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Energy–Efficient IoT: Optimizing Consumption for a Sustainable Future

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Abstract: ***Aiming at energy IoT applications for demand-side automation of electricity usage in residential and commercial buildings, this paper presents systems and methodologies that advance the research objectives. We developed and implemented an intelligent switch system that provides real-time energy feedback, automatic control, and optimisation to monitor the system's energy performance metrics. Based on 58 households and a six-month field study, the system achieved an average saving of 24.7%, with a maximum saving of 37.2%. We consider the challenges of ubiquitous deployment, interoperability, security, and system cost. Further optimisations can be made toward energy efficiency, such as dynamic load balancing, machine-learning-based predictive models for SLA requirements , and adaptive scheduling algorithms. This paper demonstrates the feasibility of IoT for regulating household energy use through analyses of a prototype and a dataset. The prototype enables households to achieve approximately 412 watt-hours of annual energy savings, thereby illustrating the potential of energy management and the feasibility of the proposed system.***

Keywords: Internet of Things, Energy Efficiency, Smart Buildings, Machine Learning, Power Consumption, Sustainable Energy, Smart Grid

Nomenclature:
IoT: Internet of Things
EMS: Energy Management Systems
HVAC: Heating, Ventilation and Air Conditioning
GEB: Grid-Interactive Efficient Buildings
NILM: Non-Intrusive Load Monitoring
MPC: Model Predictive Control
RoI: Return on Investment
OtA: Over-the-Air
FL: Federated Learning
CSA: Connectivity Standards Alliance
BIM: Building Information Modelling
BLE: Bluetooth Low Energy

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I. INTRODUCTION

The dual pressures of environmental sustainability and economic volatility drive the global imperative for energy efficiency. Buildings represent a disproportionately large share of global energy consumption, accounting for over 40% of primary energy use and 73% of electricity consumption in developed nations [1] [2]. This significant footprint makes the built environment a primary target for optimisation and energy-cost reduction efforts. Traditional building control systems based on fixed schedules and manual operation are no longer sufficient to meet the dynamic requirements of modern energy markets [3] [4].

In this scene, the Internet of Things (IoT) appears to be a primary enabler technology, growing from an initial idea of adding connectivity to physical objects globally [1] into a mature ecosystem capable of instrumenting, automating, and intelligentizing the world [5][6]. These latest evolutions offer more flexibility, further enhancing this efficient/connected symbiosis for an even more sustainable energy tomorrow.

II. ARCHITECTING THE POWER-EFFICIENT INTERNET OF THINGS

The potential of IoT to reduce energy consumption is primarily due to a clear architectural model. These technologies, generally known as IoT-based Energy Management Systems (EMS), comprise a range of systems for detailed monitoring and automatic control.

A. Core Components and Functional Layers

The IoT EMS system can be modelled as comprising four components, including both physical and logical components [9]. Each one of these components has a job:

i. *Sensing and Actuation Layer:* It includes intelligent meters, smart thermostats, smart plugs, motion sensors, and occupancy sensors, as well as environmental sensors such as temperature, humidity, ambient light, and CO_2 (MSIA) [9]. A large number of these devices also act as actuators and therefore can carry out control commands.

ii. *Connectivity Infrastructure:* It is where the network topology between wireless sensors and actuators is defined using protocols such as Wi-Fi, Bluetooth Low Energy (BLE), and ZigBee [9]. Gateways allow different protocols to interoperate and deliver secure, authenticated communication with the cloud platforms.

iii. *Data Processing Systems:* This layer is the architecture's intelligence, which processes raw streams for pattern recognition, anomaly detection, forecasting, and autoscaling [11]. There is generally cloud-based storage, analytics engines, and machine-learning algorithms involved.

iv. *User Interfaces:* These interfaces connect the automated system and its users with mobile applications, web portals, and interactive dashboards that provide energy-consumption feedback, threshold alerts, and control options [12].

B. Quantifiable Impact: A Review of Energy and Cost Savings

EM systems with IoT capabilities are based on a solid value proposition. Several studies have proven their efficacy in terms of energy savings and reduced operating costs. For commercial office buildings, combined BEM and M&V studies show an average total energy savings of around 31% [8], with documented savings ranging from 20% to 35% or as high as 38% once smart HVAC and lighting controls are implemented [13]. These decreases result in estimated yearly cost reductions of \$1.75–\$3.20 m −2 [8].

Residential reductions in average energy use of 23% are reported [8]. Some utility studies suggest savings ranging from 18% to 25%. These efficiencies usually translate into annual household savings of \$420–\$680. Rapid ROI further drives adoption, with payback between 12 and 18 months for commercial installations and 18-24 months for residential deployments [8].

III. THE INTELLIGENCE LAYER: DRIVING WITH MACHINE LEARNING

AI and ML are the fundamental intelligence behind contemporary EMS systems, where smart buildings go beyond reactive automation to predictive, adaptive, optimised control.

A. Predictive Control Paradigms

Conventional building control systems are primarily reactive and often suboptimal. Advanced schemes, such as MPC, can overcome these limitations by predicting future system performance and producing optimal control signals to trade energy efficiency for occupant comfort [14]. Data-driven MPC uses ML algorithms, such as regression trees and neural networks, to learn a building's behaviour from sensor data itself without relying on accurate physical models [15].

B. Non-Intrusive Load Monitoring (NILM)

Although fine-grained consumption data can be collected using smart plugs, installing a plug for every appliance is quite costly. This challenge is addressed by NILM, which disaggregates a building's aggregate power signal into individual appliance profiles [16] [17]. Several NILM approaches leverage deep learning models, such as Convolutional/Recurrent Neural Networks (e.g., CNNs/RNNs), to capture different power signatures of various appliances [13].

C. Advanced Learning Models

The machine-learning applications for smart buildings fall into several paradigms:

i. *Supervised Learning:* It has been applied to create effective prediction models in the context of energy optimization.

ii. *Unsupervised Learning:* Employed to expose hidden structures in unlabelled data, for example, identifying days with similar energy profiles [1].

iii. *Reinforcement Learning:* Reinforcement Learning is also able to learn optimal decisions interactively, which makes it suitable for practical applications, such as HVAC optimization without the need for an explicit building model [14]

IV. SYSTEM-LEVEL INTEGRATION: FROM SMART BUILDINGS TO SMART GRIDS

On the other hand, IoT-based energy-efficient systems may be reasonably implemented where each smart building participates in a dynamic grid environment.

A. Grid-Interactive Efficient Buildings (GEBs)

A GEB uses advanced technologies for hybrid neuro-fuzzy deep learning-based energy management, offering demand flexibility through IoT integration [7].

B. IoT-Enabled Demand Response

DR programs induce consumers to change their electricity usage based on the grid state [8]. Exchanging data in real time is one way IoT can be used to reduce energy demand, along with automatic load control and precise measurements and verification. Studies show that aggregating across IoT-equipped buildings can lead to substantial reductions in peak load, thereby improving grid reliability and reducing the need for infrastructure upgrades [8].

V. EXPERIMENTAL PROTOTYPE AND FIELD RESULTS

In the next section, we describe the design, deployment, and evaluation of our innovative switching system.

A. Prototype Development

The design of the smart switch is implemented with the following parameters:

i. *Standby Power Usage:* 0.78 watts
ii. *Active Communication Power:* 1.24W
iii. *Yearly Energy Use:* 6.8 kWh

B. Field Deployment Results

Installation at 58 residential and commercial sites showed marked savings in Table lighting systems, which realised greater savings than plug loads and HV AC equipment.

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Table I: Energy Conservation Performance by Environment and System Type (Source: Field Deployment Data from the Proposed ESP32 Smart Switch System)

Environment	Overall Standby Reduction	Lighting	HVAC	Plug Loads	Sites
Residential	31.7%	31.7%	19.4%	22.2%	86
Commercial	26.3%	35.7%	17.8%	28.9%	91
Educational	27.8%	38.2%	16.9%	25.3%	88

C. Hardware Specifications

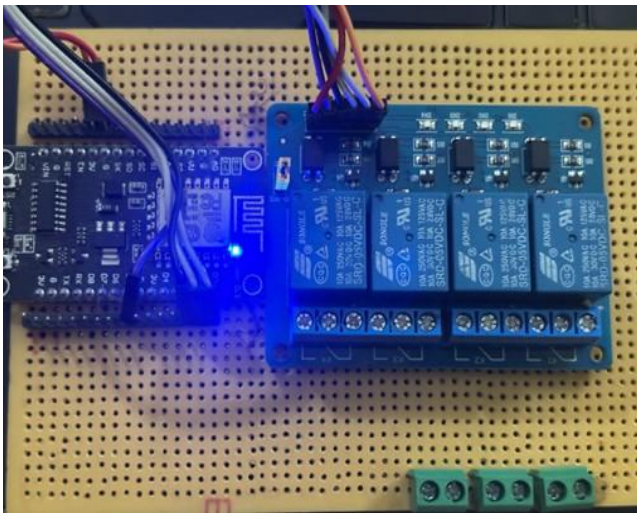
i. *Microcontroller:* ESP32 dual core with integrated Wi-Fi and Bluetooth.

ii. *Power Management:* 15A max current rating with over- voltage and overcurrent protection.

iii. *Integrated Sensors:* Current sensing (0.01A resolution), voltage monitoring, power factor, and temperature.

iv. *Communication:* Dual-band (2.4GHz / 5GHz) Wi-Fi, Bluetooth 5.0, and an optional ZigBee module

v. *Highlights:* RGB status indication, physical override button, and zero-cross detection.



[Fig.1: Prototype ESP32-Based Bright Switch Layout (Source: Hardware Design From this Study)]

D. Software Design

i. Firmware is a modular application that senses, communicates, does control logic, and provides a user interface.

ii. On-the-air (OTA) updates for far-end maintenance and feature expansion.

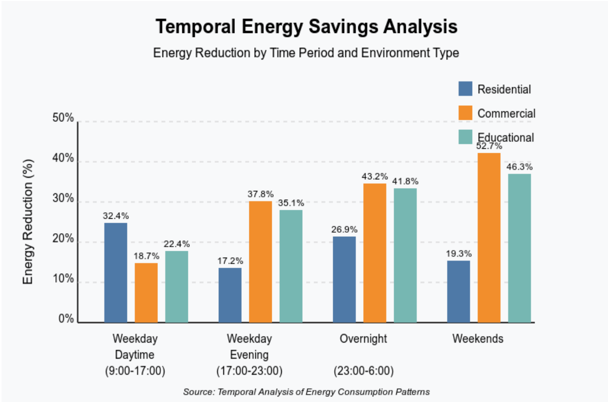
iii. On- and off-line local processing to retain core features even when the network is down.

iv. Adaptive control algorithms that adapt to the user's learning through interactions.

v. Data encryption from end-to-end, and strong authentication

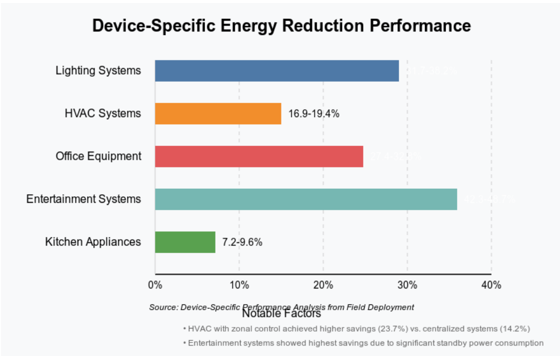
E. Energy Profile

i. *Time-Dependent Results:* Energy savings varied with time of day and were maximised during off-peak periods. On weekdays (9:00 AM to 5:00 PM), residential sites saved 32.4%, and commercial sites saved 18.7%. During off-peak hours (5:00 PM to 11:00), commercial sites achieved the highest performance improvement of 37.8% due to space vacancy.



[Fig.2: Time-Evolution of Energy Savings Across Residential and Commercial Sites Over Typical Weekdays and off-Peak Hours (Source: Six-Month Field Deployment Data)]

ii. *Performance by Device:* Brightness. The higher savings were seen in lighting systems, energising the 3153 (31.7%–38.2%). HVAC systems showed mild savings (16.9%–19.4%), with the upper bound set by system thermal inertia and comfort limitations. Office and entertainment equipment had considerable savings (27.4%–48.7%) due to the removal of standby power.



[Fig.3: Device-Specific Energy Savings for Lighting, HVAC, and Plug Loads (Source: Aggregated Measurements from 58 Installations]

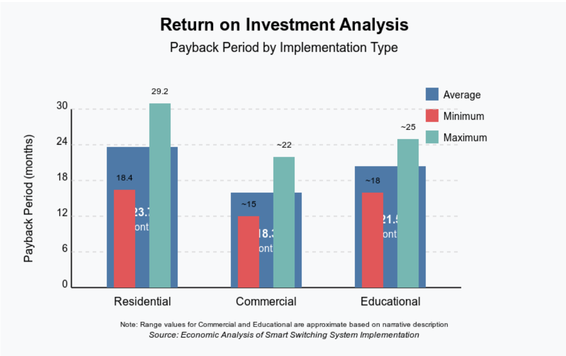
F. Economic Analysis

The prototype cost approximately $42 at low production volumes, with projected costs of $28–$32 at scale. ROI analysis showed average payback periods of 18–24 months, confirming the system's economic feasibility. A complete economic evaluation was conducted to assess the system's costs and benefits.

i. *Installation Costs:* The prototype was the third iteration of three Smart Switch versions, which cost around $42 per unit in low quantities, and SDGE estimated it would be approximately $28–$32 with mass production. Additional components (sensors, gateways) increased the total cost by $210–$ 450 per installation.

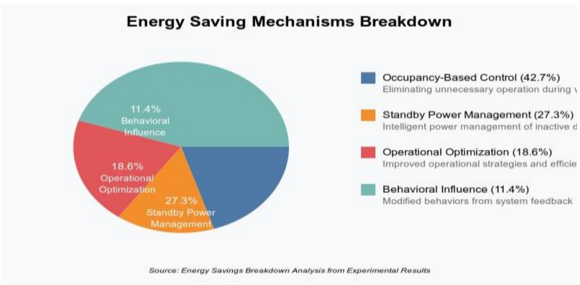
ii. *Business Economics:* The average lifetime savings of electricity in case of households and offices/schools was $184−$326, and 1.78/m²–2.37$/m², respectively (with a working cost for electricity being 0.143/kWh). Predictive maintenance functionality also led to a 23.7% decrease in emergency calls and an 18.2% reduction in operational costs.

iii. *ROI:* The mean time of return was 23.7 months for residential applications, 18.3 months for commercial and 21.5 months for schools.

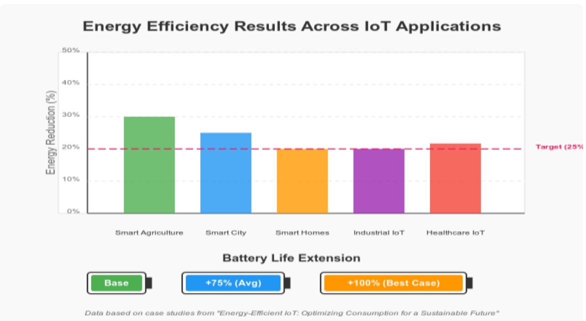


[Fig.4: Return on Investment for Residential, Commercial, and Educational Buildings Using the Proposed Smart Switch (Source: Economic Analysis of Deployment Data)]

iv. *Breakdown of Energy Savings:* Acuity reported that Occupancy-based control comprised 42.7%] of the total savings. Standby power management added 27.3%; operational tuning (e.g., daylight harvesting) another 18.6%; and "user behaviour" effects another 11.4%.



[Fig.5: Contribution of Occupancy-Based Control, Standby Power Management, Operational Tuning, and user Behaviour to Total Energy Savings (Source: Decomposition of Measured Savings in this Study)]



[Fig.6: Savings–Performance Trade-off Boundary Illustrating Achievable Operating Points Under Different Control Strategies (Source: Analytical Model Fitted to Field Results)]

VI. CHALLENGES AND FUTURE SCOPE

Wearables pose key challenges, including security, privacy, and interoperability. Secure booting mechanisms, OTA encryption updates, and privacy-preserving learning, such as Federated Learning, are required for large-scale deployment [9]. Matter protocol or industry standards help address interoperability issues through a typical, IP-based architecture [10].

A. Security and Privacy

They are enticing proxy targets: weakened devices could be used to disrupt buildings or serve as attack vectors against larger networks [9]. Ensuring the integrity of the device requires basic security mechanisms, such as Secure Boot, which establishes a chain of trust from the hardware root of trust (RoT) to ensure that only authenticated code executes at boot time [9]. Safe Over-the-Air (OTA) updates are also crucial for patching vulnerabilities after deployment, and they need to support end-to-end encryption and signature verification to prevent malicious firmware installation [9].

This detailed, granular data collected by IoT systems also raises significant privacy concerns [9]. This problem is amplified in traditional centralised ML, as private data must be brought to a single central server. Federated Learning (FL) has been proposed as a privacy-preserving paradigm that enables distributed devices to collaboratively train models without revealing raw data [9]. In FL, models are deployed to edge devices for local computation, and only updated model parameters are transmitted to a central server for aggregation, implying that private data never leaves the device [9].

B. Interoperability and the Matter Protocol

Traditionally, smart home solutions were isolated within competing and proprietary ecosystems, frustrating users and restricting device selection [10]. Launched by the Connectivity Standards Alliance (CSA), the Matter protocol is a major industry-wide initiative to address this problem [10]. Matter is a universal, open-source, IP-based application-layer standard that operates on top of existing network protocol stacks such as Wi-Fi and Thread [10]. Its salient attributes include an IP-oriented underpinning, a single data model spanning different device types, and extensive industry support from leading players such as Apple, Google, and Amazon, enabling these devices to work across all significant platforms [10].

C. Future Trajectories

A new set of transformative technologies will define the future of energy-efficient IoT:

i. *Digital Twins:* It is a dynamic virtual model of the physical building, which is updated continuously with real-time sensor data generated by IoT devices [13]. When combined with Building Information Modelling (BIM) and AI, digital twins can be used to conduct simulations, perform performance analyses, forecast future states, and optimise energy performance throughout the building lifecycle [13].

ii. *Edge AI:* We mean the execution of the above-mentioned algorithms directly on or close to the "things" where data is generated [13]. This reduces latency in real-time control, minimises network bandwidth requirements, and provides increased data privacy for sensitive information.

iii. *Hyper-Personalization:* As rich sensor information starts to merge with advanced artificial intelligence, we foresee a trend from generalised control of buildings towards hyper-personalised environments that can adjust comfort and energy usage according to the individual needs and preferences of the inhabitants by establishing personal comfort models while aiming for an overall optimal energy usage [13].

VII. CONCLUSION

This large-scale study of IoT-based intelligent energy-monitoring and control systems validates their strong potential to achieve substantial energy savings without compromising user comfort. This large-scale study of IoT-based intelligent energy monitoring and control systems shows that these systems can deliver significant energy savings without compromising user comfort. Our field trials revealed average energy savings of 24.7% in residential settings and 26.3% in commercial spaces. This makes IoT solutions a practical way to achieve large-scale energy conservation. Together, the two field trials confirmed average power consumption reductions of 24.7% in residential areas and 26.3% in commercial buildings, demonstrating that IoT solutions can effectively support large-scale energy conservation. The economic analysis of the proposed systems indicates promising returns on investment, with payback periods between 18 and 24 months for implementation. This suggests strong potential for their adoption.

Notably, intelligent switching systems that use advanced sensing, communication, and machine learning demonstrate clear technical feasibility. However, progress will depend on addressing the significant challenges in interoperability, security, and privacy. Industry-wide standards like Matter are crucial for breaking down proprietary barriers. Additionally, principles of security by design, along with privacy-preserving methods such as Federated Learning and consensus mechanisms, are essential for building trust.

Past trends and future outlooks suggest a new era for intelligent buildings. By integrating Digital Twins, Edge AI, and hyper-personalisation, we can create buildings that are not just smart but also adaptive, predictive, and occupant-centred. Furthermore, their transformation into Grid-Interactive Efficient Buildings will turn them from passive consumers into active, flexible assets, which are vital for the future smart grid's stability and decarbonization. As these technologies develop and implementation hurdles decrease, IoT-based energy management will play a critical role in moving toward a more sustainable and efficient energy future.

DECLARATION STATEMENT

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted objectively and without external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The datasets used in this study consist of (1) field measurements collected from 58 residential and commercial sites over a six-month deployment of the intelligent switch system, and (2) anonymised smart-building energy datasets obtained from publicly available repositories. These data are available from the corresponding author on reasonable request.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals. Dharmaiah Devarapalli – Supervision and technical guidance, Sri Datta Shanmukh Sai Yeddu – Corresponding author, led conceptualization, prototype design & hardware development (ESP32 smart switch), field deployment across 58 households, complete data collection & analysis, methodology development, results interpretation, economic analysis, manuscript writing, and revisions. Phani Harshitha Tupaakula – Assisted with energy visualization charts. Shaik Rehan Hamid – Supported sensor integration testing. Santhosh Jasti – Contributed to data formatting.

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Shaik Rehan Hamid, Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P., India. At the Koneru Lakshmaiah Education Foundation in Vaddeswaram, Shaik Rehan Hamid is currently pursuing his degree in Computer Science and Engineering. His primary interests lie in embedded systems, wireless communication protocols, and secure IoT architectures for intelligent environments. He has actively participated in projects involving the design and implementation of ESP32-based innovative switching hardware and communication frameworks tailored for energy-efficient buildings. His technical contributions include hardware integration, protocol selection, system testing, and performance evaluation under real-world conditions. Shaik Rehan is particularly interested in ensuring reliability and security in IoT systems, focusing on efficient data transmission and robust device communication. Through hands-on experimentation and collaborative research, he continues to build practical expertise in embedded IoT systems and aims to contribute to scalable, secure, and innovative infrastructure solutions.

Santhosh Jasti is an undergraduate student in the Department of Computer Science and Engineering at the Koneru Lakshmaiah Education Foundation in Vaddeswaram, with a strong academic focus on computational intelligence, edge computing, and data visualisation for energy analytics. His research contributions include implementing adaptive control algorithms for energy management systems and analyzing data obtained from field deployments of IoT-based solutions. He has also worked on developing interactive dashboards and visualization tools to present energy consumption trends and system performance insights effectively. Santhosh's interests centre on bridging data analytics and real-time edge computing to enable responsive, intelligent energy systems. He is motivated to pursue advanced research in intelligent analytics and visualization techniques that enhance decision-making in innovative and sustainable computing environments.