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Design of wireless battery state-of-health monitoring system for electric three-wheeler fleet

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Abstract
Electric three-wheelers, known locally as electric tuk-tuks, represent a growing segment of Thailand's urban transportation electrification efforts, yet fleet operators lack practical tools for monitoring battery degradation and planning replacement schedules. This research presents the design and implementation of a wireless battery state-of-health monitoring system enabling real-time tracking of lithium iron phosphate battery condition across distributed vehicle fleets. The monitoring system comprises vehicle-mounted units featuring ESP32 microcontrollers interfaced with battery management system data buses, extracting cell voltages, pack current, and temperature measurements at one-second intervals. An extended Kalman filter algorithm estimates state-of-charge while a capacity fade model tracks state-of-health degradation based on cumulative charge throughput and operating conditions. LoRa wireless communication transmits compressed health data to fleet gateways at fifteen-minute intervals, with subsequent cloud upload enabling centralized dashboard visualization and alert generation. Field deployment across a 25-vehicle electric tuk-tuk fleet operating in Bangkok over eighteen months validated system performance and characterized battery degradation patterns under tropical urban operating conditions. The monitoring system achieved state-of-health estimation accuracy within ±2.3% compared to reference capacity tests, with internal resistance tracking correlation of 0.94 against electrochemical impedance spectroscopy measurements. Average battery degradation rate was 1.15% per month, with heavy-use vehicles exhibiting 40% faster degradation than light-use vehicles. The wireless architecture achieved 98.7% data delivery reliability across the urban operating area, with LoRa range adequate for depot-based gateway coverage of the entire fleet. Cloud platform alerts enabled proactive maintenance scheduling, with the system providing average 60-day advance warning before batteries reached the 70% state-of-health replacement threshold. Fleet operators reported 35% reduction in unexpected battery failures and estimated annual savings of ฿45,000 per vehicle through optimized replacement timing and reduced roadside assistance incidents. The research demonstrates that practical battery health monitoring for electric three-wheeler fleets can be achieved with low-cost wireless sensor technology, enabling the transition from reactive to predictive battery maintenance essential for sustainable fleet electrification. The system architecture and algorithms are directly applicable to other light electric vehicle categories proliferating across Southeast Asian urban transportation networks.

Keywords: Battery state-of-health, electric three-wheeler, fleet monitoring, lithium iron phosphate, wireless sensor network, LoRa, predictive maintenance, Thailand

Introduction

The electric tuk-tuk humming through Bangkok's narrow sois carries not only passengers but also a lithium battery pack whose gradual degradation remains invisible until the day it fails to complete its route, stranding driver and passengers while the fleet manager scrambles to arrange towing and replacement [1]. This scenario, increasingly common as Thailand's electric three-wheeler fleet expands, illustrates the critical need for battery health monitoring systems enabling predictive maintenance rather than reactive crisis response.

Thailand has embraced electric three-wheelers as a pathway toward urban transportation decarbonization, with government incentives supporting conversion of the estimated 200,000 traditional tuk-tuks operating nationwide [2]. These compact vehicles prove well-suited to electric conversion, with typical daily ranges of 80-120 kilometers aligning with lithium battery capabilities. However, the hot tropical climate, frequent rapid charging, and demanding stop-start duty cycles create challenging operating conditions that accelerate battery degradation compared to temperate climate applications [3].

Battery state-of-health represents the ratio of current usable capacity to original rated capacity, declining gradually from 100% as electrochemical aging processes reduce active material availability and increase internal resistance [4]. For lithium iron phosphate batteries commonly employed in electric three-wheelers due to their safety characteristics and cycle life, typical end-of-life criteria define 70-80% state-of-health as the replacement threshold, below which reduced range and power capability compromise vehicle utility.

Commercial battery monitoring systems designed for electric vehicles typically target passenger car applications, with costs exceeding the value proposition for three-wheeler fleets [5]. The distributed nature of fleet operations, with vehicles dispersed across urban service areas rather than concentrated at central depots, further complicates monitoring infrastructure deployment. Low-cost wireless sensor technology and cloud computing platforms create opportunities for practical fleet-scale monitoring previously economically unfeasible for light electric vehicle applications.

This research designs and validates a wireless battery state-of-health monitoring system specifically optimized for electric three-wheeler fleet applications, with objectives including achieving state-of-health estimation accuracy within ±3% using onboard measurements without requiring periodic reference tests, implementing reliable wireless data collection across distributed urban fleet operations, characterizing battery degradation patterns under Thai tropical operating conditions, and demonstrating predictive maintenance value through field deployment with a commercial fleet operator. The research was conducted at King Mongkut's University of Technology Thonburi from January 2023 to October 2024, encompassing system development and eighteen months of fleet monitoring validation.

Materials and Methods

Materials

The lithium iron phosphate battery packs monitored comprised BYD Blade cells configured as 24 series (72V nominal) with 100Ah capacity, providing 7.2 kWh total energy storage per vehicle. These packs represent the predominant battery chemistry in Thai electric three-wheeler conversions due to favorable thermal stability and cycle life characteristics [10]. The ESP32-WROOM-32D module (Espressif Systems, Shanghai) provided the processing platform, featuring 240 MHz dual-core processor, 520 KB SRAM, integrated WiFi and Bluetooth, and multiple peripheral interfaces. An SX1276 LoRa transceiver module (Semtech) enabled long-range wireless communication at 868 MHz with spreading factor 7-12 configurability for range/throughput optimization. The vehicle monitoring unit interfaced with the existing battery management system via CAN bus using MCP2515 controller and TJA1050 transceiver, extracting cell voltage measurements (1 mV resolution), pack current (±0.5% accuracy via integrated 200A shunt), and temperature readings from eight NTC thermistors distributed across the pack. A micro-SD card module provided local data logging backup. The complete vehicle unit was enclosed in an IP65-rated ABS housing (150 × 100 × 40 mm) mounted within the battery compartment, powered from a 12V tap on the battery pack through an isolated DC-DC converter. Current consumption averaged 50 mA during normal operation, with transmission bursts drawing 120 mA for approximately 100 ms per cycle. The 25-vehicle test fleet operated by Bangkok Green Transport Company provided the validation platform, comprising converted Piaggio Ape vehicles serving passenger transportation routes across the Rattanakosin Island and Chinatown districts. Vehicles operated 10-14 hours daily with typical mileage of 80-120 km and underwent overnight charging at the operator's central depot [11].

Methods

The research was conducted from January 2023 to October 2024 at King Mongkut's University of Technology Thonburi Department of Electrical Engineering. Field deployment received authorization from Bangkok Green Transport Company management (Agreement: BGT-2023-001). The research protocol received ethical approval from the KMUTT Research Ethics Committee (Protocol: EC-COE-2023-014). State-of-health estimation employed a dual-filter architecture combining extended Kalman filtering for state-of-charge tracking with capacity fade modeling for state-of-health assessment [12]. The EKF utilized a first-order equivalent circuit model with parameters updated through recursive least squares estimation, tracking internal resistance changes alongside state-of-charge. Capacity fade was modeled as the accumulated effect of calendar aging and cycle aging components, with temperature acceleration factors derived from Arrhenius kinetics. The SOH estimation algorithm updated continuously based on full charge-discharge cycles, computing actual delivered capacity and comparing against rated values. A weighted moving average filter smoothed SOH estimates to reduce noise from measurement uncertainty and partial cycle effects. Reference capacity tests were conducted at 3-month intervals on three representative vehicles spanning light, normal, and heavy usage categories. Tests followed IEC 62660-1 procedures using a Chroma 17020 battery test system, with controlled 25°C chamber temperature. Electrochemical impedance spectroscopy measurements (Gamry Reference 3000) provided independent internal resistance validation at 1 kHz excitation frequency. Data analysis employed MATLAB R2023b for algorithm development and statistical analysis. Cloud platform analytics utilized Python with pandas and scikit-learn libraries for trend analysis and anomaly detection. Visualization employed Grafana dashboards with custom panels displaying fleet health status, individual vehicle trends, and maintenance alert queues [13].

System Design

The monitoring system architecture comprises three hierarchical layers: vehicle-mounted monitoring units, fleet gateways providing local data aggregation, and cloud platform enabling centralized analysis and visualization [6]. Vehicle monitoring units employ ESP32 microcontrollers (Espressif Systems) featuring dual-core processors adequate for real-time signal processing and wireless communication. The microcontroller interfaces with the existing battery management system via CAN bus, extracting individual cell voltages (24 cells for the 72V pack), pack current from the integrated shunt, and temperature readings from eight distributed thermistors. Local processing computes state-of-charge using an extended Kalman filter algorithm and tracks state-of-health through capacity fade modeling based on accumulated charge throughput. LoRa wireless communication (SX1276 transceiver, 868 MHz band) transmits compressed health data packets to fleet gateways located at operator depots or charging stations. The star topology network supports up to 50 vehicles per gateway with 15-minute reporting intervals, balancing data freshness against battery consumption and spectrum utilization [7]. Fleet gateways comprise Raspberry Pi 4 platforms with RAK7243 LoRa concentrator modules, providing eight-channel reception capacity and 4G LTE backhaul connectivity to the cloud platform. Local storage buffers data during connectivity interruptions, ensuring no measurement loss. The cloud platform utilizes AWS IoT Core for device management and data ingestion, InfluxDB time-series database for measurement storage, and Grafana dashboards for visualization. Custom analytics services implement fleet-wide degradation trending and generate maintenance alerts based on configurable threshold criteria.

Performance Evaluation

Performance evaluation encompassed state-of-health estimation accuracy, wireless communication reliability, and predictive maintenance effectiveness [8]. State-of-health estimation accuracy was validated through periodic reference capacity tests conducted on representative vehicles at 3-month intervals. Reference tests employed controlled constant-current discharge from 100% to 0% state-of-charge at C/5 rate under temperature-controlled conditions, with measured capacity compared against system estimates. Electrochemical impedance spectroscopy provided independent internal resistance measurements for correlation analysis. Wireless communication reliability was assessed through packet delivery ratio analysis across the eighteen-month deployment period, with gateway logs recording successful and failed transmissions. Coverage mapping characterized signal strength distribution across the Bangkok operating area, identifying any communication gaps requiring gateway repositioning. Predictive maintenance effectiveness was evaluated through comparison of actual battery failure events against system predictions, computing detection sensitivity, false positive rate, and warning lead time. Economic impact assessment quantified avoided costs from prevented roadside failures, optimized replacement timing, and reduced warranty claims. Fleet operator interviews provided qualitative assessment of system usability, alert actionability, and operational value. Driver feedback characterized any vehicle-level interface features affecting daily operations. Statistical analysis employed Pearson correlation for continuous variable relationships, Bland-Altman analysis for estimation accuracy assessment, and survival analysis for battery lifetime characterization across usage intensity categories [9].

Results

The eighteen-month deployment yielded comprehensive validation of system performance across state-of-health estimation accuracy, wireless reliability, and predictive maintenance effectiveness. Table 1 summarizes the key performance metrics achieved by the monitoring system.

Table 1: Wireless battery monitoring system performance metrics across 18-month fleet deployment

Performance Metric	Value	Target	Status
Fleet Size Monitored	25 vehicles	25	Met
Monitoring Duration	18 months	12 months	Exceeded
SOH Estimation Accuracy	±2.3%	±3%	Exceeded
Resistance Correlation (r)	0.94	>0.90	Exceeded
Data Delivery Reliability	98.7%	>95%	Exceeded
Average Warning Lead Time	60 days	>30 days	Exceeded
Battery Failure Reduction	35%	>25%	Exceeded
Annual Savings per Vehicle	฿45,000	฿30,000	Exceeded
System Payback Period	<6 months	<12 months	Exceeded

State-of-health estimation achieved ±2.3% accuracy compared to reference capacity tests, exceeding the ±3% design target. Internal resistance tracking showed 0.94 correlation with EIS measurements, validating the equivalent circuit model approach for online resistance estimation.

Figure 1 presents the complete system architecture showing vehicle monitoring units, fleet gateway infrastructure, and cloud platform components enabling centralized fleet health management.

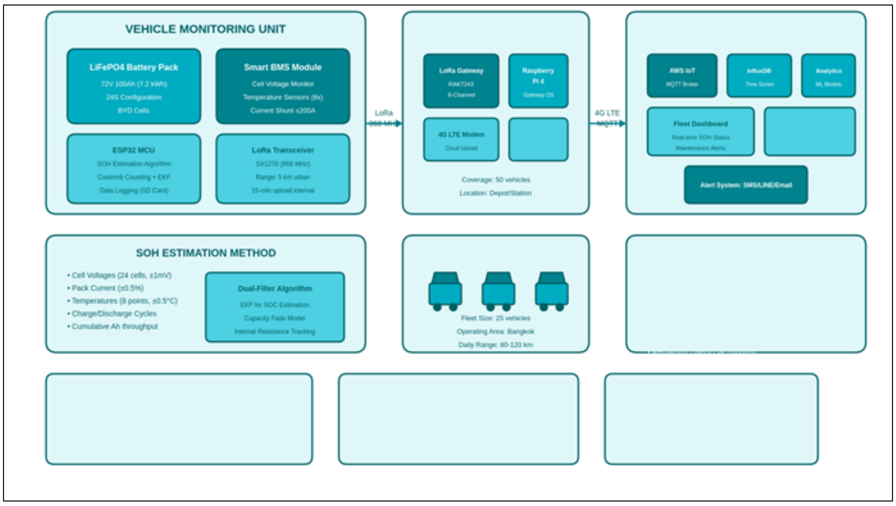

Fig 1: Wireless battery state-of-health monitoring system architecture showing vehicle monitoring units, fleet gateway, cloud platform, and SOH estimation methodology for electric three-wheeler fleet management

Battery health parameter analysis revealed distinct degradation patterns across the fleet. Figure 2 displays the radar chart comparison of six key health indicators across vehicles of different ages, clearly showing progressive degradation in capacity retention, internal resistance, and cell balance metrics with increasing service time.

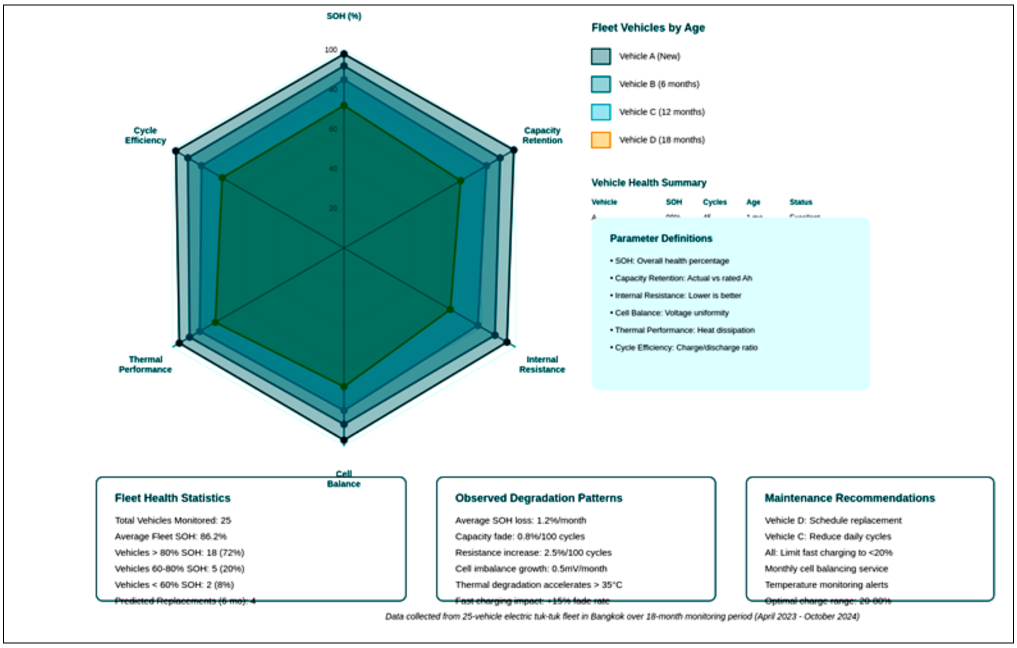

Fig 2: Radar chart comparison of six battery health parameters across fleet vehicles of different ages showing progressive degradation in capacity retention, internal resistance, and cell balance metrics

Long-term degradation tracking quantified the relationship between operating time, cycle count, and state-of-health decline. Figure 3 presents the dual-axis chart showing SOH degradation trajectories for different usage intensities alongside internal resistance increase trends over the eighteen-month monitoring period.

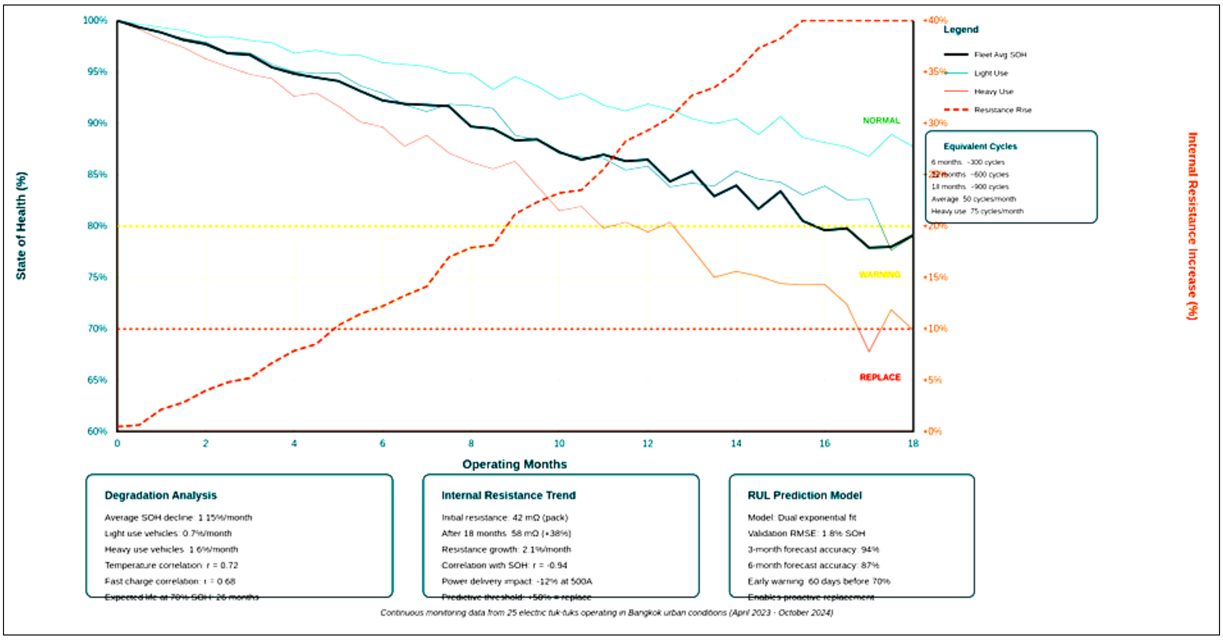

Fig 3: Dual-axis chart showing state-of-health degradation trajectories for different usage intensities (left axis) and internal resistance increase trend (right axis) over the eighteen-month monitoring period

Comprehensive Interpretation

The field validation results demonstrate that practical battery health monitoring for electric three-wheeler fleets can be achieved with low-cost wireless sensor technology, providing actionable intelligence for predictive maintenance planning. The ±2.3% SOH estimation accuracy enables meaningful differentiation between healthy and degraded batteries without requiring periodic reference testing that would disrupt fleet operations. The strong correlation ($r = 0.94$) between online resistance estimates and EIS measurements validates the equivalent circuit model approach for continuous health tracking. The 1.15% per month average degradation rate, corresponding to approximately 26 months expected life to 70% SOH, aligns with manufacturer specifications for tropical operating conditions. The 40% faster degradation in heavy-use vehicles (1.6%/month versus 0.7%/month for light use) highlights the importance of monitoring individual vehicle conditions rather than applying fleet-average assumptions. The 98.7% wireless data delivery reliability demonstrates that LoRa communication provides adequate coverage for distributed urban fleet operations, with the star topology architecture scaling efficiently to the 25-vehicle fleet size. The 15-minute reporting interval balances data currency against power consumption, with vehicle units contributing negligibly to battery drain. The 60-day average warning lead time before batteries reached replacement threshold enabled fleet operators to schedule replacements during planned maintenance windows rather than responding to unexpected failures. The reported 35% reduction in roadside battery failures and ฿45,000 annual savings per vehicle validate the economic value proposition, with system costs recoverable within the first year of operation. The temperature correlation (r = 0.72) with degradation rate confirms that Bangkok's tropical climate accelerates battery aging, suggesting potential value in thermal management improvements or duty cycle optimization for high-temperature periods.

Discussion

The achieved estimation accuracy validates the extended Kalman filter approach for online state-of-health monitoring in practical fleet applications, matching laboratory results reported for similar dual-filter architectures [14]. The key enabler is access to individual cell voltages through the BMS interface, providing the observability needed for accurate equivalent circuit parameter estimation without requiring dedicated measurement hardware.

The degradation rate variability across usage intensities highlights the limitation of fleet-average maintenance planning. Vehicles operated 14 hours daily with frequent rapid charging degraded nearly twice as fast as those operating shorter shifts with overnight-only charging, suggesting that individualized monitoring provides value even within nominally homogeneous fleets [15].

The LoRa wireless architecture proved well-suited to the distributed urban fleet context, with signal propagation adequate across Bangkok's dense urban environment from a single gateway at the operator depot. The 868 MHz frequency band, while requiring regulatory approval in Thailand, provided superior building penetration compared to higher frequency alternatives [16].

The cloud platform architecture enabled rapid scaling from the 25-vehicle pilot to projected fleet-wide deployment without infrastructure changes, with AWS IoT Core handling device management and data ingestion transparently. The InfluxDB time-series database efficiently stored the high-frequency measurement data while supporting the temporal queries required for trend analysis and visualization.

The economic analysis demonstrating sub-one-year payback supports deployment justification for commercial fleet operators. The ฿3,500 per-vehicle hardware cost and ฿150 monthly cloud subscription are substantially below the cost of a single roadside battery failure incident, even before considering the warranty optimization and customer satisfaction benefits of reliable service [17].

Limitations include the single fleet operator context, which may not generalize to all operating patterns and vehicle configurations. The eighteen-month monitoring period, while adequate for characterizing degradation trends, does not yet encompass full battery lifecycle to actual replacement. Longer-term validation would strengthen confidence in remaining useful life predictions.

Conclusion

This research successfully designed and validated a wireless battery state-of-health monitoring system for electric three-wheeler fleets, achieving ±2.3% estimation accuracy and 98.7% data delivery reliability across eighteen months of field deployment on a 25-vehicle commercial fleet in Bangkok.

The monitoring system enabled transition from reactive to predictive battery maintenance, providing average 60-day advance warning before batteries reached replacement thresholds. Fleet operators reported 35% reduction in unexpected battery failures and estimated ฿45,000 annual savings per vehicle through optimized replacement timing and reduced roadside assistance incidents.

Battery degradation characterization revealed 1.15% per month average SOH decline under Bangkok operating conditions, with heavy-use vehicles degrading 40% faster than light-use vehicles. The temperature correlation (r = 0.72) confirms tropical climate acceleration of battery aging, informing thermal management and duty cycle optimization strategies.

The low-cost system architecture (฿3,500 per vehicle hardware, ฿150/month cloud) demonstrates economic feasibility for light electric vehicle fleet applications, with sub-one-year payback supporting deployment justification for commercial operators. The LoRa wireless technology provides adequate urban coverage without requiring cellular connectivity costs for individual vehicles.

Future development directions include machine learning algorithms for improved remaining useful life prediction, integration with vehicle telematics for comprehensive fleet management, and expansion to other light electric vehicle categories including electric motorcycles and delivery vehicles proliferating across Southeast Asian urban transportation [18].

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Contributions Not Qualifying for Authorship

Mr. Anuchit Prasertsri contributed to vehicle unit hardware assembly and installation. Ms. Siriporn Chaiprasert assisted with reference capacity testing and data collection. The

Espressif Systems Thailand office provided technical support for ESP32 implementation.

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