SOC estimation in Electric Vehicles using optimized Deep Neural Networks with high-accuracy and computationally efficient approach

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Abstract.

The effectiveness and reliability of Li-ion batteries relies on an exact assessment of the state of charge (SOC). Traditional SOC estimating approaches have difficulties due to battery age, temperature changes and nonlinearity. This study introduces an improved deep neural network (DNN) oriented SOC estimate model that generates high-accuracy predictions using battery data which includes terminal voltage, load current, and temperature. The model is trained using Adam optimizer and is tested at various temperatures and drive cycles. A two-layer DNN results in the highest performance, with low root mean square of 1.47% and mean absolute error of 1.27%, outperforming other existing approaches. The proposed approach is computationally efficient, applicable across datasets, and robust under a variety of operating conditions, making it a popular choice for real-time Electric Vehicle (EV) battery management systems (BMS).

Keywords. battery management systems, electric vehicle, deep neural network, adam optimizer, hyperparameters

1. INTRODUCTION

EVs are sustainable alternatives for using fossil fuels for transportation which reduces greenhouse gas emissions. EVs are liable for combating climate changes because they generally encourage a clean usage of energy [1]. A battery pack forms the core component of an EV, mainly a Li-ion battery, which offers high energy density, long lifetime and high efficiency. The effective BMS helps to avoid over-charging and over-discharging of battery by ensuring safety and performance [2]. One of the vital indicators of the BMS is SOC, which stands for remaining capacity in the battery. A traditional book-keeping method involves coulomb counting and open circuit voltage method that uses measurements of current flow or resting voltages and suffers from cumulative errors [3]. Filter-based methods include Kalman filter and its advanced forms such as Extended, Adaptive, and Unscented Kalman filters which improves the accurateness of SOC by minimizing errors and adapting to nonlinearities. Model-based techniques that offer more accurate estimations based on physical phenomena in batteries, such as impedance and chemical characteristics, including electrochemical methods, equivalent circuit model and electrochemical impedance spectroscopy [4]. On the other hand, data-driven methods predict SOC from large datasets using various machine learning simulations such as recurrent neural networks, DNN, fuzzy logic and support vector machine. To provide reliable energy storage systems and battery management for EVs, each approach balances accuracy, computational complexity and real-time applicability [5].

The ability to manage nonlinearities and store complex correlations, DNNs are perfect for BMS in EVs. Despite its potential, research on DNN-based SOC estimates is still in its beginnings, and there are still a lot of variations to be examined. As computational power and data availability improve, DNNs are expected to establish itself as the major technology for enhancing SOC estimation, optimizing battery performance, and expanding energy storage systems [6]. The key contribution of the paper includes:

- An optimized DNN-based model that precisely predicts the SOC of Li-ion batteries trained on voltage, current, and temperature using adaptive tuning of hyperparameters.
- Analysing the impact of temperature variations and testing the model on real world drive cycles for different conditions.
- The performance analysis of evaluation metrics such as RMSE, MAE and MAX across different neural network layer configurations by identifying the best optimized parameters.
- The proposed model outperforms with high accuracy and computational power when compared to state of art techniques.

2. THE PROPOSED OPTIMIZED DEEP NEURAL NETWORK

The three layers of optimized DNN are input, hidden and output layers. The activation function is employed to accurately express nonlinearity in the DNN. DNNs are predicted to become the primary technology for improving SOC estimation, enhancing battery performance, and expanding energy storage systems as processing power and data availability rise. The model is trained using the Adam optimizer, which ensures effective weight updates as well as excellent estimation accuracy in real-world driving scenarios. Figure 2.1 depicts the process of developing the proposed optimal DNN model.

2.1. Dataset and drive cycles

The publicly available battery dataset for this study uses highway fuel economy driving schedule, supplemental federal test procedure, urban dynamometer driving schedule and unified cycle driving schedule drive cycles at four different temperatures: 0°, 10°, 25°, and -10° degrees. These various drive cycles replicate actual driving behaviours and enable a comprehensive assessment of SOC estimate performance. The study guarantees the DNN model's resilience, adaptability, and generalization in a variety of operational scenarios by training it on this dataset, which makes it appropriate for real-time BMS in EVs.

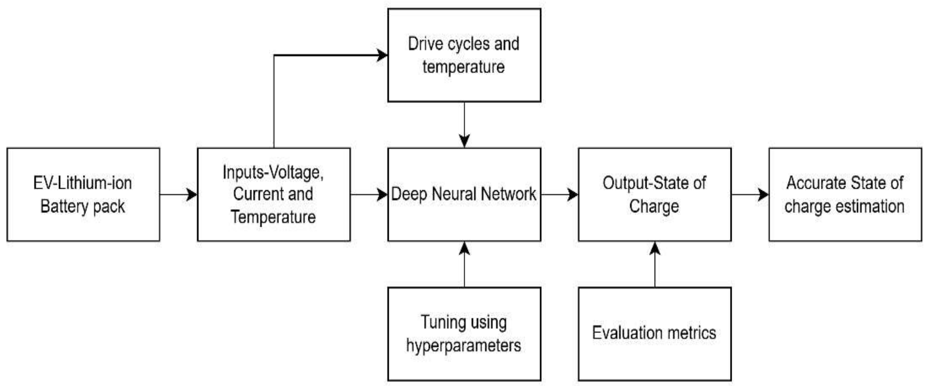

Figure 2.15. The procedure of estimating SOC using the proposed optimized DNN model.

2.2. Tuning of hyperparameters

DNNs use a variety of hyperparameters to maximize their learning and performance. The quantity of hidden neurons influences the sample's ability to learn patterns; an excessive number may result in overfitting, while a minimal number may cause underfitting. The quantity of hidden layers influences the network's ability to capture hierarchical characteristics; deeper networks are more expressive, but more computationally expensive. The speed at which weights update is determined by the learning rate in which high value causes instability and low value prevents convergence. Avoiding disappearing or exploding gradients is made easier with proper neuron initialization. Weights are efficiently changed by optimization techniques such as SGDM, RMSprop and Adam to minimize the error function. The proposed Adam optimizer, which dynamically adjusts the learning rate for each parameter, is widely used in the industry because it prevents divergence, accelerates convergence and is more effective. Nonlinear activation functions such as ReLU, sigmoid, and tanh allow the network to learn complicated patterns that go beyond basic correlations. To optimize DNN performance, some hyperparameters must be modified. The appropriate hyperparameters for the proposed DNN model are discovered by training and analysing a dataset with varying numbers of hidden layers and temperatures.

2.3. Performance Evaluation

Model performance is frequently measured and optimized using RMSE, MAE, and MAX. Significant errors greatly affect RMSE, which calculates square root of deviations of mean squared between expected and actual values. By computing average absolute differences, MAE produces a balanced error metric that is less susceptible to outliers. Activation functions frequently use the MAX function to measure worst-case errors and compute loss to ensure stability in harsh circumstances.

3. Simulation Results And Discussions

Battery charge and discharge cycles obtained from cylindrical Li-ion INR 18650 batteries under various operating circumstances were used to train the model. The training and testing were done to one-seven layers for 50 neurons each with activation functions like tanh and ReLU alternately. The model was trained for the 50 epochs and validated through the RMSE, MAE, and MAX error metrics. The trained model was then validated under several drive cycles to ensure SOC estimation operation reliability. The RMSE and number of hidden layers at various temperatures is illustrated in Figure 3.1. The MAE against one to seven hidden layers at various temperature are plotted in Figure 3.2.

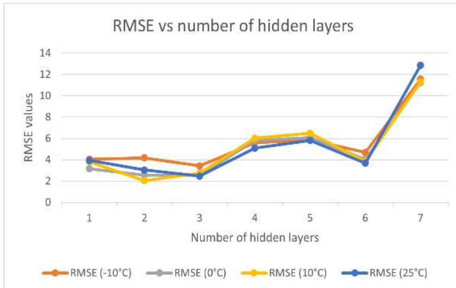

Figure 3.1 RMSE vs number of hidden layers

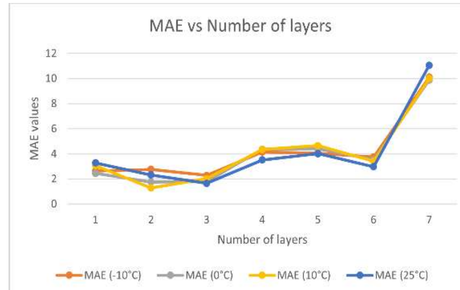

Figure 3.2 MAE vs number of hidden layers

The two hidden layers performed well, especially at 10°degree with RMSE of 2.0488 and MAE of 1.2858. The best results are observed with three hidden layers, where RMSE of 2.5628 and MAE of 1.7991 values are generally the lowest at 0°degree. At extreme temperatures such as -10° and 25°degree, RMSE and MAE values increase, indicating less accurate predictions.

4. Conclusion

SOC estimation model was performed on a variety of neural network architectures by changing the number of layers from one to seven under various temperatures such as 0°, 10°, 25°, and -10°degrees to determine the suitable model structure that is most accurate and yet computationally light. The two or three hidden layers offer the best balance of accuracy and execution time. More than four layers do not considerably enhance accuracy but contribute to higher error and longer execution times. A two-layer DNN outperforms other techniques, with a low RMSE of 1.47% and MAE of 1.27% is the appropriate neural network architecture for real-time SOC estimation in BMS. Future research can also investigate more sophisticated architectures, including hybrid and recurrent neural networks, to further improve estimation accuracy, particularly under extreme temperatures.

5. References

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Biographies

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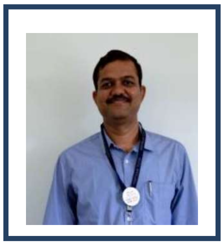

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