

Research Article

Battery Energy Forecasting in Electric Vehicle Using Deep Residual Neural Network

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In the recent decade, it is possible to use electric vehicles in a safe, cost-effective, and environmentally friendly manner, but only if accurate and trustworthy state parameter predictions are produced prior to their disposal. The state of health (SOH) of the lithium-ion batteries (LIBs) must be precisely forecasted in order to ensure that the LIB can operate safely. The inability of physical SOH estimators to cope with the dynamic character of SOH when operating in a highly nonlinear environment is a common limitation when operating in nonlinear environments. Traditional SOH estimation techniques have demonstrated that they have limits that can be overcome by data-driven methods. TCN, a new machine learning technique, combines the advantages of residual neural networks (ResNet) with the computing efficiency of neural networks to produce a technique that is both efficient and effective. The results of rgw simulation show that the proposed method has reduced placement cost, and also a TCN can accurately estimate the SOH of a LIB with an MSE error of less than 1% over the LIB lifetime. The performance of an electric car battery, which are numerous and diverse, can be anticipated more precisely using this approach.

1. Introduction

The hybrid electric vehicle (HEV) is one of the most rapidly expanding means of transportation today. As a result of research into green energy and transportation systems, electric vehicles (EVs) will be widely employed throughout the world. When compared to driving a car that is powered by gasoline, driving a battery-powered vehicle produces no hazardous exhaust fumes as a result of its operation. This is why studies that develop effective capacity estimation algorithms [1, 2] are critical to the advancement of EV battery life and range prediction research.

If the users are looking for things that run on batteries, rechargeable batteries are the best example of industrial manufacturing. In recent years, Li-ion batteries have gained popularity over other battery chemistries due to their high energy density and other advantages [3, 4]. Although Li-ion batteries have some intrinsic limitations, such as a limited temperature and voltage operating window and the need to fine-tune the accuracy of capacity estimation, they are no more restrictive than any other cell type in this regard. The performance of lithium-ion batteries is also influenced by a variety of external and internal factors [5]. To put it in another way, all of the factors described above

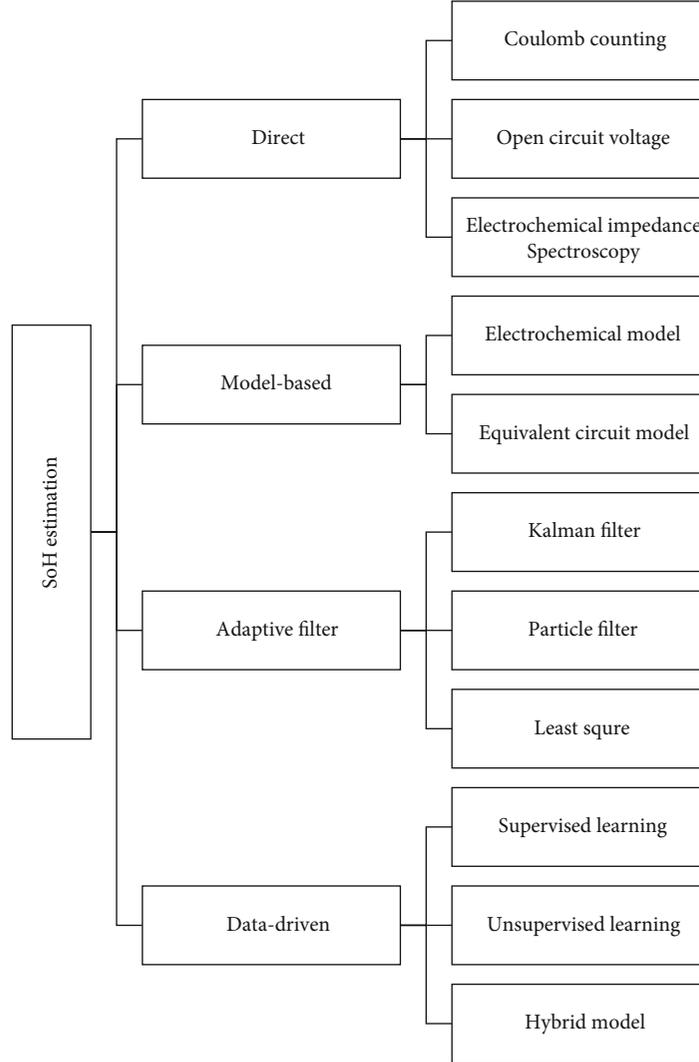


FIGURE 1: SoH estimation.

have an impact on the stability of an EV battery pack and the estimation of its range. Consequently, it is vital to have an accurate methodology for evaluating the capacity of an electric vehicle battery capacity [6]. Figure 1 shows the SoH estimation for the proposed mechanism.

If it is possible to precisely assess a used battery state of health (SOH) and remaining useful life (RUL) with the least amount of testing possible, given a specific manufacturer and model, it would have huge economic and environmental benefits. Battery management system (BMS) software has the potential to quadruple the cycle life of lithium-ion batteries [7], which implies that fewer lithium-ion batteries (LIB) and that recycles and reuses effectively. Furthermore, because some rechargeable batteries and this can be extensively used in electric vehicles [8], the resale value of older electric vehicles may be more accurately assessed. Consider the scenario of getting a rechargeable battery with increased charge-discharge cycles already in it [9]. A second charge-discharge cycle can be used to collect more I-V data in order to determine the SOH of the battery [10, 11].

The end-of-life (EoL) of a fresh battery can be represented by the integer end-of-life (EoL), in which case

$$\text{EoL} = s + a + \text{RUL}, \quad (1)$$

where

s - ground truth and

a - maximum cycle life.

The use of Residual Neural Network (ResNet) based algorithms in dynamical systems, such as the Kalman filter, is challenging the traditional use of limited-memory calculations in dynamical systems. However, while training a DNN can be computationally costly, modern hardware makes it possible to operate a ResNet in real time [12–15].

The study tests the ResNet to find the RUL with various acquisition cycles in order to determine how well they perform [16]. Other than residual life, we can assign DNNs the task of estimating their own ages and, using analysis tools, evaluate the value of various features in lowering root mean square error, as well as the value of different features

in lowering root mean square error (RMSE) [17]. This is a test to see how well the machine predictions match up with human expert intuition and intuition based on the obtained $I(t)$ - $V(t)$ - $T(t)$ cycle time sequence data [18].

According to the manufacturer, the performance of lithium-ion batteries degrades over time (calendric ageing) and with use [19]. A battery's overall capacity and internal series resistance, which are two of its most distinctive qualities, may be determined by measuring their combined capacity [20–23]. Internal resistance is increasing as a result of unfavourable responses and structural deterioration, among other factors. To put it in another way, a new LIB has the capability of storing more energy and delivering more power than a previous LIB [24]. A time-integrated calculation is used to determine the capacity of the charge or discharge current. In order to determine SOH, it is necessary to first explain and demonstrate how the battery management system measures battery consumption data such as voltage, temperature, and current.

2. Related Works

Using the same regression model, [25] generated even more LIB cell data with even more sophisticated fast-charging rules in order to increase closed-loop fast-charging protocol performance. With the use of a convolutional neural network (CNN) built [12], he was able to reduce the number of charging cycles with increased accuracy.

[15] demonstrated that by using an extreme learning model, they were able to obtain higher accuracy and computational efficiency than the existing models while modelling battery temperatures under external short-circuit conditions. Researchers have developed a multistage model fusion algorithm to estimate the capacity and SOC of an electric vehicle

According to [17], the RUL of acquisition was employed as input data for the dilated CNN design. There are numerous end-to-end training approaches described in the scientific literature, each of which corresponds to a specific set of special features and a distinct set of goal values. As a result, estimating battery EOL when only one cycle is taken into consideration is challenging. When compared to a traditional strategy, the proposed last padding technique is used in the current study. In this technique, numerous groups of characteristics are associated with a single objective value, as opposed to the old strategy.

3. Proposed Method

The four primary phases of the experiment are depicted in Figure 2. The initial stage is the extraction of model parameters, which will be used as inputs to the ResNet network. Several ResNets are trained on a range of hyperparameters during the second phase of the process. Each ResNet would be validated in order to determine which model is the most effective for estimating SOC from the given training dataset.

The battery management system (BMS) is made up of electronics and embedded software that work together to deliver safe, dependable, and application-specific optimal battery system operation. When testing batteries, it is necessary to take readings of the voltage and temperature of indi-

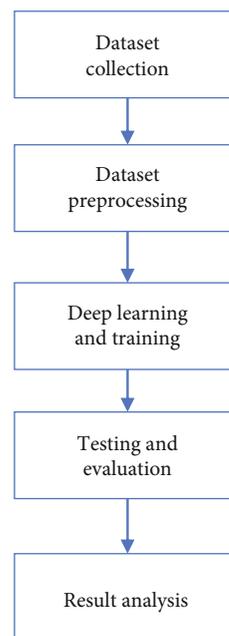


FIGURE 2: Proposed BMS model.

vidual cells, as well as the current flowing through the entire system. Extra measurement data, like pressure sensors or electrochemical impedance spectroscopy (EIS) readings, can be used to guarantee that a battery system performs at its peak performance level. The battery management system (BMS) is in charge of controlling the electric power contactors in the battery system, ensuring that the battery cells are not used beyond their permitted operating limits when the system is in operation.

Battery models at all levels, from cells to modules and up to system models (e.g., equivalent circuit, physical, or heuristics-based models), must calculate battery state parameters, such as the aforementioned SOH, in order for a battery system to operate within an application-specific optimal operating window. This is true for all battery models, regardless of their level of performance. In order for the battery system to function properly, model computations and real-time output projections must be possible. The BMS can employ its own measurement data, as well as application logic and inputs from a higher-level control unit, to ensure safety and optimal battery utilization.

Whenever data on battery utilization is collected for research or commercial objectives, it must be made publicly available outside of the embedded system so that others can take advantage of it and learn from it. The information flow through the data pipeline is depicted in Figure 3.

The measurement data is first collected by the BMS integrated into the application. The ETL (Extract, Transform, and Load) process is used to transport and further process raw data before it is saved in a database, and it is also known as data transformation. For modelling purposes, an ETL procedure is necessary in order to make use of the logged data stream in a low-level system (such as Ethernet). It is therefore necessary to preprocess the output so that it can be used for data analysis as well as model training purposes.

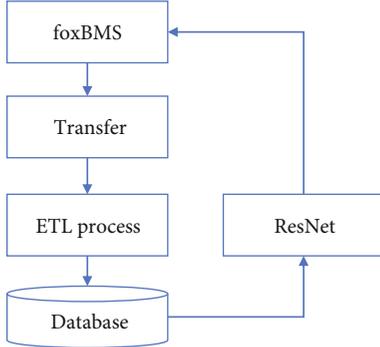


FIGURE 3: Data pipeline and feedback into BMS.

3.1. Data Extraction. Our battery tester consisted of two components: a continuous current source and an environmental chamber that was used to charge and discharge cells, respectively. It was decided to use a sampling rate of 0.1 Hz, and the results of each of the 40 CAP tests were stored on a host computer in a discrete manner. The charts clearly demonstrate how changing temperatures affect the behaviour of a LiFePO₄ cell when performing tests, including voltage and current measurements. This demonstrates the importance of training estimation models at a variety of temperatures.

3.2. ResNet for SOC Estimation. For the purpose of discovering the answers to the study questions, the learning phase for the SOC estimate was painstakingly planned and implemented. Optimization of hyperparameter trends for a ResNet with a simple setup was the objective. As a result, it is possible to develop a SOC estimation model with the lowest possible error metrics. It was discovered that the ResNet design has a tendency to use a small number of neurons and hidden layer configurations, which reduces the demand for high-specification hardware at the time of training.

A ResNet model finds the optimal number of neurons and hidden layers, as well as the appropriate values for the other ResNet hyperparameters. ResNet models were built utilizing all possible ResNet topologies and hyperparameter settings as in Table 1. Training and cross-validation of each model were performed five times using data from six out of eight cells. In order to validate the models, we employed 2 cell data, which accounts for approximately 25% of the total amount of data collected.

3.3. Residual Neural Networks. Consider $g(x)$ as one of the important functions that gets learned by the ResNet layers. In this study, we consider the ResNet layer with skip connections:

$$h(x) = g(x) + x, \quad (2)$$

where

x - skip connection.

It is necessary to alter the weights and bias values in order to match the identity function when there are no skip connections. In addition, because of the nonlinearity in the layers, it is even more difficult to learn the identity function from the beginning, leading to degeneration. Let see the

TABLE 1: ResNet hyperparameters.

Hyperparameter	Values
Hidden layers	5
Neurons	10
Learning rate	0.8
Activation method	Hyperbolic
Epochs	100

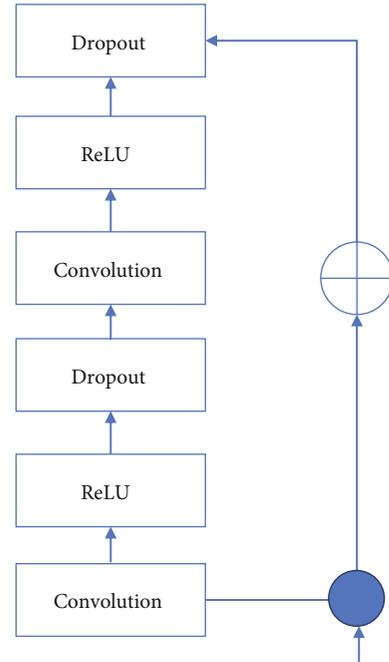


FIGURE 4: Residual block.

building blocks of Residual Neural Networks or ResNets, the residual blocks as in Figure 4.

The identity function can be elevated to a higher level of sophistication through the use of a skip connection. The residual block is distinguished by the following two characteristics:

- (i) Alternatively, if we applied relu before adding the skip connection, all of the residues would have been either positive or zero. As a result of just learning positive identity enhancements, the learning ability has been significantly diminished
- (ii) If $\sin(3/2) = -1$, the study needs to include negative residue in our sin function, which is not the case. In contrast, the use of sigmoid has the disadvantage of only producing residues between 0 and 1, which is undesirable. Nonlinearity should be produced by combining the unconstrained response of the weight layer with the activation of the skip layer, as described above

This facilitates the model's ability to learn and adapt to new situations. We might have used a single weight layer

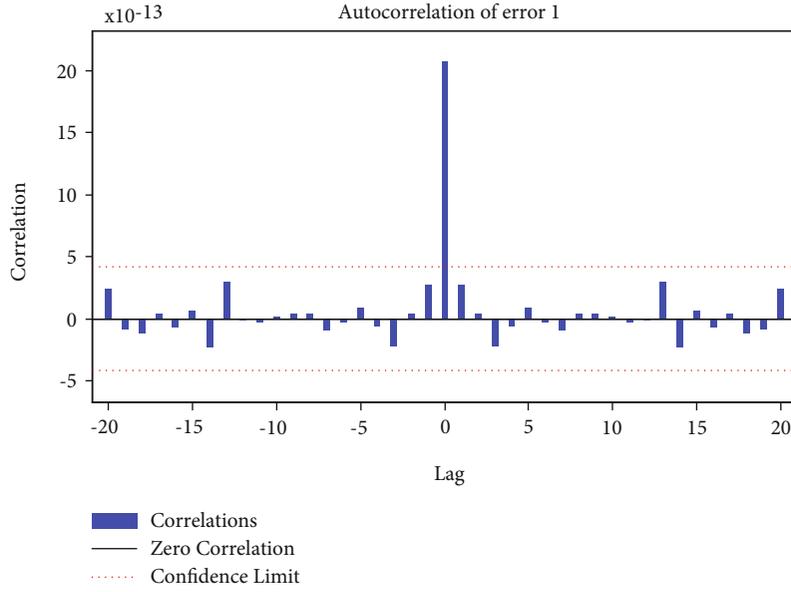


FIGURE 5: Autocorrelation for the error.

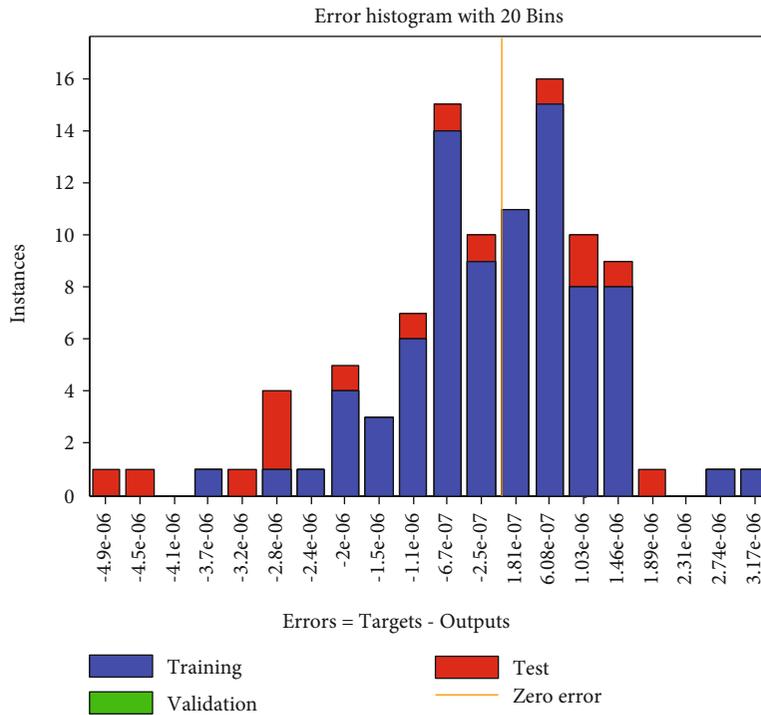


FIGURE 6: Error histogram.

in the residual block and then added a skip connection before the relu block to obtain a simple linear function:

$$F(x) = W(x) + x. \tag{3}$$

There is no need to include a skip connection because the weight of this is comparable to that of a single layer. We must first introduce at least one nonlinearity into the system before we can introduce a skip link. As we saw in the preceding section, there are learning residuals associated

with these blocks. The performance of these blocks will not deteriorate as they are stacked higher and higher in the stack.

As previously stated, the usage of skip connections can also be beneficial in deep networks [13]. A skip connection does not accomplish anything other than provide the input. A residual block is a type of connection that can be used to create a skip connection that is meaningful as well as useful. In order to assure local LIB regeneration, a residual block, which serves as a network layer, is used.

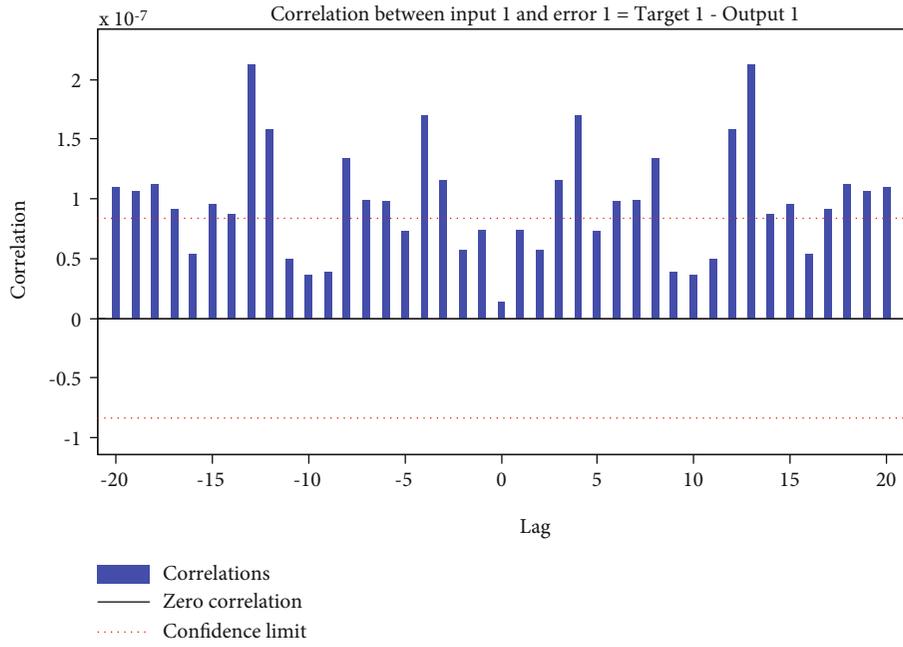


FIGURE 7: Correlation between input and error.

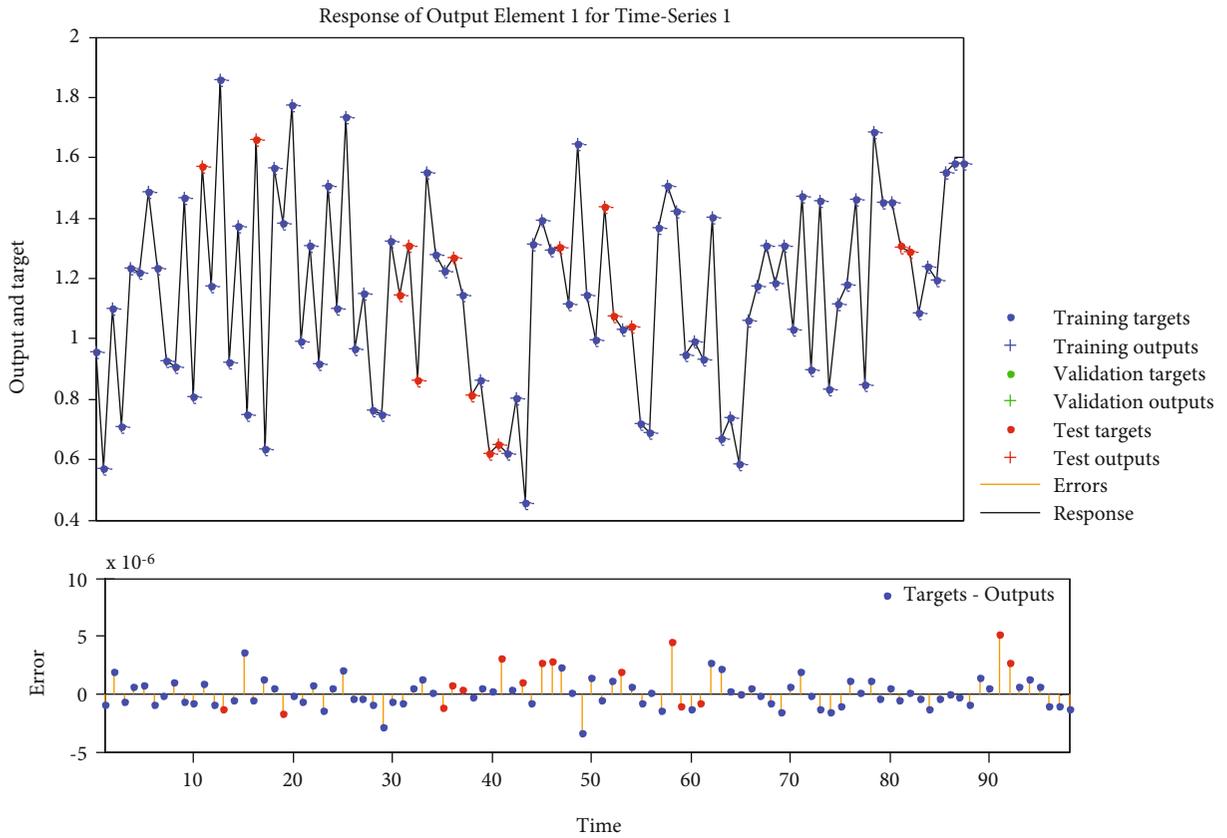


FIGURE 8: Output of the ResNet model.

4. Results and Discussions

It is expected that the design of our ResNet is trained with the 80% of the input datasets and then it is tested under 20% of the solar datasets. The results of the simulation are considered in terms of performance metrics to validate the efficacy of the entire model.

The performance of ResNet was evaluated by comparing the error between the real SoC and predicted SoC, where the proposed model achieves higher rate of prediction accuracy using the ResNet algorithm. Apart from their epoch counts, the top 20 models selected during the validation phase using ResNet architecture as in Figure 5. Its generalizability is proved by the learning rate of 0.8 for the top ten models, which is higher than the lower learning rates obtained using greedy search, demonstrating that the design is robust.

Additionally, this figure depicts the residual error at the end of each epoch, which is rather interesting. When the number of epochs was reduced by 40%, error metrics increased by less than 0.15 percent, indicating a slight improvement. The performance is assessed using a range of error indicators, including residual error, among others as in Figure 6. Figure 7 depicts the correlation between input and error.

As the model's ability to generalize its conclusions to new datasets increased from validation to testing, the error metric values reduced for each dataset under consideration. As shown in Figure 8, the best model does not overfit the training data and does an excellent job of generalizing to new data. When compared to existing methodologies, MAE on different test data sets ranges from 0.39 to 1.85 to 1.35, indicating that it is superior. Note that while the MAEs in this study had fewer learning epochs (85,500) than the best models, both the lowest and highest MAE is found to be lower than the MAE of other methods.

With increasing age, one capacity and, thus, one SOH diminish. The neural network employed in this study is composed of three layers, each of which has seven neurons. It is also taught using Adam optimizer, which is an adaptive learning rate optimization technique that was developed specifically for deep learning applications.

It is extremely crucial for real-world data in dynamically changing surroundings and operating settings to have the ability to adapt and learn on its own. This is something that neural networks excel at. Consequently, as a result of the TCN, a reliable SOH estimation for LIB is attainable throughout the duration of its existence. Finally, the proposed ResNets may be utilized in real-world applications to continuously update the model to deal with environmental change while increasing the accuracy of forecasts.

5. Conclusions

In this paper, it is shown that a minimal ResNet architecture with numerous configurations of simple designs is required in order to reliably predict the SOC of electric vehicle battery cells while maintaining performance metrics comparable to the current studies. To further reduce the timing and computational cost, the study enables the ResNet to undergo several epochs that reduces the risk of overfitting and has been deter-

mined to be significantly smaller than that used in earlier research, to the best of the author's ability to ascertain. The ResNet estimation models can be trained and evaluated using additional battery tests, such as high-performance computing testing at various temperatures and C-rates. Additional drive cycle data acquired from battery cells, both customized and standard, can be added at the training/testing datasets to improve the transfer ability of the ResNet estimation model used to predict the impacts of external influences on the behaviour of electric vehicle batteries. Next-generation research should concentrate on generating batteries with accurate characteristics of their performance and longevity while sacrificing the computational time reductions that would otherwise be achieved. This will be beneficial to both the short-term scheduling and the network planning processes.

Data Availability

The data used to support the findings of this study are included within the article. Further data or information is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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