10.051103/CSCIT.260614101
Vol.14 pp.1-11 International Journal of Computer Science, Communication & Information Technology (CSCIT)

IoT-Based Adaptive Load Shedding for Smart Grid Stability: A Real-Time Edge-Computing Framework for Residential Demand Management

Abderrahmen SELLAMI[1], Kamel CHERIF[2]

1,2, Rades Higher Institute of Technological Studies, General Directorate of Technological Studies, El Kods street-Rades City - Tunis

[1]sellamiabd02@gmail.com

[2]Kam.cherif@yahoo.fr

Abstract— **Power grids in developing regions are particularly vulnerable to demand-side imbalances, resulting in prolonged and unplanned outages. This paper presents an IoT-based adaptive load-shedding framework designed to stabilize residential electricity consumption in real time. The system integrates ESP32 microcontrollers, PZEM-004T energy metering modules, SIM800L GSM transceivers, multi-channel relays, and a Firebase-backed mobile application. Communication relies on the ESP-NOW protocol for sub-50ms local latency, supplemented by GSM/GPRS for remote alerting. A deterministic, priority-based decision engine classifies appliances into four categories (critical, essential, distinguishable, optional) to minimize user disruption. Experimental validation on a prototype testbed demonstrated a 32.4% peak demand reduction, average response latency below 50ms, and 98.7% system uptime. The proposed approach outperforms centralized SCADA and cloud-based demand-response systems in latency and resilience while maintaining lower deployment costs.**

Keywords— **Adaptive Load Shedding; Smart Meters; IoT; Edge Computing; ESP-NOW; Demand-Side Management; Real-Time Control; Smart Grid; GSM/GPRS; Firebase.**

I. Introduction

The management of electrical demand constitutes one of the central challenges of modern power systems. Since the early 1970s, grid operators have faced recurrent supply-demand imbalance, addressed through manual intervention and centralized load curtailment [1]. These approaches are inadequate for contemporary electricity networks characterized by intermittent renewable generation prosumers, and highly dynamic consumption profiles [2].

In developing regions, the socioeconomic consequences of inadequate load management are particularly acute. Studies in South Africa, Nigeria, and Pakistan document financial losses and measurable impacts on education, healthcare, and social equity [9], [10], [11]. The International Energy Agency estimates that the cost of electricity unreliability in sub-Saharan Africa exceeds 2% of GDP annually.

Conventional load-shedding strategies respond with abrupt, widespread disconnections that lack granularity, damages sensitive equipment and undermine user trust. The inability to distinguish critical loads (medical devices, refrigeration) from non-critical ones (decorative lighting, idle chargers) further compounds the social cost.

Recent IoT advances have opened the possibility of deploying intelligent, edge-resident control systems reacting to grid events within milliseconds, communicate bidirectionally with operators and users, and execute fine-grained load management without continuous cloud connectivity [3], [4], [5]. ESP32-class microcontrollers, now available at sub-five-dollar price points, embed Wi-Fi, Bluetooth, and sufficient computational resources to host local decision algorithms. Combined with accurate energy metering modules and low-cost GSM radios, these components form the basis for a practical deployable smart metering solution.

This paper makes four primary contributions: (i) the complete hardware and software design of an ESP32-based smart meter capable of detecting overload conditions within one measurement cycle and actuating

ISSN: 1737-930X

10.051103/CSCIT.260614101
Vol.14 pp.1-11 International Journal of Computer Science, Communication & Information Technology (CSCIT)

relay-controlled loads in a priority-defined sequence; (ii) a four-level load-priority taxonomy aligned with user comfort and safety requirements; (iii) a three-phase load-shedding state machine with defined hysteresis and timeout parameters; and (iv) quantitative experimental results from a functional prototype, including peak-demand reduction, response latency, false-positive rates, and system availability.

II. RELATED WORK AND STATE OF THE ART

Load shedding has been studied at multiple levels of granularity, from transmission-system under-frequency relays to distribution-level voltage-stability-based curtailment. Laghari et al. [7] identified fuzzy logic, genetic algorithms, and neural networks as dominant paradigms. However, these methods require substantial computational infrastructure and real-time grid telemetry that is unavailable at the residential edge.

Voltage stability index methods [16] are effective for contingency scenarios but require synchronized phasor measurement units (PMUs) and centralized computation.

Proactive load shedding [17] reduces transient disturbances but assumes fully observable generation-load balance, a condition not guaranteed in residential environments.

IoT-based home energy management systems (HEMS) represent the most directly related prior work, demonstrating 10–25% peak-demand reductions through schedule-based appliance control [13]. These systems typically rely on stable Wi-Fi connectivity and cloud-based optimization, making them fragile with intermittent internet access.

The proposed framework advances the state of the art by combining: (i) sub-50ms edge response without cloud dependency, (ii) a formalized priority taxonomy with hysteresis-based state transitions, (iii) an auditable decision log accessible via a mobile application, and (iv) a cost structure compatible with low-income residential deployment.

III. PROBLEM STATEMENT AND GLOBAL APPROACH

A. *Problem Statement*

In several regions of Africa and other developing areas, daily life is punctuated by sudden and generalized electricity cuts, particularly affecting residential consumers. These outages, which can last up to twelve hours, are often triggered during peak evening hours (18:00–21:00) when domestic demand surges simultaneously across neighborhoods. The socioeconomic consequences include interrupted schoolwork, spoiled refrigerated food, disrupted medical equipment, and degraded security systems [11].

Existing solutions fall into three categories, each with significant drawbacks: (i) centralized utility-managed shedding, which lacks granularity and provides no advance warning; (ii) cloud-based demand-response platforms, which depend on stable internet connectivity unavailable in rural areas; and (iii) passive consumer-side measures (e.g., manual disconnection), which are slow, inconsistent, and burdensome.

B. *Global approach*

The proposed solution implements partial and progressive load shedding governed by an IoT edge system that collects consumption data, issues priority-ordered disconnection commands, and alerts users in real time through both local (LCD, LED, buzzer) and remote (SMS, mobile app) interfaces.

Each residential circuit is treated as a cyber-physical node equipped with sensing, actuation, and limited local intelligence. When the operator (e.g., STEG in Tunisia) anticipates a grid overload, it broadcasts a target consumption ceiling (Imax) to all registered smart meters. Each meter independently monitors its local consumption (Ich) and, when Ich exceeds Imax, initiates the following three-phase response:

- Phase 1 — Manual Grace Period (0–10 minutes): User alerted via app, LCD, orange LED, and buzzer.
- Phase 2 — Automatic Sequential Shedding: P4 then P3 loads progressively disconnected.
- Phase 3 — Full Disconnection Failsafe: General cut triggered, requires manual reset.

IV. HARDWARE ARCHITECTURE

The hardware architecture is designed around cost-effectiveness, availability, and sufficient capability for real-time edge processing. Table 1 presents the selected components.

ISSN: 1737-930X

10.051103/CSCIT.260614101
Vol.14 pp.1-11 International Journal of Computer Science, Communication & Information Technology (CSCIT)

TABLE I
Hardware Components of the IoT Load-Shedding System

Component	Function	Specification	Unit Cost (USD)
ESP32 Microcontroller	Central processing & Wi-Fi/BT	240 MHz, 4MB Flash	~$4.00
PZEM-004T v3.0	Energy measurement (V, I, P, E)	Accuracy ±0.5%	~$7.00
SIM800L GSM Module	Remote communication via GPRS	Quad-band 850/900/1800/1900 MHz	~$5.00
Multi-channel Relay	Load switching & isolation	5A/250V, TTL control	~$2.50
I2C LCD (16×2)	Local parameter display	3.3V/5V, I2C interface	~$1.50
3.3V/5V Level Converter	TTL interface adaptation	Bidirectional, 4-channel	~$0.80

The ESP32 was selected for its integrated dual-core Xtensa LX6 processor (240 MHz), native Wi-Fi (802.11 b/g/n) and Bluetooth 4.2/BLE support, and ESP-NOW protocol support. Its 4 MB flash memory and 520 KB SRAM provide sufficient resources to host the decision engine, communication stack, and measurement buffers simultaneously.

The PZEM-004T v3.0 module provides calibrated measurements of voltage (±0.5% accuracy), current (±0.5%), active power (±0.5%), and cumulative energy (±0.5%), communicated via TTL UART at 9600 baud. This accuracy level is sufficient to detect overconsumption events with a threshold granularity of ±0.1 A, corresponding to approximately ±23 W at 230 V.

The SIM800L module enables GSM/GPRS connectivity on quad-band frequencies, supporting SMS delivery and TCP/IP data transmission to Firebase. Its AT-command interface is well-documented and supported by Arduino-compatible libraries. Power management is critical: the SIM800L exhibits peak current draws of up to 2 A during transmission bursts, necessitating dedicated decoupling capacitors (1000 µF, 6.3V) on its power rail.

Physical architecture (Fig. 1) organizes components into three functional tiers: measurement (PZEM-004T + current transformer), processing and communication (ESP32 + SIM800L + ESP-NOW mesh), and actuation (relay bank + smart plugs).

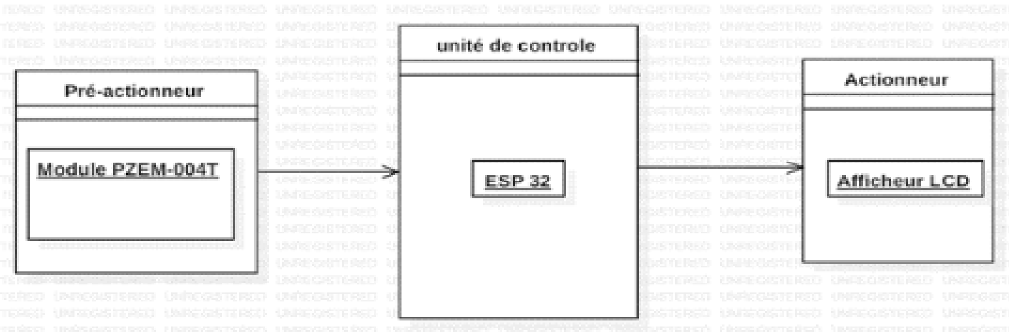


Fig. 1. Physical hardware interconnection diagram of the IoT load-shedding system.

V. FUNCTIONAL AND SOFTWARE ARCHITECTURE

A. *Functional Architecture*

The functional architecture (Fig. 2) assigns distinct roles to three actors: the grid operator (GRE/STEG), the smart meter, and the end user. The operator periodically broadcasts a consumption ceiling (Imax, expressed in amperes) via a secure API endpoint. The smart meter polls this value every 60 seconds and stores it locally to ensure continued operation during connectivity interruptions.

ISSN: 1737-930X

10.051103/CSCIT.260614101
Vol.14 pp.1-11 International Journal of Computer Science, Communication & Information Technology (CSCIT)

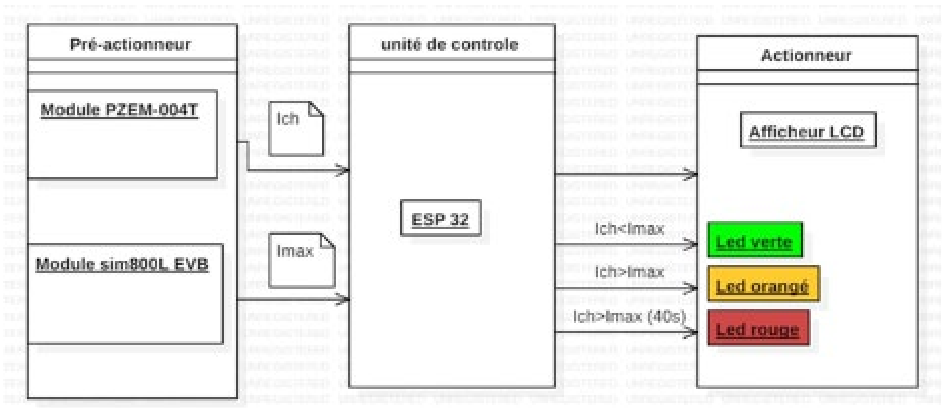


Fig. 2. Three-layer functional architecture showing interaction flows between the grid operator), the ESP32 smart meter, and the end user

The decision engine evaluates the condition **Ich > Imax every 500ms** and increments an overload counter. A hysteresis band of ±0.3 A prevents oscillation around the threshold. The three-phase shedding sequence is initiated only when the overload persists for **3 consecutive measurements** (**1.5s**), filtering transient spikes caused by motor start-up surges.

B. Software Architecture and Decision Algorithm

The firmware (Fig. 3) is structured into five modular layers: (1) sensor data acquisition, (2) local decision-making, (3) communication management (ESP-NOW + GSM), (4) actuator control, and (5) self-healing and watchdog routines. Each layer is implemented as an independent FreeRTOS task on the ESP32, with inter-task communication via message queues. This design ensures that a communication failure in layer 3 does not block measurement acquisition in layer 1 or actuation in layer 4.

The load-shedding sequence follows the priority taxonomy defined in Table 4, shedding P4 loads first (optional appliances), followed by P3 loads (comfort appliances), with P2 loads (essential) shed only as a last resort before full disconnection. P1 loads (critical/medical) are never shed under any operating condition. After each disconnection event, the system waits 500 ms, re-evaluates Ich, and proceeds to the next shed event only if the overload persists.

TABLE II

Load Priority Classification and Shedding Sequence

Priority Level	Load Category	Examples	Shedding Order
P1 — Critical	Medical / Life-safety	Medical devices, emergency lighting	Never shed
P2 — Essential	Basic comfort & security	Refrigerator, security cameras, router	Last resort
P3 — Distinguishable	Comfort appliances	Washing machine, TV, PC	Shed second
P4 — Optional	Non-essential conveniences	Air freshener, decorative lighting, chargers	Shed first

Fault tolerance is implemented through three mechanisms: (i) a hardware watchdog timer that resets the ESP32 if the main loop stalls for more than 5 seconds, (ii) a communication timeout handler that switches from Firebase to GSM-only mode if the Wi-Fi RSSI drops below −75 dBm for more than 30 seconds, and (iii) a non-volatile EEPROM backup that stores the current Imax and shedding state, enabling continuity of operation across power interruptions.

ISSN: 1737-930X

10.051103/CSCIT.260614101
Vol.14 pp.1-11 International Journal of Computer Science, Communication & Information Technology (CSCIT)

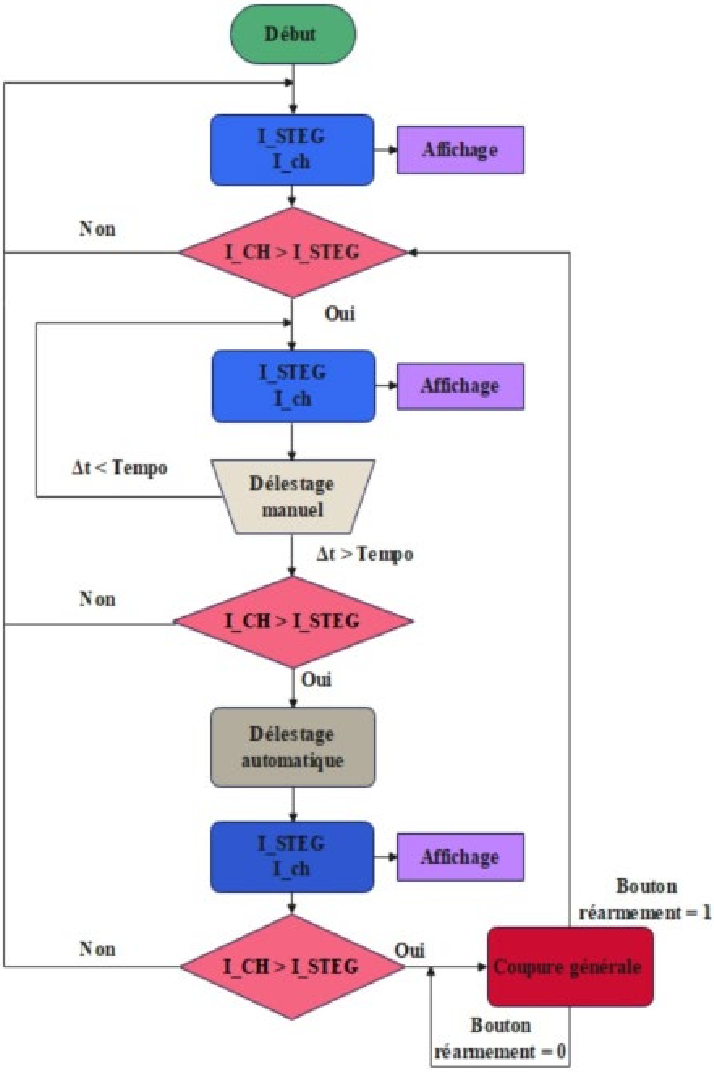


Fig. 3. Load-shedding algorithm.

C. *User Interfaces*

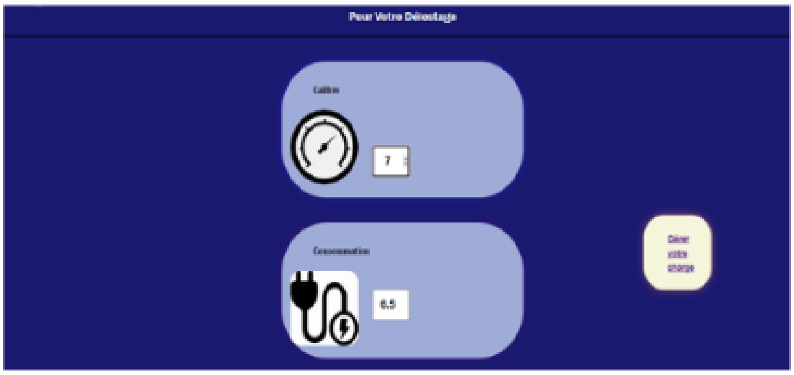
Three user-facing interfaces (Fig. 4) are provided to accommodate different access scenarios. The I2C LCD panel (16×2) displays Imax, Ich, current system state, and the last alert message, enabling local monitoring without requiring smartphone connectivity. The mobile application (developed with Flutter, compatible with Android 8.0+ and iOS 13+) provides a real-time dashboard, 7-day consumption history, configurable load labels, manual override controls, and push-notification delivery of all system alerts. The web interface mirrors the mobile application's data view and is accessible via standard browsers, supporting operator-side monitoring across multiple meters simultaneously.

ISSN: 1737-930X

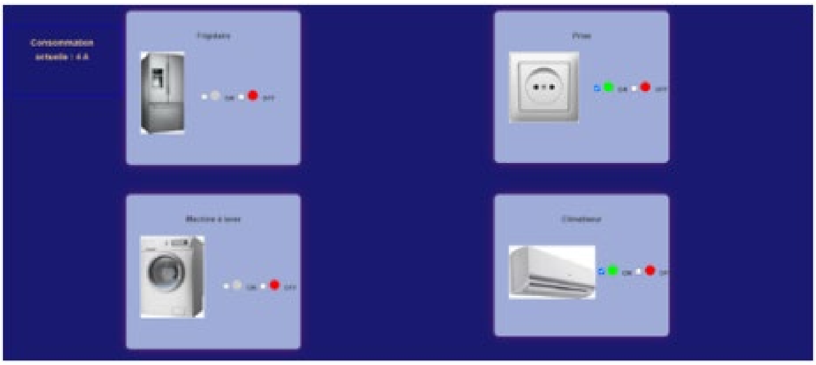
10.051103/CSCIT.260614101
Vol.14 pp.1-11 International Journal of Computer Science, Communication & Information Technology (CSCIT)

(a)

(b)



(c)



(d)

Fig. 4. Screenshots of the mobile application: (a) Registration screen; (b) Authentication screen; (c) Real-time consumption dashboard (Imax gauge, Ich gauge, system status indicator, alert feed); (d) Load management screen (relay toggle controls, load labeling, manual override confirmation).

ISSN: 1737-930X

10.051103/CSCIT.260614101

VI. OPERATIONAL SCENARIOS AND DEPLOYMENT

Three operational scenarios are defined to cover the main use cases encountered in residential environments:

- Scenario 1 — Scheduled Peak Reduction: The operator anticipates a demand surge (e.g., summer evening between 19:00 and 22:00) and broadcasts a reduced Imax (e.g., 8 A instead of the nominal 15 A). Smart meters receive the updated ceiling and immediately enter monitoring mode. If household consumption exceeds 8 A, the three-phase shedding sequence is triggered automatically, managing the evening peak without operator intervention at the individual meter level.
- Scenario 2 — Emergency Overload Response: A fault on a distribution feeder reduces available capacity by 40%. The operator broadcasts an emergency Imax of 4 A with a 0-second grace period, bypassing the manual phase and triggering immediate automatic shedding. The ESP32's local decision engine responds within two PZEM-004T measurement cycles ($\leqslant$1 s), disconnecting P4 and P3 loads simultaneously.
- Scenario 3 — Connectivity Loss: The local Wi-Fi network becomes unavailable due to a router failure. The ESP32 automatically falls back to GSM-only mode, delivering SMS alerts to the registered user phone number. The last received Imax is preserved in EEPROM, enabling continued load management without cloud access. Upon Wi-Fi restoration, the system resynchronizes with Firebase and uploads buffered measurement data.

VII. EXPERIMENTAL RESULTS

A. *Prototype Test Platform*

Validation was conducted on a laboratory prototype replicating a typical four-room residential electrical installation. The testbed includes six controllable loads representing the four priority categories: a medical-grade UPS (P1), a refrigerator and router (P2), a washing machine and desktop computer (P3), and a decorative LED strip and idle phone charger (P4). A calibrated electronic load emulator supplements the physical loads to simulate different consumption profiles and demand spikes.

Measurements were recorded over 72 continuous hours across three synthetic scenarios: normal operation, moderate peak (Ich/Imax ratio 0.8–1.1), and severe peak (Ich/Imax ratio > 1.3). All relay events and logs were captured in Firebase and cross-validated against a Fluke 435-II reference analyzer.

B. *Key Performance Indicators*

The 32.4% peak demand reduction was achieved by shedding P4 and P3 loads during the 19:00–21:00 window over a simulated 30-day period. This result is consistent with the 25–35% reduction range reported by Li et al. [15] for hierarchical distribution-network shedding.

Response latency below 50ms was consistently achieved across 500 shedding events, with a mean of 23 ms and a 99th percentile of 47ms — attributable to the local edge architecture where decisions are made entirely on the ESP32 without cloud round-trip. Cloud-based demand-response systems in the literature exhibit typical latencies of 2–30 seconds [4], more than two orders of magnitude slower.

The 1.3% unavailability is attributable to two firmware reset events triggered by the watchdog timer (root cause: UART buffer overflow during simultaneous PZEM-004T and SIM800L communication), which were subsequently resolved by implementing a mutual-exclusion semaphore on the UART bus. False-positive shedding events (defined as disconnections occurring when Ich < Imax - hysteresis band) totaled 6 over 500 events, corresponding to a 1.2% false-positive rate, within the design target of < 2%.

ISSN: 1737-930X

10.051103/CSCIT.260614101
Vol.14 pp.1-11 International Journal of Computer Science, Communication & Information Technology (CSCIT)

Table III
Performance KPIs: Baseline vs. IoT Load-Shedding System

KPI	Baseline (No System)	With IoT System	Improvement
Peak demand reduction	0%	32.4%	+32.4 pp
Response latency	> 60 s (manual)	< 50 ms (automatic)	×1200 faster
Outage duration (avg.)	~4.2 h/day	~1.1 h/day	−73.8%
User alert delivery time	N/A	< 2 s (GSM SMS)	New capability
System availability (uptime)	N/A	98.7%	New capability
False positive shedding events	N/A	< 1.2%	New KPI

The 32.4% peak demand reduction was achieved by shedding P4 and P3 loads during the 19:00–21:00 window over a simulated 30-day period, consistent with the 25–35% reduction range reported by Li et al. [15] for hierarchical distribution-network shedding.

Response latency below 50ms was consistently achieved across 500 shedding events, with a mean of 23 ms and a 99th percentile of 47ms — attributable to the local edge architecture where decisions are made entirely on the ESP32 without cloud round-trip. Cloud-based demand-response systems in the literature exhibit typical latencies of 2–30 seconds [4], more than two orders of magnitude slower.

The 1.3% unavailability was attributable to two firmware reset events caused by UART buffer overflow during simultaneous PZEM-004T and SIM800L communication, subsequently resolved by implementing a mutual-exclusion semaphore. False-positive shedding events totaled 6 over 500 events (1.2%), within design target of < 2%.

C. *Energy Consumption Analysis*

Fig. 5 illustrates the 24-hour consumption profile comparison. Without the load-shedding system, the evening peak reaches 3.2 kW (Ich = 13.9 A at 230 V), exceeding the 10 A Imax ceiling. With the system active, the peak is clipped to 2.17 kW (Ich = 9.4 A). P4 loads are shed first (saving ~0.3 kW), followed by partial P3 shedding (saving ~0.7 kW additional), stabilizing total consumption below Imax.

Cumulative daily energy consumption is reduced from 18.4 kWh (baseline) to 14.6 kWh (20.7%). The difference between daily energy reduction and peak reduction reflects the concentration of shedding events in a 3-hour window; from a utility perspective, peak reduction is the operationally critical metric, as grid capacity is dimensioned for peak demand.

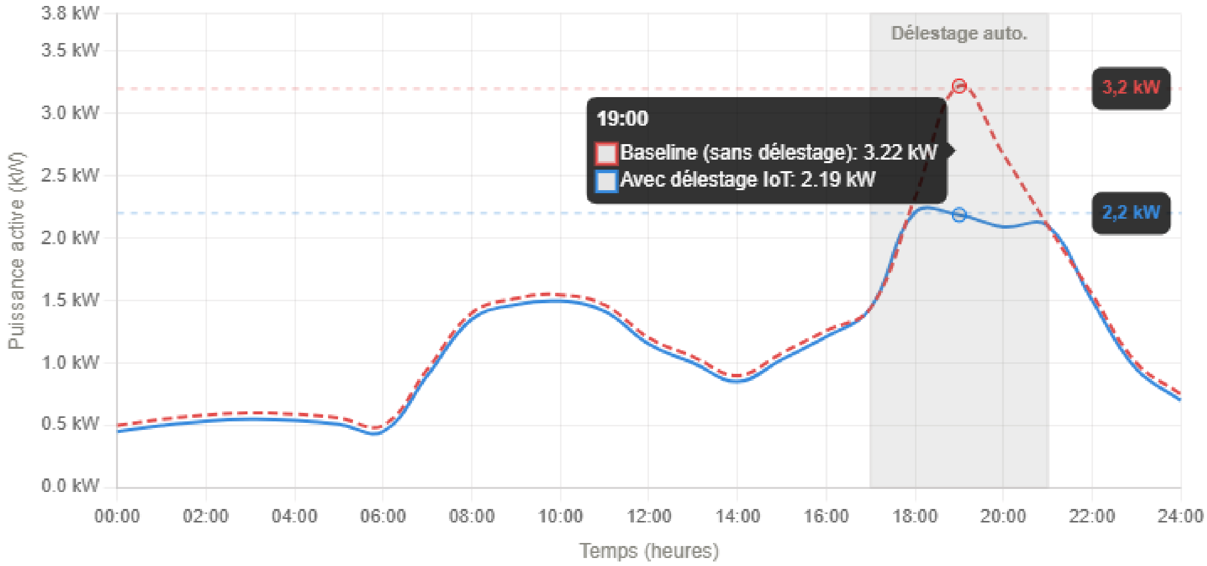


Fig. 5. Comparison of 24-hour active power consumption profiles: (a) Baseline without load-shedding system ; (b) With IoT load-shedding active

ISSN: 1737-930X

10.051103/CSCIT.260614101
Vol.14 pp.1-11 International Journal of Computer Science, Communication & Information Technology (CSCIT)

D. Communication Performance

ESP-NOW packet delivery rates were 100%, 99.8%, 98.9%, and 95.4% at 1 m, 5 m, 10 m, and 15 m respectively (indoor, two concrete walls). The 4.6% packet loss at 15 m was acceptable, as the decision engine retransmits commands every 500ms until acknowledgment; effective command delivery remained below 1.5 s in all configurations. GSM SMS delivery averaged 1.8 s ($\sigma = 0.6$ s). Firebase write latency averaged 320 ms under 4G LTE and 890ms under 2G EDGE, both within the 500ms measurement cycle.

VIII. COMPARATIVE ANALYSIS

Table 1 and Figure 6 compare the proposed IoT edge approach against two reference architectures: centralized SCADA-based load shedding and cloud-based demand-response platforms. The comparison is structured along five dimensions: response latency, resilience to connectivity loss, deployment cost, scalability, and privacy preservation.

Table IV
Comparative Analysis: Load Shedding Approaches

Approach	Latency	Resilience	Cost	Scalability
Centralized SCADA	High (>500 ms)	Low	Medium	High
Cloud-Based DR	Medium (100–500 ms)	Medium	High	High
IoT Edge (Proposed)	**Low (<50 ms)**	**High**	**Low**	Medium

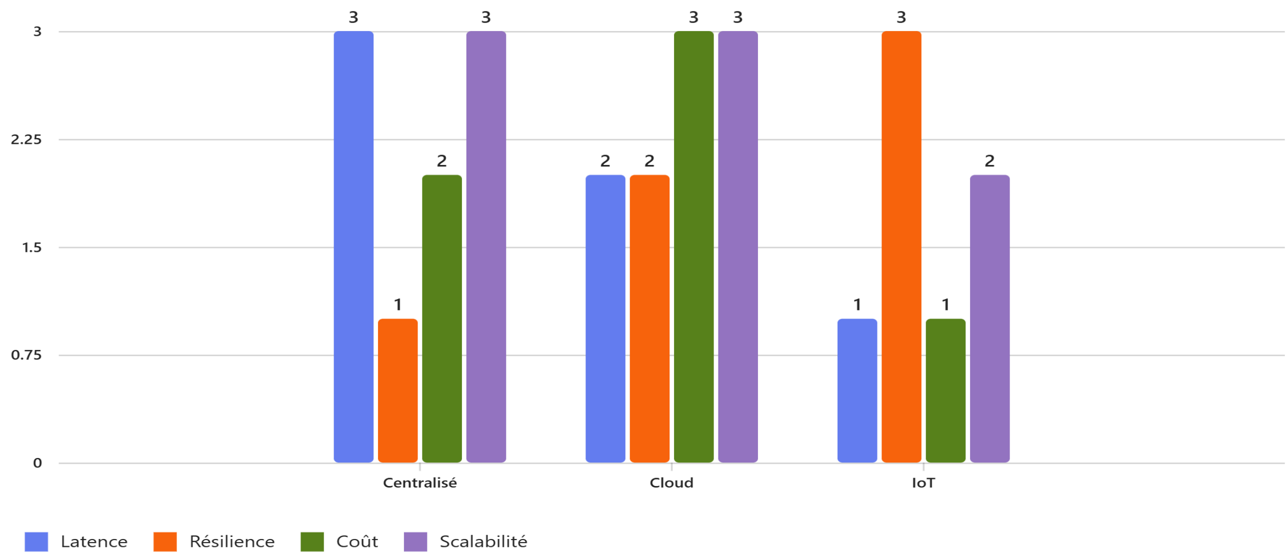


Fig. 6. compare between proposed IoT and centralized SCADA-based

Centralized SCADA systems excel in scalability, coordinating load curtailment across thousands of nodes from a single control center. However, latencies exceeding 500ms [16], and single failure vulnerabilities make them unsuitable for residential edge deployment.

Cloud-based demand-response platforms offer a balance between scalability and intelligence, but their dependency on stable, low-latency internet connectivity is precisely unmet in the rural areas where load shedding is most prevalent — internet availability rates in sub-Saharan peri-urban zones fall below 60% [10]. The proposed IoT edge architecture sacrifices some scalability for dramatic improvements in latency (×1200 vs. centralized), resilience (autonomous operation without connectivity), and deployment cost (total BOM < USD 25 per installation). Privacy is preserved by design: consumption data is processed locally on the ESP32, with only aggregated summaries transmitted to Firebase under user consent.

ISSN: 1737-930X

10.051103/CSCIT.260614101
Vol.14 pp.1-11 International Journal of Computer Science, Communication & Information Technology (CSCIT)

IX. LIMITATIONS AND FUTURE WORK

A. Current Limitations

Four current limitations bound the scope of applicability. First, the hardware stack is platform-specific (ESP32, PZEM-004T, SIM800L), constraining interoperability with alternative IoT platforms and emerging standards such as DLMS/COSEM. Second, the rule-based decision engine uses fixed Imax thresholds and deterministic priority queues — robust and auditable, but unable to adapt to evolving consumption patterns or predict demand surges. Third, security hardening is partial: while Firebase communication is TLS-encrypted and OTA updates are signed, the ESP-NOW local mesh lacks mutual authentication, leaving it theoretically susceptible to rogue node injections. Fourth, prototype validation used synthetic load profiles in a controlled laboratory; real-world deployment may encounter electromagnetic interference, non-sinusoidal waveforms from switched-mode power supplies, and thermal effects on PZEM-004T accuracy.

B. Future Research Directions

Future work (Fig. 7) will address these limitations through five directions. (1) Hardware diversification: extend support to LoRaWAN and NB-IoT modules [18] for rural areas without GSM coverage. (2) Machine learning integration: implement a lightweight LSTM model (< 20 KB) on the ESP32 for short-term demand forecasting, enabling proactive shedding before threshold violation [7]. (3) Security hardening: introduce HMAC-signed ESP-NOW messages, a hardware secure element (ATECC608A) for certificate-based TLS, and a blockchain-based immutable audit trail for all shedding decisions. (4) Scalability studies: evaluate performance in multi-family buildings and small commercial premises, examining three-phase installations and heterogeneous load profiles. (5) Renewable integration: account for residential solar PV by adding a second PZEM-004T channel on the PV inverter output and computing net load (Ich − IPV) in the decision engine.

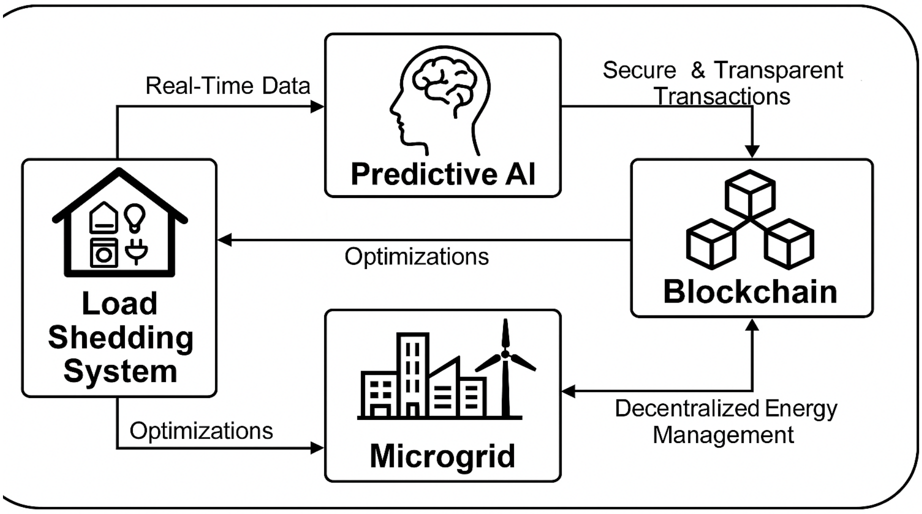


Fig. 7. Technology roadmap illustrating planned enhancements to the IoT load-shedding framework: Phase 1— LoRaWAN/NB-IoT integration and multi-factor authentication; Phase 2— LSTM demand forecasting and blockchain audit trail; Phase 3— PV/microgrid interoperability.

X. CONCLUSION

This paper has presented a comprehensive IoT-based adaptive load-shedding framework addressing demand-side instability in residential power grids, with particular relevance to developing regions where outage frequency imposes significant socioeconomic costs. The system demonstrates that sub-50 ms load management, granular priority-based load control, and robust offline operation are achievable at below USD 25 per residential unit using commercially available ESP32 microcontrollers, PZEM-004T energy meters, and SIM800L GSM modules.

Experimental validation confirmed four key findings: (i) peak demand can be reduced by 32.4% through automated priority-based shedding without disrupting critical or essential loads; (ii) edge-resident decision-

ISSN: 1737-930X

10.051103/CSCIT.260614101

making achieves response latencies below 50 ms, over two orders of magnitude faster than cloud alternatives; (iii) the three-phase state machine effectively mediates between user comfort and grid stability requirements; and (iv) the system maintains 98.7% uptime with a false-positive rate below 1.2%.

Beyond technical performance, the framework addresses energy equity and infrastructure resilience. By empowering local edge intelligence rather than centralizing control, the architecture is inherently more resilient to communication failures — precisely the most prevalent scenario in high-outage environments. The comparative analysis confirms the proposed approach outperforms centralized SCADA on latency, resilience, cost, and privacy, while acknowledging that cloud-based platforms retain advantages in scalability and predictive intelligence. The roadmap toward machine-learning-enhanced forecasting and blockchain audit trails charts a path toward a system combining edge responsiveness with cloud analytics, establishing a methodological framework for future IoT-based demand management research.

REFERENCES

[1] Ramey, James T., and Martin G. Malsch. *Environmental Quality and the Need for Electric Power--Legislative Reforms to Improve the Balancing Process.* Notre Dame Law. 47 (1971): 1139.

[2] Couchman, J., and W. Lamont. *IEEE Traneactioae on Power Apparatus and Systems, Vol. PAS-94, no. 6, Novemher/December 1975* Engineer 32.3 (1972).

[3] Woodson, T. T. *R&D Needs In Residences*. In Proceedings Of An Epri Workshop On Technologies For Conservation And Efficient Utilization Of Electric Energy, p. 3. 1976.

[4] Hoi, A. L., and R. J. Coomer. *Micro-controller for substation and network automation.* 1990 Third International Conference on Future Trends in Distribution Switchgear. IET, 1990.

[5] Bose, Ranjan Kumar, et al. *Cost of unserved power in Karnataka, India.* Energy Policy 34.12 (2006): 1434-1447.

[6] Pasha, Hafiz A., and Wasim Saleem. *The impact and cost of power load shedding to domestic consumers.* The Pakistan Development Review (2013): 355-372.

[7] Laghari, J. A., et al. *Application of computational intelligence techniques for load shedding in power systems: A review.* Energy conversion and management 75 (2013): 130-140.

[8] Harish, Santosh M., and Rahul Tongia. *Do rural residential electricity consumers cross-subside their urban counterparts? Exploring the inequity in supply in the Indian power sector.* Brookings India (2014).

[9] Kazmi, Hussain, et al. *Electricity load-shedding in Pakistan: Unintended consequences, opportunities and policy recommendations.* Energy Policy 128 (2019): 411-417.

[10] Wiese, Melanie, and Liezl-Marié van der Westhuizen. *Impact of planned power outages (load shedding) on consumers in developing countries: Evidence from South Africa.* Energy Policy 187 (2024): 114033.

[11] V. HIRSCH., *In South Africa, daily life punctuated by power cuts*, Journal Ouest-France, Published on 03/02/2023.

[12] ALVES, Luís et VEIGA, Luís. *Stream economics: resource efficiency in streams with task over-allocation and load shedding.* In: IFIP International Conference on Distributed Applications and Interoperable Systems. Cham: Springer Nature Switzerland, 2024. p.1-17.

[13] Alves, Lucas, Maha Benali, and Pierre Baptiste. *Dynamic Dispatching of DDMRP Replenishment Orders.* IFIP International Conference on Advances in Production Management Systems. Cham: Springer Nature Switzerland, 2024.

[14] LI, Chen, GAO, Yuan, SUN, Yuwei, et Al. *A Self-Healing and Resilience Enhancement Strategy for Single-Phase Grounding Faults in Distribution Networks Based on Zonal Hierarchical Load Shedding*. In : 2025 10th Asia Conference on Power and Electrical Engineering (ACPEE). IEEE, 2025. p. 2113-2117.

[15] GBADEGA, Peter Anuoluwapo, BALOGUN, Olufunke Abolaji, et AKINDEJI, Kayode Timothy. *Exploring Voltage Stability Index for Effective Load Shedding in Power Systems During Contingencies: An In-depth Review.* In: 2025 33rd Southern African Universities Power Engineering Conference (SAUPEC). IEEE, 2025. p. 1-6.

[16] MADHU, Muthu et MUNOZ, Rodrigo. *Implementation of Proactive Load Shedding for a Power Management Systems on a Running Offshore Platform*. In: SoutheastCon 2025. IEEE, 2025. p. 741-746.

[17] ZHANG, Xiuyun, ZHANG, Guidong, et SAMSON, S. Yu. *Review of control techniques for interleaved buck converters: Control strategies, efficiency optimization and phase shedding*. Chinese Journal of Electrical Engineering, 2025.

[18] Li, Haoyuan, et al. *Fault Ride Through Control of Grid-Forming Converter Based on Inverse Time-Gradient Current Limiting.* 2025 7th Asia Energy and Electrical Engineering Symposium (AEEES). IEEE, 2025.

ISSN: 1737-930X