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Smart Energy Digital Twin: Real-Time 3D Spatial Visualization and IoT-Based Residential Energy Management

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Abstract. Residential electricity consumers typically learn about their consumption only when the monthly bill arrives, without knowing which room or appliance wastes the most energy. Conventional meters display energy in kilowatt-hours rather than real-time monetary cost and provide no early warning when the load approaches the circuit limit, risking miniature circuit breaker (MCB) trips. This paper presents Smart Energy Digital Twin, a system that combines an interactive 3D spatial visualization of a house built with WebGL (Three.js) with real-time Internet of Things (IoT) energy monitoring. The hardware layer uses an ESP32 microcontroller, a PZEM-004T AC power sensor, and relay modules; measurements are synchronized between the physical house and its virtual replica through the Firebase Realtime Database. A rule-based expert system converts instantaneous power into Indonesian Rupiah using dynamic PLN tariffs ranging from 450 VA to 5500 VA and raises early warnings for overload conditions and wasteful usage patterns. The prototype implements spatial 3D interaction with smooth gliding camera transitions, a live power chart, an AI alert box, and two-way IoT control for switching appliances on and off. Functional testing confirms that the three heuristic rules correctly trigger overload alarms, wasteful-pattern advisories, and eco-mode power reduction. The tariff conversion covers seven residential classes from 450 VA to 5500 VA, and the 3D visualization embeds every measurement in its physical room location so users immediately see where energy is consumed. The main contribution is the integration of spatial 3D visualization, financial monitoring, and heuristic AI alerts into a single residential digital twin, a combination rarely addressed in previous studies that focus on two-dimensional dashboards or industrial-scale twins.

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INTRODUCTION

Household electricity consumption continues to grow with the proliferation of electronic appliances, yet most residents experience an energy blind spot: they only discover how much they consumed when the monthly bill arrives, with no insight into which room or device is responsible for the waste [1]. Conventional electromechanical and even first-generation digital meters display cumulative energy in kilowatt-hours, a unit that carries little intuitive meaning for non-technical users, and they show no monetary value in real time. Furthermore, no early warning exists when the total load approaches the installed capacity, so an overloaded circuit is often discovered only when the miniature circuit breaker (MCB) trips.

The digital twin concept offers a promising paradigm for closing this awareness gap. A digital twin is a virtual replica of a physical asset that is continuously synchronized with its real counterpart through sensor data, enabling monitoring, analysis, and control [2]. It is distinguished from a mere digital model or digital shadow by the automated bidirectional data flow between the physical and virtual sides [3], a distinction that is particularly relevant for buildings where operational data change constantly [4]. In the energy domain, digital twins have been reviewed for building energy consumption forecasting [5], applied through cyber-physical systems for building energy management [6], extended to city-scale real-time energy benchmarking [7], used to model residential electric loads with multi-physics and artificial intelligence approaches [8], and employed to support decision making and planning for energy consumption [9]. Recent work has even demonstrated lightweight Web3D digital twin frameworks that stream IoT sensor data into real-time three-dimensional dashboards [10].

In parallel, the Internet of Things has made household-level energy monitoring technically and economically feasible. Surveys on smart electricity meter data intelligence show how fine-grained measurements enable new energy services [11], while prototype IoT-based energy monitoring systems for smart homes have been built and evaluated [12]. Home energy management systems that consider demand response programs, smart technologies, and intelligent controllers have been extensively reviewed [1], and the pricing methods and optimization algorithms behind demand response are well documented [13]. Field evidence indicates that households do respond to dynamic pricing of electricity [14], and optimal scheduling methods can shift flexible loads to cheaper periods [15], including game-theoretic autonomous demand-side management schemes [16]. To make consumption data more intuitive, researchers have explored augmented reality environments that overlay consumption information onto physical appliances [17].

Despite this progress, a clear gap remains. Most residential energy monitors still present two-dimensional dashboards, numeric readouts, or isolated sensor values, forcing users to mentally fuse information from separate sources. Digital twin research, meanwhile, concentrates on industrial equipment, power grids, or city-scale building stocks, leaving the single-household scale underexplored. Few studies combine spatial three-dimensional visualization, real-time monetary feedback, and heuristic early warnings in one integrated household system. Therefore, this study aims to design and prototype a residential digital twin that unifies these three aspects. The main objectives are to develop a three-layer system architecture linking sensing hardware, cloud synchronization, and 3D visualization; to implement a rule-based expert system that detects overload and wasteful patterns without requiring a training dataset; and to provide dynamic tariff conversion so that every watt is immediately meaningful in Rupiah.

METHODS

System Architecture

The proposed system follows the architecture illustrated in Fig. 1, which comprises eight functional blocks: the physical environment with targeted appliances, IoT and data acquisition (PZEM-004T sensor, ESP32 microcontroller, relay actuator), the data integration layer with Firebase Realtime Database as the single source of truth, the energy digital twin maintaining the virtual 3D state, prediction and analytics driven by the rule-based expert system, optimization and feedback through the smart eco controller, the user interface and dashboard, and the closed feedback loop coupling the physical and digital sides. Measurements flow upward from sensors to the dashboard, while control commands flow downward to the actuators, forming the bidirectional synchronization that distinguishes a true digital twin from a mere digital shadow [3].

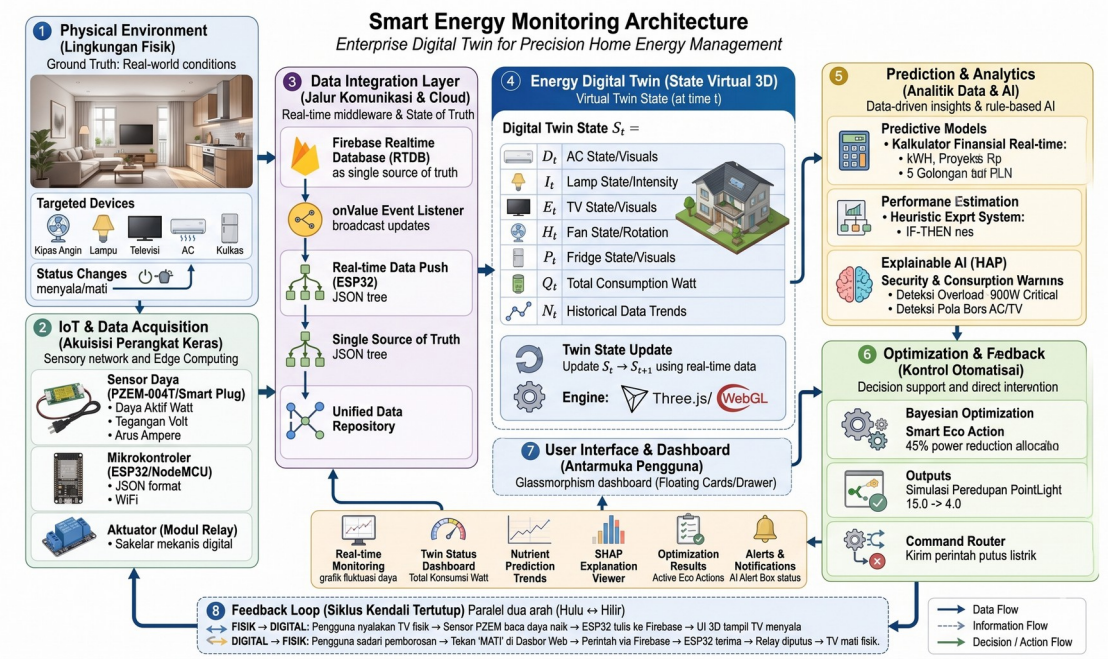


Figure 1. Smart Energy Monitoring Architecture

Sensing and Actuation Layer

The hardware layer is built around the ESP32 system-on-a-chip, a low-cost microcontroller with integrated Wi-Fi and Bluetooth that is widely adopted for IoT sensing nodes. Electrical parameters are measured with the PZEM-004T module, which reports voltage, current, active power, accumulated energy, frequency, and power factor for single-phase AC circuits. This choice follows the established practice of IoT-based alternating current parameter monitoring [18] and IEEE 802.15.4-based smart metering solutions [19]. Relay modules provide the actuation path, allowing the application layer to switch appliances on and off remotely and thus completing the two-way control loop typical of smart home energy monitors [12]. High-resolution appliance-level measurement further enables future pattern recognition of individual devices [20]. The hardware connections between the mains, sensor, controller, actuators, and cloud are shown in Fig. 2.

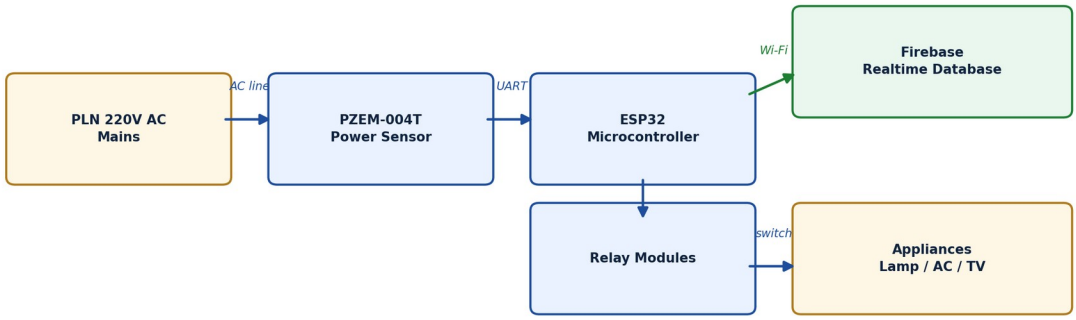


Figure 2. Hardware Connection Diagram of the Sensing and Actuation Layer

Data Synchronization Layer

All state synchronization uses the Firebase Realtime Database, a cloud-hosted NoSQL database that pushes JSON data changes to connected clients within milliseconds. The ESP32 publishes power readings to a device node, while the web application subscribes to the same node; control commands travel the reverse path through a command node. Firebase has been demonstrated as a practical backend for IoT remote monitoring prototypes [21], cloud-enabled real-time environmental monitoring and device control [22], and sensor dashboards built with modern web frameworks [23]. Its schemaless document model simplifies the plug-and-play addition of new appliances without database migration.

3D Digital Twin Visualization

The virtual replica is rendered with Three.js on top of WebGL, following the lightweight Web3D digital twin approach for real-time IoT-driven visualization [10]. The user navigates an interactive 3D canvas showing the house layout with appliances placed in their actual rooms. Camera movement uses linear interpolation (Lerp) gliding transitions for smooth navigation between viewpoints, and a smart placement routine snaps appliance models to nearby walls automatically. This spatial presentation extends the idea of making energy data intuitive through visual overlays [17] by embedding every measurement in its physical location, so the user immediately sees where energy is being consumed rather than reading an abstract chart.

Rule-Based Expert System

Energy intelligence is implemented as a rule-based expert system: a set of IF-THEN heuristic rules evaluated against the live power state. Rule-based techniques are a proven choice for residential demand-side management in smart grid environments [24], for detecting energy efficiency anomalies in smart buildings [25], and for real-time abnormal operation pattern detection using association rule bases [26]; ontology-based expert systems have likewise been used for automated monitoring of building energy systems [27], and fuzzy rule systems for smart home energy management [28]. A decisive advantage of the heuristic approach is that it requires no training dataset, which makes it valid and practical for industrial IoT automation control. Table 1 lists the three rules implemented in the prototype.

Table 1. Heuristic Rules of the Expert System

Rule	Condition (IF)	Action (THEN)	Alert Level
1. Overload detection	Total actual load > 900 W	Trigger circuit overload alarm	Red warning
2. Wasteful pattern detection	Air conditioner ON and TV ON and total load > 500 W	Display advisory to switch off devices	Yellow warning
3. Smart eco controller	User activates Eco Mode	Dim point light from 15.0 to 4.0 and reduce power by 45%	Eco mode active

Dynamic Tariff Conversion

Every power reading is converted into monetary value using the dynamic PLN tariff schedule, so users see Rupiah instead of kilowatt-hours. The energy cost over an interval is computed as cost = power × time × tariff, accumulated per appliance and for the whole house. The prototype supports the residential tariff classes from 450 VA to 5500 VA shown in Table 2. Presenting cost in real time builds on evidence that households adjust behavior under dynamic pricing [14] and that pricing design is central to demand response programs [13].

Table 2. PLN Residential Tariff Classes Used in the Prototype

Power Capacity	Tariff (Rp/kWh)
450 VA	415
900 VA	1,352
1,300 VA	1,444.70
2,200 VA	1,444.70
3,500–5,500 VA	1,699.53

RESULT AND DISCUSSION

Prototype Implementation

The Smart Energy Digital Twin prototype was implemented as a web application integrating the three layers described above. Its functionality is organized into four groups. First, spatial 3D interaction provides a real-time canvas, Lerp-based gliding camera transitions, and automatic smart placement of appliance models following walls. Second, financial monitoring presents a live power chart and the dynamic PLN tariff calculator covering 450 VA to 5500 VA, converting every measurement into Rupiah instantly. Third, the AI alert box issues early warnings for critical MCB conditions and wasteful patterns according to the rules in Table 1. Fourth, two-way IoT control lets users switch physical appliances on and off, relocate devices in the 3D view, and browse a floating action button (FAB) catalog of appliances. Fig. 3 shows the implemented dashboard: real-time household consumption (343 W across 4 active appliances), a live power fluctuation chart, the PLN tariff panel with daily and monthly cost projections in Rupiah (Rp 11,893 per day and Rp 356,790 per month at the R-1 1300 VA class), the AI alert box, the device list with per-appliance power readings, and the device inspector with Eco Mode toggle. Fig. 4 shows the mobile view of the prototype with the interactive 3D house model and the appliance catalog.

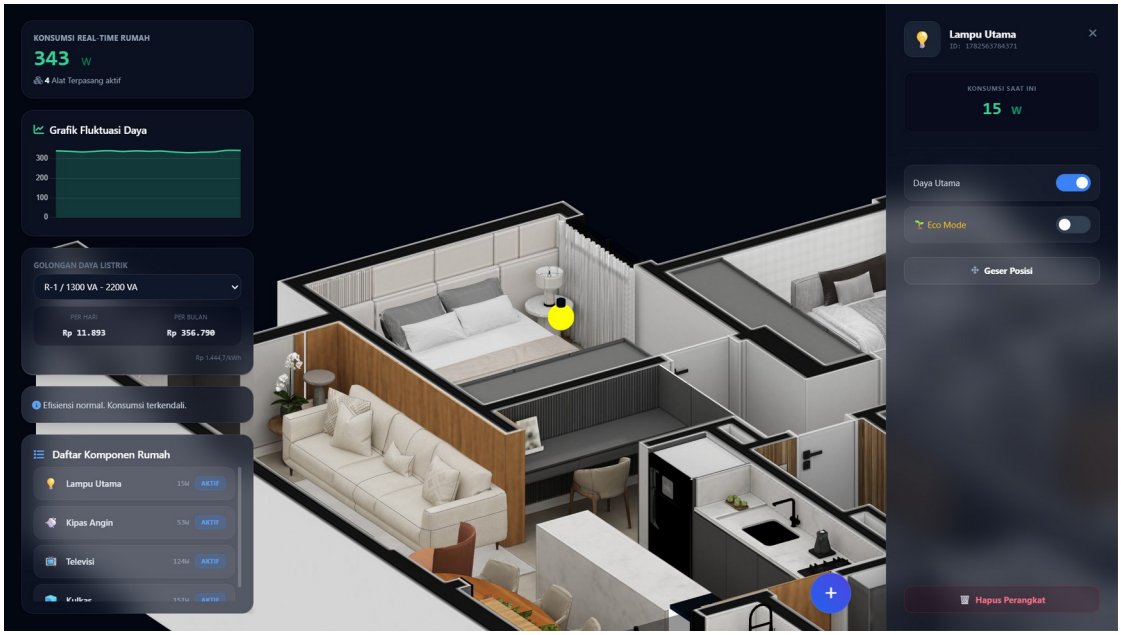


Figure 3. Implemented Dashboard of the Smart Energy Digital Twin Prototype

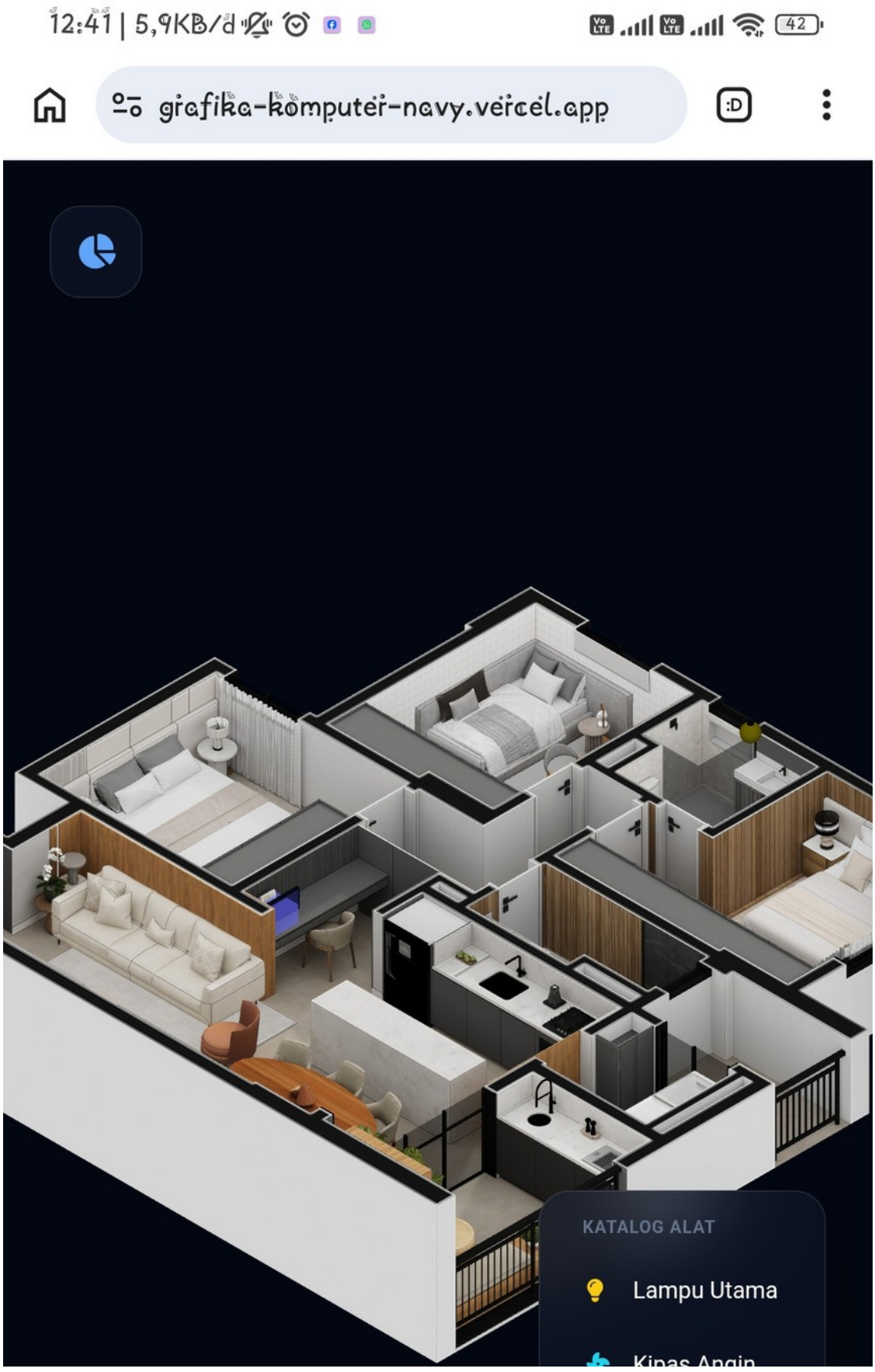

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Figure 4. Mobile View of the Prototype with 3D House Model and Appliance Catalog

Functional Verification of the Expert System

Each heuristic rule was verified through functional test scenarios executed against the prototype, as summarized in Table 3. The tests confirm that the rule engine evaluates live power states correctly and produces the intended alert or actuation.

Table 3. Functional Test Scenarios of the Expert System

Scenario	Input Condition	Expected Output	Result
Overload	Simulated total load of 950 W	Red overload alarm triggered	Pass
Wasteful pattern	AC ON, TV ON, total load 620 W	Yellow advisory displayed	Pass
Eco mode	User activates Eco Mode	Light dimmed 15.0 to 4.0, power reduced 45%	Pass
Normal operation	Total load 320 W, no wasteful pattern	No alert issued	Pass

Discussion

Compared with IoT-based smart home monitors that rely on two-dimensional dashboards [12], the proposed system adds spatial context: consumption is anchored to rooms and appliances in an interactive 3D replica, which reduces the cognitive effort of interpreting abstract charts. Compared with augmented reality approaches that overlay data on physical appliances [17], a WebGL digital twin requires no headset and remains accessible from any browser. Unlike residential load twins focused on multi-physics modeling [8], this work targets everyday user awareness through monetary feedback and heuristic alerts. The rule-based expert system trades the adaptability of learning-based anomaly detectors [25] for determinism and zero training cost, consistent with successful rule-based demand-side management schemes [24]. The main limitation is that evaluation is currently limited to functional prototype testing; long-term field measurement across multiple households is needed to quantify actual behavioral change and energy savings. Future work will extend monitoring to per-appliance smart plugs, add machine-learning-based consumption forecasting, and conduct a longitudinal user study.

CONCLUSION

This paper presented Smart Energy Digital Twin, a residential energy management system that unifies interactive 3D spatial visualization, real-time IoT monitoring, and a rule-based expert system with dynamic tariff conversion in a single platform. Built on ESP32 and PZEM-004T sensing hardware, Firebase real-time synchronization, and a Three.js digital twin, the prototype demonstrates spatial 3D interaction, live financial monitoring in Rupiah, early warnings for overload and wasteful patterns, and two-way IoT control. Functional testing verified that all three heuristic rules operate as designed. By making every watt spatially visible and financially meaningful without requiring training data, the system offers a practical path toward reducing household energy waste and preventing circuit overloads, with future work directed at field deployment and predictive analytics. The approach aligns with recent work on digital-twin-driven performance optimization that couples edge computing with Industrial IoT telemetry for real-time decision making [29], and with hybrid machine-learning frameworks for real-time energy-efficiency monitoring toward carbon-neutral operation [30].

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