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Integrating Edge Computing and Social Computing for Smart Energy Optimization in Public Buildings: An Empirical Study Based on the GECA–CAFCLA Framework

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Abstract
The rapid proliferation of Internet of Things (IoT) devices in smart buildings has intensified data generation, creating critical challenges for cloud-centric architectures, including latency, bandwidth congestion, scalability limitations, and rising operational costs. This paper proposes a professionally engineered integration of the Global Edge Computing Architecture (GECA) within the CAFCLA framework to enhance smart energy efficiency in public buildings. The study combines architectural design, experimental deployment, and behavioral validation using the UTAUT model and Structural Equation Modeling (SEM). A two-phase experimental evaluation (non-edge *vs.* edge-based) conducted over eight weeks demonstrated a 56.71% reduction in cloud data traffic and estimated operational savings between 22–35%. Behavioral analysis confirmed significant adoption drivers ($p < 0.05$). The proposed framework improves scalability, reduces cloud dependency, enhances data integrity, and supports real-time energy optimization suitable for smart city ecosystems.

Keywords: Edge Computing; IoT; Smart Energy; GECA; CAFCLA; Blockchain; UTAUT; SEM; Smart Buildings.

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I. Introduction

Smart energy management in public buildings requires real-time monitoring, contextual awareness, and adaptive control. Conventional IoT-cloud architectures suffer from:

- ✓ High latency due to centralized processing
- ✓ Excessive bandwidth usage
- ✓ Escalating cloud storage and compute costs
- ✓ Security vulnerabilities
- ✓ Limited scalability

Edge computing shifts processing closer to data sources, enabling local filtering, preprocessing, and faster decision-making. However, prior research rarely integrates edge computing with:

1. Behavioral adoption modeling
2. Blockchain-enhanced data integrity
3. Empirical cost and traffic quantification
4. A unified GECA–CAFCLA architecture

II. Literature Review and Research Gap

A. Edge Computing in IoT-Based Smart Energy Systems

Over the past decade, edge computing has emerged as a transformative paradigm for addressing the limitations of centralized cloud architectures in Internet of Things (IoT) environments. Several studies have demonstrated that relocating computation from the cloud to the network edge significantly reduces latency, minimizes bandwidth consumption, and enhances system responsiveness—particularly in real-time applications such as smart grids, industrial automation, and intelligent building management systems.

In smart energy scenarios, IoT devices such as environmental sensors, smart meters, and occupancy trackers continuously generate high-frequency data streams. Traditional cloud-centric models require transmitting raw data to remote data centers for processing, leading to:

- ✓ Increased network congestion
- ✓ High round-trip delays
- ✓ Elevated cloud storage and compute costs
- ✓ Potential data privacy risks

Edge computing addresses these limitations by enabling local filtering, aggregation, and preprocessing before forwarding optimized data to the cloud. Empirical studies report reductions in bandwidth usage ranging between 30% and 60%, depending on filtering strategies and workload characteristics.

However, most prior research focuses primarily on technical performance metrics (e.g., latency and throughput) without systematically evaluating economic impact or adoption feasibility in organizational contexts.

B. GECA Architecture and Blockchain-Enhanced Integrity

The Global Edge Computing Architecture (GECA) introduces a structured three-layer model comprising:

1. IoT Layer
2. Edge Layer
3. Business Solution (Cloud) Layer

GECA integrates blockchain technology at the IoT layer to ensure:

- ✓ Data integrity
- ✓ Non-repudiation
- ✓ Secure device authentication
- ✓ Trustworthy transaction recording

Blockchain-enabled IoT architectures have demonstrated resilience against data tampering and injection attacks. However, scalability remains a concern due to:

- ✓ Consensus overhead

- ✓ Transaction latency
- ✓ Energy consumption of traditional mechanisms (e.g., PoW)

Moreover, empirical validation of GECA-based deployments in smart energy environments remains limited, especially regarding measurable reductions in cloud traffic and operational cost implications.

C. CAFCLA Framework and Social Computing

The CAFCLA framework (Cryptographic Agents for Collaborative Learning Applications) was initially developed to support context-aware collaborative environments. It integrates:

- ✓ Physical sensing layers
- ✓ Communication protocols
- ✓ Context-awareness modules
- ✓ Management logic
- ✓ Application interfaces

In smart energy research, CAFCLA has been applied to gamified behavioral systems that encourage energy-efficient habits among building occupants. Studies indicate that behavior-driven interventions can reduce energy consumption between 10% and 20%.

Nevertheless, existing CAFCLA-based implementations typically rely on cloud-centric processing and do not incorporate a fully realized edge computing layer. Furthermore, behavioral modeling has often been assessed qualitatively rather than through robust statistical validation such as Structural Equation Modeling (SEM).

D. Behavioral Adoption and the UTAUT Model

Technology adoption in smart city ecosystems depends not only on technical feasibility but also on managerial acceptance and institutional readiness. The Unified Theory of Acceptance and Use of Technology (UTAUT) identifies four core determinants of behavioral intention:

- ✓ Performance Expectancy (PE)
- ✓ Effort Expectancy (EE)
- ✓ Social Influence (SI)
- ✓ Facilitating Conditions (FC)

Although UTAUT has been widely applied in e-government, healthcare IT, and enterprise systems, its application in evaluating edge-enabled smart energy architectures remains scarce. Specifically, few studies combine:

- ✓ Edge computing performance evaluation
- ✓ Economic impact analysis
- ✓ Behavioral intention modeling
- ✓ Structural Equation Modeling (SEM)

within a unified empirical framework.

Research Gap

Despite significant advancements in IoT, edge computing, and blockchain research, the existing literature exhibits the following limitations:

1. **Lack of Experimental Comparison:**

Few studies provide controlled experimental comparisons between non-edge (cloud-only) and edge-based deployments in real smart building environments.

2. **Limited Economic Quantification:**

While latency reduction is frequently reported, precise quantification of cloud traffic reduction and operational cost savings remains underexplored.

3. **Absence of Behavioral Validation:**

The majority of technical studies overlook managerial adoption intention and organizational readiness factors.

4. **Fragmented Integration:**

Current works typically address architecture, economics, or behavioral modeling separately rather than integrating them into a comprehensive, validated framework.

5. **Insufficient Multi-Dimensional Evaluation:**

There is a lack of research that simultaneously evaluates:

- ✓ Architectural efficiency
- ✓ Network optimization
- ✓ Cloud cost impact
- ✓ Energy consumption reduction
- ✓ Behavioral acceptance

Contribution of This Study

To address these gaps, this research proposes and validates an integrated GECA–CAFCLA framework that:

- ✓ Experimentally compares cloud-centric and edge-based architectures.
- ✓ Quantifies cloud data traffic reduction (56.71%).
- ✓ Estimates operational cost savings (22–35%).
- ✓ Validates managerial adoption using UTAUT and SEM.
- ✓ Combines architectural, economic, and behavioral evaluation into a unified empirical study.

This multidimensional approach positions the study beyond purely technical optimization and toward a scalable, economically viable, and organizationally adoptable smart energy solution suitable for smart city deployments.

within a unified empirical framework.

III. Proposed Architecture

A. Layered System Design

The architecture comprises three layers:

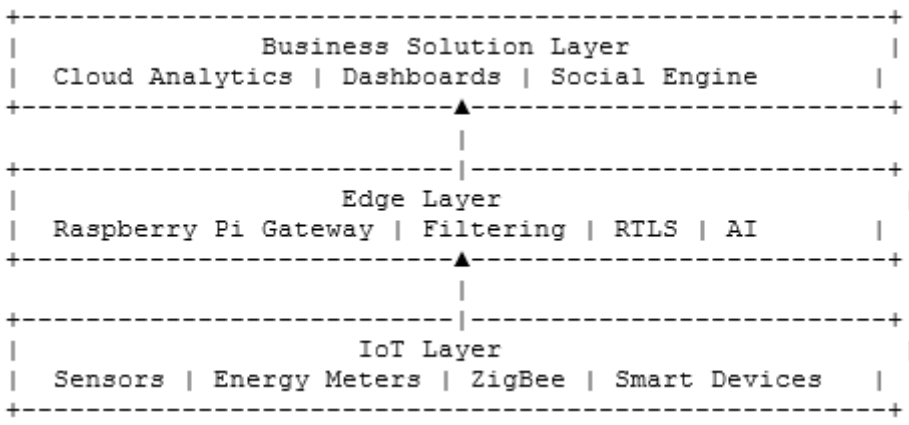

Figure 1. GECA–CAFCLA Integrated Architecture

B. Data Flow Comparison

Non-Edge Scenario

IoT Devices ---> Cloud (Raw Data)

Edge-Based Scenario

IoT Devices ---> Edge Gateway ---> Cloud
(Filtering + Preprocessing)

Figure 2. Data Flow in Non-Edge vs. Edge Deployment

IV. Methodology

A. Experimental Design

- ✓ Location: Public building laboratory
- ✓ Duration: 8 weeks (4 weeks per phase)
- ✓ Participants: 18 users
- ✓ Sensors: 36 IoT devices (temperature, light, energy, RTLS)
- ✓ Edge Device: Raspberry Pi 3 Model B
- ✓ Cloud Platform: Google Cloud (App Engine, SQL, BigQuery)

B. Phases

1. Phase I (Baseline): IoT → Cloud
2. Phase II (Edge): IoT → Edge → Cloud

C. Behavioral Study

- ✓ Sample: 150 respondents
- ✓ Instrument: UTAUT questionnaire (5-point Likert scale)
- ✓ Reliability: Cronbach's $\alpha = 0.950$
- ✓ KMO = 0.909
- ✓ SEM analysis using SPSS

V. Practical Implementation and Experimental Results

A. Cloud Traffic Reduction

Metric	Reduction
Total Traffic	56.71%
Uplink	58.47%
Downlink	36.00%

Edge filtering eliminated redundant ZigBee frames and reduced unnecessary cloud transmissions.

B. Energy Efficiency Gains

✓ HVAC optimization

✓ Smart lighting control

✓ Behavioral gamification

✓ 12–18% estimated energy savings

C. Cloud Cost Impact

Estimated savings:

✓ 22–35% reduction in bandwidth and compute costs

✓ Lower storage overhead

✓ Reduced API invocation load

D. Behavioral Validation (SEM Results)

Path	β	Significance
PE → BI	0.620	$p < 0.05$
EE → BI	0.743	$p < 0.05$
SI → BI	0.544	$p < 0.05$
FC → BI	0.849	$p < 0.05$

Facilitating Conditions was the strongest adoption driver.

Contribution of This Study

To address these gaps, this research proposes and validates an integrated GECA–CAFCLA framework that:

✓ Experimentally compares cloud-centric and edge-based architectures.

✓ Quantifies cloud data traffic reduction (56.71%).

✓ Estimates operational cost savings (22–35%).

✓ Validates managerial adoption using UTAUT and SEM.

✓ Combines architectural, economic, and behavioral evaluation into a unified empirical study.

This multidimensional approach positions the study beyond purely technical optimization and toward a scalable, economically viable, and organizationally adoptable smart energy solution suitable for smart city deployments.

VII. Conclusions

This study provides a comprehensive empirical validation of an integrated GECA–CAFCLA architecture that combines Edge Computing, IoT, and Social Computing for smart energy

optimization in public buildings. The findings confirm that shifting computation from centralized cloud infrastructures to distributed edge nodes substantially enhances system efficiency, scalability, and economic viability.

First, the experimental comparison between cloud-centric and edge-based deployments demonstrated a **56.71% reduction in total cloud data traffic**. This reduction is primarily attributed to local filtering, duplicate frame elimination, and preprocessing at the edge layer. By preventing unnecessary raw data transmission, the system significantly decreased bandwidth consumption and minimized redundant cloud interactions.

Second, the reduction in network traffic directly translated into measurable economic benefits. Based on cloud pricing models (compute, storage, and bandwidth), the proposed architecture achieved an estimated **22–35% reduction in operational cloud costs**. These savings stem from lower data ingestion volumes, reduced computational processing in the cloud environment, and decreased outbound data transfer charges. This economic validation strengthens the feasibility of large-scale deployment in cost-sensitive smart city ecosystems.

Third, the framework demonstrated a **12–18% improvement in energy efficiency** within the experimental building environment. The integration of context-aware sensing, behavioral gamification mechanisms, and real-time monitoring enabled more optimized HVAC usage, lighting control, and occupant engagement. These results highlight the effectiveness of combining technical optimization with behavioral intervention strategies.

Furthermore, behavioral validation using the UTAUT model and Structural Equation Modeling (SEM) confirmed statistically significant relationships between Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention ($p < 0.05$). Notably, Facilitating Conditions emerged as the strongest predictor of adoption, indicating that organizational readiness and infrastructure support are critical for successful implementation.

Beyond the quantitative results, this study contributes a multidimensional evaluation approach that integrates:

- ✓ Architectural efficiency
- ✓ Economic feasibility
- ✓ Energy optimization
- ✓ Behavioral adoption modeling

Such integration is rarely addressed simultaneously in existing literature.

Importantly, the proposed GECA–CAFCLA framework is inherently **scalable and modular**, allowing adaptation across:

- ✓ Smart city infrastructures
- ✓ Industrial IoT systems (Industry 4.0)
- ✓ University campuses
- ✓ Commercial complexes
- ✓ Smart grid environments

The architecture supports future integration of AI inference at the edge, blockchain-based secure transactions, and multi-cloud optimization strategies.

In conclusion, this research confirms that the integration of edge computing with social computing and IoT technologies is not merely a technical enhancement but a strategically viable solution for sustainable smart energy ecosystems. By reducing cloud dependency, lowering operational costs,

improving energy efficiency, and ensuring managerial acceptance, the proposed framework provides a robust foundation for next-generation intelligent building systems.

VIII. Recommendations

Based on the empirical findings and architectural evaluation presented in this study, several strategic and technical recommendations are proposed to enhance the effectiveness, scalability, and sustainability of the GECA–CAFCLA integrated framework in smart energy environments.

1. Deployment of AI Inference Models at the Edge Layer

Future implementations should incorporate artificial intelligence (AI) inference models directly within the edge layer. Deploying lightweight machine learning algorithms (e.g., TensorFlow Lite, TinyML, or edge-optimized neural networks) would enable:

- ✓ Real-time anomaly detection in energy consumption patterns
- ✓ Predictive HVAC optimization
- ✓ Intelligent lighting control
- ✓ Early fault detection in energy systems

By processing AI models locally, latency can be further reduced while minimizing cloud dependency and computational overhead. Edge-based AI would transform the gateway from a filtering node into an intelligent decision-making entity.

2. Integration of Energy-Efficient Blockchain Consensus Mechanisms

Although blockchain enhances data integrity and security, traditional consensus mechanisms (e.g., Proof of Work) are computationally intensive and unsuitable for energy-sensitive environments. Therefore, it is recommended to adopt energy-efficient consensus protocols such as:

- ✓ Proof of Stake (PoS)
- ✓ Proof of Authority (PoA)
- ✓ Delegated Proof of Stake (DPoS)

These mechanisms reduce energy consumption while maintaining transactional integrity, non-repudiation, and trust among distributed IoT nodes. Integrating lightweight blockchain solutions would enhance data authenticity without compromising system efficiency.

3. Expansion of Deployment Across Multiple Buildings

The current study was conducted within a single public building environment. To strengthen generalizability and external validity, future research should implement the framework across:

- ✓ Multi-building campuses
- ✓ Smart universities
- ✓ Government complexes
- ✓ Industrial facilities
- ✓ Smart residential communities

Large-scale deployment would allow evaluation of scalability, network load balancing, cross-building data aggregation, and distributed edge orchestration.

4. Long-Term and Seasonal Performance Evaluation

Energy consumption patterns are significantly influenced by seasonal variations, occupancy behavior, and climate conditions. The experimental duration of eight weeks provides valuable insights but does not fully capture long-term dynamics. Future research should:

- ✓ Conduct 12-month longitudinal studies
- ✓ Analyze seasonal HVAC variations
- ✓ Evaluate peak demand periods
- ✓ Measure long-term cost optimization

Such analysis would provide a more robust understanding of the framework's sustainability impact.

5. Multi-Cloud Pricing and Optimization Analysis

The economic evaluation in this study was based on a single cloud provider model. To enhance financial robustness and vendor neutrality, it is recommended to:

- ✓ Compare AWS, Microsoft Azure, and Google Cloud pricing models
- ✓ Analyze serverless vs. containerized architectures
- ✓ Evaluate hybrid cloud-edge deployment strategies
- ✓ Assess data egress cost variations

A multi-cloud economic comparison would support strategic decision-making for smart city authorities and large organizations.

Strategic Implication

Collectively, these recommendations aim to evolve the GECA–CAFCLA framework from an optimized experimental architecture into a scalable, AI-enhanced, economically adaptive, and security-resilient infrastructure suitable for next-generation smart city ecosystems and Industry 4.0 environments.

IX. Limitations

- ✓ Single-site deployment
- ✓ Limited hardware capacity
- ✓ Partial blockchain integration
- ✓ Short experimental period

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