

Intelligent Identification and Linked Early Warning of Electrical Hazards in University Dormitories Based on Multi-Parameter Fusion

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ABSTRACT: University dormitories, characterized by high occupant density and diverse electrical usage patterns, present significant fire safety challenges. This study proposes a multi-parameter fusion-based intelligent system for identifying electrical hazards and providing linked early warnings in university dormitories. The system integrates real-time monitoring of voltage, current, power, and environmental parameters through an IoT sensor network, employs machine learning algorithms for anomaly detection, and implements a multi-agent architecture for distributed decision-making and autonomous response. By combining physics-based threshold detection with data-driven pattern recognition, the system achieves high accuracy in identifying unauthorized high-power appliances, overload conditions, and abnormal consumption patterns while minimizing false alarms. Experimental validation demonstrates the system's effectiveness in real-time hazard identification and rapid response capability. The proposed framework provides a scalable and cost-effective solution for enhancing dormitory electrical safety in higher education institutions.

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I.INTRODUCTION

University dormitories represent critical infrastructures where electrical safety remains a persistent concern. Statistical data indicate that over 2,000 fire incidents occurred in university collective dormitories in recent years, with approximately 80% attributed to electrical fires caused by improper electricity usage. The widespread adoption of personal electronic devices, the use of unauthorized high-power appliances, and irregular usage behaviors generate complex electrical load patterns that conventional monitoring systems struggle to manage effectively.

Existing approaches to dormitory electrical safety exhibit three fundamental limitations. Manual inspections, relying on periodic checks, cannot provide continuous real-time monitoring, which makes timely hazard detection difficult. Conventional electrical monitoring systems typically depend on single-parameter threshold alarms, which tend to produce high false-positive rates and fail to identify subtle anomalies. The absence of integrated early warning mechanisms means that even when hazards are detected, the response is often delayed, increasing the risk of fire incidents.

Recent advancements in Internet of Things (IoT) technology, artificial intelligence, and edge computing offer promising solutions to these challenges. IoT-enabled sensor networks enable continuous, real-time data collection from distributed points across dormitory buildings. Machine learning algorithms, particularly artificial neural networks and isolation forest methods, have demonstrated effectiveness in identifying anomalous consumption patterns that deviate from learned normal behaviors. Multi-agent architectures provide a distributed framework for autonomous, coordinated decision-making suitable for complex campus environments. The integration of physics-based models with data-driven approaches has been shown to enhance detection accuracy while reducing false positives.

This study presents a comprehensive system design that addresses these limitations through three key aspects. A multi-parameter fusion approach combines electrical parameters (voltage, current, power factor) with contextual information (time-of-day, occupancy patterns) to enable context-aware hazard identification. A hybrid detection architecture pairs physics-based threshold detection with machine learning anomaly detection, leveraging the strengths of both approaches. A linked early warning mechanism enables rapid, coordinated responses ranging from local alerts to automatic power disconnection.

II. RESEARCH METHODS

System Architecture

The proposed system adopts a three-tier architecture comprising perception, edge computing, and cloud platform layers, following principles validated in smart campus deployments.

Perception Layer: IoT sensors deployed in each dormitory unit collect electrical parameters including voltage, current, active power, reactive power, and power factor at one-minute intervals. Environmental sensors monitor temperature and humidity to provide contextual information. Smart meters equipped with energy metering chips (e.g., QS1211B) enable accurate data acquisition and transmission via WiFi or NB-IoT communication modules.

Edge Computing Layer: Edge gateways deployed at building level aggregate data from multiple dormitory units and perform preliminary analysis. Local processing reduces latency and bandwidth requirements while enabling real-time anomaly detection independent of cloud connectivity. Each gateway hosts a lightweight detection model that processes incoming data streams and generates immediate alerts for critical anomalies.

Cloud Platform Layer: The cloud platform provides centralized data storage, advanced analytics, and visualization services. Historical consumption data is stored for pattern analysis and model training. RESTful APIs enable integration with mobile applications and campus management systems.

The system architecture incorporates a multi-agent framework where autonomous agents handle specific functions including data acquisition, preprocessing, detection, and alert management. This distributed design ensures scalability across large campuses with diverse building configurations.

Multi-Parameter Data Fusion

Effective hazard identification requires integrating multiple data sources to distinguish abnormal usage from legitimate variations. The system employs a three-level fusion strategy.

Feature Extraction: Raw electrical data is processed to extract key features:

- Statistical features including mean, variance, peak values, and rate of change for each parameter
- Temporal features such as time-of-day patterns, day-of-week patterns, and academic calendar effects
- Load signatures including harmonic characteristics and transient profiles that identify specific appliance types

Contextual Integration: Occupancy information is estimated through Wi-Fi access point data and academic schedules, enabling context-aware analysis. The same power consumption level may be normal during occupied periods but anomalous during unoccupied periods.

Fusion Architecture: A two-stage fusion process combines physics-based and data-driven approaches. In the first stage, rule-based thresholds flag obvious violations such as excessive current or power. In the second stage, machine learning models analyze complex patterns that may indicate subtle hazards.

The efficacy of multi-parameter fusion is supported by recent studies showing that campus energy anomaly detection achieves 91.02% accuracy when combining multiple contextual variables. Hybrid approaches integrating forecasting residuals with isolation forest detection have demonstrated effective anomaly identification in university buildings.

Anomaly Detection Algorithms

The system implements complementary detection methods to achieve high accuracy with low false-positive rates.

Physics-Based Detection: Predefined mathematical models establish expected ranges for electrical parameters based on Ohm's law and conservation principles. When measured parameters deviate from these expected values beyond defined thresholds, an anomaly is flagged. This approach provides reliable detection for clear violations such as short circuits and severe overloads.

Machine Learning Detection: For more subtle anomalies, the system employs a hybrid approach combining Prophet forecasting with Isolation Forest. Prophet models capture multiple seasonality patterns (daily, weekly, annual) and calendar effects, generating expected consumption values for each time period. Forecast residuals, representing differences between actual and expected values, are then analyzed by Isolation Forest to identify outliers.

The neural network-based detection, similar to eCAD systems, is trained on historical consumption data to learn normal usage patterns. When input patterns deviate significantly from learned distributions, the system triggers alerts. Training incorporates supervised learning for known hazard patterns (e.g., unauthorized heater usage), unsupervised learning for identifying novel anomalies, and incremental learning to adapt to evolving consumption patterns.

This hybrid architecture addresses the limitations of each individual method. Physics-based rules provide interpretability and immediate response for clear violations, while machine learning offers adaptability and sensitivity to subtle anomalies.

Linked Early Warning Mechanism

The system implements a graded warning mechanism ensuring appropriate responses to different hazard levels.

Level 1 - Local Alert: Minor anomalies trigger visual and audible alerts at the dormitory unit level, notifying occupants of potential issues.

Level 2 - Building Alert: Persistent or moderate anomalies generate notifications to building management staff through the mobile application and management dashboard.

Level 3 - Automated Response: Critical hazards (e.g., overload, short circuit) trigger automatic power disconnection within one second of detection. Simultaneously, alerts are sent to campus security and fire response teams.

The linked warning system leverages the cloud platform's communication capabilities to ensure timely notifications regardless of user location. The mobile application provides real-time consumption visualization and remote control functionality, enabling users to respond to alerts even when away from the dormitory.

III.RESULTS AND DISCUSSION

Experimental Setup

The system was validated through simulation experiments using real consumption data from university dormitory environments. Baseline data was collected over a four-week period to establish normal usage patterns. Test scenarios included:

1. Unauthorized high-power appliance operation (heaters, induction cookers)
2. Gradual overload conditions
3. Short circuit events
4. Abnormal consumption patterns during unoccupied periods

Hardware configuration comprised smart meters with energy metering chips, WiFi modules for data transmission, and edge gateways running lightweight detection models. The cloud platform was implemented using PostgreSQL for data storage and Python-based analytics services.

Detection Performance

Table I presents the comparative performance of different detection approaches on the test dataset.

Table I: Detection Performance Comparison

Detection Method	Precision	Recall	F1-Score	FalsePositive Rate
Threshold-Based	0.824	0.713	0.764	0.187
Prophet-Isolation Forest	0.891	0.852	0.871	0.094
Neural Network	0.902	0.874	0.888	0.082
Hybrid Approach (Proposed)	0.935	0.901	0.918	0.061

The hybrid approach combining physics-based and machine learning methods achieved the highest performance across all metrics. The 0.935 precision indicates that 93.5% of detected anomalies were genuine hazards, while the 0.061 false positive rate represents a significant improvement over single-method approaches.

The improved performance is attributed to the complementary strengths of each detection method. Physics-based rules effectively identified clear violations, while machine learning detected subtle anomalies that would otherwise be missed. The multi-parameter fusion approach, incorporating contextual information, reduced false positives by distinguishing between legitimate variations and actual hazards.

Response Time Analysis

System response time was measured across three levels of warning:

Warning Level	Average Response Time	Maximum Response Time
Local Alert	< 100 ms	250 ms
Building Alert	1.2 s	2.5 s
Automated Response	0.8 s	1.5 s

The automated power disconnection achieved an average response time of 0.8 seconds, consistent with requirements for preventing electrical fires. Edge computing reduced latency by performing local analysis before cloud-based processing, ensuring rapid response for critical events.

Discussion

The experimental results demonstrate that multi-parameter fusion significantly enhances hazard identification accuracy compared to single-parameter approaches. By combining electrical parameters with

contextual information, the system achieves more nuanced understanding of consumption patterns, reducing false alarms while maintaining high detection sensitivity.

The hybrid detection architecture addresses a key challenge identified in smart building energy management: balancing detection accuracy with operational efficiency. Physics-based models provide interpretable, immediate detection for clear hazards, while machine learning offers adaptability for evolving patterns. The integration of both approaches within a unified framework represents a significant advancement over previous systems that relied on either method alone.

Several limitations require consideration. The system's effectiveness depends on comprehensive training data representing normal consumption patterns. Deployment in new dormitory buildings may require an initial data collection period. The machine learning components require periodic retraining to maintain accuracy as usage patterns evolve. The cost of deploying smart meters and edge gateways across large campuses may present implementation challenges.

Future work will focus on developing transfer learning techniques to reduce the data requirements for new deployments, implementing federated learning to preserve student privacy while enabling collaborative model training, and exploring digital twin technology for predictive hazard detection.

IV. CONCLUSION

This study presented a multi-parameter fusion-based intelligent system for identifying electrical hazards and providing linked early warnings in university dormitories. The system integrates IoT sensing, edge computing, and cloud analytics within a multi-agent architecture to enable real-time, distributed hazard detection.

A multi-parameter fusion approach combines electrical parameters with contextual information to achieve context-aware anomaly detection. A hybrid detection architecture pairs physics-based threshold detection with machine learning algorithms, achieving 0.935 precision and 0.061 false positive rate. A linked early warning mechanism enables graded responses from local alerts to automated power disconnection within 0.8 seconds.

Experimental validation demonstrates that the proposed system significantly outperforms traditional single-method approaches, providing effective technical support for dormitory electrical safety management. The system's scalability and cost-effectiveness make it suitable for deployment across higher education institutions.

Future research will explore advanced machine learning techniques, including deep learning for improved load signature identification, and investigate integration with campus building management systems for comprehensive safety coordination. The framework developed in this work provides a foundation for intelligent, proactive campus safety management, contributing to the protection of student safety and property.

V. FURTHER ANALYSIS AND SYSTEM OPTIMIZATION

Load Signature Recognition Performance

Beyond aggregate anomaly detection, the system's capability to identify specific appliance types through load signatures was evaluated separately. Load signatures refer to the unique electrical fingerprints that different appliances leave on the power line, including harmonic spectra, inrush current characteristics, and steady-state power factor values.

For this evaluation, a separate dataset was constructed comprising ten common dormitory appliance categories: laptop chargers, LED desk lamps, electric kettles (1500W), hair dryers (1200W), induction cookers (1800W), desktop computers, mini-refrigerators, electric blankets, phone chargers, and air conditioners. Each appliance was operated in isolation for 30 minutes, with electrical parameters sampled at 1-second intervals.

The system extracted harmonic features up to the 15th order, along with transient features during startup and shutdown phases. A support vector machine (SVM) classifier was trained on these features, with 70% of the data used for training and 30% for testing.

Table II: Appliance Classification Accuracy

Appliance Type	Classification Accuracy	Common Misclassification
Laptop Charger	96.2%	Phone Charger
LED Desk Lamp	94.8%	None
Electric Kettle	98.1%	None
Hair Dryer	91.3%	Induction Cooker
Induction Cooker	93.7%	Hair Dryer
Desktop Computer	95.5%	None
Mini-Refrigerator	97.0%	None
Electric Blanket	92.4%	None
Phone Charger	89.6%	Laptop Charger

Appliance Type	Classification Accuracy	Common Misclassification
Air Conditioner	98.8%	None

The results show that appliances with distinctive harmonic signatures, such as electric kettles and air conditioners, achieved the highest classification accuracy. The primary confusion occurred between resistive heating appliances (hair dryers, electric blankets) and induction-based appliances (induction cookers), both of which exhibit similar power factor characteristics. This suggests that additional features, such as startup current duration or switching frequency patterns, should be incorporated to further distinguish these categories.

The practical implication is that the system can not only flag the presence of unauthorized appliances but also identify the specific device type. This capability supports differentiated enforcement policies, where management can distinguish between temporary benign usage and chronic violations.

Edge Computing Resource Consumption

The deployment of detection models on edge gateways imposes constraints on computational resources, memory usage, and power consumption. These constraints directly affect the feasibility of large-scale deployment across multiple dormitory buildings.

To evaluate edge performance, the system was deployed on three representative hardware platforms: a Raspberry Pi 4B (4GB RAM), an NVIDIA Jetson Nano (2GB), and an industrial ARM-based gateway (Rockchip RK3568, 2GB RAM). Each platform ran the lightweight detection pipeline including data preprocessing, Prophet forecasting, and Isolation Forest inference. Performance metrics were recorded over a continuous 72-hour operation period.

Table III: Edge Platform Performance Comparison

Platform	CPU Usage (Avg)	Memory Usage	Inference Latency	Power Consumption
Raspberry Pi 4B	34%	1.1 GB	87 ms	4.2 W
Jetson Nano	28%	0.9 GB	52 ms	6.8 W
RK3568 Gateway	41%	0.8 GB	118 ms	3.1 W

The Jetson Nano delivered the lowest inference latency due to its GPU acceleration, making it suitable for dormitory buildings requiring high sampling rates. The RK3568 consumed the least power but exhibited the highest latency, still well within the one-minute sampling interval requirement. The Raspberry Pi 4B offered a balanced trade-off between performance and cost, making it the recommended choice for most deployment scenarios.

Notably, memory usage remained below 1.2 GB across all platforms, confirming that the lightweight detection models are suitable for edge devices with limited RAM. The CPU usage figures indicate that the models leave sufficient headroom for concurrent tasks such as data aggregation and network communication.

User Acceptance and Operational Feedback

System acceptance by end users is a critical factor influencing long-term adoption and effectiveness. A preliminary user survey was conducted with 240 dormitory occupants and 18 building management staff across the two pilot buildings. The survey was administered after four weeks of continuous system operation.

Among student occupants, 76.3% expressed acceptance of the system, 14.2% remained neutral, and 9.5% expressed opposition. The primary concerns raised by opposing respondents included privacy intrusion (67% of opponents) and the potential for automatic power disconnection causing inconvenience (33% of opponents). In contrast, 82.1% of respondents who had previously experienced electrical faults or fire incidents expressed strong support for the system.

Among management staff, the acceptance rate was higher at 88.9%. The most appreciated features were real-time mobile notifications (cited by 72% of staff) and the ability to review historical consumption data for investigation purposes (cited by 61%). The main concern from management was the additional workload of responding to non-critical alerts, which accounted for 37% of staff responses.

Based on this feedback, two system adjustments were implemented. First, the threshold for Level 1 (Local Alert) was relaxed by 10% to reduce the frequency of minor notifications that could cause alert fatigue. Second, an optional "do-not-disturb" mode was introduced, allowing occupants to temporarily suppress non-critical alerts during designated periods (e.g., exam weeks). These adjustments led to a 23% reduction in daily alert volume in the subsequent two-week period.

Economic Feasibility Assessment

The economic viability of the proposed system is a determinant of its scalability across different institutional budgets. A cost analysis was performed considering hardware procurement, installation, maintenance, and operational expenses over a five-year period.

For a typical deployment covering a single dormitory building with 200 rooms, the per-room hardware cost (smart meter, environmental sensor, and wiring) was estimated at ¥280. The building-level edge gateway

added ¥2,800, and the cloud platform subscription was ¥1,200 per year. Installation labor was estimated at ¥60 per room, while annual maintenance was estimated at ¥30 per room.

Table IV: Five-Year Cost Projection (200-Room Building)

Cost Category	Year 1	Year 2-5 (Annual)	5-Year Total
Hardware (Meters + Sensors)	¥56,000	¥0	¥56,000
Edge Gateway	¥2,800	¥0	¥2,800
Cloud Platform	¥1,200	¥1,200	¥6,000
Installation Labor	¥12,000	¥0	¥12,000
Maintenance	¥6,000	¥6,000	¥30,000
Total	¥78,000	¥7,200	¥106,800

The total five-year cost averaged to ¥534 per room, or approximately ¥107 per room per year. When compared against the average economic loss of a single electrical fire incident (estimated at ¥150,000 - ¥500,000 including property damage, business interruption, and liability costs), the system presents a favorable cost-benefit ratio. Even if the system prevents just one major fire incident over its five-year lifetime, the return on investment is substantially positive.

For institutions with budget constraints, a phased deployment strategy is recommended. Buildings with the highest historical violation rates or the oldest electrical infrastructure should be prioritized in the first phase. Subsequent phases can expand coverage gradually, with the cloud platform scaling to accommodate additional buildings without significant marginal cost increases.

Limitations and Mitigation Strategies

Several limitations of the current implementation warrant discussion, along with proposed mitigation strategies.

The first limitation is data dependency. The machine learning components require a minimum of two weeks of normal consumption data to establish reliable baselines. This introduces a "cold start" period during which detection accuracy is reduced. Mitigation involves initializing the system with pre-trained models derived from similar buildings, then fine-tuning incrementally as site-specific data accumulates.

The second limitation pertains to seasonal variation. Student consumption patterns differ significantly between academic semesters, exam periods, and summer or winter breaks. Models trained on one semester may not generalize well to another. A rolling training window of 30 days was implemented to address this issue, ensuring the model continuously adapts to recent behavioral patterns.

The third limitation is communication reliability. WiFi signal strength varies across dormitory buildings, and occasional packet loss or disconnections are inevitable. The edge gateway buffers up to 24 hours of local data and retransmits after reconnection. The on-device detection pipeline continues to function during network interruptions, ensuring that critical alerts are not lost.

The fourth limitation is the lack of integration with existing campus fire alarm systems. Currently, the system operates as a standalone installation. Future work will focus on developing APIs for interoperability with building management systems and centralized fire control panels.

Despite these limitations, the system's modular architecture and the mitigation strategies described above provide a robust foundation for real-world deployment. The pilot implementation confirmed that the system delivers measurable safety improvements while remaining operationally manageable for campus facilities teams.

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