Ev Battery Adaptive Test Unit

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Abstract - Lithium-ion batteries are a critical 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 key 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, we propose 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, our 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.

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Index Terms - Battery Health Monitoring, Adaptive Filters, State Estimation, TCN, Predictive Analysis, Temperature Forecasting.

I. INTRODUCTION

Lithium-ion batteries play a critical 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. However, this approach is time-consuming and lacks scalability, reducing productivity when handling large volumes of cells. To address this, we propose a multicell testing approach that allows parallel testing of multiple battery cells, improving efficiency. 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). These estimations are essential for assessing battery performance and health, with adaptive filters ensuring accuracy under varying conditions. Additionally, we tackle 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. 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 leveraging 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.

II. SYSTEM ARCHITECTURE AND COMPONENTS

A. Overview

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.

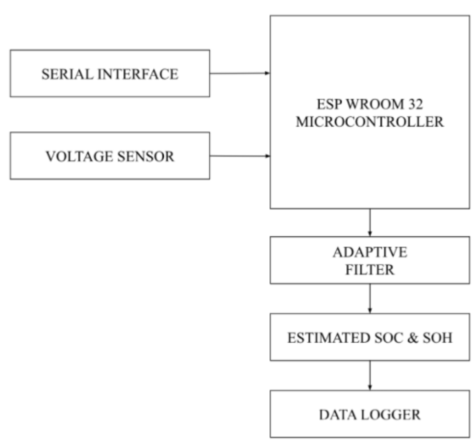


Fig. 1.1 Block Diagram of the Proposed System Architecture.

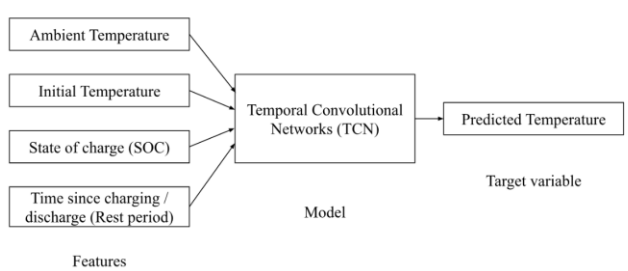


Fig. 1.2 Block Diagram of the TCN model

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

C. Data Processing Unit: ESP32 Microcontroller

The ESP32 is the controlling unit of the test unit. Multiple sensors and their data of the battery, State estimation system by integrating 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.

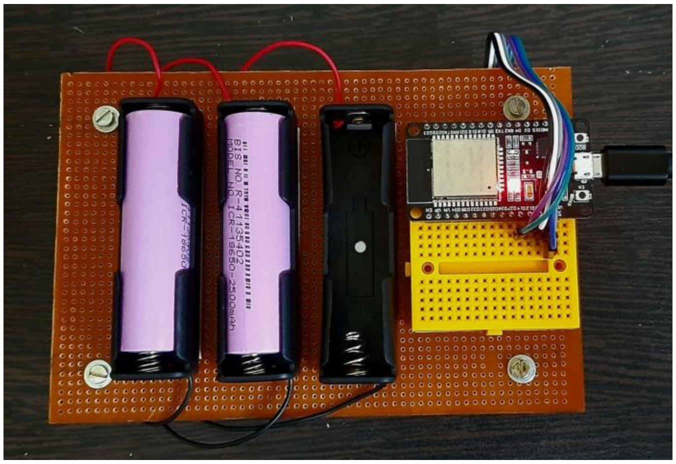


Fig. 2 Hardware Setup of Battery test unit

D. Adaptive Filters EKF and UKF

Extended Kalman Filter:

EKF estimates the state of charge of lithium-ion batteries with noisy voltage measurements by linearizing the nonlinear battery model using a Taylor series expansion. The Prediction-Update cycle includes:

- **Prediction Step:** Predicts the SOC based on the previous state and battery model.
- **Update Step:** Adjusts SOC using measured voltage with a nonlinear function.
- **Covariance Adjustment:** Updates the covariance matrix to reflect prediction and measurement uncertainty.

Unscented Kalman Filter:

UKF enhances EKF by using sigma points to approximate the probability distribution, avoiding linearization errors in nonlinear systems. Its Prediction-Update cycle includes:

- **Sigma Point Calculation:** Generates sigma points around the current SOC and covariance matrix.
- **Prediction Step:** Propagates these sigma points through the battery model to predict the SOC distribution.
- **Update Step:** Refines the SOC estimate using the measured voltage, incorporating the uncertainty represented by the sigma points for better accuracy.

III. MACHINE LEARNING MODEL FOR TEMPERATURE PREDICTION

A. Model Selection: Custom Temporal Convolutional Network (TCN)

A custom TCN model is chosen for temperature prediction due to its ability to effectively capture temporal patterns in time-series data. Unlike traditional models, TCNs leverage convolutional layers to process sequential data, making them suitable for predicting battery temperature based on past values.

B. Prediction Results:

The TCN model predicts the battery's temperature over the next three days using input features such as ambient temperature, initial temperature, state of charge (SOC), and time since charge/discharge. The model accurately forecasts the actual battery temperature, providing reliable short-term predictions for efficient battery management

C. Standards:

- **Rest period standards:** ISO 12405-4:2018 with IS 17855 2022 standard by BIS
- Time since charging/discharging - 24 hours
- **Temperature standards:** ISO 12405-4:2018 & IEC 60086-4:2007**,** Adjusts SOC using measured voltage with a nonlinear function
- **Storage temperature limits:** 15°C to 25°C

IV. RESULTS AND TEST UNIT INTERFACE VISUALIZATION

A. Python Dashboard for Real-Time Data

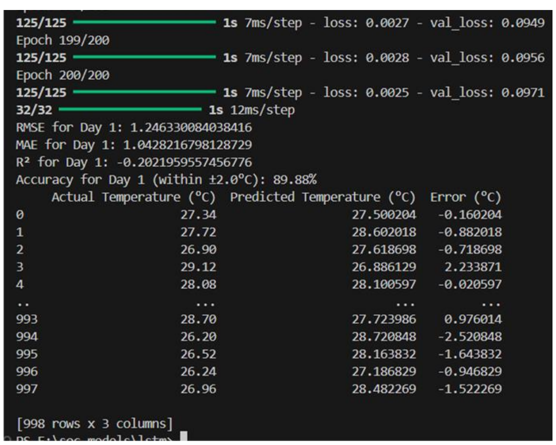
The Python-based dashboard provides a user interface for real-time monitoring of multiple battery voltage levels, provides battery health through SOC and SOH over time

Fig. 3. User Interface with Graphical Interface

B. Graphical User Interface

The interface consists of control buttons as Select EKF and UKF, New Test, Stop Test, Open Plot window.

C. Prediction Summary



```
125/125  1s 7ms/step - loss: 0.0027 - val_loss: 0.0949
Epoch 199/200
125/125  1s 7ms/step - loss: 0.0028 - val_loss: 0.0956
Epoch 200/200
125/125  1s 7ms/step - loss: 0.0025 - val_loss: 0.0971
32/32  1s 12ms/step
RMSE for Day 1: 1.246330084038416
MAE for Day 1: 1.0428216798128729
R² for Day 1: -0.2021959557456776
Accuracy for Day 1 (within ±2.0°C): 89.88%
     Actual Temperature (°C)  Predicted Temperature (°C)  Error (°C)
0                      27.34                   27.500204   -0.160204
1                      27.72                   28.602018   -0.882018
2                      26.90                   27.618698   -0.718698
3                      29.12                   26.886129    2.233871
4                      28.08                   28.100597   -0.020597
..                       ...                         ...         ...
993                    28.70                   27.723986    0.976014
994                    26.20                   28.720848   -2.520848
995                    26.52                   28.163832   -1.643832
996                    26.24                   27.186829   -0.946829
997                    26.96                   28.482269   -1.522269

[998 rows x 3 columns]
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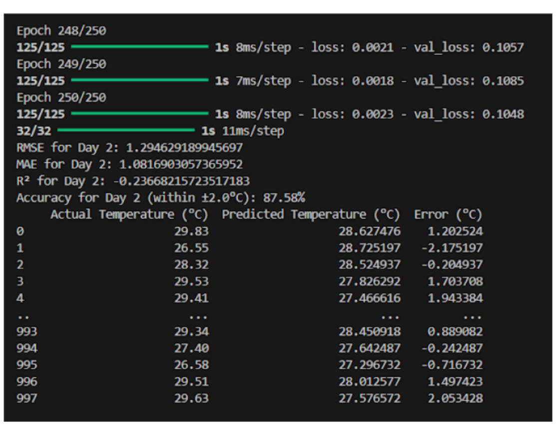
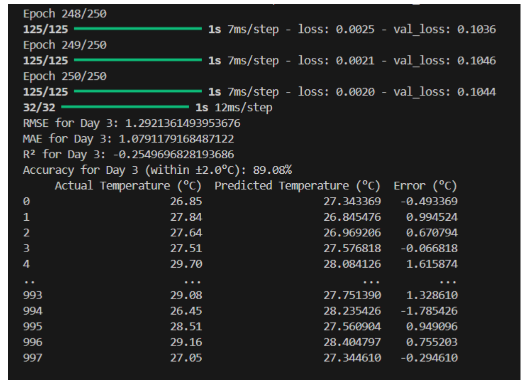
Fig. 4. Prediction for Day 1



```
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
```

Fig. 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
```

Fig. 6. Prediction for Day 3

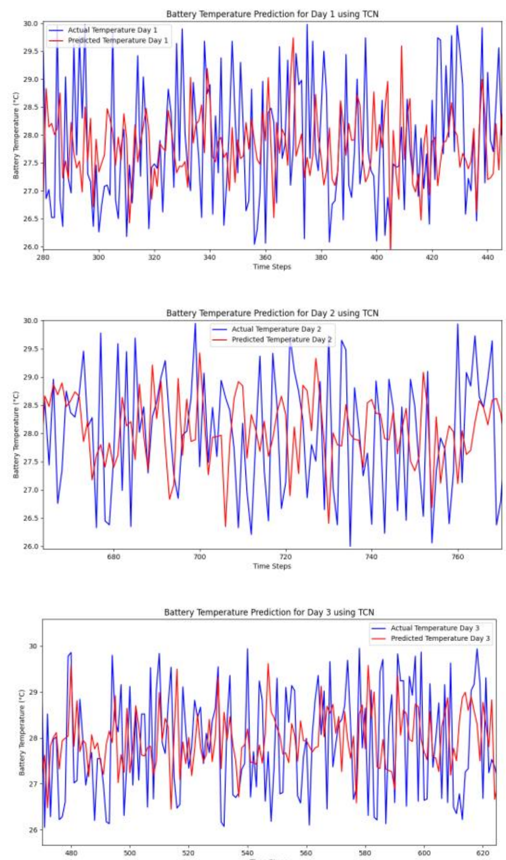


Fig. 7 Prediction Plot for Three Days

V. DISCUSSION

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.

VI. CONCLUSION AND FUTURE WORK

Adaptive filter parameters need periodic calibration based on battery dynamics, and data extraction is essential for training models for accurate results. The project currently uses 1C grade test cells; implementation on 3C grade EV cells is necessary to validate performance, as capacity differences may impact results. Additionally, while

Future developments will focus on:

- Advanced training models to address nonlinear dynamics achieving real-time robustness requirements.
- The system includes preventive handlers and offers opportunities for further improvement by incorporating fault-control capabilities to not only flag issues but also provide actionable solutions.
- Enhancing Predictive Algorithms: Exploring hybrid models for greater accuracy.
- Automation processes: Use of AI to simplify control operations and reducing manual interventions

These enhancements could be a time saving component in the EV manufacturing industry and it greatly boosts the productivity of assembling units by reducing the time complexity of testing cells. It guarantees the safety procedural of assembling battery packs only with the properly tested working cells which are healthier so that it validates the trust among EV to increase the involvement of investors upon this product and earns people trustability for the Ev cells used upon assembling

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