in series.

After identifying particular concerns, we employed a network of neural networks to categorize errors based on battery which is the State of Health, as well as Temperature variations. Hand-adjusting these electrical parameters yields data. 150 points indicated a fully charged battery and 150 a critically drained one. 240 samples have been used for model training and 60 for testing. Table 1 describes gathering information. We check our data for missing or incorrect information and clean it.

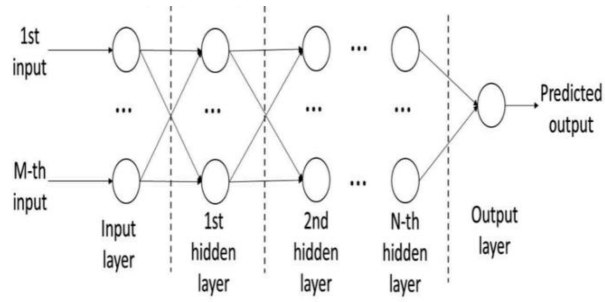
Table. 1. Data distributions Table

Battery's status	Train	Test
Healthy	125	31.5
Normal	125	31.5

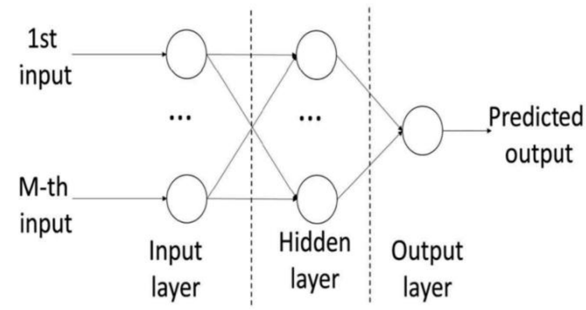
B. Modeling

MLPs improve feed-forward neural network performance. Hidden layers power the structure's inputs as well as output layers [13]. The network receives data in the input layer. The output layer determines a prediction or categorization. The MLP's hidden layers, which lie between the input and output layers, house the system's true intelligence. Like a feed-forward network, an MLP has one input layer and one output layer. The MLP uses backpropagation, a method for teaching neurons via experience, to learn from its mistakes. MLPs aim to approximate any continuous function, and they are able to deal with problems that cannot be separated into linear subproblems. Any continuous function, not simply linear functions, may be approximated using MLPs. A three-tiered MLP architecture is shown in Figure 3a. Multilayer perceptrons (MLPs) utilise perceptrons with more complex activation functions than just a step function. The buried layer often employs sigmoid functions for its neurons. In contrast to step functions, which provide discrete transition points, sigmoid functions result in gradual changes. The output layer neurons' activity function is usually sigmoid for classification tasks. The MLP, a popular ANN, is based around the perceptron. The linear mixture of real-valued inputs is found using a perceptron.s

One common ANN used to approximate a function is the radial basis function (RBF) network. RBFs stand out from the crowd of NNs because of their rapid learning and ability to approximate any function. There are three main parts to an RBF, and they are the input, hidden, and output layers. Each layer is responsible for a unique set of responsibilities [15,16]. In this article, we'll take a quick look at the RBF. RBF model training is complete when the goal error value or duration of training iterations is reached. The RBF's hidden layer will consist of 10 nodes. Gaussian functions, used in computing, are transfer functions. RBF networks train faster than MLP networks, however this varies. The next chapters conduct extensive testing on the chosen MLP and RBF networks. Both models' predictions will be evaluated against experimental data by comparing their respective predictions. Next, the network with the lowest computed error is chosen. The underlying data processing is concealed in RBF, which sets it apart. The simplified design for an RBF architecture is shown in Figure 3b.



a)



b)

Fig 3The NN Model's Internal Structure [17]

III.NN Model Evaluation

Electric vehicles' batteries are removed and studied. Finding the source of the battery's malfunction is a primary goal of this study, which should ultimately improve public security. At the beginning, MATLAB is used to model the battery. After that, data on the battery's health, as well as any errors or problems, is compiled, and the error is entered by hand. 300 records were produced. The MLP & RBF models receive training data from 240 of the 300. Next, the model is tested with the remaining 60 data.Assessment of test findings (FPR) can be done using a variety of metrics, some of which include the F1-

Score, the false negative rate (FNR), the false positive rate (FPR), and the accuracy, precision, sensitivity, and specificity of the test. In terms of a wide variety of indicators, the results of MLP and RBF are presented to the reader in Table 2.

Table. 2. NN model comparison table

Model	Accuracy	Precision	Sensitivity	Specificity	F1-Score	FNR	FPR
MLP	93.3333%	90.3226%	96.5517%	90.3226%	93.333%	3.44828%	9.67742%
RBF	95%	93.5484%	96.6667%	93.3333%	95.082%	3.33333%	6.66667%

Both MLP and RBF result in a model accuracy of 93.33%, with MLP being somewhat more accurate. Better precision is achieved with RBF than with MLP. In comparison, RBF has a 93.54% accuracy whereas MLP only achieves 90.32%. The resulting sensitivity of MLP and RBF, respectively, is 96.55% and 96.66%. Both models have similar specificity, at 90.32% and 93.33% respectively. The F1-Score is the final measure of success; MLP has a rating of 93.33 percent and RBF, 95.08 percent. FNR and FPR are the negative metrics used in the study of research. Both measures will be greater for MLP, while they are lower for RBF. Figure 4 displays the values of the aforementioned measures. The outcomes of the two models are quite comparable, as seen by the graph. As compared to MLP, RBF has somewhat better positive metrics and worse negative metrics. When compared to MLP, this demonstrates the superiority of the RBF model..

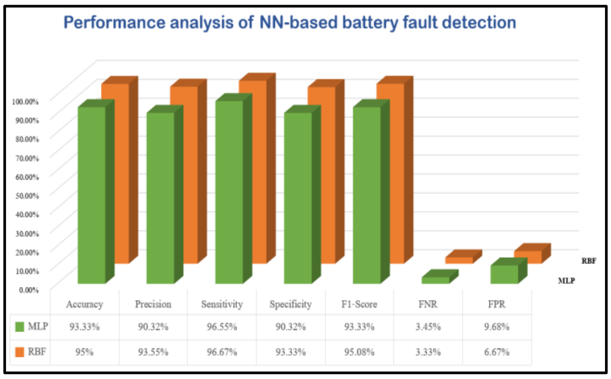


FIG. 4. EVALUATING SEVERAL NN MODELSCONCLUSION

The difficulties associated with the provision of energy are a relatively recent hurdle. The situation gets much more severe on an annual basis as the number of cars on the road rises. Rechargeable batteries are the source of electricity for electric cars. For electric vehicles to maintain their high levels of dependability and safety, an accurate and speedy diagnosis of LIB failures is very necessary. This article proposes a strategy for identifying battery failure based on data from electric vehicle simulations. The information that constitutes a battery includes things like its current, voltage, temperature, state of health, and objective criteria such as whether or not it is unhealthy. The test case was only given 60 data points, while the train was given 240. The MLP and RBF models are trained and tested using positive and negative metrics respectively. RBF places a higher importance on positive metrics than it does on negative measurements, in contrast to MLP. The RBF is the most effective statistic for the identification of battery failure. There is an issue with the battery, and further inspections will uncover each and every form of malfunction. Users may boost EV safety and extend the life of their batteries by using this information.

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