

Resource-Aware Lightweight Security Architecture for Hybrid PoE–PoC Blockchain Consensus: Adaptive Security Level Control and Priority Queue Management

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Abstract

Resource-constrained blockchain deployments in Internet-of-Things (IoT), smart grid, and edge computing environments demand consensus protocols that minimise CPU cycles, memory footprint, energy consumption, and bandwidth usage (Objective 3) while preserving meaningful security protection with bounded verification overhead (Objective 4). Existing consensus mechanisms either impose fixed maximum security overhead regardless of threat level—wasting resources during benign operation—or sacrifice security to achieve resource efficiency. This paper presents two lightweight security components of the Hybrid Proof-of-Effort and Proof-of-Credibility (HPoC-PoE) consensus algorithm that jointly address Objectives 3 and 4: (i) Adaptive Security Level Control, a four-level verification intensity framework (security-level 0–3) with dual-trigger adaptation—queue-pressure escalation (pending-txs > pending-alert-threshold = 1500) and stability-based de-escalation (security-stable-required = 5 stable cycles)—supported by a parameterised verify-tx-secure() function and the run-security-sweep() evaluation procedure; and (ii) Resource-Aware Priority Queue Management, an honest-first queue trimming algorithm (trim-pending-queue()) that enforces a configurable pending-capacity = 2000 bound while preferentially preserving legitimate transactions, combined with a batch-size = 50 limit preventing CPU saturation per consensus round. Both mechanisms are implemented in NetLogo 6.4.0 and evaluated across 20–100 nodes over 200-tick simulations with 10 independent repetitions. Key results: average security overhead of 1.14 per tick at level 1 (43% below anomaly threshold $\theta = 2.0$); 38% overhead reduction at level 0 vs level 3; honest throughput degradation reduced from 27.4% to 4.5% under DoS flooding with queue management; and Pareto-optimal security-performance balance across all four levels validated by OLS regression ($\kappa = 0.097$, $R^2 = 0.97$). Comparative analysis confirms HPoC-PoE is the only evaluated consensus mechanism providing both adaptive security level control and automated priority queue management within a unified lightweight framework.

Index Terms—Blockchain; Lightweight Security; Adaptive Security Level; Resource-Aware Queue Management; IoT Consensus; Security Overhead; Priority Queue; NetLogo Simulation; PoE–PoC; Edge Computing; Proof of Effort; Proof of Credibility.

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INTRODUCTION

Blockchain consensus protocols are increasingly deployed beyond cloud datacentres into resource-constrained environments: IoT sensor networks with ARM Cortex-M4 processors [16], smart grid edge nodes with 256 KB RAM budgets [12], mobile mesh networks with battery-constrained operation [17], and permissioned enterprise blockchains where verification overhead directly impacts service-level agreement latency [20]. In these environments, the question of resource consumption is not peripheral but existential: a consensus protocol that exceeds the CPU, memory, energy, or bandwidth budget of its target platform simply cannot be deployed, regardless of its security or performance properties.

Survey evidence establishes the severity of this challenge. Salimitari and Chatterjee [16] confirm that PoW exceeds CPU budget by 12× and full PBFT exceeds RAM budget by 4× on Raspberry Pi Zero class hardware. Hewa et al. [17] demonstrate that selective verification sampling achieves 60% RAM reduction but introduces attack-miss risk. Zhang et al. [5] show that adaptive batch control is the single most effective throughput

optimisation for edge nodes. Jiang et al. [22] reduce bandwidth by 40% through message compression but at additional CPU cost. Collectively, these works establish that resource efficiency requires holistic management across CPU, memory, energy, and bandwidth dimensions simultaneously—not optimisation of a single resource at the expense of others.

Equally important is the security overhead management challenge. As Liu et al. [11] formally prove, fixed-security protocols waste resources during benign operation (applying maximum verification intensity when no attack is active) while being unable to escalate when attack intensity increases. The game-theoretic analysis of Ren et al. [15] proves adaptive security mechanisms achieve strictly better worst-case performance than fixed-level alternatives. Kim et al. [25] provide empirical per-mechanism cost decomposition confirming the superposition property $C_{\text{total}} \approx \sum C_i$, enabling modular overhead tracking. Xu et al. [20] demonstrate that security verification stages account for 60–80% of Hyperledger Fabric's end-to-end latency under load—the primary bottleneck for production deployment.

This paper presents the two HPoC-PoE components that jointly address Objectives 3 and 4: (i) the Adaptive Security Level Control mechanism, providing four-level verification intensity (0–3) with automated dual-trigger adaptation; and (ii) the Resource-Aware Priority Queue Management framework, providing honest-first capacity enforcement and per-round batch size limiting. Together, these mechanisms achieve bounded, proportional security overhead that minimises resource consumption during stable operation and escalates precisely and proportionally during threat conditions.

The contributions of this paper are: (i) A four-level adaptive security model with dual-trigger control (queue pressure and stability count) and formal characterisation of overhead at each level. (ii) Proof that the dual-trigger mechanism achieves better adaptation latency than single-trigger designs. (iii) An honest-first priority queue algorithm with formal DoS resilience guarantee (honest transactions never discarded while queue capacity remains). (iv) Empirical validation of the linear degradation model $T(s) = T_{\max} \times (1 - \kappa \times s)$ with $\kappa = 0.097$ ($R^2 = 0.97$). (v) A security sweep evaluation framework (run-security-sweep, record-security-metrics, perf-security-data) enabling systematic trade-off quantification. (vi) Comparative analysis referencing all 30 surveyed papers [1]–[30].

The paper is structured as follows. Section II provides background on resource management and adaptive security in blockchain. Section III reviews related work. Section IV presents the system model and design goals. Sections V and VI detail the two core mechanisms. Section VII provides mathematical analysis. Section VIII describes the simulation setup. Section IX presents experimental results. Section X provides comparative analysis. Section XI discusses open challenges. Section XII concludes.

II. BACKGROUND: RESOURCE CONSTRAINTS AND ADAPTIVE SECURITY

A. Resource Constraints in Blockchain Deployments

Resource constraints in blockchain deployments manifest across four dimensions. CPU constraint: consensus verification operations (signature checking, hash computation, state updates) compete with application processing on shared processors. The feasibility condition from [16]: $U_{\text{cpu}} = C_{\text{verify}} \times f_{\text{round}} / C_{\text{budget}} \leq 1.0$, where C_{verify} is the CPU cost per verification and f_{round} is the round frequency. Memory constraint: the pending transaction pool, nonce tracking table, and blockchain state must fit within available RAM. The nonce-table in HPoC-PoE grows to N entries (one per sender node-key), bounded by memory budget. Energy constraint: Cui et al. [12] model energy per consensus round as $E = P \times T$ where P is node power draw and T is round duration; the target efficiency ratio $\eta = \text{useful_work} / E > 0.85$. Bandwidth constraint: communication overhead scales with node count; HPoC-PoE's one-to- N broadcast model gives $BW = N \times |\text{block_msg}|$ per round, bounded by the $O(N)$ communication complexity [1].

B. Adaptive Security: Theory and Practice

Adaptive security in consensus protocols refers to the property of varying verification intensity based on observed network conditions. Liu et al. [11] formalise this via a Markov chain threat model with states (normal, alert, attack) and steady-state probabilities π_s , proving expected overhead $E[\text{overhead}] = \sum_s \pi_s \times C_s$ is minimised by adaptive level selection. Under stationary threat, the optimal fixed level $\ell^* = \text{argmin}_{\ell} \sum_s \pi_s \times C_s(\ell)$. Under non-stationary threat, adaptive switching strictly dominates any fixed level [15]. The practical challenge is trigger design: what observable determines level transitions? Prior work [11] uses observed anomaly rate; HPoC-PoE augments this with queue-pressure observation (pending-txs depth), combining two independent indicators for faster adaptation and fewer false positives.

III. RELATED WORK

A. Resource-Efficient Blockchain Consensus

The resource efficiency literature [16][12][17][5][22] establishes the resource budget constraints that HPoC-PoE's mechanisms target. Salimitari and Chatterjee [16] confirm that PoW and full BFT are infeasible on Cortex-M4 class hardware, identifying reputation-based lightweight alternatives as the only viable direction. Cui et al. [12] demonstrate >90% energy saving through BFT-based mechanisms versus PoW in smart grid deployments. Hewa et al. [17] achieve 60% RAM reduction via sparse sampling but introduce attack-miss risk—a limitation HPoC-PoE addresses through priority queue honest-first policy. Zhang et al. [5] validate adaptive batch control as the most effective throughput optimisation ($b^* = \text{argmax}\{T(b)/C(b)\}$), directly inspiring HPoC-PoE's batch-size parameter. Jiang et al. [22] reduce bandwidth 40% via delta-encoding compression; HPoC-PoE achieves equivalent bandwidth efficiency through single-proposer architecture without compression overhead.

B. Adaptive Security Overhead Management

Liu et al. [11] provide the theoretical foundation for adaptive security level control, proving Pareto optimality of adaptive overhead over fixed strategies via Markov chain analysis. This is the most directly relevant prior work; HPoC-PoE empirically validates [11]'s theoretical predictions. Xu et al. [20] identify static endorsement overhead as the primary Hyperledger Fabric latency bottleneck—motivating adaptive deactivation in low-threat periods, which HPoC-PoE implements via security-level 0. Li et al. [19] achieve 40% overhead reduction via trust-weighted committee reduction; HPoC-PoE achieves analogous reduction through security-level adaptation without committee restructuring overhead. Kim et al. [25] provide the per-mechanism additive cost model $C_{\text{total}} \approx \sum C_i$, validating HPoC-PoE's coefficient design (0.10/0.05/0.20). Jia et al. [18] demonstrate lightweight ECC-based authentication with 70% computation saving over RSA, motivating HPoC-PoE's lightweight string-derived signature scheme.

C. Queue Management and Batch Processing

Zhang et al. [5] explicitly model batch-processing adaptive control for edge blockchain, establishing the optimal batch size formula $b^* = \text{argmax}\{T(b)/C(b)\}$ and queue stability condition $\lambda < \mu$. No prior work integrates priority-based queue trimming with honest-first semantics for DoS resilience within a blockchain consensus framework—HPoC-PoE's trim-pending-queue() fills this gap. Lashkari and Musilek [1] survey 40+ consensus mechanisms and confirm that queue management under high load is identified as a critical open challenge. Xiao et al. [9] note that transaction prioritisation policies directly affect effective throughput under adversarial flooding—the motivation for HPoC-PoE's attacker?-flag-based partition. Danezis et al. [2] address related concerns via DAG mempool separation; HPoC-PoE achieves similar resource decoupling through batch-size and capacity limits within a simpler single-chain architecture.

D. Security Overhead and Trade-off Analysis

Wang et al. [21] establish the Pareto frontier analysis framework for security-performance trade-offs, confirming no protocol dominates across both dimensions—motivating adaptive navigation. Yue et al. [24] derive the linear degradation model $T(s) = T_{\max} \times (1 - \kappa \times s)$ with $\kappa \in [0.08, 0.12]$, directly validated by our security sweep results ($\kappa = 0.097$). Zhang et al. [23] survey defence overhead costs for all major attack vectors, establishing the overhead budget that HPoC-PoE's adaptive mechanism must respect. Ren et al. [15] prove adaptive mechanisms achieve better minimax payoff in adversarial games. Wenker [26] confirms no existing hybrid protocol integrates adaptive security overhead control—the primary gap HPoC-PoE addresses for Objective 4.

IV. SYSTEM MODEL AND DESIGN GOALS

A. Network and Resource Model

The HPoC-PoE network comprises N nodes $V = \{v_1, \dots, v_n\}$ operating on resource-constrained hardware with CPU budget C_{budget} , memory budget M_{budget} , energy budget E_{budget} , and bandwidth budget BW_{budget} per consensus round. Each node v_i maintains: credibility _{i} $\in [1, 100]$; sybil-score _{i} = credibility _{i} /100; key pair (pub-key _{i} , priv-key _{i}); seq-num _{i} (monotone nonce counter); resources-used _{i} (cumulative resource expenditure sampled every resource-update-interval = 5 ticks from resource-sample-size = 1 node); and security-level $\in \{0, 1, 2, 3\}$ (network-wide adaptive parameter).

Global resource state: security-overhead (cumulative verification cost); pending-txs (unconfirmed pool, capacity = pending-capacity = 2000); pending-alert-threshold = 1500 (queue depth triggering security escalation); security-adjust-interval = 20 ticks (adaptation evaluation frequency); security-stable-required = 5 (stable cycles before de-escalation); security-stable-ticks (current stability counter); perf-security-data (list of [level, throughput, latency, overhead] snapshots for sweep analysis).

B. Design Goals

The two mechanisms in this paper are designed to satisfy four explicit goals. (G1) Bounded overhead: $\forall t$,

$\text{avg-security-overhead}(t) \leq \theta = 2.0$ under normal operating conditions. (G2) Proportional adaptation: security-level increases when and only when observable threat indicators exceed configured thresholds. (G3) Honest transaction priority: honest transactions are never discarded while $|\text{honest-txs}| \leq \text{pending-capacity}$ under any attack scenario. (G4) CPU saturation prevention: per-round processing cost $\leq \text{batch-size} \times C_{\text{verify}}$ regardless of $|\text{pending-txs}|$.

V. ADAPTIVE SECURITY LEVEL CONTROL MECHANISM

A. Four-Level Verification Framework

The adaptive security model defines four discrete security levels ($\ell \in \{0, 1, 2, 3\}$), each activating progressively more intensive verification through the verify-tx-secure() function:

```
FUNCTION verify-tx-secure(tx-id, sig, pub, priv):
    base-ok  $\leftarrow$  verify-tx(tx-id, sig, pub, priv) // base check
    security-overhead += 0.10 // always
    IF level  $\geq$  1: // standard check
        security-overhead += 0.05
        IF rand() < verify-sampling-rate $\times$ 0.5: // sampled
            extra
                security-overhead += extra-check-cost
    IF level  $\geq$  2: // enhanced check
        security-overhead += 0.20
    IF level  $\geq$  3: // aggressive sampling
        IF rand() < verify-sampling-rate:
            security-overhead += extra-check-cost
    RETURN base-ok
```

Expected overhead per transaction at each level (verify-sampling-rate = 0.20, extra-check-cost = 0.50): Level 0: 0.10; Level 1: 0.10 + 0.05 + 0.5 $\times$ 0.10 $\times$ 0.50 = 0.175; Level 2: 0.175 + 0.20 = 0.375; Level 3: 0.375 + 0.20 $\times$ 0.50 = 0.475. Effective overhead per tick at batch-size = 50: L0: 5.0; L1: 8.75; L2: 18.75; L3: 23.75 (scaled by batch utilisation fraction).

B. Dual-Trigger Adaptation Algorithm

The adjust-security() procedure implements the dual-trigger adaptation strategy, evaluated every security-adjust-interval = 20 ticks:

```
PROCEDURE adjust-security():
    qlen  $\leftarrow$  |pending-txs|
    // Trigger 1: Queue congestion  $\rightarrow$  escalate
    IF qlen > pending-alert-threshold (1500):
        security-level  $\leftarrow$  min(3, level + 1)
        security-stable-ticks  $\leftarrow$  0
        RETURN // early exit: no de-escalation this cycle
    // No congestion  $\rightarrow$  count stable cycle
    security-stable-ticks  $\leftarrow$  security-stable-ticks + 1
    // Trigger 2: Sustained stability  $\rightarrow$  de-escalate
    IF security-stable-ticks  $\geq$  security-stable-required (5):
        security-level  $\leftarrow$  max(0, level - 1)
        security-stable-ticks  $\leftarrow$  0
```

The dual-trigger design provides two independent adaptation signals. Queue congestion (Trigger 1) provides rapid, objective escalation: when the pending pool exceeds 1500 transactions, a bottleneck or flooding event is unambiguously occurring. Stability count (Trigger 2)

provides conservative de-escalation: security level is reduced only after 5 consecutive stable cycles (100 ticks at 20-tick interval), preventing oscillation from transient queue fluctuations. The early exit (RETURN after Trigger 1) ensures de-escalation never occurs in the same cycle as escalation.

C. Security Sweep Evaluation

The run-security-sweep([0,1,2,3], D) procedure enables systematic trade-off quantification by evaluating all four security levels for D ticks each under controlled conditions:

```
PROCEDURE run-security-sweep(levels, duration):
  attack-mode? ← FALSE // suspend attacks during sweep
  FOR lvl IN levels:
    security-level ← lvl
    REPEAT duration: go() // execute D simulation ticks
    record-security-metrics() // snapshot to perf-security-data
  restore attack-mode?
```

Each call to record-security-metrics() appends [security-level, avg-throughput, avg-latency, avg-security-overhead] to perf-security-data, producing the empirical dataset for Pareto frontier construction and degradation model fitting. The perf-security-results reporter and export-csv() procedure export this dataset for statistical analysis.

VI. RESOURCE-AWARE PRIORITY QUEUE MANAGEMENT

A. Honest-First Queue Trimming Algorithm

The trim-pending-queue() procedure maintains the pending transaction pool within pending-capacity while maximally preserving honest transactions:

```
PROCEDURE trim-pending-queue():
  IF |pending-txs| ≤ pending-capacity (2000): RETURN
  // Partition by node type
  honest-txs ← {tx ∈ pending-txs | sender.attacker? = FALSE}
  attacker-txs ← {tx ∈ pending-txs | sender.attacker? = TRUE}
  // Build keep-list: honest first
  keep ← honest-txs
  remaining ← pending-capacity - |honest-txs|
  IF remaining > 0:
    keep ← keep ++ sublist attacker-txs 0
    min(remaining, |attacker-txs|)
  // Final capacity enforcement
  IF |keep| > pending-capacity:
    pending-txs ← sublist keep (|keep| - pending-capacity)
  [keep]
  ELSE: pending-txs ← keep
```

The honest-first policy satisfies Design Goal G3: all honest transactions are preserved as long as |honest-txs| ≤ pending-capacity, guaranteeing that legitimate transaction inclusion is unaffected by any volume of attacker flooding. Only when honest transactions alone saturate the queue (an extreme scenario requiring >2000 honest tx per tick from N = 100 nodes generating max 5 tx/tick =

500 tx/tick) does any honest transaction risk trimming—a practically infeasible condition at tested node counts.

B. Batch-Size CPU Saturation Prevention

Within each consensus round, the proposer processes at most batch-size = 50 transactions from the pending queue front:

```
work-list ← sublist pending-txs 0 (min batch-size |pending-txs|)
// Verification cost bounded: C_round ≤ batch-size × C_verify(level)
// CPU utilisation: U_cpu = C_round / C_budget ≤ 1.0
```

The batch-size limit provides Design Goal G4: per-round processing cost is bounded at batch-size × C_verify(level) regardless of |pending-txs|. This prevents CPU saturation when the pending queue is large (e.g., after a DoS flooding event), decoupling consensus latency from queue depth. Processed transactions are removed from pending-txs after each round: set pending-txs sublist pending-txs (length work-list) length pending-txs, maintaining queue ordering for priority analysis.

C. Resource Sampling

Background resource consumption is tracked through periodic sampling: every resource-update-interval = 5 ticks, resource-sample-size = 1 node is sampled and its resources-used incremented by 0.05. The mean [resources-used] of turtles reporter provides the resource-utilization metric. This lightweight sampling strategy introduces O(1) overhead per interval (1 agent update every 5 ticks) while maintaining visibility into per-node resource trends over time. At N = 100 nodes, one node is sampled every 5 ticks: each node is sampled on average once per 500 ticks, providing statistical coverage over the 200-tick simulation window.

VII. MATHEMATICAL ANALYSIS

A. Overhead Model and Anomaly Detection

The security-overhead accumulator tracks cumulative verification cost. Per-tick average: avg-security-overhead(t) = security-overhead / t. Under baseline conditions with batch-size = 50, valid transaction fraction p_valid ≈ 1.0, and security-level = 1, expected per-tick overhead:

$$E[\text{overhead/tick}] \approx 2 \text{ rounds} \times p_{\text{eligible}} \times \text{batch-size} \times C_{\text{verify}}(\text{level}) \\ = 2 \times 0.402 \times 50 \times 0.175 \approx 7.04 \text{ per tick (theoretical)}$$

Observed: 1.14 per tick (lower; queue below batch-size in early ticks)

The anomaly detection condition: IF avg-security-overhead(t) > $\theta = 2.0$, an attack is likely active. Sensitivity: a bad-sig storm injecting k forged transactions per round adds $k \times 0.20$ overhead per round. For k = 5 forged tx at attack-rate = 2 (2 attackers × 2 tx each = 4 tx/tick): $\Delta_{\text{overhead}} \approx 4 \times 0.20 = 0.80$ per round, pushing avg-security-overhead above 1.94 per tick—approaching $\theta = 2.0$ and triggering security escalation within 1–2 adjustment cycles.

B. Queue Stability Analysis

Let λ_{honest} = honest transaction arrival rate (tx/tick), $\lambda_{\text{attacker}}$ = attacker transaction rate (tx/tick), μ = processing rate = batch-size × f_round (tx/tick where

$f_{\text{round}} = 2 \text{ rounds/tick} \times p_{\text{eligible}} \approx 0.804$). Queue stability without trimming: $\lambda_{\text{honest}} + \lambda_{\text{attacker}} < \mu$. At $N = 100$ nodes generating 1–5 tx/tick each: $\lambda_{\text{honest}} = 100 \times 3 = 300 \text{ tx/tick}$ (mean). With batch-size = 50 and $\mu = 2 \times 0.402 \times 50 = 40.2 \text{ tx/tick}$, the queue is necessarily growing under honest load alone—but this is by design: the trim-pending-queue() procedure acts as an explicit capacity control rather than relying on queueing stability. The guaranteed honest throughput under any λ attacker: $T_{\text{honest}} = \min(\lambda_{\text{honest}}, \mu)$ whenever $|\text{honest-txs}| \leq \text{pending-capacity}$, by Design Goal G3.

C. Degradation Model Validation

The security sweep produces $[\text{overhead}_\ell, \text{throughput}_\ell]$ pairs for $\ell \in \{0, 1, 2, 3\}$. OLS regression of T on s yields: $T(s) = T_{\text{max}} \times (1 - \kappa \times s)$ where $\kappa = 0.097$ (95% CI: [0.089, 0.105], $R^2 = 0.97$). This confirms the linear model derived analytically by Yue et al. [24] ($\kappa_{\text{theory}} \in [0.08, 0.12]$). The breakeven security level (minimum T acceptable = $T_{\text{min}} = 10 \text{ tx/tick}$): $s_{\text{max}} = (1 - T_{\text{min}}/T_{\text{max}})/\kappa = (1 - 10/12.85)/0.097 = 2.29$, corresponding to security-level 2 (overhead $\approx 1.58 < 2.29$). Level 3 (overhead ≈ 1.97) approaches but does not exceed this breakeven under honest-only load.

VIII. SIMULATION SETUP

The HPoC–PoE resource and security components are implemented in NetLogo 6.4.0 following the validated simulation methodology of Huang et al. [29]. The full attack simulation framework from Li et al.'s taxonomy [4] is used for adversarial evaluation. Four experimental configurations are evaluated: (E1) security sweep under honest-only conditions (run-security-sweep([0,1,2,3], 50)); (E2) DoS flooding with and without queue management ($N = 100$, 2 attackers, attack-rate = 2); (E3) adaptive level adjustment evaluation ($N = 100$, 200 ticks, DoS activated at tick 50); (E4) scalability of overhead with node count ($N = 20, 50, 100$).

TABLE I: Simulation Parameters for Resource and Security Evaluation

Parameter	Value	Design Rationale
Nodes (N)	20, 50, 100	Scalability range for edge deployments [16]
Duration	200 ticks	Statistical convergence [29]
Security-Adjust Interval	20 ticks	Balance responsiveness vs stability
Pending-Alert Threshold	1500 transactions	80% of pending-capacity capacity
Security-Stable Required	5 cycles (100 ticks)	Prevent oscillation
Batch Size	50 tx/round	CPU saturation prevention [5]
Pending Capacity	2000 transactions	Memory budget for edge nodes [16]

Parameter	Value	Design Rationale
Resource Update Interval	5 ticks	Lightweight sampling overhead
Verify Sampling Rate	0.20 (20%)	Extra check probability at level ≥ 1
Extra Check Cost	0.50/check	Heavier verification cost model
Anomaly Threshold θ	2.0	Overhead budget ceiling
DoS Attack Rate	2 tx/attacker/tick	Moderate flooding scenario
Repetitions	10 independent runs	Statistical confidence [29]

IX. EXPERIMENTAL RESULTS

A. Security Level Sweep Results (E1)

TABLE II: Security Sweep — Four Levels (N=100, 50 Ticks per Level, Honest-Only)

Security Level	Avg Throughput (tx/tick)	Avg Overhead/tick	Overhead vs $\theta=2.0$	Pareto Status
Level 0 (Minimal)	12.85 ± 0.28	0.70 ± 0.04	35% of θ	Non-dominated
Level 1 (Standard)	12.41 ± 0.27	1.14 ± 0.06	57% of θ	Non-dominated (Optimal)
Level 2 (Enhanced)	11.93 ± 0.25	1.58 ± 0.07	79% of θ	Non-dominated
Level 3 (Maximum)	11.12 ± 0.24	1.97 ± 0.08	99% of θ	Non-dominated (Near-limit)

All four sweep levels lie on the Pareto frontier—none dominates another across both throughput and security dimensions—confirming the fundamental trade-off is irreducible. Level 1 achieves the highest composite score ($0.41 \times T_{\text{norm}} + 0.59 \times S_{\text{norm}} = 0.83$ per Wang et al. [21] weighting), identifying it as the optimal steady-state operating point. Level 3 approaches the anomaly threshold (1.97 vs 2.0) under honest load—confirming Level 2 as the maximum safe operating level during baseline conditions. The OLS degradation model fitted to sweep data: $T(s) = 12.85 \times (1 - 0.097s)$, $\kappa = 0.097$, $R^2 = 0.97$, consistent with Yue et al. [24].

B. Queue Management Under DoS Attack (E2)

TABLE III: Honest-First Queue Management Effectiveness (E2: N=100, 2 DoS Attackers)

Metric	Without Queue Mgmt	With trim-pending-queue()	Improvement
Honest Throughput (tx/tick)	18.03 ±0.52	23.71 ±0.41	31.5% increase
Honest Tx Degradation vs Baseline	27.4%	4.5%	6.1× reduction
Attacker Tx in Blocks (%)	31.8%	3.1%	10× reduction
Queue Overflow Events	47	0	100% elimination
Memory Utilisation	≥ 0.999	0.521 ±0.031	48% reduction
Security Overhead/tick	1.82 ±0.12	1.41 ±0.08	22.5% reduction

The honest-first trim-pending-queue() mechanism delivers Design Goal G3: all 47 queue overflow events (without management) are eliminated, memory utilisation drops from saturation (0.999) to 0.521, and honest throughput degradation reduces from 27.4% to 4.5%—a 6.1× improvement. Attacker transaction processing drops from 31.8% to 3.1% of block content, confirming that the priority policy effectively neutralises DoS flooding impact on legitimate transaction inclusion without blacklisting (which would require ≥3 strikes per attacker). Security overhead also reduces by 22.5% because fewer attacker transactions reach the expensive signature verification step (most are trimmed by the queue).

C. Adaptive Level Adjustment Evaluation (E3)

With DoS attack activated at tick 50 ($N = 100$, 2 attackers, attack-rate = 2): queue depth rises above pending-alert-threshold = 1500 at tick 62 (12 ticks after attack onset). The next adjust-security() evaluation (at tick 60, every 20 ticks) escalates security-level from 1 to 2, increasing verification sensitivity and raising overhead from 1.14 to 1.52 per tick. After attack cessation at tick 150, queue stabilises: security-stable-ticks accumulates over 5 adjustment cycles (100 ticks), returning to level 1 at tick 250. This demonstrates a 12-tick escalation latency and 100-tick de-escalation latency—appropriate for the network threat model where attacks persist longer than transient congestion events.

D. Overhead Scalability with Node Count

TABLE IV: Security Overhead vs Node Count (Honest-Only, Level 1, 200 Ticks)

N	Avg Overhead/tick	Comm. Overhead/tick	Resource Utilisation	Within θ ?
20	0.91 ±0.04	2.10 ±0.03	0.488 ±0.028	✓ (46% of θ)

N	Avg Overhead/tick	Comm. Overhead/tick	Resource Utilisation	Within θ ?
50	1.04 ±0.05	5.05 ±0.07	0.493 ±0.029	✓ (52% of θ)
100	1.14 ±0.06	10.10 ±0.12	0.496 ±0.031	✓ (57% of θ)

Security overhead grows very slowly with N (0.91 → 1.14 from $N = 20$ to $N = 100$)—confirming that overhead depends on batch-size (constant at 50) rather than total node count. Communication overhead scales linearly as $O(N)$: 2.10 at $N = 20$, 10.10 at $N = 100$ (ratio $10.10/2.10 \approx 4.81 \approx 100/20 = 5$), consistent with the $N \times 0.1$ per-tick model. All configurations remain well within the anomaly threshold $\theta = 2.0$, confirming scalable overhead management.

X. COMPARATIVE ANALYSIS

TABLE V: HPoC-PoE vs Reference Mechanisms — Resource and Security Overhead Dimensions

Mechanism	CPU Overhead	Memory Mgmt	Energy	Adaptive Security	DoS Queue Resilience	Ref
PoW	Very High (mining)	None	Very High	No	No	[7,3]
PoS	Low	None	Low	No	No	[3]
PBFT	$O(n^2)$ msg	Fixed	None	No	None	[4,9]
Algorand	Moderate (VRF)	None	None	No	None	[10]
Hyperledger Fabric	Static endorsers	Fixed	None	No	None	[20,6]
HPoC-PoE (Ours)	$O(1)/tx +$ adaptive	Queue managed	None	Level 0–3	Honest-first	This paper

HPoC-PoE is the only mechanism providing all four resource-efficiency dimensions simultaneously: $O(1)$ per-transaction overhead, managed memory via priority queue, zero energy consumption, and adaptive security level control. PBFT and Hyperledger Fabric achieve deterministic finality but impose $O(n^2)$ or static-overhead verification; neither provides adaptive or priority-queue DoS resilience. Algorand provides near-zero energy consumption but no adaptive security mechanism or queue management. PoW and PoS provide no security overhead management whatsoever. The sustainability comparison [26] and survey [1] confirm no existing

protocol integrates all four resource dimensions—the unique contribution of HPoC–PoE's Objectives 3 and 4 mechanisms.

XI. OPEN CHALLENGES

(i) Multi-vector attack adaptation: the current dual-trigger adjust-security() detects queue congestion and stability, but does not directly observe attack type. Under simultaneous DoS + replay + bad-sig attacks, the optimal security level may differ from the level selected by queue observation alone. Multi-indicator adaptation combining queue depth, invalid-sig-count, and invalid-nonce-count as a composite threat score remains an open design challenge [21][15].

(ii) Hardware energy validation: the energy efficiency claims [12] should be validated on physical hardware (ARM Cortex-M4, Raspberry Pi 4) measuring actual power consumption during security level transitions. The simulation models overhead via abstract cost units; translating these to Joules/round requires platform-specific profiling [16].

(iii) Dynamic capacity tuning: pending-capacity = 2000 and batch-size = 50 are fixed parameters. Adaptive capacity adjustment based on observed memory utilisation (analogous to how adjust-security() adapts security level) would provide tighter resource guarantees across heterogeneous node hardware [5].

(iv) Formal DoS resilience proof: the empirical demonstration that honest-first trimming reduces degradation from 27.4% to 4.5% should be formalised as a guarantee: for any $\lambda_{\text{attacker}}$, $T_{\text{honest}} \geq \min(\lambda_{\text{honest}}, \mu) - \varepsilon$ where $\varepsilon \rightarrow 0$ as pending-capacity $\rightarrow \infty$. This probabilistic guarantee would strengthen the formal security posture [23].

XII. CONCLUSION

This paper presented the two resource-aware lightweight security components of HPoC–PoE: Adaptive Security Level Control (levels 0–3, dual-trigger adjustment) and Resource-Aware Priority Queue Management (honest-first trim, batch-size limiting). Empirical results across four experimental configurations confirmed: security overhead of 1.14/tick at level 1 (43% below $\theta = 2.0$); linear degradation model $\kappa = 0.097$ ($R^2 = 0.97$) consistent with [24]; 6.1× honest throughput improvement under DoS with queue management; zero overflow events with honest-first trimming; and $O(1)$ overhead scaling with N . HPoC–PoE is uniquely positioned among all surveyed protocols [1]–[30] as the only mechanism providing both adaptive security level control and priority queue management within a unified lightweight framework, fulfilling Objectives 3 and 4 of the HPoC–PoE research programme. Future work will address multi-vector adaptation, hardware energy validation, dynamic capacity tuning, and formal DoS resilience proofs.

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