

Overcoming limited battery data challenges: A coupled neural network approach

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Summary

The electric vehicle (EV) industry has seen extraordinary growth in the last few years. This is primarily due to an ever increasing awareness of the detrimental environmental effects of fossil fuel powered vehicles and availability of inexpensive lithium-ion batteries (LIBs). In order to safely deploy these LIBs in electric vehicles, certain battery states need to be constantly monitored to ensure safe and healthy operation. The use of machine learning to estimate battery states such as state-of-charge and state-of-health have become an extremely active area of research. However, limited availability of open-source diverse datasets has stifled the growth of this field, and is a problem largely ignored in the literature. In this work, we propose a novel method of time-series battery data augmentation using deep neural networks. We introduce and analyze the method of using two neural networks working together to alternatively produce synthetic charging and discharging battery profiles. One model produces battery charging profiles, and another produces battery discharging profiles. The proposed approach is evaluated using few public battery datasets to illustrate its effectiveness, and our results show the efficacy of this approach to solve the challenges of limited battery data. We also test this approach on dynamic electric vehicle drive cycles as well.

KEYWORDS

data augmentation, deep learning, electric vehicle, lithium-ion batteries, machine learning

1 | INTRODUCTION

Lithium ion batteries (LIBs) are more relevant than ever before for meeting energy demands in the modern day. Apart from the environmental benefits of using these rechargeable batteries over conventional fossil fuels,¹ these batteries are very energy dense and inexpensive. This makes them an ideal energy source for a variety of applications, from powering smartphones^{2,3} to electric vehicles (EVs).

The intersection of machine learning and battery technology has become a very active area of research over the last few years. Deep learning has seen a lot of interest

for various tasks such as state-of-health (SOH)⁴⁻⁸ and state-of-charge (SOC)⁹⁻¹⁵ estimation. Conventional battery modeling requires extensive battery parameterization by domain experts,¹⁶⁻¹⁸ whereas deep learning models have the ability to automatically learn the most relevant battery features along with transient dynamics. Although these methods show a lot of promise, and seem to have the potential to become the dominant method for SOC and SOH estimation, there is a major roadblock that must first be overcome. The accuracy of any machine learning algorithm is highly correlated with the quality and quantity of training data.¹⁹ A model trained on a limited amount of data is unable to accurately capture all the

relevant battery dynamics. In this scenario, data augmentation techniques provide a viable solution to increase the training data. Limited data challenges are largely ignored in the literature, and this work aims to elucidate the problem and offer a simple and novel solution.

Most papers that suggest new and improved machine learning-based battery parameter estimation models use confidential proprietary data. This data is very rarely made open-source, essentially stifling the research in this area. There is no legitimate way to compare different approaches in two research papers if the underlying data used to train the models are different. Moreover, battery manufacturers routinely generate vast quantities of data during quality control tests, and this data is also not made available to researchers due to privacy and confidentiality reasons. There is thus a dire data scarcity of diverse battery datasets within publicly available battery data, which is needed to foster growth in this area of research.

The use of Markov chains for the purpose of augmenting battery dynamics has also been explored in Pyne et al.²⁰ This method is akin to simulating the underlying battery electrochemistry behavior to generate adequate data for training purposes. They report that their model is able to capture the battery capacity fade over time. Most research related to data-augmentation are based around statistical and probabilistic approaches. For example, in Kamthe et al.,²¹ copula theory was used to formulate a synthetic data generation methodology. About 3 million voltage vs capacity curves were generated using the approach introduced in Dubarry et al.¹⁹ The authors used a mechanistic approach to capture the most vital battery dynamics for diagnostics and prognosis purposes. The problem with these approaches is that they require extensive battery parameter estimation testing, which is quite expensive and tedious.

The use of generative adversarial networks (GANs)²² for the purpose of data augmentation has also become very popular,^{23–26} especially in the field of image data augmentation.²⁷ GANs have been known to suffer from convergence issues,²⁸ and typically only manage to capture limited range of the time series variations (maximum and minimum values) but fail to capture the intrinsic dynamics of the data. Moreover, training of GANs are extremely resource intensive, as it requires both the generator and discriminator networks to be trained together thus rendering them ineffective for resource constrained remote devices.

In this paper, we introduce a novel method of data augmentation for time-series data. This method can be used in data scarce scenarios, and helps to significantly increase the amount of training data. We use the popular

Oxford Battery Degradation Dataset²⁹ to train and test our synthetic data generator, and then test the model architecture on the US06 and BJDST drive cycles of the Center for Advanced Life Cycle Engineering dataset³⁰ to evaluate the effectiveness of the proposed approach.

The primary contributions of the present work are listed here:

- This is the first work to use two simple feedforward neural networks to generate battery synthetic data
- This is the first time a coupled neural network approach has been employed to produce synthetic charge/discharge data to overcome limited data challenges
- This is the first work to use computationally simple neural networks which can be employed in resource constrained remote devices

The paper is organized as follows: fundamentals of deep neural networks are provided in section 2, details of the methodology introduced in this paper is given in section 3, dataset details are provided in section 4, hyper-parameter tuning is covered in section 5. The results obtained are illustrated in section 6, followed by conclusion in section 7.

2 | DEEP NEURAL NETWORKS

A neural network is made up of several layers, and each layer has multiple neurons. These neurons are essentially the computational units of the entire model. They consist of weights and biases. An input to the neuron undergoes specific computations based on the values of these parameters, and the result is the input for the subsequent layer. The output of the last layer, which can be a regression output or a classification label, is the final output of the neural network.

The neural network has a pre-defined error also known as the loss function. The goal of training a neural network is to minimize this loss function over the sample space. In our work, the mean squared error shown in Equation (1) is considered as the loss function. A popular algorithm called Adam³¹ is used to iteratively reduce the loss function, as it is computationally efficient. The loss is back-propagated and adjustments are made to the values of weights and biases until an optimal model is obtained. After training is completed satisfactorily, the model can be deployed to predict the target variable in a real-life setting. It essentially behaves like a function approximator.

$$\mathcal{L}_{\text{MSE}} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2 \quad (1)$$

In Equation (1), n is the number of samples in a minibatch, y_i is the input vector and \hat{y}_i is the output vector at the i th instance.

Traditional neural network approaches use one or two computational layers. These are usually referred to as artificial neural networks (ANNs). Extending this idea, we can add more layers to the mix, resulting in a deeper model architecture called deep neural networks (DNN). The capability of these architectures to learn non-linear relations among the inputs and outputs is greatly enhanced. Simply put, a multilayer stack of neural layers constitutes a deep learning model. In principle, a DNN with enough layers can approximate any function. In this article, we use the traditional feedforward neural network. In this network, information flows from the input layer to the output layer (forward direction).

3 | METHODOLOGY

In this article, we confine the discussion to feedforward neural networks. The dataset used has three battery parameters: voltage, temperature and charge capacity (which is converted to state-of-charge). We formulate the artificial sequence generation task as follows:

1. Two separate neural networks are trained for each battery parameter.
2. One neural network is trained to generate a discharging profile, and another neural network is trained to produce a charging profile.

For each battery parameter, it is also possible to couple the two neural networks together sequentially to produce a large amount of synthetic battery parameter data.

For the sake of brevity, we will use the following nomenclature throughout this work:

1. *DischargeNet*: This is the neural network that is trained to produce a discharging profile. One DischargeNet model is trained for each battery parameter (DischargeNet-V, DischargeNet-T and DischargeNet-S).

2. *ChargeNet*: This is the neural network that is trained to produce a charging profile. For each battery parameter, one ChargeNet model is trained (ChargeNet-V, ChargeNet-T and ChargeNet-S).

As shown in Figure 1, one neural network is trained for the generation of a discharging profile, and one for the generation of the charging profile. The DischargeNet model produces the parameter discharging profile (voltage [V], charge capacity [mAh] or temperature [C]) of a cell. Similarly, a neural network dubbed “ChargeNet” is trained to produce the charging profile. These models can be used for synthetic data generation, as in the case when only a limited discharging profile data is available, DischargeNet can be used to provide the corresponding discharging profile. In the same way, ChargeNet can be used to produce charging profiles if limited battery charging data is provided to the model.

It is possible to use both these models sequentially. This synthetic data generation process can be continued until the accumulated error passes a certain threshold. The net result is to produce a large amount of synthetic data which can be used to develop machine learning-based battery parameter estimation models. This process is elucidated in Figure 1.

In this work, we have focused on the feedforward neural network (FNN) architecture. Although FNNs have been used in the field of lithium ion battery parameter estimation before, ours is the first work to propose a concise methodology for sequential synthetic battery cyclic data generation. Previous approaches used a single neural network to estimate battery parameters like state-of-charge and state-of-health. In this work, we propose a novel methodology of combining two neural networks working together sequentially to supplement existing datasets, with the aim of increasing the amount of data available for training purposes.

The architecture of the neural network that is optimal for each of these battery parameters must first be discovered. There are several factors that influence a neural network's architecture. In the case of the FNN, these are the number of layers and the number of neurons in each

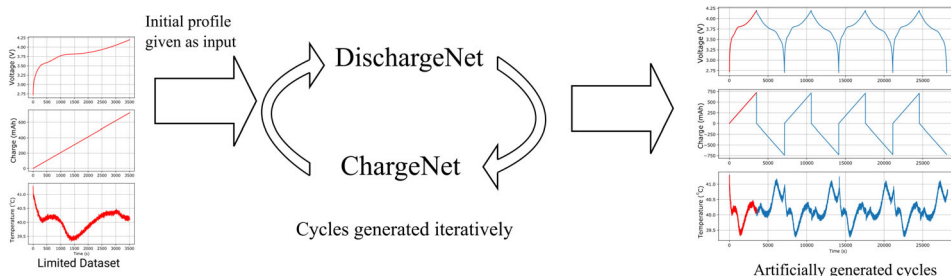


FIGURE 1 Diagram illustrating the methodology followed to produce synthetic cell cycles

layer, which are jointly referred to as the neural network's hyperparameters. This means that there must first be a hyperparameter tuning step before we can proceed to generate artificial data. For each of the battery parameters, we perform this hyperparameter tuning.

Our method allows a model that has been trained on data for a specific cell to be used to supplement existing datasets. A model that is trained once for a specific battery chemistry can be used to augment other charging-discharging datasets. For example, if a model can take one cycle and then sequentially generate 50 more cycles artificially, the dataset can essentially be increased 50 times. In this work, we will explore several different FNN architectures for the generation of artificial data on a Kokam Co. Ltd. (SLPB533459H4, 740 mAh) cell from the Oxford Battery Degradation Dataset.²⁹

We first use a limited amount of the full dataset and train several different model architectures for 50 epochs. We do this for the DischargNet models first, and in this work we make the assumption that for a particular battery parameter, the optimal DischargNet and ChargeNet model architectures are identical. This is a reasonable assumption to make given that both processes are highly similar in terms of internal battery dynamics.

4 | DATASET

The Oxford Battery Degradation dataset^{29,32} was used in this work. It consists of charging-discharging cycles of eight Kokam Co. Ltd., SLPB533459H4 cells. Of these eight cells, we have used the profiles of the first three cells, henceforth referred to as Cells 1, 2 and 3. The cell specifications are shown in Table 1. The voltage, temperature and charge values of the cells as they were repeatedly charged and discharged were captured using the Bio-Logic MPG-205 battery tester, with a controlled ambient temperature of 40°C. There are 78 cycles corresponding to cell 1, 73 cycles for cell 2 and 76 cycles for cell 3. A few of these cycles are shown in Figure 2.

One of the constraints imposed by the neural network training process in this current research work is that the input and output sequences must have similar dimensions. This means that the time-series sequence given as input must cover the same amount of time as the output time-series. In order to achieve this, a pre-processing step is introduced in order to make sure that the charging and discharging profiles are of equal length. Since the discharging profiles are longer than the charging profiles by roughly 100 time steps, we extend the charge profiles by this amount at the end with the last voltage, charge or temperature value of the series. This ensures that the charging and discharging profiles are of equal length,

TABLE 1 Cell specifications of Kokam SLPB533459H4 cells²⁹

Specification	Value
Nominal capacity	740 mAh
Nominal voltage	3.7 V
Maximum voltage	4.2 V
Discharging cut-off voltage	2.7 V
Cycle life	500 cycles
Charging temp. range	0°C to 40°C
Discharging temp. range	−20°C to 60°C

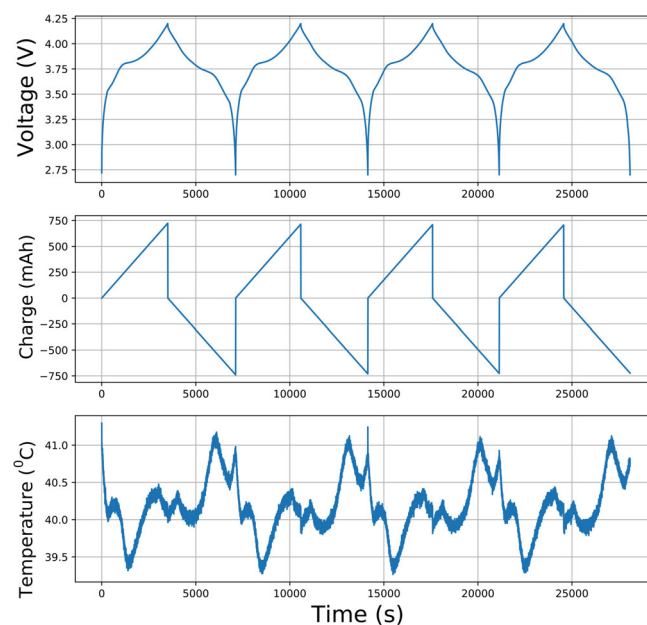


FIGURE 2 Four charge-discharge cycles of cell 1

without introducing unrealistic battery observations into the data. The Center for Advanced Life Cycle Engineering Dataset was also used to test the models for dynamic situations. Two drive cycles (BJDST and US06) sampled at 25°C were used from the INR 18650-20R cell dataset.³⁰

5 | HYPERPARAMETER TUNING

5.1 | Voltage

In order to find the best network architecture for this voltage profile modeling task, we must first perform hyperparameter tuning. Initially, different model architectures are trained on only the first two cycles of cell 1, for 50 epochs, to select the best parameters and loss values, 19 553 and 0.00578 were the metrics used in this case, which provide the best accuracy.

The number of parameters help to measure the network complexity. A neural network consists of neurons, each having a specific weight and bias. These weights and biases together constitute the number of trainable parameters of a neural network. Using total number of trainable parameters to gauge network complexity is vital in order to allow researchers to compare the performance of their models with those of other researchers.¹³ The larger the number of parameters, complexity of the model increases. A deeper network with a large number of layers will have more neurons, and hence more number of parameters.

It was observed that, the neural network with 19 553 parameters was the best performing model. This model consisted of 10 layers. We will proceed with training this architecture using the full training dataset for 400 epochs. The training dataset comprises of cycle data of cell 1 and cell 2, a total of 151 charge-discharge cycles. We use cell 3 for testing purposes, which has 76 cycles. For DischargeNet, we train it to produce discharging profiles. All the cycles from cell 3 are used for testing, and one output

is shown in Figure 3. In similar fashion, ChargeNet was trained to predict charging profiles.

5.2 | State-of-charge

The charge capacity (mAh) values are first converted to state-of-charge values (%). We repeat the same procedure as that done with the voltage profile generation for generation of state-of-charge data. Model with 7041 parameters, with six layers, provided the best performance. The charging and discharging state-of-charge profiles are shown in Figure 4. There is marked agreement between the predicted and real datapoints as seen from the plots.

5.3 | Temperature

We employ the DischargeNet and ChargeNet models to produce synthetic battery temperature data. In this scenario, the model with 7041 parameters (six layers), with a

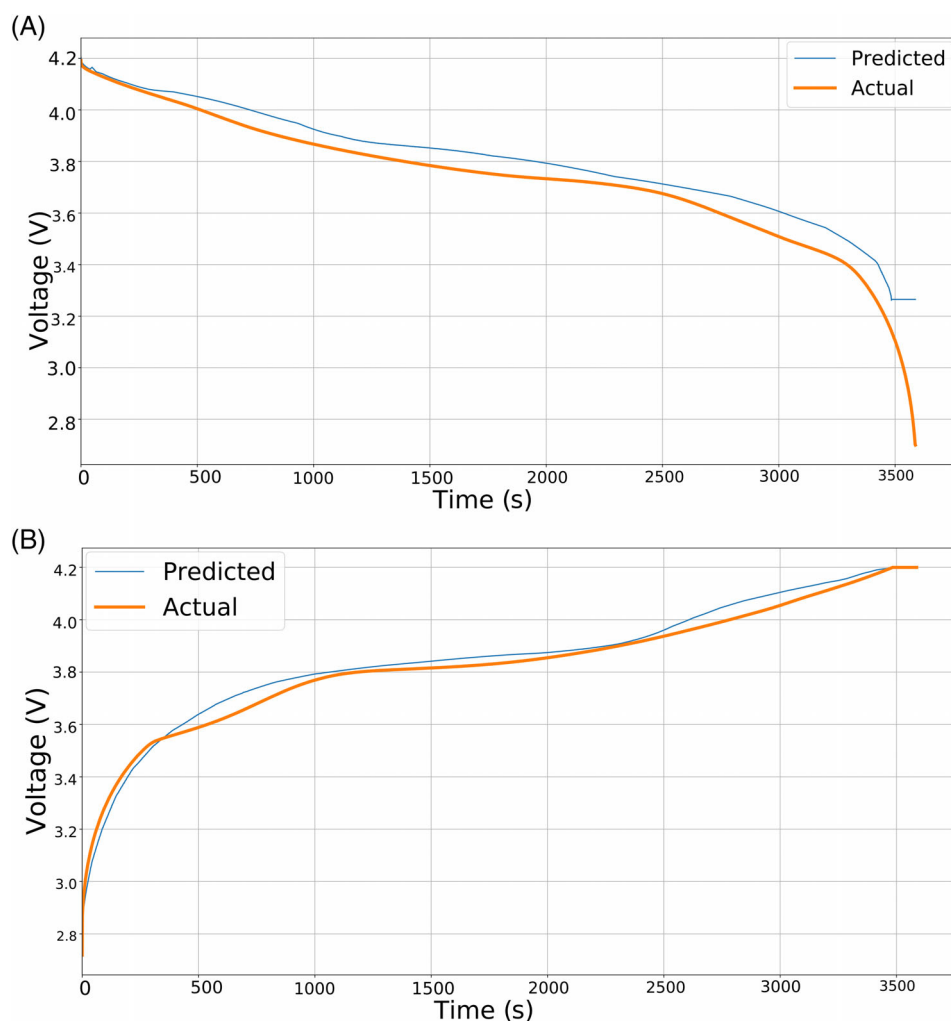


FIGURE 3 DischargeNet output for cell 3 cycle 1 voltage profile is shown in (A) ChargeNet output for cell 3 cycle 1 voltage profile is shown in (B)

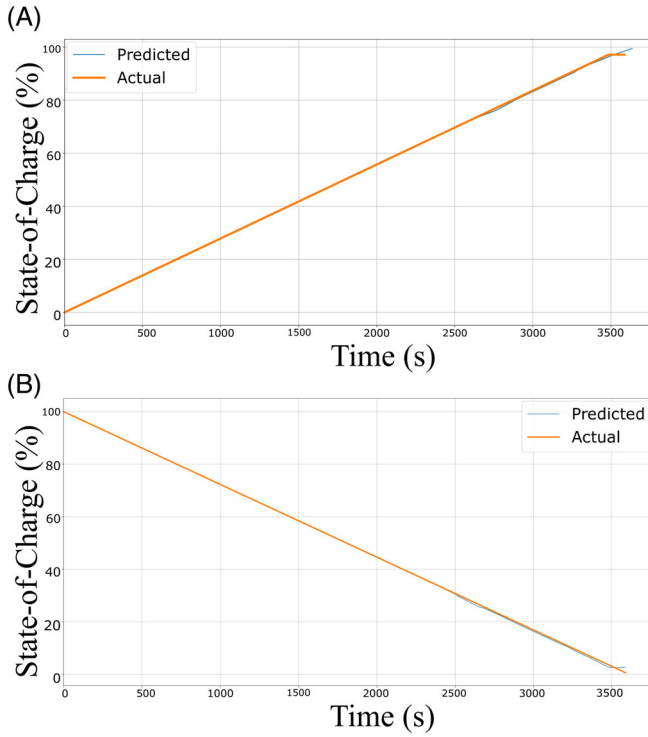


FIGURE 4 ChargeNet output for cell 3 cycle 1 state-of-charge profile as shown in (A) and DischargeNet output for cell 3 cycle 1 state-of-charge profile as shown in (B)

final loss value of 0.1247, provided the best performance. The plots are shown for temperature data in Figures 5 and 6. The model is able to effectively capture the highly non-linear dynamics of the temperature profile. The plots show the ground-truth values and the values predicted by the model. It must be noted that the variation show a close-up version of the temperature profile, spanning about 0.8°C .

6 | RESULTS AND DISCUSSION

We use the mean squared error (MSE), mean absolute error (MAE) and root mean square error (RMSE) as evaluation metrics for our models. The equations are provided for each of the evaluation metrics. These metrics have been computed for various battery parameters and have been tabulated in Table 2.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2 \quad (2)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - x_i| \quad (3)$$

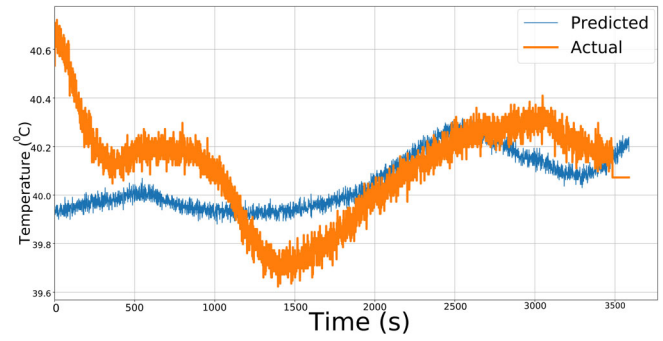


FIGURE 5 ChargeNet output for cell 3 cycle 1 temperature profile

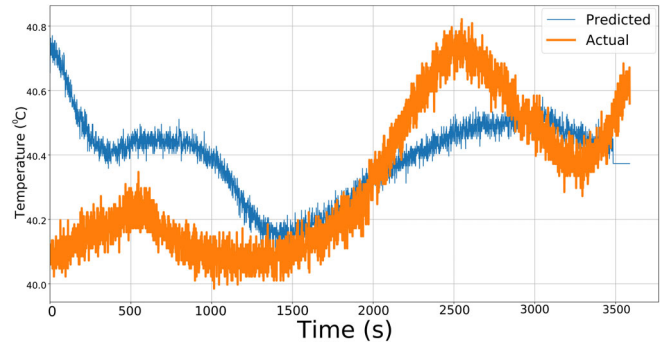


FIGURE 6 DischargeNet output for cell 3 cycle 1 temperature profile

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (y_i - x_i)^2}{n}} \quad (4)$$

where n is the number of data-points, y_i is the predicted value at the i th instance and x_i is the true value at the i th instance.

Table 2 shows the average error over the entire 76 cycles of cell 3 for the voltage profile of the batteries. As can be observed from the results, the average of the error metrics are very low, depicting that the model is able to reconstruct the charging and discharging profiles accurately. The error does not vary significantly over the 76 cycles of cell 3 for the voltage profile.

It must be noted that these small errors showcase a desirable feature of our approach. The errors are small, which illustrates that the model captures the dynamics of the cells, but the small differences between the actual and predicted values serves to introduce minor variations in the generated data. These variations are vital for any data-augmentation tasks because otherwise there would not be any advantage gained by using a larger dataset which held identical copies of the same battery parameter sequences.

Battery parameter	Model	MSE	MAE	RMSE
Voltage	ChargeNet-V	0.0003	0.0148	0.0177
	DischargeNet-V	0.0015	0.0214	0.0385
State-of-charge	ChargeNet-S	0.1542	0.1797	0.3853
	DischargeNet-S	0.1611	0.2052	0.3953
Temperature	ChargeNet-T	0.076	0.191	0.258
	DischargeNet-T	0.070	0.208	0.259

TABLE 2 Table listing the accuracy metrics for voltage, state-of-charge and temperature profile generation

Abbreviations: MAE, mean absolute error; MSE, mean squared error; RMSE, root mean square error.

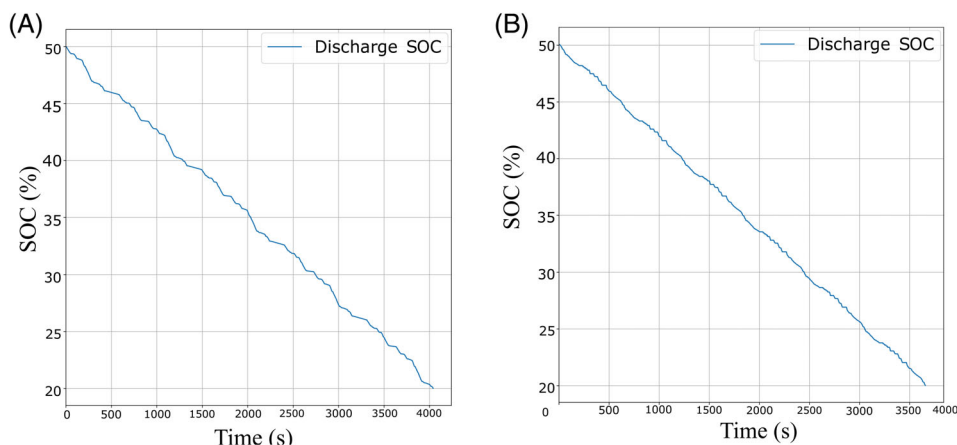


FIGURE 7 Plots describing synthetic dynamic state-of-charge discharge profiles of BJDST (A) and US06 (B) drive cycle

We can see in Table 2 that the error metrics for the state-of-charge parameter are also very low. However, there is an upward trend in the error, as the values of MSE, MAE and RMSE increase steadily with the number of cycles. This can be attributed to the capacity fade of the cells. For example, the final charge value of cell 3 reduces by approximately 25% from the first to the 76th cycle. Note that the predictions show a very good fit between the actual and predicted values. The temperature profile data error averaged over the 76 cycles of cell 3 are shown in Table 2. The error metrics are within acceptable limits, showcasing the neural networks ability to capture the highly non-linear variation of the temperature profile. It can be seen that a simple coupled neural network approach is good enough to capture all the temporal dynamics of the dataset. The coupled methodology is highly beneficial to produce synthetic charge/discharge data during limited data cases.

6.1 | Dynamic drive cycle profile

In order to test our approach on the more challenging scenario of a dynamic drive cycle, the BJDST and US06 drive cycle of an INR 18650-20R cell at 25°C is used. These results

TABLE 3 Table depicting accuracy metrics for state-of-charge battery profile generation for BJDST and US06 drive cycles

Drive cycle	Model	MAE	RMSE
BJDST	ChargeNet	1.88	5.03
	DischargeNet	4.81	5.91
US06	ChargeNet	2.23	2.47
	DischargeNet	8.16	10.76

Abbreviations: MAE, mean absolute error; RMSE, root mean square error.

are shown in Figure 7. The state-of-charge (%) is synthetically generated using the ChargeNet and DischargeNet model architecture elucidated previously. The model is trained on state-of-charge data of this cell and the error metrics obtained after testing are shown in Table 3. There is an increase in the MAE and RMSE values for these dynamic profiles when compared with simpler charging and discharging battery profiles described in earlier cases. This is due to the transient nature of the battery discharge characteristics which is difficult to model, leading to higher error values. It can be seen that ChargeNet performs better than the DischargeNet model, because charging dynamics are much easier for the neural network to capture than the challenging discharging scenario.

7 | CONCLUSION

In this work, we have proposed the use of two coupled neural networks to produce synthetic battery parameter cyclic data to overcome limited dataset challenges. We first perform hyperparameter tuning using limited battery data, and then train the best neural network architecture on the complete dataset. The fully trained networks work together to generate synthetic charge/discharge data for battery parameter values such as voltage, state-of-charge and temperature. It was seen that the feedforward neural network algorithm used in this work was successful in capturing the complete battery dynamics during each cycle, thereby proving the efficacy of this method for data-augmentation purposes. This method was also tested for challenging scenarios of dynamic discharge drive profiles to evaluate the performance of the proposed approach. This is the first work to illustrate the efficacy of simple coupled neural network approach for synthetic data generation which is advantageous for resource constrained devices. Further work can be done to explore the use of recurrent neural networks like long short-term neural networks for this task, as these are specifically designed to capture temporal dynamics.

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