

An Enhanced Kalman Filter-Based Hybrid Battery Management System for Energy Optimization in IoT-Enabled Smart Agriculture

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Abstract—Battery-powered sensor nodes operating in a remote environment are used in IoT-based smart agriculture deployments, where the maintenance of these devices is impractical. Thus, precise SOC (state-of-charge) estimation is critical to enhance both energy efficiency and system stability. A new hybrid BMS for SOC estimation based on a transaction-oriented adaptive Kalman Filter that merges traditional voltage-based SOC estimation has been developed in this study. Results show that our proposed method removes noise sensitivity and reduces SOC drift subjected to dynamic IoT workloads by integrating model prediction with measurement correction. Application experiments based on 30 days' real sensor workload data indicate that the cumulative battery consumption index of the proposed algorithm decreased from 78% to 56%, and provided a performance improvement of approximately 22.7% compared to the baseline method. Moreover, the proposed method shows better stability in terms of daily consumption fluctuation and drift. The findings demonstrate that the improved Kalman Filter-based hybrid BMS serves as an efficient and effective alternative for achieving long-term energy optimization in IoT-enabled smart agriculture applications.

Keywords—Internet of Things; smart agriculture; battery management system; state-of-charge estimation; Kalman Filter; energy optimization

I. INTRODUCTION

Agriculture is the backbone industry for global food security and economic growth. A growing demand for food, coupled with climate change, has increased the need to develop more efficient and sustainable farming methods [1], [3]. To solve the aforementioned issues, smart agriculture leveraging Internet of Things (IoT) technologies has proven to be a promising solution that increases productivity via real-time monitoring, automated operations and data-driven decision making [2], [8], [11].

Climate change, environmental degradation, and increasing agricultural demand continue to affect global food sustainability and farming efficiency [4], [6], [7]. Furthermore, adoption barriers associated with cost, scalability, and infrastructure limitations remain significant challenges in smart agriculture deployment [5].

However, in spite of these remarkable benefits, IoT-based agriculture systems come up against important energy efficiency

challenges. Most of the IoT devices are deployed in remote and open-field environments with access to power strings, thus have greater reliance on energy stored within batteries [10], [11]. Continuous sensing, on-device processing, and wireless communication drain the battery quickly, resulting in increased maintenance requirements and reduced system reliability [12].

Battery management systems (BMS) are crucial for monitoring battery health, ensuring safety during operation, and optimizing energy efficiency [13], [16]. One of their core functions, accurate estimation of the battery State of Charge (SOC), is crucial to optimizing energy management. Voltage-based methods and Coulomb counting are traditional SOC estimation approaches, which are highly sensitive to measurement noise, suffer from cumulative drift, and have low accuracy at dynamic working conditions [14], [15].

Consequently, KF-based SOC estimation methods have been widely utilized since they provide the advantages of combining system models and noisy sensor measurements [17], [18]. However, current KF implementations only focus on estimation accuracy and do not specifically consider optimization of battery consumption for IoT workloads applied to smart agriculture contexts. To fix this limitation, this study proposes an advanced Kalman Filter-based hybrid BMS to establish a direct relationship between SOC estimation accuracy and energy consumption optimization.

The key contributions of this work include:

1. A hybrid BMS architecture based on the voltage-based estimate and a Kalman filter correction approach.
2. An adaptive SOC modelling technique based on transactions for dynamic IoT workload variations.
3. Using 30-day real workload data for the experimental validation shows improved energy efficiency, stability, and less SOC drift.

Unlike existing SOC estimation approaches designed primarily for electric vehicle applications, the proposed method specifically targets low-power IoT smart agriculture workloads using transaction-based adaptive covariance adjustment to improve long-term energy optimization and SOC stability.

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The remainder of this study is organized as follows: Section II reviews related work on IoT energy challenges and SOC estimation techniques. Section III presents the proposed hybrid battery management system architecture and transaction-based adaptive Kalman Filter methodology. Section IV describes the experimental setup, hardware configuration, and data collection process. Section V discusses the experimental results, comparative analysis, and system performance evaluation. Section VI details the limitations of the study. Finally, Section VII concludes the study and outlines future research directions.

II. RELATED WORK

A. IoT Energy Challenges in Smart Agriculture

The swift adoption of Internet of Things (IoT), also known as smart agriculture technologies, has led to its myriad applications, such as automated irrigation, crop & soil health monitoring, and environmental sensing. Typically, these systems do operate on distributed sensor nodes placed around an open-field environment, a greenhouse, or a remote farm. While the productivity and resource utilization rise with IoT-based agriculture, energy efficiency is still one of the major critical problems due to the limited power available for sensor nodes [11], [12]. Power is a major concern in this domain as most of the agricultural IoT deployments are battery-powered, which makes it either difficult or costly to replace batteries frequently [10]. Energy consumption mainly comes from continuous sensing, local processing, and wireless data transmission. This is especially true, since communication overhead often accounts for a considerable portion (more than 90% in some cases) of the energy cost [8] associated with such workloads. Outdoor environments (i.e., temperature variability, humidity, and erratic connectivity) result in quick battery drain of these systems as well as low overall reliability of the system. Energy in IoT-based smart agriculture systems is desired to be sustained by the long-term existence, hence energy-aware level monitoring and power optimization methodologies are required.

B. SOC Estimation Techniques

BMS is able to enhance its performance, but also control and ensure battery and overcharging in an exceptional way. In order to optimize the energy, BMS will calculate the state of charge (SOC) of the battery pack for every essential task and used for remaining battery life estimation [13], [16]. Meanwhile, SOC estimation algorithms can also be grouped into measurement mode, model-based products, data-driven techniques, and filter-based mechanisms [14], [15]. By this combination of groups, voltage-based SOC estimation becomes simple and low in computation. It is greatly affected by loading conditions, aging of the battery, and measuring noise [14]. Earlier studies on battery SOC determination have also highlighted the limitations of conventional voltage-based approaches and emphasized the need for more robust estimation techniques [20]. At the same time, SOC can also be estimated by Coulomb counting to track the previous flow over time. However, a periodic calibration based on cumulative error is needed to avoid long-term drift [15]. Therefore, some of the function and demonstration using SOC estimation techniques still have a limitation when transferring to operational conditions. That way, SOC are considered active areas of research for improvement especially

for IoT applications with limited computational resources and energy budgets [9], [10].

C. Kalman Filter-Based SOC Estimation

The Kalman Filter (KF) approach is one of the most theoretically established methods for SOC estimation because it combines system modelling with noisy sensor measurements [16], [17]. Early work by Plett demonstrated the effectiveness of Extended Kalman Filtering (EKF) for battery management systems and lithium-ion battery SOC estimation [21]. To account for battery model nonlinearities, EKF and Unscented Kalman Filter (UKF) variants have subsequently been proposed [19], [21], [23]. Furthermore, comparative studies have shown that adaptive Kalman filtering techniques can outperform conventional SOC estimation approaches under varying operating conditions by dynamically adjusting noise covariance parameters [22]. Adaptive KF methods, therefore, improve robustness against measurement uncertainty and model mismatch while reducing SOC drift and transient voltage fluctuation effects [17], [22].

D. Research Gap and Motivation

Demonstrated to be very accurate and robust, the KF-based SOC estimation approaches are nowadays more applied to obtaining a (possible) more accurate estimation for the SOC than being able to explicitly extract an energy optimization link between the SOC estimation, and performing these optimizations actually on location and paradigm that targets IoT workloads of sensors. For example, in smart agriculture realized through IoT, sensor nodes have different energy consumption patterns owing to periodic sensing, burst transmission of sensed data from the field to data centers or cloud servers for aggregation and processing, sleep scheduling, and sudden environmental conditions [3]. If traditional estimation methods are used, these time-variant workloads might cause SOC drift, inaccurate estimation, and unsuitable use of battery power. Furthermore, research is limited regarding hybrid SOC estimation techniques that combine voltage-based methods with adaptive filtering in smart agriculture scenarios. For this, a low-cost and energy-aware SOC estimation framework can be proposed to avoid drift and ensure stability for transaction-driven IoT workloads. This interaction causes the proposed hybrid BMS architecture, combining a voltage-based estimation strategy with transaction-based adaptive Kalman Filter (AKF), to provide embedded smart agriculture deployments a way to learn long-term energy optimization.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. Overall System Architecture

The purpose of battery management system (BMS) is to manage the battery used in IoT-based Smart Agriculture sensor nodes functioning under limited capacity. We present a system consisting of a lithium-ion battery pack, sensing and measurement unit, SOC estimation module, and data processing and monitoring layer. The measurement subsystem constantly samples battery parameters, including voltage, current and temperature, to estimate SOC in a time continuous way.

Fig. 1 illustrates the baseline voltage-based SOC estimation architecture used in the conventional monitoring framework. Although such method is computation inexpensive and can be

applied to low-power IoT devices, it is susceptible to noisy voltage operation and load variations. Meanwhile, Fig. 2 presents the proposed hybrid adaptive Kalman Filter architecture, which integrates voltage-based estimation with transaction-aware adaptive filtering. The SOC estimation module predicts and updates based on the battery model and real-time measurements in this architecture.

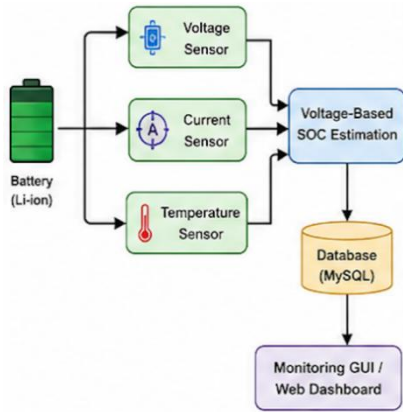


Fig. 1. Baseline voltage-based SOC estimation architecture.

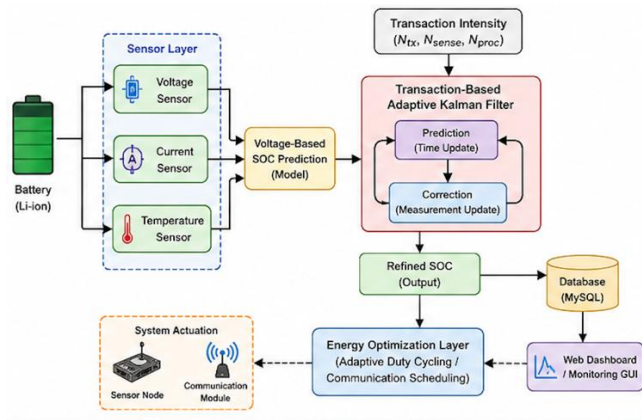


Fig. 2. Proposed hybrid adaptive Kalman Filter architecture.

In order to verify the performance of the proposed hybrid BMS, two estimation algorithms are executed and compared with each other in parallel:

- 1) *Algorithm A*: Charge status (SOC) estimation based on baseline voltage.
- 2) *Algorithm B*: Moving-based transaction adaptive Kalman Filter hybrid SOC estimation.

B. Battery SOC State-Space Model

SOC estimation is modelled as a state-space model in the implementation of the Kalman Filter. The SOC dynamic equation can be written as:

$$SOC_k = SOC_{(k-1)} - (I_k \Delta t / C) = w_k \quad (1)$$

where, SOC_k is the SOC at time step k , I_k is the measured current, Δt is the sampling interval, C is the rated battery capacity, and w_k represents process noise.

The voltage measurement model is expressed as:

$$V_k = f(SOC_k) + v_k \quad (2)$$

where, V_k is the measured terminal voltage, $f(\cdot)$ represents the battery voltage model, and v_k denotes measurement noise.

C. Baseline SOC Estimation (Algorithm A)

Algorithm A or Algorithm 1 follows a conventional voltage-based SOC estimation approach with Coulomb counting integration. This technique uses the measured voltage, current, and temperature values to estimate the SOC of the battery. So a voltage compensation factor is introduced to represent measurement error under the open-circuit and closed circuit conditions, and a temperature compensation coefficient is kept for the SOC value in terms of its influence by the change of temperature.

Algorithm 1: Voltage-Based SOC Estimation (Algorithm A)

Input: Measured voltage $V(t)$, current $I(t)$, temperature $T(t)$, battery capacity C , internal resistance R_{int} , initial SOC SOC_{init} , temperature coefficient α , reference temperature T_{ref} , voltage correction factor ΔV , sampling interval Δt .

Output: Estimated SOC $SOC(t)$.

Step 1 (Initialization):

$$SOC(0) = SOC_{init}$$

Step 2 (Voltage Correction):

$$V_{corr}(t) = V(t) - \Delta V$$

Step 3 (Charge Integration):

$$Q(t) = \int_0^t I(\tau) d\tau$$

$$\text{Discrete form: } Q(t) = \sum I(k)\Delta t$$

Step 4 (SOC Estimation):

$$SOC(t) = SOC_{init} - Q(t)/C$$

Step 5 (Temperature Compensation):

$$SOC_{temp}(t) = SOC(t)[1 + \alpha(T(t) - T_{ref})]$$

Step 6 (Multi-Cell Voltage Averaging):

$$V_{avg} = (1/n) \sum x_i$$

Return: $SOC_{temp}(t)$

D. Proposed Transaction-Based Adaptive Kalman Filter Estimation (Algorithm B)

Algorithm B or Algorithm 2 estimates SOC using two transaction-based workload models. Additionally, for IoT workloads, it uses the Kalman Filter correction mechanism to minimize SOC drift. Rather than being continuous, as in sensing and data transmission, discrete operational events and activity periods determine the battery consumption of IoT smart agriculture systems. These activities, which are represented as energy transactions, cause battery consumption. In this context, "transaction" is the term used to describe a unitary energy event associated with IoT activities, such as sensing, processing, and wireless transmission. The noise covariance of the Kalman process is adaptively adjusted based on transaction intensity, since transactions include multiple sensing cycles and communication events per unit of time.

Algorithm 2: Transaction-Based Adaptive Kalman Filter SOC Estimation (Algorithm B)

Input: $V(t)$, $I(t)$, $T(t)$, C , SOC_{init} , ΔV , α , T_{ref} , Δt , process noise covariance Q , measurement noise covariance R .

Output: Kalman-filtered SOC estimate SOC(t).

Step 1 (Initialization):

$$\hat{x}_0 = \text{SOC_init}, P_0 = P_{\text{init}}$$

Step 2 (Voltage Correction):

$$V_{\text{corr}}(t) = V(t) - \Delta V$$

Step 3 (SOC Prediction):

$$\text{SOC_pred}(t) = \text{SOC_init} - (\int_0^t I(\tau) d\tau) / C$$

Step 4 (Temperature Compensation):

$$\text{SOC_temp}(t) = \text{SOC_pred}(t) [1 + \alpha(T(t) - T_{\text{ref}})]$$

Step 5 (Kalman Prediction):

$$\hat{x}_{\{k|k-1\}} = \text{SOC_temp}(t)$$

$$P_{\{k|k-1\}} = P_{\{k-1|k-1\}} + Q$$

Step 6 (Kalman Update):

$$y_k = V_{\text{corr}}(t) - V_{\text{model}}(\hat{x}_{\{k|k-1\}})$$

$$K_k = P_{\{k|k-1\}} / (P_{\{k|k-1\}} + R)$$

$$\hat{x}_{\{k|k\}} = \hat{x}_{\{k|k-1\}} + K_k y_k$$

$$P_{\{k|k\}} = (1 - K_k) P_{\{k|k-1\}}$$

Step 7 (Pack SOC Output):

$$\text{SOC}(t) = (1/N) \sum \text{SOC_cell}_i(t)$$

Return: SOC(t)

E. Transaction-Based Adaptive Noise Adjustment

To improve SOC estimation robustness under dynamic IoT workloads, the proposed Adaptive Kalman Filter (AKF) modifies the process noise covariance Q according to transaction intensity. In IoT-enabled smart agriculture, battery consumption varies depending on sensing frequency, wireless communication activity, local processing tasks, and environmental events. Therefore, the uncertainty of the SOC prediction model changes over time.

The adaptive process noise covariance is defined as:

$$Q_k = Q_0 (1 + \beta T_k)$$

where,

Q_k represents the adaptive process noise covariance at time step k ,

Q_0 is the nominal process noise covariance,

β is the workload sensitivity coefficient,

T_k denotes the normalized transaction intensity.

The transaction intensity T_k is computed as:

$$T_k = (N_{\text{tx}} + N_{\text{sense}} + N_{\text{proc}}) / N_{\text{max}}$$

where,

N_{tx} is the number of wireless transmission events,

N_{sense} is the number of sensing operations,

N_{proc} is the number of local processing tasks,

N_{max} is the maximum expected transaction count during one sampling interval.

When transaction activity increases, the value of Q_k becomes larger, allowing the Kalman Filter to react faster to rapid SOC changes. During low activity periods, Q_k decreases,

stabilizing the SOC estimate and reducing unnecessary fluctuations.

This adaptive mechanism enables the proposed hybrid BMS to maintain estimation stability while remaining responsive to highly dynamic IoT sensor workloads commonly observed in smart agriculture deployments.

F. Hybrid SOC Output and Refinement

In such a hybrid mechanism, the final SOC is obtained from a Kalman Filter output that has been filtered. The use of a voltage-based methodology allows for an initial estimation, and a Kalman filter adjusts this prediction error while also reducing noise. Enhanced SOC estimate, drift mitigation, and stability of the proposed hybrid mechanism provide significant contributions towards long-run IoT-based smart agriculture procedures.

IV. EXPERIMENTAL SETUP

A. Hardware and Software Configuration

The database used in this experiment is MySQL. It was chosen for its reliability, ease of use, and ability to query and manipulate large amounts of data. Furthermore, it can quickly organize and analyze large amounts of information. Meanwhile, an Arduino R4 device programmed in C can control a variety of sensors and components. For the hybrid BMS model experiment, this combination simplifies the integration and control of the hardware and database.

Table I summarizes the hardware and software configuration used in the experimental implementation of the proposed hybrid BMS framework.

TABLE I. HARDWARE AND SOFTWARE CONFIGURATION

Parameter	Specification
Microcontroller	Arduino UNO R4 WiFi
Battery Type	3.7 Lithium-ion Battery
Battery Capacity	2200 mAh
Voltage Sensor	INA219 Voltage Sensor Module
Current Sensor	INA219 Current Monitoring Sensor
Temperature Sensor	DS18B20 Digital Temperature Sensor
Communication Module	ESP32 WiFi Module
Programming Language	Embedded C (Arduino IDE)
Database	MySQL
Data Storage Platform	Ubuntu Server 22.04
Experimental Duration	30 days
Sampling Interval	1 hour
Operating Voltage	3.3 V – 5 V
Wireless Connectivity	WiFi IEEE 802.11 b/g/n

B. Data Collection and Processing

Table II presents sample hourly SOC data collected during the experimental evaluation over the 30-day monitoring period.

Table III presents the sample hourly battery usage computation derived from the SOC measurements, while

Table IV summarizes the daily battery usage recorded throughout the 30-day experimental period.

TABLE II. SAMPLE HOURLY SOC DATA COLLECTED DURING EXPERIMENT.

Day	Hour	SOC_A (%)	SOC_B (%)
1	00	100.00	100
1	01	98.8	99.1
1	02	97.2	98.4
...	...	...	...

TABLE III. SAMPLE HOURLY BATTERY USAGE COMPUTATION

Hour	Used A (%)	Used B (%)
1	1.4	0.9
2	1.4	0.7
3	1.6	1.0

TABLE IV. DAILY BATTERY USAGE OVER 30-DAY EXPERIMENT

Day	Algorithm A Daily Used (%)	Algorithm B Daily Used (%)
1	32.4	24.8
2	30.9	25.1
3	34.2	26.0
...	...	...

C. Performance Metrics

Table V summarizes the overall battery consumption and average daily energy usage achieved by Algorithm A and Algorithm B, enabling a direct comparison of their energy optimization performance.

Table VI presents the stability and drift characteristics of both SOC estimation methods, including standard deviation and drift spike measurements, to evaluate long-term estimation reliability.

Table VII reports the SOC estimation accuracy in terms of Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), providing a quantitative assessment of the effectiveness of the proposed hybrid Kalman Filter approach.

TABLE V. OVERALL BATTERY CONSUMPTION AND AVERAGE DAILY ENERGY USAGE.

Algorithm	Total Battery Consumption (%)	Average Daily Consumption B (%)
Algorithm A	78	32.6
Algorithm B	56	25.2

TABLE VI. STABILITY AND DRIFT COMPARISON

Metric	Algorithm A	Algorithm B
Standard Deviation (%)	3.8	1.6
Drift Spike	41.2	29.5
Drift Trend	High	Low

TABLE VII. SOC ESTIMATION ERROR COMPARISON

Metric	Algorithm A	Algorithm B
MAE (%)	5.6	2.3
RMSE (%)	7.9	3.4

V. RESULTS AND DISCUSSION

A. Battery Management System Implementation

In order to test the introduced hybrid SOC estimation framework, a prototype battery management system (BMS) was created. The proposed system monitors the parameters of the battery, such as voltage, current, and temperature, in real-time, to store measured data in a database for future analysis. Moreover, a GUI (Graphical User Interface) was developed to display SOC estimation results, battery consumption trends, and sensor readings. Fig. 3 compares daily battery consumption between Algorithm A and Algorithm B over the 30-day experiment, and Fig. 4 illustrates the drift spike comparison between the estimation methods.

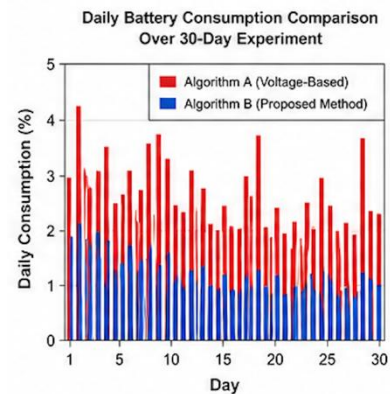


Fig. 3. Daily battery consumption comparison over a 30-day experiment.

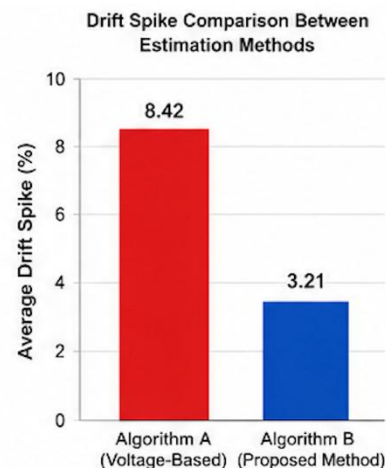


Fig. 4. Drift spike comparison between estimation methods.

B. Definition of Battery Consumption Metric

The battery consumption percentage is defined as the SOC reduction over time and is used to evaluate the performance of energy usage. This study does not use “Battery % Used” as the percentage of battery's SOC value but rather as the difference

between SOC estimates for certain cycles. This hourly battery consumption is calculated as:

$$Used_hour(k) = SOC_k(k-1) - SOC(k) \quad (3)$$

Similarly, daily battery usage is computed as the accumulated hourly SOC reduction over a 24-hour period:

$$Used_day(d) = \sum Used_hour(k), d = 1 \text{ to } 30 \quad (4)$$

This definition enables consistent comparison between Algorithm A and Algorithm B in terms of discharge behavior and SOC stability.

C. Comparison of Battery Consumption Performance

The comparison between Algorithm A (baseline voltage-based SOC estimation) and Algorithm B (transaction-based adaptive Kalman Filter hybrid SOC estimation) was performed based on workload data collected over 30 days. The experimental results showed that Algorithm A produced higher battery consumption compared to Algorithm B. Algorithm A showed a total battery usage of 78%, while Algorithm B exhibited an aggregate battery usage of 56%. This shows that the estimated battery usage is reduced by roughly 22.7% for the proposed method compared to the baseline approach.

Moreover, the final average daily power consumption values for Algorithm A and Algorithm B are 32.6% and 25.2%, respectively. These results show that the hybrid method proposed offers more energy-efficient SOC estimation, a parameter relevant to prolonging sensor node life in IoT smart agriculture implementations.

D. Stability and Drift Analysis

Besides lowering overall battery consumption, Algorithm B also displayed enhanced stability in SOC estimation. Standard deviation was used to measure the variability of daily battery usage. The higher value of 3.8% was the standard deviation for Algorithm A, whereas Algorithm B had a lower value of 1.6%. This means that the proposed Kalman Filter refinement mechanism is more stable during dynamic IoT workloads.

The proposed method proved robust for models with strongly drifted classes. Both algorithms showed a drift spike of 41.2% in Algorithm A, and decreased to 29.5% in Algorithm B. This enhancement is due to the working mechanism of Kalman correction, which mitigates errors and iteratively updates the SOC prediction as more measurements become available. The lower drift behavior plays an important role in long-term deployments since drift accumulation can give rise to inaccurate battery depletion prediction and inefficient energy scheduling.

E. Estimation Accuracy Evaluation

SOC estimation results were then compared to reference discharge measurements to assess the accuracy of the estimations. Evaluation metrics, including mean absolute error (MAE) and root mean square error (RMSE), were used. Algorithm A achieved a MAE of 5.6% while Algorithm B's MAE was significantly lower at 2.3%. The RMSE also showed improvement, going from 7.9% in Algorithm A to 3.4% in Algorithm B.

The presented transaction-based adaptive Kalman Filter method effectively improves SOC estimation accuracy through

cumulative drift minimization and noise sensitivity reduction, as evidenced by these cumulative results. The enhanced precision additionally aids battery consumption prediction, leading to energy optimization within IoT sensor nodes.

F. Comparison with Existing KF-Based SOC Estimation Methods

To further evaluate the effectiveness of the proposed transaction-based adaptive Kalman Filter method, its performance was compared with several SOC estimation approaches reported in previous studies, including conventional Kalman Filter (KF), Extended Kalman Filter (EKF), and Adaptive Kalman Filter techniques.

The selected comparison methods are based on established SOC estimation approaches reported in the literature, including EKF-based battery management systems [21], adaptive Kalman filtering techniques [22], and adaptive unscented Kalman filtering methods [23].

Table VIII compares the proposed method with existing SOC estimation techniques in terms of estimation accuracy, computational complexity, and suitability for IoT-based smart agriculture applications.

TABLE VIII. SOC ESTIMATION ERROR COMPARISON

Method	MAE (%)	RMSE (%)	Complexity	IoT Suitability
Voltage-Based	5.6	7.9	Low	Moderate
Conventional KF	3.8	5.2	Moderate	Moderate
EKF	3.1	4.5	High	Low
Adaptive KF	2.7	3.9	Moderate	Good
Proposed Method	2.3	3.4	Low-moderate	Excellent

The comparison demonstrates that the proposed method achieved the lowest MAE and RMSE values while maintaining relatively low computational complexity suitable for embedded IoT sensor nodes. Unlike EKF-based approaches that require higher nonlinear computation, the proposed transaction-based adaptive Kalman Filter provides improved SOC stability and energy optimization with a lightweight implementation suitable for smart agriculture deployments.

G. Discussion

In general, the experimental performance shows that Algorithm B outperforms Algorithm A in energy efficiency, being more stable and with an improved estimation accuracy. The decrease in overall battery consumption suggests that more realistic state-of-charge (SOC) tracking can be achieved with the proposed method, thus preventing unnecessary overestimation of the battery's depletion. It can be observed from the enhanced stability and decreased drift spikes that the adaptive Kalman Filter algorithm in this study is helpful for reducing SOC fluctuation under dynamic load condition.

The proposed hybrid BMS is a suitable and cost-effective approach to long-term monitoring in sensor nodes powered by energy limited resources present in IoT-enabled smart agriculture systems. This ensures greater adaptability to fluctuation in sensing and transmission activity, making

effective utilization of charge within battery limit and enhancing longevity and maintenance period.

H. Practical Implications for Smart Agriculture

In general, the experimental performance shows that the proposed hybrid BMS architecture provides several practical benefits for IoT-enabled smart agriculture systems. Since many agricultural monitoring systems are deployed in remote farms and open-field environments, minimizing battery replacement frequency is essential for reducing maintenance costs and improving operational reliability.

The proposed transaction-based adaptive Kalman Filter enables more accurate prediction of remaining battery energy, allowing sensor nodes to optimize sensing intervals and communication schedules dynamically. This capability is particularly beneficial for precision agriculture applications involving soil moisture monitoring, irrigation automation, greenhouse environmental sensing, and crop health monitoring.

Furthermore, improved SOC stability can reduce unexpected sensor downtime caused by inaccurate battery depletion prediction. The lightweight computational requirement also makes the proposed method suitable for low-cost embedded microcontrollers commonly used in agricultural IoT deployments.

VI. LIMITATIONS OF THE STUDY

Although the proposed hybrid BMS demonstrates improved SOC estimation performance, several limitations remain. First, the experimental evaluation was conducted using a single battery configuration and a limited number of IoT sensor nodes. Different battery chemistries and larger-scale deployments may exhibit different performance characteristics.

Second, the current implementation focuses on WiFi-based communication workloads. Other communication technologies, such as LoRaWAN, ZigBee, and NB-IoT, may introduce different energy consumption patterns that require further investigation.

Finally, the proposed adaptive Kalman Filter relies on manually selected tuning parameters, including the workload sensitivity coefficient β . Future research should investigate self-optimizing parameter tuning methods using machine learning or reinforcement learning approaches.

VII. CONCLUSION AND FUTURE WORK

This study proposed an enhanced Kalman Filter-based hybrid battery management system (BMS) for SOC estimation and energy optimization in IoT-enabled smart agriculture applications. The proposed method combines voltage-based SOC estimation with a transaction-based adaptive Kalman Filter correction mechanism to improve estimation stability and reduce SOC drift under dynamic IoT workloads.

Experimental evaluation using real sensor workload data collected over a 30-day period demonstrated that the proposed method reduced cumulative battery consumption from 78% to 56%, corresponding to approximately 22.7% improvement compared to the baseline voltage-based approach. In addition, the proposed method achieved lower MAE and RMSE values, improved SOC stability, and reduced drift spikes.

The adaptive transaction-based noise covariance adjustment enabled the Kalman Filter to dynamically respond to changing sensing and communication activities, making the proposed approach particularly suitable for energy-constrained IoT sensor nodes deployed in remote agricultural environments.

Future work will focus on extending the proposed framework to multi-node IoT deployments, integrating LoRaWAN-based communication systems, and comparing the proposed method against EKF, UKF, and machine learning-based SOC estimation techniques. Additional investigation into self-adaptive parameter optimization and renewable energy integration is also planned.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Fundamental Research Grant Scheme (FRGS), the Ministry of Higher Education (Kementerian Pendidikan Tinggi, KPT), Malaysia, for providing financial support for this research under Grant No. FRGS/1/2022/ICT02/UNISZA/02/6.

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