International Journal for Modern Trends in Science and Technology, 9(01): 43-53, 2023

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST0901008
Available online at: http://www.ijmtst.com/vol9issue01.html

Analysis of Optimal Deep Learning Approach for Battery Health Condition Monitoring inElectric Vehicle

Dr.S.Lakshmi Kanthan Bharathi[1] | P.Sujidha[1] | Dr.A.Manjula[1] | N.Ahamed Hussain Asif[1] | A.Usha[1]

[1]EEE, Mohamed Sathak Engineering college , Ramanathapuram, Tamil Nadu, India.

To Cite this Article
Dr.S.Lakshmi Kanthan Bharathi, P.Sujidha, Dr.A.Manjula, N.Ahamed Hussain Asif and A.Usha. Analysis of Optimal Deep Learning Approach for Battery Health Condition Monitoring inElectric Vehicle. International Journal for Modern Trends in Science and Technology 2022, 9(01), pp. 43-53. https://doi.org/10.46501/IJMTST0901008

Article Info
Received: 20 December 2022; Accepted: 15 January 2023; Published: 20 January 2023.

ABSTRACT

Compared with other commonly used batteries, lithium-ion batteries are featured by high energy density, high power density, long service life and environmental friendliness and thus have found wide application in the area of consumer electronics. The narrow area in which lithium-ion batteries operate with safety and reliability necessitates the effective control and management of battery management system. This present paper, through the analysis of literature and in combination with our practical experience, gives a brief introduction to the composition of the battery management system (BMS). First-principles models that incorporate all of the key physics that affect the internal states of a lithium-ion battery are in the form of coupled nonlinear PDEs. While these models are very accurate in terms of prediction capability, the models cannot be employed for on-line control and monitoring purposes due to the huge computational cost. A reformulated model is capable of predicting the internal states of battery with a full simulation running in milliseconds without compromising on accuracy. This paper demonstrates the feasibility of using this reformulated model for control-relevant real-time applications. The reformulated model is used to compute optimal protocols for battery operations to demonstrate that the computational cost of each optimal control calculation is low enough to be completed within the sampling interval in model predictive control (MPC). Observability studies are then presented to confirm that this model can be used for state-estimation-based MPC. A moving horizon estimator (MHE) technique was implemented due to its ability to explicitly address constraints and nonlinear dynamics. The MHE uses the reformulated model to be computationally feasible in real time. The feature of reformulated model to be solved in real time opens up the possibility of incorporating detailed physics-based model in battery management systems (BMS) to design and implement better monitoring and control strategies

KEYWORDS: *Management System, Deep Neural Network, Li-ion batteries, Long Short Time Memory, State of Health, Remaining useful life, State of charge.*

1. INTRODUCTION

Highlight Climate change is a hot topic and the world is facing huge challenges. Petroleum based fuels dominate the transportation sector which is a substantial contributor to the release of carbon dioxide and other pollutants to the atmosphere. Electrification of vehicles and machines on land, water and in the air is a growing trend and a measure of reducing our environmental impact. Renewable electric energy stored in batteries is a greener substitute to petrol and diesel and the lithium-ion battery (LIB) market is growing rapidly

Since commercialized in 1991, LIBs have increased in popularity thanks to their high energy density, low discharge rate and low maintenance. The battery packs in vehicular applications however need a sophisticated control system in order to function properly. The available energy of a battery, known as state of charge (SOC), is comparable to the fuel gauge of a vehicle powered by a combustion engine. SOC is not directly measurable and therefore require some type of method to be estimated, often by utilizing a mathematical model. The deterioration of battery cells leading to decreased performance is an issue that limits battery lifetime.

With the rapid growth of the practicability and diversity of electric vehicles (EVs) in recent years, the industry and market share of this new transportation tool entered into a prosperous era of rapid development. And it's likely to maintain the trend of high-speed growth due to the more stringent emission policies and more investment around With the advantages of high energy density and low self-discharge rate, lithium-ion power battery pack can achieve longer endurance time and driving mileage . Thus, lithium-ion batteries are widely used as power source and energy storage device of electric vehicles. However, one of the problems that lithium-ion batteries still face is the degradation of battery performance, which is characterized by capacity fade or power attenuation An accurate SOH of lithium-ion batteries is of vital importance

As the advent of information age, the development of big data technologies brings opportunities to realize the unified monitoring of battery packs health status. SOH monitoring at big data level not only benefits the security supervision of public transportation, but also facilitate the disposal of the batteries retired from EVs or in long term idle. Supposing every battery pack is effectively calibrated for its SOH and residual value, these information can be shared on cloud servers, and the application of secondary use and vehicle-to-grid (V2G)

Technology will become more convenient. In some cities and countries, the big data collection and monitoring platform has been applied to collect and analyze the real-time operating data of floating EVs
The large-capacity data acquisition system will generate and store massive data. How to effectively utilize these data to estimate SOH is the key problem that needs to be considered. As is demonstrated, the reaction mechanism of cycle aging involves many variables, such as charging/discharging current rate, temperatures, etc. However, unlike the charge-discharge cycles in laboratory experiment, the work condition of battery pack changes dramatically in actual vehicular operations due to the various driving environment and individual behaviors. The performance degeneration is more complicated with cross dependence factors and dynamic situation. Therefore, based on big data platform, the accurate SOH estimation for on-board battery packs remains both promising and challenging

Electrochemical model, equivalent circuit model, etc. Among the data-driven methods, a variety of methods based on machine learning have been proposed and developed. Those techniques mainly include support vector machine (SVM) artificial neural network (ANN) , random forest (RF) probabilistic models from Bayesian framework like gaussian process regression (GPR) and relevance vector machine (RVM), etc. For instance, Ref. provided a solution to cycle life forecast by combining the infrared thermography with ANN and SVM techniques. Qin et al. adopted SVM to explore the global degradation trend of SOH and the kernel parameter is obtained by particle swarm optimization (PSO). Li et al. estimated the SOH of different batteries under varied cycling conditions based on RF regression

2. PROPOSED METHODOLOGY

Lithium-ion batteries are essential to our modern lifestyle supplying power to handheld electronics, laptops and vehicles. Despite continuous improvements to battery cell technology, aging is a large flaw. The reduction of capacity and performance occur both with time and usage and is a well-studied phenomenon
The deterioration process is complicated since multiple variables such as charge and discharge rates, temperature and SOC affect the aging rate . The battery pack is in many cases the most expensive component of electric vehicles, with the largest environmental impact and in order to minimize the deterioration of battery cells, the mechanisms causing aging must be understood.

Extensive research has been carried out in the area of LIBs. The recent shift in demand from the increased production of electric vehicles (EV) pushed the LIB into the spotlight of scientific literature and popular press. Research and development of more effective material compositions of the battery cells is not slowing down, where a lot of attention is directed towards the current and future availability of metals such as lithium, nickel and cobalt

The BMS is in charge of assessing battery SOC and SOH. Both of these states are non-measurable and of grand importance for the safety and efficiency of the battery system. Due to the complexity of LIBs a big variety of methods and models are being used for the estimation of these states. The methods for SOC estimation applied in electrical vehicles range from conventional resistance- and open circuit voltage measurements to learning algorithms such as neural networks and fuzzy logic

The aging process of LIBs can be divided into two distinguished types: during use and in storage. The large variety of material compositions, in especially the cathode material, makes it difficult to give an exhaustive picture of the reactions leading to aging in a battery cell. The basics of LIB deterioration and its affect on capacity reduction is presented in a research article by M. Broussely . The 1.4 Objective of the thesis 3 work by Groot on cycle life test methods concluded that a good cycle life estimation model requires a very detailed evaluation of load cycle properties. The article by Anthony Barré discuss the validity of studies based on controlled test bench measurements

SOH estimation methods can, as done in the review article by Rui Xiong, be separated into two categories: Experimental methods and model-based estimation methods. The experimental methods estimate the SOH by analysis of stored cycle data taking advantage of parameters correlated to aging. The four methods to be focused on in this thesis are all examples of experimental methods. They all study the current or voltage curves during the charging phase and are related to coulomb counting and differential voltage analysis. The slope estimation method takes advantage of the increased derivative of the voltage/capacity-curve A research article from 2013 studies patterns in this curve during charging, similar to the slope estimation method, declaring it a relatively simple method with low computational complexity. ZengkaiWang looks at the decrease in current during constant voltage phase and how the shape of this curve changes during aging. The two remaining methods use characteristics connected to the charge derivative peak with regards to voltage

Lithium-Ion batteries have been on the market since 1991 and are of secondary battery type, in other words rechargeable . A BMS is required to prevent overcharge and over-discharge. The BMS can also keep track of the battery SOC, SOH and safety features such as over-heating and over-current conditions . Inside the battery casing the anode and cathode are submerged in a electrolyte and divided by a separator as seen in Figure 2.1. During a charge/discharge cycle, lithium ions are exchanged between the positive and negative electrodes. The LIB technology provides unique characteristics compared to other battery types such as high energy density, low maintenance, low cost, no memory effect, no need for periodic deliberate full discharge, capability of accepting high charging and discharging rate, high depth of discharge and low rate of self-discharge .

3. EXISTING METHODOLOGY

A.Issues in Battery

A real-time Battery Monitoring System (BMS) using the coulomb counting method for SOC estimation and messaging-based MQTT as the communication protocol, based on ease of implementation and less overall complexity. The BMS is implemented using sufficient sensing technology, central processor, interfacing devices, and Node-RED environments on the hardware platform.In existing system Slope defined capacity trend analysis (SDCTA) has been implemented.Battery capacity is measured in ampere hours [Ah] and the duration of the constant current charging phase has a very direct connection to capacity and SOH since it stands for most of the energy charged into the battery. Because the battery is rarely or never completely discharged this duration is problematic to measure. With inspiration from the regional capacity method where the minimal slope of the voltage curve is located, this novel method locates this location and measures the time (or capacity) needed to reach cut off voltage as shown in figure 3.12. The method works within the mid ranges of SOC and can be implemented either through polynomial fitting or numerical differentiation.

B.Slope estimation

The decrease in capacity occurring through battery aging affects the shape of the polarization during the CC-phase curve clearly increases with aging as the CC-time period shortens. The derivative of the voltage curve in the time interval just before cut-off voltage is reached, as seen in Figure 3.14, is easily differentiated and can be used as an aging factor of the battery. The slope can also be calculated using linear least square method on a population of data just before the end of the CC-phase. The key to this method being consistent is measuring the slope at same part of the voltage curve as the CC-phase shortens with use and time. Slope at a fixed SOC would be ideal but just like SOH, SOC has to be estimated and therefore is somewhat inaccurate. By choosing the interval just before cut-off voltage is reached, where the voltage curve is close to linear and easily found, the accuracy of the method is increased. The SOC at cut-off voltage in room temperature is around 70%, a level that is commonly circulated during operation.

C.Support Vector Machine (Svm)

Lithium-ion batteries are widely used in electric vehicles because of their high energy density and low self-discharge rate. Not only that, lithium-ion batteries are also widely used in high-tech products such as mobile phones and various portable information processing terminals, however, the service life of lithium-ion battery has limited its further promotion and development of electric vehicles. As the remaining life decreases, the overall performance of the battery decreases, which is characterized by capacity attenuation and internal resistance increase Therefore, accurate SOH estimation is of great importanceIn existing algorithm x-Boost, can be divided into three parts: Feature selection, XGBoost estimation, Markov correction. First, we use voltage difference, temperature difference, and average voltage as the XGBoost model inputs to describe the discharge process of lithium-ion battery. Then, the XGBoost estimation model is established to predict the SOH of the battery. Finally, the Markov chain is used to correct the estimation results to further improve the accuracy of SOH estimation.

The PHM of the battery has to be included as part of the condition-based maintenance (CBM)plan of the system. The CBM plan is considered as a preventive strategy, which means that maintenance tasks will be performed only when need arises. This need can be determined by

Continuously evaluating health status of a particular system's components, or the health state of the system as a whole CBM has included two major tasks: diagnostics and prognostics. Diagnostics is the process of the identification of faults and part of the current health status of the system, which is described as an SoH, whereas prognostics is the process of forecasting the time to failure. The time left before observing a failure is described as the remaining useful life (RUL) of such a system . To avoid severe negative consequences when systems run until failure, the maintenances must be performed when the system is still up and running. These type of maintenance require early plans and preparation . Thus, CBM must properly be included as part of the system's operation, especially for the critical systems. The prognostic of the system is a crucial factor in CBM

This method depends on the given environmental conditions and load conditions. It is a Kernel function-based method, which uses regression algorithm to convert the nonlinear model in lower dimension to the linear model in high dimension. To avoid degeneracy phenomenon in model building and keep the diversity of the particle, this method was used. Klass et al. measured capacities and instantaneous resistance over temperature and SoC range, and then, allow it for online estimation of battery degradation. By using the support vector machine (SVM) method, not only SoH but also many other useful parameters like SoC, remaining useful life (RUL), etc. can be measured accurately. Nuhic et al. had developed a SVM model to identify the SoH of battery for electric vehicles. Nuhic had divided the available data into two-third of the data being for training and one-third of the data being for testing and predicted SoH with less than 0.0007 mean square error in real driving conditions, considering temperature change, SoC, and C-rat

Kalman Filter. Kalman filtering is a well-designed and time-proven method to filter the measurements of system input and output to produce an intelligent estimation of a dynamic system's state. In the KF method, both input and output data are experimentally measured which help in obtaining the minimum mean square error assessment of the true state. In KF, linear optimal filtering happens. If the system is nonlinear, extended Kalman filter (EKF) is used. In this method, its nonlinearity is linearized by using a linear time varying system. Claude et al. presented mathematical equations to study the BMS of the electric vehicle and developed a battery electrical model. Mastali et al. implemented both the extended Kalman filter and the dual Kalman filter where they used both the prismatic and cylindrical cell. Zheng and Fang used relevance vector regression (a nonlinear time series production model) to give a prediction of the remaining useful life of a battery. Gholizadeh and Salmasi proposed an inclusive and unobservable model for the determination of SoH and SoC. They developed multiscaleEKF and used the macroscale to estimate the system parameter and the microscale to estimate the system state. Reliability and accuracy of this method

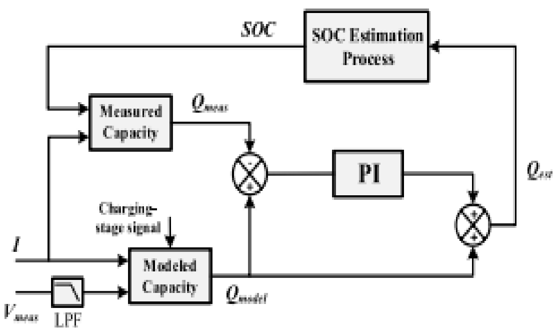
Sliding Mode Observer. In recent years, sliding mode observer (SMO) is becoming a popular method for its flexibility to adapt with system uncertainty and noise during the SoH estimation process. Lin et al. proposed the estimation of lithium-ion battery SoC/SoH using SMO for the electric vehicle. A single particle model was proposed for modeling the lithium-ion battery ignoring the spatial distribution in homogeneity of local volumetric transfer current density and the Li+ concentration in solid phase electrode and electrolyte. SMO algorithm proposed the offline identification of the model parameters. The offline model parameters were identified by the urban dynamometer driving schedule (UDDS) test. This model showed good performance in estimating the terminal voltage and the model parameters. The SMO method is advantageous since it can elude chattering effects Kim et al. projected a dual sliding mode observer model for estimating both SoH and SoC.

Fault Diagnostic Methods. The major faults such as overdischarge and over charge causing large model parameter variation are used to form a multiple nonlinear model for the detection of faults. Identification of such failure aids in the evaluation of health condition of the battery, as such failures are inversely proportional to a good health condition of a battery. The equivalent circuit methodology combined with impedance spectroscopy of lithium-ion batteries was used in the formation of the nonlinear model for fault detection of lithium-ion batteries in Ref.. Estimation of the terminal voltage for generation of residual signal was done using Kalman filtering. Then, the probability of fault occurrence was predicted accurately from these residual signals using a multiple model adaptive estimation technique. Similarly, a reduced order electrochemical-thermal model of the lithium-ion cell was used and the electrochemical faults were modeled as parametric/multiplicative faults in the system. Sliding mode methodology was used to design the observer and its convergence as well as design was verified via Lyapunov's direct method. The effect of modeling uncertainties may be considered to improve the fault diagnostic scheme. However, Marcicki et al. Proposeda larger faults diagnostic method which also helped in estimation of SoH in the lithium-ion battery. A modified nonlinear parity equation was used for fault detection on lithium-ion batteries in EVs. Input voltage to the battery was estimated by sliding mode observer, and output voltage estimation was done by the open loop model. Minimum fault magnitude was accessed by estimation error of the observers using real-world driving cycle data. Maximum allowable probability of the error was taken into consideration by selection of optimal threshold. Smaller faults are difficult to determine by the fault detection technique presented in this paper as these faults are smaller than the normal estimation error of the observer. These faults could be corrected by performing a constant diagnostic test

Integration of Mechanical Aspects with TemperatureRelated Problems. It is also known that the temperature is the main enemy of the battery. The temperature-related problems such as thermal runaway, rupture, explosion, etc. can be well integrated with the existing research on safety design of the battery/battery pack. For example, the sensors (stress)-based monitoring of the battery is performed at a given temperature. However, in very cold or hot weather conditions, the results may not be applicable. Also, the battery pack enclosure design incorporates only mechanical aspects such as deformation, strength, frequency, etc. which can be well integrated with another objective of uniform temperature distribution (with maximum temperature below the threshold abnormal temperature). This shall result in robust battery pack and its components (enclosure) design, which can withstand impact from both the mechanical and thermal unforeseen shocks/accidents. 4.4 Redesign, Installation, Placement of Battery Pack, and Its Components. An important research direction could be to redesign the battery packs and its components so that it can be easily placed in the vehicle to optimize its space, have minimum impact from crash, and can be easily dismantled, disassembled, and replaced for user friendly and efficient recycling. Topology design optimization of the electric vehicle and its integrated components including battery packs could be studied and explored in detail. The other growing aspects are the integration of batteries with photovoltaic systems and super capacitors for improving the efficiency, range of vehicle, and storage in the context of excess energy production from the hybrid systems. For example, combinations of photovoltaic system, wind power, and lithium-ion battery storage into microgrid EV charging station can offer backup power during loss of grid connection and permits exporting power when generation go beyond demand within the microgrid.

Minimization of Safety-Related Problems and Negative Impact on the Environment. Major concern should be taken toward safety-related problems such as cathode breakdown, electrolyte breakdown, over current, over voltage, low current, low voltage, etc. so as to protect the cells from irrecoverable damage. To diminish such problems, integration and improvization of pressure vent controller, circuit interrupter, advance switching techniques, and a reliable thermal management module inside BMS will be helpful. Also, materials (like cobalt, nickel, etc.) used in the lithium-ion battery are not environmental friendly Extensive research on it shows that it paves a way toward global warming and environmental toxicity.

4. EXISTING BLOCK DIAGRAM



5. PROPOSED SYSTEM

A.Neural network model

Neural Network. A neural network (NN) is a mathematical model whose parameters have no direct reflection of the physical or chemical structures of the original model. Feed forward and recurrent are the types of NN architecture design. They utilized a time series prediction system. Yang et al. used maximum available capacity to indicate the battery's SoH based on a back propagation neural network. A direct parameter extraction method was employed to identify the parameters of the first-order ECM. Then, a three-layer back propagation neural network was proposed to estimate SoH, whose inputs were the parameters of the first-order ECM and output was the current value of SoH. From the experiments, it was found that when ohmic resistance increases SoH reduced and when SoC ranges between 20% and 90% ohmic resistance increases and SoC decreases. Artificial neural network (ANN) is known for its simplicity. It can handle nonlinear data, and it is not necessary to take all the details of the battery during modeling

B.Feature extraction

For data-driven model, the feature extraction is a crucial part to determine the input variables. The available capacity largely depends on the lithium ion inventory and active materials in the electrodes. The electrochemical side reaction, such as the formation of solid electrolyteinterphase and lithium plating, can lead to the irreversible consumption of cyclable lithium ions. The loss of active materials mainly originates from structural deterioration of electrode and the dissolution of transition metal into the electrolyte. However, the cyclic ageing remains changeable due to the different rate of side reaction in complex working environment. Some abusive conducts can accelerate these processes.We take advantage of the factors associated with degradation reactions to capture and trace the aging paths. Therefore, the operating condition that contribute to battery degradation should be identified comprehensively.

C.Depth of charge/discharge (DOD)

The significant growth of micro-cracks comes with wide DOD condition and leads to faster capacity deterioration. Moreover, the degradation behaviors of lithium-ion battery cycled under different SOC ranges with the same DOD are in varying degrees

D.Using intensity of SOC ranges, SOCUSE.

To distinguish the SOC using ranges and DOD, the whole SOC range (0–100%) is divided into five ranges with 20% SOC interval, that is, range ii(1, 2, , 5) = … . The historical charging data is sought out for frequency counting. The coverage of SOC curve (from SOCstart to SOCend) can be obtained for each completed charging process noted as Chg. The SOC ranges included in the coverage area are considered to have been used, so the usage frequency Ni of these ranges are accumulated,

E.Selection of training data

As the most common health indicator the actual capacity is used to determine SOH of battery pack. Although the pack capacity is defined by discharging capacity in common, the distinction between charging capacity and discharging capacity can be neglected due to the high coulombic efficiency of commercial lithium-ion battery. In addition, since the charging current profiles have identifiable consistency in actual operation, it is beneficial for precision of current integration method to use charging capacity. Therefore, this paper uses the charging data to obtain the benchmarks of capacity

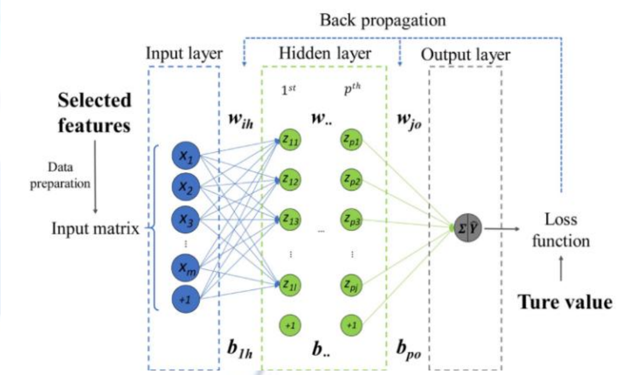
The charging scheduling strategy adopted by the sample vehicles in this paper mostly consists of constant current (CC) charging in multiple stages and constant voltage (CV) charging. Taking a certain charging event as an example, the monitored pack voltage, pack current and pack SOC during charging are shown in Fig. 2. As can be seen in Fig. 2 (b), two flat plateaus exist in the charging current curve. The first CC phase was carried on with a level of 64A in the SOC range of 27%-84%, and then the second phase lasted at 43.7A until pack SOC reaches 95%. Next, the current in CV process dropped steadily to nearly 17.7A and the battery arrived at fully charged state

According to the collected data, the charging fragment always do not to cover the whole SOC range with the effects of driver behavior habits and energy management strategy. In order to detect the reliable charging capacity, partial charging data can be utilized for SOH estimation,

Interval of data acquisition. As with most charging behaviors, the first CC phase that is accompanied by higher current occupies a wider SOC range than the second, so the partial charging data should be selected from the first CC phase. In addition, to determine the specific SOC range for extracting charge segments, the principle that ensures the sufficient amount of training data is considered. After pre-processing and statistical analysis of driving log data, the phenomenon is found that nearly 12.7% of charge behaviors covered 40%-80% SOC range. Therefore, the charging segments in this interval are used to obtain the benchmarks of battery pack capacity, that are the desired outputs of estimation model. To further ensure the reliability of benchmarks, the criteria for similarity of charging conditions is the same extreme voltage difference of cells when SOC reaches 40% and 80%.

where the sampling interval is t = 10s . The partial charging capacity CPartCHG is calculated by the ampere-hour integralWhereΔSOC is the SOC changed in charging process, that is 40% here. By traversing all the log files acquired from the sample EVs, the charging segments that match the selection conditions are extracted. Their corresponding values of CCHG are calculated.

Neural network trained data



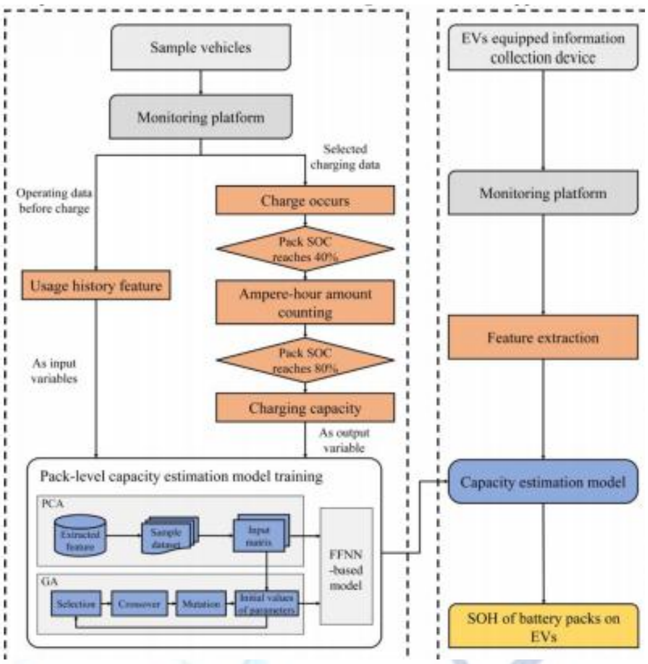
F.Feedforward neural network

Feedforward neural network (FFNN) is adopted to capture the correlation between extracted features and capacity degradation. First of all, data platform has no limitation of calculation effort unlike onboard application, and the database is large enough for creating the sample dataset with sufficient quality and size. Furthermore, as the inherent property, FFNN has great superiority for multidimensional non-linear problems and high fault-tolerance FFNN model are comprised of the interconnected neurons distributed in multiple layers. In the process of creating closer mapping between inputs and desired outputs, the network learns the weights and thresholds of each neurons by gradient descent method. The loss function decides how to measure the network performance on training data. Then in the backpropagation process, the final loss act on each layer reversely by the chain rule. Based on the contribution of each parameter to the loss, the optimizer will update the weight of each connected neurons and minimize the loss.

G.SOH estimation based on FFNN

Based on the methods introduced above, the SOH estimation framework for big data platform is proposed and the flowchart is presented It consists of two parts: the off-line identification of estimation model parameters and the online application. In the part of model establishment, the benchmarks of pack capacity and health features are obtained based on the monitoring data of sample vehicles. After the construction of sample dataset, it is randomly split into three parts for training, validation and test respectively. Supervised by the training set, the FFNN-based model is produced adaptively. Before the dataset is imported into the learning algorithm, the parameters in feature matrix are standardized and the bounds are adjusted to be compliant with model training requirements. In addition, the computation load in the process of iteration needs is also considered. In order to reduce the dimension of the model input, principal components analysis (PCA) is used to compress the dataset before training process.

Flow diagram



According to Eq. (14), λ is the eigenvalue of $\sum$, and the target function is equal to it. Therefore, PCA can generate the principal components sorted by eigenvalue in descending order, and they are selected until the accumulated variance contribution rate reaches 90%. After data preparation, the training process is conducted to identify the parameters in FFNN model. With the expansion of network capacity (the number of neurons and layers), the deeper information can be learned. In this work, following the input layer, 4 densely connected layers of network is employed to improve the forecast capability of model when applied to actual driving cycle. However, at the same time of improving convergence ability and reducing loss, model optimization is always followed by higher probability of over-fitting that will damage the generalization performance of the model. Therefore, after obtaining training data as much as possible and selecting the memorization capacity of model reasonably, the regularization approach is adopted. The weight regularization and dropout layers are added in network to limit high weights and the complexity of model. In order to prevent the network training from falling into local optimum, the effective measures to tune and optimize training process are also adopted. Besides choosing the appropriate activation function and loss function, improved techniques are introduced in network learning, including momentum and variable learning rate

In addition, the preliminary selection of weights and thresholds matrix before the learning process will produce an effect on the training speed and error range. As a result, the genetic algorithm (GA) is embedded for optimization. In this step, the network parameters are encoded by floating-point numbers, and a population representing the potential solution set of the problem is generated within the boundary. By the operation of selection, crossover and mutation, the better approximate solutions are generated in evaluation. The fitness of individual is evaluated by the reciprocal of the sum of squared errors. When iterations reach the upper limit, the optimal solution in the last generation is decoded as the initial parameter of the network

H.Fuzzy logic based method

It offers a modern approach to solve SoC related queries that may contain ambiguous, vague and imprecise input information/data. Fuzzy Logic is relatively less complicated when compared to ANN and this intelligent technique allows the translation of logic statements into non-linear mapping. Such a method can work with no or minimal data making the necessity for prerequisites ruled out. The modelling is not so cumbersome and makes it a flexible, user-friendly approachFuzzy logic is an approach to computing based on degrees of truth rather than the usual true or false (1 or 0) Boolean logic on which the modern computer is based. It consists mainly of four things.

6. SIMULATION

A.Simulation Results

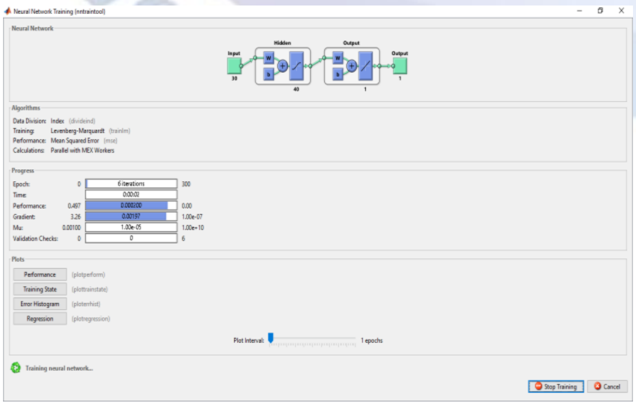


Figure 5.1: neural network training

We trained the data into the neural network into the layers for training the data into neural layers for training data .

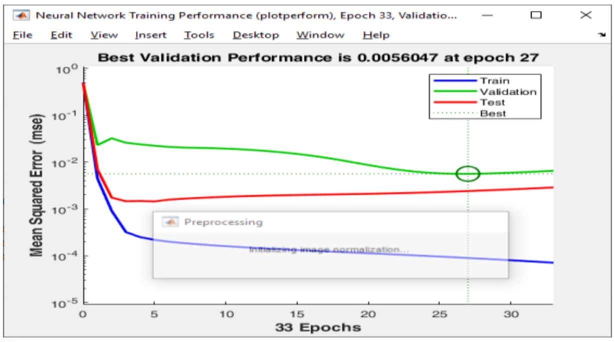


Figure 5.2 Performance curve

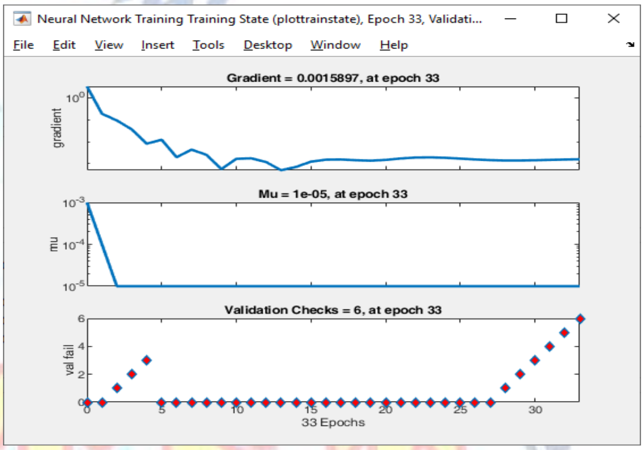


Figure 5.3 Error histogram

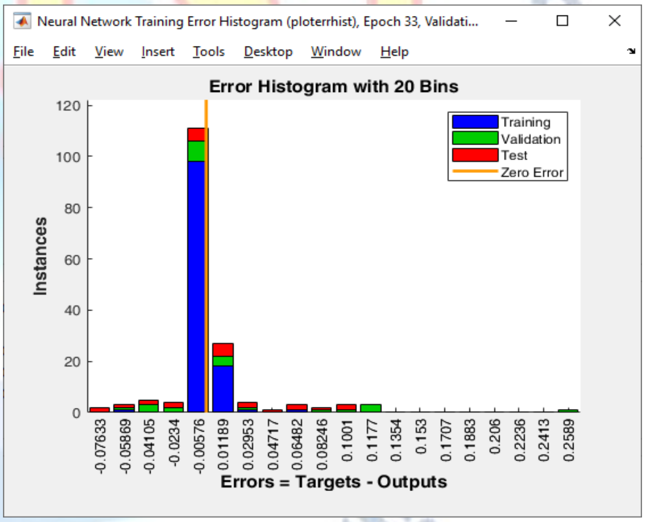


Figure 5.4 Regression curve

Before utilizing battery data set as experimental data, we preprocess data by removing outliers and securing available data. Eventually, we obtain four sets of battery data with degradation characteristics per cycle .batteries #5, #6, #7, and #18

The overall specification of batteries and charging/discharging conditions are summarized in Table 1. Meanwhile, even though there are many data points during charging process according to the setting of BMS, it is not efficient to utilize all data due to data sensitivity and complexity in estimation, and thus we use the

subsampled data that preserve the apparent changes during the charging interval. The inputs of the proposed models are the extracted features, which are obtained, Machine Learning-Based Lithium-Ion Battery Capacity Estimation sampling of the raw battery data. Specifically, we configure the input matrix as 30-dimensional vectors by concatenating the V, I, T charging profiles, each with 10 samples. The number of samples is chosen to consider the distinct changes in time and the model complexity. In addition, we average the data over sampling interval to prevent oscillation in short time interval

We first present the result of capacity estimation using only voltage charging profiles with 10 uniformly sampled data point as in . Since the available datasets are limited, we need to fully exploit the available datasets. Thus, out of 4 datasets, we select three battery sets as a training set and the remaining one as a test set, and repeat this process four times to have four test results.

Then we average four cases of simulation to evaluate the average performance. Fig. 5 shows the capacity estimation results of FNN, CNN and LSTM. In overall, LSTM shows very accurate capacity estimation, even in the case of battery #18 where FNN and CNN based methods show high fluctuations,10 neurons in serves as our baseline. We summarize the capacity estimation errors in Table 3 where LSTM shows the substantially better performance than other methodologies. This is because LSTM is good for time series data regression

initially expected that MC-CNN would show good performance because having multi-channel charging profiles well matches to multiple convolutional filters well. However, it turns out that MC-CNN is not good for capacity estimation. Specifically, MC-CNN-1 shows the worst error rate compared to other methods even though MC-CNN-1 has the smallest number of parameters. Next we set the numbers of parameters for MC-FNN-2 and MC-CNN-2 similar (i.e., 1,281 and 1,276, respectively) to compare the learning capability of two neural networks. As can be seen in Fig. 7, even though they have similar number of parameters, (i.e., 1,281 and 1,276 respectively), the MAPE of MC-CNN-2 is higher than that of MC-FNN-2 by 0.64 percent point. This confirms that FNN is better than CNN for estimating battery degradation. Furthermore, when the data includes regeneration phenomenon, CNN is not adequate for time series data with high volatility and uncertainty even though CNN is good for other applications such as image recognition.

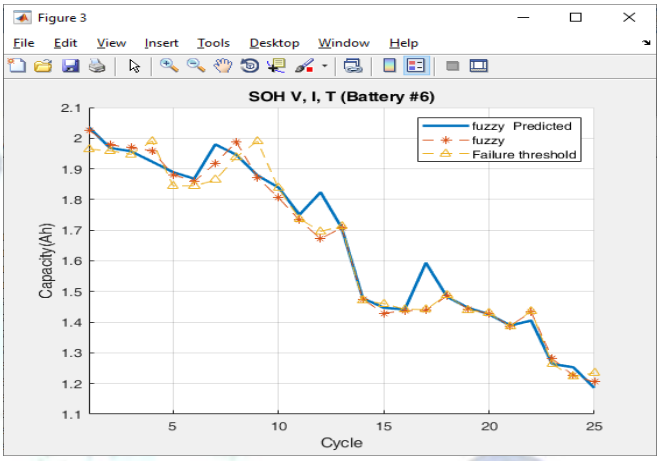


Figure 5.5 SOH- Fuzzy

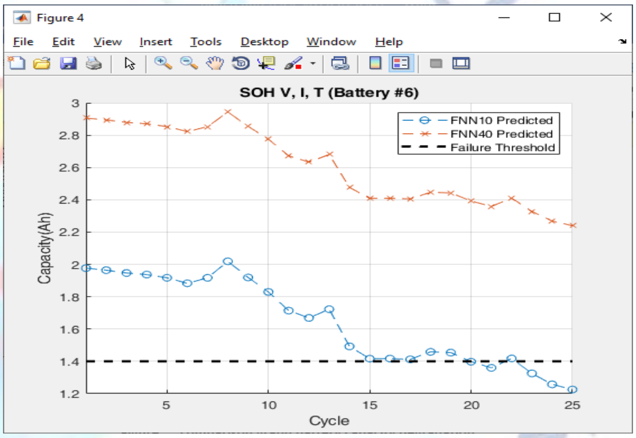


Figure 5.6 SOH -Neural Network

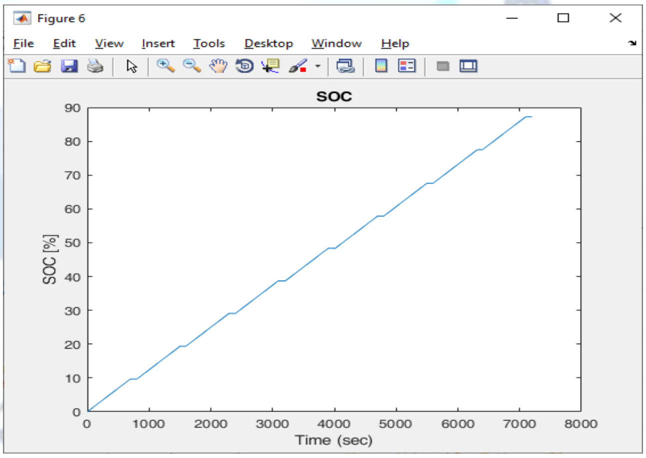


Figure 5.7 SOC

SOC is the measure of the remaining energy in a battery, physically, the amount of energy left in a battery (ψ) is defined as the average concentration of lithium-ions in the cathode (Cs, avg) over the maximum possible concentration

Theoretically, ψ = 0 and ψ = 100 is possible; however, it is not feasible as the removal of too many lithium-ions from the cathode will damage the structure and increase degradation. Therefore, a ψ window is defined for LiBs where ψ0% > 0 and ψ100% < 1. The SoC can now be defined by a ratio of the defined ψ window

$$\text{SoC} = \frac{\psi_k - \psi_{0\%}}{\psi_{100\%} - \psi_{0\%}}$$

This graph describes the state of health condition of battery. We loaded the battery parameters as the input we predict the battery health condition. We maintain the Battery health condition 100 percent of battery, we can analyses the battery health condition, and we maintain the battery parameter aging of cell battery

7. Conclusion

In this project, the SOH of the battery is estimated by the GRNN. The time of constant current in the charge process, and the output energy under a certain discharge depth, and the drop in the voltage in the discharge are used as the inputs of the proposed GRNN based SOH, while the SOH is the output of the model. When there is more charge/discharge characteristics of batteries used in the model in the future, the estimated effect will be better. The state of charge provides users with information on how long a battery can perform before it has to be charged or replaced. It is of foremost importance to track the SoC, especially in EVs. An innovative estimation method that integrates coulomb counting and fuzzy logic system and neural network has been proposed to combine the quality features available in them. This MATLAB simulation model boosted the accuracy of SoC estimation.

Appendix

Appendixes, if needed, appear before the acknowledgment.

Acknowledgment

The preferred spelling of the word "acknowledgment" in American English is without an "e" after the "g." Use the singular heading even if you have many acknowledgments. Avoid expressions such as "One of us (S.B.A.) would like to thank ... ." Instead, write "F. A. Author thanks ... ." **Sponsor and financial support acknowledgments are placed in the unnumbered footnote on the first page**.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

References

[1] Yao, L.; Wang, Z. Research on the charging mode of lithium ion power battery. J. Automot. Eng. 2015, 37, 72–77.

[2] Berecibar, M.; Gandiaga, I.; Villarreal, I.; Omar, N.; Mierlo, J.V.; Bossche, P. Critical review of state of health estimation methods of Li-ion batteries for real applications. Renew. Sustain. Energy Rev. 2016, 56, 572–587. [CrossRef]

[3] Salminen, J.; Kallio, T.; Omar, N.; Gualous, H.; Mierlo, J.V. Chapter 14-Transport Energy-Lithium Ion Batteries. In Future Energy, 2nd ed.; Letcher, T.M., Ed.; Elsevier: Amsterdam, The Netherlands, 2014; pp. 291–309.

[4] Andwari, A.M.; Pesiridis, A.; Rajoo, S.; Martinez-Botas, R.; Esfahanian, V. A review of battery electric vehicle technology and readiness levels. Renew. Sustain. Energy Rev. 2017

[5] Corey, G.P. Batteries for stationary standby and for stationary cycling applications part 6: Alternative electricity storage technologies. In Proceedings of the 2003 IEEE Power Engineering Society General Meeting, Toronto, ON, Canada, 13–17 July 2003

[6] Sheraz Aslam,Michalis P. Michaelides and Herodotos Herodotou, "Internet of Ships: A Survey on Architectures,Emerging Applications, and Challenges, IEEE INTERNET OF THINGS JOURNAL, VOL. , NO. , MAY 2020

[7] R. Karthickmanoj, J. Padmapriya, T. Sasilatha, "A novel pixel replacement-based segmentation and double feature extraction techniques for efficient classification of plant leaf diseases, Materials Today: Proceedings, Elseveir(Article in Press)

[8] R. Karthickmanoj, J. Padmapriya, T. Sasilatha, "Automated machine learning based plant stress detection system", Materials Today: Proceedings, Elseveir(Article in Press)

[9] W. Menghua and X. Bing, "A Real-time Android-based Monitoring System for the Power Lithium-ion Battery Used on EVs," 2017 10th Int. Conf. on Intelligent Computation Technology and Automation, 245-249, 2017.

[10] S.Amirtharaj, D.Lakshmi, V.Madhan kumar, R.Zahira, "Switching Loss reduction and simulation of Quasi Z-Source Inverter System fed BLDC motor", International Journal of Ad.