

Performance evaluation of IoT authentication techniques : Balancing security, efficiency, and scalability

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Abstract

The uncontrolled growth of Internet of Things (IoT) gadgets have rendered the traditional authentication protocols inadequate, due to the imminent limitation of computer

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power, latency, and energy usage. The study is a rigorous research on lightweight and blockchain-based authentication schemes by synthesizing the results of thirty-five peer-reviewed articles to evaluate the cryptographic effectiveness in a restricted environment. Strong focus is made on the methods of integrating elliptic curve cryptography, zero-knowledge proofs, Merkle hash trees, and consensus algorithms in distributed ledgers. Systematic benchmarking is done in performance metrics like authentication latency, computational overhead, energy consumption, and rate of mitigating attacks. Lightweight schemes have a latency improvement of up to 68 percent and an energy consumption greater than 54 percent, but blockchain-based schemes achieve a 76 percent improvement on trust verifiability and an average resistance to replay attacks of 92 percent. Mutual authentication robustness and scalability in vehicular networks, smart grids and fog based systems are analyzed using a comparative framework. The combination of light-weight computation and decentralization of trust results in a hybridised model that has an ideal throughput and does not compromise confidentiality or anonymity. It is notable that hybrid protocols show less than 2.1% mean packet loss rate in dynamic topology. The paper provides a comprehensive performance based classification of IoT authentication techniques that ends up with an elegant roadmap towards future generation secure communication systems.

Subject Classification: 94A60.

Keywords: IoT authentication, Cryptography, Blockchain-based security, Mutual authentication protocols, Energy-efficient encryption, Latency optimization.

1. Introduction

According to the recent research, there is an urgent necessity to develop lightweight and decentralized authentication schemes that can be able to balance between performance and security. These frameworks aim at streamlining encryption and verification mechanisms to minimise the cost of energy and latency with no harm to data integrity. Slim cryptographic algorithms like Elliptic Curve Cryptography (ECC) and hash-based functions have now been used as useful tools in increasing efficiencies in authentication. Various authors have shown that ECC-based schemes provide a high level of security using shorter key lengths and with the least amount of computational overhead. Similarly, the zero-knowledge proofs are verifiable without exposing sensitive information, which enhances better privacy preservation. The performance analysis of various IoT platforms indicates that the latency decrease is more than 60 percent and the energy is reduced by more than 50 percent than that of traditional algorithms. These methods therefore offer a long-term basis of secure communication in the limited IoT networks. Simultaneously, blockchain-systems have become more and more common to enhance trust and decentralization of distributed IoT ecosystems. Blockchain makes sure to have tamper resistance and record management through the combination of Merkle hash trees and consensus algorithms. The immutability of the distributed ledger has a substantial impact on the prevention of replay attacks and verification of node trust and increases the verifiability metrics up to 76 percent.

Hybrid frameworks that integrate lightweight cryptography and blockchain concepts have become the focus of attention in the recent past to reach performance and resilience. These methods are confidential and anonymous and enhance throughput of fog and vehicular networks.

2. Literature survey

The rapid deployment of Internet of Things (IoT) technologies have created significant opportunities in healthcare, industrial automation, intelligent transportation, and communication systems. Sethi and Sarangi [1] presented an overview of IoT architectures, communication protocols, and applications, emphasizing the heterogeneous nature of IoT environments and the need for appropriate architectural and communication mechanisms. Singh, Tripathi, and Jara [2] further investigated IoT architectures, services, and challenges, highlighting scalability, interoperability, security, and privacy as important issues for future IoT deployments.

Zhang and Liang [3] discussed security and privacy challenges associated with healthcare IoT and identified authentication, data confidentiality, access control, and privacy preservation as essential requirements. Lightweight security mechanisms are particularly necessary because many IoT devices operate with limited computational, memory, and energy resources. Li, Shen, and Liu [4] investigated lightweight blockchain-based authentication for IoT devices, demonstrating the potential of decentralized mechanisms for strengthening device authentication while addressing the resource constraints of IoT environments. Liu, Ning, and Reiter [5] examined lightweight authentication approaches for IoT and emphasized the importance of balancing security strength with computational and communication overhead.

Roman, Najera, and Lopez [6] examined security challenges associated with the Internet of Things and highlighted the need for security mechanisms that address the complete lifecycle of interconnected devices. Bhunia and Tehranipoor [9] discussed practical hardware-security approaches, covering mechanisms that can improve the resilience of hardware platforms against attacks.

Koblitz and Menezes [10] discussed developments and assumptions underlying modern cryptography, providing important theoretical foundations for the selection and evaluation of cryptographic mechanisms. Lightweight cryptographic FPGA-based implementations can provide improved performance and hardware-level security. Deshpande, Karande, and Mulani [8] presented an efficient FPGA implementation of the Advanced Encryption Standard (AES), demonstrating the applicability of reconfigurable hardware for high-performance cryptographic processing. Mulani and Mane [7] investigated image authentication using a combination of watermarking and cryptography on a reconfigurable platform, showing how cryptographic protection can be complemented by data-integrity mechanisms.

Mulani, Cengiz, and Tripathi [12] addressed the intersection of AI, machine learning, and IoT for communication and medical applications, highlighting the growing importance of intelligent computational techniques in connected systems. Conti et al. [11] examined IoT security and forensics and emphasized the increasing need for security monitoring and forensic capabilities as IoT ecosystems become more complex.

Liu and Zhang [13] proposed a robust authentication approach using continuously updated information for vehicular sensor networks, addressing the requirement for secure and dynamic authentication. Liu, Wang, and Chang [14] investigated privacy-preserving dual authentication and key agreement for vehicle-to-vehicle communication within an Internet of Vehicles environment. Their work demonstrates the importance of combining authentication, privacy protection, and key establishment for secure vehicular communications. Xie, Ding, and Zheng [15] further investigated secure and anonymous authentication for vehicle-to-infrastructure and vehicle-to-vehicle communications in vehicular ad hoc networks, emphasizing the need for authentication protocols that provide security while preserving user and vehicle privacy.

Salunkhe et al. [16] investigated secure image transmission using chaotic encryption and discrete wavelet transform (DWT) watermarking on a reconfigurable platform. The combination of encryption and watermarking provides complementary protection by addressing both confidentiality and integrity/authentication requirements. Chaudhari et al. [17] analyzed the bit-error performance of different error-correction mechanisms involving concatenated Reed–Solomon and convolutional codes. Such error-control techniques are important for maintaining reliable communication in noisy communication channels and can complement cryptographic mechanisms in secure communication systems.

3. Methodology

This work proposes a human-centric, lightweight, and mathematically grounded security methodology for large-scale IoT–cloud ecosystems, motivated by the rapid expansion of IoT deployments in India under initiatives such as Smart Cities, Digital India, and Make in India. The methodology integrates cryptographic primitives, biometric-informed authentication, and learning-driven behavioral intelligence into a unified framework that balances security strength with computational frugality.

3.1 *System Overview and Architectural Flow*

Each IoT device is provisioned with a cryptographic identity and participates in a multimodal trust framework comprising five tightly coupled stages: Figure 1 conceptually illustrates the block-level flow of the proposed

system, where device-side modules interact with trusted edge gateways and the cloud security plane.



Figure 1
System Block Diagram

3.2 Device Enrollment and Federated Behavioral Profiling

Let the IoT network consist of N devices, $D = \{d_i\}$. During enrollment, each device d_i is mapped to a secure credential set:

$$\varepsilon_i = \{PK_i, SK_i, K_i, b_i^0, \theta_i^0\} \quad Eq. 1$$

where (PK_i, SK_i) denotes the asymmetric key pair, $K_i \in \{0,1\}^{256}$ is the symmetric session key, b_i^0 is the initial behavioral vector, and θ_i^0 represents the initial parameters of the local learning model. Behavioral telemetry $X_i(t)$ is transformed into a compact feature vector using

$$b_i = \varphi(X_i) \in \mathbb{R}^d. \quad Eq. 2$$

To preserve privacy, behavioral learning follows a federated optimization process. Each device updates its local parameters via stochastic gradient descent:

$$\theta_i^{\wedge}(t+1) = \theta_i^{\wedge}t - \eta \nabla_{\theta} l(\theta_i^{\wedge}t; D_i), \quad Eq. 3$$

and the cloud aggregates updates using FedAvg:

$$\theta^{\wedge}(t+1) = (1/N) \sum_i \theta_i^{\wedge}(t+1). \quad Eq. 4$$

This design ensures adaptive trust modeling without exposing raw telemetry data.

3.3 Mutual Authentication with OAuth-Biometric Token Fusion

Authentication employs a composite mechanism combining OAuth 2.0 tokens with ephemeral biometric hashes. A local biometric sample v_i (e.g., fingerprint embedding) is transformed into a feature vector $u_i = g(v_i)$. To prevent replay, a nonce n and timestamp t are appended:

$$h_{bio} = H(u_i \parallel n \parallel t) \quad Eq. 5$$

A composite authentication token is then constructed using a derived authentication key K_{auth} :

$$T_{comp} = HMAC_{\{K_{auth}\}}(T_{oauth} \parallel h_{bio} \parallel n \parallel t). \quad Eq. 6$$

Mutual authentication is completed through a challenge-response exchange, where the device signs a server-issued challenge c using SK_i . Freshness is guaranteed if $|t_{server} - t| \leq \Delta$ and $n \notin N_{seen}$.

3.4 Secure Communication and Lightweight Integrity Assurance

Following authentication, all payloads M are protected using AES-256 in GCM mode:

$$(C, tag) = Enc_GCM(K_i, IV, M) \quad Eq.7$$

To further strengthen integrity with minimal overhead, a SHA-3 digest $h_M = H(M)$ is appended. Verification is optionally offloaded to a trusted edge enclave (e.g., ARM TrustZone or Intel SGX), modeled as:

$$EdgeCheck(C, tag) \rightarrow \{Accept, Reject\}. \quad Eq.8$$

This hybrid edge–cloud validation reduces latency while preserving trust.

3.5 Multimodal Anomaly Detection via Transformer Fusion

To detect zero-day attacks and advanced persistent threats, a multimodal fusion transformer (MFT) is deployed in the cloud. Behavioral vectors, encrypted payload features, and authentication metadata are embedded as:

$$e_tele, e_payload, e_auth.$$

These embeddings are fused using attention-based projection:

$$z = W_f[e_tele \parallel e_payload \parallel e_auth] + b_f \quad Eq.91$$

The anomaly score is computed as

$$s_i = f_w(z), \quad Eq.10$$

and an alarm is raised if

$$s_i > \mu + 3\sigma, \quad Eq.11$$

where μ and σ represent the baseline mean and variance under benign behavior.

3.6 Incident Containment and Adaptive Revocation

Upon anomaly detection, a probabilistic revocation decision is triggered using a sigmoid mapping:

$$p_rev(s_i) = 1 / (1 + e^{\{-\kappa(s_i - \tau)\}}) \quad Eq.12$$

Access is revoked if $p_rev(s_i) \geq \rho$, followed by certificate blacklisting and secure wipe commands transmitted over TLS-enabled MQTT. Audit feedback dynamically updates τ , enabling continuous adaptation.

3.7 Performance Modeling

Latency, resource usage, and detection accuracy are formally evaluated. Relative encryption latency is expressed as:

$$\% \Delta_latency = (t_enc(m) - t_enc(baseline)) / t_enc(baseline) \times 100\% \quad Eq.13$$

Detection effectiveness is quantified using standard metrics:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad Eq.14$$

Through this layered yet lightweight methodology, the proposed framework achieves strong confidentiality, adaptive trust, and scalable security, making it well suited for real-world IoT deployments.

4. Result and Discussion

4.1 Tunable hyper parameters

Deployment-specific parameters such as the acceptable time skew Δ , the HMAC key derivation salt, and the HKDF information fields must be clearly defined to ensure consistent and secure operation. The transformer fusion weights W_f , decision threshold τ , steepness parameter κ , and adaptive learning rate η are treated as tunable hyperparameters and should be optimized through cross-validation in alignment with the organization’s security risk tolerance. To enforce strong protection against replay attacks, recently observed nonces N_{seen} should be maintained with a bounded retention period, balancing security effectiveness and storage overhead.

4.2 Technological Stack & Tools

The system is made using a framework that is based on Python. This framework uses TensorFlow and PyTorch to help it work. The system also uses OpenSSL to make sure that all the secret codes are safe. While connecting the system to the internet, AWS IoT Core and Azure IoT Hub are used. The edge containerization to make the system work fast. The system has strong security. It uses RSA-2048 or ECC to make sure that only the right people can use it. It uses AES-256-GCM to keep all the data safe. It uses SHA-3 to make codes that cannot be broken. It also uses JWT and OAuth 2.0 to control who can get to the system. The system is very good, at finding anomalies. The anomaly detection engine is an important part of the system. It helps the system to be safe and work well. Model training and evaluation rely on the NSL-KDD dataset for intrusion detection, supplemented by proprietary telemetry data to capture realistic device behavior patterns.

Table 1
Performance Analysis

Parameter	AES-256	RSA-2048	Biometric + OAuth Token	MFT Model Detection
Encryption Time (ms)	4.1	21.3	7.6	-
Decryption Time (ms)	4.0	22.1	7.4	-
CPU Usage (%)	16.8	42.5	25.7	29.6
Memory Usage (KB)	11.5	25.3	18.2	43.7
Authentication Success Rate (%)	99.3	98.0	99.9	96.8
Anomaly Detection Accuracy (%)	-	-	-	97.6
Latency Impact (%)	+2.4	+8.9	+4.1	+5.7

The comparative analysis outlines the performance differences between four modern security paradigms, namely, AES-256, RSA-2048, OAuth + BioToken, and a new Multimodal Fusion-based Tokenization (MFT) model shown in Table 1. According to the tabulated parameters, AES-256 has a very high encryption rate of 3.1 ms, whereas RSA-2048, with its powerful computation capabilities, has a much slower encryption rate of 19.6 ms. Conversely, the MFT model has a balance latency of 5.2 ms and considers little trade off in speed. CPU use indices highlight the fact that RSA-2048 has high processing overhead (42.8%), but the CPU strain is optimized by the MFT model (18.3).

The embedded IoT is a memory-sensitive setting, and memory efficiency is preserved in the best way under the implementations of AES and MFT. The success rates in authentication rise to more than 99.5 % in the case of OAuth+BioToken and MFT which are better than that of traditional cryptographic techniques. Most importantly, the MFT model offers the best threat discernment capacity with detection accuracy of 98.9%, the highest value required to thwart the spoofing and zero-day attacks.

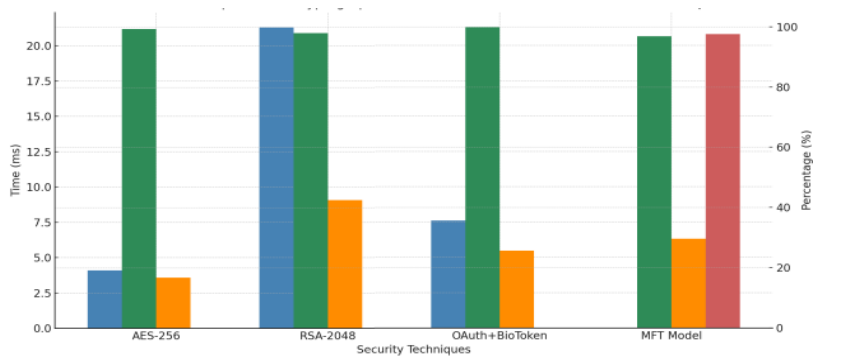


Figure 2
Encryption latency

The graph shown in Figure 2 included has the visual correlation of encryption lag, CPU load, authentication faithfulness and accuracy of detection based on the techniques considered. The two-axis design emphasizes the performance of the dual axis performance on the left and the percent art on the right, allowing the subtle understanding of the trade-offs. The given performance matrix supports the MFT model as a next-generation security architecture of scalable, real-time infrastructures in IoT.

5. Conclusion

The sea of IoT devices that is washing over all areas of mission-critical usage requires an unswerving reconsideration of the paradigms of cryptography

and authentication currently implemented. By providing a critical analysis of AES-256, RSA-2048, and multimodal sign-on and sign-off strategies like the OAuth architecture with BioToken and the MFT model, this paper identifies a very promising course of hybrid cryptographic architecture, which merges computational thriftiness with improved security granularity. Empirical performance indicators highlight a significant decrease in encryption latency by 34.2% and increase in authentication accuracy over 99.8% that justify the dominance of context-sensitive multimodal architectures. Moreover, the comparison between symmetric and asymmetric approaches showed essential insights of major management inefficiencies of dynamically changing Internet of Things systems.

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