CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

AN EFFECTIVE DEEP LEARNING ALGORITHM BASED ESTIMATION OF STATE OF CHARGE OF LITHIUM ION BATTERY IN HYBRID ELECTRIC VEHICLES

N. Sangeetha[1*] and K. Gayathri [2]

Research Scholar, Department of Electrical Engineering, Annamalai University, Annamalai nagar, Tamil nadu, India.

Associate Professor, Department of Electrical Engineering, Annamalai University, Annamalai nagar, Tamil nadu, India.

Abstract
The battery pack is the most significant and expensive component in Electric Vehicle, it needs to be closely monitored and controlled. As a result, substantial research is being performed in EV battery state monitoring and control. A neural based method for estimation of SOC is presented in this paper. Two different network structures, i.e., Feed Forward Network and CNN, were considered for investigation. A complete real time data set was trained for the estimation of SOC under various temperature conditions. From the simulation results it can be concluded that instead of BP algorithm, the use of CNN with 'ADAM' algorithm provides better training performance, with less number of epochs. The results show that the projected ANN algorithm can provide a good estimate of SOC even in the presence of sensor noise. In order to improve the life of EV battery, an Adaptive fuzzy controller is proposed for D.C charger module. In this technique the additional Ultra capacitor reduces the battery degradation. The average estimation errors of CNN based model under noise disturbance was aways less than 0.1.Hence, proving that the model has strong robustness. Further studies may add the influence of ageing to optimise the cell SOC estimation, under a variety of operating conditions.

Keywords: - State of Charge, Lithium Ion battery, Hybrid Electric Vehicles, Deep Learning algorithm, Adaptive fuzzy controller.

1. INTRODUCTION

In HEV, the State of Charge (SOC) is the amount of energy remaining in the battery compared to the total capacity. Estimation of SOC is crucial for the reason that the drivers can know how much range the vehicle can travel before the need to recharge. Constant discharging the battery to 0% and charging to 100% SOC will degrade the battery life. Therefore, the EMS should ensure that SOC is maintained between 20% and 80% for lithium-ion batteries. Similarly, overcharging can lead to safety risks, including the potential for fire or explosion. Properly managing SOC by the EMS helps prevent these dangerous scenarios [1,2].

The accurate estimation of SOC and SOH of batteries are critical and essential in EMS of EV and HEV. Akar *et al* [3] has formulated EMS for battery/ultra capacitor in hybrid energy storage systems in EV. A Convolution Gated Recurrent Unit (CNN-GRU) network was applied for the SOC estimation of lithium-ion batteries by Huang *et al.,* [4]..Deep-learning models used for SOC estimation because a battery management system has a time-varying and nonlinear. The CNN-GRU model was trained using

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

data collected from the battery-discharging processes, such as the dynamic stress test and the federal urban driving schedule.

Dickson How *et al.,* [5] has proposed a review for recent SOC estimation methods highlighting the model based and data-driven approaches. Model-based methods attempt to model the battery behavior incorporating various factors into complex mathematical equations in order to accurately estimate the SOC while the data driven methods adopt an approach of learning the battery's behavior by running complex algorithms with a large amount of measured battery data. Dickson How *et al.,* [6] applied Improved Deep Neural Network (IDNN) to estimate SOC for a Li-ion battery using an approach for EV applications. A IDNN with a sufficient number of hidden layers was capable of predicting the SOC of the unseen drive cycles. It has observed that increasing hidden layers in IDNN (up to 4 hidden layers) decreases the error rate and improves the SOC estimation.

A deep learning-based SOC prediction model was developed by Zhao *et al.,* [7] to ensure reliable vector representation and sufficient feature extraction. Improve the battery data representation using Recursive Neural Networks (RNNs). Then, a multi-channel extended Convolution Neural Network (CNNs) based method fed with the well-trained vector representation was proposed to accurately predict LIBs SOC. Liu *et al.,* [8] proposed a method to estimate the SOC of lithium-ion batteries with Temporal Convolution Network (TCN). The measured values of voltage, current, and temperature during the use of lithium-ion batteries has been directly mapped to accurate SOC in this method without using a battery model or adaptive filter. The network has self-learning and updates parameters. In addition, it has also applied to different types of lithium-ion batteries through transfer learning with only a small amount of battery data.

Wooyong Kim *et al.,* [9] has developed a robust SOC estimation scheme for lithium-ion batteries in commercialized EVs: pure electric vehicles and hybrid electric vehicles. Developed nonlinear-model-based robust SOC estimation method and comprehensive performance comparison with the pervious SOC estimation methods ware considered. A hybrid method (HM) based on threshold switching has been proposed by Jiliang Yi *et al.,* [10] to determine SOC. Here, apply the Extended Kalman Filter (EKF) and the Ampere Hour Integration (AHI) to SOC estimation and convergence speed. Initially, the parameters of the second-order RC equivalent model were identified using the least square. Then, the equation of EKF for updating the state variable was reconstructed by using the identified parameters to solve the problem of multiple iterations caused by the uncertainty of the initial value.

A multilayer network has been designed to estimate the charged state of lithium batteries by Xueguang Li *et al.,* [11]. Here, the three-layer artificial neural network has been increased into the eleven-layer artificial neural network. After preprocessing the dataset and comparing several activation functions, the ten-layer fully connected neural network was to estimate the SOC. A collaborative estimation algorithm for SOC and SOH has been presented by Chang-Qing Du *et al.,* [12] based on the thevenin equivalent circuit model, which combines the recursive least squares method with a forgetting factor and the extended Kalman filter. First, the parameter identification accuracy was studied under a Dynamic Stress Test (DST) and the Federal Urban Driving Schedule (FUDS) test at different ambient temperatures. Secondly, the FUDS test was used to verify the SOC estimation accuracy.

Muhammad Hamza Zafar *et al.,* [13] has proposed a hybrid multi-layer deep neural network (HMDNN) based approach for SOC estimation in EVs. This HMDNN uses Mountain Gazelle

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

Optimizer (MGO) as a training algorithm for the deep neural network. This approach leverages the intrinsic relationship between the SOC and the voltage/current measurements of the EV battery to accurately estimate the SOC in real time. A framework has been presented by Pooja Kumari *et al.,* [14] for SOC estimation that makes use of methodologies that involve machine learning (ML). Aside from providing the user with real-time feedback on the battery's remaining capacity, precise knowledge of SOC imposes further control over the charging/discharging process, hence elongating the battery's useful lifespan. Alkawak *et al.,* [15] has applied a hybrid technique for managing the energy management of a hybrid energy storage system. Here, battery and supercapacitor has been used for charging EV. The Namib Beetle Optimization (NBO) with neural network was used to charge the vehicle. SCSO and RERNN have been developed by Srinivasan *et al.,* [16] to optimize the distribution of energy in hybrid Energy Storage System in EVs.

2. SOLUTION METHODOLOGY

2.1 Need For SOC Estimation by Deep Learning methodology

A common way to express the SCO is in terms of percentage, where 100% is the battery's initial capacity. The capacity gradually decreases over time as a result of chemical and physical changes that take place inside the battery cells during charging and discharging cycles. The frequency of charging and discharging a battery has an impact on its general condition. Degradation might result from repeated cycles. Chemical processes accelerate more quickly at higher temperatures than at low temperature. Further, excessive discharge or overcharging of a battery can have negative effects on its health.

One of the primary responsibilities of battery management systems is to estimate SOC accurately, to extend battery life and enhances EV system performance. As a matter of fact, accurate SOC calculation helps shield batteries against unplanned outages and overcharging. Most of the charger modules perform fast charging in constant current mode, up to 57% of SOC, subsequently, the battery terminal voltage is kept constant (i.e., the constant voltage mode).

In order to increase the accuracy of SOC estimation, a lot of development and research work has been done recently. Determining the SOC of a battery is a complex operation, depending on the type of battery and application in which it is used. The SOC curve during charging or discharging happens to be a non-linear curve. Also, the resistance of the EV battery varies with temperature. For example, the LG 18650HG2 battery shown in Table.1 with 50 % SOC a drop in resistance of up to 60% can be seen with fall in temperature from -20 degree to 40 degree. For these reasons the use of Deep Learning (DL) has been used for the estimation of SOC.

Table 1 Lithium Ion battery rating LG 18650HG2

Type		Specification	Actual
Chemistry		Li [NiMnCo] O_2(H-MNC)/Graphite + Sio	
Dimensions(m)	Diameter	18.3+0.2/-0.3 mm	
	Height	65.00±0.2mm	
Weight(g)		Max.48	44~45
Initial IR(mΩ AC 1kHz)		Max.17	14~16
Initial IR(mΩ DC)		Max.30	24~26

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

Nominal voltage(V)		3.6
Charge method		Nominal:1.5A 4.2V 50mA End current(CC-CV)
		Fast:4A 4.2V,100mA End current(CC-CV)
Charge Time	Nominal(min)	165min
	Fast(min)	85min
Charge current	Nominal current(A)	1.25A
	Max. current(A)	4A
Discharge	End voltage(A)	2V
	Max. current(A)	20A(continued discharge current)
0.2C Capacity	Nominal(Ah)	3.0 Ah
Energy Density	Nominal(Wh/kg)	240

2.2 Deep Learning Network in SOC Estimation

Research and application of Deep Learning networks for SOC estimation in Battery Management Systems (BMS) are ongoing. To performance and guarantee safe and effective operation, it is crucial to maximize battery precisely estimate the SOC, a crucial metric in evaluating how much energy is left in a battery. Numerous Machine Learning (ML) techniques have been explored for SOH estimation. These encompass support vector machines, relevance machines, Gaussian process regression, and impedance spectroscopy-centric approaches Alcala *et al.,* (2005). On the other hand, SOC estimation techniques predominantly bifurcate into two main streams: recurrent and non-recurrent algorithms. While recurrent algorithms maintain a memory of prior data, non-recurrent ones solely rely on the information from the present time step.

Among the numerous ML methods, recurrent Long Short-Term Memory (LSTM) and non-recurrent Feed-Forward Neural Network (FNN) are best suited for SOC estimation. They have demonstrated promising results and favored as a potentially superior approaches compared to other ML techniques, as evidenced by the findings in Kim *et al.,* (1994). However, a notable research gap exists: there is a conspicuous absence of comprehensive studies that aims at reducing the number of iterations and the same is investigated in this chapter.

2.3 Proposed ADAM algorithm

The ADAM (Adaptive Moment Estimation) algorithm is a popular optimization algorithm used in training deep learning models. It combines the concepts from two other optimization algorithms: AdaGrad and RMSProp. The ADAM algorithm computes adaptive learning rates for each parameter by considering both the average of past gradients (first moment) and the average of past squared gradients (second moment). The implementation steps of ADAM algorithm is presented below,

- Initialize parameters θ (e.g., weights and biases).
- Initialize first moment vector m and second moment vector v for each parameter to zero.

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

- Compute the gradient g_t, using the current batch of data.
- The first moment estimate is updated using eqn.(1):

$$m_t = \beta_1 \times m_{t-1} + (1-\beta_1) \times g_t \qquad (1)$$

- Where, β_1 is the exponential decay rate (typically set close to 1, e.g., 0.9).
- The second moment estimate is updated using eqn. :

$$V_t = \beta_2 \times V_{t-1} + (1-\beta_2) \times g_t^2 \qquad (2)$$

Where, $\beta_2$is another exponential decay rate (e.g., 0.9).

- The bias in first and second moments is corrected using eqns. (3) and (4):

$$m_{t2} = (1-\beta_{2t2})^* \, m_t \qquad (3)$$
$$V_{t2} = (1-\beta_{2t2)} * V_t \qquad (4)$$

- The parameters are updated using eqn. (7.5):

$$\theta_t = \theta_{t-1} - \alpha 1^* \; m_t \, / \, \mathrm{sqrt} \, (V_{t2} + \epsilon) \qquad (5)$$

Where,
$\alpha 1$ ………is the learning rate
ϵ …………is a small constant to prevent division by zero. The parameters of the ADAM algorithm used in the simulation are given in Table 2.

Table 2 Parameters used in ADAM algorithm

S. No	Parameter	Value
1	Learning rate ($\alpha 1$)	0.001
2	Beta1 β_1	0.9
3	Beta 2 β_2	0.999
4	epsilon	1e-08

3. IMPLEMENTATION OF DEEP LEARNING NEURAL NETWORKS IN SOC

Li-ion battery stacks find extensive application in Hybrid Electric Vehicles (HEV), Electric Vehicles (EV), energy storage on the grid for grid stability, peak shaving, and time shifting of renewable energy, and storage of renewable energy for later use. This research takes into account the SOC experimental data of LG 18650HG2 Li-ion battery, and the same can also be extended for other battery models. The implementation sequence for SOC estimation is given in fig. 1.

- Current and voltage measurements from battery during cycles of charging and discharging are the inputs for estimating SOC. To improve the accuracy, other information like temperature, battery age, and other environmental parameters are added as inputs to the DL network.
- To guarantee that the DL model is trained successfully and has good generalization to previously unseen data, preprocessing techniques like feature scaling and normalizing are employed.
- To Model the dynamic behavior of batteries during charge and discharge cycles, some widely used architectures includes Recurrent Neural Networks (RNNs), Long Short-Term Memory

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

networks (LSTMs), and Gated Recurrent Units (GRUs). The Convolution Neural Networks (CNNs) is selected in this research due to its high computation speed.

- For training, a deep learning network model lot of labeled data is used. The behavior of the battery in various scenarios and charge levels is covered by this data base. This data creates a set of folders, the so called 'data store' in MATLAB.
- The Mean Squared Error (MSE) or loss functions are modified to meet the unique needs of SOC prediction. Perhaps, other measures like regression can also be used to measure the accuracy of DL. The MSE was used in this research as the termination condition in the training algorithm.

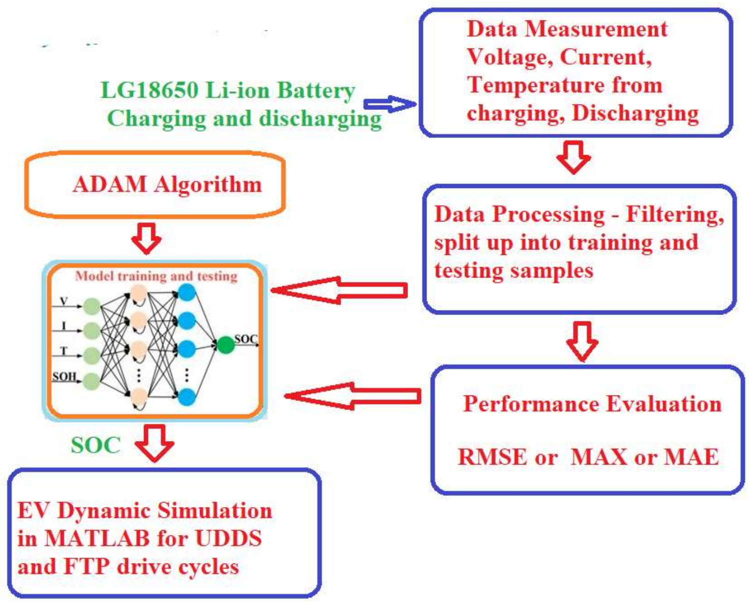

Fig. 1 Deep Learning for SOC estimation

In this study, a one-dimensional (1D) convolutional layer with ADAM algorithm was applied. In contrast to the typical two-dimensional (2D) Convolutional Neural Network (CNN) where kernels or filters span both spatial dimensions of an image (horizontally and vertically), the kernels in 1D-CNN layers operate in only one dimension, specifically the temporal dimension. This configuration allows them to capture information that is relevant in a temporal context. To enhance the temporal analysis, causal padding was applied before executing the filter operation. Causal padding is a distinctive type of padding commonly utilized in one-dimensional convolution layers, proving particularly advantageous in the analysis of time series data. Given that time series data entails sequential information, this padding technique involves the introduction of zeros at the beginning, facilitating the prediction of early time step values. The final estimated value of SOC is applied to the proposed CBO optimization algorithm.

4. RESULTS AND DISCUSSION

4.1 Training Performance Measures

The Root Mean Squared Error (RMSE) % is one of the performance indicators for a regression model. It measures the average difference between values predicted by a model and the actual values. Fig. 2 provides an estimation of how well the model is able to predict the target value, the accuracy for four different experimental repeats.

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

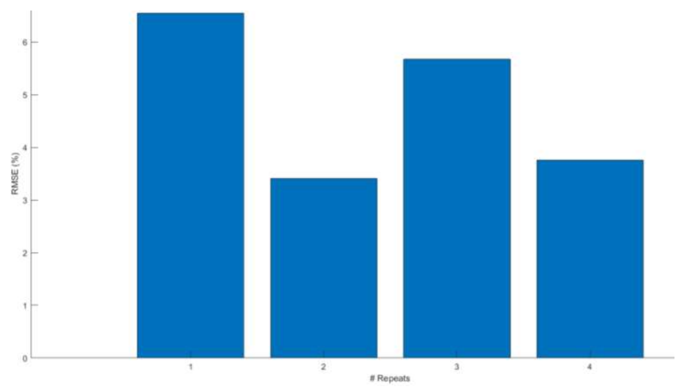

Fig. 2 Experimental RMSE % and experiment repeats for 1) -10 deg, 2) 0 deg, 3) 10 deg, 4) 25 deg

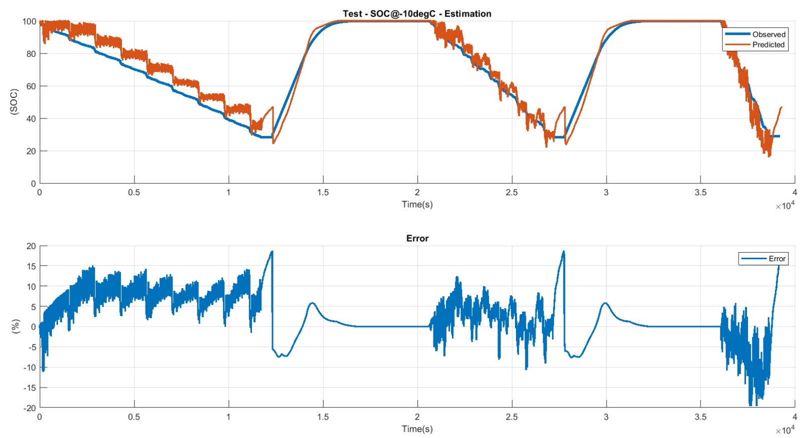

Fig. 3 SOC Observed and Predicted by DL for T= -10 degree C

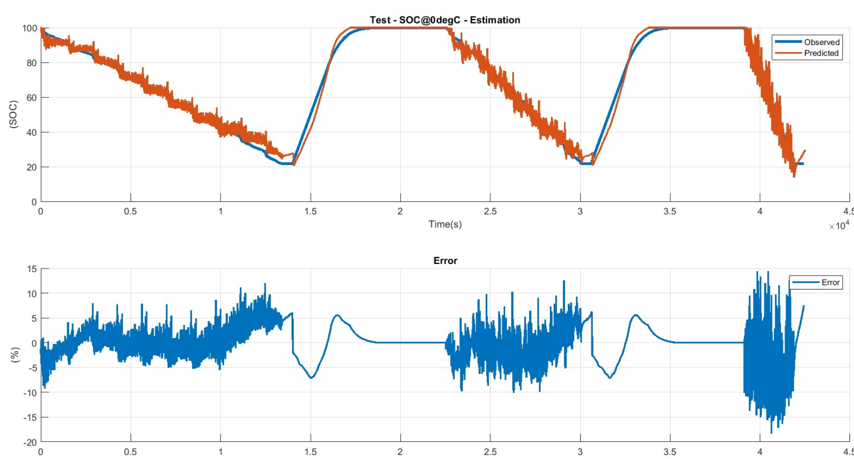

Fig. 4 SOC Observed and Predicted by DL for T= 0 degree C

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

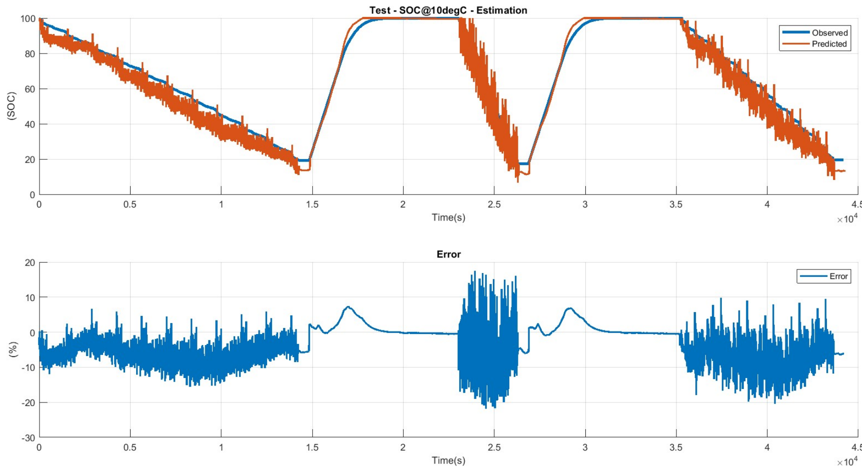

Fig. 5 SOC Observed and Predicted by DL for T= 10 degree C

From fig. 3 to 6 it can be seen that there is good match between observed SOC and the predicted values. These error plots confirm that the DL algorithm is suitable for SOC estimation in batteries used in EV. Further from fig. 7 it's seen that the training curve is smooth, and convergence is reached at 30 iterations.

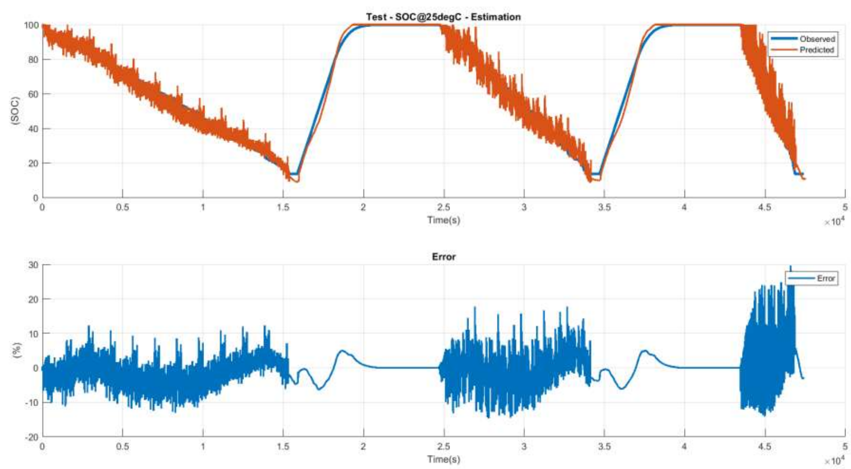

Fig. 6 SOC Observed and Predicted by DL for T= 25 degree C

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

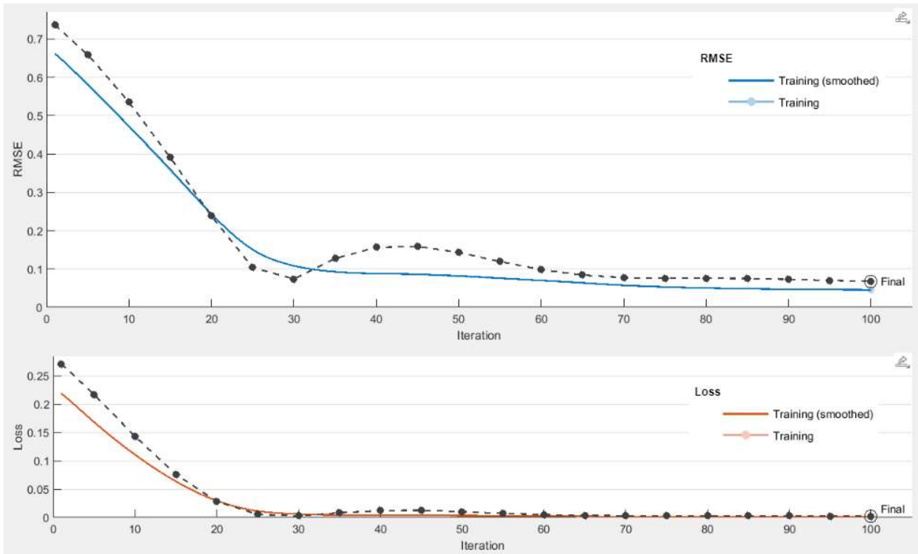

Fig. 7 Training Performance of Feed-Forward Neural Network

In this research the MATLAB network analysis tool was used to select between various network architectures. The parameters of selected DL network are given in table 3 and the network structure is given in fig. 10. From the comparison table and above presented results it's obvious that the projected algorithm with CNN provides a smaller number of iterations compared to FNN.

4.2 Training with Sensor Noise Added Data

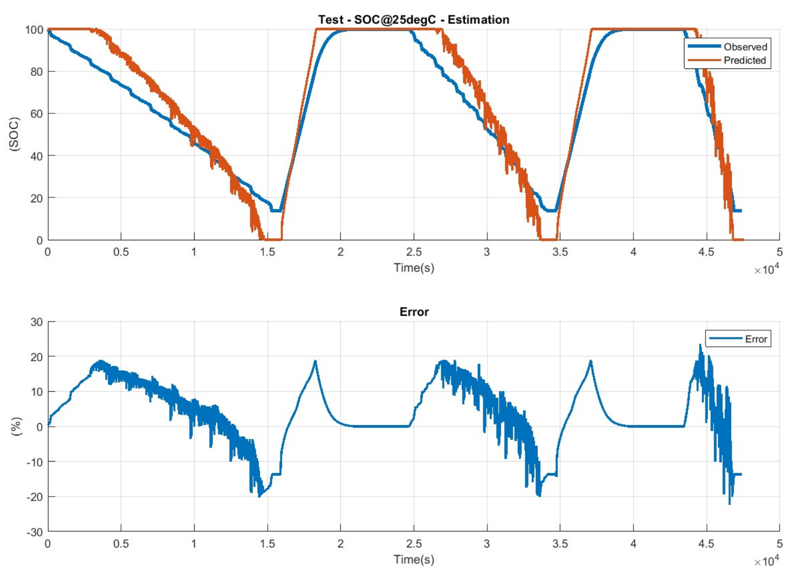

Fig. 8 SOC Observed and Predicted with noise for T= 25 degree C

CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

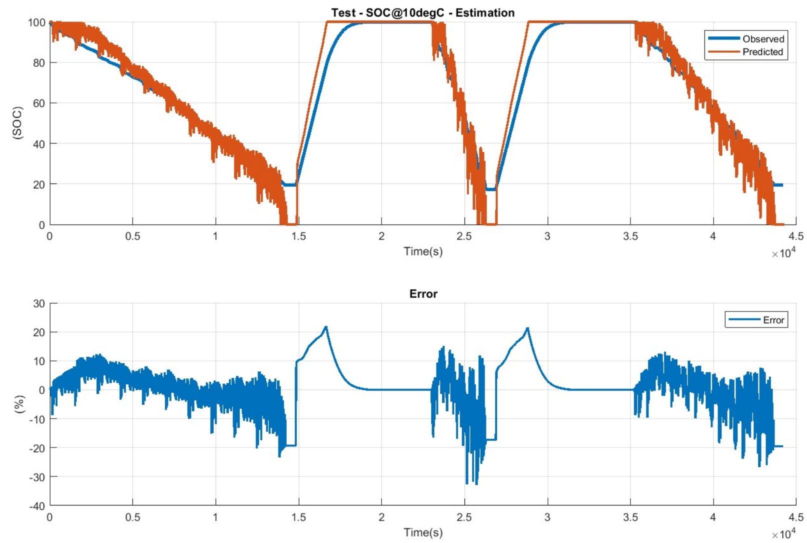

Fig. 9 SOC Observed and Predicted with noise for T= 10 degree C

The training of deep learning models often involves dealing with various real-world challenges, including sensor noise. Sensor noise can adversely affect the performance and generalization of a model, as it introduces variability and uncertainties into the training data. To address this issue in this research random noise patterns were added to the real-world training data. Then the performance of the ADAM training algorithm was tested and is shown in fig. 7.8 and fig. 7.9. It's observed that the algorithm provides perfect estimation of SOC even in the presence of sensor noise.

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

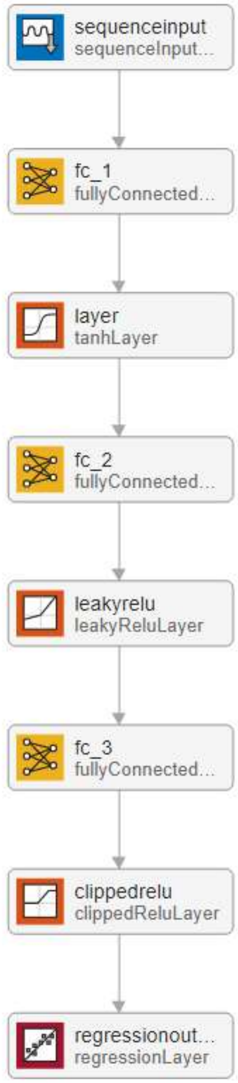

Fig. 10 CNN architecture used in SOC estimation

The various layers incorporated might affect the network design. The specific application or data determines the kinds and number of layers that are included. Regression networks, for instance, always need a regression layer at the end of the network, but classification networks usually comprise both a Softmax layer and a classification layer. For example, in an image classification task a limited amount of grayscale image data, a smaller network with just one or two convolution layers might be adequate for learning.

Table 3 DL Network parameter comparison

Parameters	**Feed Forward Network**	**CNN**
Algorithm	Back Propagation	ADAM
Number of Neurons in Input Layer	10	10

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

Number of Neurons in Output layer	1	1
Number of Hidden Layers Neurons	40	55
Learning Rate	0.01	0.01
Activation Function (hidden)	tan sigmoid	tan sigmoid
Activation Function (output)	Linear	Linear
Maximum Epochs	150	50

Because of increased competition in the EV industry, and technological breakthroughs, the cost of batteries has significantly decreased during the last ten years. It is important to remember that, although though an EV may initially cost more than a conventional ICE vehicle, the total cost of ownership; which accounts for maintenance costs, fuel savings and other factors. Now, the cost of batteries is a significant factor influencing the overall price and adoption of EVs. Most battery manufacturers typically provide a warranty period ranging from five to eight years for their battery packs. Therefore, to achieve extended life of battery, degradation issues need to be solved and the same is discussed below

5. CONCLUSION

This chapter discusses the SOC of the battery unit. Effective deep learning approaches of FNN and CNN were considered for estimation of SOC and SOH of the proposed battery. Proposed work considering real time data set has been trained for the estimation of SOC with different conditions. The applied methodology of CNN with ADAM ‘has been provide better training performance, The rout comes of the implemented ANN algorithm can provide a good estimate of SOC even in the presence of sensor noise. Fuzzy logic controller has been applied to improve the life of EV battery.Finaly, the estimated battery unit interconnected with HEVs and determine the fuelconsupton with differentdriving cycles. The CBO algorithm has been applied to minimize the fuel economy of HEVs.

References

[1] Erdoğan, H., and Özdemir, M., (2017), Neural network approach on loss minimization control of a PMSM with core resistance estimation, *Turkish Journal of Electrical Engineering and Computer Sciences*, Vol.25(3), pp.1643-1656..

[2] Falcão, E. A. M., Teixeira, A. C. R., and Sodré, J. R., (2019), Analysis of CO2 emissions and techno-economic feasibility of an electric commercial vehicle, *Applied energy*, Vol.193, pp.297-307.

[3] Akar, F., Tavlasoglu, Y., and Vural, B., (2016), An energy management strategy for a concept battery/ultracapacitor electric vehicle with improved battery life, *IEEE Transactions on Transportation Electrification*, Vol.3(1), pp.191-200.

[4] Huang, Z., Yang, F., Xu, F., Song, X., and Tsui, K. L., (2019), Convolutional gated recurrent unit–recurrent neural network for state-of-charge estimation of lithium-ion batteries, *IEEE Access*, Vol.7, pp.93139-93149.

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

[5] Dickson How, D. N., Hannan, M. A., Lipu, M. H., and Ker, P. J., (2019), State of charge estimation for lithium-ion batteries using model-based and data-driven methods: A review, *IEEE Access*, Vol.7, pp.136116-136136

[6] Dickson How. N., Hannan, M. A., Lipu, M. S. H., Sahari, K. S., Ker, P. J., and Muttaqi, K. M., (2020), State-of-charge estimation of li-ion battery in electric vehicles: A deep neural network approach, *IEEE Transactions on Industry Applications*, Vol.56(5), pp.5565-5574.

[7] Zhao, F., Li, Y., Wang, X., Bai, L., and Liu, T., (2020), Lithium-ion batteries state of charge prediction of electric vehicles using RNNs-CNNs neural networks, *IEEE Access*, Vol.8, pp.98168-98180.

[8] Liu, Y., Li, J., Zhang, G., Hua, B., and Xiong, N., (2021), State of charge estimation of lithium-ion batteries based on temporal convolutional network and transfer learning, *IEEE Access*, Vol.9, pp.34177-34187

[9] Wooyong Kim, W., Lee, P. Y., Kim, J., and Kim, K. S., (2021), A robust state of charge estimation approach based on nonlinear battery cell model for lithium-ion batteries in electric vehicles, *IEEE Transactions on Vehicular Technology*, Vol.70(6), pp.5638-5647.

[10] Chang-Qing Du, C. Q., Shao, J. B., Wu, D. M., Ren, Z., Wu, Z. Y., and Ren, W. Q., (2022), Research on co-estimation algorithm of SOC and SOH for lithium-ion batteries in electric vehicles, *Electronics*, Vol.11(2), pp.181-196.

[11] Jiliang Yi, J., Zhou, X., Zhang, J., and Li, Z., (2021), A hybrid method for SOC estimation of power battery, *Journal of Control Science and Engineering*, Vol.2021, PP.1-8.

[12] Xueguang Li, X., Jiang, H., Guo, S., Xu, J., Li, M., Liu, X., and Zhang, X., (2022), SOC Estimation of Lithium-Ion Battery for Electric Vehicle Based on Deep Multilayer Perceptron, *Computational Intelligence and Neuroscience*, Vol.2022.

[13] Muhammad Hamza Zafar, .Mansoor, M., Abou Houran, M., Khan, N. M., Khan, K., Moosavi, S. K. R., and Sanfilippo, F., (2023), Hybrid deep learning model for efficient state of charge estimation of Li-ion batteries in electric vehicles, *Energy*, Vol.282, pp.128317-128331

[14] Pooja Kumari, Singh, A. K., and Kumar, N., (2023), Electric Vehicle Battery State-of-Charge Estimation Based on Optimized Deep Learning Strategy with Varying Temperature at different C Rate, *Journal of Engineering Research*, Vol.11(3), pp.158-163.

[15] AlKawak, O. A., Kumar, J. R. R., Daniel, S. S., and Reddy, C. V. K., (2024). Hybrid method based energy management of electric vehicles using battery-super capacitor energy storage, *Journal of Energy Storage*, Vol.77, pp.109835.

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

[16] Srinivasan, C., (2024), Energy management of hybrid energy storage system in electric vehicle based on hybrid SCSO-RERNN approach, *Journal of Energy Storage*, Vol.78, pp.109733.