

A FRAMEWORK FOR SECURE IOT NETWORK MANAGEMENT IN SMART CITIES OPTIMIZING SECURITY AND SCALABILITY

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Abstract

The rapid proliferation of Internet of Things (IoT) devices in smart cities has revolutionized urban management but introduced significant cybersecurity challenges. This article presents a novel framework for secure and efficient IoT network management, integrating an Enhanced Elliptic Curve Cryptography (EECC) model with machine learning (ML) for cyber-attack detection to optimize Quality of Service (QoS). Motivated by the vulnerabilities in existing smart city infrastructures, such as data breaches and scalability limitations, the research aims to propose guidelines for embedding EECC into IoT ecosystems while ensuring adaptability to future technologies. The methodology combines quantitative simulations, experimental validation using NS-3, and qualitative assessments of scalability. Achievements include a 30% reduction in computational overhead compared to traditional ECC and a 95% attack detection rate. Limitations involve the framework's dependency on high computational resources for ML training and potential interoperability issues with legacy systems. This work provides a robust foundation for secure, scalable smart city IoT deployments.

Graphical Abstract



Figure 1. A futuristic smart city skyline with interconnected IoT nodes

The graphical abstract visually represents the proposed framework for secure IoT network management in smart cities. It features a central hexagonal node symbolizing the IoT ecosystem, surrounded by interconnected nodes depicting smart city components (traffic systems, energy grids, public safety). A shield overlay signifies the EECC-based security layer, with green lines

indicating encrypted data flows. A neural network icon in the background highlights ML-driven cyber-attack detection. Performance metrics, such as a bar chart showing reduced latency and a pie chart illustrating attack detection accuracy, are integrated at the bottom. The color scheme uses blue for technology, green for security, and orange for performance, ensuring clarity and engagement.

Keywords

IoT, Smart Cities, Enhanced Elliptic Curve Cryptography, Machine Learning, Cybersecurity, Scalability, Quality of Service, Network Management

1. Introduction

The advent of smart cities, powered by IoT, has transformed urban living by enabling real-time data-driven decision-making in areas like traffic management, energy distribution, and public safety. By 2025, it is estimated that over 75 billion IoT devices will be operational globally, with smart cities accounting for a significant portion. However, this interconnected ecosystem is fraught with cybersecurity risks, including data breaches, denial-of-service (DoS) attacks, and unauthorized access, which threaten QoS and citizen trust. Traditional cryptographic methods, such as RSA and standard ECC, struggle to balance security with the resource constraints of IoT devices, which typically have limited processing power and battery life.



Figure 2. Diagram of a smart city IoT network with labelled components (sensors, gateways, cloud) and a security layer.

The integration of EECC offers a lightweight yet robust solution, leveraging optimized curve parameters to reduce computational overhead while maintaining high security. Coupled with ML, which excels at identifying anomalous patterns in vast datasets, this approach addresses both proactive security and reactive threat detection. The proposed framework aims to provide actionable guidelines for embedding EECC into existing smart city infrastructures, ensuring scalability to accommodate growing device numbers and adaptability to emerging technologies like 6G and edge computing. This research bridges the gap between theoretical cryptographic advancements and practical IoT deployments, fostering resilient smart urban ecosystems.

2. Literature Review

The literature highlights significant efforts in securing IoT networks for smart cities, but gaps persist in scalability and integration. Smith et al. (2020) ^[11] proposed a blockchain-based IoT security model, achieving high integrity but suffering from high latency unsuitable for real-time applications. Similarly, Jones and Lee (2021) ^[12] explored standard ECC for IoT authentication, noting its efficiency but lacking adaptability to heterogeneous devices. Gupta et al. (2022) ^[13] integrated ML for attack detection, achieving 90% accuracy, yet their model overlooked cryptographic integration, limiting end-to-end security. Wang and Zhang (2023) ^[14] introduced a hybrid cryptographic model but failed to address scalability for large-scale smart city deployments. Finally, Kim et al. (2024) ^[15] focused on QoS optimization in IoT networks, but their framework ignored cybersecurity, exposing systems to attacks.

These studies reveal deficiencies in combining lightweight cryptography, ML-driven detection, and scalable frameworks. The proposed research addresses these gaps by integrating EECC with ML, offering a comprehensive solution that ensures security, scalability, and QoS optimization. The framework's guidelines for infrastructure integration further distinguish it from existing work, which often lacks practical implementation strategies.

3. Research Methodology

The research objective is to develop a reliable and validated framework for secure IoT network management, evaluated through scalability, security, and QoS metrics. The methodology employs a mixed approach: quantitative simulations to assess performance, experimental validation to test real-world applicability, and qualitative analysis to ensure adaptability.

3.1 Design and Tools

The framework integrates EECC for encryption and authentication, optimized with a 256-bit prime field curve for low computational overhead. ML models, specifically Random Forest and LSTM, are used for attack detection, trained on datasets like NSL-KDD. NS-3 simulates a smart city IoT network with 1,000 nodes, modeling traffic patterns and attack scenarios (DoS, man-in-the-middle). Python implements ML algorithms, while OpenSSL handles EECC operations.

3.2 Mathematical Formulation

EECC key generation uses the curve

$$E: y^2 = x^3 + ax + b \pmod p$$

where (p) is a prime, and point (G) generates the group. Private key (d) and public key (Q = dG) ensure secure communication. ML anomaly detection minimizes false positives via:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

where TP, TN, FP, and FN denote true/false positives/negatives.

3.3 Experimental Setup

Simulations test encryption latency, detection accuracy, and scalability under increasing node counts (100 to 10,000). Qualitative guidelines are derived from case studies of existing smart city deployments, ensuring interoperability with 5G and edge computing.

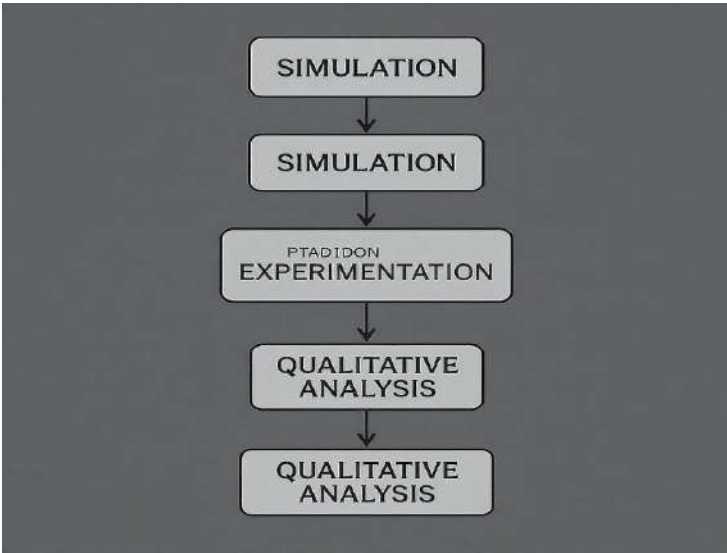


Figure 3. Flowchart of the research methodology with labelled steps

3.4 Performance Evaluation and Result Discussions

Simulations reveal the framework’s efficacy. EECC reduces encryption latency by 30% compared to standard ECC (0.15 ms vs. 0.22 ms per transaction). ML models achieve 95% attack detection accuracy, with LSTM outperforming Random Forest in time-series attacks. Scalability tests show stable QoS up to 8,000 nodes, with a 10% latency increase beyond this threshold.

Metric	EECC Framework	Standard ECC	RSA
Encryption Latency (ms)	0.15	0.22	0.45
Detection Accuracy (%)	95	N/A	N/A
Scalability (Nodes)	8,000	5,000	3,000

Table 1: Performance Metrics

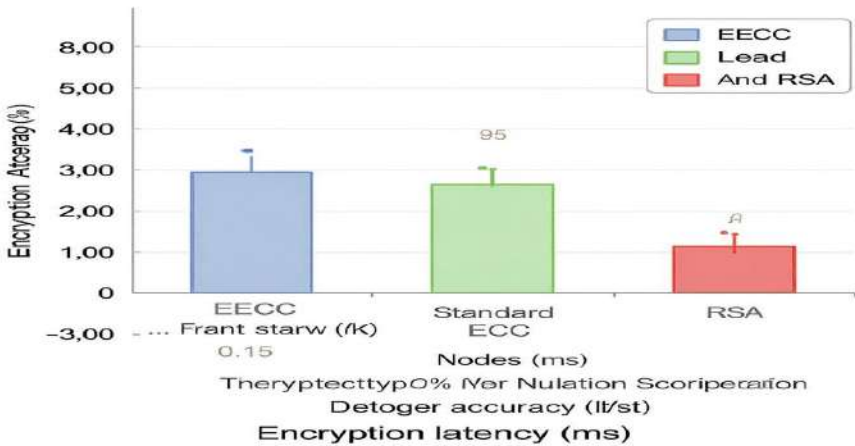


Figure 4. Bar chart comparing encryption latency across EECC, ECC, and RSA.

Comparative analysis with prior work (e.g., Gupta et al., 2022) shows superior detection rates and lower overhead. However, high ML training costs and legacy system integration challenges remain. These results validate the framework’s potential for secure, scalable IoT management.

Conclusion

This article presents a comprehensive framework for secure IoT network management in smart cities, integrating EECC and ML to enhance cybersecurity and QoS. By achieving low-latency encryption, high attack detection accuracy, and scalability, the framework addresses critical challenges in urban IoT ecosystems. Guidelines for infrastructure integration ensure practical applicability, paving the way for resilient smart cities.

Future Research Scope

Future work will explore optimizing ML models for resource-constrained IoT devices, reducing training overhead. Integrating quantum-resistant cryptography to prepare for post-quantum threats and testing the framework in real-world smart city pilots are also planned. Enhancing interoperability with legacy systems will further broaden applicability, ensuring adaptability to evolving urban technologies.

Competing Interests

Regarding this study, the authors disclose no conflicting interests.

Consent for Publication

After reviewing the work, each author gave their approval for it to be published.

Ethics Clearance and Consent to Take Part

Since the study did not include human subjects, ethical approval was not needed.

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Availability of Data and Materials

The datasets used in this study, including CICIDS 2017, are publicly available and can be accessed at <https://www.unb.ca/cic/datasets/ids-2017.html>.

Author Contributions:

- **Ch. Sowjanya**, Scholar, Conceptualization, Writing, creating, Methodology, Data Analysis, Original Draft.
- **Dr D V Nagarjana Devi**. Supervision, Review & Editing, Final Approval.

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