Visvesvaraya National Institute of Technology,Nagpur.

Final year project Electrical and Electronics Engineering.

EED 401 Project Phase -I

<u>Battery Management System</u>

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1.ABSTRACT

Battery Management Systems (BMS) play a pivotal role in ensuring the reliability and efficiency of modern energy storage solutions. One of the critical parameters monitored by a BMS is the State of Charge (SOC), which reflects the available capacity of a battery. In our project, we explored and implemented two prominent methods to estimate SOC: the Coulomb counting method and the Kalman filter method. The Coulomb counting approach calculates SOC by integrating the current flow over time, providing a straightforward and effective estimation under controlled conditions. However, it is sensitive to measurement inaccuracies and errors that accumulate over time.

To address these limitations, we employed the Kalman filter method, a model-based approach that combines real-time measurements with dynamic system modelling to provide robust and accurate SOC estimations. Our work included developing a Simulink model for SOC estimation using the Coulomb counting method and MATLAB code implementation of the Kalman filter. These implementations demonstrated the strengths and trade-offs of each method, highlighting the importance of balancing computational complexity and accuracy in practical applications. This study provides insights into the design and optimization of SOC estimation techniques in advanced BMS technologies.

2. INTRODUCTION AND LITERATURE REVIEW

This project develops efficient State of Charge (SOC) estimation techniques for Battery Management Systems (BMS) using the Coulomb counting and Kalman filter methods. Implemented in Simulink and MATLAB, these methods were analyzed for accuracy, efficiency, and practical applicability.
Accurate estimation of the State of Charge (SOC) is crucial for ensuring the performance and longevity of batteries in renewable energy systems and electric vehicles. Lead-acid batteries, widely used in renewable energy applications, require precise SOC monitoring to avoid overcharging or over-discharging, which can result in performance degradation. The Coulomb Counting method, a commonly employed technique, estimates SOC by summing the charge flowing into and out of the battery. However, its reliance on the initial SOC value and sensor precision makes it prone to cumulative errors, limiting its effectiveness in dynamic conditions.

To address these limitations, hybrid approaches combine traditional methods with corrections for real-time inaccuracies. For example, an Enhanced Coulomb Counting (ECC) method integrates the Coulomb Counting and Open Circuit Voltage (OCV) techniques. This method accounts for battery aging and dynamic parameter variations, improving the accuracy of SOC and State of Health (SOH) estimations. By compensating for drift errors and degradation effects, the ECC method provides a reliable framework for long-term battery management.

Battery modelling is another critical aspect of SOC estimation. Studies have evaluated various battery models, including Simple, Thevenin, and Modified Thevenin, to enhance estimation accuracy. Among the methods tested, the Kalman Filter has proven superior, outperforming Coulomb Counting and OCV techniques. Its ability to handle dynamic system changes makes it highly effective, as it provides accurate SOC estimates while quickly correcting errors caused by incorrect initial assumptions.

Lithium-ion batteries, commonly used in electric vehicles and portable devices, pose unique challenges for SOC estimation. Advanced models specifically designed for these batteries integrate the Kalman Filter to manage uncertainties and noise effectively. This approach enhances estimation precision, ensuring that the method is robust even in highly dynamic operating conditions. As a result, it is well-suited for applications requiring high accuracy and reliability, such as electric vehicles.

Comparative research highlights the effectiveness of Kalman-based filters, including the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF). Both filters perform well under various conditions, but the UKF demonstrates greater accuracy, particularly in non-linear environments. This makes it a promising tool for advanced battery management systems.

Additionally, adaptive battery models, building on traditional frameworks like Randles' model, have improved SOC estimation. These models dynamically adjust circuit parameters to account for aging and other changes, enhancing performance in lead-acid batteries and extending their operational lifespan.

Finally, integrating Kalman Filters with MATLAB Simulink models has shown promise for Lithium-ion batteries. This combination leverages simulation tools to address challenges such as overcharging and discharging, thereby improving performance and extending battery life. These advancements demonstrate the value of combining theoretical approaches with practical simulations to optimize energy storage solutions.

In summary, ongoing developments in SOC estimation techniques, particularly those leveraging the Kalman Filter and adaptive models, have significantly improved the reliability, accuracy, and efficiency of battery management systems. These advancements address critical challenges across diverse battery chemistries and applications.

The Battery Management System (BMS) is an essential component, especially for lithium-ion batteries, which are widely used in energy storage and electric vehicles. These batteries require precise management to ensure safety and optimal performance. Lithium-ion cells must operate within the "Safe Operation Area" (SOA) of voltage, current, and temperature to prevent damage. A BMS acts as a protective device built into each battery pack to maintain safe operation. It monitors critical parameters, such as voltage, current, and temperature, and makes decisions about charge and discharge rates based on load demands, estimated State of Charge (SOC), capacity, and impedance. As a part of a fast-acting and complex power management system, the BMS ensures reliability and efficiency in energy systems.

Importance of BMS

The primary role of a BMS is to ensure the safety, longevity, and performance of a battery. It achieves this by detecting unsafe operating conditions, such as overcharging, deep discharging, or overheating, and responding promptly to mitigate risks. Additionally, the BMS protects the battery cells from damage in abuse or failure scenarios, thus preventing costly replacements. It also plays a crucial role in prolonging battery life by maintaining optimal operating conditions. Furthermore, the BMS ensures that the battery remains in a suitable state for reliable performance. These capabilities make the BMS an indispensable part of any advanced battery-powered system.

State of Charge (SOC) and Its Importance

The SOC is a fundamental parameter managed by the BMS, defined as the ratio of the current capacity $Q(t)$ to the nominal capacity $Q(n)$.The nominal capacity, specified by the manufacturer, represents the maximum charge the battery can store. SOC can be expressed mathematically as:

$$SOC(t) = Q(t)/Q(n)$$

SOC changes due to current flow—either charging or discharging—and due to self-discharge within the cell. Accurate SOC estimation is essential for preventing overcharging and deep discharging, both of which can degrade battery performance and lifespan. It also improves battery performance, supports cell balancing in multi-cell configurations, and ensures optimal operation in energy storage systems and electric vehicles.

Methods for SOC Estimation

Various methods are used for SOC estimation, broadly categorized into direct measurement, book-keeping, adaptive systems, and hybrid approaches.

Direct measurement methods include the Open Circuit Voltage (OCV) method, Terminal Voltage method, and Impedance Spectroscopy. These methods rely on measurable parameters but may face challenges due to dependency on steady-state conditions.

Book-keeping methods, such as Coulomb counting and its modified versions, estimate SOC by integrating the current over time. However, they are prone to cumulative errors and require accurate initial SOC values.

Adaptive systems, including neural networks, support vector machines, fuzzy logic systems, and the Kalman filter, offer dynamic and robust SOC estimation. These techniques use predictive modelling and real-time data to address the limitations of traditional methods, such as measurement noise and non-linearities.

Hybrid methods combine the strengths of multiple techniques, such as Coulomb counting and EMF, or Coulomb counting and Kalman filter combinations, to enhance accuracy and reliability.

Coulomb Counting method

This method measures the discharging current of a battery and integrates the discharging current over time in order to estimate SOC. Coulomb counting method is done to estimate the SOC(t), which is estimated from the discharging current, I(t), and previously estimated SOC values, SOC(t-1).

SOC is calculated by the following equation

$SOC(t) = SOC(t-1) + (1 / Q_n) \int I(t)\, dt$ .... (1)

Kalman Filter method

It is designed to strip unwanted noise out of a stream of data. It operates by predicting the new state and its uncertainty, then correcting this with a new measurement.

•It is suitable for systems subject to multiple inputs and is used extensively in predictive control loops .

•With the Kalman Filter the accuracy of the battery SOC pre- diction model can be improved and thus battery performance is enhanced .

SoC is calculated by:

Linear Kalman Filter Formulas:

Prediction Step:

1. State Prediction:
   $\hat{x}_k^{-} = A_k \hat{x}_{k-1} + B_k u_k$
2. Covariance Prediction:
   $P_k^{-} = A_k P_{k-1} A_k^T + Q_k$

Update Step:

1. Kalman Gain:
   $K_k = P_k^{-} H_k^T (H_k P_k^{-} H_k^T + R_k)^{-1}$
2. State Update:
   $\hat{x}_k = \hat{x}_k^{-} + K_k (z_k - H_k \hat{x}_k^{-})$
3. Covariance Update:
   $P_k = (I - K_k H_k) P_k^{-}$

3. PROBLEM DEFINITION

Accurately estimating the State of Charge (SOC) of a battery is crucial for ensuring the safe, efficient, and reliable operation of energy storage systems. SOC estimation helps prevent overcharging or deep discharging, optimizes battery performance, and enables accurate range predictions in applications like electric vehicles.

However, SOC estimation faces *challenges* such as:

1.Nonlinear battery behaviour under varying loads.

2.Measurement errors due to sensor noise and drift.

3.Battery aging, causing capacity degradation.

4.Environmental factors, like temperature changes.

To address these challenges:

Coulomb Counting Method integrates current over time to calculate SOC, providing a simple, real-time estimation. However, it is prone to cumulative errors from sensor drift and inaccuracies.

Kalman Filter Method combines battery models with real-time data, accounting for noise and dynamic conditions. It corrects estimation errors and adapts to battery aging, offering improved accuracy and robustness.

By leveraging the strengths of both methods, this project aims to enhance SOC estimation, overcoming the limitations of individual approaches.

4.METHODOLOGY

SoC is estimated using various techniques mentioned above, of which we are focusing on
(A) Coulomb Counting method and
(B) Kalman filter method

(A)Evaluation of SOC Estimation via Coulomb Counting Under Different Scenarios

1. SOC Estimation Using Coulomb Counting (Discharge):

The battery is connected across a resistor to discharge it. The state of charge (SOC) is calculated using the Coulomb counting method, which integrates the current over time to estimate the remaining charge.

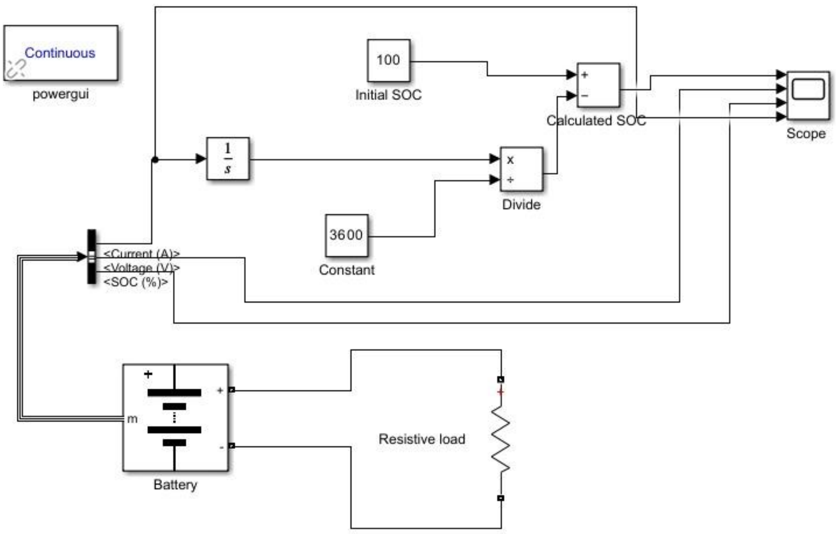
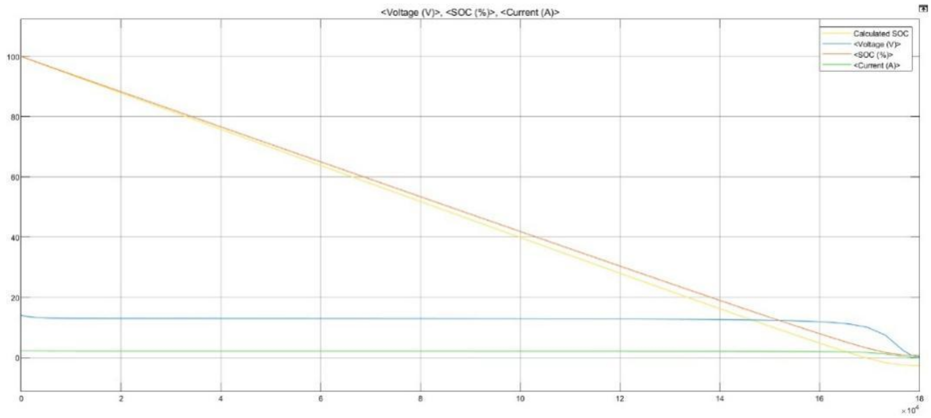


Fig 1: Soc estimation of battery under resistive load



Graph 1: Calculated SOC, SOC, Voltage, Current V/s Time curve

The graph shows a gradual decrease in SOC over time as the battery discharges. This validates the basic principle of SOC estimation via current integration

2. SOC Estimation During Charging with DC Machine:

The battery is charged using a DC machine, instead of being discharged. The setup likely monitors the current flowing into the battery during charging and calculates the SOC increase using Coulomb counting.

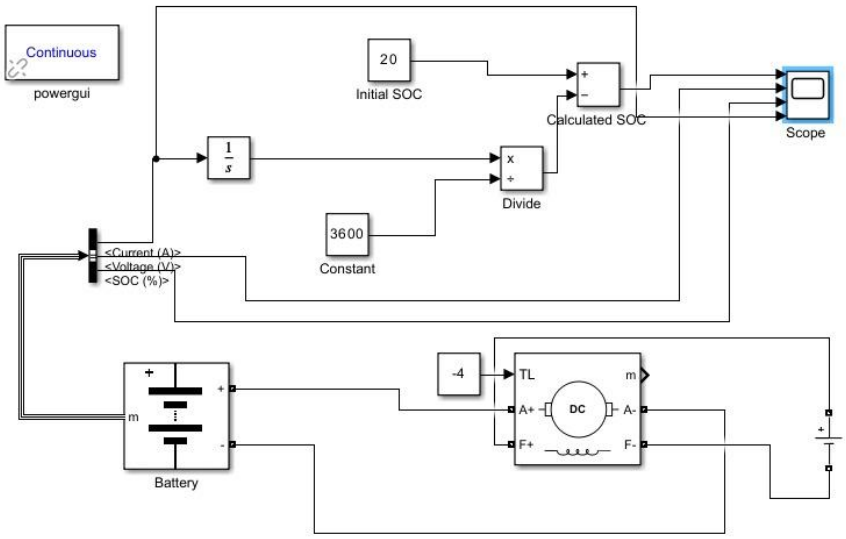
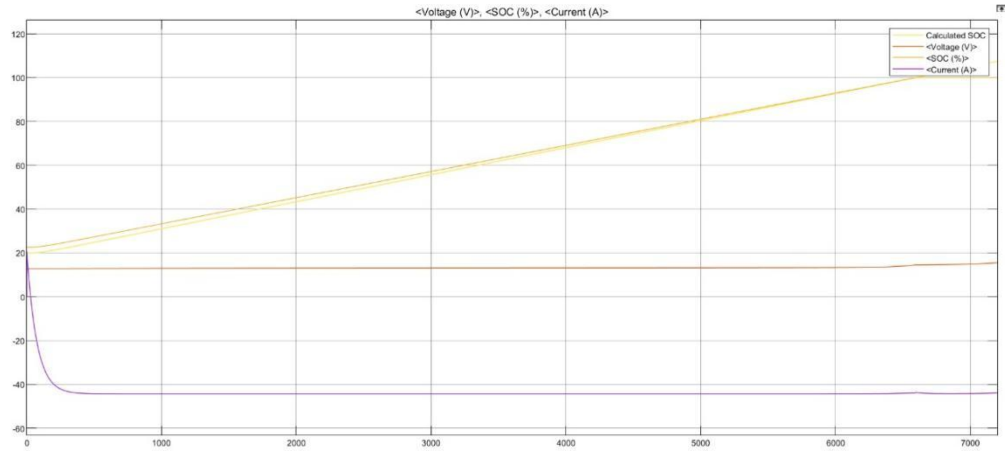


Fig 2: SOC Estimation During Charging with DC Machine



Graph 2: Calculated Soc, Soc, Voltage, Current V/s time Curve

The SOC graph shows an increasing trend as the battery charges. This demonstrates how charging can also be modelled for SOC estimation using the same method.

3. Comparison Between Battery Model and Actual Battery SOC:

In this setup, the SOC estimated using a mathematical battery model is compared with the actual SOC of a real battery to evaluate the model's accuracy. The purpose is to validate whether the model can reliably mimic the real battery's performance and provide accurate SOC estimates under varying conditions.

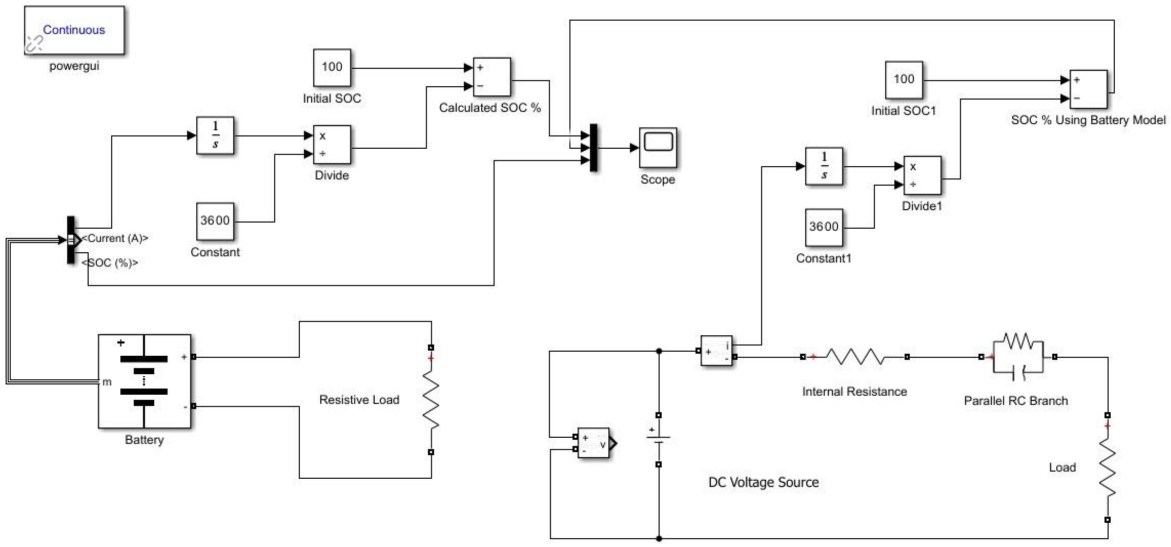
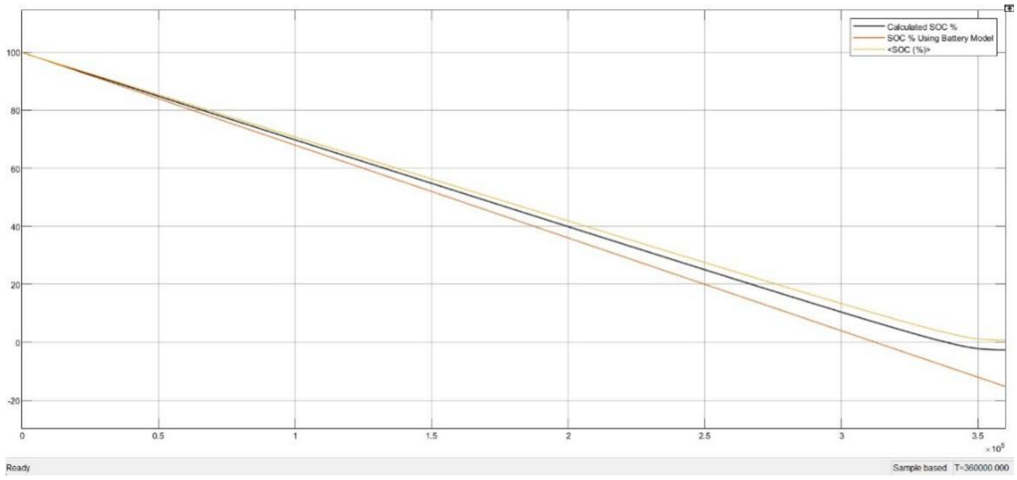


Fig 3: Comparison Between Battery Model and Actual Battery SOC



Graph 3: Calculated Soc, Soc of battery Model, Soc V/s Time

The graph displays two SOC curves—one derived from the battery model and the other from measurements of the actual battery. The close alignment between the two curves indicates that the model is effective in capturing the dynamics of the real battery. Minor discrepancies may be observed due to slight inaccuracies in parameter estimation.

4. Effects of Temperature and Noises in Current Measurement in Soc estimation:

This setup investigates how temperature variations and noise in current measurement independently affect the SOC estimation. Temperature changes can alter the internal resistance and capacity of the battery, thereby influencing SOC calculations. Additionally, current measurement noise introduces fluctuations in the input current data, which directly impacts the accuracy of the Coulomb counting method. Both factors are considered separately to isolate their effects on SOC.

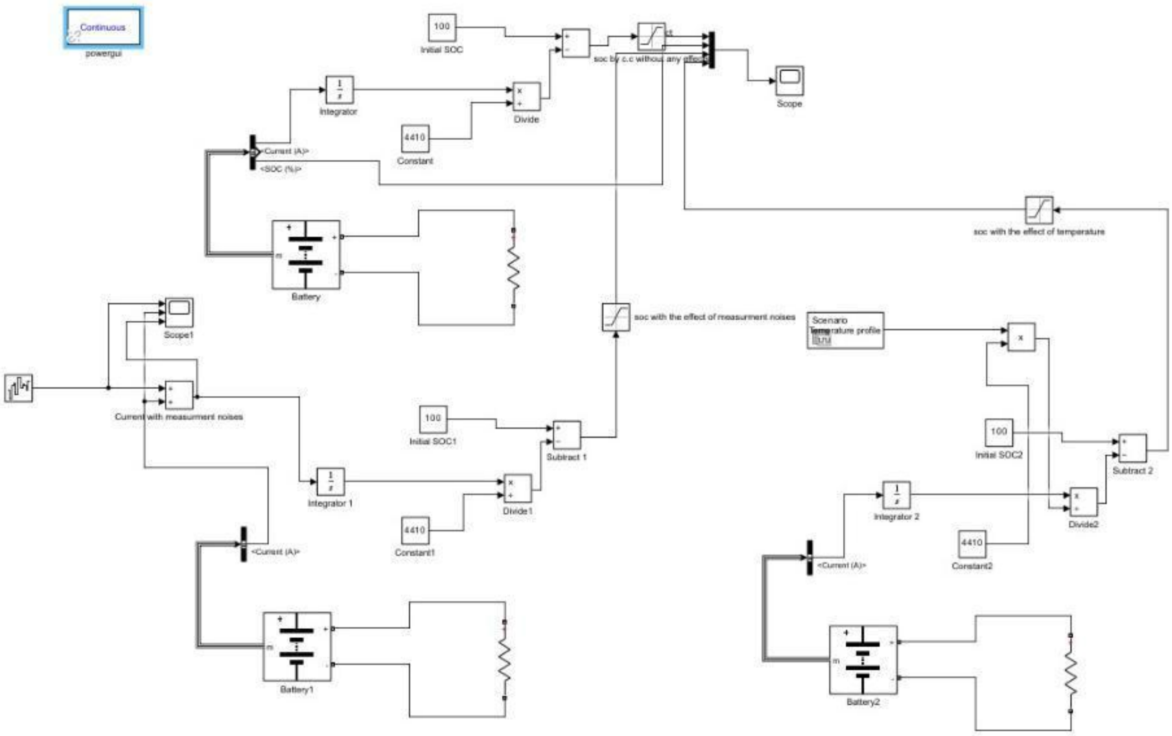
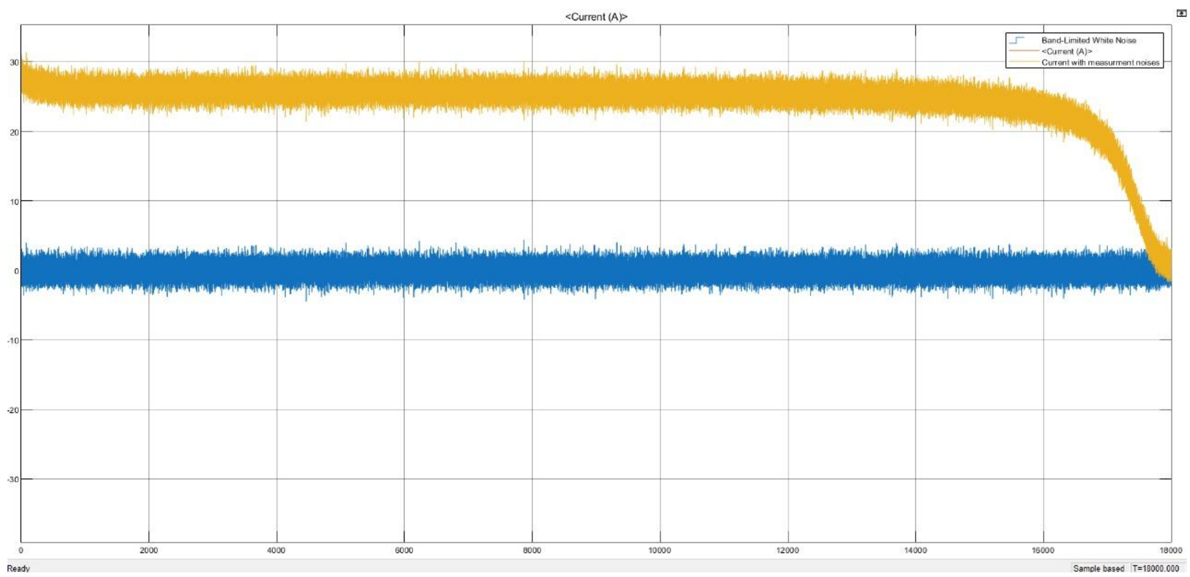
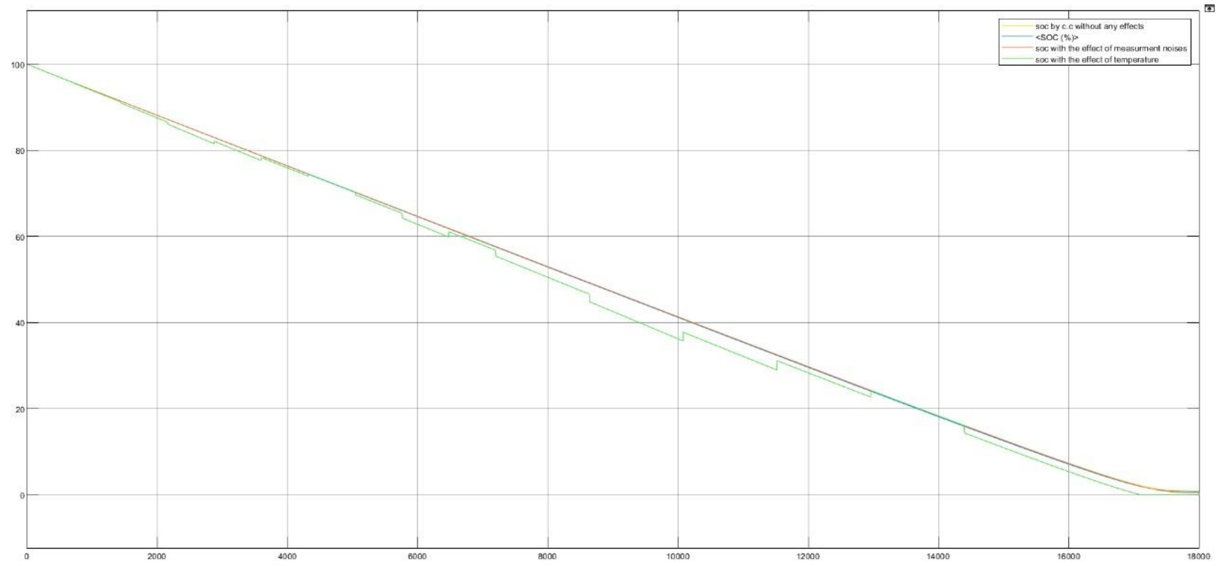


Fig 4: Effects of Temperature and Noises in soc estimation



Graph 4: Value of current after taking noises into account



Graph 5: Soc without any effects, soc, soc with the effect of measurement noises, Soc with the effect of temperature V/s Time

Temperature Effects: The SOC graph shows slight deviations compared to the baseline SOC. These deviations highlight that temperature variations lead to errors in SOC estimation due to the thermal dependency of battery parameters. The sensitivity of SOC to temperature indicates the need for incorporating temperature compensation in battery models.

Noise in Current Measurement: The SOC graph exhibits irregular fluctuations caused by noise in the measured current. These inconsistencies reflect the vulnerability of Coulomb counting to measurement errors. Without proper filtering or noise mitigation techniques, such inaccuracies can accumulate over time, degrading the reliability of SOC estimation.

5. Combined Effects of Temperature, Noise, and Initial SOC Error:

In this case, the cumulative impact of three critical factors—temperature variations, noise in current measurement, and error in initial SOC estimation—is analysed. This scenario simulates real-world conditions where multiple uncertainties affect SOC estimation simultaneously. Temperature introduces nonlinear variations, current measurement noise leads to fluctuating input data, and an inaccurate initial SOC adds a baseline error that propagates over time. The combination of these factors creates a complex challenge for reliable SOC estimation.

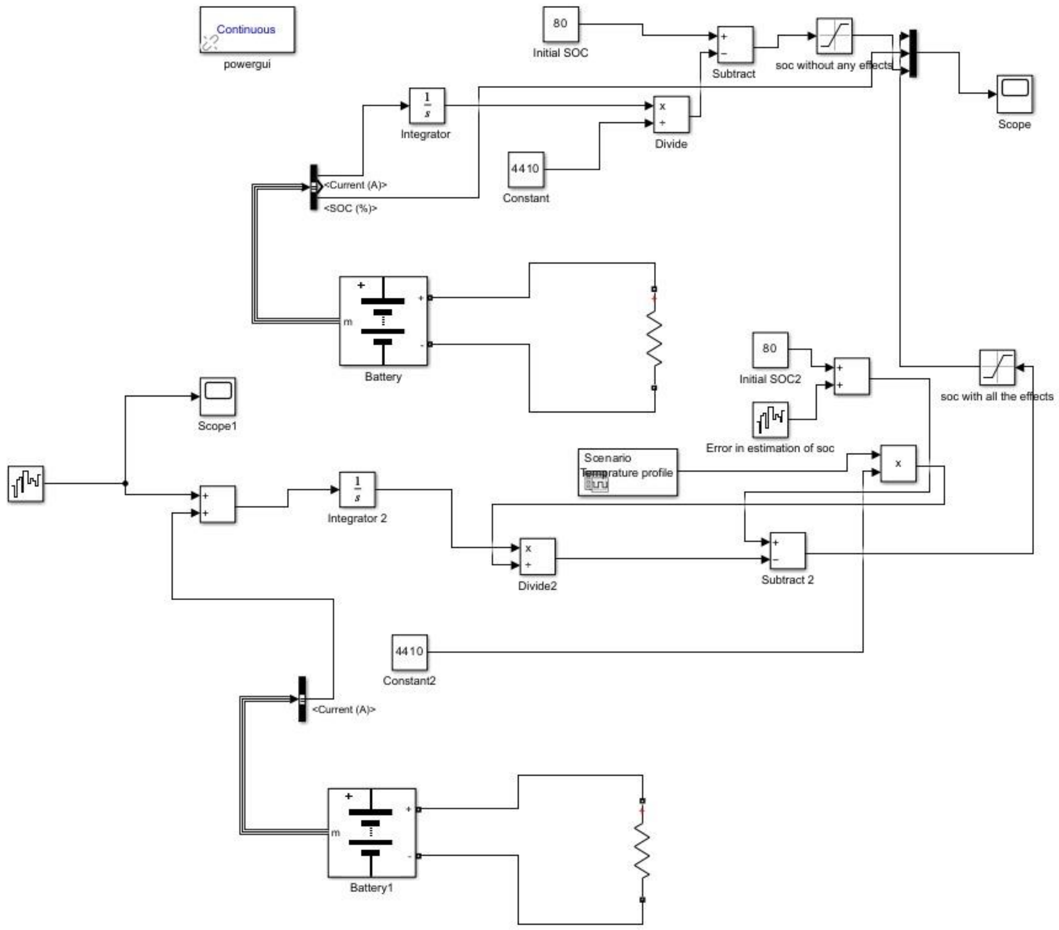
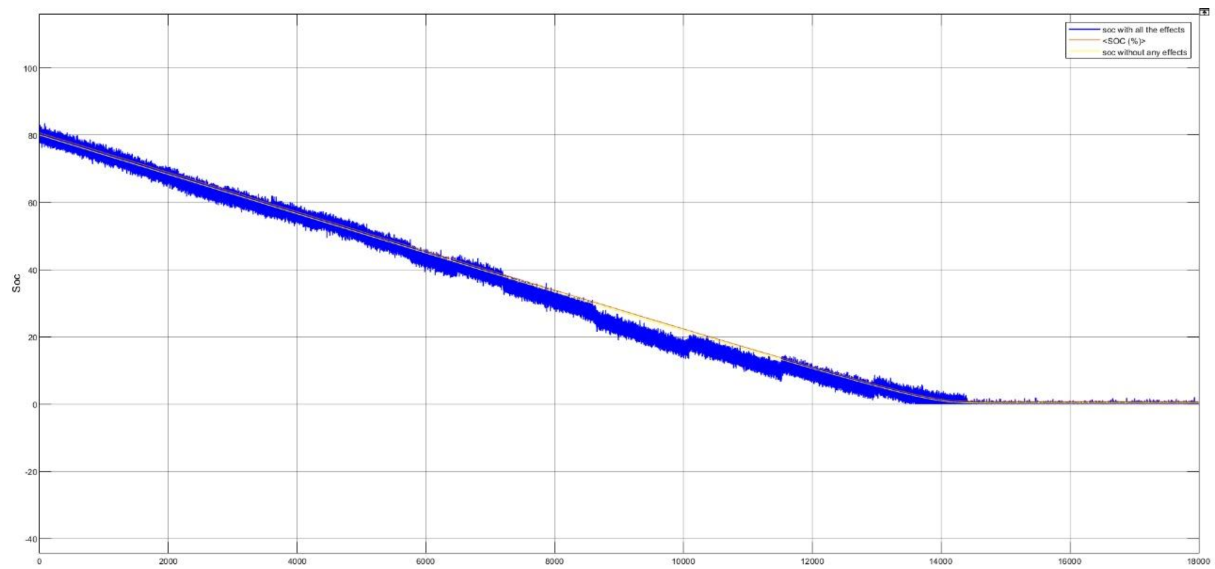


Fig 5: Combined Effects of Temperature, Noise, and Initial Soc Error in Soc Estimation



Graph 6: Soc Estimation with all effect, Soc, Soc without any effects

The SOC graph exhibits significant deviations from the baseline SOC due to the combined effects. The graph shows how errors compound, leading to a notable mismatch between the estimated and actual SOC. This demonstrates the necessity of robust SOC estimation algorithms that can simultaneously account for multiple uncertainties. Techniques such as Kalman filtering or model-based estimation methods may help mitigate these cumulative errors and improve overall accuracy.

(B) SoC estimation using Kalman Filter Method

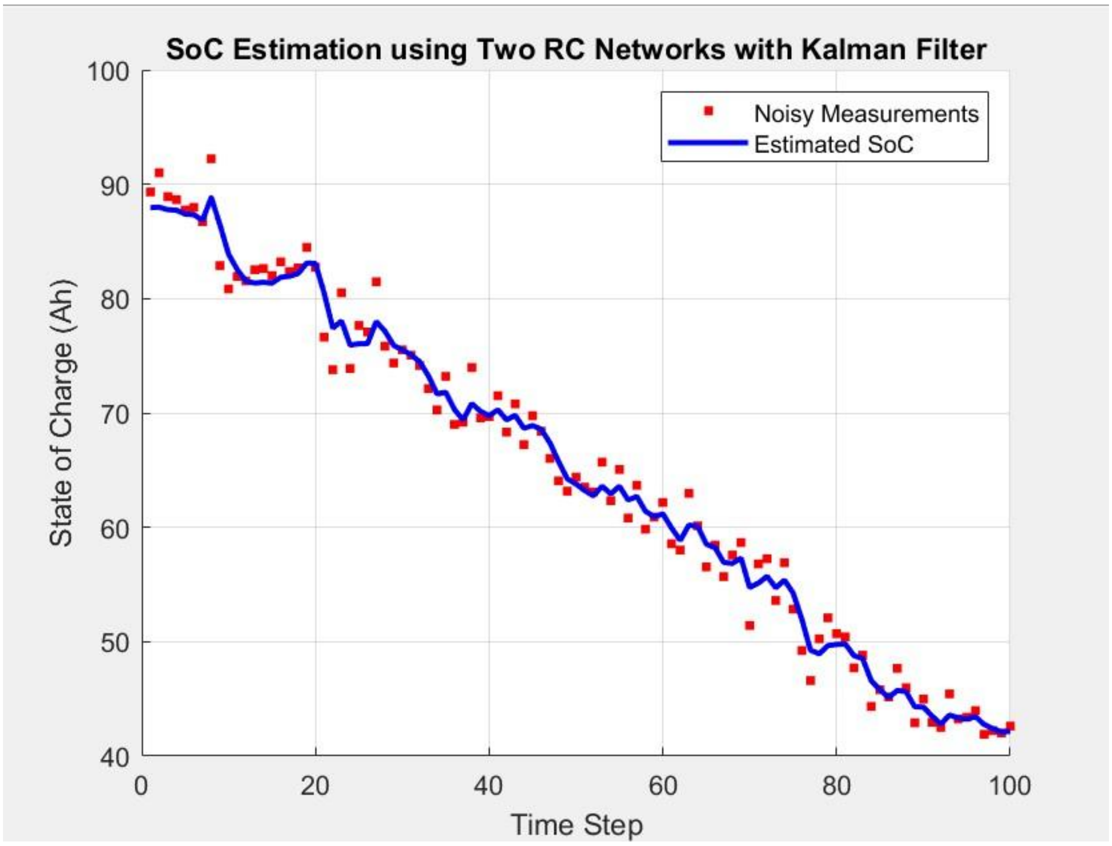
1. MATLAB code for soc estimation by Kalman Filter for discharging of battery:

```
% Two RC Networks for State of Charge (SoC) Estimation with Kalman Filter
% Simulation Parameters
dt = 1; % Time step (1 second)
n = 100; % Number of time steps
% RC Circuit Parameters for Network 1
R1 = 100; % Resistance in Ohms for network 1
C1 = 1; % Capacitance in Farads for network 1
% RC Circuit Parameters for Network 2
R2 = 150; % Resistance in Ohms for network 2
C2 = 0.5; % Capacitance in Farads for network 2
% Initial State of Charge (SoC) and Capacity
initial_soc = 90; % Initial State of Charge in Ah
capacity = 100; % Total capacity in Ah
% Initial Rate of Change (Negative for discharging)(Positive for charging)
initial_rate_of_change = -0.5; % Example negaitive rate of change
% State Transition Matrix (A)
A = [1 - dt/(R1*C1) - dt/(R2*C2), dt/C1; 0, 1]; % Combined dynamics
% Measurement Matrix (H)
H = [1, 0]; % Measurement relates only to SoC
% Process Noise Covariance (Q)
Q = [0.1, 0; 0, 0.1]; % Process noise
% Measurement Noise Covariance (R)
R = 5; % Measurement noise
% Initial State
x = [initial_soc; initial_rate_of_change]; % [SoC; rate of change]
% Initial Covariance Estimate
P = eye(2);
% Allocate arrays for results
soc_est = zeros(1, n); % Estimated SoC
```

```
 measurements = zeros(1, n); % Simulated measurements

% Simulate the Two RC Networks
for k = 1:n
    % Simulate true SoC value (simple discharge model)
    true_soc = initial_soc + initial_rate_of_change * k; % Decreasing SoC

    % Add noise to the measurement
    measurements(k) = true_soc + sqrt(R) * randn; % Noisy measurement
    % Prediction step
    x = A * x; % State prediction
    P = A * P * A' + Q; % Covariance prediction
    % Measurement update step
    y = measurements(k) - H * x; % Measurement residual
    S = H * P * H' + R; % Residual covariance
    K = P * H' / S; % Kalman gain
    x = x + K * y; % State update
    P = (eye(2) - K * H) * P; % Covariance update
    % Store estimated SoC
    soc_est(k) = x(1); % Estimated SoC
end
% Plotting results
figure;
hold on;
plot(1:n, measurements, 'r.', 'MarkerSize', 10, 'DisplayName', 'Noisy Measurements');
plot(1:n, soc_est, 'b-', 'LineWidth', 2, 'DisplayName', 'Estimated SoC');
xlabel('Time Step');
ylabel('State of Charge (Ah)');
title('SoC Estimation using Two RC Networks with Kalman Filter');
legend;
grid on;
hold off;
```



Graph 7: SoC estimation by Kalman filter for discharging of battery

2. MATLAB code for soc estimation by Kalman Filter for charging of battery:

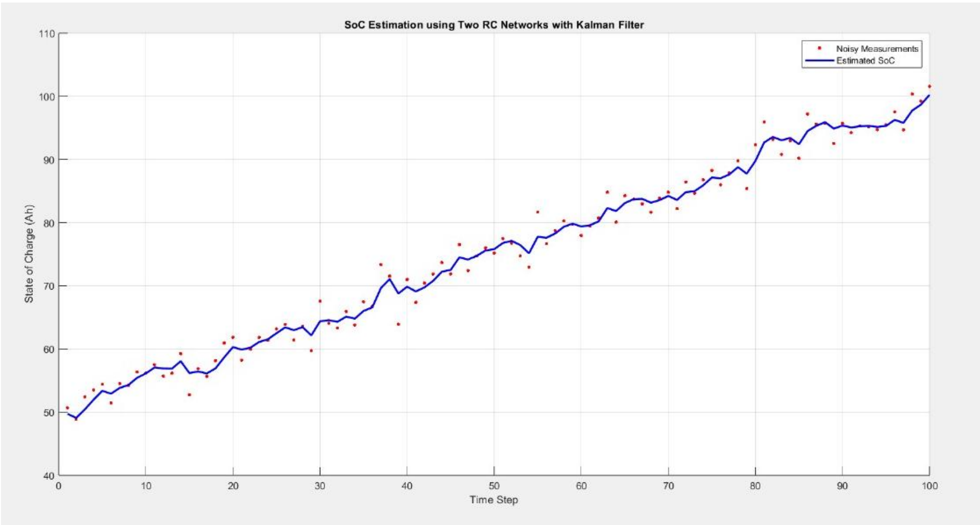
```
% Two RC Networks for State of Charge (SoC) Estimation with Kalman Filter
% Simulation Parameters
dt = 1; % Time step (1 second)
n = 100; % Number of time steps
% RC Circuit Parameters for Network 1
R1 = 100; % Resistance in Ohms for network 1
C1 = 1; % Capacitance in Farads for network 1
% RC Circuit Parameters for Network 2
R2 = 150; % Resistance in Ohms for network 2
C2 = 0.5; % Capacitance in Farads for network 2
% Initial State of Charge (SoC) and Capacity
initial_soc = 50; % Initial State of Charge in Ah
capacity = 100; % Total capacity in Ah
```

```
% Initial Rate of Change (Negative for discharging)(Positive for charging)
initial_rate_of_change = 0.5; % Example negaitive rate of change
% State Transition Matrix (A)
A = [1 - dt/(R1*C1) - dt/(R2*C2), dt/C1; 0, 1]; % Combined dynamics
% Measurement Matrix (H)
H = [1, 0]; % Measurement relates only to SoC
% Process Noise Covariance (Q)
Q = [0.1, 0; 0, 0.1]; % Process noise
% Measurement Noise Covariance (R)
R = 5; % Measurement noise
% Initial State
x = [initial_soc; initial_rate_of_change]; % [SoC; rate of change]
% Initial Covariance Estimate
P = eye(2);
% Allocate arrays for results
soc_est = zeros(1, n); % Estimated SoC
measurements = zeros(1, n); % Simulated measurements

% Simulate the Two RC Networks
for k = 1:n
    % Simulate true SoC value (simple discharge model)
    true_soc = initial_soc + initial_rate_of_change * k; % Decreasing SoC

    % Add noise to the measurement
    measurements(k) = true_soc + sqrt(R) * randn; % Noisy measurement
    % Prediction step
    x = A * x; % State prediction
    P = A * P * A' + Q; % Covariance prediction
    % Measurement update step
    y = measurements(k) - H * x; % Measurement residual
    S = H * P * H' + R; % Residual covariance
    K = P * H' / S; % Kalman gain
    x = x + K * y; % State update
    P = (eye(2) - K * H) * P; % Covariance update
    % Store estimated SoC
    soc_est(k) = x(1); % Estimated SoC
end
% Plotting results
figure;
hold on;
plot(1:n, measurements, 'r.', 'MarkerSize', 10, 'DisplayName', 'Noisy Measurements');
plot(1:n, soc_est, 'b-', 'LineWidth', 2, 'DisplayName', 'Estimated SoC');
```

```
xlabel('Time Step');
ylabel('State of Charge (Ah)');
title('SoC Estimation using Two RC Networks with Kalman Filter');
legend;
grid on;
hold off;
```



Graph 8: SoC estimation by Kalman filter for charging of battery

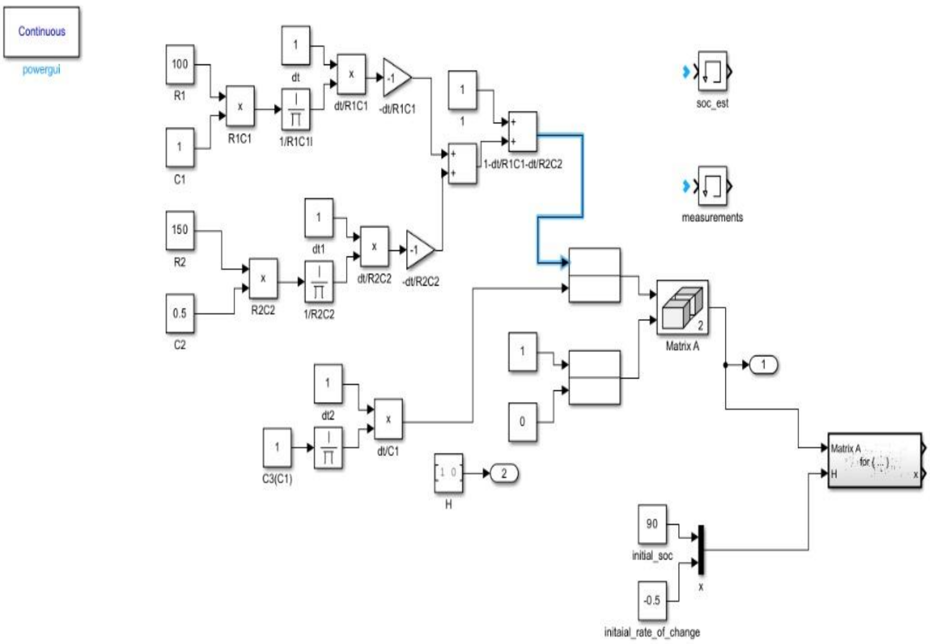


Fig 6(a): Simulink representation of Kalman Filter algorithm for SoC Estimation

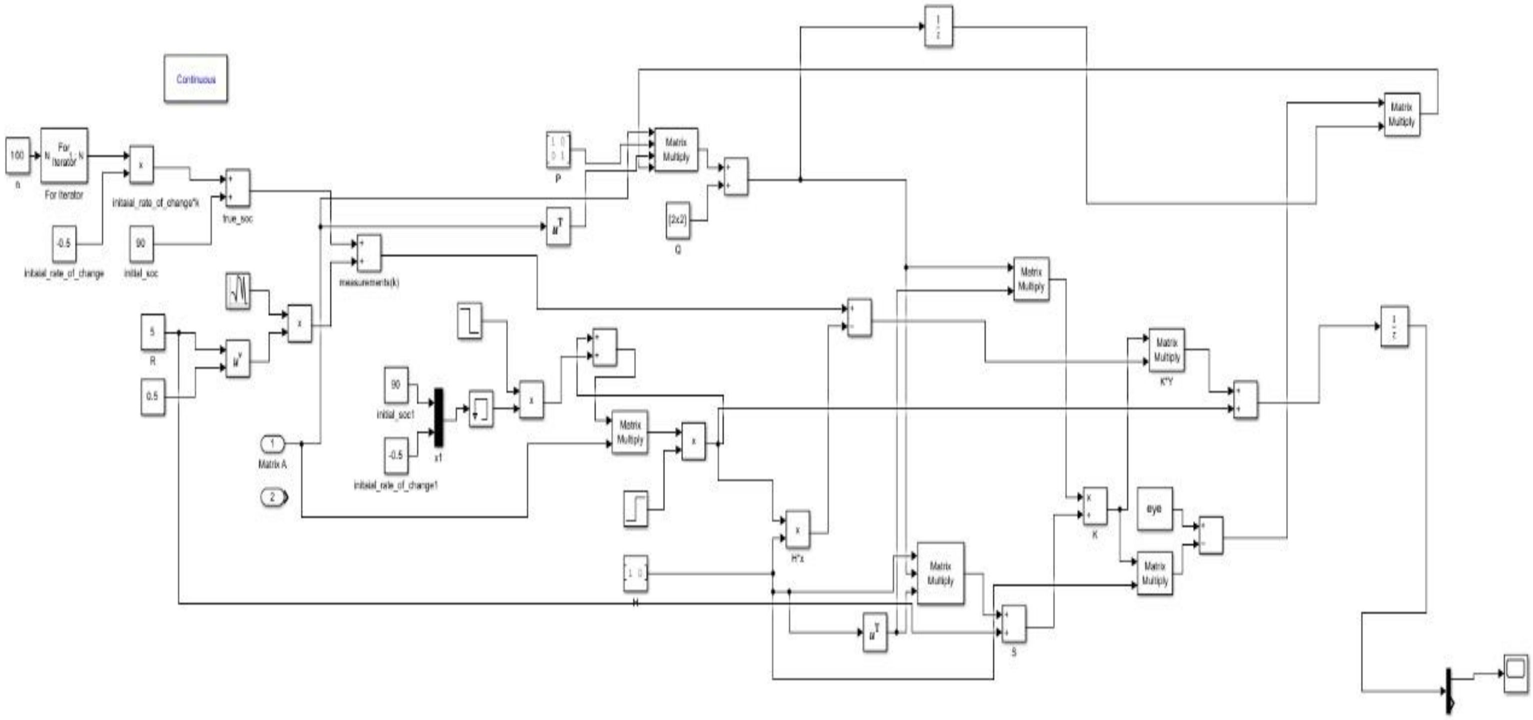


fig 6(b): Simulink representation of Kalman Filter algorithm for SoC Estimation
(For Iterator subsystem)

5. RESULT ANALYSIS

The Coulomb Counting method is an effective and simple approach for SOC estimation, but it requires enhancements to improve its robustness in real-world conditions (e.g., temperature changes, noise in current measurements).
The Kalman filter, while offering great potential, requires careful debugging and parameter tuning to function correctly alongside the Coulomb Counting method.
The integration of these two methods is essential for a reliable SOC estimation system. The next step involves resolving the errors in the Kalman filter and combining both methods to account for measurement errors and uncertainties.

In the first phase of the project, we successfully carried out the simulation of the Coulomb Counting method for State of Charge (SOC) estimation. The simulation demonstrated how current integration could effectively estimate the SOC of a battery under controlled conditions. By connecting the battery across a resistor and measuring the current flow, we were able to track the battery's charge and discharge cycles, and estimate the SOC at any given time. The results aligned well with the expected behaviour, confirming the Coulomb Counting method's validity for SOC estimation in basic scenarios.

In addition, we developed and implemented the initial code for the Kalman filter in MATLAB. Although the simulation was conducted, we encountered some issues with the filter simulation, particularly related to undesirable results due to errors in the setup and implementation. These errors prevented us from achieving the expected performance from the Kalman filter model, highlighting the need for further debugging and optimization before it can be applied to a practical system.

6. CONCLUSION

The first phase of the project has successfully laid the groundwork for our SOC estimation system. The Coulomb Counting method showed promising results in estimating SOC during battery charge and discharge, and the model was validated against expected outcomes.
The Kalman filter, although partially implemented, requires additional work to resolve existing errors and improve its accuracy.This will be carried out in our future work for phase 2 (evaluation1)

7. PLAN FOR NEXT SIX MONTHS (FUTURE WORK)

Project Goals: The primary objectives over the next six months are to:
Debug and finalize the Kalman filter simulation in MATLAB, ensuring that the errors preventing the results are resolved.
Implement the Coulomb Counting method practically on a real battery system, integrating it with necessary hardware components such as current sensors and measurement tools.
Integrate the Kalman filter with the Coulomb Counting system to enhance SOC estimation accuracy by considering uncertainties and external factors like noise and temperature variations.
Conduct extensive testing of the combined system to assess its performance under various real-world conditions, including different charging/discharging cycles, temperature variations, and noise in current measurement.
Minimize errors in the system and refine the algorithms to ensure accurate and reliable SOC estimation.
Document the entire process and prepare a final report and presentation for the successful completion of the project.

Approach: Initially, we will focus on debugging the Kalman filter simulation in MATLAB. The errors that we encountered in the simulation will be systematically addressed, ensuring that all mathematical and logical issues are resolved. Once the Kalman filter simulation works correctly, we will proceed with practical implementation.

The Coulomb Counting method will then be implemented on a real battery system. This will involve setting up the necessary hardware, including a battery, current measurement devices, and resistors for discharging, and integrating them with the MATLAB code. This will allow us to estimate the SOC of the battery in real-time using the Coulomb Counting method.

Next, the Kalman filter will be integrated into the system to improve the SOC estimation. The filter will account for measurement errors and uncertainties, including noise in the current measurement and potential inaccuracies in estimating the initial SOC. By fine-tuning the process and measurement noise parameters in the Kalman filter, we aim to enhance the accuracy and robustness of the SOC estimation.

Once the combined system is operational, we will conduct extensive testing. We will evaluate the system's performance under a range of conditions, such as different temperatures, charging/discharging rates, and noise in current measurement. The goal is to understand how well the system performs under real-world conditions and whether the Kalman filter effectively reduces the errors present in the Coulomb Counting method.

8. REFERENCES

[1]H. Suryoatmojo, S. Anam, Z. Rahmawan, D. A. Asfani, M. A. Faurahmansyah and P. Prabowo, "State of Charge (SOC) Estimation on Lead-Acid Batteries Using the Coulomb Counting Method," 2022 10th International Conference on Smart Grid and Clean Energy Technologies (ICSGCE), Kuala Lumpur, Malaysia, 2022, pp. 78-84

[2] Lee, Jeong, and Jehyuk Won. "Enhanced coulomb counting method for SoC and SoH estimation based on coulombic efficiency." IEEE Access vol.11 (2023) pp: 15449-15459.

[3] G. Fathoni, S. A. Widayat, P. A. Topan, A. Jalil, A. I. Cahyadi and O. Wahyunggoro, "Comparison of State-of-Charge (SOC) estimation performance based on three popular methods: Coulomb counting, open circuit voltage, and Kalman filter," 2017 2nd International Conference on Automation, Cognitive Science, Optics, Micro Electro--Mechanical System, and Information Technology (ICACOMIT), Jakarta, Indonesia, 2017, pp. 70-74

[4] Spagnol, Pierfrancesco, Stefano Rossi, and Sergio M. Savaresi. "Kalman filter SoC estimation for Li-ion batteries." In 2011 IEEE International conference on control applications (CCA), pp. 587-592. 2011

[5] D. Kanchan, Nihal and A. P. Fernandes, "Estimation of SoC for Real Time EV Drive Cycle using Kalman Filter and Coulomb Counting," 2022 2nd International Conference on Intelligent Technologies (CONIT), Hubli, India, 2022, pp. 1-6,

[6] Hu L, Hu R, Ma Z, Jiang W. State of Charge Estimation and Evaluation of Lithium Battery Using Kalman Filter Algorithms. Materials (Basel). 2022 Dec 7.

[7] I. Jokić, Ž. Zečević and B. Krstajić, "State-of-charge estimation of lithium-ion batteries using extended Kalman filter and unscented Kalman filter," 2018 23rd International Scientific-Professional Conference on Information Technology (IT), Zabljak, Montenegro, 2018, pp. 1-4

[8] Frqan Asghar, Muhammad Talha, Sung Ho Kim, In-Ho Ra, “Simulatiom study on Battery State of Charge Estimation using Kalman Filter” , Journal of Advanced Computational Intelligence and Intelligent informatics, Vol.20 No.6,2016