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COMBINING AN ARTIFICIAL NEURAL NETWORK WITH THE EXTENDED KALMAN FILTER TO PREDICT THE STATE OF CHARGE OF A BATTERY

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ABSTRACT
Assessing the state of charge (SOC) in battery management systems (BMS) is essential for extending battery lifespan and guaranteeing dependable performance, with a particular focus on SOC prediction techniques for lithium-ion batteries. This paper examines two approaches for determining the SOC in batteries: Artificial Neural Networks (ANN) and the Extended Kalman Filter (EKF). The EKF is a modification of the regular Kalam Filter that is intended to deal with nonlinear systems. A non-linear optimal estimator utilizes a state-space model to predict and update the internal state of a non-linear dynamic system. ANNs are effective computational models that imitate the neural networks of the brain to complete tasks such as identifying patterns, making predictions, and performing classifications. ANN is made up of artificial neurons connected to mimic natural neural systems, and it is employed to predict the outputs of dynamic systems using past data. Different battery systems and conditions were assessed on a Li-ion cell to collect data for assessing those techniques. The suggested BMS is a major advancement in the electric vehicle battery management industry. The combination of ANN and EKF provides a reliable, efficient, and economical method for controlling EV battery cells. The results are evaluated and shown in a MATLAB Simulink model.

Keywords:
Battery management system (BMS), State of charge (SOC), Artificial Neural Network (ANN), and Extended Kalman Filter (EKF).

I. Introduction
The battery management system is vital in current battery systems, especially in rechargeable battery packs for electric automobiles, sustainable energy storage, and mobile electronics. The main roles of a BMS consist of monitoring, balancing, protection, state estimation, and thermal management. Overall, the BMS is essential for ensuring the protection, efficiency, and lifespan of battery systems. SOC is an important factor in BMS to monitor and manage battery performance, ensuring that the battery functions within safe parameters and is used efficiently. precise SOC prediction is essential for assessing the remaining charge available in the battery. In soc estimation, there are two main categories for State of Charge (SoC) estimation methods: direct method and indirect method. direct methods measure a physical property that correlates with SOC, such as open-circuit voltage or impedance and coulomb counting method. the open circuit method evaluates the SOC by analyzing the battery voltage without any load or during charging, based on the connection between a battery's open circuit voltage and its predicted SOC. The process of Coulomb counting also referred to as the current integration method, is utilized for determining the SOC of a battery. It can provide SOC updates in real-time through current measurements and is usually precise. This technique is straight forward and uncomplicated to carry out. To predict the SOC of a battery there are various indirect techniques. Artificial Neural Networks (ANN)and extended Kalman filters are both indirect methods for predicting the SOC of a battery. Both of these methods offer a high level of accuracy and reliability, making them preferred choices for applications where precise battery management is essential. The extended Kalman filter is an advanced version of the standard Kalman filter, specifically designed to handle non-linear dynamic systems, such as those found in battery management. ANNs are Machine learning-

based models that are trained on past data to predict SOC based on various inputs like voltage, current, temperature, etc. The network using EKF will generate lower errors than systems based on ANN. This paper presents the performance of methods that can provide accurate SOC estimation and reliable operation of a battery system using ANN and EKF. The advantages, disadvantages, and applications are also studied and compared in this research.

1.1 Parameters of a battery

To assess the effectiveness and performance of the aforementioned techniques (ANN and EKF), Li-ion battery data was collected with the following specifications:

1. The battery is rated with a nominal voltage of 12 volts.
2. The battery has a rated capacity of 10 Ah.
3. The initial SOC is 100%.
4. The time it takes for the battery to respond is 5 seconds.

1.2 Data Collection and Preprocessing

• Data Collection:
- Gather a large dataset with current, voltage, temperature, and known SoC values for battery management system (BMS) analysis.
- Ensure a wide range of operating conditions by varying temperature, charge/discharge rates, and battery aging states.

• Data Preprocessing:
- Create relevant features, such as cumulative charge/discharge, voltage drop, and temperature history.
- Divide the data into training, validation, and testing data groups.

II. The Role of the Extended Kalman Filter in SoC Estimation

The Kalman filter (KF) is a method utilized to predict the condition of a linear dynamic system based on imprecise data. The EKF is designed for nonlinear systems and is used for estimating parameters such as SOC when the system dynamics are nonlinear. The KF and EKF both consist of two primary stages: prediction and correction (also referred to as update). In the prediction stage, the SoC is calculated using the system's model and the previous state estimation. During the correction process, the estimation of the SoC is regularly updated to match the actual system performance by including real-world measurements. The illustration in Figure 1. Operational block diagram of ANN and EKF.

2.1. EKF Methodology

1. Prediction Step:
- Predicted SOC estimate: $SOC_{k|k-1} = SOC_{k-1|k-1} + f(u_k)$ (1)
- Predicted covariance estimate: $P_{k|k-1} = P_{k-1|k-1} + Q$ (2)

2. Update Step:
- Measurement Residual: $y_k = z_k - h\left(SOC_{k|k-1}\right)$ (3)
- Innovation Covariance: $S_k = HP_{k|k-1}H^T + R$ (4)
- Kalman Gain: $K_k = P_{k|k-1}H^T S_k^{-1}$ (5)
- Updated SOC Estimate: $\mathrm{SOC}_{k|k} = SOC_{k|k-1} + \mathrm{K}_{\mathrm{kYk}}$ (6)

Where $f(uk)$ is the function relating SOC to the measurement, Q is the dynamic noise covariance, R is the sensor noise covariance, H is the output matrix and zk is the measurement vector (e.g., voltage, current).

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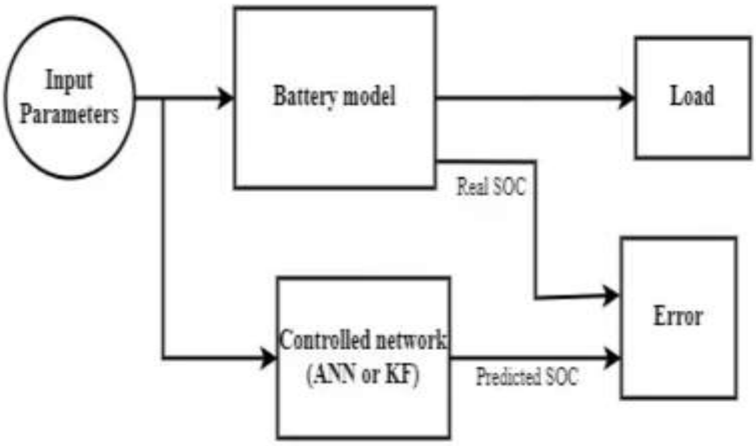

Figure 1. Operational block diagram of ANN and EKF.

2.2 Battery Characterization and SOC Measurement

A precise battery model is crucial in accurately estimating the SOC using the EKF in a nonlinear time-variant dynamic system (e.g., battery). Briefly outlined below are a few current battery models, including the Shepherd battery model, the Unnewehr battery model, and the Nernst battery model.

Simple linear model: Figure 2 illustrates the linear equivalent circuit model in detail. In a linear model, the terminal voltage of a battery can be determined by adding the OCV at a specific SOC and the voltage drop caused by the internal resistance. The voltage drop is typically a result of the current flowing through the internal resistance of the battery. The corresponding mathematical relationship is detailed in Equation (7).

$$y_k = \mathrm{OCV}(z_k) + Ri_k \tag{7}$$

Where $i_k > 0$ indicates that the battery is charging and $i_k < 0$ signifies that the battery is discharging.

RC circuit Model: The RC model comprises an RC circuit and internal resistance, as depicted in figure3.

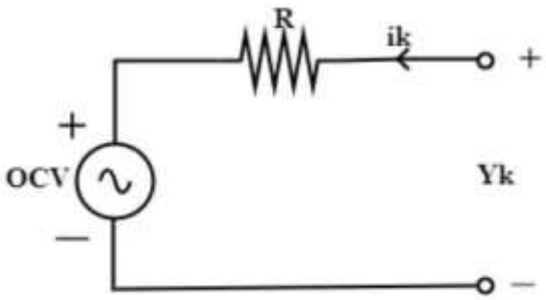

Figure 2. Linear Electrical Equivalent Model.

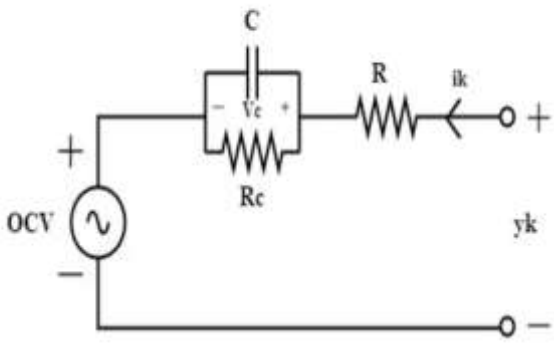

Figure 3. RC Electrical Model of a Battery.

The resister-capacitor electrical network is incorporated to account for the time constant during transients, which in practice is equivalent to the cell's double layer and diffusion capacitance. The equation for this model is provided in equation (8).

$$y_k = OCV(z_k) + Ri_k + v_c \exp\left(\frac{-t}{R_c C}\right) \quad (8)$$

Where $i_k > 0$ indicates that the battery is charging and $i_k < 0$ signifies that the battery is discharging.

III. Artificial Neural Network [ANN]

ANNs are models for processing data that mimic the human brain, aiming to identify patterns and make forecasts through the process of data learning. They are made up of linked nodes organized in layers - input, hidden, and output - with weights on each connection that are adjusted during training to minimize errors and enhance accuracy in activities such as classification, regression, and pattern detection. Figure 4 illustrates the functioning of ANNs. these are more reliable and resilient because they can grasp intricate patterns and effectively extrapolate from the data used for training. An ANN is made up of input nodes, hidden layers, and output nodes, with neurons in each layer interconnected.

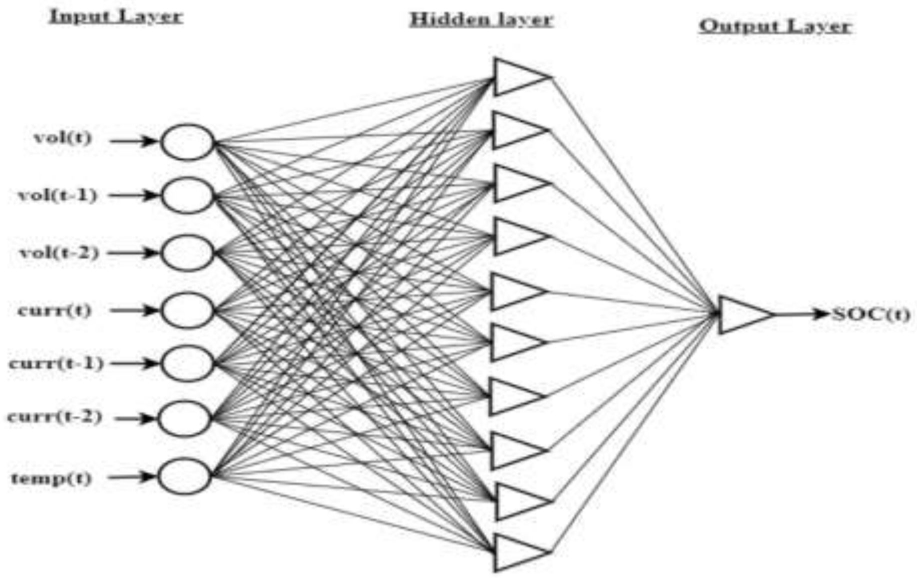

Figure 4. Functioning of ANNs.

3.1 SOC Estimation

The SOC was estimated through a nonlinear input-output feed-forward system, trained using the Levenberg-Marquardt back-propagation algorithm to evaluate the performance of the ANN.

The NIO feed-forward network predicts a time series by utilizing both current and past values from an input time series, as shown in Figure 5. Predicting the SOC involves using the battery's terminal voltage and current in the input time series x(t), with the SOC as the output or target variable.

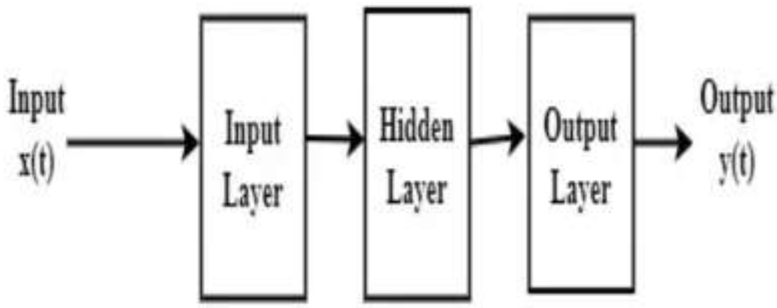

Figure 5. Fundamental Design of a Feedforward Neural Network.

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These results estimate the training performance metrics of the ANN over 1,000 epochs, which are illustrated in Figure 6.

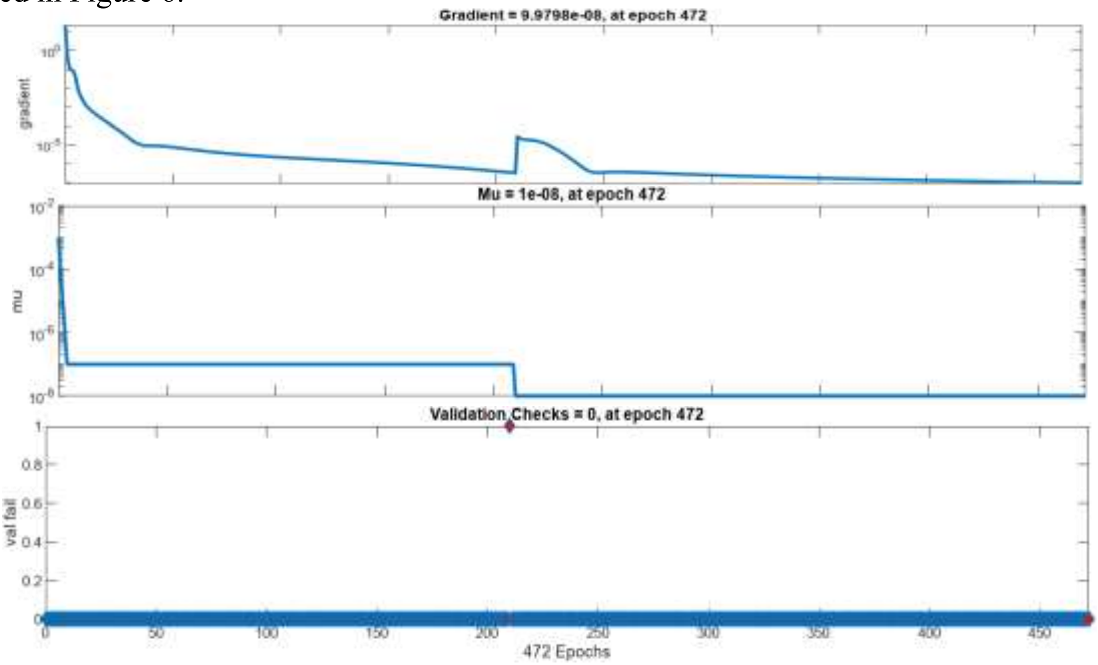

Figure 6. Training Performance Metrics of ANN Over 1000 Epochs.

IV. Summary of Results Comparison.

In this section, the proposed methods are assessed and compared. The more advanced design of the linear electrical equivalent model and resister-capacitor electrical model of a battery makes them superior to the Shepherd, Unnewehr, and Nernst models. The resister-capacitor circuit outperformed all the other models because it accounts for the battery's internal voltage drop and transient (capacitance) voltage.

The advantage of the EKF is provides optimal state assessment using a state-space model and measurement data. EKF has been widely adopted in various engineering applications due to its robustness. Another advantage is that the EKF can provide accurate performance even when the process and measurements are noisy. The estimated SOC results from the ANN and EKF are shown in Figure 7, and Figure 8 is provided below.

S.NO	LOAD	ACTUAL SOC %	ANN SOC %	ERROR%
1	20W	8.079	4.464	3.6
2	40W	8.19	4.464	3.7
3	60W	8.519	4.465	4
4	80W	8.887	4.483	4.4
5	100W	9.29	4.916	4.3
6	120W	9.731	4.916	4.8
7	140W	10.21	-0.7943	11

Table 1. Comparison of Actual and ANN- Predicted SOC Under Various Load Conditions.

Another observation regarding the ANN systems was that the system showed minimal correlation with the number of neurons in the hidden layer. It was observed that when the hidden layer contained 2, the accuracy was marginally lower compared to when it had 4 neurons.

However, varying the number of neurons in the hidden layer between 32 and 128 at random did not affect the performance of the NIO system. Comparison of Actual and ANN- Predicted SOC Under Various Load Conditions in Table 1.

The MATLAB function (plot regression) was used to find the regression in Table 1, and Equation (9) was employed to calculate the RMSE.

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{k=1}^{N}(z_{actual}-z_{pred})^2} \tag{9}$$

Where z_{actual} and z_{pred} denote the actual and predicted SOC, and N is the number of predictions.

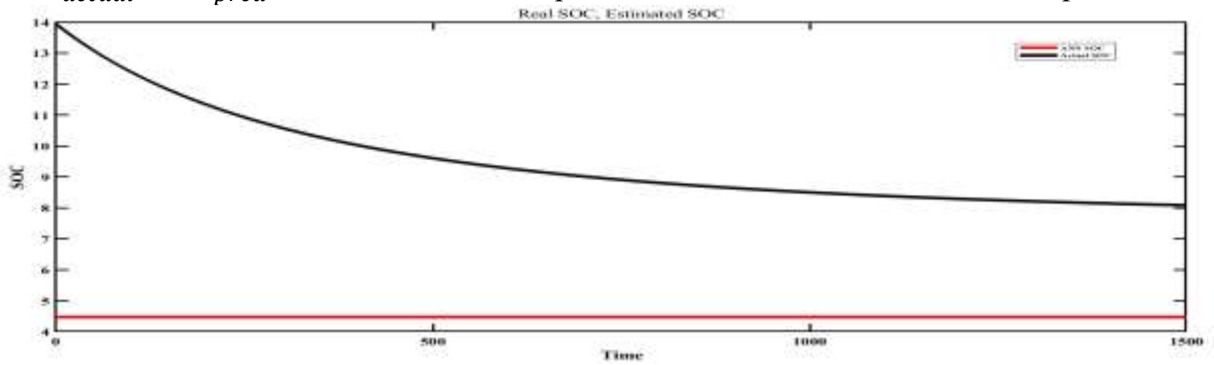

Figure 7: ANN output for a 20W load

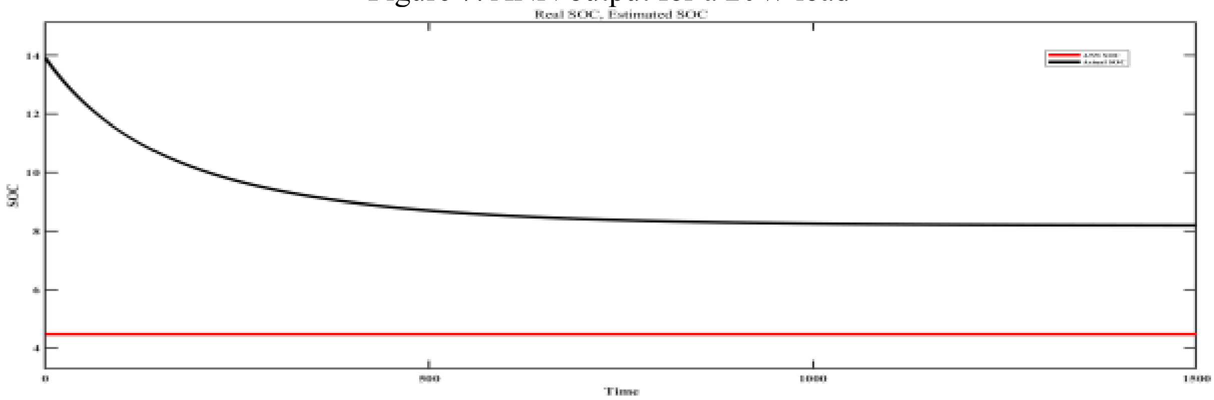

Figure8: ANN output for a 40W load

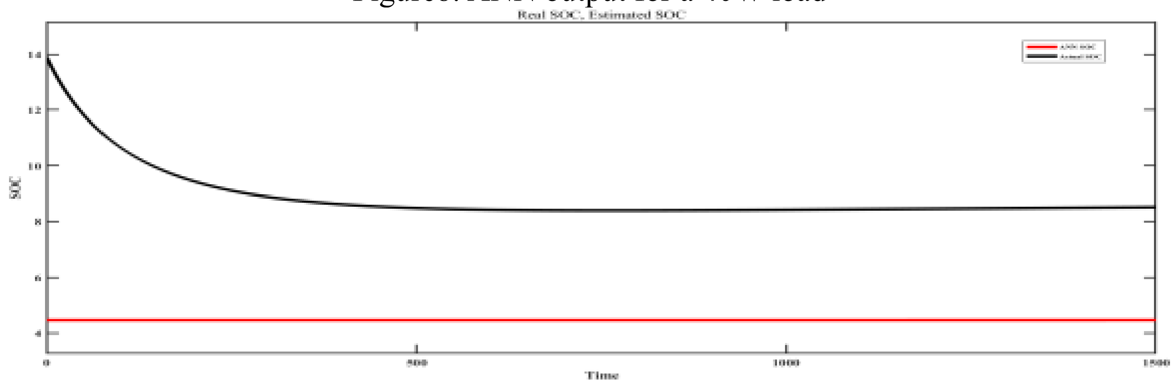

Figure 9: ANN output for a 60W load

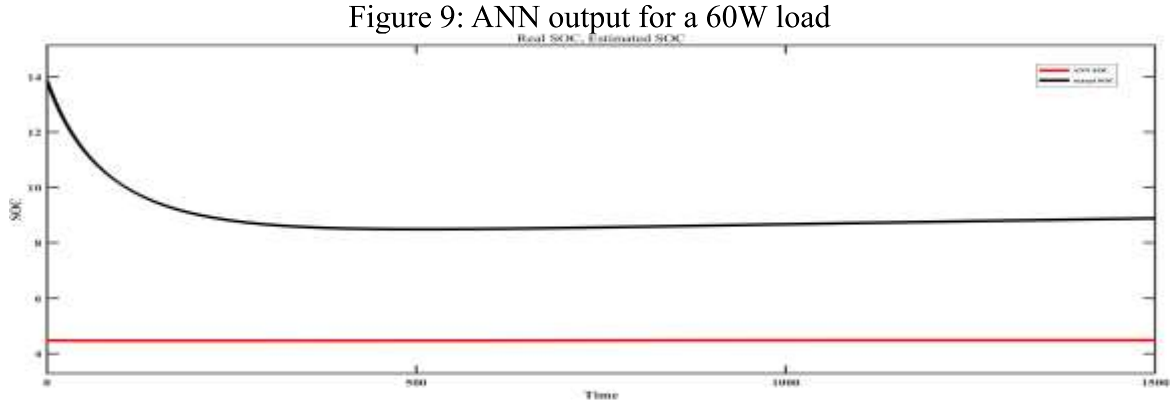

Figure 10: ANN output for a 80W load

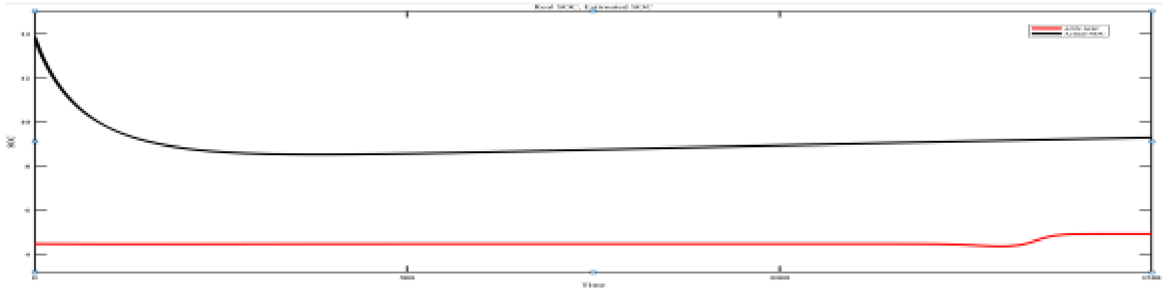

Figure 11: ANN output for a 100W load

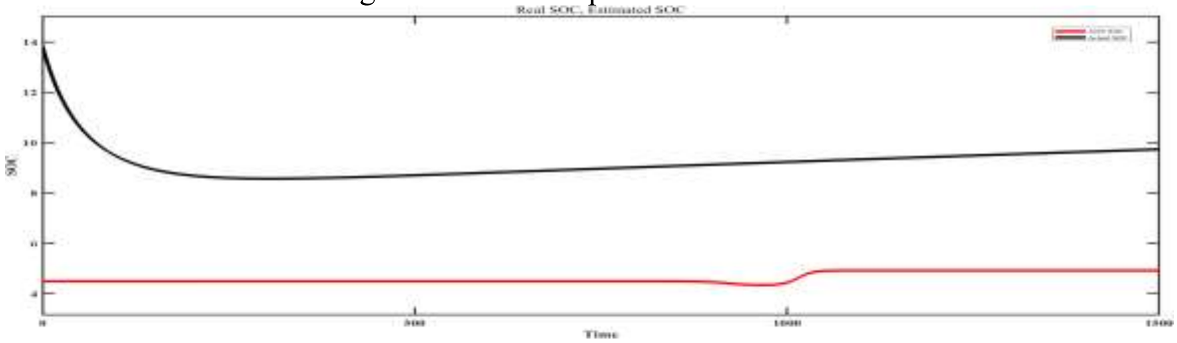

Figure 12: ANN output for a 120W Load

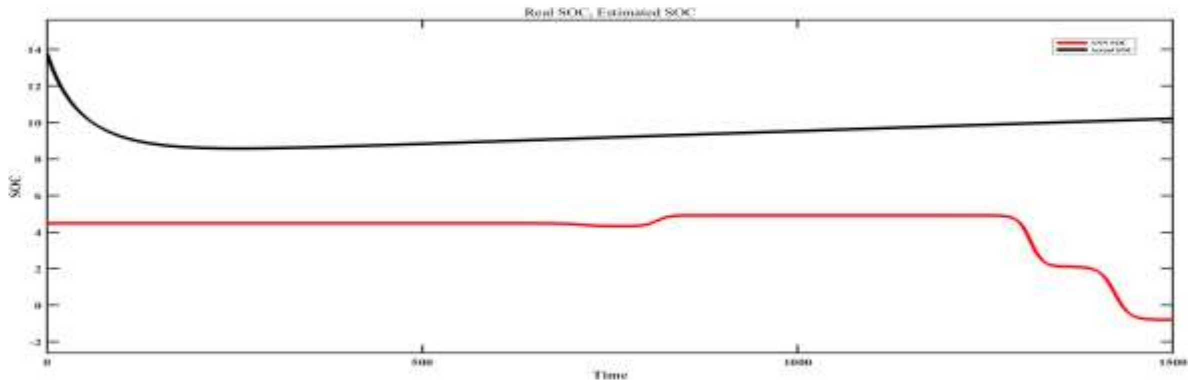

Figure 13: ANN output for a 140W load

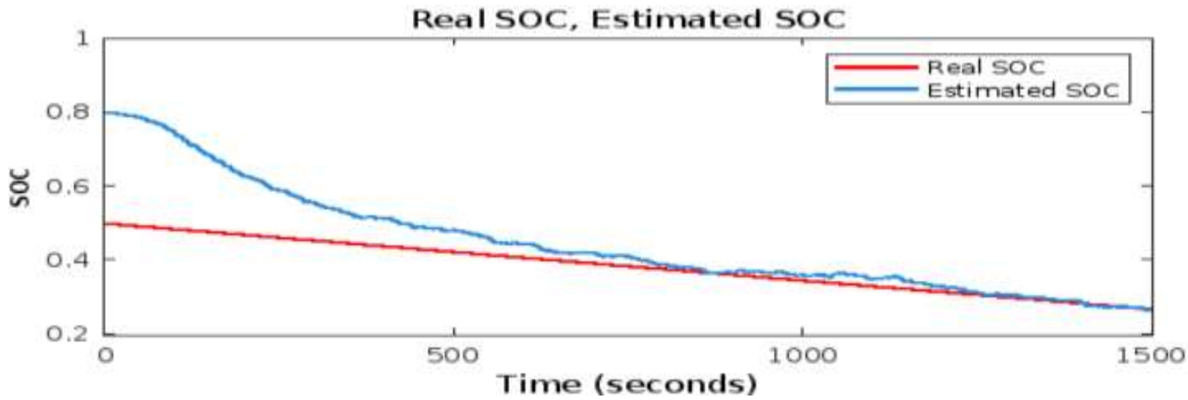

Figure 14. Results of EKF predicted SOC

V. Conclusion

ANN and EKF, two sophisticated techniques, were evaluated in particular circumstances. Of the two methods, EKF can provide precise results even when incorporating noise models and accurate battery parameters. often resulting in lower error compared to ANN-based systems. Conversely, ANNs excel when trained with synthetic data closely resembling real-world conditions. Their effectiveness varies depending on application needs, making it essential to understand the differences between them. Additional factors to consider when designing a SOC estimator include the Battery thermal state dependence and the changes in battery specifications (e.g., energy storage capacity, Internal voltage drop) over its lifespan. Therefore, adaptability is crucial for ensuring highly reliable SOC estimators throughout the battery's life.

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