



C&ESAR 2025 by DGA

32nd Computer & Electronics Security Application Rendezvous



TRUST-AWARE VERTICAL INTRUSION DETECTION FOR IoT VIA EVOLUTIONARY GRAPH NEURAL NETWORKS (V-IDS)

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OUTLINE



CONTEXT AND MOTIVATION

PROBLEM STATEMENT

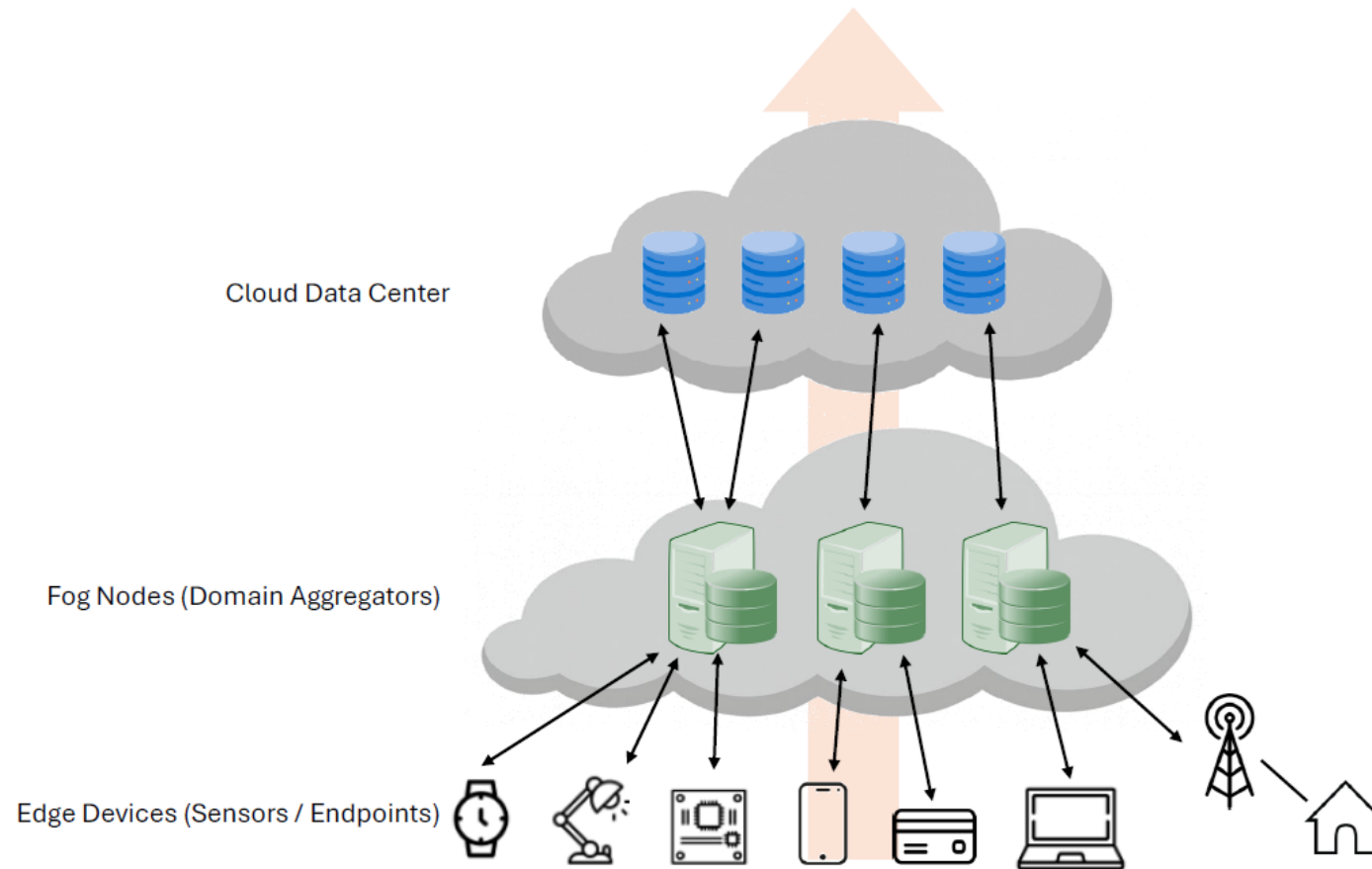
PROPOSED FRAMEWORK

EXPERIMENTAL EVALUATION

CONCLUSION AND FUTURE WORK

CONTEXT AND MOTIVATION:

FROM SMART HOMES TO SMART CITIES , AND NEW THREATS



“The same device that measures temperature can, tomorrow, be used to exfiltrate industrial secrets.”

IoT ATTACKS ARE RAPIDLY INCREASING

32.7 million IoT cyberattacks in 2018 → 112 million in 2022
(+243% in four years)

Over 1.7 billion IoT attacks detected in 2024 (Kaspersky)

Around 820,000 IoT attack attempts per day expected in 2025

More than 50% of IoT devices contain critical vulnerabilities

1 in 3 global data breaches now involves an IoT device

IoT SECURITY WEAKNESSES AND EMERGING ATTACK VECTORS



Weak security defaults:
default passwords,
outdated firmware



Resource constraints:
limited CPU/RAM →
weak/no encryption



Insecure protocols:
MQTT, CoAP, UPnP,
Telnet



Poor patching & maintenance: long-lasting exploitable flaws

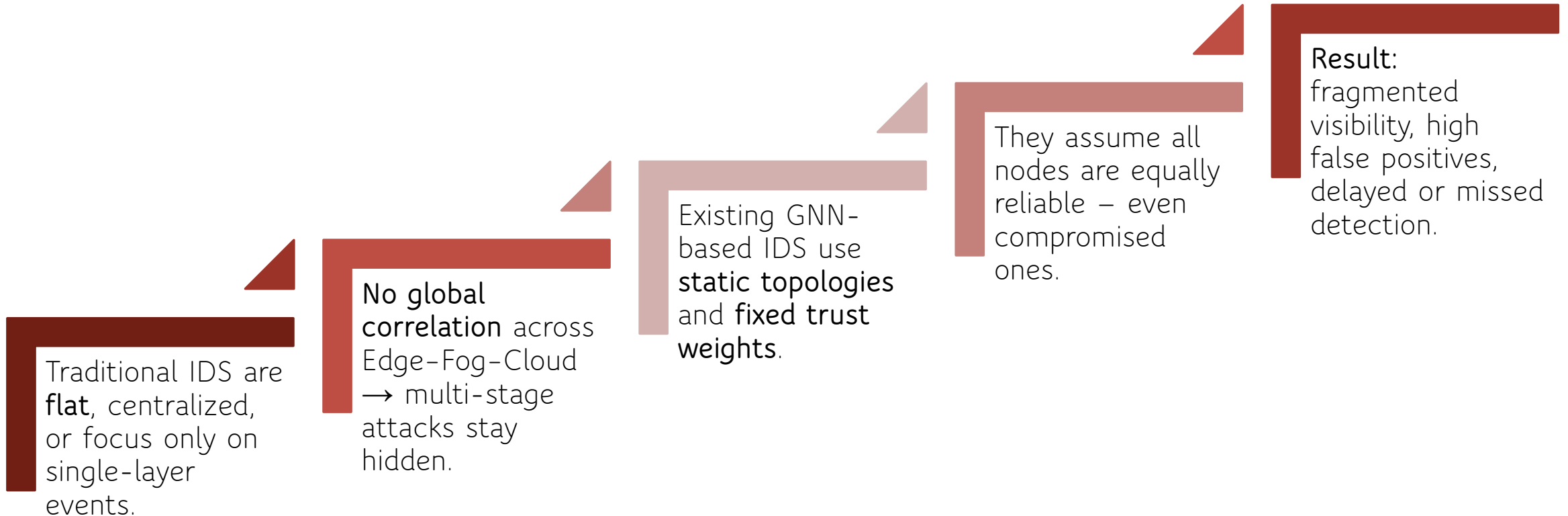


Layered architecture:
edge-fog-cloud blind
spots



High heterogeneity:
diverse devices,
inconsistent security

WHY EXISTING IDS FAIL IN MODERN IOT ENVIRONMENTS



TOWARD ADAPTIVE VERTICAL DETECTION AND TRUST REASONING

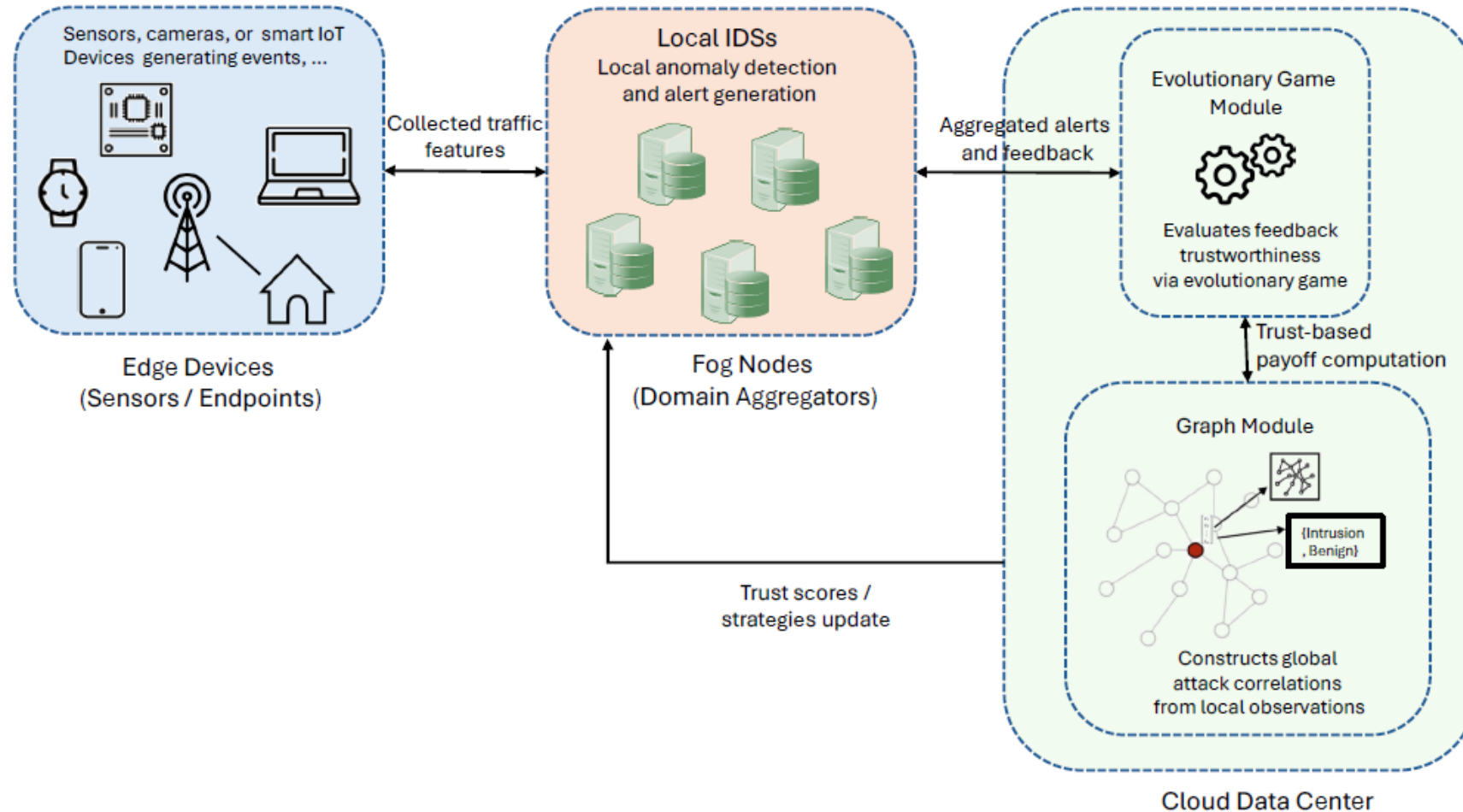
Correlates alerts across Edge, Fog, and Cloud layers
→ enabling true multi-level IoT visibility

Integrates a dynamic trust mechanism
→ based on evolutionary game theory

Injects trust into a Graph Neural Network
→ for structural and temporal reasoning

Remains robust under adversarial and noisy conditions

A VERTICAL VIEW OF INTRUSION DETECTION



LOCAL DETECTION & METRIC EXTRACTION AT FOG NODES

- Each Fog node F_i monitors its Edge devices $\mathcal{E}_i$ and extracts structured security metrics from raw detection events:

$$\phi_i(t) = [A_i(t), H_i(t), \Delta_i(t), R_i(t)]$$

Where:

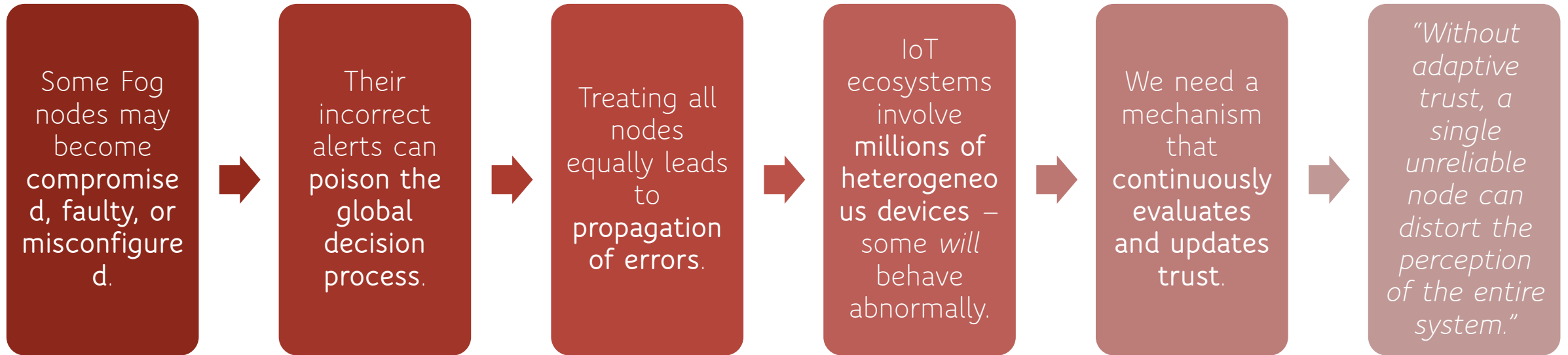
- A_i - *Anomaly intensity*
Average anomaly score across all events in $\mathcal{D}_i(t)$.
- H_i - *Event-type entropy*
Diversity of observed event types (Shannon entropy).
- Δ_i - *Temporal dispersion*
Std deviation of inter-arrival times between events.
- R_i - *Detection rate*
Number of events per device per time window.

GLOBAL FUSION AT CLOUD LEVEL

Step 2 – Global Correlation using a Graph Neural Network (GNN)

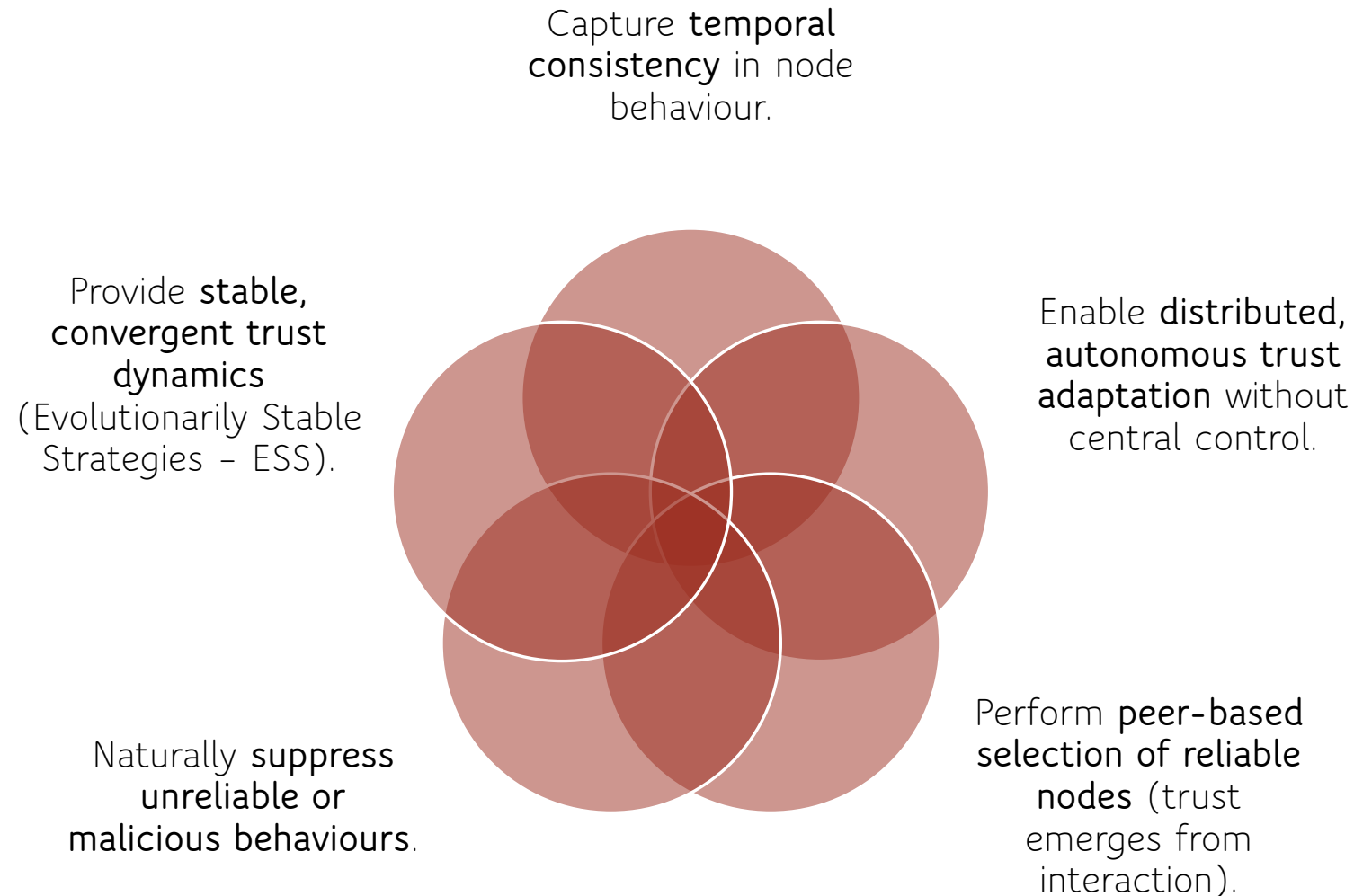
- The cloud constructs a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ from all Fog nodes.
- **Nodes** = Fog entities; **Edges** encode connectivity or behavioural similarity.
- Initial edge weights w_{ij} reflect **baseline trust** / communication links.
- → At this stage, we have the global structure... but trust is still static.

WHY WE NEED ADAPTIVE TRUST BETWEEN NODES



WHY EVOLUTIONARY GAMES MATTER

THE POWER OF EVOLUTIONARY DYNAMICS IN CYBERSECURITY



INSPIRATION FROM NATURE : EVOLUTIONARY ADAPTATION FOR TRUST

- Nodes behave like agents in a population.
- Honest / cooperative behaviour → reinforced.
- Unreliable or inconsistent behaviour → penalized and loses influence.
- Replicator Dynamics adjusts trust levels based on performance over time.
- “Trust evolves – it is not assigned once and for all.”

EVOLUTIONARY GAME THEORY FOR TRUST MODELING

- Nodes act as players adapting their strategies over time.
 - Fitness = consistency & correctness of their detections.
 - Cooperative (honest) nodes $\rightarrow$ higher payoff $\rightarrow$ trust increases.
 - Unreliable nodes $\rightarrow$ lower payoff $\rightarrow$ trust decays automatically.
 - Replicator Dynamics adjust trust levels based on performance.
- Trust becomes an emergent, self-adjusting property – not a fixed rule.

FROM UTILITY TO EVOLUTIONARY DYNAMICS

- Node utility: $u_i = \sum_{j \in \mathcal{N}(i)} w_{ij} \text{sim}(\varphi_i, \varphi_j)$
- Average utility: $\bar{u} = x_H u_H + x_U u_U$
- Replicator equation: $\dot{x}_s = x_s (u_s - \bar{u})$
- Node replicator coefficient: $r_i = u_i - \bar{u}$

STEP 3 – TRUST-WEIGHTED MESSAGE PASSING

- We incorporate the trust scores into the GNN message-passing process:

$$\tilde{\varphi}_i = r_i \cdot \varphi_i, \quad \tilde{w}_{ij} = r_i \cdot r_j \cdot w_{ij}$$

$$h_i^{(l+1)} = \sigma \left(\sum_{j \in \mathcal{N}(i)} \tilde{w}_{ij} W^{(l)} h_j^{(l)} \right)$$

We have:

- High-trust nodes $\rightarrow$ stronger influence in the graph.
- Low-trust or inconsistent nodes $\rightarrow$ attenuated messages.
- The GNN progressively filters out unreliable contributors.

“Trust acts as an adaptive volume control on each node’s voice in the graph.”

STEP 4 – END-TO-END VERTICAL IDS PIPELINE



Edge $\rightarrow$ Fog: local data collection + lightweight anomaly metrics



Fog $\rightarrow$ Cloud: transmit summary vectors $\phi_i(t)$



Compute node utilities u_i + trust/replicator coefficients r_i



Construct a trust-weighted graph for GNN reasoning



Run GNN inference $\rightarrow$ fuse alerts across layers



Output global intrusion decisions with confidence scores

EXPERIMENTAL EVALUATION: GOALS & METHODOLOGY

Assess robustness of the Vertical IDS under

- noisy environments
- compromised Fog nodes
- coordinated / stealthy attacks

Validate trust dynamics

- Does the evolutionary game penalize malicious nodes?
- Does the trust-weighted GNN reduce their influence?

Compare against baselines

- Flat IDS
- Horizontal-only GNN
- GNN without trust adaptation

SIMULATING ADVERSARIAL BEHAVIOUR IN IoT FOG NETWORKS

Scenario 1 – Low-level corruption:
10% of Fog nodes generate **systematic false alerts**.

Scenario 2 – Mixed malicious activity:
20% of nodes behave **maliciously** and inject **random noise** into their reports.

Scenario 3 – Coordinated adversaries:
A group of Fog nodes cooperates to **mimic legitimate patterns** while pushing false information.

Goal: Stress-test the **trust mechanism** under realistic and stealthy adversarial conditions.

DATASET AND SIMULATION PARAMETERS

Dataset: UNSW-NB15 (2.5M records, 9 attack categories).

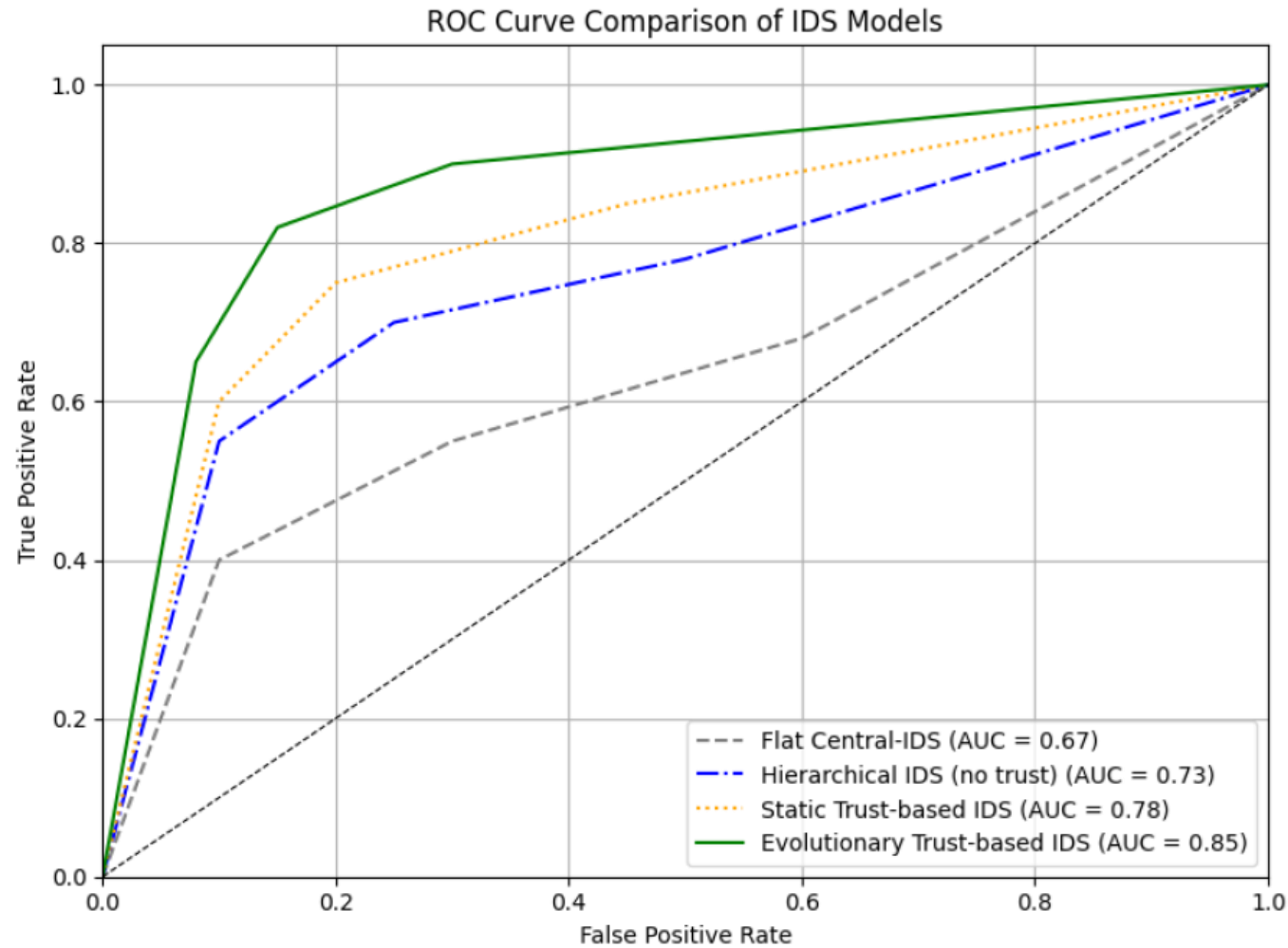
IoT environment: 3-tier Edge → Fog → Cloud topology.

Implementation: PyTorch + PyTorch-Geometric, 50 epochs, Adam optimizer.

Evaluation focus: accuracy and resilience under adversarial stress.

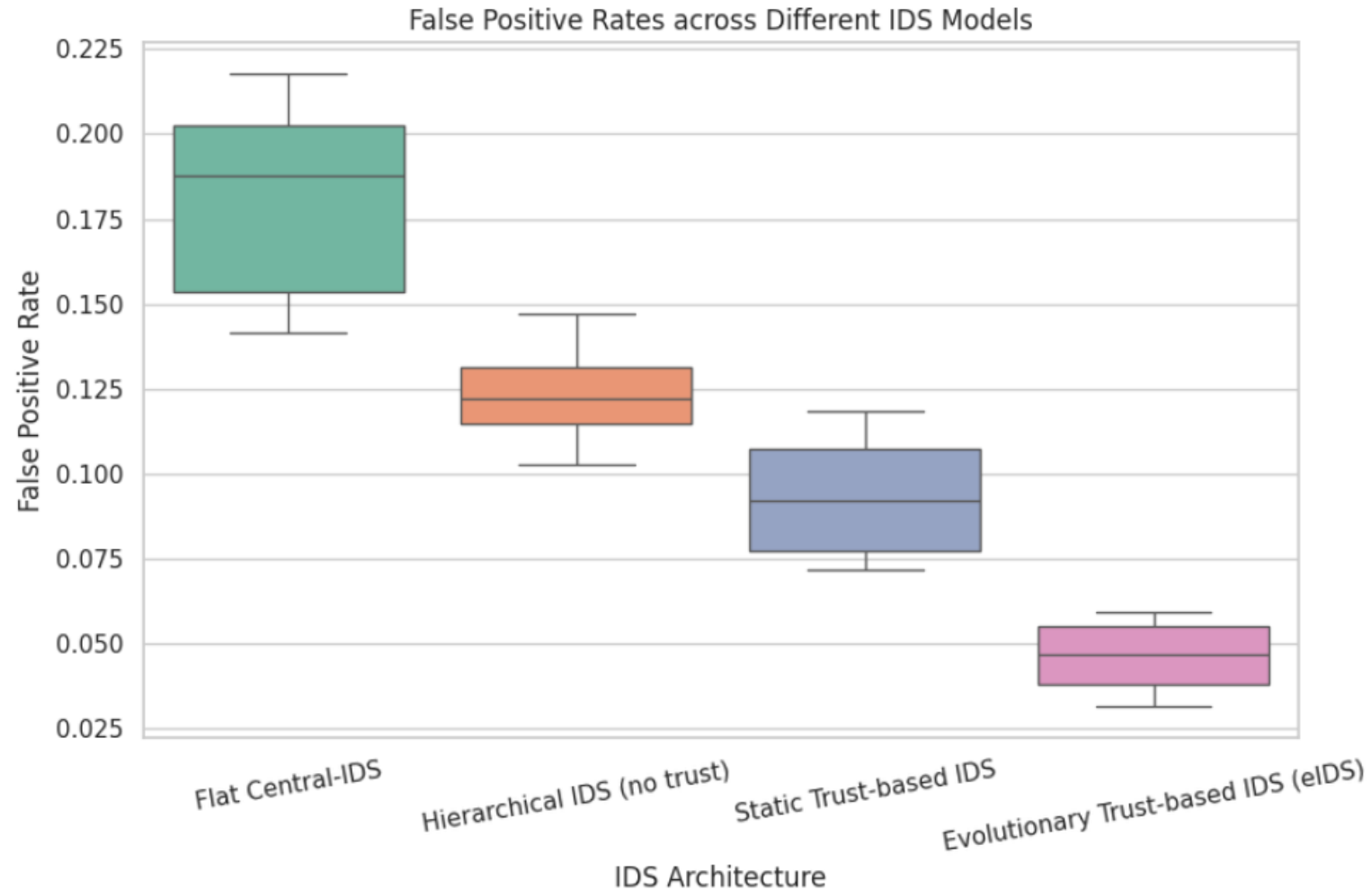
RESULTS (ROC AND AUC)

GLOBAL DETECTION PERFORMANCE

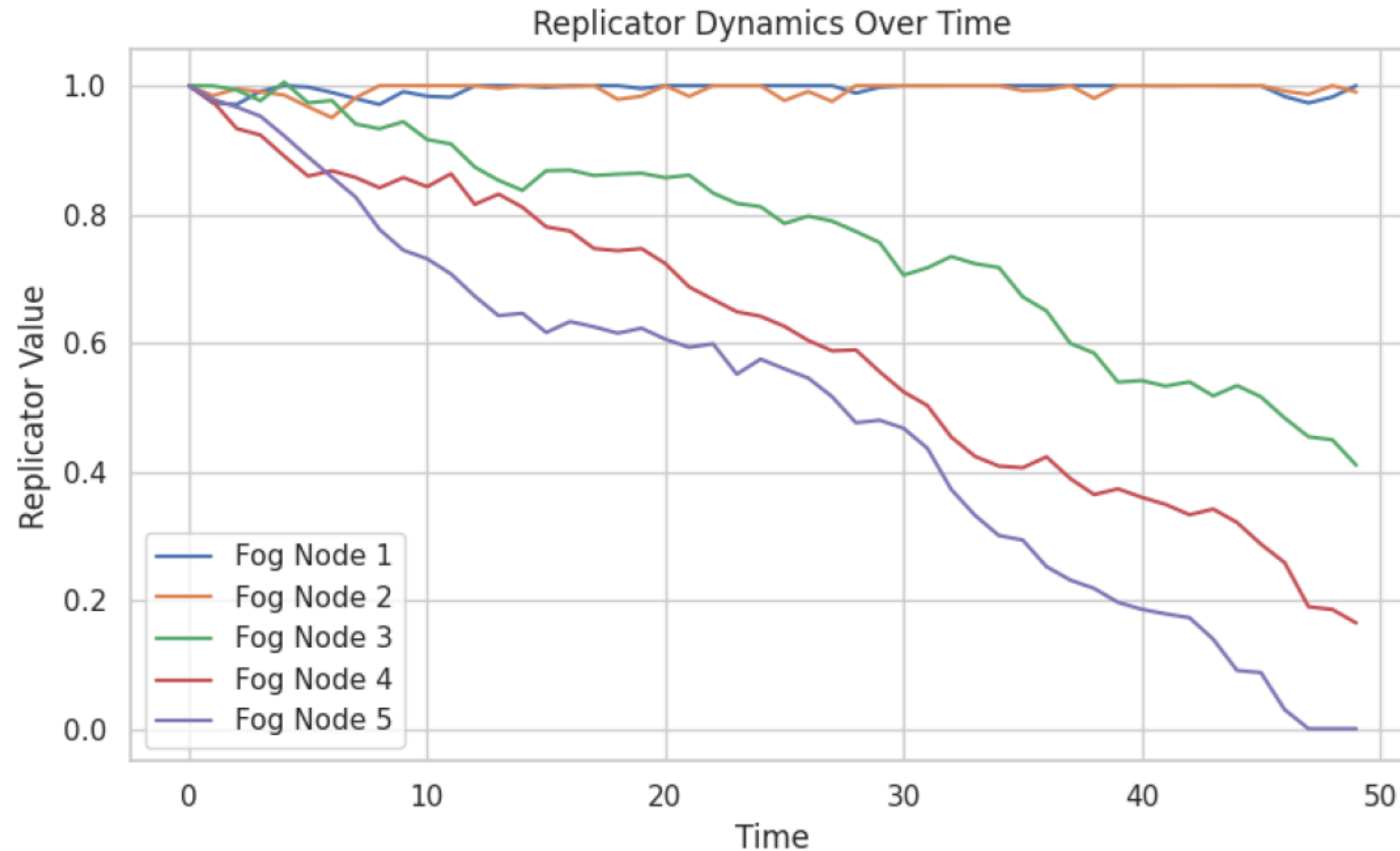


RESULTS (FALSE POSITIVES & STABILITY)

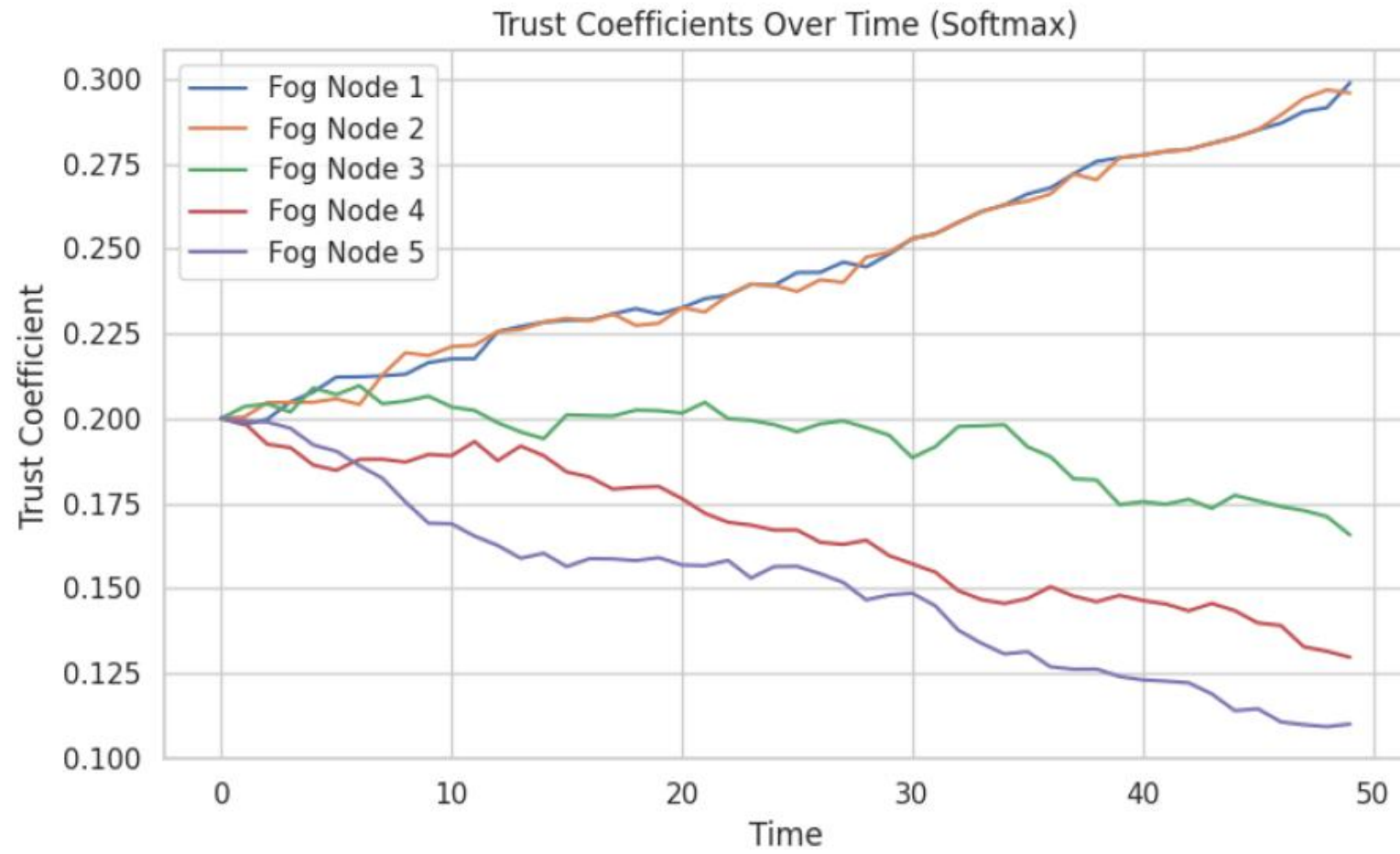
REDUCING FALSE ALARMS THROUGH ADAPTIVE TRUST



HOW TRUST EMERGES OVER TIME



TRUST CONVERGENCE ACROSS FOG NODES



CONCLUSION AND FUTURE WORK

Toward Adaptive & Trust-Aware IDS for IoT

V-IDS provides multi-layer intrusion detection with **evolving trust**.

Combining **GNN + Evolutionary Games** improves **robustness** under adversarial drift.

Next steps: Edge-Fog-Cloud deployment, scalability experiments, federated trust learning.



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Thank You! Questions?

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