Smart Energy System Deployment in Developing Nations: Addressing Infrastructure Challenges

***Abstract*—This paper examines the practical challenges of deploying a smart energy monitoring system in a residential setting within a developing nation. It details a comprehensive sensor network implementation in India, capturing electrical, water, and environmental data. The study highlights obstacles such as unreliable power grids and intermittent internet connectivity, and proposes a resilient data acquisition architecture to ensure robust data collection. The findings offer insights for researchers and practitioners seeking to implement similar systems in resource-constrained environments.**

I. Introduction

Buildings across the globe account for a substantial fraction of total energy consumption—estimated to be over 30% of global energy usage. In the Indian context, residential buildings alone contribute nearly 93% of this consumption [1]. This rising demand underscores the critical need for innovative and scalable energy-efficiency solutions. Advances in Information Technology (IT), particularly in cyber-physical systems, embedded controllers, wireless sensor networks, real-time data acquisition, simulation frameworks, and machine learning algorithms, have opened up new avenues for intelligent resource management in buildings. These technologies support a wide range of applications, including behavior-aware control systems, proactive fault detection, automated energy regulation, and seamless integration of renewable energy sources.

One of the key enablers of intelligent energy systems is the deployment of sensor-based infrastructure that captures granular data on user activities and consumption behavior. Such detailed monitoring—especially around Activities of Daily Living (ADLs)—provides vital insights for optimizing home automation strategies and enhancing energy efficiency. Datasets collected from sensor deployments in residential spaces serve as essential testbeds for validating algorithms and understanding usage dynamics. Prominent examples include the REDD dataset [2], BLUED [3], and Smart* [4], all of which focus on fine-grained monitoring of electrical loads and environmental conditions within U.S.-based homes. These datasets have become benchmarks for a wide range of applications, from load disaggregation and behavioral modeling to predictive control and policy evaluation [5], [6].

Despite these advancements, existing efforts are predominantly limited to developed nations, where energy infrastructure is relatively stable, and user behavior patterns differ from those in emerging economies. Developing countries such as India face distinct challenges including unreliable electricity supply, rapidly growing urban infrastructure, and a diverse range of consumption behaviors. The architectural designs, appliance usage norms, and even the presence of decentralized power controls (such as individual socket switches) result in operating conditions that differ significantly from the assumptions embedded in current datasets. Consequently, there exists a critical data gap that hampers the design and validation of energy-efficient systems suitable for these contexts.

To address this gap, our research has undertaken a series of sensing deployments across a variety of Indian residential and institutional settings [7]. These include the installation of smart energy meters in 25 urban households, ambient environment sensors within a university research building, and real-time monitoring of electricity usage across 52 dormitory rooms. This paper concentrates on our most comprehensive deployment to date: an instrumentation effort within a multi-floor residence located in Delhi. Operational since May 25, 2013, this site features an integrated monitoring system that captures electricity and water usage at both aggregate and appliance-specific levels, while also logging ambient data (e.g., temperature, humidity, motion, and light) from 33 sensors distributed throughout the home. The deployment yields approximately 400 MB of time-stamped sensor data each day, forming a rich and multi-modal dataset.

To the best of our knowledge, this deployment represents the most detailed and long-term residential sensing study conducted in a developing country context. In this paper, we outline the challenges encountered and insights gained from deploying sensor networks in environments characterized by infrastructural unreliability and varied user behavior. We highlight how local constraints, such as frequent power outages, intermittent internet connectivity, and unique load-switching practices, influence sensing strategies and system design. Furthermore, we draw parallels with prior residential deployments in more stable settings, such as those in the United States, to explore the transferability and limitations of existing approaches. To support future research, we openly share curated metadata—such as appliance specifications, usage logs, and deployment schematics—alongside documentation of our methodological choices. Our goal is to contribute toward the development of adaptive, resilient, and context-aware energy systems that are capable of operating across a wide spectrum of socio-economic and infrastructural conditions.

II. Related Work

A wide body of research has investigated sensor deployments in buildings to enhance energy efficiency.

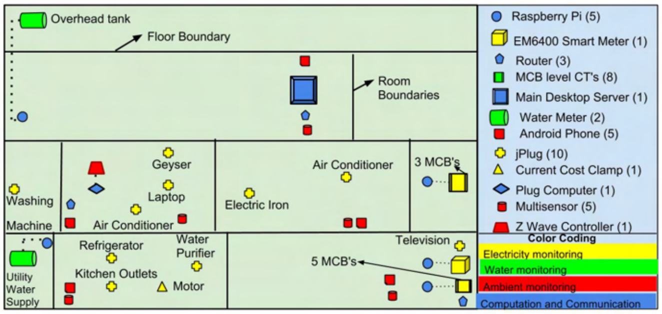


Fig. 1: Schematic showing overall home deployment

In institutional and commercial environments, studies like those by Yuvraj et al. [8] and Batra et al. [7] showed significant energy savings through intelligent HVAC and plug load control mechanisms enabled by sensing.

Within residential settings, Non-Intrusive Load Monitoring (NILM) has been a central focus. The REDD dataset, introduced by Kolter et al. [2], includes circuit and appliance-level energy usage from six homes and has become a benchmark in NILM research. Similarly, BLUED [3] presents high-frequency, event-labeled data over one week. Our dataset differs in scope and duration—it spans 73 days, integrates both standard and custom sensors, and includes water and environmental monitoring alongside electricity usage.

Barker et al. [4] developed a multi-modal deployment across three homes, incorporating environmental data, renewable energy, and occupancy for applications like peak demand reduction [6] and dynamic pricing [9]. Our deployment shares this multi-modal philosophy but emphasizes context-specific adaptations such as handling power and connectivity constraints.

The long-term deployments by Hnat et al. [10] provide insights into daily activity tracking in residential settings. Building on their findings, our deployment addresses challenges unique to developing regions, including grid unreliability, limited commercial sensor availability, and sparse communication infrastructure.

III. Deployment Overview

We instrumented a three-story residence in Delhi, India, with 33 sensors between May and August 2013. These sensors capture electricity, water, and ambient parameters at various levels of granularity. Our goals were to: (1) evaluate sensor feasibility in the Indian market, (2) understand consumption behaviors, and (3) assess infrastructure resilience in the presence of inconsistent power and connectivity. The layout is shown in Figure 1.

A. Sensing Infrastructure

We deployed a mix of imported and locally sourced devices to monitor physical parameters (e.g., power, water flow, ambient conditions) and network performance. Sensor installation was designed to be minimally invasive. Figure 2 highlights the hardware components used.

1) **Home-level Monitoring:** A Schneider EM6400 smart meter (Figure 2a) provided 1 Hz readings of voltage, current, frequency, and energy, using the RS485 Modbus protocol. This high-resolution data supports NILM analysis.
2) **Circuit-level Monitoring:** Eight circuit breakers were instrumented with split-core CTs (Figure 2b) connected to a custom SBC-microcontroller system. The sensors report RMS current at 20 Hz over UART and were developed in-house due to limited commercial options.
3) **Appliance-level Monitoring:** Ten appliances were monitored using jPlug devices (Figure 2c)—a WiFi-enabled power meter variant of nPlug [11]—reporting voltage, current, power, and energy every second. For the electric motor used in water pumping (a high-consumption, non-plug-load device), a Current Cost (CC) sensor (Figure 2d) was used, reporting apparent power via USB at 6-second intervals.

Water Monitoring: In Indian households, due to limited daily water supply, overhead tanks (typically 1000 liters) are commonly used for storage. Water is pumped into these tanks using electric motors during supply windows. Figure **??** illustrates this flow pattern—one meter measures incoming water at the utility inlet, and another captures outflow from the storage tank.

Given the high cost of digital water meters in India, we opted for Zenner Aquamet multijet meters[1], which produce pulse outputs via a 4-20 mA loop. The inlet meter (0.5-inch pipe) generates a pulse per liter, while the tank outlet meter (1.25-inch pipe) produces a pulse every 10 liters. Figure 2e shows the installed tank meter.

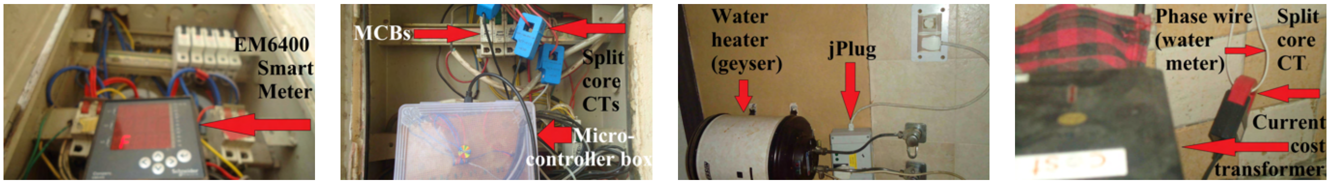
Ambient Monitoring: To track indoor environmental conditions, we deployed Z-Wave-based Express Controls HSM100 sensors[2] in five rooms. These imported devices, operating at 868.4 MHz (EU standard), measure light and temperature at 1 Hz, with motion events reported asynchronously. Additionally, stationary Android phones running the FunF journal app[3] recorded ambient light and audio data every 30 seconds over a 5-second sampling window.

Other Measurements: The Android phones also scanned for nearby WiFi, Bluetooth, and GSM signals at 60-second intervals. Occupants were asked to keep Bluetooth enabled for better localization. External weather data (e.g., temperature, humidity, wind speed) was logged every 10 minutes using APIs from Forecast, World Weather, and OpenWeatherMap. These multimodal data streams support applications such as occupant-specific energy apportionment and contextual analytics.

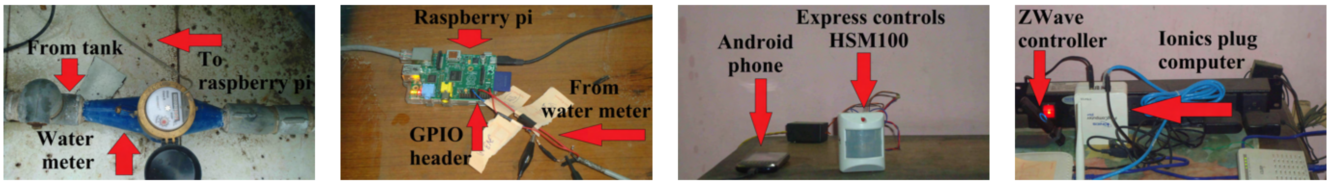
B. Computation and Communication

We used a hybrid architecture comprising Single Board Computers (SBCs), microcontrollers, and a central desktop server for data aggregation. Five Raspberry Pi (RPi) units and an Ionics Stratus plug computer handled primary sensing,

[1] www.aquametwatermeters.com/multijet.html
[2] http://goo.gl/Bszg0u
[3] http://www.funf.org/journal.html



(a) EM6400 Smart Meter (b) CT system for circuit-level monitoring (c) Plug-level appliance monitoring using jPlug (d) CT-based monitoring using Current-Cost



(e) Water flow meter (f) RPi capturing water pulses via GPIO (g) Z-Wave multisensors for ambient parameters (h) Plug computer transmitting Z-Wave data

Fig. 2: Overview of the sensing, processing, and networking components utilized in the residential deployment

Sensor Type	Source	Sampling Rate	Deployment Level	Units Used	Communication Mode	Captured Metrics
EM6400	Commercial (India)	1 sample/sec	Whole-home metering	1	RS-485 Serial	Voltage, Current, Frequency, Phase Angle, Active/Reactive/Apparent Power, Energy Usage
Aquamet Multijet	Commercial (India)	5 samples/sec	Inlet and storage tank	2	4–20 mA analog to GPIO	Water flow: 10-liter pulses (tank) and 1-liter pulses (main inlet)
Express Controls HSM100	Commercial (Imported)	Light/Temp: 1 Hz, Motion: event-driven	Room-level	6	Z-Wave Protocol	Motion Events, Light Intensity, Ambient Temperature
Android Smartphones	Commercial (India)	Audio/Light: 5s per 30s; Network scan: every 60s	Room-level	5	Manual Data Extraction	Audio Features, Light, Nearby WiFi/Bluetooth/Cell Towers
CT Clamp Monitor	Custom Built	20 samples/sec	Electrical Sub-circuits (MCBs)	8	Serial Communication	RMS Current Values
jPlug Monitors	Custom Prototype	1 sample/sec	Individual Appliances	10	WiFi-based	Voltage, Current, Frequency, Power (Active/Apparent), Energy, Phase Information
Current Cost Monitor	Commercial (Imported)	One sample every 6 seconds	Appliance Level	1	Serial Port	Apparent Power

TABLE I: Specifications of sensing infrastructure deployed across the household

while a 2 GHz Linux desktop served as the main collection point.

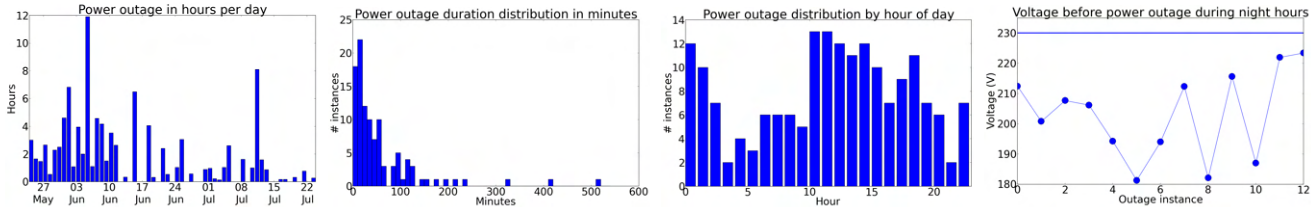
An RPi interfaced with the EM6400 via a USB-RS485 converter using a custom pyModbus script. Another RPi collected XML-formatted output from the CurrentCost meter. Dedicated RPis managed circuit-level and water flow monitoring. Initially, GPIO interrupts were used for water pulse detection, but due to noise from long wiring, polling at 5 Hz was adopted to ensure accurate readings.

jPlug appliance meters sent HTTP POST data to a server-side web daemon, which stored values in MySQL. The Ionics plug computer interfaced with all Z-Wave sensors using OpenZWave wrappers. Due to limited range, a USB Z-Wave controller was added to extend coverage. Data from Android devices was manually offloaded every 15 days.

Throughout deployment, we identified system bottlenecks—e.g., OpenZWave logs consumed the limited 512MB storage on the plug computer. This motivated the creation of soft-sensor streams [12] to monitor resource usage (disk, RAM, CPU) and support real-time fault alerts.

To ensure WiFi coverage, we deployed three Netgear JNR1010 routers[4], with one acting as the master and the other two as bridged repeaters across floors.

[4]www.support.netgear.com/product/JNR1010



(a) Power outage vs Time (b) Power outage duration (c) Power outage by hour of day (d) Voltage before outages (10 PM to 1 AM)

Fig. 3: Illustration of unreliable grid situation during our deployment. Rated voltage in India is 230V.

IV. Deployment Insights

Unreliable Grid Power: Frequent blackouts and voltage drops are common in Indian homes, especially during summer peaks. We tracked outages using the desktop's `last` command and by identifying concurrent sensor data gaps. Figure 3a shows daily outage duration, with some days exceeding 12 hours. Figure 3b indicates 107 outages over 61 days, averaging 1 hour each. Figure 3c highlights peak outage times at 10 AM and midnight. Voltage drops preceding outages (shown in Figure 3d) corroborate earlier findings [11] linking grid instability to voltage/frequency dips.

Observation: Disaggregation approaches should normalize for voltage variations [13], and hardware must record both current and voltage for accuracy.

Power Recovery Mechanisms: To minimize downtime, all sensing scripts were added to startup services. This allowed simple recovery via power-cycling by occupants. However, achieving consistent system recovery across heterogeneous devices remains a non-trivial engineering challenge.

Observation: Resilience to power failure must be explicitly tested in smart home platforms.

Network Instability: Despite growth in internet usage, Indian homes face frequent packet drops. We measured connectivity by pinging the internet every 15 seconds. Figure 4a shows packet loss up to 22%, with a daily average of 6%. About 20% of days exceeded 10% drop (Figure 4b).

Observation: Monitoring systems should operate independently of reliable internet. This need informs our architecture in Section V.

Value of Metadata: We collected appliance metadata (e.g., make, usage habits), which proved useful. For instance, after a refrigerator repair on July 2, its power usage jumped by 1 kWh/day (see Figure 5). Upon inspection, it was found that the cooling setting was inadvertently set to the lowest level, which we later corrected.

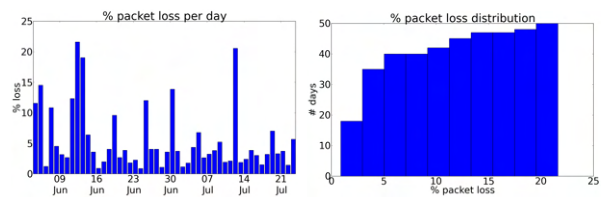
Observation: Detailed appliance metadata helps contextualize NILM results and inform corrective action.

Load Characteristics: Indian homes often use decentralized systems—individual ACs and water heaters per room—leading to sharp consumption peaks. These devices can account for 70% (summer) and 50% (winter) of total load. Their distinctive consumption patterns make them easier to detect using NILM methods.

Observation: Even simple NILM techniques can yield meaningful results in Indian households.

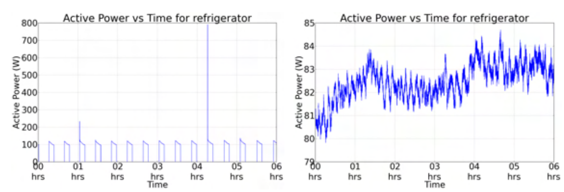
Energy-Water Interplay: Due to low pressure, electric pumps are used to fill water tanks. Pumping 1 liter with a 700W motor takes 4–8 seconds. Likewise, RO filters consume 40W to purify 1 liter in 1 minute. Together, they represent a class of water-energy coupled loads.

Observation: Joint monitoring of electricity and water can uncover interdependencies useful for conservation.



(a) Internet packet loss over time (b) CDF of daily packet loss

Fig. 4: Network reliability observations



(a) Before repair (b) After repair

Fig. 5: Impact of appliance metadata on energy analytics

Appliance Usage via Mains Switching: A unique behavioral trait observed in Indian households is the routine use of physical switchboards to cut power to appliances when not in use, rather than leaving them in standby mode—a common practice in Western countries like the USA. This habit significantly impacted our plug-level monitoring. For instance, jPlugs connected to kitchen appliances like microwave ovens failed to register any data during brief usage periods. This was primarily because jPlugs require nearly a full minute to boot up and establish WiFi connectivity before initiating data logging. In cases where appliances were operated for less than one minute, data was entirely missed as the devices were turned off before the plug had completed its setup.

We also experimented with Z-Wave-based plug monitors and controllers (operating at EU frequencies). However, a critical limitation emerged—these plugs defaulted to the OFF state when power was restored via physical switches, possibly as a safeguard against surge currents. Consequently, even after restoring power from the wall switch, the plugs required an

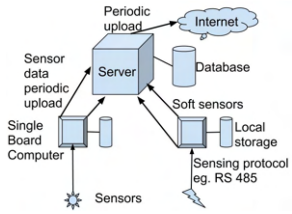


Fig. 6: Sense Local-store Upload architecture

additional software command (or external Z-Wave switch) to power the appliance. In Indian households where plug points are routinely toggled off, this led to inconsistent operation and user inconvenience.

Learning: *Plug-level monitoring systems must consider short-duration appliance usage and manual power disconnections via wall switches to ensure accurate and uninterrupted data collection. Seamless control mechanisms are essential for practicality in daily household usage.*

V. Sense Local-store Upload Architecture

Middleware platforms such as sMAP [14], BuildingDepot [15], and SensorAct [16] have been utilized for collecting and managing building-related sensor data. However, these systems fall short in addressing practical challenges common in developing regions—namely, unreliable internet and frequent power interruptions. Inspired by our field experiences and insights from prior research [10], we propose the Sense Local-store Upload architecture, which is structured around the principles of local buffering and deferred synchronization.

At the heart of Sense Local-store Upload lies the concept of a distributed sensing and storage model, referred to as SLsU. This model is built on two foundational principles: (1) using SBCs (Single Board Computers) equipped with local storage at each sensing node, and (2) performing periodic data uploads from these SBCs to a central in-home server and then asynchronously to the cloud.

As described in Section III-B, our deployment included six SBCs and several Android phones with local storage, each interfacing with various sensors deployed throughout the household. Sensor data was first saved locally in CSV format on the SBCs, then transferred at fixed intervals to a Linux-based central desktop server. In case an upload failed, automatic retries were scheduled. Each SBC had sufficient flash storage to buffer several days' worth of data, ensuring resilience against prolonged outages.

A web-based dashboard hosted on the central server allowed household members to visualize real-time and historical data. Simultaneously, cloud synchronization enabled researchers to monitor deployment status and perform remote diagnostics. Figure 6 depicts the overall SLsUarchitecture. Its distinguishing features include:

Separation of Sensing and Uploading: By decoupling data acquisition from network transmission, SLsUensures that failures in network connectivity do not disrupt sensing, and vice versa.

Minimal Internet Dependence: Internet connectivity is required only for cloud syncing or remote monitoring. In-home data collection continues uninterrupted, with buffered uploads occurring once connectivity resumes.

Server Load Optimization: Periodic bulk uploads reduce the computation and bandwidth strain on both SBCs and the central server. Analysis indicates that 1 GB of onboard SBC storage suffices for most real-world usage scenarios.

To demonstrate SLsU's effectiveness, consider this anecdote: one of the researchers accidentally terminated the server process responsible for collecting water flow data. Despite a week-long lapse, data was not lost—upon fixing the issue, the SBC pushed all buffered records to the server within an hour.

VI. Hitchhiker's Guide Revisited

We now revisit key insights from "The Hitchhiker's Guide to Successful Residential Sensing Deployments" [10], validating them through our experiences while also introducing context-specific observations unique to Indian households.

Residential Settings Are Error-Prone: One multisensor repeatedly failed post power restoration. Investigation revealed that it was connected to a battery backup socket, preventing it from power-cycling during outages. When the power resumed, the Z-Wave controller failed to re-register it, assuming the device to be non-responsive. Moving it to a regular power socket resolved this. Despite extensive pre-deployment testing, over 60 service requests arose post-deployment, underscoring the unpredictability of real homes.

Additionally, despite our use of zip ties to organize cables, accidental disconnections due to wire snags led to device shutdowns, as shown in Figure 8b.

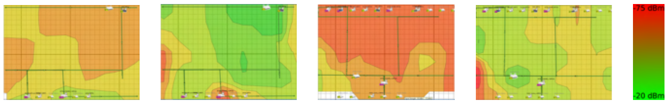
Design and Aesthetics Matter: Our system introduced 63 additional LEDs into the household. As evident in Figure 8a, the blinking lights disturbed sleep patterns. While careful placement mitigated some of these issues, future deployments should include LED shielding or smart enclosures. Another unexpected concern was the noise from our central desktop server, attributed to dust accumulation—a common issue in Indian homes.

Learning: *Long-term residential monitoring requires regular maintenance and dust-proofing to avoid system degradation. Aesthetic considerations also play a crucial role in user acceptance.*

Homes Lack Sensing Infrastructure: On the ground floor, MCBs were placed too close together, causing electromagnetic interference in CT-based monitoring circuits (Figure 8c). Data from these circuits was noisier compared to the more spaced MCBs on the first floor.

Expect Sensor Failures: We experienced failures in three jPlugs and one multisensor. Pre-planning for redundancy and having backup sensors enabled us to continue operations with minimal disruption.

Connectivity is Often Inadequate: The home's original WiFi router (first floor) failed to adequately cover ground and second floors. Using Ekahau Heat Mapper[5], we recorded poor signal strength in many rooms. By installing bridged routers on other floors, we significantly improved connectivity. Figure 7a through Figure 7e show heatmaps of signal strength before and after improvement.



(a) Ground floor (without additional router) (b) Ground floor (with additional router) (c) Second floor (without additional router) (d) Second floor (with additional router) (e) Scale

Fig. 7: WiFi Heatmap before and after router augmentation.

(a) Glowing LEDs at night (b) Cable snag causing shutdown (c) MCB proximity interference

Fig. 8: Common real-world deployment challenges

VII. Dataset and Code Availability

We have prepared a publicly available subset of our dataset, comprising fully labeled data from a representative day. This dataset includes detailed annotations for 63 appliances across their various operational states. Water flow measurements are similarly annotated for 18 fixtures, with calibration data documenting one-minute water use per device. Appliance metadata includes MCB mapping, rated power, purchase dates, and energy efficiency ratings.

VIII. Conclusion and Future Work

This paper presents our extensive deployment experience of a multimodal residential sensing system in Delhi, India, encompassing electricity, water, and ambient environmental monitoring. To our knowledge, this represents one of the most comprehensive such deployments in a developing country context.

Our work highlights how key regional differences—such as unstable grid electricity, inconsistent internet connectivity, manual appliance switching, and water-energy coupling—require architectural adaptations not addressed by prior smart home platforms developed in Western settings. The SLsUarchitecture proposed here mitigates these issues through local data buffering and periodic uploads, ensuring robustness against outages.

We also provide a cross-contextual comparison with earlier efforts [10], validating known challenges while uncovering new context-driven constraints unique to Indian households.

Looking ahead, we plan to extend our deployments to additional homes across Delhi to capture seasonal usage variations and evaluate long-term system resilience. A larger annotated dataset will be made publicly available to encourage further research in smart infrastructure for diverse residential environments.

[5] www.ekahau.com/products/heatmapper/overview.html

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