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Temperature Monitoring of Lithium Battery Using Kalman Filter: A Simulation-Based Study

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Abstract - Battery temperature plays a vital role in determining the performance, safety, and lifespan of lithium-ion batteries in electric vehicle (EV) applications. This study presents a simulation-based approach for monitoring surface temperature using Kalman filter estimation, which integrates air temperature, current load, and battery characteristics. A mathematical model of thermal dynamics is developed and used for real-time temperature prediction. The results demonstrate that the Kalman filter is effective in estimating the surface temperature accurately, even with uncertain measurements. This work also discusses the integration of an actuator (fan/cooler) and PID control to maintain the temperature around the ideal level of 25°C, showcasing the potential of this system for smart thermal battery management in cost-constrained embedded systems.

Keywords - Temperature Monitoring; Kalman Filter; Thermal Modeling; Estimation Algorithm; State Estimation; Simulation;

1. INTRODUCTION

Lithium-ion batteries are widely used in electric vehicles due to their high energy density and performance. However, battery performance and safety are strongly affected by temperature. Excessive heat can accelerate battery degradation, reduce efficiency, and in extreme cases, lead to thermal runaway. Monitoring and controlling battery temperature is thus essential, especially in real-time and embedded environments where cost-effective and adaptable solutions are required. Kalman filter-based temperature estimation presents an effective technique that can work with minimal sensor input and accommodate uncertainty, making it suitable for microcontroller-class devices.

Lithium-ion batteries (LIBs) have become the cornerstone of modern energy storage systems, particularly in electric vehicles (EVs), due to their high energy density, lightweight nature, and long cycle life. However, their performance, lifespan, and most critically, their safety, are highly sensitive to temperature. Elevated operating temperatures can accelerate capacity fade, increase internal resistance, and in extreme cases, lead to thermal runaway—a hazardous condition that may result in fire or explosion. Conversely, low temperatures can diminish battery efficiency and increase charging time. Therefore, precise and continuous temperature monitoring is not merely a recommendation but a necessity in the reliable operation of LIBs.

To manage battery temperature effectively, thermal battery management systems (TBMS) have been developed. These systems typically consist of a combination of hardware (sensors, cooling fans, thermal insulation) and software (control algorithms, estimators) to maintain optimal thermal conditions. Conventional methods rely on direct contact temperature sensors, such as thermocouples or thermistors, placed on or within battery cells. However, these approaches increase system complexity and cost, and often fail to capture the internal temperature dynamics, which are more critical than surface temperature alone.

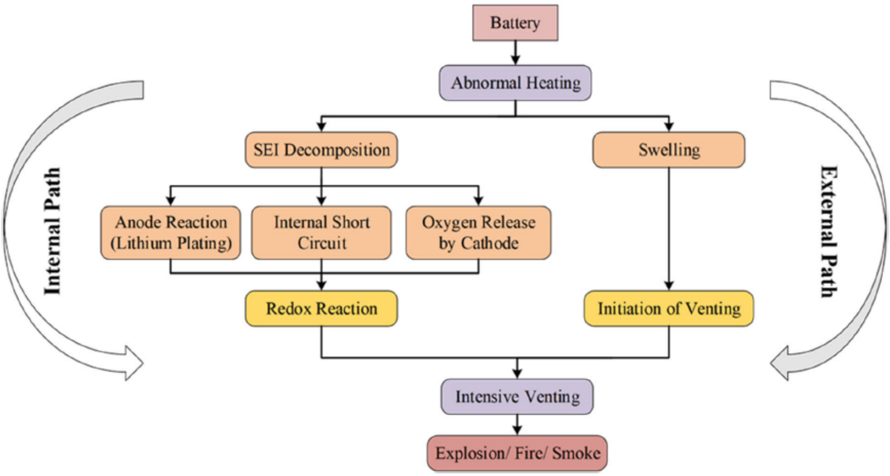


Figure 1. The Sequence of the Thermal Runaway Process

This has prompted the exploration of indirect, model-based thermal estimation methods, which can infer the internal or surface temperature from accessible operational data, such as current, voltage, and ambient conditions. Among these, the Kalman Filter has emerged as a powerful algorithm for state estimation under uncertainty. It can provide reliable real-time temperature estimation even in the presence of measurement noise or sparse sensor data, making it ideal for low-cost embedded systems where extensive sensor deployment is impractical.

In this context, our study proposes a simulation-based thermal monitoring approach using the Kalman Filter to estimate battery surface temperature. We focus on reconstructing temperature profiles based on current flow, ambient temperature, and thermal characteristics of the battery, without relying on internal or direct-contact temperature sensors. This approach is not only cost-effective but also platform-independent, allowing implementation on microcontroller-level hardware with limited computational resources. The proposed method is further enhanced with PID-based actuator control, enabling dynamic regulation of battery temperature through external cooling mechanisms.

2. RESEARCH METHOD

This study develops a thermal model of a lithium-ion battery, incorporating thermal transfer properties between the battery surface and ambient air. A discrete Kalman filter algorithm is applied to estimate surface temperature using ambient temperature and current input as indirect measurements. The process involves the following steps:

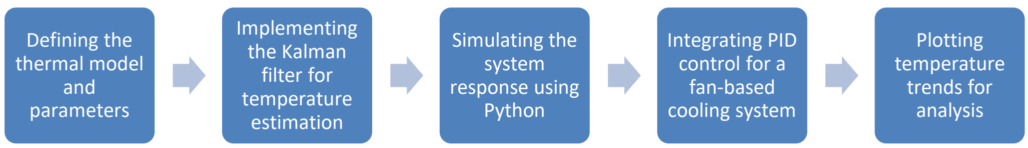


Figure 2. Research Method

2.1. Defining the thermal model and parameters

Defining the Thermal Model and Parameters

To estimate battery surface temperature, a simplified lumped thermal model is used, where the battery is treated as a single thermal mass exchanging heat with the surrounding environment. The primary heat source is internal Joule heating, which is proportional to the square of the current multiplied by the internal resistance of the battery. The heat dissipation to the ambient air is modeled using Newton's law of cooling. Key parameters defined in this model include the thermal capacity (C_t) of the battery, heat transfer coefficient (h) between the battery surface and ambient air, and effective surface area (A). These parameters form the basis of the thermal differential equation:

$$C_t.\frac{dT}{dt} = I^2R - hA(T - T_{ambient})$$

Where:

T	= battery surface temperature
I	= current input/output
R	= internal resistance
$T_{ambient}$	= ambient temperature

The model assumes uniform temperature distribution and is discretized for implementation in the Kalman filter. These thermal parameters can be estimated from manufacturer data or through empirical testing for greater accuracy.

2.2. Implementing the Kalman filter for temperature estimation

The Kalman filter is implemented to estimate the surface temperature of the battery using indirect measurements such as current input and ambient air temperature. This recursive algorithm optimally estimates the internal state of the system by minimizing the mean of the squared error. The system model is defined using a discrete-time state-space representation of the battery's thermal dynamics, with the state variable being the surface temperature. The process model incorporates internal heat generation due to current flow, while the observation model relates the state to the measured ambient temperature. The Kalman filter operates in two main steps: prediction and correction. In the prediction step, the filter projects the current state estimate forward in time, while the correction step updates this estimate using new measurements. The model is discretized using known thermal parameters, and process and measurement noise covariance matrices are carefully tuned to reflect real-world uncertainties. This setup allows the Kalman filter to perform robustly even under noisy input conditions and limited sensing capability.

System Model:

$$T_k = T_{k-1} + \alpha \cdot I_k \cdot V_k + \beta \cdot (Tenv - T_{k-1})$$

T_k : Battery temperature at time *k*.
I_k : Current at time *k*.
Vk : Voltage at time *k*.
$Tenv$: Ambient temperature.
α dan *β* : Thermal coefficients.

Prediction Calculate:

Prediction of state ($\mathrm{x_{pred}}$) and covariance ($\mathrm{P_{pred}}$) using the system model.

$$\mathrm{x_{pred}} = A \cdot x_{k-1} + B \cdot uk$$
$$\mathrm{P_{pred}} = A \cdot P_{k-1} \cdot A^T + Q$$

(uk)	: Control input (current, voltage, ambient temperature).
(x_0)	: Initial state, initial battery temperature (e.g., 25°C).
(P_0)	: Initial covariance (e.g., 1.0).
(A)	: State transition matrix, representing state changes (temperature).
(B)	: Control matrix, representing the influence of inputs (current, voltage, ambient temperature).
(H)	: Measurement matrix, linking state to measurements (identity matrix if state and measurement are the same).
(Q)	: Process noise or uncertainty in the model.
(R)	: Measurement noise or uncertainty in the measurements.

Update

Calculate Kalman Gain (K)

$$K = P_{pred} \cdot H^T \cdot (H \cdot P_{pred} \cdot H^T + R)^{-1}$$

Update the state (x_k) and covariance (P_k) based on the actual temperature measurement (Z_k).

$$x_k = x_{pred} + K \cdot (Z_k - H \cdot x_{pred})$$
$$P_k = (I - K \cdot H) \cdot P_{pred}$$

Time Update (Prediction)	Measurement Update (Correction)
1. Project the state ahead	1. Computer the Kalman Gain
$x_{pred} = A \cdot x_{k-1} + B \cdot uk$	$K = P_{pred} \cdot H^T \cdot (H \cdot P_{pred} \cdot H^T + R)^{-1}$
2. Project the error covariance ahead	2. Update the estimate via Z_k
$P_{pred} = A \cdot P_{k-1} \cdot A^T + Q$	$x_k = x_{pred} + K \cdot (Z_k - H \cdot x_{pred})$
	3. Update the error covariance
	$P_k = (I - K \cdot H) \cdot P_{pred}$

The output at K will be the input fo k+1

2.3. Simulating the system response using Python

To validate the performance of the proposed temperature monitoring system, simulations are conducted using Python. The thermal model is implemented using state-space representation and numerically solved with discrete-time steps. The Kalman filter is applied to estimate the surface temperature based on inputs such as ambient temperature and current load. Python libraries such as NumPy and SciPy are used for numerical computations, while Matplotlib is employed to visualize the temperature profiles. The simulation also includes the implementation of a PID controller to regulate the fan speed for thermal management. This simulation framework enables the observation of real-time system dynamics, assessment of filter accuracy, and evaluation of the system's ability to maintain temperature stability under varying load and environmental conditions.

2.4. Integrating PID control for a fan-based cooling system

To actively regulate the surface temperature of the battery, a Proportional-Integral-Derivative (PID) controller is integrated with a fan-based cooling system in the simulation. The PID controller takes the difference between the estimated temperature (from the Kalman filter) and the desired setpoint (typically 25°C) as the error input. It then adjusts the fan's cooling effect based on this error using proportional, integral, and derivative actions. The controller is tuned to ensure fast response, minimal overshoot, and stable convergence. This closed-loop system dynamically modulates cooling intensity to maintain optimal battery temperature despite fluctuations in ambient temperature or load, making it suitable for real-time embedded implementations.

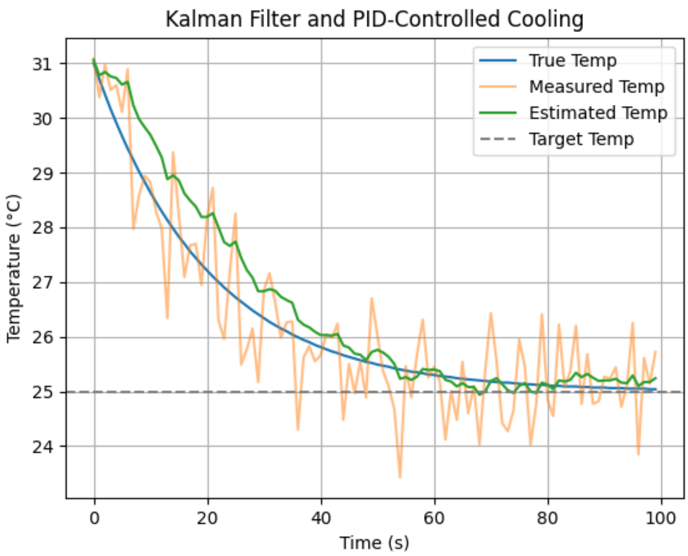
2.5. Plotting temperature trends for analysis

After the Kalman filter and PID control system are implemented in the simulation, the next crucial step is to visualize the temperature data over time. This involves plotting the estimated surface temperature, ambient temperature, and setpoint temperature on the same graph to analyze system behavior, convergence accuracy, and control effectiveness. Through these plots, one can assess how well the Kalman filter tracks the real surface temperature and how effectively the PID controller maintains the target temperature. These visual insights help validate the model, highlight system delays or overshoots, and identify opportunities for optimization in real-world implementations.

3. RESULTS AND DISCUSSION

Two simulation scenarios were conducted to analyze the impact of different cooling system configurations on battery temperature estimation. In both simulations, the ambient temperature was fixed at 31°C with the initial surface temperature of the battery set to 31°C.

1. **Scenario A – Low Cooling Coefficient (k_cooling = 0.1):** The Kalman filter accurately estimated the battery surface temperature with minimal error. Without strong cooling influence, the fan’s effect was limited. As the temperature started above 30°C, the PID controller attempted to regulate it down to 25°C. However, the weaker cooling efficiency only gradually lowered the temperature, highlighting that the fan requires adequate effectiveness to achieve rapid thermal control.

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Time: 0s | True Temp: 31.00°C | Measured Temp: 30.92°C | Estimated Temp: 30.95°C |
Time: 1s | True Temp: 30.71°C | Measured Temp: 32.43°C | Estimated Temp: 31.55°C |
Time: 2s | True Temp: 30.43°C | Measured Temp: 30.89°C | Estimated Temp: 31.35°C |
Time: 3s | True Temp: 30.16°C | Measured Temp: 30.15°C | Estimated Temp: 31.06°C |
Time: 4s | True Temp: 29.91°C | Measured Temp: 29.24°C | Estimated Temp: 30.68°C |
Time: 5s | True Temp: 29.67°C | Measured Temp: 29.72°C | Estimated Temp: 30.51°C |
Time: 6s | True Temp: 29.44°C | Measured Temp: 28.84°C | Estimated Temp: 30.22°C |
Time: 7s | True Temp: 29.23°C | Measured Temp: 28.46°C | Estimated Temp: 29.94°C |
Time: 8s | True Temp: 29.02°C | Measured Temp: 29.75°C | Estimated Temp: 29.91°C |
Time: 9s | True Temp: 28.83°C | Measured Temp: 29.17°C | Estimated Temp: 29.80°C |
Time: 10s | True Temp: 28.64°C | Measured Temp: 29.24°C | Estimated Temp: 29.72°C |
Time: 11s | True Temp: 28.46°C | Measured Temp: 28.41°C | Estimated Temp: 29.54°C |
Time: 12s | True Temp: 28.29°C | Measured Temp: 29.44°C | Estimated Temp: 29.52°C |
Time: 13s | True Temp: 28.13°C | Measured Temp: 27.03°C | Estimated Temp: 29.18°C |
Time: 14s | True Temp: 27.98°C | Measured Temp: 28.38°C | Estimated Temp: 29.07°C |
Time: 15s | True Temp: 27.83°C | Measured Temp: 28.13°C | Estimated Temp: 28.95°C |
Time: 16s | True Temp: 27.70°C | Measured Temp: 27.13°C | Estimated Temp: 28.70°C |
Time: 17s | True Temp: 27.56°C | Measured Temp: 28.25°C | Estimated Temp: 28.64°C |
Time: 18s | True Temp: 27.44°C | Measured Temp: 27.55°C | Estimated Temp: 28.50°C |
Time: 19s | True Temp: 27.32°C | Measured Temp: 26.92°C | Estimated Temp: 28.29°C |
Time: 20s | True Temp: 27.21°C | Measured Temp: 27.69°C | Estimated Temp: 28.21°C |
Time: 21s | True Temp: 27.10°C | Measured Temp: 27.16°C | Estimated Temp: 28.07°C |
Time: 22s | True Temp: 27.00°C | Measured Temp: 27.48°C | Estimated Temp: 27.99°C |
Time: 23s | True Temp: 26.90°C | Measured Temp: 26.52°C | Estimated Temp: 27.80°C |
Time: 24s | True Temp: 26.81°C | Measured Temp: 26.61°C | Estimated Temp: 27.64°C |
Time: 25s | True Temp: 26.72°C | Measured Temp: 26.69°C | Estimated Temp: 27.52°C |
Time: 26s | True Temp: 26.64°C | Measured Temp: 26.56°C | Estimated Temp: 27.39°C |
Time: 27s | True Temp: 26.56°C | Measured Temp: 27.09°C | Estimated Temp: 27.35°C |
Time: 28s | True Temp: 26.48°C | Measured Temp: 27.45°C | Estimated Temp: 27.36°C |
Time: 29s | True Temp: 26.41°C | Measured Temp: 26.86°C | Estimated Temp: 27.30°C |
Time: 30s | True Temp: 26.34°C | Measured Temp: 27.58°C | Estimated Temp: 27.33°C |
Time: 31s | True Temp: 26.27°C | Measured Temp: 26.27°C | Estimated Temp: 27.19°C |
Time: 32s | True Temp: 26.21°C | Measured Temp: 25.54°C | Estimated Temp: 26.98°C |
Time: 33s | True Temp: 26.15°C | Measured Temp: 25.64°C | Estimated Temp: 26.80°C |
Time: 34s | True Temp: 26.10°C | Measured Temp: 26.54°C | Estimated Temp: 26.77°C |
Time: 35s | True Temp: 26.04°C | Measured Temp: 25.13°C | Estimated Temp: 26.55°C |
Time: 36s | True Temp: 25.99°C | Measured Temp: 26.33°C | Estimated Temp: 26.52°C |
Time: 37s | True Temp: 25.94°C | Measured Temp: 26.05°C | Estimated Temp: 26.46°C |
Time: 38s | True Temp: 25.90°C | Measured Temp: 26.35°C | Estimated Temp: 26.44°C |
Time: 39s | True Temp: 25.85°C | Measured Temp: 26.03°C | Estimated Temp: 26.39°C |
Time: 40s | True Temp: 25.81°C | Measured Temp: 25.26°C | Estimated Temp: 26.24°C |
Time: 41s | True Temp: 25.77°C | Measured Temp: 25.50°C | Estimated Temp: 26.14°C |
Time: 42s | True Temp: 25.73°C | Measured Temp: 26.22°C | Estimated Temp: 26.15°C |
Time: 43s | True Temp: 25.70°C | Measured Temp: 26.28°C | Estimated Temp: 26.17°C |
Time: 44s | True Temp: 25.66°C | Measured Temp: 25.70°C | Estimated Temp: 26.11°C |
Time: 45s | True Temp: 25.63°C | Measured Temp: 25.31°C | Estimated Temp: 26.00°C |
Time: 46s | True Temp: 25.60°C | Measured Temp: 26.82°C | Estimated Temp: 26.11°C |
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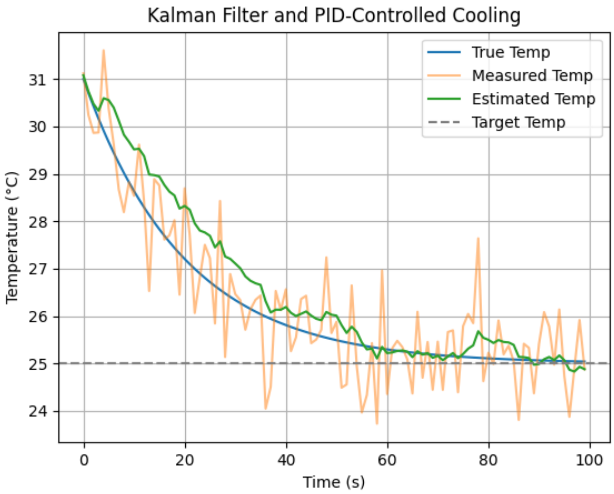
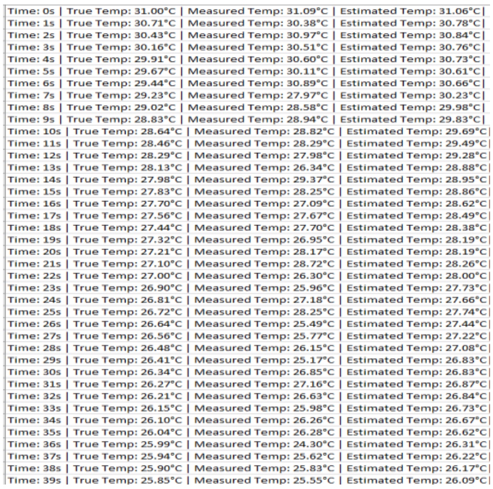
Figure 3. Demonstrates the thermal response and Kalman estimation accuracy for Scenario A, where the system approached but did not consistently stay below 30°C

To enhance thermal management flexibility and reduce unnecessary fan actuation, the system is designed to maintain the battery surface temperature within a target range of 25°C to 30°C, rather than enforcing a strict single-point setpoint. This range-based control introduces a hysteresis mechanism where the cooling fan is activated only when the estimated temperature exceeds 30°C, and deactivated when the temperature drops below 25°C. Within this buffer zone, the fan remains off to prevent rapid toggling and excessive energy usage. The PID controller dynamically adjusts the fan power when cooling is required, using 25°C as the internal control target during active cooling phases. This approach not only mimics real-world embedded thermal control strategies but also contributes to energy-efficient operation while ensuring the battery remains within its safe operating temperature band.

2. **Scenario B – High Cooling Coefficient (k_cooling = 1):** With increased cooling coefficient and efficiency, the PID-controlled fan effectively managed the battery surface temperature. The Kalman filter maintained accurate estimation even during active cooling. The estimated temperature reached the target range of 25–30°C more quickly. This suggests that stronger thermal dissipation combined with precise estimation supports more stable and responsive battery thermal management.





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Time: 0s | True Temp: 31.00°C | Measured Temp: 31.09°C | Estimated Temp: 31.06°C|
Time: 1s | True Temp: 30.71°C | Measured Temp: 30.38°C | Estimated Temp: 30.78°C|
Time: 2s | True Temp: 30.43°C | Measured Temp: 30.97°C | Estimated Temp: 30.84°C|
Time: 3s | True Temp: 30.16°C | Measured Temp: 30.51°C | Estimated Temp: 30.76°C|
Time: 4s | True Temp: 29.91°C | Measured Temp: 30.60°C | Estimated Temp: 30.73°C|
Time: 5s | True Temp: 29.67°C | Measured Temp: 30.11°C | Estimated Temp: 30.61°C|
Time: 6s | True Temp: 29.44°C | Measured Temp: 30.89°C | Estimated Temp: 30.66°C|
Time: 7s | True Temp: 29.23°C | Measured Temp: 27.97°C | Estimated Temp: 30.23°C|
Time: 8s | True Temp: 29.02°C | Measured Temp: 28.58°C | Estimated Temp: 29.98°C|
Time: 9s | True Temp: 28.83°C | Measured Temp: 28.94°C | Estimated Temp: 29.83°C|
Time: 10s | True Temp: 28.64°C | Measured Temp: 28.82°C | Estimated Temp: 29.69°C|
Time: 11s | True Temp: 28.46°C | Measured Temp: 28.29°C | Estimated Temp: 29.49°C|
Time: 12s | True Temp: 28.29°C | Measured Temp: 27.98°C | Estimated Temp: 29.28°C|
Time: 13s | True Temp: 28.13°C | Measured Temp: 26.34°C | Estimated Temp: 28.88°C|
Time: 14s | True Temp: 27.98°C | Measured Temp: 29.37°C | Estimated Temp: 28.95°C|
Time: 15s | True Temp: 27.83°C | Measured Temp: 28.25°C | Estimated Temp: 28.86°C|
Time: 16s | True Temp: 27.70°C | Measured Temp: 27.09°C | Estimated Temp: 28.62°C|
Time: 17s | True Temp: 27.56°C | Measured Temp: 27.67°C | Estimated Temp: 28.49°C|
Time: 18s | True Temp: 27.44°C | Measured Temp: 27.70°C | Estimated Temp: 28.38°C|
Time: 19s | True Temp: 27.32°C | Measured Temp: 26.95°C | Estimated Temp: 28.19°C|
Time: 20s | True Temp: 27.21°C | Measured Temp: 28.17°C | Estimated Temp: 28.19°C|
Time: 21s | True Temp: 27.10°C | Measured Temp: 28.72°C | Estimated Temp: 28.26°C|
Time: 22s | True Temp: 27.00°C | Measured Temp: 26.30°C | Estimated Temp: 28.00°C|
Time: 23s | True Temp: 26.90°C | Measured Temp: 25.96°C | Estimated Temp: 27.73°C|
Time: 24s | True Temp: 26.81°C | Measured Temp: 27.18°C | Estimated Temp: 27.66°C|
Time: 25s | True Temp: 26.72°C | Measured Temp: 28.25°C | Estimated Temp: 27.74°C|
Time: 26s | True Temp: 26.64°C | Measured Temp: 25.49°C | Estimated Temp: 27.44°C|
Time: 27s | True Temp: 26.56°C | Measured Temp: 25.77°C | Estimated Temp: 27.22°C|
Time: 28s | True Temp: 26.48°C | Measured Temp: 26.15°C | Estimated Temp: 27.08°C|
Time: 29s | True Temp: 26.41°C | Measured Temp: 25.17°C | Estimated Temp: 26.83°C|
Time: 30s | True Temp: 26.34°C | Measured Temp: 26.85°C | Estimated Temp: 26.83°C|
Time: 31s | True Temp: 26.27°C | Measured Temp: 27.16°C | Estimated Temp: 26.87°C|
Time: 32s | True Temp: 26.21°C | Measured Temp: 26.63°C | Estimated Temp: 26.84°C|
Time: 33s | True Temp: 26.15°C | Measured Temp: 25.98°C | Estimated Temp: 26.73°C|
Time: 34s | True Temp: 26.10°C | Measured Temp: 26.26°C | Estimated Temp: 26.67°C|
Time: 35s | True Temp: 26.04°C | Measured Temp: 26.28°C | Estimated Temp: 26.62°C|
Time: 36s | True Temp: 25.99°C | Measured Temp: 24.30°C | Estimated Temp: 26.31°C|
Time: 37s | True Temp: 25.94°C | Measured Temp: 25.62°C | Estimated Temp: 26.22°C|
Time: 38s | True Temp: 25.90°C | Measured Temp: 25.83°C | Estimated Temp: 26.17°C|
Time: 39s | True Temp: 25.85°C | Measured Temp: 25.55°C | Estimated Temp: 26.09°C|
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Figure 4. Highlights Scenario B, with effective control maintaining the temperature in the desired range.

These results validate the proposed method's feasibility for smart battery monitoring using embedded systems. The system also reduces unnecessary fan activity by applying hysteresis: activating cooling only when temperature exceeds 30°C and stopping when it drops below 25°C.

Aspect	Scenario A – Low Cooling Coefficient	Scenario B – High Cooling Coefficient
Temperature Setpoint	Constantly fixed at 25°C	A flexible range between 25°C and 30°C
PID Control Response	PID remains active until it reaches 25°C	PID activates only when temperature exceeds 30°C
Temperature Stability	Quickly converges to 25°C, fan operates more frequently	Stabilizes within the range, with minor fluctuations
Energy Efficiency	Higher energy consumption due to continuous fan operation	More energy efficient by introducing hysteresis control
Estimation Noise	Kalman estimation is smooth and closely follows real temp	Similar behavior, slight delay due to intermittent fan control
Overshoot/Undershoot	Minimum, system settles near 25°C	Slight oscillations, but always within the safe temperature band

4. CONCLUSION

The simulation results validate the effectiveness of the Kalman filter combined with a PID-controlled cooling system for thermal management of battery surfaces. In the first scenario (Figure 2), where the target temperature is strictly set at 25°C, the system demonstrates the ability to stabilize the estimated temperature close to the desired setpoint despite sensor noise and dynamic thermal disturbances. This confirms the Kalman filter's accuracy in estimation and the PID controller's responsiveness in regulating fan operation. In the second scenario (Figure 3), a more flexible control strategy is employed by introducing a target temperature range of 25°C to 30°C. This range-based approach successfully maintains battery temperatures within a safe thermal band while reducing unnecessary fan activation, thus enhancing energy efficiency and operational stability. The hysteresis-based control prevents rapid toggling, making the system more suitable for real-world embedded applications. These findings affirm the system's potential for implementation in low-cost hardware platforms for electric vehicle battery thermal management.

The Kalman filter provides an effective and efficient solution for real-time temperature estimation in lithium-ion battery systems. Combined with a thermal model and PID-based actuator control, it offers robust performance even with limited sensing capabilities. This approach supports the development of low-cost, embedded smart thermal monitoring systems critical to battery safety and longevity in EVs. Comparison between low and high cooling efficiency scenarios emphasizes the importance of adequate actuator design in maintaining optimal battery conditions.

Future work will focus on implementing the proposed control algorithm in a real-time embedded system using microcontrollers or single-board computers. Additionally, experimental validation will be conducted using actual battery modules under varying thermal and electrical load conditions. To further enhance accuracy and robustness, comparisons with other state estimation algorithms such as Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), and Particle Filter will be explored. Integration with wireless sensor networks and IoT platforms is also a potential direction to enable remote monitoring and smart energy management. Ultimately, the goal is to transition this system from a simulation environment to a deployable component of intelligent Battery Management Systems (BMS) in electric vehicles or energy storage systems.

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