

HFTEA: A HIERARCHICAL FEDERATED TRUST-AWARE EDGE COMPUTING ARCHITECTURE FOR SECURE AND SCALABLE IOT SYSTEMS

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Abstract: The convergence of the Internet of Things (IoT) and edge computing has created transformative opportunities for latency-sensitive, data-intensive applications. However, heterogeneous device ecosystems introduce profound security vulnerabilities and formidable scalability constraints that existing architectures inadequately address. This paper proposes HFTEA, a Hierarchical Federated Trust-Aware Edge Computing Architecture that addresses these challenges through four novel contributions: (i) a three-tier dynamic hierarchy comprising device, fog, and macro-edge layers with adaptive workload migration governed by a context-aware scheduling policy; (ii) a Federated Learning-based Intrusion Detection System (FL-IDS) that preserves data privacy while achieving distributed anomaly detection without centralizing sensitive IoT telemetry; (iii) a Lightweight Zero-Trust Adaptation Protocol (LZTAP) engineered for resource-constrained devices operating under intermittent connectivity; and (iv) a Blockchain-Anchored Trust Scoring Mechanism (BATSM) that maintains tamper-proof reputation ledgers for edge nodes using a DAG-based lightweight consensus. Simulation experiments on NS-3 with 1,200 heterogeneous IoT nodes demonstrate that HFTEA achieves a 94.7% intrusion detection accuracy with only 3.2% false positives, reduces end-to-end latency by 41% compared to centralized cloud architectures, and sustains scalable operation up to 10,000 concurrent devices with sub-linear overhead growth. Security analysis confirms resistance against seven critical attack vectors including Byzantine fault injection, Sybil attacks, and gradient poisoning in federated rounds.

Keywords: Edge computing, IoT security, federated learning, zero-trust architecture, blockchain, scalability, intrusion detection, trust management.

I. INTRODUCTION

The Internet of Things has expanded from a niche academic concept to a global infrastructure backbone encompassing over 17 billion active connected devices as of 2024, with projections suggesting 32 billion by 2029 [1]. These devices span industrial control systems, autonomous vehicles, smart healthcare monitors, precision agriculture sensors, and urban management platforms—each

generating high-velocity data streams that demand real-time processing with millisecond-level response guarantees. The conventional paradigm of forwarding all device-generated data to centralized cloud infrastructures is increasingly untenable: bandwidth bottlenecks create unacceptable latency, transmission costs are prohibitive at scale, and exposing sensitive operational data to wide-area network transit substantially enlarges the attack surface [2], [3].

Edge computing has emerged as a compelling architectural response, positioning computational resources in geographic proximity to data sources [4]. By processing data at or near the

network periphery, edge computing can reduce round-trip latency from hundreds of milliseconds to single-digit milliseconds, dramatically improving the viability of real-time applications [5]. However, this distribution of processing introduces new complexities that existing literature has not fully resolved. First, the resource heterogeneity across edge nodes—varying in CPU capacity, memory availability, and network bandwidth—makes static workload allocation schemes fragile and inefficient [6]. Second, the security posture of edge deployments is fundamentally weaker than enterprise data centers; edge nodes often reside in physically unsecured locations and operate under reduced administrative oversight, making them attractive targets for adversarial interference [7], [8]. Third, the federated nature of multi-operator edge environments complicates trust establishment, as different nodes may be owned and managed by independent entities with misaligned incentive structures [9].

The security landscape for IoT edge deployments is particularly alarming. Distributed Denial-of-Service (DDoS) attacks originating from compromised IoT devices caused an estimated \$2.7 billion in economic damage in 2023 alone [10]. Sophisticated persistent threats targeting edge infrastructure have exploited weak authentication protocols, unencrypted inter-node communication channels, and the absence of anomaly detection at the network periphery [11]. Conventional intrusion detection systems designed for enterprise networks cannot be directly transplanted to resource-constrained edge environments due to computational overhead and their dependence on centralized data aggregation—which itself violates data privacy requirements under regulations such as GDPR and emerging IoT-specific frameworks [12], [13].

Scalability represents an equally critical and underexplored challenge. While numerous proposals exist for scaling individual aspects of edge architectures—such as container orchestration using Kubernetes at the edge [14] or microservice migration strategies [15]—a holistic treatment of concurrent scalability across the security, computation, and communication dimensions remains absent from the literature. Most existing architectures assume a relatively static device topology, yet practical IoT deployments must accommodate massive fluctuations in connected device count, workload intensity, and mobility patterns [16].

To address these intertwined challenges, this paper makes the following primary contributions:

- 1) We propose a three-tier Hierarchical Edge Architecture with context-aware dynamic workload migration that adapts to

real-time resource and latency constraints across device, fog, and macro-edge layers.

- 2) We design FL-IDS, a privacy-preserving Federated Learning-based Intrusion Detection System that trains a shared detection model across distributed edge nodes without centralizing raw device telemetry, incorporating differential privacy guarantees.

3) We introduce LZTAP, a Lightweight Zero-Trust Adaptation Protocol that extends zero-trust principles to devices as resource-constrained as 8-bit microcontrollers by offloading cryptographic verification to nearby fog nodes through a delegation chain mechanism.

4) We develop BATSM, a Blockchain-Anchored Trust Scoring Mechanism using a Directed Acyclic Graph (DAG) consensus appropriate for edge latency budgets, which maintains auditable, tamper-resistant reputation records for all participating edge and fog nodes.

The remainder of this paper is structured as follows. Section II surveys related work across five relevant research dimensions. Section III formalizes the research gap. Section IV presents the system model and problem formulation. Section V details the HFTEA architecture. Section VI provides the security analysis. Section VII analyzes scalability. Section VIII presents simulation-based performance evaluation. Section IX concludes with directions for future work.

II. RELATED WORK

A. Edge Computing Architectures for IoT

The foundational edge computing paradigm for IoT was articulated by Shi et al. [4], who introduced MEC (Mobile Edge Computing) and demonstrated its potential for latency reduction. Subsequent work by Mach and Becvar [17] provided a comprehensive taxonomy of task offloading strategies. Abbas et al. [18] examined mobile cloud computing convergence with IoT, identifying energy-latency tradeoffs that remain central to architectural design. PremSankar et al. [19] studied MEC in the context of ultra-reliable low-latency communication (URLLC), establishing baseline performance targets. Mouradian et al.

[20] provided an extensive survey of fog computing architectures, introducing the notion of hierarchical fog tiers that inspired our three-layer design. Mahmud et al. [21] formalized application scheduling in fog environments as an optimization problem, while Yousefpour et al. [22] delivered a systematic review of fog research challenges, noting that security and scalability remain understudied relative to their practical importance.

More recent contributions have explored specific architectural components. Sonmez et al. [23] evaluated CloudSim-based performance models for edge-cloud integration. Brogi and Forti [24] addressed QoS-aware application deployment in fog environments. Liu et al. [25] proposed latency-optimized task scheduling in vehicular edge computing. Deng et al. [26] examined workload offloading with heterogeneous hardware accelerators at the edge. However, none of these works holistically integrate security frameworks with scalability mechanisms, treating them as orthogonal concerns rather than deeply coupled design dimensions.

B. Security Frameworks for Edge-IoT Systems

Roman et al. [27] provided one of the earliest comprehensive security analyses of mobile edge computing, identifying seven major threat categories including unauthorized access, eavesdropping, and compromised infrastructure. Stojmenovic and Wen [28] analyzed fog computing security and privacy, proposing mitigation strategies for rogue gateway attacks. Alrawais et al. [29] proposed a fog-based authentication scheme that reduces latency relative to cloud-based certificate authorities. Ni et al. [30] introduced a decentralized access control framework using attribute-based encryption for edge resources. Zhang et al. [31] designed a lightweight authentication protocol optimized for constrained IoT endpoints, achieving significant reduction in handshake overhead compared to TLS 1.3.

The zero-trust security paradigm, originally articulated by Kindervag [32] and subsequently refined in NIST SP 800-207 [33], has attracted growing interest for edge deployments. Gilman and Barth [34] argued for zero-trust network architecture as a fundamental shift from perimeter-based defense. Stafford [35] analyzed zero-trust deployment models. He et al. [36] explored zero-trust integration with IoT device provisioning but noted that computational requirements render full zero-trust implementation impractical for severely resource-constrained devices—a gap our LZTAP protocol directly addresses through delegation chains.

C. Federated Learning for Edge Intelligence

McMahan et al. [37] introduced FedAvg, the seminal federated learning algorithm, establishing the paradigm of collaborative model training without data sharing. Konecny et al. [38] advanced communication-efficient federated learning through gradient compression. Li et al. [39] analyzed convergence properties under non-IID data distributions characteristic of heterogeneous IoT deployments. Wang et al. [40] proposed adaptive federated optimization schemes for edge systems with intermittent connectivity.

Federated learning applied specifically to intrusion detection has been explored by several groups. Rey et al. [41] demonstrated federated anomaly detection for IoT networks but did not address adversarial model poisoning. Nguyen et al.

[42] proposed DIoT, a self-learning intrusion detection system using recurrent neural networks in federated settings. Mothukuri et al. [43] surveyed federated learning security challenges, identifying gradient inversion and model poisoning as primary concerns. Our FL-IDS builds upon these foundations but adds robust aggregation and differential privacy mechanisms absent from prior work. Zhao et al. [44] studied data heterogeneity effects on federated model accuracy, informing our client selection strategy.

D. Blockchain for Trust in IoT

The application of blockchain to IoT trust management was pioneered by Dorri et al. [45], who proposed a lightweight private blockchain for smart home systems. Novo [46] introduced a scalable blockchain-based access management system for IoT. Zhang and Wen [47] designed a blockchain-based IoT security framework addressing device identity and data integrity. Fernandez-Carames and Fraga-Lamas [48] provided a comprehensive review of blockchain for IoT, noting that transaction throughput constraints limit direct applicability of proof-of-work consensus mechanisms to latency-sensitive edge environments.

DAG-based distributed ledger technologies have been proposed to overcome transaction throughput limitations. Popov [49] introduced IOTA's Tangle, a DAG structure designed for IoT micropayments that eliminates mining overhead. Silvano and Marcelino [50] analyzed IOTA's security properties, identifying vulnerabilities in low-activity network conditions that inform our BATSM consensus design. Recent work by Xu et al. [51] proposed a DAG-based trust management framework for vehicular edge computing, demonstrating throughput improvements over blockchain alternatives, but without integration with federated learning or zero-trust principles.

E. Scalability in Edge Computing

Kubernetes-based orchestration at the edge has been studied by Hoque et al. [52], who demonstrated dynamic container scheduling under varying IoT workloads. Santos et al. [53] proposed microservice migration strategies for minimizing service disruption during node failures. Mahmoud et al. [54] introduced predictive scaling mechanisms using LSTM-based workload forecasting.

Cheng et al. [55] examined serverless edge computing as a scalability mechanism. Li and Buyya [56] formalized the latency-constrained microservice placement problem as an NP-hard optimization and proposed a greedy approximation algorithm. Despite this rich literature, no prior work has co-designed scalability mechanisms with security enforcement, leaving open the question of how security overhead scales with increasing device populations—a question our architecture explicitly quantifies.

III. RESEARCH GAP ANALYSIS

A systematic analysis of the literature surveyed in Section II reveals five critical gaps that individually limit the practical deployability of existing edge-IoT architectures and collectively prevent any existing solution from fully satisfying the security-scalability requirements of large-scale heterogeneous IoT deployments.

Gap 1 — Absence of Co-designed Security-Scalability Frameworks: Existing work treats security and scalability as separable concerns addressed by independent system components. This separation is architecturally problematic because security mechanisms impose computational overhead

that directly affects scalability, while scalability techniques such as aggressive task offloading can introduce new attack surfaces. No prior architecture has quantified the security-scalability tradeoff curve or co-optimized across both dimensions simultaneously.

Gap 2 — Inapplicability of Zero-Trust to Constrained Devices: While zero-trust architectures have been advocated for edge security, their direct deployment on Class 0 and Class 1 IoT devices (as defined by RFC 7228, with <10 KB RAM and <100 KB flash) is computationally infeasible. Existing adaptations either relax security guarantees unacceptably or assume minimum hardware capabilities that exclude the vast majority of deployed IoT devices.

Gap 3 — Federated Learning Vulnerability to Adversarial Participants: FL-based intrusion detection systems reviewed in Section II-C do not adequately address the threat of Byzantine edge nodes that intentionally submit poisoned model updates to degrade global detection accuracy. Robust aggregation methods from the federated learning literature have not been integrated with IoT-specific deployment constraints.

Gap 4 — Lack of Tamper-Proof Edge Node Trust Accountability: Existing edge trust management schemes rely on centralized trust authorities or require high-throughput blockchain consensus unsuitable for edge latency budgets. No existing work provides a tamper-resistant, low-latency trust scoring mechanism that functions correctly under the intermittent connectivity characteristic of edge deployments.

Gap 5 — Static Hierarchical Architectures: Current multi-tier edge architectures define static tier membership and routing rules at deployment time. The dynamic nature of IoT deployments—with devices joining, leaving, and changing workload profiles continuously—demands adaptive hierarchical reconfiguration that existing architectures do not support.

Table I summarizes how existing representative works address or fail to address each identified gap, confirming the novelty of the proposed HFTEA architecture.

TABLE I: Gap Analysis of Representative Prior Work (✓=Addressed, X=Not Addressed, Partial=Partially Addressed)

Work	Gap 1	Gap 2	Gap 3	Gap 4	Gap 5
Mouradian et al. [20]	Partial	✗	✗	✗	✗
He et al. [36]	✗	Partial	✗	✗	✗
Rey et al. [41]	✗	✗	Partial	✗	✗
Xu et al. [51]	✗	✗	✗	Partial	✗
Santos et al. [53]	✗	✗	✗	✗	Partial
HFTEA (Proposed)	✓	✓	✓	✓	✓

IV. SYSTEM MODEL AND PROBLEM FORMULATION

A. Network Model

We model the IoT-edge network as a directed graph $G = (V, E)$, where $V = D \cup F \cup M$ denotes the vertex set comprising D

$= \{d_1, d_2, \dots, d_n\}$ IoT devices at the device tier, $F = \{f_1, f_2, \dots, f_m\}$ fog nodes at the fog tier, and $M = \{\mu_1, \mu_2, \dots, \mu_k\}$ macro-edge nodes at the macro-edge tier. Edges E represent communication channels with associated latency $l(u,v)$ and bandwidth $b(u,v)$ attributes. Each device $d_i \in D$ is characterized by a tuple (C_i, M_i, E_i, A_i) representing CPU capacity in MIPS, available memory in KB, remaining energy budget in mJ, and assigned application type respectively. Each fog node $f_j \in F$ is characterized by (C_j, M_j, S_j) representing computational capacity, memory, and storage. Macro-edge nodes μ_k have substantially larger resources and function as aggregation points for multiple fog clusters.

The network operates in discrete time steps $t \in \{0, 1, 2, \dots\}$, with device population dynamics modeled as a Poisson arrival process with rate λ for device joins and exponential inter-departure times with rate μ . This models the realistic scenario of device churn in industrial and urban IoT deployments.

B. Task Offloading Model

An IoT task τ is defined as a tuple $(w_\tau, d_\tau, l_{\max}, s_\tau)$ representing computational workload in CPU cycles, data size in bits, maximum tolerable latency in milliseconds, and security classification level respectively. The classification level $s_\tau \in \{0, 1, 2\}$ indicates whether a task can be processed locally (0), at fog tier (1), or requires macro-edge resources (2) based on computational requirements.

For a task τ offloaded from device d_i to fog node f_j , the total execution latency is:

$$L(\tau, d_i, f_j) = (d_\tau / b(d_i, f_j)) + (w_\tau / C_j) + (r_\tau / b(f_j, d_i))$$

where r_τ denotes the result size. The offloading decision is valid only if $L(\tau, d_i, f_j) \leq l_{\max}$. The global scheduling objective minimizes total weighted latency subject to resource capacity constraints, energy constraints at devices, and security policy compliance.

C. Security Threat Model

We adopt a comprehensive threat model encompassing external adversaries and compromised internal nodes. External adversaries Eve can eavesdrop on communications, inject malicious packets, and launch DDoS amplification attacks. Internal adversaries Mallory represent compromised edge or fog nodes that may deviate from protocol specifications, inject false data, submit poisoned federated learning updates, or collude with other compromised nodes.

We assume up to $f < n/3$ Byzantine faults among fog nodes (consistent with BFT consensus requirements) and that at most 30% of FL clients may submit poisoned gradients in any given federated round.

The security objectives are formally defined as: (O1) Confidentiality—task data must not be accessible to unauthorized parties during transit or processing; (O2) Integrity—processing results must be verifiable as unaltered; (O3) Availability—the system must maintain operational capability under DDoS conditions; (O4) Privacy—device telemetry used for anomaly detection must not be reconstructable by any single party; (O5) Accountability—all node actions must be traceable through the trust ledger.

V. HFTEA ARCHITECTURE

A. Three-Tier Hierarchical Structure

The HFTEA architecture organizes edge resources into three distinct operational tiers with well-defined responsibilities, interfaces, and trust boundaries. This hierarchical decomposition is motivated by the observation that different computational tasks have fundamentally different latency, security, and resource requirements that cannot be optimally served by a flat architecture.

Tier 1 — Device Tier: IoT devices execute lightweight local tasks, perform first-stage data filtering, and maintain peer-to-peer communication with adjacent devices for fault detection. Devices implement a minimal LZTAP client stack (described in Section V-C) consuming less than 4 KB of program memory. Each device maintains a local task queue and a connectivity map of reachable fog nodes, updated through periodic beacon exchanges. Devices classify their own tasks and issue offloading requests to the fog tier when local resources are insufficient.

Tier 2 — Fog Tier: Fog nodes serve dual roles as computation accelerators and security enforcement points. Each fog node f_j maintains a resource availability vector updated at 500 ms intervals and a service registry listing deployed microservices. Fog nodes execute the FL-IDS local training loop (Section V-B), participate in BATSM consensus (Section V-D), and enforce LZTAP verification on behalf of resource-constrained devices. A fog cluster supervisor is elected through a lightweight weighted leader election algorithm, with weight proportional to uptime history and available resources.

Tier 3 — Macro-Edge Tier: Macro-edge nodes aggregate information from multiple fog clusters, execute global FL model aggregation, maintain the authoritative BATSM ledger replica, and serve as the interface to upstream cloud infrastructure. The macro-edge tier runs full zero-trust policy enforcement and maintains Certificate Authority functions for fog-tier node onboarding.

Tier-to-tier communication uses TLS 1.3 with mutual authentication. Fog-to-device communication uses DTLS 1.3 with pre-provisioned shared keys to minimize handshake overhead on constrained devices.

B. Federated Learning Intrusion Detection System (FL-IDS)

FL-IDS trains a Bidirectional LSTM anomaly detection model in a federated manner across fog nodes, enabling collaborative learning from network behavior patterns observed across the entire IoT deployment without centralizing raw traffic data. The model input is a 48-dimensional feature vector derived from flow-level statistics including inter-arrival time statistics, packet size distribution, protocol distribution, and connection directionality features extracted over a 60-second sliding window.

Algorithm 1 presents the FL-IDS training procedure. In each federated round r , the macro-edge aggregator selects a subset of K fog nodes from the eligible pool using a reputation-weighted sampling strategy biased toward nodes with higher BATSM trust scores. Selected nodes execute local SGD for E epochs

on their local traffic datasets, compute gradient updates Δw_k , and transmit these updates—protected by differential privacy through Gaussian noise calibrated to sensitivity—to the aggregator. The aggregator applies Byzantine-robust aggregation using coordinate-wise trimmed mean, removing the 10th and 90th percentile values for each gradient dimension before averaging, providing theoretical robustness against up to 20% poisoned updates.

The differential privacy guarantee is formalized as (ϵ, δ) -DP with $\epsilon = 1.0$ and $\delta = 10^{-5}$ per federated round, achieved by clipping gradients to L_2 norm $C = 1.0$ and adding calibrated Gaussian noise $\sigma = C\sqrt{(2\ln(1.25/\delta))/\epsilon}$. The privacy budget is tracked using the moments accountant method, ensuring cumulative privacy cost across all rounds remains within acceptable bounds.

Anomaly detection at inference time operates at individual fog nodes using the current global model without requiring network round trips, enabling detection latency under 10 ms for common attack patterns. When a fog node's detection confidence exceeds a configurable threshold θ (default 0.85), it triggers a lightweight containment procedure: rate-limiting the suspected device's traffic and escalating to the macro-edge tier for coordinated response.

C. Lightweight Zero-Trust Adaptation Protocol (LZTAP) LZTAP extends zero-trust principles to constrained devices by decomposing the verification burden through a hierarchical

delegation chain. Rather than requiring each device to execute full mutual TLS with certificate verification—computationally infeasible for 8-bit microcontrollers—LZTAP introduces the concept of a Trust Delegation Chain (TDC) where verification duties are offloaded to the nearest capable fog node.

The protocol operates in three phases: (1) Provisioning Phase, during which devices receive a 128-bit symmetric provisioning key K_p via secure out-of-band channel during manufacturing or installation; (2) Attestation Phase, during which devices periodically send a compact attestation token $AT = \text{HMAC-SHA256}(K_p, \text{timestamp} || \text{device_id} || \text{state_hash})$ to their assigned fog node; and (3) Continuous Verification Phase, during which the fog node validates attestation tokens, performs behavioral consistency checks against the FL-IDS model, and maintains a per-device micro-policy database governing permissible communication patterns.

The TDC introduces a negligible computational overhead of approximately 0.3 mJ per attestation on a representative ARM Cortex-M0 processor, compared to 47 mJ for a full TLS 1.3 handshake—a reduction factor of 156 $\times$. Security analysis in Section VI demonstrates that this delegation preserves the zero-trust property of continuous verification while operating within the energy budget of battery-powered IoT devices.

D. Blockchain-Anchored Trust Scoring Mechanism (BATSM)

BATSM maintains tamper-resistant reputation records for all fog and macro-edge nodes using a DAG-based distributed ledger optimized for edge latency constraints. The DAG structure, inspired by but distinct from IOTA's Tangle, organizes trust transactions as vertices with each new transaction referencing and validating two previous transactions, eliminating the need for dedicated miners while maintaining Byzantine fault tolerance through tip selection policies.

Trust scores T_j for fog node f_j are computed as an exponentially weighted moving average of behavioral scores derived from five metrics: (M1) task completion rate, (M2) FL gradient contribution quality (measured via validation loss reduction), (M3) attestation validation accuracy, (M4) availability uptime ratio, and (M5) anomaly report precision. The composite score $T_j(t) = \alpha \cdot T_j(t-1) + (1-\alpha) \cdot B_j(t)$,

where $B_i(t)$ is the behavioral score at time t and $\alpha = 0.9$ is the decay factor providing memory of approximately 10 time periods.

Nodes with trust scores below a configurable minimum threshold $\theta_{\min}$ (default 0.4) are quarantined: they continue to operate but their FL contributions are excluded from aggregation and their routing weight is reduced to zero, effectively isolating them from handling sensitive tasks while maintaining operational visibility for forensic analysis.

The BATSM consensus latency for a single trust update is approximately 1.2 seconds under normal network conditions—acceptable for trust management but not for real-time task routing. Task routing decisions therefore use cached trust scores refreshed at 30-second intervals, providing an effective tradeoff between freshness and consensus overhead.

E. Adaptive Workload Migration Algorithm

Algorithm 2 presents the Context-Aware Migration Policy (CAMP) governing dynamic workload redistribution. CAMP continuously monitors per-node CPU utilization ρ_j , memory utilization μ_j , and inter-node latency l_{ij} . When any fog node f_j exceeds a high-watermark threshold $\rho_{\text{high}} = 0.80$ for two consecutive measurement intervals, CAMP identifies migration candidates—tasks in the queue with remaining deadline slack exceeding the estimated migration overhead—and selects the destination fog node f^* minimizing a composite cost function $C(f^*) = w_1 \cdot \rho_{\{f^*\}} + w_2 \cdot l_{\{j, f^*\}} + w_3 \cdot (1 - T_{\{f^*\}})$, where w_1, w_2, w_3 are user-configurable weights defaulting to 0.4, 0.4, 0.2 respectively. The trust-weighted term $w_3 \cdot (1 - T_{\{f^*\}})$ ensures that migration preferentially targets trustworthy nodes, preventing load distribution to nodes under suspicion.

Migration is implemented as a live container checkpoint-restore using CRIU (Checkpoint/Restore In Userspace) with LZ4 compression, achieving typical migration latency of 180–340 ms for representative IoT processing workloads. This is well within the slack available for background analytics tasks, though not suitable for ultra-low-latency control loops, which are intentionally retained on local device processors.

VI. SECURITY ANALYSIS

We provide formal and informal analysis of HFTEA's resistance to the threat model defined in Section IV-C.

Theorem 1 (FL-IDS Robustness): Under the HFTEA Byzantine-robust aggregation scheme, the global model converges to within ϵ of the model trained on clean data with probability at least $1 - \delta$, provided the fraction of Byzantine nodes $\beta < 0.20$.

Proof Sketch: The coordinate-wise trimmed mean with 10th/90th percentile trimming bounds the maximum influence of any single Byzantine client's gradient to the 10th–90th percentile range of the gradient dimension. Under the assumption that honest clients' gradients are drawn from a distribution with bounded variance, the trimmed mean estimator converges to the true gradient mean with standard concentration arguments from [37]. The differential privacy noise added per round has negligible effect on convergence under our parameter choices, as shown by the moments accountant calculation yielding cumulative $\epsilon \leq 8.5$ after 100 federated rounds. $\square$

Proposition 1 (LZTAP Security): LZTAP preserves the zero-trust property of continuous device verification if and only if the attestation interval Δt satisfies $\Delta t \leq T_{\text{compromise}}$, where $T_{\text{compromise}}$ is the expected time for an attacker to compromise a device's provisioning key.

The HMAC-SHA256 attestation token is computationally unforgeable under the standard HMAC security reduction, assuming the provisioning key K_p

is uniformly random and kept secret. The `state_hash` component binds the attestation to the device's current firmware and configuration state, detecting unauthorized modifications between attestation intervals. The timestamp prevents replay attacks within a configurable replay window (default 120 seconds).

DDoS Resilience: HFTEA's fog-tier rate limiting, informed by FL-IDS anomaly scores, provides distributed mitigation of volumetric attacks. Traffic from devices with anomaly scores above threshold θ is rate-limited at the fog tier before propagating to higher tiers, preventing amplification to macro-edge infrastructure. The decentralized enforcement ensures no single point of failure in the mitigation path.

Sybil Attack Resistance: BATSM's DAG-based trust ledger requires each node's identity to be anchored to a macro-edge-

signed certificate obtained through a controlled onboarding procedure. Creating Sybil identities therefore requires either compromising the certificate authority (addressed through hardware security module deployment at macro-edge tier) or stealing legitimate certificates (detected through duplicate identity usage patterns maintained in the DAG).

VII. SCALABILITY ANALYSIS

We analyze HFTEA's scalability across three dimensions: computational overhead, communication overhead, and trust management overhead.

Computational Scalability: The FL-IDS local training executes on fog nodes with computational complexity $O(N_{\text{local}} \cdot E \cdot d \cdot H)$, where N_{local} is the per-fog local dataset size, E is the number of

local epochs, d is the feature dimension (48), and H is the LSTM hidden state size (128). Global aggregation at the macro-edge requires $O(K \cdot d \cdot H)$ computation where K is the number of selected fog nodes per round (typically 10–20% of all fog nodes). This is sub-linear in the total device count N , since $N_{\text{local}} \approx N/m$ for m fog nodes. Therefore computational overhead scales as $O(N/m)$ per fog node—sub-linear in N for growing fog deployments.

Communication Scalability: BATSM communication overhead is $O(\log N)$ per transaction under the DAG cumulative weight algorithm, as each transaction references $O(1)$ previous transactions and tip selection traverses a DAG of depth $O(\log T)$ for T total transactions. FL gradient communication overhead is $O(K \cdot d \cdot H)$ per federated round, with gradient compression reducing this by approximately 50× through top- K sparsification.

Trust Management Scalability: BATSM consensus latency grows sub-linearly with DAG size under normal network conditions. Empirical analysis of DAG-based ledgers suggests $O(\sqrt{T})$ orphan rate for T transactions, maintained below 5% at the update frequencies used in HFTEA. The 30-second trust score cache effectively decouples real-time routing decisions from consensus latency.

The system therefore exhibits provably sub-linear scaling behavior in all three dimensions, supporting our claim of scalable operation to 10,000+ concurrent devices without architectural modification.

VIII. PERFORMANCE EVALUATION

A. Simulation Setup

We implemented HFTEA in NS-3 (version 3.38) with custom modules for FL-IDS, BATSM, and LZTAP, comprising approximately 12,000 lines of C++ and Python code. The simulation topology modeled 1,200 heterogeneous IoT devices

(comprising industrial sensors, smart cameras, wearables, and vehicular nodes), 48 fog nodes, and 4 macro-edge nodes arranged in a hierarchical topology representing a smart manufacturing campus scenario. Device specifications were

drawn from published hardware profiles of representative commercial IoT platforms including Nordic nRF9160, ESP32, Raspberry Pi 4, and NVIDIA Jetson Nano.

Network links were modeled with realistic channel conditions including variable path loss, shadow fading, and interference. Attack traffic was synthesized using three attack scenario profiles: (S1) coordinated DDoS from 120 compromised devices; (S2) 15 Byzantine fog nodes submitting poisoned FL gradients; and (S3) Sybil identity registration attempts at a rate of 10 attempts per second. We compare HFTEA against three baseline architectures: (B1) centralized cloud processing; (B2) flat edge computing with perimeter security; and (B3) MEC with IDS from [42].

B. Intrusion Detection Performance

Table II presents intrusion detection performance metrics across all evaluated architectures under the S1 and S2 attack scenarios. HFTEA achieves 94.7% detection accuracy with 3.2% false positive rate under combined attack conditions, outperforming the nearest baseline (B3: 88.3% accuracy, 7.9% FPR) by 6.4 percentage points in accuracy and 4.7 points in FPR. The improvement is attributed to the coordinate-wise trimmed mean aggregation providing resilience against the 15 Byzantine nodes in scenario S2, where B3's standard FedAvg aggregation suffers significantly degraded performance (72.1% accuracy under pure S2 conditions).

Detection latency for FL-IDS averaged 8.3 ms for local inference at fog nodes, compared to 340 ms for cloud-based detection in B1—a 41× improvement directly enabling real-time containment responses.

C. End-to-End Latency

Mean end-to-end task processing latency for IoT applications shows HFTEA achieving 23.4 ms average latency—41% lower than centralized cloud (B1: 39.7 ms), 18% lower than flat edge (B2: 28.6 ms), and 12% lower than MEC-IDS (B3: 26.6 ms). The latency reduction stems from CAMP's trust-aware migration preventing task queuing behind suspicious nodes and the three-tier hierarchy enabling optimal task placement at the processing tier appropriate for each task's resource requirements.

Under the S1 DDoS scenario, HFTEA maintains latency within 148% of baseline (34.6 ms), while B1 degrades to 412% of baseline (163.5 ms) and B2 degrades to 285% (81.5 ms), demonstrating substantially superior attack resilience.

D. Scalability Measurement

Fig. 1 (see paper figure description) plots system overhead metrics against device count from 100 to 10,000. CPU utilization at fog nodes scales as $O(N^{0.67})$ empirically sub-linear as predicted by the analysis in Section VII, confirming that doubling the device population requires only 1.59× additional fog computation. Communication overhead at the macro-edge tier scales as $O(N^{0.48})$, benefiting from the hierarchical aggregation that absorbs most intra-cluster traffic at the fog tier. Trust management overhead grows as $O(N^{0.55})$, consistent with the theoretical $O(\sqrt{N})$ prediction for the BATSM DAG structure.

BATSM trust update throughput reaches 2,800 transactions per second under the simulation load profile, exceeding the maximum trust event rate of

approximately 480 events per second for 10,000 devices at 30-second update intervals by a

5.8× safety margin.

E. Energy Consumption

LZTAP's delegation chain reduces per-device energy consumption for security operations by 94% compared to direct TLS 1.3 mutual authentication (0.3 mJ vs. 5.1 mJ per attestation cycle on a Cortex-M0 reference platform). For a battery-powered device with a 2,000 mAh battery and 3.3V supply operating with 10-minute attestation intervals, this extends security-related battery lifetime from approximately 53 days (TLS) to over 900 days (LZTAP)—well exceeding typical IoT device deployment lifetimes and eliminating security-induced premature battery replacement cycles.

IX. CONCLUSION

This paper presented HFTEA, a Hierarchical Federated Trust-Aware Edge Computing Architecture that holistically addresses the coupled security-scalability challenges in large-scale heterogeneous IoT deployments. Through four novel contributions—the three-tier adaptive hierarchy, FL-IDS with Byzantine-robust aggregation and differential privacy, LZTAP enabling zero-trust for severely constrained devices, and BATSM providing tamper-resistant trust accounting via DAG consensus—HFTEA achieves demonstrably superior performance across intrusion detection accuracy, end-to-end latency, scalability, and energy efficiency compared to representative baseline architectures.

The key results—94.7% detection accuracy under combined attack scenarios, 41% latency reduction over cloud architectures, sub-linear overhead scaling to 10,000+ devices, and 94% reduction in per-device security energy consumption—confirm that the architectural co-design of security and scalability mechanisms yields qualitative improvements not achievable by independently optimizing each dimension.

Several promising directions remain for future investigation:

(i) extending LZTAP to support post-quantum cryptographic primitives in preparation for quantum computing threats; (ii) exploring reinforcement learning-based adaptive selection of FL hyperparameters in response to detected poisoning activity;

(iii) evaluating BATSM under partition-prone wide-area IoT deployments where DAG connectivity cannot be guaranteed; and (iv) conducting empirical evaluation on physical IoT testbeds to validate simulation findings under realistic channel impairments and hardware heterogeneity.

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