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EV Battery Adaptive Test Unit

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Abstract

Lithium-ion batteries are an important component in electric vehicles (EVs), and ensuring their optimal performance is vital for the longevity and efficiency of the vehicle. Efficient testing of battery cells plays a major role in verifying their performance. Traditionally, a single-cell testing unit is used for batch processing during battery pack assembly. However, this method is time-consuming and lacks scalability, which limits productivity. To address this, the research proposes a multicell testing approach that concurrently estimates the state of charge (SOC) and state of health (SOH) of multiple battery cells in parallel. By doing so, the approach significantly reduces testing time and improves efficiency. The dual filter concept is incorporated to categorize cells based on their performance, ensuring only high- quality cells are selected for inclusion in the battery pack. Furthermore, a custom Temporal Convolutional Network (TCN) model, achieving an accuracy of 89%, is employed to accurately estimate SOC and SOH. In addition, a predictive battery temperature forecasting model is introduced to forecast the temperature of the battery cells over the next three days, which aids in proactive temperature management and prevents potential degradation. Overall, the proposed approach enhances battery testing productivity and ensures higher accuracy in SOC and SOH estimation, contributing to the development of more reliable and efficient EV batteries.

Keywords: Battery Health Monitoring, Adaptive Filters, State Estimation, TCN, Predictive Analysis, Temperature Forecasting.

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1. Introduction

Lithium-ion batteries play an important role in the performance of electric vehicles (EVs), making efficient battery testing essential to ensure quality and reliability. Traditionally, battery testing has been carried out using single-cell test units that test each cell individually in a batch process [1]. However, this approach is time-consuming and lacks scalability, reducing productivity when handling large volumes of cells. To address this, the research proposes a multicell testing approach that allows parallel testing of multiple battery cells, improving efficiency[2]. This method incorporates adaptive filter-based estimators, such as Extended Kalman Filters (EKF) and Unscented Kalman Filters (UKF), to provide accurate estimations of key parameters like the state of charge (SOC) and state of health (SOH)[3,4]. These estimations are essential for assessing battery performance and health, with adaptive filters ensuring accuracy under varying conditions. Additionally, the method addresses the challenge of predicting battery temperature during the three-day storage period before assembly by introducing a machine learning model that forecasts temperature for the next few days. This predictive model aids in managing battery temperature and preventing damage due to improper storage [5-7]. The proposed system integrates real-time data, predictive temperature forecasting, and adaptive SOC/SOH estimation, optimizing battery testing and improving both productivity and accuracy. By utilizing the parallel testing and advanced estimation techniques, the multicell testing system provides a comprehensive solution for efficient battery testing, ensuring better performance and longevity for EV batteries [8-10].

2. System Architecture and Components

The proposed solution features a multicell adaptive testing unit that integrates algorithms for SOC estimation and temperature forecasting. It includes a voltage sensor for battery monitoring and an ESP32 microcontroller for data processing. The system uses Extended Kalman Filters (EKF) and Unscented Kalman Filters (UKF) for accurate SOC estimations and a custom Temporal Convolutional Network (TCN) model to forecast battery temperature for the next three days. This approach improves testing efficiency, accuracy, and predictive capabilities.

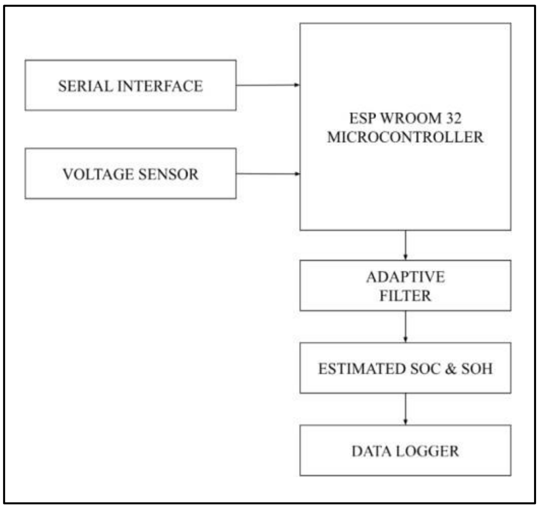

Figure 1. Block Diagram of the Proposed System Architecture

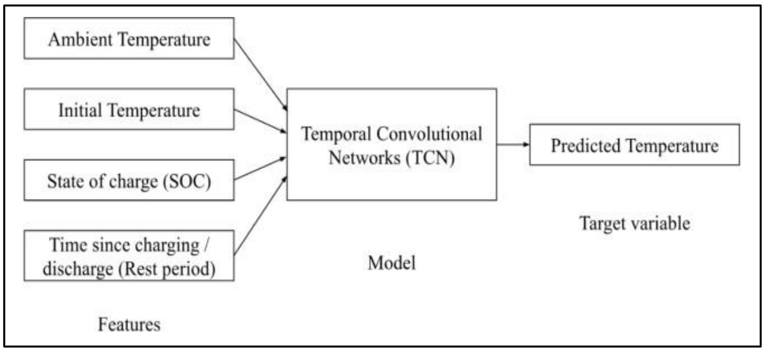

Figure 2. Block Diagram of the TCN Model

The block diagram for the EV battery adaptive testing and the TCN model are illustrated in Figure 1 and 2 respectively.

2.1 Battery and Sensor Network

The voltage sensor network forms the backbone of the system, enabling real-time and comprehensive battery data collection. The system utilizes the following components:

Voltage Sensor: These 25V DC voltage sensors continuously measure the real-time voltage levels of the batteries under observation. This data acquisition is fundamental as battery voltage correlates directly with its SOC, enabling precise estimation of how much charge remains.

Lithium Ion Battery: The ICR-18650-2500mAh is the component under test in the state estimation system. Its role is to provide the voltage data necessary for monitoring and evaluating its state.

2.2 Data Processing Unit: ESP32 Microcontroller

The ESP32 is the controlling unit of the test unit. It integrates with multiple sensors and the state estimation system (specifically with voltage sensors) to acquire real-time battery voltage data, which it preprocesses for accuracy. Multiple voltage sensors are integrated through analog and digital input pins for data acquisition.

- It implements both the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) algorithms to estimate the SOC and SOH by handling nonlinearities through linearization techniques.
- It manages real-time user inputs through the serial interface for selecting filter modes, starting new tests, or stopping ongoing tests, ensuring seamless control and adaptability during testing.
- It logs the state estimation results which includes SOC and SOH in real-time, and updates the resulting data for instant monitoring.

2.3 Adaptive Filters EKF and UKF Extended Kalman Filter

The Extended Kalman Filter (EKF) estimates the State of Charge (SOC) of lithium-ion batteries by linearizing the nonlinear battery model using a Taylor series expansion. It operates through a Prediction-Update cycle to refine SOC estimation under noisy voltage measurements. In the Prediction Step, the SOC is forecasted based on the previous state and the battery model dynamics. The Update Step then adjusts the SOC estimate using the measured voltage through a nonlinear function. Finally, the Covariance Adjustment step updates the covariance matrix to reflect prediction and measurement uncertainties, thereby improving estimation accuracy. While effective in handling mild nonlinearities, the EKF can introduce errors due to its reliance on linearization techniques.

2.4 Adaptive Filters - Unscented Kalman Filter (UKF)

The Unscented Kalman Filter (UKF) improves upon the EKF by avoiding linearization errors through the use of sigma points to approximate the probability distribution of the SOC. Its Prediction-Update cycle begins with Sigma Point Calculation, where sigma points are generated around the current SOC and covariance matrix. In the Prediction Step, these sigma points are propagated through the nonlinear battery model to predict the SOC distribution. The Update Step then refines the SOC estimate using the measured voltage while incorporating the uncertainty represented by the sigma points, leading to enhanced estimation accuracy. The UKF offers superior performance over the EKF, particularly in highly nonlinear systems, ensuring more reliable SOC estimation.

3. Temperature Prediction System

A custom Temporal Convolutional Network (TCN) model is employed for battery temperature prediction due to its ability to effectively capture temporal patterns in time-series data. Unlike traditional models, TCNs utilize convolutional layers to process sequential data, making them highly suitable for forecasting battery temperature based on historical values. This predictive capability enables proactive thermal management, reducing the risk of degradation due to temperature fluctuations.

The TCN model forecasts battery temperature over the next three days using key input features, including ambient temperature, initial temperature, state of charge (SOC), and time elapsed since charging or discharging. By accurately predicting short-term temperature variations, the model supports efficient battery management, ensuring optimal operating conditions and preventing thermal-related performance issues.

The system adheres to industry standards to ensure reliability and accuracy. Rest period standards comply with ISO 12405-4:2018 and IS 17855:2022 as specified by BIS, while temperature guidelines follow ISO 12405-4:2018 and IEC 60086-4:2007 regulations. The required storage temperature limits range between 15°C and 25°C, and the recommended rest period between charge and discharge is set at 24 hours. These standards ensure safe and consistent battery operation, enhancing overall system performance.

The dataset was split into training and testing sets, with 80% allocated for training and 20% reserved for evaluation (specified by test_size=0.2). Prior to this split, a sequence creation process was applied to the data, generating sequences of 10 consecutive time steps. Each such sequence was then structured to predict the subsequent next value in the series.The Table 1 shows the dataset collected for three days.

Table 1. Dataset Sample

	A	B	C	D	E	F	G	H
1	Timestamp	Ambient Temp (°C)	Initial Temp (°C)	SOC (%)	Time Since Last Discharge (hrs)	Actual Battery Temp Day 1 (°C)	Actual Battery Temp Day 2 (°C)	Actual Battery Temp Day 3 (°C)
2	2024-01-01 00:00:00	26.13	21.35	72.28	3.51	26.85	26.89	26.45
3	2024-01-01 01:00:00	26.79	21.9	72.51	4.4	26.1	28.85	28.93
4	2024-01-01 02:00:00	27.49	20.08	76.14	4.12	27.26	25.86	28.24
5	2024-01-01 03:00:00	24.67	21.88	77.35	2.65	26.02	27.71	29.09
6	2024-01-01 04:00:00	29.06	20.33	76.66	2.13	26.37	27.29	28.19
7	2024-01-01 05:00:00	29.85	21.04	75.02	3.36	27.39	26.88	28.21
8	2024-01-01 06:00:00	29.62	24.52	71.2	3.89	27.8	27.63	28.73
9	2024-01-01 07:00:00	27.13	23.29	77.51	2.51	27.53	27.73	27.53
10	2024-01-01 08:00:00	26.93	24.07	73.64	4.34	26.39	27.04	27.94

4. Results and Discussion

The proposed system features a Python-based dashboard for real-time monitoring of battery parameters, providing a comprehensive interface for assessing battery health. The dashboard continuously tracks multiple battery voltage levels and visualizes SOC and SOH variations over time, enabling efficient data analysis and decision-making.

The Graphical User Interface (GUI) (Figure 3) enhances user interaction by integrating control buttons for test operations. Users can select between EKF and UKF for SOC estimation, initiate a new test, stop an ongoing test, and open the plot window for detailed data visualization. This interactive system streamlines battery testing, offering a user-friendly approach to monitoring and analyzing real-time battery performance

Figure 3. User Interface with Graphical Interface

The interface illustrated in Figure 3 consists of control buttons, such as Select EKF and UKF, New Test, Stop Test, Open Plot window.

Figure 4, 5, and 6, illustrates the prediction summary observed for Day 1, Day 2, and Day 3 respectively, where Figure 4 shows the temperature prediction for the day 1 with an overall efficiency of 89.88%, Figure 5 shows the temperature prediction for the day 2 with an overall efficiency of 88.18%, and Figure 6 shows the shows the temperature prediction for the day 3 with an overall efficiency of 89.08%.

```
Epoch 199/200
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0027 - val_loss: 0.1050
Epoch 200/200
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0021 - val_loss: 0.1047
32/32 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step
RMSE for Day 1: 1.2944658806516802
MAE for Day 1: 1.0731836841101638
R² for Day 1: -0.283984029216787
Accuracy for Day 1 (within ±2.0°C): 88.18%
     Actual Temperature (°C)  Predicted Temperature (°C)  Error (°C)
0                      27.02                   27.956718   -0.936718
1                      26.12                   28.376266   -2.256266
2                      26.43                   28.091328   -1.661328
3                      28.36                   27.816692    0.543308
4                      26.32                   28.179920   -1.859920
..                       ...                         ...         ...
993                    29.66                   27.913143    1.746857
994                    26.17                   27.931734   -1.761734
995                    29.00                   27.553265    1.446735
996                    27.66                   27.706137   -0.046137
997                    29.67                   27.390612    2.279388
```

Figure 4. Prediction for Day 1

```
Epoch 248/250
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 0.0021 - val_loss: 0.1057
Epoch 249/250
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0018 - val_loss: 0.1085
Epoch 250/250
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 0.0023 - val_loss: 0.1048
32/32 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step
RMSE for Day 2: 1.294629189945697
MAE for Day 2: 1.0816903057365952
R² for Day 2: -0.23668215723517183
Accuracy for Day 2 (within ±2.0°C): 87.58%
     Actual Temperature (°C)  Predicted Temperature (°C)  Error (°C)
0                      29.83                   28.627476    1.202524
1                      26.55                   28.725197   -2.175197
2                      28.32                   28.524937   -0.204937
3                      29.53                   27.826292    1.703708
4                      29.41                   27.466616    1.943384
..                       ...                         ...         ...
993                    29.34                   28.450918    0.889082
994                    27.40                   27.642487   -0.242487
995                    26.58                   27.296732   -0.716732
996                    29.51                   28.012577    1.497423
997                    29.63                   27.576572    2.053428
```

Figure 5. Prediction for Day 2

```
Epoch 248/250
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0025 - val_loss: 0.1036
Epoch 249/250
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0021 - val_loss: 0.1046
Epoch 250/250
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - loss: 0.0020 - val_loss: 0.1044
32/32 ━━━━━━━━━━━━━━━━━━━━ 1s 12ms/step
RMSE for Day 3: 1.2921361493953676
MAE for Day 3: 1.0791179168487122
R² for Day 3: -0.2549696828193686
Accuracy for Day 3 (within ±2.0°C): 89.08%
     Actual Temperature (°C)  Predicted Temperature (°C)  Error (°C)
0                      26.85                   27.343369   -0.493369
1                      27.84                   26.845476    0.994524
2                      27.64                   26.969206    0.670794
3                      27.51                   27.576818   -0.066818
4                      29.70                   28.084126    1.615874
..                       ...                         ...         ...
993                    29.08                   27.751390    1.328610
994                    26.45                   28.235426   -1.785426
995                    28.51                   27.560904    0.949096
996                    29.16                   28.404797    0.755203
997                    27.05                   27.344610   -0.294610
```

Figure 6. Prediction for Day 3

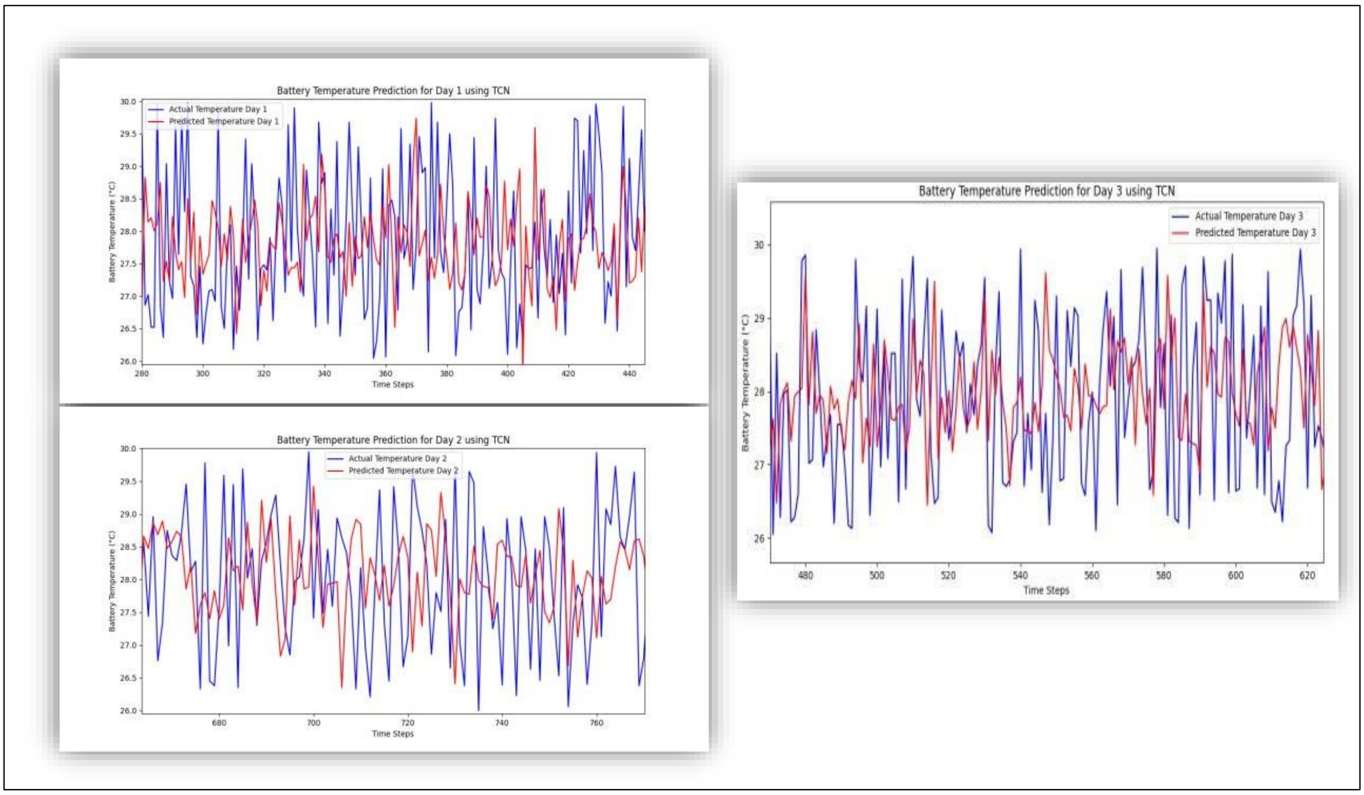

Figure 7. Prediction Plot for Three Days

Figure 7 illustrates the prediction plot attained for three days.

4.1 Evaluation Metrics

The RMSE and the accuracy values for the three prediction was determined using the following equation 1 and 2.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\tilde{y}_i - y_i)^2}{n}} \quad (1)$$

$$Accuracy\ (\%) = \frac{Number\ of\ predictions\ within\ tolerance}{Total\ number\ of\ predictions} \times 100 \quad (2)$$

Accuracy was calculated from the predictions with the Tolerance assumed to be ±2°C

The Table 2 below illustrates the performance values of TCN

Table 2. Performance of TCN

Prediction day	RMSE	MAE	Accuracy in %
Day 1	1.2463	1.0428	89.88
Day 2	1.2946	1.0816	87.58
Day 3	1.2921	1.0791	89.08

The custom Temporal Convolutional Network (TCN) model reliably estimates SOC (State of Charge) and SOH (State of Health). The temperature prediction model forecasts battery temperature over three days, achieving prediction accuracies of 89.88% on Day 1, 87.58% on Day 2, and 89.08% on Day 3, thereby ensuring proactive thermal management and preventing potential degradation. The combination of adaptive filtering and machine learning enhances battery performance assessment, ensuring improved reliability, longevity, and productivity in EV battery pack development. Thus, the overall efficiency achieved by the proposed system is 89%.

5. Conclusion

The proposed system integrates multicell testing, adaptive algorithms, and machine learning to improve battery performance evaluation. Using Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) for accurate state of charge (SOC) and state of health (SOH) estimations, the system enhances the testing process compared to traditional methods. A custom Temporal Convolutional Network (TCN) model effectively predicts battery temperature over the next three days, optimizing battery management. The multicell testing unit’s parallel processing capability reduces testing time and increases throughput.Despite these advantages, challenges remain. Sensor calibration errors and battery aging effects may affect SOC and SOH accuracy. Extreme conditions, such as rapid temperature changes or irregular discharge rates, may also impact predictions. Additionally, the system's reliance on hardware components introduces potential limitations in power consumption and signal stability. Nevertheless, the system’s real-time data processing and predictive capabilities offer significant improvements in battery testing and monitoring.

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