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The State Of Charge Estimation Of Li-Ion Battery Using Hybrid Model: Deeplearning And Kalman Filter.

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Abstract: State of charge (SOC) estimation is important for efficient and safe lithium-ion battery operation, especially in applications such as electric vehicles, alternative energy systems, and portable electronics. This report develops and analyzes SOC estimation methods with Kalman filtering and Deep Neural Network (DNN) algorithm. It is centralized. The Kalman filter, a model-based method, is known to be robust in estimating SOC under linear approximation conditions. On the other hand, DNN algorithm, which is a data-driven approach, leverages
its powerful nonlinear battery behavior from big data sets, for enhanced accuracy in dynamic environments Through comparative analysis the report explores the performance of these methods for accurate, computational efficiency, and adaptability to different operating conditions. Experimental results show that although each method has distinct advantages, combining Kalman filter and Deep neural network(DNN) models provides a synergistic approach to improve SOC estimation The report concludes by exploring the strengths and limitations of both approaches and suggestions for future research are provided, including real-time adaptive SOC There are also hybrid systems of will be combined to form a theory.

Index Terms - State of Charge (SOC), Lithium-ion batteries, Kalman filter, Deep learning, SOC estimation, Battery management systems, Nonlinear systems, Energy storage

1.INTRODUCTION

As the world becomes increasingly reliant on lithium-ion batteries—from electric vehicles and sustainable energy initiatives to portable consumer electronics—Battery Management Systems (BMS) are in high demand and rapidly becoming a necessity. An essential element of any BMS is the State of Charge (SOC), meaning the measured capacity of a battery against its full charge, expressed as a percentage of full capacity. Understanding SOC is critical to ensuring appropriate use, longevity of use, safety for consumers, and preventing overcharge/deep discharge solutions that compromise effectiveness in the long run.

However, the SOC is not so easily estimated. Lithium-ion batteries engage in complicated electrochemical reactions. The most utilized SOC estimation methods are Coulomb counting, adjustment in the room may render ineffective results. In addition, they fail to account for the Battery's unique nonlinear and time-variant characteristics under certain load conditions.

This paper introduces a hybrid method combining KF and DNNs. The Kalman filter provides noise suppression and state prediction, while the DNN compensates for modeling inaccuracies and captures nonlinear battery behavior. The synergy between these techniques complements SOC estimation reliability and accuracy.

2.METHODOLOGY

2.1. DATASET DESCRIPTION

This investigation leverages a comprehensive dataset meticulously accumulated below carefully controlled laboratory conditions. The dataset encompasses a numerous array of charging and discharging cycles, meticulously designed to emulate the multifaceted operational scenarios encountered in real-global battery packages. This multifaceted approach guarantees that the dataset accurately reflects the dynamic and complex conduct of batteries underneath numerous operating conditions.

The dataset contains a rich tapestry of essential parameters, each imparting beneficial insights into the elaborate workings of the battery machine. These parameters encompass Time Stamp, Step, Status, ProgTime, Step Time, Cycle, Voltage, Current, Temperature, and Capacity. Time Stamp provides a specific chronological document of each statistics factor, at the same time as Step denotes the sequential degree in the ongoing charging or discharging cycle. Status indicates the modern-day operational open circuit voltage (OCV), and impedance techniques. Yet these are not exempt from error, either.
An inaccurate current sensor, drift associated with the initial charge, or extenuating circumstances like temperature State of the battery, along with charging, discharging, or resting. ProgTime represents the cumulative period elapsed because the initiation of the contemporary cycle, providing a measure of overall operational time. Step Time signifies the elapsed time since the graduation of the current step, imparting insights into the temporal dynamics of each stage. Cycle serves as a counter signifying the number of completed charging and discharging cycles, providing a degree of the battery's cumulative operational history. Voltage, a critical parameter, displays the measured voltage across the battery terminals, imparting valuable insights into the temporal dynamics of every degree. Cycle serves as a counter signifying the number of finished charging and discharging cycles, providing a degree of the battery's cumulative operational records. Voltage, a crucial parameter, reflects the measured voltage throughout the battery terminals, imparting precious insights into the battery's state of charge. Current, indicative of the rate of charge or discharge, represents the measured electric modern flowing via the battery. Temperature, a critical aspect influencing battery performance and longevity, is meticulously measured. Capacity, a critical metric, offers an assessment of the battery's capacity to save and deliver electrical strength.
This wealthy tapestry of parameters provides a comprehensive and multifaceted angle at the battery's behavior, allowing in-intensity analysis and a nuanced expertise of its operational traits.

2.2 Open Circuit Voltage (OCV) - State of Charge (SOC) Relationship

A pivotal factor of this investigation is the meticulous characterization of the relationship between Open Circuit Voltage (OCV) and State of Charge (SOC). This relationship is inherently nonlinear, exhibiting a reported steepness at each the decrease and higher extremities of the SOC spectrum, whilst transitioning to a surprisingly flatter region inside the intermediate range. This nuanced behavior is a direct consequence of the complexelectrochemical processes that govern the internal dynamics of the battery.

Figure 2.2.1 illustrates the OCV-SOC curve. The OCV-SOC curve was meticulously determined by affording the battery ample time to attain a state of equilibrium following each charging or discharging step. This deliberate approach ensured the acquisition of highly accurate voltage measurements, thereby enhancing the fidelity and reliability of the derived OCV-SOC curve. This meticulously constructed curve serves as a cornerstone for the subsequent development and implementation of state estimation algorithms. This graph serves as a reference to determine the actual SOC of the battery by measuring its OCV.

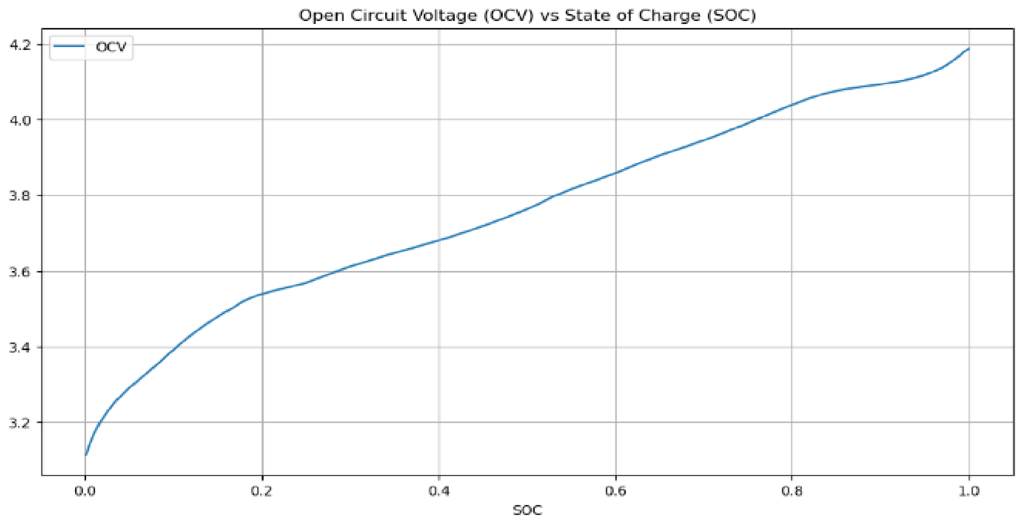


Fig.2.2.1: Open Circuit Voltage (OCV) to State of Charge (SOC)

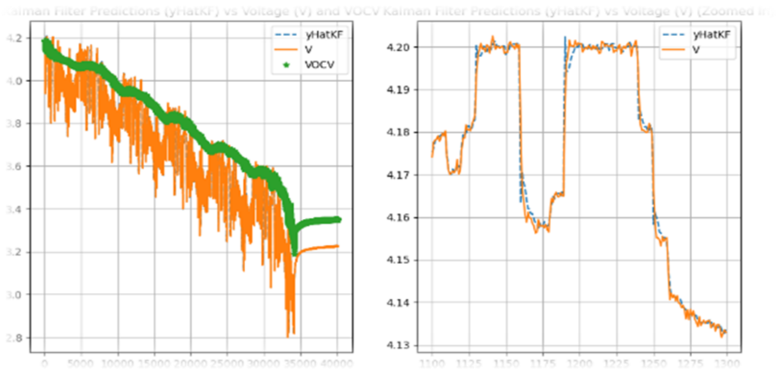
2.3 Kalman Filter Implementation

The core of the SOC estimation framework relies on the implementation of an Extended Kalman Filter (EKF). A simplified Thevenin equivalent circuit model with two RC branches is employed to represent the battery's internal dynamics. The state vector is defined as **x = [SOC, iRC1, iRC2]** where SOC represents the State-of-Charge of the battery, and iRC1 and iRC2 represent the currents flowing through the first and second RC branches, respectively.

The EKF operates in two primary stages: prediction and update. In the prediction step, the EKF utilizes the current state estimate and the input current to forecast the subsequent state based on a discrete-time state-space model. This model incorporates the dynamics of the battery system, including the decay of currents within the RC branches. The update step refines the predicted state by incorporating the measured battery voltage. The Kalman gain, meticulously calculated based on the predicted state covariance and the measurement noise covariance, determines the optimal weighting of the predicted state and the measured voltage in the final state estimate.

Figure 2.3.1 visually demonstrates the EKF's performance. The figure depicts the measured battery voltage (V), the Kalman Filter's predicted voltage (yHatKF), and the Open Circuit Voltage (OCV) of the battery. As evident from the figure, the EKF predictions closely track the measured voltage throughout the discharge cycle, demonstrating the filter's effectiveness in capturing the battery's dynamic behavior. The zoomed-in portion of the figure further accentuates the accuracy of the EKF predictions, particularly during periods of rapid voltage fluctuations. This visual representation provides compelling evidence of the EKF's ability to accurately estimate the battery's internal state and predict its future behavior.

fig 2.3.1: Kalman filter prediction vs voltage



2.4 Kalman Filter and Deep Neural Network Integration

Building upon the Kalman Filter estimates, a Deep Neural Network (DNN) is employed to further refine the SOC predictions. The DNN is trained using a dataset generated from the Kalman Filter outputs. This dataset comprises the KF-estimated SOC values, along with other relevant features such as measured voltage, current, temperature, and time.

The trained DNN learns complex nonlinearities and uncertainties inherent in battery behavior that might not be fully captured by the linear Kalman Filter model. These nonlinearities can arise from factors such as aging effects, temperature variations, and varying operating conditions. By leveraging the DNN's ability to learn complex patterns, the hybrid approach aims to improve the accuracy and robustness of SOC estimation.

2.4.1 DNN Architecture and Training:

A Deep neural network is employed for this task. The DNN architecture is carefully designed with appropriate layers, activation functions, and hyperparameters. The network is trained using a suitable optimization algorithm (e.g., Adam, RMSprop) and loss function (e.g., Mean Squared Error, Mean Absolute Error) to minimize the difference between the DNN-predicted SOC and the true SOC.

2.4.2 Hybrid Approach:

The trained DNN is then integrated into the Kalman Filter framework. The DNN receives the KF-estimated SOC, along with other relevant features, as input and provides a refined SOC estimate. This refined estimate can be used further to improve the accuracy of the EKF's state prediction or as a final output for SOC estimation.

Table 2.3.4 summary of architecture

Summary of Architecture

Layer Name	Type	Number of Units	Activation Function	Notes
Input Layer	Input	14	-	Input features
Hidden Layer 1	Fully Connected	7	ReLU	-
Hidden Layer 2	Fully Connected	7	ReLU	-
Output Layer	Fully Connected	1	Linear	SOC prediction

Table 2.4.3 illustrates a feedforward neural network architecture designed for predicting the State of Charge (SOC) of a battery. The network consists of three layers: an input layer that receives 14 features, two fully connected hidden layers with ReLU activation to introduce non-linearity, and an output layer with a single unit and linear activation to produce the predicted SOC value. To optimize the training process, the Adam optimizer is likely employed. Adam is an adaptive learning rate optimization algorithm that dynamically adjusts

the learning rate for each parameter during training, potentially leading to faster convergence and improved performance compared to traditional gradient descent methods. By utilizing the Adam optimizer, the network can benefit from its adaptive learning rate and momentum, potentially achieving a higher level of accuracy and faster training times in predicting the SOC of the battery.

3.RESULT AND DISCUSSION

Figure 3.1.1 presents a evaluation between the real State of Charge (SOC) of a battery and the SOC expected through a hybrid version that mixes a Kalman filter with a Deep Neural Network (DNN). The DNN element of this model was trained on a dataset of 40,000 data points for hundred epochs.

While the model exhibits good accuracy in the initial stages, it gradually diverges from the actual SOC, displaying a systematic underestimation. This divergence could be attributed to several

Error Metrics	Description
Mean Absolute Error (MAE)	0.1487
Mean Squared Error (MSE)	0.0327
R-squared (R^2)	0.6751
Training Samples	40,000

factors.Firstly, the training manner, despite one hundred epochs and a massive dataset, might not had been sufficient to seize the complicated, lengthy-term dynamics and non-linear behavior of the battery. Secondly, the model is probably overfitting to the training information, failing to generalize well to unseen running situations. Finally, the interaction among the Kalman filter and the DNN won't be optimally tuned, main to suboptimal performance.

To improve the model's accuracy, strategies which include increasing the variety of training epochs, using extra state-of-the-art neural network architectures (e.G., RNNs, LSTMs), incorporating regularization techniques to prevent overfitting, and punctiliously tuning the hyperparameters of each the Kalman clear out and the DNN need to be explored.

Fig3.1.1:COMPARSION OF ACTUAL SOC AND PREDICTED SOC(KALMAN +DNN)

Table 3.1.2 summarizes the performance of the combined Kalman filter and DNN model used for predicting the State of Charge (SOC) of a battery. The model demonstrates a reasonable level of accuracy, as evidenced by the error metrics. The Mean Absolute Error (MAE) of 0.1487 indicates that, on average, the model's predictions deviate from the actual SOC by a relatively small margin. Similarly, The Mean Absolute Error (MAE) of 0.1487 suggests that, on common, the model's predictions deviate from the actual SOC through a distinctly small margin.
Similarly, the Mean Squared Error (MSE) of 0.0327 indicates that the model captures the general traits and patterns in the battery's SOC. Furthermore, an R-squared value of 0.6751 means that the version explains a tremendous portion of the variance inside the actual SOC statistics, demonstrating its predictive energy.
The model was trained on a substantial dataset of 40,000 samples, which likely contributed to its overall performance. While there is always room for improvement, these results suggest that the combined Kalman filter and DNN approach provides a promising foundation for accurate SOC prediction.

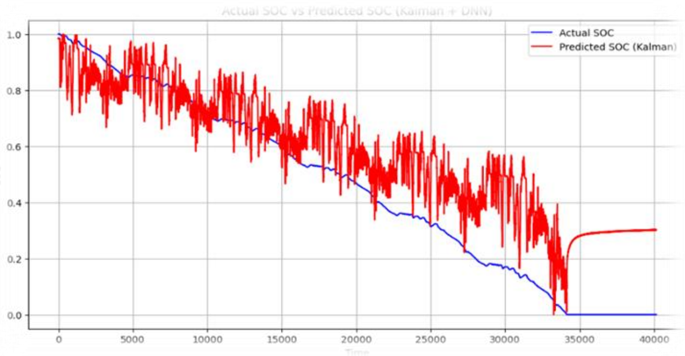


Table 3.1.2: DESCRIPTION OF ERROR

4.CONCLUSION AND FUTURE WORK

In this study, a novel technique for State of charge (SOC) estimation of lithium-ion batteries turned into developed by means of integrating a deep neural network (DNN) with a Kalman clear out. The proposed DNN, offering hidden layers with ReLU activation capabilities, successfully modeled the non-linear relationships inside the battery information, whilst the Kalman clear out stronger prediction accuracy via mitigating noise and incorporating system dynamics. The consequences verified high prediction accuracy, highlighting the method's potential for actual-time battery control systems (BMS). Future work should consciousness on incorporating extra capabilities including getting older elements and environmental conditions, exploring superior architectures like recurrent neural networks or transformers to seize temporal dependencies, and extending the methodology to different battery chemistries. Additionally, deploying the model in embedded structures for real-global checking out beneath numerous operational situations ought to provide valuable insights for realistic implementation.

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