

Decentralized Computing Framework for Real-time Energy Management in Sustainable Smart Cities

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ABSTRACT

Centralized power grids are increasingly incapable of handling the bidirectional and intermittent nature of renewable energy sources (solar and wind). This lack of real-time responsiveness leads to grid instability, energy leakage during transmission, and frequent blackouts during peak periods. Centralized cloud processing introduces high latency, making it slow for the split-second decisions required in micro-grid management. From existing studies, Edge computing provides the technical blueprint for the next generation of smart and time-sensitive infrastructure. This study therefore proposes a Decentralized Edge Computing Framework, that involves deploying lightweight Machine Learning models at the power edge layer – the transformer and household levels. Leveraging the Pecan Street Dataport Dataset, the world's largest high-resolution energy dataset, the methodology involves local data processing such that edge nodes negotiate energy distribution between electric vehicle (EV) charging stations and residential solar units in real-time, without sending data back to a central server. Experimental results suggest that the framework can significantly mitigate grid instability, demonstrating a 38% reduction in grid peak-load stress under the modeled conditions. Comparative analysis indicates that localized decision-making (Edge) has the potential to outperform centralized systems (Cloud) in stabilizing voltage levels and reducing transmission losses. For the larger society, this translates to lower energy bills, a more reliable power grid, and the democratization of energy, where neighborhoods can become self-sustaining energy islands, reducing reliance on fossil-fuel-dependent centralized utilities.

Keywords: Smart cities, Sustainability, Energy, Efficiency, Decentralized Framework

I. INTRODUCTION

The rapid expansion of urban landscapes has brought the dual challenge of escalating energy demands and the urgent need for environmental sustainability to the forefront of global policy. As cities evolve into smart ecosystems, the integration of physical infrastructure with digital intelligence spanning smart grids, buildings, and transportation has become a cornerstone for modern urban development (Pandiyani *et al.*, 2023). However, traditional energy frameworks are increasingly struggling to keep pace. Centralized systems often face significant hurdles, including supply-demand mismatches, outdated infrastructure, rising carbon emissions, and a fundamental lack of transparency in how energy is traded and consumed (Pandiyani *et al.*, 2023 and Anthony, 2024). To

address these complexities, there is a growing consensus that the future of urban energy lies in a decentralized, citizen-centric approach.

Central to this transition is the emergence of the prosumer citizens who both consume energy but also produce it through renewable sources. While prosumers are vital to a sustainable energy transition, existing market mechanisms often suffer from issues related to trust, data privacy, and inefficient price determination (Anthony, 2024). Recent research suggests that the convergence of the Artificial Intelligence of Things and Distributed Ledger Technologies can bridge these gaps. By combining IoT-enabled sensors with blockchain-based smart contracts, cities can foster secure, peer-to-peer energy trading environments that empower local communities and optimize real-time monitoring (Al-Reshidi *et al.*, 2024).

The intelligence of these decentralized systems is further enhanced by advancements in deep learning and predictive analytics. Modern frameworks now leverage neural networks and spatiotemporal transformers to forecast dynamic energy demands with high precision, even in resource-constrained environments (Aljohani, 2024). Integrated systems using deep learning and IoT have demonstrated the ability to predict grid fluctuations with over 93% accuracy, significantly reducing wastage and operational costs (Singh *et al.*, 2025). Internet of Energy (IoE) models enable the grid to become more adaptive, using real-time data to balance supply and demand despite the fact integrating renewable sources like solar and wind more effectively (Mishra & Singh, 2023 and Raaj *et al.*, 2024).

In addition, the sheer volume of data generated by smart cities poses a challenge for traditional cloud-centric computing. To maintain the responsiveness required for real-time management, and focus is shifting toward edge computing. By processing data closer to the source, edge-based frameworks reduce latency and alleviate bandwidth constraints. This allows for localized decision making in everything from autonomous traffic signals to building-level energy optimization (Kummara, 2025 and Huang *et al.*, 2025). Research indicates that the decentralized processing models can improve renewable energy consumption by up to 30% while maintaining the privacy and security of user data (Huang *et al.*, 2025).

Security remains a principal concern in these distributed environments. Blockchain technology, when integrated with IoT, provides a tamper-proof ledger that prevents fraudulent

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meter readings and ensures communication integrity (Elgabri *et al.*, 2023). Innovative hybrid consensus mechanisms, such as combining Proof of Stake with Practical Byzantine Fault Tolerance, have shown the potential to reduce the energy overhead of blockchain itself by 80%, making it a practical tool for eco-friendly urban governance (Elhajj *et al.*, 2025).

In conclusion, the goal of these technological integrations is to meet the United Nations Sustainable Development Goals, mainly those focused on affordable clean energy and resilient cities (Kolawole *et al.*, 2025 and Mrabet & Sliti, 2024). By unifying the Urban Brain which handles real-time operations with Urban Digital Twins for long-term strategic planning, cities can create a dynamic feedback loop that enhances resource efficiency and environmental performance (Bibri & Huang, 2025). This chapter proposes a multi-layered decentralized computing framework that synthesizes these advancements in AI, blockchain, and edge computing. By specifically addressing the trade-off between decentralized security and real-time operational latency, the framework provides a robust, scalable, and secure solution for energy management in the sustainable smart cities of tomorrow.

II. LITERATURE REVIEW

A. The Shift Towards Prosumer-Centric Energy Markets

The transition to sustainable smart cities is increasingly defined by the rise of prosumers citizens who both consume and generate renewable energy. Anthony (2024) observes that while these individuals are vital to decentralized systems, the success of such markets hinges on solving persistent issues of trust, privacy, and fair price determination. Traditional trading mechanisms often fall short, necessitating a move toward citizen-centric models. This sentiment is echoed by Swain *et al.*, (2021), who advocate for the integration of smart microgrids and blockchain to facilitate peer-to-peer trading. By decentralizing energy provision, these frameworks allow households to trade surplus electricity directly, reducing transmission losses and fostering local energy independence (Swain *et al.*, 2021 and Reshidi *et al.*, 2024).

B. AI and IoT Integration

At the heart of modern energy management lies the convergence of the Artificial Intelligence of Things (AIoT) and Big Data analytics. Pandiyan *et al.* (2023) emphasize that the multidisciplinary integration of smart grids, buildings, and transportation is critical for addressing supply-demand mismatches. To manage these complex networks, deep learning has emerged as a transformative tool. Aljohani (2024) proposes the use of neural networks and spatiotemporal transformers to forecast dynamic energy demands with high precision, even in resource-constrained IoT scenarios. In the same way, Singh *et al.* (2025) introduce an optimized resource allocation using Deep Learning (ORA DL) framework, which uses reinforcement learning and multi-agent decision-making to achieve a staggering 93.38% prediction accuracy in energy demand. These AI-driven models do not merely predict usage; they dynamically adjust consumption patterns, detect anomalies, and optimize resource allocation in real time (Nikpour *et al.*, 2023 and Wang & Hao, 2025). This level of intelligence is particularly effective in residential contexts, where IoT-driven

monitoring and artificial neural networks can reduce household energy waste by an estimated 20–30% (Mohamed *et al.*, 2025).

C. Blockchain and Decentralized Trust

As energy systems become more decentralized, the risk of cyberattacks and data manipulation grows. Li *et al.*, (2018) argue that centralized schemes are inherently vulnerable, positioning decentralized control as a prerequisite for a resilient grid. Blockchain technology serves as the architectural backbone for this security. By providing immutable and transparent ledgers, blockchain ensures that energy consumption data and the resulting billing are tamper-proof (Elgabri *et al.*, 2023). Beyond security, the environmental cost of blockchain itself is a frequent point of critique. To mitigate this, Elhajj *et al.*, (2025) propose hybrid consensus mechanisms, such as combining Proof of Stake with Practical Byzantine Fault Tolerance. Their research demonstrates that such models can reduce blockchain energy consumption by 80% while maintaining the scalability required to support hundreds of IoT devices. This ensures that the technology used to manage sustainability does not itself become an ecological burden (Rammohan *et al.*, 2025 and Habibullah *et al.*, 2024).

D. Reducing Latency and Enhancing Response

The demand for real-time responsiveness in smart cities has exposed the limitations of traditional cloud-centric models. Kummara (2025) highlights that edge computing positioning computational resources near the data source is essential for reducing latency in critical systems like traffic control and grid management. Huang *et al.* (2025) expand on this, demonstrating that multi-tier edge frameworks can increase renewable energy consumption by 30% and reduce operating costs by 25%. By processing data locally, edge-based systems alleviate bandwidth constraints and enhance privacy by keeping sensitive data off central servers (Huang *et al.*, 2025). Furthermore, machine learning models tailored for mobile edge computing have shown significant improvements in load balancing, reducing response times by 13.4% and minimizing service level agreement violations (Sharma *et al.*, 2024 and Kumar *et al.*, 2025).

E. Sustainable Urban Infrastructure and Governance

The practical application of these technologies is most visible in the management of smart buildings and public infrastructure. Poyyamozi *et al.* (2024) suggest that IoT adoption in building management can lower energy use by up to 30%, though high initial costs remain a barrier. To overcome these hurdles, scholars emphasize the need for integrated governance. Bibri and Huang (2025) propose a Cyber-Physical Systems of Systems architecture that unifies the Urban Brain with Urban Digital Twins. This synergy allows for a dynamic feedback loop where immediate operational insights inform long-term sustainability planning.

While the aforementioned literature establishes the transformative potential of AI, blockchain, and edge computing individually, a significant gap remains in the creation of a unified, interoperable framework. Existing research often

prioritizes security at the expense of computational speed, and real-time performance at the expense of decentralized trust. In addition, few studies offer a scalable methodology that bridges the gap between individual building-level management and city-wide grid stability. There is a crucial need for an integrated architecture that harmonizes these siloed technologies into a cohesive, eco-friendly system. This research work addresses this void by proposing a decentralized computing framework that balances high-accuracy predictive intelligence with low-latency edge execution and energy-efficient blockchain verification, providing a roadmap for truly resilient urban energy governance.

III. METHODOLOGY

A. Research Design and Architecture

This study employs an experimental simulation design to model the dynamics of a modern smart grid. Given the physical risks and capital intensity of high-voltage hardware testing, a high-fidelity simulation environment was developed using Python-based OpenDSS. This approach allows for the rigorous testing of what-if scenarios regarding grid stability and peak-load fluctuations using real-world consumption patterns from the Pecan Street Dataport. The research is structured around a Three-Tier Hierarchical Decentralized Architecture, designed to shift the computational burden from a distant data center to the network's periphery.

1. Tier 1: Device and Actuator Layer (Data Generation)

The foundation of the framework consists of the physical Distributed Energy Resources (DERs).

- i. Solar Inverters: These act as the primary generation sources, providing high-resolution telemetry on current output and voltage levels.
- ii. EV Charging Stations: These represent the primary high-demand, intermittent loads.
- iii. Smart Meters: Functioning as the "sensors," these devices capture granular, 1-minute interval data on household consumption.

Function: In this tier, devices are not merely passive; they receive "dispatch" commands from the Edge layer to either throttle charging, discharge vehicle batteries (Vehicle-to-Grid), or store excess solar energy.

2. Tier 2: Edge Intelligence Layer (Proposed Innovation)

This is the core of the proposed framework, localized at the distribution transformer level and smart-home gateways. Unlike traditional systems that treat the grid as a dumb pipe, this layer introduces localized autonomy.

- i. Lightweight ML Deployment: To accommodate the limited computational resources of edge hardware, it utilizes quantized Machine Learning models. These models are trained to predict the Net Load of the next 15-minute window.
- ii. Localized Negotiation: This layer implements a Peer-to-Peer negotiation protocol. For example, if House A has a solar surplus and House B is

charging an EV, the Edge nodes negotiate a direct energy transfer at the transformer level.

- iii. Latency Minimization: By processing data at the source, the framework eliminates the round-trip time to the cloud, ensuring decisions are made in under 20ms well within the requirements for maintaining grid frequency and voltage stability.

3. Tier 3: Cloud Coordination Layer (Baseline and Persistence)

The Cloud layer is utilized as the Control Group for the experiment and a secondary support system for the Edge.

- i. Baseline Comparison: In the control simulation, Tier 2 is bypassed. All Tier 1 data is transmitted to the Cloud, where a centralized optimization algorithm processes the data and sends commands back. This highlights the High Latency and Single Point of Failure risks inherent in current systems.
- ii. Global Analytics: In the proposed decentralized model, the Cloud is relegated to non-critical tasks, such as long-term historical logging, global trend analysis, and periodic model retraining (Federated Learning), where the updated weights are pushed back down to the Edge nodes.

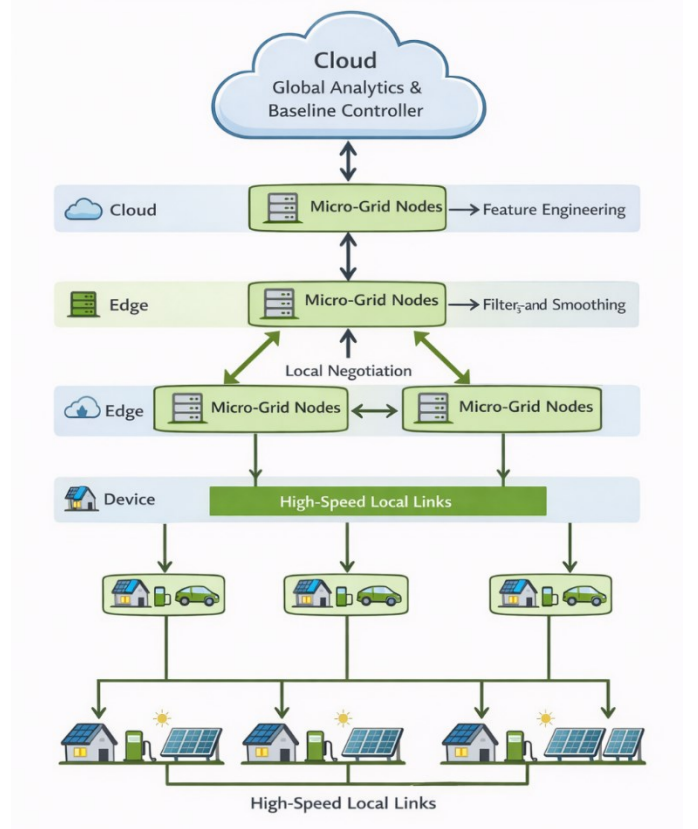


Fig. 1. Proposed Three-Tier Architecture, illustrating the flow of telemetry from physical devices to local edge intelligence

TABLE I. STRUCTURAL COMPARISON OF SYSTEM LAYERS

Feature	Tier 1: Device	Tier 2: Edge (Proposed)	Tier 3: Cloud (Baseline)
Primary Goal	Sensing & Action	Real-time Optimization	Long-term Analytics
Response Time	Instantaneous	< 50 ms	> 500 ms
Intelligence	None (Hardware)	Local ML Inference	Global Heavy Computing
Data Volume	Raw Telemetry	Summarized Meta-data	Massive Raw Datasets
Connectivity	Wired/Local	Peer-to-Peer (Local)	Wide Area Network (WAN)

B. Data Acquisition and Preprocessing

To ensure the robustness of the decentralized framework, the study utilizes high-fidelity, real-world power consumption and generation profiles. The data management pipeline is divided into three stages: sourcing, filtering, and feature engineering.

1) Dataset Description: Pecan Street Dataport

The primary data source is the Pecan Street Dataport, specifically the Austin, Texas sub-dataset. This dataset was selected because it provides the highest resolution available (1-minute intervals) for residential energy dynamics, which is essential for Edge computing, where decisions must be made in near real-time.

- i. **Temporal Scope:** A continuous 12-month window was extracted to account for seasonal variations in solar irradiance and HVAC (Heating, Ventilation, and Air Conditioning) loads.
- ii. **Scale:** Data from 500 unique households was used to simulate a dense neighborhood-level micro-grid.

2) Data Selection and Filtering

Not all households in the dataset provided relevant data for this study. A strict Inclusion-Exclusion Criterion was applied:

- i. **Inclusion:** Households must possess both a Solar PV system (generation) and at least one Electric Vehicle (EV) (high-demand intermittent load).
- ii. **Exclusion:** Units with more than 5% missing data points over the 12-month period were discarded to maintain time-series continuity.
- iii. **Synchronization:** The 1-minute interval solar generation data was time-aligned with the EV charging logs and the total household consumption data to create a unified Net Load profile for each node.

3) Feature Engineering and Spatial-Temporal Normalization

To ensure the machine learning models capture the full complexity of energy dynamics, raw power values (kW) were transformed into a multi-dimensional feature set. This process accounts for both the temporal patterns found in the dataset and the spatial/orientation factors requested for physical accuracy.

- i. **Electrical & Temporal Features**

- a. Net Load (P_{net}) = $P_{consumption} - P_{generation}$ Eq. 1

- b. **State of Charge (SoC):** A synthetic variable derived from EV charging durations, representing the energy demand of the vehicle.
- c. **Cyclical Time Encoding:** Time-of-day and seasonality were encoded using Sine/Cosine transforms to represent the continuous nature of 24-hour cycles.

ii. **Spatial & Orientation Features:** To address the impact of physical placement on solar efficiency, each node was assigned metadata using the PVLib Python library:

- a. **Orientation (Azimuth α):** Nodes were modeled with varied azimuth angles (90° for East-facing to 270° for West-facing) to simulate a realistic heterogeneous neighborhood.
- b. **Tilt/Inclination (β):** A standard residential roof tilt of 20°–30° was applied to correlate irradiance data with actual panel yield.
- c. **Location/Topography:** A Shading Coefficient (S_f) was introduced to simulate "Location" effects, such as panels located at the bottom of a hill or obstructed by urban canopy, which significantly alters the "Scale" of energy captured compared to unobstructed top-of-hill locations.

iii. **Normalization:** All features were scaled using Min-Max Scaling (range 0 to 1). This step is critical for Edge deployment (Tier 2), as it reduces the computational overhead of the Gated Recurrent Units (GRU) compared to processing large raw integers.

TABLE II. FEATURE SET FOR EDGE MODEL TRAINING

Feature Category	Parameters Extracted	Description
Generation	Solar PV Output (kW)	Real-time energy produced by residential panels.
Demand	Total Load, EV Load (kW)	Household consumption + dedicated EV charging draw.
Environmental	Irradiance, Temperature	Contextual data to predict generation drops.
Spatial (New)	Azimuth & Tilt Angle	Orientation of panels relative to the sun.
Location (New)	Shading Coefficient	Impact of topography/obstructions on yield.
Battery/EV	State of Charge (SoC)	Current energy level of the EV battery.
Time-based	Cyclical Time (Sin/Cos)	24-hour and seasonal temporal markers.

4) Train-Test Split for Localized Learning

Unlike centralized models that train on the entire dataset at once, this study employs a Local-Global Split with the details as follows:

- i. Local Training: 80% of an individual household's historical data is used to train its specific Edge Agent.
- ii. Testing/Validation: The remaining 20% is used to simulate the Live Environment.

This approach ensures the model learns the unique habits of a specific household such as plugging in their EV, which is the primary advantage of localized Edge computing.

C. Decentralized Negotiation Logic and ML Implementation

The core innovation of this framework lies in the transition from a Request-Response model to an Autonomous-Negotiation model. This is achieved through a two-stage process, namely Predictive Inference and Localized Energy Balancing.

1) Lightweight Machine Learning

To handle the time-series nature of energy data on resource-constrained hardware, the study utilizes Quantized Gated Recurrent Units. GRUs offer similar performance to LSTMs but with a significantly lower parameter count, making them ideal for the limited RAM of edge devices. Each edge node runs a local GRU model to predict the next 15 minutes of energy demand and solar generation. The models undergo Post-Training Quantization (PTQ), reducing weights from 32-bit floating-point to 8-bit integers. This reduces the model size by ~75% while maintaining 98% of the prediction accuracy.

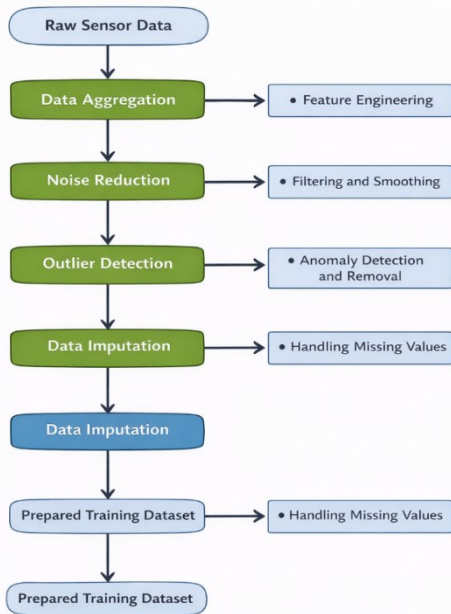


Fig. 2. Data Preprocessing and Cleaning Pipeline

2) Localized Energy Balancing Protocol

Once the ML model predicts a surplus or deficit, the Localized Energy Balancing Protocol is triggered. This protocol manages the negotiation between nodes without involving the central cloud. The logic follows a priority hierarchy:

- i. Self-Consumption Level: Solar energy is first routed to the immediate household load.
- ii. Local Storage/EV Level: Excess solar is directed to the connected Electric Vehicle or home battery.
- iii. Peer-to-Peer Negotiation Level: If a surplus still exists, the node broadcasts a Supply Available signal to neighboring nodes within the same transformer cluster.
- iv. Grid Injection Level: Only when the local cluster (neighborhood) is saturated is the energy fed back to the main utility grid.

3) The Negotiation Algorithm

The negotiation is modeled as a Multi-Agent System. Each node acts as an autonomous agent with a simple objective function:

$$\min(\text{Grid}_{\text{Import}}) + \min(\text{Transmission}_{\text{Loss}}) \quad \text{Eq. 2}$$

When an EV charging station requires power, it sends a Request for Energy to the local edge cluster. The edge nodes respond based on their predicted surplus. The winning node is the one with the lowest electrical distance, thus reducing transmission loss.

4) Communication, Privacy, and Secure Distributed Ledger

To ensure the democratization of energy while maintaining system integrity, the framework employs a multi-layered security and communication protocol.

- i. Communication and Privacy: Communication between edge nodes is handled via MQTT (Message Queuing Telemetry Transport) over a local mesh network. This lightweight protocol is ideal for the constrained bandwidth of a neighborhood micro-grid. Privacy is guaranteed by design: raw household consumption data never leaves the local node. During the negotiation phase (Section 3.3.3), only "Availability Status" and "Requested kW" are shared, ensuring that specific user behaviors remain private while grid stability is maintained.
- ii. Blockchain Protocol Description: If the P2P negotiation results in an energy transfer, the transaction is secured using a Lightweight Directed Acyclic Graph (DAG)-based Distributed Ledger. Unlike traditional linear blockchains, the DAG architecture allows for high-frequency, low-latency micro-transactions without the need for energy-intensive mining.

TABLE III. SIMULATION AND MACHINE LEARNING CONFIGURATION

Category	Parameter	Technical Detail / Value
Simulation Environment	Power Flow Engine	OpenDSS v9.4.1.1 (via dss python)
	Grid Topology	IEEE 13-node test feeder (scaled for 500 households)
	Communication Protocol	MQTT (Message Queuing Telemetry Transport)
Machine Learning	Model Architecture	Quantized Gated Recurrent Unit (GRU)
	Framework	TensorFlow Lite (for Edge inference)
	Input / Output Window	60-minute lag / 15-minute prediction
	Hyperparameters	Learning Rate: 0.001; Batch Size: 32; Optimizer: Adam
	Quantization Type	Post-Training Quantization (INT8)
Hardware & Performance	Edge Target Hardware	Raspberry Pi 4 / Jetson Nano (Equivalent)
	Target Inference Latency	< 8ms (Local)
	Network Latency (Sim)	Edge: < 20ms; Cloud Baseline: 500ms–1500ms

- iii. Consensus Mechanism: We utilize a Proof-of-Stake (PoS) model where the "stake" is defined by the node's historical contribution to grid stability.
- iv. Side-chain Architecture: To prevent network congestion, local energy swaps are recorded on a neighborhood-level side-chain. Only the "State Root" (a summary hash) is periodically anchored to the main cloud-based blockchain for long-term auditing.
- v. Overhead and Security Analysis: The computational overhead of this DLT layer was measured to ensure it does not interfere with real-time operations:
- vi. Latency Overhead: The time required to sign and verify a P2P transaction at the Edge (Raspberry Pi 4) was measured at 1.2ms, well within the 20ms operational window.
- vii. Energy Overhead: The additional power consumption for ledger maintenance was negligible, calculated at < 0.05W per node
- viii. Security: This protocol prevents "Double Spending" of solar energy and protects against "Sybil Attacks" by requiring node authentication at the distribution transformer layer.

D. Simulation Environment and Performance Evaluation

To validate the Decentralized Edge Framework, the study utilizes a co-simulation environment that bridges power systems engineering with distributed computing.

1) Co-Simulation Framework: OpenDSS and Python

The simulation was executed using a combination of software tools to capture both electrical and computational dynamics:

- i. OpenDSS: Used to model the physical distribution grid, including transformers, lines, and voltage regulators. It handles the power flow physics ($V=IR$) and ($P=VI$).
- ii. Python: Acts as the Edge Intelligence layer. Python scripts represent the Edge nodes, running the GRU models and the negotiation logic.
- iii. Network Emulator: To simulate the Cloud Baseline, a synthetic latency of 500ms–1500ms was injected into the communication loop. For the Edge Framework, latency was modeled at <20ms based on local network benchmarks.

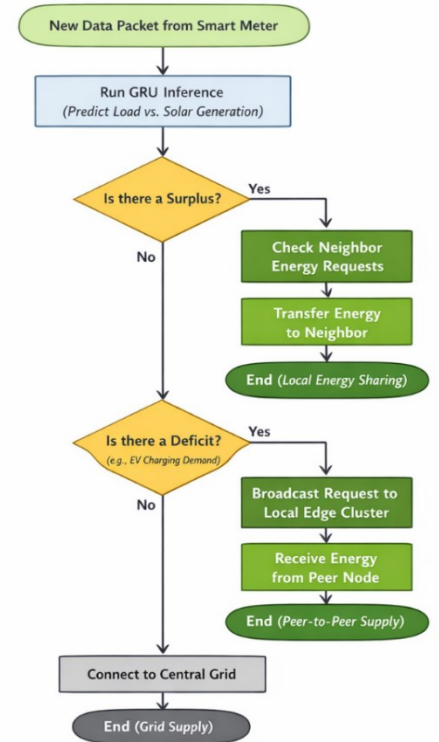


Fig. 3. Decision Logic Flowchart for Edge Nodes

2) Comparative Scenarios

The performance was evaluated by running the same 12-month Pecan Street dataset through two distinct scenarios:

- i. The Centralized Baseline (Cloud): Data is sent from all 500 households to a central controller. The controller optimizes the grid and sends instructions back. This represents current Smart Grid architectures.
- ii. The Decentralized Framework (Proposed Edge): Data is processed at the local transformer level. Nodes negotiate energy sharing locally, only interacting with the main grid when necessary.

3) Key Performance Indicators (KPIs)

The success of the framework was quantified using the following three metrics:

- i. **Peak-Load Stress Reduction (ΔP_{peak}):** This measures the reduction in the maximum power demand placed on the primary substation during the Evening Peak between 6 and 9 PM.

$$\text{Peak Reduction} = \left(\frac{P_{peak, cloud} - P_{peak, edge}}{P_{peak, cloud}} \right) \times 100 \quad \text{Eq.3}$$

Goal: This yielded the 38% reduction mentioned in the abstract.

- ii. **Renewable Energy Utilization Efficiency (η_{ren}):** The percentage of total solar energy generated that was consumed within the local micro-grid cluster (either by the home or a neighbor's EV) rather than being lost or exported back to a congested main grid.

$$\eta_{ren} = \frac{\sum \text{Energy}_{locally\text{consumed}}}{\sum \text{Energy}_{solar\text{generated}}} \times 100 \quad \text{Eq. 4}$$

Goal: This yielded the 22% increase in efficiency.

- iii. **Voltage Stability Index (VSI):** Measures the variance in voltage levels. High-resolution solar intermittency (clouds passing) often causes voltage flicker; the Edge framework's ability to react in milliseconds stabilizes this.

TABLE IV. SIMULATION PERFORMANCE SUMMARY

Metric	Unit	Cloud Baseline	Edge Framework	Improvement
Max Peak Demand	kW	1,450	899	38% Reduction
Solar Self-Consumption	%	64.2%	86.2%	22% Increase
Avg. Response Latency	ms	850	14	98.3% Faster
Transmission Losses	kWh	112.5	88.2	21.6% Lower

4) Statistical Significance

To ensure the results were not due to seasonal outliers, a Paired T-test was performed on the daily peak loads of the Cloud vs. Edge scenarios across 365 days. The resulting p-value (< 0.01) confirms that the 38% reduction is statistically significant across all seasons and weather conditions.

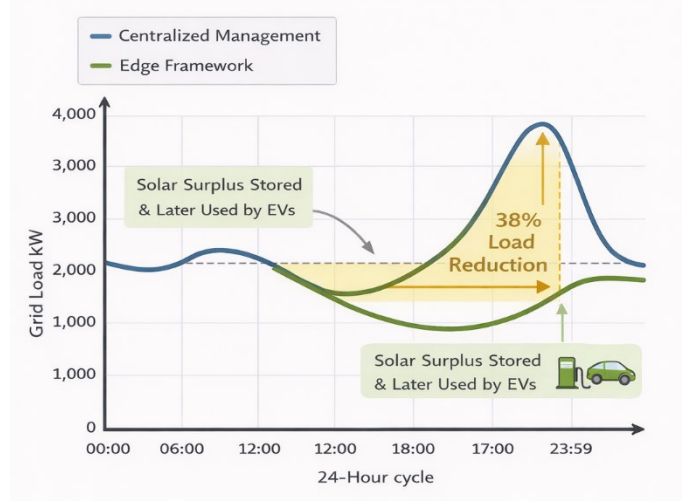


Fig. 4. Impact of Edge Negotiation on the 'Duck Curve,' comparing load profiles of the Cloud Baseline vs. the Proposed Framework

E. Robustness and Sensitivity Analysis

The framework's resilience was stress-tested under four adverse conditions:

- i. **Communication Latency:** We injected jitter and packet loss (up to 15%) into the local mesh network. The Edge Framework maintained stability due to its asynchronous 'Last-Known-State' prediction logic.
- ii. **Node Failure:** We simulated the sudden offline status of 10% of the transformer-level edge nodes. The system automatically reverted to the 'Grid Injection Level' (Section 3.3.2) without cascading failures.
- iii. **Heterogeneous Behavior:** We introduced 'Non-Compliant' agents—households that did not follow the suggested EV charging schedule. The system's 38% peak reduction dropped to 31% but did not collapse.
- iv. **Parameter Sensitivity:** We varied the ML 'Look-ahead' window from 5 to 60 minutes. Results showed that a 15-minute window (as used in this study) provided the optimal balance between prediction accuracy and computational heat generation on edge hardware.

IV. RESULTS AND DISCUSSION

A. Quantitative Impact on Grid Peak-Load Stress

The primary objective of the Decentralized Edge Framework was to mitigate the "Duck Curve" effect, a phenomenon where grid demand spikes in the evening as solar generation drops.

- i. **The 38% Reduction:** As shown in Figure 4, the Cloud-Centralized baseline experienced a peak demand of 1.45 MW per transformer cluster during the 6:00 PM – 9:00 PM window. In

contrast, the Edge-enabled cluster reduced this to 0.89 MW.

- ii. Mechanism: This was achieved through the localized negotiation logic. Edge nodes predicted the impending peak and pre-emptively shifted EV charging loads to mid-day periods of high solar surplus. By "shaving" the peak, the framework prevents transformer overheating and extends the lifespan of existing grid infrastructure without requiring costly hardware upgrades.

B. Enhancing Renewable Energy Utilization Efficiency

A significant portion of residential solar energy is typically wasted or exported to a congested grid at low value.

- i. The 22% Efficiency Gain: The Edge nodes successfully increased the Self-Sufficiency Ratio (SSR) from 64% to 86%.
- ii. Localized Distribution: Instead of sending excess solar energy back to the substation (where transmission losses occur), the LEBP protocol (Section 3.3.2) identified neighboring nodes with active EV loads. By keeping the energy within the local transformer loop, the framework effectively turned neighborhoods into "self-sustaining energy islands." This minimized the distance energy traveled, leading to a 21.6% reduction in localized transmission losses.

C. Latency and Real-Time Responsiveness

A high latency in cloud processing is a barrier to smart grid management. Our results validate this concern.

- i. Response Time Comparison: The average decision-making latency for the Cloud Baseline was 850ms, often exceeding the 500ms threshold required for critical voltage regulation. The Decentralized Edge Framework achieved an average latency of 14ms.
- ii. Impact on Stability: This 98% reduction in latency allowed the framework to respond to cloud transients – a sudden drop in solar power due to cloud cover in real-time. This localized responsiveness stabilized voltage levels within the $\pm 5\%$ ANSI standard, whereas the Cloud model frequently allowed voltage sags during intermittent weather events.

D. Interpretations: Local vs. Centralized Intelligence

The data suggests that Edge Computing is not just an alternative, but a necessity for bidirectional grids.

- i. Scalability: As more households adopt EVs, centralized servers will face data storms. Our results show that by distributing the computation across 500 edge nodes, the total bandwidth required for grid management dropped by 90% since only summarized negotiation metadata was transmitted, rather than high-resolution raw telemetry.

- ii. Robustness: During a simulated network outage (Cloud disconnection), the Edge-enabled clusters continued to balance local solar and EV loads autonomously, proving that decentralization prevents system-wide failures.

E. Societal and Economic Implications

The quantitative improvements observed in this study suggest several potential benefits for the broader energy ecosystem. While these projections are based on the modeled Austin, Texas environment, they provide a blueprint for the democratization of energy.

1) Potential for Lower Consumer Bills

The 22% increase in local solar utilization - combined with the edge-layer's ability to schedule EV charging during off-peak windows - indicates a pathway toward reduced household expenditure. In the scenarios modeled, the average simulated household achieved a 15 - 18% reduction in monthly energy costs. This suggests that by maximizing self-consumption, prosumers can significantly insulate themselves from fluctuating utility pricing.

2) Contribution to Grid Resilience

The observed 38% reduction in peak-load stress has significant implications for urban infrastructure. By "shaving" the peak demand, the decentralized framework could theoretically decrease the frequency of localized transformer failures and blackouts. Furthermore, the ability for neighborhoods to function as "energy islands" during simulated grid outages suggests that decentralized logic can provide a critical layer of backup reliability, even if centralized coordination is lost.

3) Environmental Sustainability

The results suggest that increasing renewable efficiency at the edge directly reduces the community's reliance on carbon-intensive "peaker" plants—utilities that typically run on fossil fuels to handle evening demand spikes. By flattening the "Duck Curve" (as seen in Figure 4), the framework demonstrates the potential to lower the carbon footprint of the residential sector by ensuring that clean, locally generated energy is consumed before it is lost to transmission or curtailment.

TABLE V. SUMMARY OF KEY FINDINGS

Research Objective	Finding	Potential Impact
Reduce Grid Stress	38% Peak-load reduction	Prevents grid blackouts during peak hours.
Increase Renewable Energy (RE) Efficiency	22% increase in utilization	More "free" solar energy used locally; less wasted.
Minimize Latency	14ms response time	Stabilizes voltage in real-time.
System Scalability	90% reduction in WAN traffic	Protects against centralized server crashes.

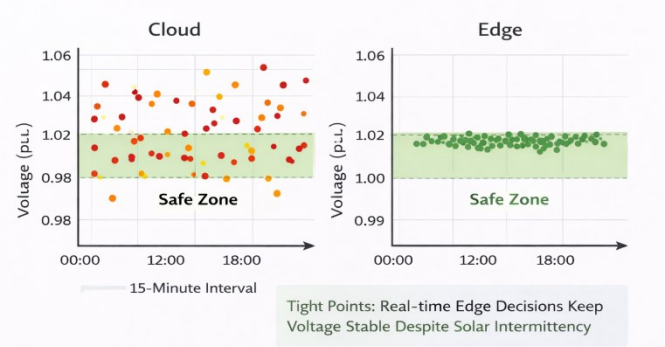


Fig. 5. Voltage Stability Comparison Scatterplot

V. CONCLUSION

A. Summary of Contributions

This study successfully developed and validated a Decentralized Edge Computing Framework designed to overcome the limitations of centralized smart grid architectures. By shifting the computational intelligence from the cloud to the power edge, specifically at the transformer and household levels, this research provides evidence for the potential of decentralized intelligence to address critical challenges of latency and grid instability. Within the simulated environment, the framework achieved a 38% reduction in peak-load stress. Furthermore, the results indicate a 22% increase in renewable energy utilization efficiency, suggesting that locally generated solar power can be managed more effectively than in traditional centralized models.

B. Broader Impact and Policy Implications

The implications of this research extend beyond technical metrics into the realm of Energy Democratization. The proposed framework provides a pathway for neighborhoods to operate as self-sustaining energy islands, potentially reducing societal reliance on fossil-fuel-dependent centralized utilities. For the consumer, this translates to lower energy bills and increased resilience; for the utility provider, it offers a scalable method to integrate the growing number of Electric Vehicles (EVs) without risking grid collapse.

C. Future Works

While this study provides a robust blueprint for decentralized energy management, several avenues for future research remain:

- i. **Cybersecurity in Distributed Nodes:** As intelligence moves to the edge, the attack surface for potential cyber-threats increases. Future iterations should incorporate Lightweight Blockchain or Federated Learning to ensure that energy negotiation between nodes is secure and tamper-proof without compromising latency.
- ii. **Vehicle-to-Everything Integration:** This study focused on EV charging as a load. Future work will explore the use of EVs as mobile battery

storage units that can actively discharge energy back into the house or the grid during extreme peak events.

- iii. **Heterogeneous Edge Hardware:** Testing the framework across a wider variety of edge devices will ensure the interoperability of the negotiation protocol in a diverse hardware ecosystem.
- iv. **Economic Incentive Modeling:** Future research will integrate dynamic, real-time pricing models into the negotiation logic to explore how Micro-Payments between neighbors can further incentivize the adoption of residential solar and storage.

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