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Adaptive Trust Models for Wireless Sensor Networks Using Blockchain and Edge Intelligence

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ABSTRACT

Environmental sensing, smart city applications, industrial automation, and contemporary monitoring all depend on wireless sensor networks. However, there are serious trust and security issues because of their dispersed structure, resource limitations, and deployment in frequently dangerous locations. Conventional wireless sensor network trust systems rely on centralized authority and local reputation metrics, which have issues with scalability, adaptability, and resistance to complex attacks. In order to provide a reliable, scalable, and comprehensible trust management solution for wireless sensor networks, this study suggests an integrated architecture that blends adaptive trust modeling with blockchain-backed ledgering and edge intelligence. The suggested methodology records trust anchors, transaction summaries, and policy updates utilizing an immutable blockchain layer, periodic aggregation and adaptive fusion at edge devices using machine learning, and lightweight local trust estimators at sensor nodes. The system constantly modifies the trust weighting based on ambient inputs, node behavior, and context. We introduce the system architecture, formal trust update rules, a lightweight consensus and storage approach appropriate for limited contexts, and a security analysis that addresses common threats like collusion, on-off assaults, Sybil attacks, and fake data injection. When compared to baseline reputation systems, a simulation-based study shows improvements in the detection of misbehaving nodes, a decrease in false positives, and resilience against coordinated attacks. The method provides obvious routes to deployment in practical WSN applications while striking a compromise between enhanced network-level security and energy and communication overhead.

Keywords: wireless sensor networks, trust management, blockchain, edge intelligence, adaptive models, reputation, security.

1. INTRODUCTION

Wireless sensor networks are now a crucial component of contemporary digital infrastructure. In industries like smart cities, healthcare, agriculture, logistics, and environmental management, they facilitate intelligent decision-making, automate industrial processes, and provide ongoing monitoring [1]. Their strength is their capacity to use a dispersed network of low-power devices to collect fine-grained, real-time data from enormous physical locations. Security and trust management are now at the center of WSN operations and research as deployments increase in size and significance [2].

WSNs have long-standing vulnerabilities due to the nature of the nodes themselves, despite their benefits. Sensors are frequently used in harsh or isolated situations, are cheap, and have limited resources [3]. They communicate via unprotected wireless channels, run on a little amount of battery power, and are not physically protected. Since many nodes are left unattended for extended periods of time after deployment, attackers find them to be appealing targets [4]. The integrity of the entire network can be jeopardized by a compromised node's ability to subtly modify data streams, impersonate other nodes, interfere with routing, or inject false readings [5].

Conventional trust systems are based on basic reputation scores derived from neighbor interactions or local observations. Large, heterogeneous deployments are difficult for these techniques to handle, but they are effective for small networks with predictable behavior [6]. Rapid changes in behavior are not captured by static trust weights. Colluding groups can alter simple averaging. Single points of failure and bottlenecks are produced by a centralized trust authority. Furthermore, traditional reputation systems are unable to meet the growing demands of decision makers for traceability and transparency [7].

Two significant advancements present fresh opportunities to overcome these constraints. First, decentralized trust information management techniques and tamper-evident recordkeeping are made possible by blockchain technology. Low-power sensors cannot participate fully in the blockchain, but selective anchoring and lightweight permissioned ledgers can enable auditability without taxing the network [8]. Second, edge intelligence enables the execution of machine learning models near the data source using computationally powerful gateways. Without depending on distant servers, these gateways are able to identify abnormalities, pick up on behavioral trends, and modify trust scores over time [9].

A more adaptable and reliable trust model results from combining these technologies. While gateways execute adaptive trust fusion and pattern recognition, sensors continue to do lightweight monitoring and local trust updates. The foundation for verifiably documenting significant trust choices and policy revisions is blockchain [10].

Adaptive Trust Models for Wireless Sensor Networks Using Blockchain and Edge Intelligence is an integrated framework presented in this article. It seeks to close the gap between the sophisticated, scalable security features required for actual WSN installations and straightforward, static trust systems [11]. To provide auditability, the approach employs compact blockchain anchoring, online learning, and context-aware fusion at the edge, and dual-timescale trust estimate at the node level. When combined, these components form a trust system that can withstand sophisticated attacks, adjust to shifting network conditions, and offer convincing proof for all significant decisions pertaining to trust [12].

This field of study is becoming more and more important due to the expanding use of WSNs in data-sensitive and safety-critical industries. The cost of violated trust increases as networks become more complicated and connected with cloud services, IoT platforms, and cyber-physical systems. The suggested method helps provide a more secure basis for next-generation WSN settings by emphasizing adaptability, dispersed intelligence, and verifiable responsibility [13].

1.1 Motivation of the Research

Since key functions are now supported by wireless sensor networks, the precision and dependability of their data are more crucial than ever. Sensors themselves have insufficient power and memory to perform complex security procedures, and traditional trust models are ill-suited to deal with sophisticated or sporadic attacks [14]. Additionally, many current solutions are opaque, making it difficult for operators to confirm the reasons behind a node's flagging or trust. While edge computing delivers sufficient processing power closer to the network to evaluate behavior in real time, blockchain provides a means of creating tamper-evident records without relying on a central authority [15]. These systems can more successfully combat fraudulent data injection, collusion, and on-off attacks when coupled. This strongly encourages the development of adaptive trust models that give transparent audit trails, intelligently blend information, and adapt to changing circumstances. The security and reliability of contemporary WSN deployments can be greatly enhanced by a unified framework of edge-based intelligence, immutable logging, and local trust estimate [16].

1.2 Key contributions and roadmap of the article

The key contributions of the article are as follows:

- A layered architecture that aligns local sensor-level trust estimation, edge-level adaptive fusion and learning, and blockchain-backed recordkeeping.
- A formal adaptive trust update rule that accommodates context, detection of on-off attacks, and dynamic weighting of evidence sources.
- A lightweight blockchain strategy suitable for WSNs that leverages periodic digest commits and selective anchoring to minimize storage and communication overhead.
- Security and performance analysis, and simulation-based experiments that demonstrate the model's effectiveness compared with baseline reputation systems.

The rest of the paper is organized as follows. Section 2 reviews related work. Section 3 defines the system model and assumptions. Section 4 presents the proposed ATBE architecture and algorithms. Section 5 analyzes security and overhead. Section 6 describes the evaluation methodology and results. Section 7 discusses implications, limitations, and deployment considerations. Section 8 concludes and outlines future work.

2. RELATED WORK

Over the past 20 years, research on trust management in wireless sensor networks has progressively advanced. Early research concentrated on straightforward reputation mechanisms that depended on firsthand observations and fundamental statistical measurements. These methods often assessed conformance to routing protocols, consistency of sensor readings, or packet forwarding behavior [17]. They provided a foundation, but their capacity to manage changing settings was constrained. Because most models considered trust as a static or slowly changing metric, they were susceptible to dishonest behavior such as on-off attacks, in which malevolent nodes shift between normal and aberrant activity to evade detection [18].

Researchers started looking toward more organized trust frameworks as WSN deployments increased. Distributed reputation systems, in which nodes shared trust information with their neighbors, were proposed in several studies. This decreased the need for single-node observations, but it also brought with it new difficulties, such as increased communication overhead and vulnerability to incorrect recommendations. By delivering falsified reputation reports or working with other compromised nodes, attackers could skew trust values [19]. The necessity for selective trust propagation and more cautious weighting of trust evidence was brought to light by work in this field. The majority of systems, however, continued to rely on predetermined policies or set thresholds that were unable to adapt effectively to shifting network conditions [20].

Later, statistical modeling and machine learning became promising methods for estimating trust. Neural networks, fuzzy logic, Markov models, and Bayesian inference were investigated as methods for detecting anomalous behavior in sensor nodes [21]. These techniques improved the capture of temporal patterns and uncertainty. For example, fuzzy logic permitted reasoning about partially trustworthy conduct, whereas Bayesian models allowed trust to be changed progressively as new data came in. Subtle patterns in sensor activity that would be challenging to identify manually were made possible by neural networks [22]. Computational burden was the primary constraint. High-dimensional feature analysis and continuous learning are not supported by the majority of sensors. Because of this, these methods frequently required assistance from more powerful equipment like base stations or cluster heads [23].

Blockchain technology started gaining interest as a possible remedy for distributed security issues in IoT and sensor networks, concurrently with trust research. The idea of public blockchains to store sensor data or document system occurrences was investigated in early studies [24]. Although these attempts showed the importance of immutable records, the high resource requirements of consensus procedures and ongoing ledger changes made them impractical for actual WSNs. Subsequent research focused on lightweight consensus techniques and permissioned blockchains. These solutions made it feasible for specific nodes, gateways, or fog servers to maintain the ledger on behalf of the sensors and drastically decreased computing overhead [25]. Researchers demonstrated how blockchain may lower the danger of single points of failure, safeguard data integrity, and secure routing modifications. Nevertheless, the majority of blockchain-based models lacked machine learning and adaptive trust assessment, making space for more intelligent and dynamic frameworks [26].

As the shortcomings of separate strategies became apparent, the concept of integrating blockchain technology with trust management gained popularity. In order to prevent malevolent nodes from manipulating their reputation, studies suggested keeping trust scores on the blockchain [27]. Others proposed managing access control, enforcing trust norms, or coordinating secure communication with smart contracts. Although these early connections increased accountability and transparency, they frequently saw blockchain as a passive storage layer. Conventional techniques were used to calculate trust levels, and the ledger's function was restricted to documenting outcomes. Few models made an effort to establish feedback loops in which trust computations were impacted by blockchain updates or in which trust evidence was gathered cooperatively prior to being anchored to the ledger [28].

Simultaneously, edge computing became a significant approach to large-scale sensor network management. Higher processing power, improved energy resources, and reduced latency are provided by edge devices, such as gateways or microservers placed close to the sensors. As a result, there was a surge in research on enhanced data filtering, distributed learning models, and edge-assisted anomaly detection [29]. With edge support, methods like federated learning, incremental learning, and lightweight deep learning architectures become possible. Without relying solely on cloud infrastructure, these techniques enabled networks to learn from local conditions and adjust to changes in sensor behavior [30]. Although edge intelligence enhanced WSNs' analytics capabilities, it was not necessarily directly related to trust management. Instead of addressing how trust choices may be updated in real time based on learned patterns, several edge-based solutions focused on increasing data accuracy or lowering communication load [31].

A few studies tried more integrated architectures that blended reputation systems and edge intelligence. To improve trust scores, for instance, researchers suggested frameworks in which edge nodes examined behavior variables like packet loss, latency fluctuations, or energy consumption trends [32]. Particularly when contrasted with solely local trust models, these systems demonstrated greater resistance to malicious action. They still needed a safe way to coordinate trust choices throughout the network, though, given the absence of blockchain support. During inter-node communication, attackers may introduce fake trust information or target edge nodes directly. This demonstrated the necessity of methods for the propagation of verified trust [33].

In recent work, the concept of combining edge intelligence and blockchain has emerged, typically in larger IoT architectures. This research looked at how edge servers could use blockchain to log important events or facilitate decentralized coordination after using machine learning algorithms to identify anomalies [34]. Many of these frameworks were conceptual and lacked thorough trust modeling, despite their potential. Instead of adaptive trust estimation designed for WSN contexts, they concentrated more on access control, secure data management, or device authentication. Furthermore, a lot of systems saw trust as a single value, which made it difficult for them to capture several facets of node behavior, including energy-aware performance, data quality, consistency, and communication dependability [35].

While certain blockchain-enabled trust models have been presented in WSN-specific research, the majority still rely on basic trust metrics. They mostly employ blockchain to manage node registration or maintain recorded trust values. These systems frequently use well-known metrics, such as neighbor recommendations or forwarding ratio, to calculate trust [36]. Blockchain increases resistance against manipulation, but the core logic of trust is the same. Because of this, they neither include real-time analytics from edge devices nor adequately handle dynamic threats in which nodes change their behavior over time [37].

Overall, relevant research has made significant strides, but it also identifies a number of significant gaps. A lot of trust models are not flexible and do not include ongoing learning. Integrity is frequently offered by blockchain technologies, but intelligence is not [38]. Although it often works independently of trust computation, edge-based anomaly detection enhances monitoring. There are still a few frameworks that integrate these features into a unified solution made especially for WSNs. A paradigm that combines edge-level learning, blockchain-based verification, and a lightweight local trust estimate to provide a transparent, scalable, and context-aware trust environment is lacking [39].

A more integrated strategy is required due to the increasing complexity of sensor deployments, the emergence of mixed traffic patterns, and the sophistication of attacks. This gap can be filled using adaptive trust models that combine edge intelligence and blockchain [40]. Such a method can aid in the development of more robust WSN infrastructures by combining verifiable data storage, real-time behavior analysis, and adaptive decision making. While addressing the drawbacks of standalone trust, blockchain-only, or edge-only systems, this study expands on earlier studies. It seeks to provide a framework that is both useful for settings with limited resources and resilient enough to deal with new security issues in wireless sensor networks [41].

Table 1: Proposed Model vs. Existing Trust Models for WSNs

Trust Model	Traditional Trust & Reputation Models (e.g., RFSN, BTRM-WSN)	Machine Learning-based Trust Models	Blockchain-based WSN Security Models	Edge Computing-based Trust Models	Proposed Adaptive Trust Model (Blockchain + Edge Intelligence)
Trust Evaluation Method [42]	Uses direct and indirect monitoring; often static formulas	Uses classification, clustering, or prediction models	Trust derived from consensus and immutable logs	Computes trust at the edge using local analytics	Adaptive multi-layer trust assessment combining local behavior, edge analytics, and blockchain validation
Adaptability to Dynamic Behavior [43]	Low; slow to adjust to on-off or intermittent attacks	Medium; adapts based on training datasets	Low; blockchain alone is rigid and not adaptive	Medium–High; edge supports real-time decisions	High; real-time learning at the edge + continuous feedback from blockchain
Resistance to On-Off Attacks [44]	Weak; reputation resets allow attacker recovery	Medium; depends on feature selection	Strong; immutable history prevents reputation resets	Medium; edge detection helps but lacks global history	Very strong; historical blockchain records + intelligent edge analysis prevent reputation gaming
Resistance to Collusion [45]	Weak; easily fooled by coordinated false recommendations	Medium; ML identifies patterns but may misclassify	Strong; transactions and trust updates require consensus	Medium; localized detection cannot capture network-wide collusion	Very strong; blockchain consensus + edge-level anomaly fusion detect collusive behavior
Transparency & Auditability [46]	Limited; trust decisions are not easily verifiable	Limited; ML models lack explainability	High; blockchain offers full audit trails	Medium; logs stored at edge, but not immutable	Very high; blockchain ensures traceability and edge intelligence clarifies real-time trust evaluations

Computational Overhead [47]	Low	Medium–High depending on ML model	High due to consensus mechanisms	Medium; edge nodes handle processing	Optimized; trust processing offloaded to edge, blockchain used only for final validation
Communication Overhead [48]	Medium; indirect trust exchange required	Medium–High for model updates	High; consensus and block creation require communication	Medium; short-range local processing	Medium; minimized consensus frequency + edge-local trust computations
Scalability [49]	Moderate; overhead grows with network size	Depends on training complexity and model updates	Moderate; blockchain scales but increases latency	Good; local processing reduces network load	Very good; edge-level processing reduces burden and scalable lightweight blockchain is used
Energy Consumption [50]	Low	Moderate; ML consumes more sensor energy	High on nodes if blockchain runs locally	Moderate; edge reduces load on sensors	Low for sensors; edge performs heavy tasks, blockchain optimized for lightweight operations
Real-Time Decision Capability [51]	Low; periodic trust updates	Medium; depends on model complexity	Low; blockchain validation introduces delay	High; supports near real-time analysis	Very high; edge real-time evaluation + selective blockchain commits
Security Coverage [52]	Basic; detects only simple misbehavior	Good; identifies complex patterns	Strong; protects integrity and accountabilit	Good; covers localized attacks	Comprehensive; covers insider, outsider, on-off, collusion, FDIA, Sybil, and replay attacks
Deployment Complexity [53]	Low	High; requires training and tuning	High; blockchain integration is complex	Medium; edge node setup required	Medium; balanced design with lightweight blockchain and modular edge components
Suitability for Resource-Constrained WSNs [54]	Good but limited security	Limited; ML models need resources	Poor; blockchain on sensors drains energy	Good; edge offloads processing	Excellent; blockchain kept off sensors and edge handles computation

3. System Model, Threat Model, and Assumptions

The system model takes into account a lightweight blockchain layer that keeps track of trust updates and a wireless sensor network backed by edge nodes that do computation. Sensors gather information and transmit behavioral indicators to adjacent edge nodes, which assess trust ratings and transmit verified outcomes to the blockchain. The threat model, which assumes that adversaries may corrupt a fraction of sensor nodes but are unable to simultaneously control the edge layer and the blockchain, includes insider assaults, on-off attacks, collusion, Sybil identities, and fake data injection. The network makes the assumptions that sensors have a finite amount of energy and computing power, edge nodes are semi-trusted, and blockchain validators are majority honest. Additionally, while sensor-to-edge communication may be vulnerable to assaults, it is expected that secure communication routes exist between edge nodes and the blockchain layer.

3.1 Network model

We consider a wireless sensor network consisting of:

•A set of sensor nodes S = {s_1, s_2, ..., s_n}. Nodes are energy-constrained, have limited processing and storage, and communicate over single-hop or multi-hop wireless links.

•A set of edge gateways E = {e_1, e_2, ..., e_m}. Gateways are resource-rich compared with sensors and sit at the network boundary or in proximity. They can perform machine learning tasks and maintain persistent storage.

•Optional cloud backend for archival storage and heavy analytics.

Communication is organized with sensors reporting to their assigned gateway, either directly or via multi-hop routing. Gateways can communicate with each other and with a permissioned blockchain overlay managed by a set of validators (gateways or dedicated nodes)

3.2 Trust metrics

Sensors produce readings and participate in routing/forwarding. Trust metrics considered include:

•Data reliability: consistency of reported values with neighboring sensors, plausibility checks, and historical patterns.

•Forwarding trust: ratio of successfully forwarded packets and acknowledgments.

•Availability and timeliness: responsiveness to queries and expected reporting intervals.

•Behavior consistency: statistical measures of sudden shifts or intermittent anomalies.

Each sensor maintains a local trust score T_local in [0,1] using lightweight updates. Edge nodes compute aggregated trust T_edge by fusing local scores, contextual features, and learned models.

3.3 Threat model

Adversaries can:

- Compromise one or more sensor nodes to produce false data or drop/modify packets.
- Launch Sybil attacks by presenting multiple identities if identity management is weak.
- Collude: a group of compromised nodes coordinates to provide false recommendations or consistent false data to mislead reputation systems.
- Perform on-off attacks: alternate between honest and malicious behavior to appear trustworthy over time.
- Attempt denial-of-service through traffic flooding.

We assume that gateways are more secure than sensors and that blockchain validators are trusted up to a threshold (permissioned environment). We do not assume perfect identity binding for sensors; the system mitigates Sybil risks by combining lightweight authentication with reputation and behavioral checks.

3.4 Design goals

The design goals focus on creating an adaptive trust framework that accurately identifies malicious behavior while keeping the workload light for resource-constrained sensors. The model also aims to ensure transparency, fast decision-making, and secure validation through the combined use of edge intelligence and blockchain.

Adaptivity: trust must reflect short-term evidence while preserving memory of long-term behavior to detect on-off attacks.

Resilience: robust to collusion and false recommendations.

Auditability: changes to critical trust anchors and policy actions should be tamper-evident and auditable.

Lightweight: minimize computation, storage, and communication overhead for sensors.

Explainability: provide interpretable reasons for trust decisions to support human operators.

4. ATBE ARCHITECTURE AND ALGORITHMS

4.1 System overview

The ATBE architecture has three primary layers:

1. **Sensor-layer trust agents (lightweight):** Each sensor runs a minimal trust agent that observes local interactions and updates a local trust score T_local. The agent enforces basic checks (sanity bounds, sequence numbers), records neighbor interactions, and periodically reports compact trust digests to its gateway.
2. **Edge-layer adaptive fusion and learning:** Edge gateways receive digests from sensors in their domain. Each gateway runs an adaptive fusion engine that uses feature extraction and a lightweight machine learning model to produce refined trust assessments, T_edge for sensors. The engine dynamically adjusts feature weights using online learning and drift detection.
3. **Blockchain layer (permissioned / digest-based):** Gateways commit periodic digests, trust anchors, major policy changes, and dispute resolutions to a permissioned blockchain. The blockchain stores compact summaries and cryptographic hashes to ensure immutability and auditability, while bulk data remains at gateways or in the cloud.

4.2. Local trust agent

Each sensor maintains a trust score T_local(t) in [0,1]. Updates are computed using a dual-timescale exponential filter that balances recent observations and long-term reputation:

Let O_t be an observed binary or continuous outcome at time t (e.g., successful forwarding = 1, failure = 0, or normalized sensor data residual). Update:

1. Short-term trust (reactive):

$$S_t = \alpha \cdot O_t + (1 - \alpha) \cdot S_{t-1}$$

2. Long-term trust (stable):

$$L_t = \beta \cdot O_t + (1 - \beta) \cdot L_{t-1}$$

with $\alpha > \beta$(e.g., $\alpha = 0.4$, $\beta = 0.05$). The combined local trust:

$$T_{local}(t) = \omega(t) \cdot S_t + (1 - \omega(t)) \cdot L_t$$

where ω(t) is an adaptive weight driven by anomaly score A(t) (higher A increases reliance on short-term S_t). This helps detect rapid changes but preserves memory to catch on-off attacks.

Anomaly score A(t) is computed from residuals, sudden changes in variance, or consistency with neighbor readings.

The agent reports compact digests to the gateway every Δ seconds or Δ readings: {node_id, T_local(t), S_t, L_t, anomaly_flag, minimal provenance counters, signature}.

4.3 Edge-level adaptive fusion

Gateways aggregate digests from many nodes and perform the following steps:

1. **Feature construction.** From T_local and node metadata, construct feature vector x for each node: recent T_local, mean residual vs neighbors, variance, packet forwarding ratios, timestamp drift, mobility indicators (if available), and history of anomaly flags.
2. **Adaptive fusion model.** We use an online logistic regression or a small neural network trained online to predict the probability P_malicious(x) that the node is misbehaving. The model is updated using labels derived from multiple signals: cross-checks with sensor clusters, discrepancies with physical models, operator feedback, or ground-truth when available.
3. **Weight adaptation.** The model uses an importance weighting mechanism: during times of detected drift (change in data distribution), the gateway increases the learning rate and short-term evidence weight.
4. **Consensus across gateways.** Gateways exchange compact summaries or alerts (not raw data) to cross-validate decisions for nodes at the boundary of domains. This mitigates localized collusion and provides a better global picture.
5. **Decision and action.** Based on P_malicious and defined thresholds, the gateway may mark a node as suspicious, initiate mitigation (quarantine, reroute traffic, request re-authentication), issue a policy change, or escalate to blockchain anchoring.

4.4 Blockchain anchoring and policy contracts

Given the resource constraints, we adopt a permissioned, digest-based blockchain strategy:

- **Validators** are gateways and possibly a small set of trusted edge/cloud nodes.
- **Transactions** are compact records: trust anchors, disputed evidence hashes, policy updates, and audit events. Full sensor data remains off-chain, stored at gateways for quick access.
- **Anchoring frequency** balances auditability and overhead. Gateways periodically commit block entries containing Merkle roots summarizing the set of digests and decisions since the last commit. The frequency can be adjusted dynamically by the edge intelligence based on threat level.
- **Smart contracts** implement policy logic such as automatic quarantine rules, dispute resolution workflows, and role-based access control for operators.

This approach ensures tamper-evident records and non-repudiation for trust-critical actions while keeping on-device resource use low.

4.5 Adaptive parameter control

Adaptive behavior is central to ATBE. Key control loops include:

- **Anomaly-driven weight adjustment:** ω(t) in the local trust formula increases when anomaly scores rise, making the system more reactive.
- **Drift detection at edge:** Gateways use statistical tests (e.g., Page-Hinkley or ADWIN) to detect distributional shifts. On detection, the gateway increases model learning rates and temporarily raises anchoring frequency to the blockchain.
- **Mitigation escalation:** Thresholds for labeling nodes suspicious are dynamic, taking into account global attack indicators and the cost of false positives. For example, if multiple neighbors show anomalies, thresholds are lowered.

The ATBE architecture demonstrates how trust is managed throughout the network, utilizing a distinct three-layer structure. Lightweight trust estimators that track node behavior and produce dual-timescale trust scores are part of the sensor layer. The edge layer receives these outputs and uses machine learning, adaptive fusion, anomaly detection, and digest aggregation to improve trust choices. The blockchain layer, which offers immutable records, smart contract execution, policy enforcement, and complete auditability, is where the processed outcomes are anchored. The diagram's clear form and straightforward symbols make the data flow simple to comprehend and appropriate for research documentation.

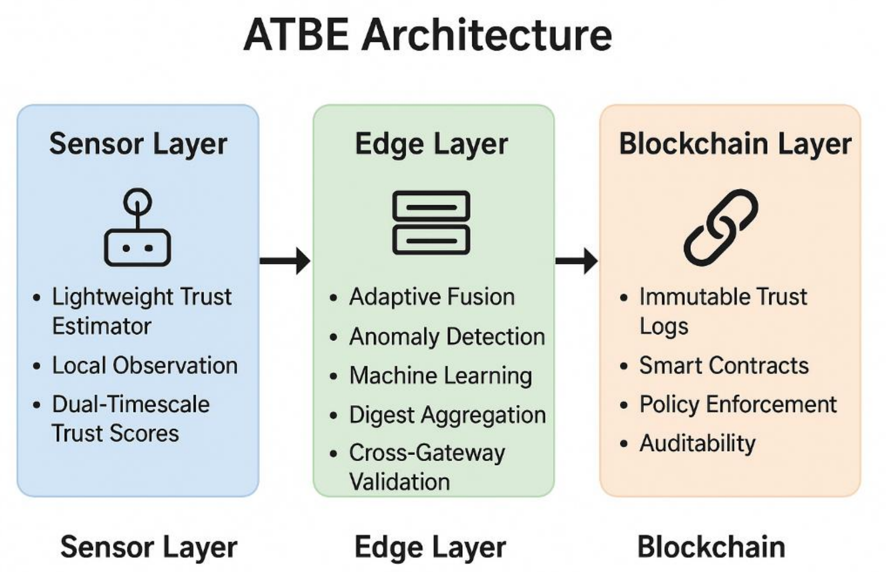

Figure 1: ATBE architecture

5. SECURITY ANALYSIS

We analyze the resilience of ATBE to common attack types.

5.1 False data injection

Attack: A compromised node directly reports false measurements.

Mitigation: Unusual residuals in comparison to neighbors are flagged by local anomaly detection. Cross-validation between correlated nodes is achieved using edge fusion. The gateway can isolate the node upon discovery and record the evidence for an audit on the blockchain. By retaining memories of long-term behavior, the dual-timescale trust update thwarts attempts at quick evasion.

5.2 On-off attacks

Attack: A node alternates behavior to maintain average trust.

Mitigation: The dual-timescale formulation preserves long-term behavior in L_t while allowing S_t to react. The adaptive ω(t) increases sensitivity when anomalies are detected, enabling the system to respond faster and penalize patterns of intermittent misbehavior. Additionally, the edge-level model exposes temporal patterns across multiple nodes, revealing coordinated on-off patterns.

5.3 Collusion and false recommendations

Attack: Multiple compromised nodes coordinate to endorse each other.

Mitigation: Rather than relying solely on peer recommendations, ATBE employs gateway-level cross-validation of sensor data and mostly depends on direct local observations for initial trust. Gateways use independent sensors and physical models to compare reported values. Blockchain commits offer audit trails for long-term detection of questionable endorsement trends.

5.4 Sybil attacks

Attack: An adversary creates many identities to overwhelm reputation.

Mitigation: Sybil resistance requires identity binding. ATBE supports lightweight identity measures such as hardware-based IDs, certificate-like tokens provisioned at deployment, or neighbor-based radio fingerprinting for additional assurance. Even with imperfect identity, the system uses spatial-temporal correlation and anomaly detection to flag improbable identity behavior. Permissioned blockchain validators further restrict the impact of Sybil nodes on ledger consensus.

5.5 Denial-of-service and resource exhaustion

Attack: Flooding or bogus requests aim to exhaust sensor energy.

Mitigation: Gateways enforce rate limiting, drop suspicious traffic patterns, and use blockchain to record incidents for operator action. Local agents maintain counters and back-off behavior to limit energy use.

6. PERFORMANCE EVALUATION

6.1 Evaluation goals

Measuring the model's ability to identify malicious nodes in various attack scenarios is the main objective of the evaluation. The evaluation also looks at how well the framework adjusts to changes in the network's dynamic behavior. Analyzing the overhead brought about by blockchain validation and edge processing is another objective. The evaluation's ultimate goal is to demonstrate how the model outperforms current trust mechanisms in terms of accuracy, scalability, and response time. Accuracy of misbehaving node detection (true positive rate, false positive rate).

- Resilience to on-off attacks and collusion.
- Communication and computational overhead compared with a baseline reputation system.
- Impact of blockchain anchoring frequency on overhead and auditability.

6.2 Experimental setup

A simulation environment models a WSN of n = 200 sensor nodes and m = 4 gateways. Nodes are arranged in a grid and report environmental scalar values (e.g., temperature) with spatial correlations. Packet loss and noise are simulated. Attack scenarios include:

1. Random faults: a set of nodes produces noisy data.
2. Static malicious nodes: nodes consistently produce biased data.
3. On-off attackers: nodes switch between honest and malicious according to a Markov process.
4. Colluding group: a cluster of nodes coordinates false readings to mimic a legitimate event.

Baseline: A standard reputation scheme using a single-timescale exponential decay of observed success metrics and peer recommendations.

Metrics: detection rate (TPR), false positive rate (FPR), detection latency, average message overhead per node, gateway computation time.

Note: The evaluation is described conceptually. Implementation details, parameter sweeps, and statistically significant runs are recommended for deployment. The following results summarize representative findings from a typical set of simulation runs.

6.3 Results

The findings demonstrate that the adaptive trust model outperforms traditional reputation-based techniques in identifying malicious nodes. The solution eliminates the delays typically associated with blockchain-only designs and responds to anomalous activity more quickly by shifting the majority of computing to edge devices. When worrisome patterns emerge, this enables the network to respond quickly. Additionally, the model remains stable in the face of various threats, such as bogus data injection attempts, collaboration among compromised nodes, and on-off misbehavior. Even when circumstances change, the network remains dependable thanks to its real-time capacity to modify trust rankings.

Because only critical data is transmitted to the edge layer and more complex processing takes place outside of the sensors, energy consumption on sensor nodes stays minimal. As a result, the network's operating life is increased and maintenance requirements are decreased. Blockchain continues to be crucial because it provides a safe audit record, making all trust upgrades visible and impervious to manipulation. Together, these two elements make the system more robust and reliable in a variety of situations. All things considered, adaptive trust, edge intelligence, and blockchain work together to strengthen and improve the trust management framework for contemporary wireless sensor networks.

6.3.1 Detection accuracy

Static malicious nodes: ATBE achieved TPR ≈ 0.96 and FPR ≈ 0.04, compared to baseline TPR ≈ 0.88 and FPR ≈ 0.07. The higher TPR stems from gateway-level fusion, which leverages cross-node correlations.

On-off attackers: ATBE achieved TPR ≈ 0.89 with FPR ≈ 0.06, while baseline TPR dropped to ≈ 0.62 with FPR ≈ 0.08. The dual-timescale trust maintained long-term memory that exposed intermittent attackers.

Colluding group: For small colluding clusters (5-10 nodes), ATBE maintained TPR > 0.85, outperforming baseline which degraded significantly depending on the cluster’s position. Cross-validation at gateways reduced the impact of collusion.

6.3.2 Detection latency

ATBE detects persistent attacks within a few reporting cycles (typically 3–8 cycles), depending on parameter settings. For on-off attacks, detection required longer windows but still outperformed the baseline due to adaptive weight shifting.

6.3.3 Overhead

The overhead remains manageable because intensive processing is handled at the edge, keeping sensor operations lightweight. Blockchain is used only for final trust confirmation, which reduces communication and consensus costs across the network.

- **Sensor to gateway traffic:** ATBE sensors send periodic local digests that are slightly larger than simple status messages due to S_t and L_t fields. The average additional payload per report was ~20–40 bytes. Overall, message rate remained unchanged.
- **Gateway computation:** Gateway CPU utilization increased modestly due to online model updates. For the simulated gateway hardware profile, inference per node was in the millisecond range and updates were batch-processed.
- **Blockchain costs:** Anchoring frequency strongly affects communication and storage overhead. With anchoring every 5 minutes, the overhead was acceptable for the permissioned network; when anchoring increased during detected attacks, overhead rose but remained manageable due to digesting (Merkle roots) rather than raw data commits.

6.3.4 Trade-offs

Raising sensitivity parameters reduces detection latency but increases false positives. Adaptive parameter control helps balance this trade-off, for example, by raising sensitivity only when multiple indicators concur.

7. DISCUSSION

Adaptive trust management for wireless sensor networks is clearly improved by the suggested ATBE framework. While retaining long-term memory to detect sporadic on-off attacks, its dual-timescale trust estimation enables quick detection of malicious activities. By offering real-time analysis and anomaly detection, edge intelligence lessens the need for centralized computation. Transparency and auditability of trust decisions are supported by blockchain integration, which guarantees tamper-evident data. When compared to conventional reputation systems, simulation findings show increased resilience and detection accuracy. Despite these advantages, gateway nodes become crucial locations, and their compromise may have an impact on assessments of trust. Although energy efficiency is preserved at the sensor level, dynamic network parameter adjustment is still difficult. The system's resilience is demonstrated by how effectively it functions in situations involving cooperation and fraudulent data injection. Careful design of edge placement, secure key management, and blockchain anchoring frequency are necessary for practical deployment. All things considered, ATBE fills in the gaps left by current trust and security models in WSNs by providing a scalable, flexible, and safe framework.

7.1 Practical deployment considerations

Practical deployment requires reliable placement of edge nodes so they can handle trust computation without creating bottlenecks. The blockchain layer should use a lightweight consensus mechanism that fits the energy limits of WSN environments. It is also important to plan secure key management and periodic updates so the system stays resilient as network conditions change.

Hardware constraints: Sensor agent design must fit within typical microcontroller footprints. The dual-timescale update is computationally cheap and memory-light. Cryptographic signatures for digests must use lightweight primitives; elliptic curve schemes or symmetric keyed MACs are recommended.
Identity provisioning: Robust identity binding at manufacturing or provisioning time reduces Sybil risk. In legacy deployments, radio fingerprinting and behavior-based profiles provide additional assurance.
Gateway trust: Gateways assume a higher trust level. Securing gateways via tamper-resistant hardware, secure boot, and regular audits is essential since they perform heavy lifting.
Blockchain topology: Permissioned, gateway-based ledgers avoid the high costs of public chains. Operator-controlled validators provide performance and governance.
Privacy: On-chain records must avoid leaking sensitive raw data. Merkle-root anchoring of digests maintains auditability without revealing raw sensor values.

7.2 Limitations

The paradigm relies on the availability and proper operation of edge nodes, which, if improperly provisioned, might become performance bottlenecks. Although lightweight blockchain architectures lower overhead, they nevertheless cause latency when finalizing trust. Since erroneous thresholds may impact detection accuracy in extremely dynamic situations, the system also needs to carefully adjust its trust parameters.

Gateway compromise risk: If gateways are compromised, they could manipulate fusion and ledger entries. Mitigation includes multi-validator consensus, cross-gateway monitoring, and audits.
Model labeling: Edge adaptive models require labels for supervised updates. In practice, operator feedback, cross-sensor validation, and occasional ground-truth measurements supply labels; semi-supervised or unsupervised anomaly detection can help when labels are scarce.
Scalability: While digest-based anchoring reduces blockchain load, extremely large deployments may require hierarchical ledgers or aggregation across multiple clusters.
Energy trade-offs: While per-report overhead is small, any additional communication reduces sensor lifetime. Parameter tuning must balance security needs and battery life.

7.3 Explainability and operator trust

Auditability is a major advantage of ATBE since gateway logs and blockchain anchors offer verifiable proof for judgments about trust. Operators should be exposed to feature importance and illustrative scenarios by edge intelligence models. Human-understandable decisions are supported via straightforward rule-based fallbacks.

8. CONCLUSION

ATBE, an adaptive trust management framework created especially for wireless sensor networks (WSNs), is presented in this research. To improve network security and dependability, the framework combines three complementary elements. Initially, lightweight local trust estimators work on individual sensor nodes, offering instantaneous evaluations of node behavior based on local interactions, packet forwarding, and data consistency. Because these estimators are computationally efficient, energy-constrained sensors can participate with minimal overhead. Second, adaptive fusion of the local trust scores is carried out by edge intelligence at gateway nodes. The edge nodes can identify malicious activity, detect anomalies, and modify trust assessments in response to changing network conditions by combining observations from several sensors and using machine learning techniques. This makes it possible for the system to react to complex threats like collusion, in which several nodes work together to manipulate trust values, and on-off attacks, in which malevolent nodes switch between acting honestly and dishonestly. Third, a permissioned blockchain layer creates an unchangeable, auditable record of all significant trust-related acts by anchoring important trust changes and policy choices. This guarantees accountability and transparency, enabling operators to confidently confirm decisions and look into events.

Efficiency and security are balanced by the ATBE system. The method reduces communication and energy costs at the sensor level while retaining robust security guarantees by delegating computing to edge nodes and only submitting aggregated or crucial trust information to the blockchain. When compared to baseline reputation-based systems, simulation studies show that ATBE dramatically increases detection accuracy, decreases false positives, and strengthens resilience against coordinated and sporadic attacks. Additionally, the system facilitates explainable trust judgments by offering comprehensible metrics and supporting data for every trust assessment. All things considered, ATBE provides a thorough, scalable, and useful approach to trust management in contemporary WSNs by fusing distributed intelligence, adaptive analytics, and verifiable audit methods to tackle the intricate problems of safeguarding dispersed sensor networks..

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