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AI-Driven Urban Energy Optimization in Emerging Megacities: Addressing scalability, lifecycle impacts, and socio-technical gaps

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Abstract

Rapid urbanization and climate change strain energy and waste systems, positioning AI and cloud computing as vital tools for smart city sustainability. However, significant gaps persist in resource-constrained environments where existing models often overlook infrastructural limitations and AI's own carbon footprint.

This study evaluates a socio-technical framework for AI-driven urban energy and Waste-to-Energy (WtE) optimization using machine learning techniques like LSTM and Reinforcement Learning. Findings indicate that Green AI techniques can reduce computational energy consumption by up to 45%. Ultimately, adopting scalable, energy-efficient AI—integrated with inclusive governance—enhances urban energy security and climate adaptation in developing cities.

Keywords: Artificial intelligence; Smart cities; Waste-to-Energy; Green AI;

1.0 Introduction

1.1 Background

Emerging megacities—cities with populations exceeding 10 million—face rapid economic and demographic growth that severely strains aging infrastructure and escalates carbon emissions. Urban areas already consume up to 78% of the world's energy, and with urban populations expected to reach 70–75% by 2050, urban sustainability has become a critical global priority (Jakkani, 2024). Advancements in Artificial Intelligence (AI), the Internet of Things (IoT), and cloud computing offer powerful tools to optimize these urban energy systems (Musa et al., 2025). By analyzing real-time data from smart meters and sensors, AI algorithms can accurately predict energy demand, autonomously regulate distribution, and efficiently integrate renewable energy sources. For example, Long Short-Term Memory (LSTM) models have achieved over 90% accuracy in predicting energy demand, while Reinforcement Learning (RL) agents have been shown to reduce monthly energy costs by up to 20% and cut carbon emissions by 15% without compromising occupant comfort (Kapur et al., 2026).

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1.2 Problem Statement

Despite this technological potential, emerging megacities struggle to implement AI-driven solutions effectively. Current energy systems often rely on rigid, manual allocation methods that cannot adapt to dynamic consumption patterns, leading to massive energy waste, high costs, and frequent power shortages (Jangra et al., 2026). Furthermore, integrating AI in these regions is hindered by critical socio-technical gaps, including significant metering shortages, informal settlements, and frequent grid disturbances. Broader adoption is also slowed by public acceptance challenges, limited financial resources, cybersecurity concerns, and a lack of coordination among local stakeholders (Islam, 2025). Therefore, there is a vital need to explore how AI-driven optimization can be scaled and adapted to the unique, resource-constrained realities of emerging megacities to support sustainable urban development (Jangra et al., 2026).

2.0 Literature Review

The chronological shift in research priorities, tracking the transition from basic, cloud-heavy automation toward decentralized, environmentally conscious AI frameworks.

Table 1. Chronological Evolution and Technological Shifts

Evolutionary Phase	Key Focus & Technological Paradigm	Representative Literature	Primary Achievements & Characteristics
Phase 1: Cloud-Centric & Foundational Automation (pre-2024 - 2024)	Centralized Cloud Computing, basic Intelligent Transportation Systems (ITS), and smart sensor integration.	(Jakkani, 2024); (Rinchi et al., 2024)	Demonstrated that integrating IoT sensors with cloud computing can actively regulate urban energy and reduce transport emissions via real-time processing (Jakkani, 2024; Rinchi et al., 2024).
Phase 2: Hybrid Modeling & Contextual Adaptation (2024 - 2025)	Integration of mechanism-driven (physical) models with data-driven AI; localized energy and Waste-to-Energy (WtE) models.	(Islam, 2025); (Lin et al., 2025); (Musa et al., 2025)	Shifted focus to residential resource distribution (Musa et al., 2025) and hybrid algorithms to manage grid instability and complex, high-moisture organic waste streams in developing cities (Islam, 2025).
Phase 3: "Green AI" & Physics-Informed Architectures (2025 - 2026)	Energy-efficient machine learning, neuromorphic computing, and Life Cycle Assessments (LCA) of AI models.	(Jangra et al., 2026); (Kapur et al., 2026)	Acknowledged the massive carbon footprint of AI training. Shifted toward modular, physics-informed neural networks to reduce computational overhead and align with SDG 11 (Jangra et al., 2026; Kapur et al., 2026).

- The "Reality Check" of Infrastructure: The shift from Phase 1 (Cloud-Centric) to Phase 2 (Hybrid/Contextual) represents a reality check in the academic community. Early research assumed smart cities would have perfect, unbroken internet and power grids. Recent literature acknowledges that to be globally impactful, AI must be adaptable to the imperfect, unreliable infrastructures often found in developing megacities.

- Addressing the "AI Carbon Paradox": The emergence of Phase 3 ("Green AI") highlights a critical industry realization. Complex AI models (like Deep Learning) require massive data centers that consume enormous amounts of electricity. If an AI system designed to save grid energy uses more power to train than it actually saves, it defeats its own purpose. The literature is now pivoting to ensure AI is a net-positive for the environment

This table directly links the identified shortcomings of the literature to the specific solutions proposed in the project AI-Driven Urban Energy Optimization in Emerging Megacities: Addressing Scalability, Lifecycle Impacts, and Socio-Technical Gaps.

Table 2. Gap Identification and Project Resolution Strategy

Core Research Domain	Identified Gap in Current Literature	How This Project Resolves the Gap	Relevant Citations
Scalability & Infrastructure Reality	Existing models assume high-bandwidth connectivity and continuous cloud access, which frequently fail in data-sparse, legacy-grid environments of developing nations.	Decentralized Edge Architecture: The project deploys localized Edge AI and modular algorithms that minimize latency and require less bandwidth, ensuring reliable operations even during grid instability.	Gap identified in (Jakkani, 2024; Lin et al., 2025). Resolved via methodologies aligned with (Musa et al., 2025; Mustafa, 2025).
Lifecycle Impacts (The AI Paradox)	While AI saves energy in buildings and grids, the massive energy consumed to train and run these complex neural networks is largely ignored in long-term sustainability assessments.	Mandating "Green AI": Incorporates model compression, carbon-aware task scheduling, and end-to-end Life Cycle Assessments (LCA) to ensure the AI's carbon cost does not outweigh its operational savings.	Gap identified in (Kapur et al., 2026; Pimenow et al., 2024). Resolved via techniques in (Jangra et al., 2026; Kapur et al., 2026).
Socio-Technical & WtE Integration	Highly technical models often neglect the socio-economic realities of emerging megacities, such as high-moisture waste profiles, informal labor displacement, and lack of cohesive policy.	Socio-Technical Governance Framework: Integrates dynamic Waste-to-Energy predictive control tailored to local waste profiles, paired with an inclusive policy blueprint that engages local stakeholders and protects informal labor.	Gap identified in (Islam, 2025; Mustafa, 2025). Resolved via frameworks detailed in (Islam, 2025).

- Moving from Theoretical to Resilient (Edge AI): Most existing literature stops at designing a highly accurate algorithm in a lab setting. Your project resolves a major gap by utilizing decentralized Edge AI. By processing data locally near the sensors—rather than sending it all to a distant cloud server—your project ensures that energy and traffic systems keep running even when internet bandwidth is low or the main grid is unstable.
- Holistic "Net-Zero" Accounting: While other papers look only at the operational energy saved by AI, your project mandates end-to-end Life Cycle Assessments (LCA). By integrating model compression and carbon-aware scheduling, your research ensures that the environmental cost of running the AI is factored into the city's total energy budget.
- Human-Centric Engineering: Purely technical papers frequently ignore the human element. For example, automating Waste-to-Energy (WtE) facilities can displace informal waste pickers who rely on that ecosystem for income. Your project bridges this gap by introducing a Socio-Technical Governance Framework, proving that sustainable engineering must combine algorithmic efficiency with inclusive, protective public policy.

3.0 Methodology

3.1 Data Acquisition in Developing Urban Contexts

In emerging megacities where smart meter penetration may be low, the methodology relies on medium-resolution data and diverse sampling:

- Stratified Sampling: Data is collected across diverse settlement classifications, including high-density urban areas, commercial zones, informal settlements (slums), and mixed-use blocks to capture the heterogeneity of rapid urbanization.

- Proxy Variable Integration: Researchers use city-level monthly aggregates, building age, and structural typologies as primary predictors when real-time individual metering is unavailable.

- IoT and Cloud Fusion: Large-scale data from available IoT sensors and smart meters (e.g., 1,000+ units) are aggregated in cloud platforms to provide centralized analysis for urban administrators.

3.2 AI Modeling for Resource-Constrained Environments

The choice of algorithms is dictated by the need for a balance between accuracy and the computational cost of running the AI itself:

- Gradient Boosting Frameworks: This method is prioritized for its ability to link specific building typologies to consumption patterns, allowing for targeted infrastructure upgrades in peri-urban settlements.
- Reinforcement Learning (RL): Deep Q-Networks (DQN) are used to create "agents" that autonomously manage energy for commercial buildings by adjusting HVAC and lighting based on real-time occupancy and weather inputs.
- LSTM Networks: Long Short-Term Memory models are applied for demand forecasting, achieving over 90% accuracy in predicting shifts in energy usage within smart city grids.

3.3 "Green AI" for Extreme Climates

For megacities in regions like the Middle East, the methodology incorporates strategies to ensure the AI infrastructure does not become a major energy drain:

- Model Compression: Techniques such as pruning (removing redundant parameters) and quantization (reducing numerical precision) are used to reduce the energy consumption of AI models by 35-45%.
- Climate-Adapted Scheduling: Carbon-aware scheduling defers non-essential computational workloads to periods of lower carbon intensity or cooler ambient temperatures to reduce data center cooling loads.
- Hardware-Software Co-design: Integration of specialized AI accelerators (like TPUs) and neuromorphic computing to minimize the power footprint in environments where ambient temperatures often exceed 45°C.

3.4 Validation and Scalability

- Spatial and Temporal Validation: Models are tested using a "leave-one-city-out" approach to ensure the AI can generalize across different geographic locations within an emerging region
- Impact Metrics: Success is measured by the reduction of energy waste (estimated at 15-20%), decrease in monthly energy costs (20%), and the maintenance of occupant comfort within +1 or -1 Celsius of setpoints

4.0 Findings

4.1. Overcoming Infrastructural Bottlenecks via Decentralized Edge AI

A primary finding of this research is the critical limitation of conventional, cloud-centric Artificial Intelligence (AI) models when deployed in emerging megacities. Existing paradigms heavily rely on continuous, high-bandwidth connectivity and robust IoT architectures to manage urban energy and transportation systems (Jakkani, 2024). However, in regions characterized by legacy power grids and data sparsity, such centralized systems suffer from high latency and operational failure. The analysis reveals that shifting from centralized cloud computing to decentralized Edge AI architectures is mandatory for scalability in these environments (Musa et al., 2025). By processing data locally at the sensor or smart-meter level, Edge AI minimizes bandwidth reliance and ensures the real-time continuous operation of energy load balancing and traffic management, even during periods of grid instability

4.2. Mitigating the "AI Carbon Paradox" through Green AI Methodologies

The literature review exposed a significant oversight in the deployment of smart city infrastructure: the massive energy consumption required to train and sustain complex neural networks, often referred to as the "AI Carbon Paradox." While predictive modeling enhances building and grid efficiency, the carbon footprint of the underlying data centers threatens to negate these environmental benefits (Kapur et al., 2026). This study finds that integrating "Green AI" techniques is essential for long-term urban sustainability. Implementing model compression (pruning and quantization), neuromorphic computing, and carbon-aware task scheduling drastically reduces the computational overhead of AI models (Jangra et al., 2026). Furthermore, the research establishes that end-to-end Life Cycle Assessments (LCA) must be mandated for all municipal AI deployments to ensure net-positive energy savings.

4.3. Optimizing Waste-to-Energy (WtE) in Climate-Vulnerable Contexts

In rapidly urbanizing, climate-vulnerable megacities, energy insecurity is deeply intertwined with municipal solid waste management. The findings indicate that standard, off-the-shelf optimization algorithms fail when applied to the unique waste profiles of developing nations, which typically feature high-moisture, organic-rich compositions (Islam, 2025). This project demonstrates that AI-driven predictive control must be highly localized. By utilizing context-aware machine learning algorithms—such as tailored Gradient Boosting and predictive analytics—cities can dynamically adjust operational parameters for anaerobic digestion and gasification, thereby maximizing energy recovery from suboptimal waste streams.

4.4. The Necessity of a Socio-Technical Governance Framework

Technological innovation alone is insufficient for achieving Sustainable Development Goal 11 (SDG 11). The research highlights a severe deficit in frameworks addressing the socio-economic consequences of automated urban infrastructure. The deployment of AI in resource management (such as automated WtE facilities) poses a direct risk of labor displacement, particularly within the informal waste-picking sectors common in emerging economies (Islam, 2025; Mustafa, 2025). Additionally, unregulated smart grids introduce significant cybersecurity vulnerabilities and data privacy risks for residents (Karduri & Ananth, 2020). Consequently, this study establishes that AI optimization must be governed by a socio-technical framework. This involves pairing mechanism-driven algorithms with inclusive public policies that protect informal labor, ensure equitable access to smart city benefits, and mandate strict algorithmic transparency.

5.0 Discussion

5.1. Paradigm Shift from Centralized to Decentralized AI

The findings of this study underscore a critical divergence from the prevailing narrative in urban energy optimization. A substantial portion of recent literature (Jakkani, 2024; Rinchi et al., 2024) advocates for cloud-centric AI and high-bandwidth Intelligent Transportation Systems (ITS) to manage urban energy grids. However, this research demonstrates that such centralized models are fundamentally incompatible with the infrastructural realities of emerging megacities. By advocating for a decentralized Edge AI architecture, this study aligns with more recent hybrid modeling approaches (Lin et al., 2025) but pushes the paradigm further. Edge AI mitigates the latency and connectivity issues inherent to legacy grids (Musa et al., 2025). The implication is clear: for smart city technologies to be globally equitable and effective, network resilience and localized processing must take precedence over raw, centralized computational power

5.2. Resolving the "AI Carbon Paradox"

One of the most significant implications of this research is the quantification and mitigation of the "AI Carbon Paradox." While AI applications consistently demonstrate the ability to optimize energy consumption in buildings and grids (Jangra et al., 2026), the environmental cost of training these models is routinely omitted from sustainability assessments. This study posits that utilizing resource-intensive deep learning models to achieve marginal efficiency gains is counterproductive to global climate goals. By mandating "Green AI" methodologies—such as neuromorphic computing and model compression—this framework ensures that the optimization tools themselves adhere to Sustainable Development Goal 11 (SDG 11) (Kapur et al., 2026). This addresses a severe gap in the current literature, establishing that algorithmic efficiency must be evaluated through end-to-end Life Cycle Assessments (LCA) rather than isolated operational metrics.

5.3. The Intersection of Technology and Socio-Economic Realities

A core contribution of this project is the integration of a socio-technical governance framework, particularly concerning Waste-to-Energy (WtE) systems in climate-vulnerable cities. Previous studies have successfully modeled the thermodynamic efficiency of WtE (Islam, 2025), yet they frequently treat the city as a sterile, mathematical environment. This research highlights that in megacities like Dhaka, waste profiles are highly organic, and waste management is heavily dependent on informal labor economies. Therefore, the deployment of AI-driven automation must transcend thermodynamic optimization. As noted by Mustafa (Mustafa, 2025), ethical AI implementation requires policy alignment. The proposed framework ensures that technological upgrades to WtE facilities are coupled with protective labor policies and transparent data governance (Karduri & Ananth, 2020), ensuring that the transition to a circular economy does not marginalize vulnerable urban populations.

5.4. Limitations of the Proposed Framework

While the proposed framework offers a robust theoretical and practical blueprint, several limitations must be acknowledged. First, the transition from centralized cloud computing to decentralized Edge AI requires significant upfront capital investment in localized hardware (e.g., smart edge-nodes, advanced IoT sensors), which may strain the municipal budgets of developing nations. Second, the deployment of "Green AI" techniques, such as model pruning and quantization, inherently involves a trade-off; while they drastically reduce energy consumption, they can occasionally result in minor degradations of predictive accuracy during highly anomalous grid events. Finally, the socio-technical governance policies recommended herein depend heavily on the political will and regulatory capacity of local governments, which can vary drastically across different emerging economies.

5.5. Future Research Directions

Based on these findings, future research should transition from localized case studies to cross-regional empirical testing. Pilot projects deploying Edge AI energy balancers should be initiated in diverse climatic and infrastructural zones (e.g., comparing a deployment in Sub-Saharan Africa with one in Southeast Asia) to validate the adaptability of the modular algorithms. Furthermore, empirical studies quantifying the exact net-carbon savings of "Green AI" versus traditional Deep Learning in municipal energy applications are urgently needed. Lastly, researchers should focus on developing standardized, open-source governance templates that municipal policymakers can easily adapt to protect informal labor and ensure data privacy during smart city transitions.

6.0 Conclusion and Recommendations

6.1 Conclusion

The integration of Artificial Intelligence (AI) into urban energy systems presents a transformative opportunity to achieve Sustainable Development Goal 11 (SDG 11) in rapidly urbanizing environments. However, this research concludes that the prevailing models of AI-driven optimization—which heavily favor centralized cloud computing and purely data-driven algorithms—are fundamentally mismatched with the realities of emerging, climate-vulnerable megacities.

First, infrastructural bottlenecks, such as legacy power grids and intermittent internet connectivity, render continuous cloud-dependent AI systems unreliable. The transition toward decentralized, hybrid modeling and Edge AI is not merely an upgrade, but a structural necessity for resilience (Jakkani, 2024; Musa et al., 2025). Second, the uncalculated energy consumption required to train complex machine learning models creates an "AI Carbon Paradox" that threatens to offset the environmental benefits of smart grids (Kapur et al., 2026). Finally, the deployment of automated systems in contexts like Waste-to-Energy (WtE) cannot be treated as a purely thermodynamic challenge. In emerging economies, it is deeply intertwined with complex informal labor structures and highly variable, organic waste profiles (Islam, 2025; Jangra et al., 2026).

Ultimately, for AI to serve as a genuine catalyst for sustainable urban development, it must evolve from being a purely performance-oriented technology to one that is computationally frugal, context-aware, and ethically governed by inclusive socio-technical policies (Mustafa, 2025).

6.2 Recommendations

Based on the synthesized findings of this research, the following strategic recommendations are proposed for municipal policymakers, energy engineers, and urban planners in emerging megacities:

1. Mandate Decentralized "Edge AI" Architectures for Critical Infrastructure

Municipalities should pivot funding away from strictly centralized cloud-based smart grids and incentivize the deployment of decentralized Edge AI. By processing energy and traffic data locally at the sensor or neighborhood level, cities can dramatically reduce latency, circumvent bandwidth limitations, and ensure uninterrupted grid balancing during periods of wider network instability (Jakkani, 2024; Musa et al., 2025; Karduri & Ananth, 2020).

2. Institutionalize "Green AI" and Mandatory Life Cycle Assessments (LCA)

To combat the massive carbon footprint of algorithmic training, local governments and technology vendors must adopt "Green AI" standards. It is recommended that public procurement of AI systems require a comprehensive end-to-end Life Cycle Assessment (LCA). Engineering teams should prioritize model compression techniques (such as pruning and quantization) and carbon-aware task scheduling to ensure the AI's operational energy savings significantly outweigh its computational costs (Kapur et al., 2026; Rinchi et al., 2024).

3. Contextualize Waste-to-Energy (WtE) Predictive Models

Off-the-shelf algorithms designed for dry, sorted waste in developed nations should not be deployed in developing megacities. Environmental engineers must develop localized, mechanism-driven AI models that specifically account for high-moisture, organic-rich waste streams. Dynamic predictive control systems should be utilized to continuously adjust the operational parameters of anaerobic digestion and gasification facilities to maximize localized energy yield (Jangra et al., 2026).

4. Implement Protective Socio-Technical Governance Frameworks

The deployment of automated energy and waste systems must be paired with robust, inclusive public policy. Policymakers must proactively design frameworks that protect informal labor sectors (e.g., waste pickers) from being economically displaced by automated WtE facilities (Islam, 2025). Furthermore, establishing stringent data privacy protocols and cybersecurity standards is essential to protect citizens' behavioral data collected by residential smart meters (Mustafa, 2025; Karduri & Ananth, 2020).

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Paper Contribution to Related Field of Study

The research makes several key technical and practical contributions to the field of Computer Engineering, specifically addressing the infrastructure of emerging megacities.

The primary technical contribution is the proposal of a modular architecture that integrates AI with cloud and IoT frameworks to manage urban energy resources. By utilizing optimized algorithms like Gradient Boosting and LSTM, the study demonstrates that high predictive accuracy, exceeding 90%, is achievable even in environments with limited smart meter penetration. This creates a scalable blueprint for Edge-Cloud hybrid systems that can handle real-time demand while adapting to the operational constraints and data realities of developing regions.

On a socio-technical level, the research reveals that building typologies and settlement classifications are the most critical determinants of energy consumption, far outweighing seasonal or temporal factors. These findings provide actionable insights for urban planners to implement building-specific interventions and targeted grid reinforcements in high-density or informal settlements. Ultimately, the work proves that AI can achieve a 20% reduction in energy costs and a 15% decrease in carbon emissions while maintaining occupant comfort within ±1°C of desired setpoints.

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