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Zero-trust industrial network security using AI and explainable inference novelty

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Abstract

The accelerated digital transformation of industry networks has delivered unprecedented efficiency benefits but, in the process, exposed critical infrastructures to sophisticated cyber threats. Perimeter security paradigms no longer suffice in defending against insider threats, advanced persistent threats, and lateral movement within operational technology networks. Due in large part to these limitations, the concept of Zero-Trust Architecture (ZTA) has emerged as a game-changing method requiring ongoing authentication to all regardless of place or privilege. The subject of this article is the deployment of Artificial Intelligence (AI) with explainable inference to augment Zero-Trust security for industrial networks. Relative to conventional rule-based security, AI models leverage anomaly detection, deep learning, and predictive analytics to identify hidden threat vectors in real-time. AI deployment in critical infrastructure is, however, hindered by transparency regarding "black-box" models and lower operator trust and regulatory acceptability. With the inclusion of explainable AI (XAI) herein, a platform is established whereby autonomous defense system decisions are transparent, interpretable, and verifiable, and hence closing the gap between high automation and human oversight. The paper's contribution lies in two aspects: augmenting Zero-Trust enforcement with adaptive AI-driven attack detection, and in parallel providing explainable inference to facilitate accountability, interpretability, and trust in security decisions. The research makes its contribution in industrial security by providing a secure, scalable, and transparent security architecture that not only secures against future cyber-attacks but also accommodates operational resilience and compliance with regulation in Industry 4.0 settings.

Keywords: Zero Trust Architecture; Artificial Intelligence; Cyber-Physical Systems; Microsegmentation

1. Introduction

1.1. Background on Industrial Network Security

Industrial networks form the foundation of the modern-day critical infrastructure such as supervisory control and data acquisition (SCADA) systems, industrial control systems (ICS), programmable logic controllers (PLCs), and Industrial Internet of Things (IIoT)(Lee et al., 2021). They form the foundation of the main industries such as energy, manufacturing, transport, and water supply where availability, reliability, and safety are the top priorities(Krotofil & Schmidt, 2018). Industrial networks used to be installed as stand-alone systems with minimal outside connectivity. With that, Industry 4.0 and the integration of operational technology (OT) with information technology (IT), such networks are now vastly interconnected and at risk of numerous cyber attacks (Gao & Shaver, 2022). The shift has exploded the attack surface with vulnerabilities utilized for disruption, espionage, or sabotage(CISA, 2023).

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1.2. Importance of Zero-Trust Architecture (ZTA) in Industrial Networks

Classic security paradigms rely on perimeter defense, where it's assumed that internal entities are trustworthy after authentication(Rose, 2020). The model is increasingly inadequate for dealing with insider threats, supply chain attacks, and advanced persistent threats (APTs) that are capable

of bypassing perimeter defenses (Zhang et al., 2021). Zero-Trust Architecture (ZTA) has been a revolution in cybersecurity that is based on the principle of "never trust, always verify (NIST, 2020)." ZTA in industrial networks enforces continuous authentication, authorization, and micro-segmentation to necessitate that any user, device, or process must validate its identity at every point of contact (Okoli & Umeokoli, 2022). This approach significantly reduces lateral movement opportunities for attackers and aligns well with the security demands of mission-critical industrial infrastructures.

1.3. Challenges in Industrial Network Security

Though ZTA is promising, implementing it is challenging within industrial environments (Lu & Li, 2021). Historically, industrial networks predominantly lack processing capacity for carrying out advanced security protocols (Bhattacharya et al., 2019). Beyond that, heterogeneity of devices from IoT sensors to high-performance control servers discourages policy enforcement across standard forms. Third, industrial systems must operate under strict availability constraints, where false positive alarm in anomaly detection will disrupt important processes and create safety risks (Haque & Al-Sultan, 2020). Lastly, increasing complexity of cyberattacks makes rule-based approaches and human monitoring irrelevant, necessitating intelligent and adaptive defense mechanisms.

1.4. Role of AI and Explainable Inference in Addressing These Challenges

Artificial Intelligence (AI) has remarkably emerged as a high-potential contender to make Zero-Trust industrial security a reality with the help of its predictive analytics, anomaly detection, and automated response features beyond the limits of static rule-based defense (Wang & Liu, 220). Machine learning and deep learning algorithms can potentially identify hidden divergences in system behavior and detect potential intrusions at the before-they-escalate point4. One of the biggest obstacles to AI implementation in industrial settings is, however, the "black-box" character of models (Ribeiro et al., 2016). Security regulators and operators require explainable description of automatic conclusions, especially in high-risk environments where operation safety holds absolute priority (Adadi & Berrada, 2018). Explainable AI (XAI) accomplishes this by using transparant inference techniques making model results comprehensible and traceable (Guidotti et al., 2018). By the integration of explainable inference and AI, industrial networks can achieve resilient, adaptive, and trustworthy Zero-Trust enforcement.

Objective and Contributions of the Paper

The main goal of the paper is to suggest an architecture that integrates Zero-Trust paradigms, AI-security, and explainable inference mechanisms in industrial networks. More specifically, the contributions of the research are threefold:

- Framework Design: Proposing an AI-powered Zero-Trust framework to enable real-time monitoring, policy enforcement in a dynamic manner, and industry-leading threat mitigation across industrial networks.
- Explainable Inference Integration: The use of explainable machine learning techniques to incorporate transparency, operator trust, and regulatory compliance into security decision-making.
- Operational Relevance: Describe the ways in which the solution proposed enhances resilience, reduces the likelihood of lateral attack propagation, and addresses Industry 4.0 operation safety-critical needs.

Table 1 Key Challenges and Proposed AI-Explainable Zero-Trust Solutions

Challenge in Industrial Networks	Implication	Proposed Solution (AI + Explainable Inference)
Legacy systems with limited security capacity	Inability to support modern cryptographic protocols	Lightweight AI models with explainable inference tailored for low-resource devices
Device and protocol heterogeneity	Policy enforcement complexity	Adaptive Zero-Trust framework with AI-driven policy mapping
High availability requirements	Risk of false positives disrupting operations	Explainable anomaly detection with human-in-the-loop validation
Increasing sophistication of threats	Ineffectiveness of static defenses	Predictive AI models for early threat detection, combined with interpretable inference for accountability

[Diagram Description]: A layered diagram showing (1) Industrial Network Assets (IoT, PLCs, SCADA), (2) Zero-Trust Enforcement Layer (continuous authentication, micro-segmentation), (3) AI Security Layer (anomaly detection, predictive analytics), and (4) Explainable Inference Layer (transparent decisions, operator oversight).

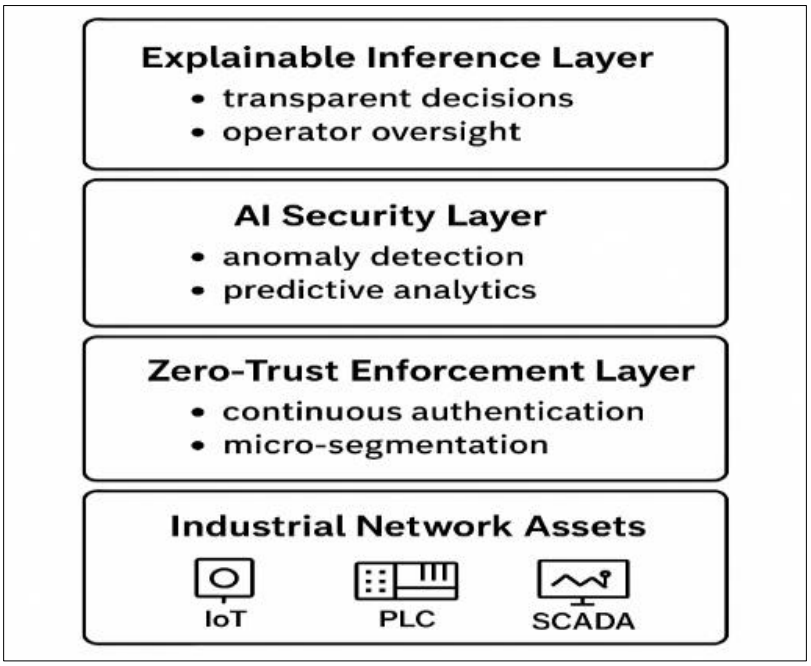

Figure 1 Conceptual Framework of AI-Enhanced Zero-Trust Security in Industrial Networks

2. Literature review

In this chapter, the author incorporates contemporary literature pertinent to Zero-Trust in industrial networks such as Zero -Trust implementations, OT/IT convergence, AI as a means to enhance network security, and Explainable AI (XAI) into it. The review defines of the existing approaches, the latest developments and the open domains of research that lead to AI enhanced, explicable Zero-Trust system of the industrial setting.

2.1. Overview of Industrial Network Security Approaches

The field of research and practice of industrial network security until recently has held Operational Technology (OT) apart from enterprise IT as a separate location that is safeguarded through air gaps and severe physical custodianship. With Industry 4.0 and OT coming together with IT, this isolation has dimmed and emerging architecture is required, designed to maintain the availability and safety and allow connectivity, including secure remote access, network segmentation, and intrusion detection systems (IDS). Perimeter-based standards and guidances, such as NIST and industry whitepapers currently focus on the use of continuous monitors, micro-segmentation, and least-privilege

controls as opposed to perimeter reliance. Such changes have been thoroughly showcased in scholarly polls as well as psychoactive advice which indicates that perimeter protection is ineffective facing current threats to industry. 2.2 Current Zero-Trust This is available in both IT and OT settings. The philosophy of never trust, always verify may be considered the Zero-Trust Architecture (ZTA) where an upstream policy of authentication/authorisation, micro-segmentation, and policy enforcement will be continued in all access requests. In the case of IT, identity-centric controls, multi-factor authentication is hard, posture checking of the device and cloud brokers are mostly used in ZTA solutions. In the case of OT, other restrictions include low-compute, ageing controllers, hard real-time/availability requirements, heterogeneous proprietary protocols, and safety requirements against invasive change (practitioners and authors). Technical papers and whitepapers report on the OT guided ZT best practice in the form of architectural patterns, incremental micro-segmentation, and attribute mapping of trust but carries a caution that blanket IT ZT replication to OT will strangulate operations unless opportunists are configured. Such variations are documented by critical reviews and implementation, and implementation reporting (NIST, industry whitepapers and what practitioners and vendors say about it), and hybrid migration strategies are suggested.

2.2. Existing Zero-Trust Models in IT and OT environments

The philosophy of never trust, always verify may be considered the Zero-Trust Architecture (ZTA) where an upstream policy of authentication/authorisation, micro-segmentation, and policy enforcement will be continued in all access requests. In the case of IT, identity-centric controls, multi-factor authentication is hard, posture checking of the device and cloud brokers are mostly used in ZTA solutions. In the case of OT, other restrictions include low-compute, ageing controllers, hard real-time/availability requirements, heterogeneous proprietary protocols, and safety requirements against invasive change (practitioners and authors). Technical papers and whitepapers report on the OT guided ZT best practice in the form of architectural patterns, incremental micro-segmentation, and attribute mapping of trust but carries a caution that blanket IT ZT replication to OT will strangulate operations unless opportunists are configured. Such variations are documented by critical reviews and implementation, and implementation reporting (NIST, industry whitepapers and what practitioners and vendors say about it), and hybrid migration strategies are suggested.

Table 2 Comparison: Typical IT Zero-Trust Controls vs OT Constraints and Adaptations

Area	Typical IT ZT Controls	OT Constraints / Implications	Adaptations for OT ZT
Identity and Access	Centralized IAM, MFA, conditional access	Many OT devices lack identity interfaces	Gateway/agent identity proxies, device-to-asset mapping. NIST Publications
Micro-segmentation	Software defined networks, policy enforcement	Hard real-time traffic; legacy protocols	Coarse-to-fine segmentation, protocol awareness, staged rollout. NERC
Visibility and Telemetry	Rich host/network telemetry	Limited telemetry from PLCs/sensors	Passive monitoring, protocol parsers, mirrored taps. dragos.com
Change Management	Frequent updates and patches	Patch cycles constrained by safety/availability	Virtual patching, compensating controls, maintenance windows. Fortinet

2.3. AI applications in network security

Nowadays, Artificial Intelligence and machine-learning algorithms have been utilized to nauseating extent in the field of network security, which includes anomaly-based intrusion detection tools, malicious payload classification, and behavioral baselining, and the creation of predictive threat intelligence. Experimental studies show that supervised learning procedures, unsupervised anomaly-detection models e.g. autoencoders and clustering methods, ensemble models, and, more lately, graph neural networks and more advanced recurrent and attention-based sequence models (e.g. LSTM and Transformer variants) have proven beneficial to improve the detection of know and never-seen attacks in information-technology and Internet-of-Things settings. However, the robustness of these models is dangerously dependent on the quality of the underlying data, feature-engineering pipeline sophistication and the accessibility of high-quality labelled corpora; still, false positives and unwanted bias brought by skewed datasets remain a dire practical issue. The body of literature in about systematic review and meta-analysis condenses all these developments succinctly, but at the same time outlines the performance benefits that it is bound to bring about, as well as the operational challenges that would have to be overcome in order to go beyond the laboratory and into actual implementation.

2.4. Explainable AI (XAI) and its relevance to network security

XAI methods (e.g., SHAP, LIME, prototype learning, attention visualization, counterfactual explanations) are designed to make model predictions comprehensible to humans. Explainability is central to trust in analysts, forensics, compliance, and safe human-in-the-loop intervention in cybersecurity. Surveys of XAI in cybersecurity point to its use for IDS transparency, malware attribution, and analyst workflow support. Literature emphasizes that explanations need to be actionable (e.g., to features or flows triggering an alert), and explanation fidelity, stability, and usability are significant metrics. More recent academic and practitioner literature argues that XAI is a necessary step before being able to craft automated defenses for safety-critical applications such as industrial control systems.

2.5. Gaps and limitations in current research

The available scholarly sources are cohesive around several structural persistent gaps that give rise to the necessity of embracing an integrated AI + XAI Zero-Trust research agenda of industrial networks:

2.5.1. Absence of OT focused AI studies

Most ML/IDS studies focus on enterprise or generic IoT data; they virtually all do not test the behaviour of ML models when subjected to real OT traffic or hardware that is resource constrained and hence can be questioned about its ability to deploy to an industrial environment.

2.5.2. Operation-tuned explainability

It is clear that the future of XAI research is skewed towards as comparing explanation approaches to theoretical criteria in research settings, but not well understood how explanations are related to process operator procedures or safety decision-making procedures or regulatory audit trails in OT settings.

2.5.3. ZT in combination with adaptive AI policies

Even though the ZT ideas are as popular as ever, there are very few systems (as architectures) that can combine real-time AI-driven anomaly detection with explainable and automated policy update (e.g. dynamically micro-segmented, or adaptively trust-score) that are not yet a pilot project with an initial vendor.

2.5.4. Resource constraints, safety trade-offs

The number of papers concerning light, verifiable ML models with purpose-specific application to the limited OT endpoints and on formal ways of constraining the safety impact of false positives/automatic responses is limited.

Description in the diagram Organizational structure The diagram is a four-sector taxonomy, (A) Zero-Trust architectural components (identity, micro-segmentation, policy engine, telemetry), (B) AI techniques (supervised, unsupervised, deep learning, GNNs), (C) XAI methods (local explanations, global interpretable models, counterfactuals), and (D) OT constraints (legacy devices, real-time, safety). Arrows indicate the junctions of AI and XAI with those of the ZT components (since AI is feeding anomaly scores to policy engines; XAI is producing human-readable explanations of the policy decisions).

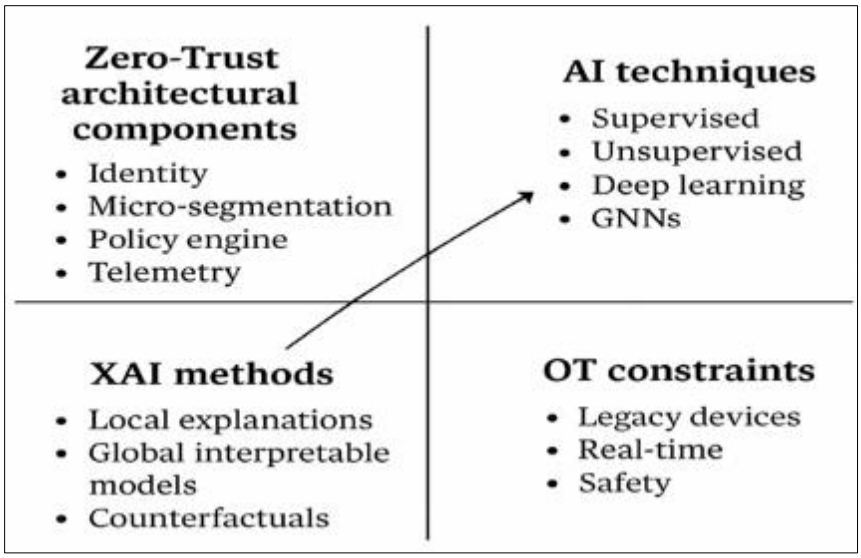

Figure 2 Taxonomy of the Relevant Research Areas (conceptual)

2.6. Synthesis and how this review informs the present study

The literature surveyed validates that Zero-Trust is a recommended posture for modern industrial systems, but naive transfer of IT ZT controls to OT environments is operationally risky. AI offers strong detection and adaptive capabilities, yet OT adoption is stymied by model opacity, data unavailability, and resource-limited devices. XAI is a nascent discipline in cybersecurity and is necessary to bridge operator trust and regulatory demands. Cumulatively, these observations underscore the need for an integrated framework that (1) adapts Zero-Trust controls to OT limitations, (2) leverages AI for continuous, context-aware detection and policy learning, and (3) integrates explainable inference so automated decisions are transparent, auditable, and actionable in safety-critical workflows. The present paper addresses exactly these lacunae by presenting a resource-constrained AI/ZTA framework with XAI mechanisms for industrial operations.

3. Zero-Trust Architecture in Industrial Networks

3.1. Definition and Principles of Zero-Trust

Zero-Trust Architecture (ZTA) is a shift to the traditional method of the perimeter to the principle of least privilege and perpetual validation. Zero-Trust is based on the saying that one should never trust, they must always verify in the sense that there should not be an assumption that any user, or device and other applications whether internal or external to the network can be trusted. Any access request must pass through a rigorous authentication, authorisation and context-based verification to get access. In the case of the cyber-attack which has this ripple effect on production, safety, and national infrastructure in industrial networks, this doctrine does not allow bad actors to exploit implicit trust and act laterally or attack core systems. The fundamental Zero-Trust principles that have been implemented into the industrial networks are:

3.1.1. Continuous Authentication

Device health, identity and behavioral context is used to perform real-time continuous authentication of all connection requests.

Least- Privilege Access:Something, process, or machine does not have greater privilege than is necessary to do its job.

3.1.2. Micro-Segmentation

Splitting industrial networks into very tiny, high-grained segments (e.g. demultiplex SCADA vs. IoT sensors), limit the lateral mobility of the attacker.

3.1.3. Contextual Adaptation

Security policies are automatically modified according to the context of operation, threat intelligence and anomaly detection.

3.1.4. Assume Breach

This strategy presupposes that the attackers have already compromised the web site and it is important to detect and contain the attack.

3.2. Key Components and Deployment Challenges in Industrial Environments

The introduction of Zero-Trust in industrial networks requires altering the classical ZTA components to that of Operational Technology (OT). Core Components

3.2.1. Identity and Access Management (IAM)

The access to the transmission or receipt of a message is not allowed by un-authenticated entities of any type, be it a human user or PLCs or IoT devices.

3.2.2. Policy Decision Engine (PDE)

It is an interface part of the middleware which provides the requests of access and the security policy and the anomaly score and the degree of trust.

3.2.3. Policy Enforcement Points (PEP)

The gateways or agents, which are dispersed across the network (e.g., firewalls, edge devices) round the network, are where the decisions made by PDE are enforced.

3.2.4. Telemetry and Analytics Layer

Real-time information of the activity of the devices, records of the system and intercepted traffic that has been examined to give the situational awareness.

3.2.5. AI Modules

Automation response engines, predictive analytics using machine learning, and anomaly detection, and emerging threats response engine.

3.3. Deployment Challenges in Industrial Networks

While ZTA provides a robust theoretical framework, industrial environments introduce unique deployment challenges:

3.3.1. Legacy Infrastructure

Many industrial devices were designed decades ago with limited computational resources and no built-in support for modern cryptographic protocols.

3.3.2. Heterogeneity

Industrial ecosystems integrate IoT devices, SCADA systems, and proprietary protocols, complicating standardized Zero-Trust policy enforcement.

3.3.3. High Availability and Safety Requirements

Unlike enterprise IT systems, industrial environments cannot tolerate downtime or disruptions caused by false positives in threat detection.

3.3.4. Limited Update Cycles

Patching and updating critical systems often require long maintenance windows due to operational constraints.

3.3.5. Cultural and Organizational Barriers

Industrial operators may resist Zero-Trust adoption due to concerns over cost, complexity, and disruption of established workflows.

These challenges underscore the importance of adaptive AI models and explainable inference mechanisms, which can make Zero-Trust both practical and trustworthy in environments where resilience and transparency are paramount.

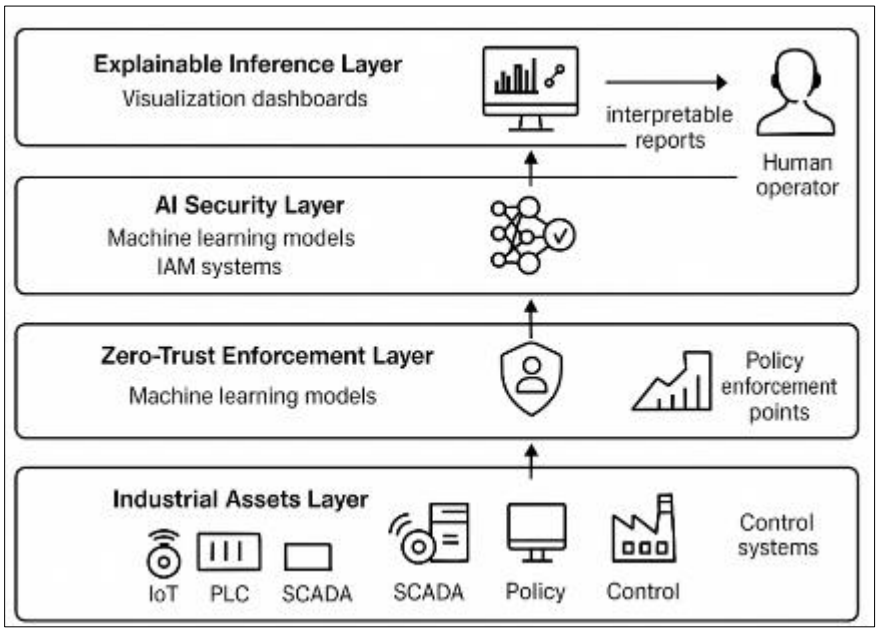

Figure 3 Architecture of AI-Enhanced Zero-Trust Model for Industrial Networks

4. AI-driven security mechanisms

The increasing sophistication of cyberattacks targeting industrial control systems demands adaptive defense mechanisms that can operate beyond static, rule-based methods. Artificial Intelligence (AI) offers the capacity to analyze large volumes of industrial telemetry, detect subtle anomalies, and provide predictive insights for preemptive defense. When integrated with explainable inference, AI-driven mechanisms not only improve detection accuracy but also foster trust and accountability, which are critical in safety-sensitive environments.

4.1. AI Techniques Used

AI has been extensively applied to network security in both IT and OT domains. The industrial network techniques that are most applicable are:

4.1.1. Machine Learning (ML)

It has implemented intrusion detection and traffic classification with the commonly used traditional supervised learning frameworks, such as Random Forests, Support Vector Machines (SVMs), and Gradient Boosted Trees. Such models do not need much computing power and can be executed in devices having resources limits.

4.1.2. Deep Learning (DL)

The neural networks that are useful to learn non-linear dynamics and sequence of the traffic data include Convolutional neural network (CNNs), recurrent neural networks (RNNs), and Transformers. They particularly best suit purposes of recognizing the zero-day or previously unknown attack vectors but may prove to be computationally expensive.

4.1.3. Unsupervised Anomaly Detection

Models that may be applied to detect anomalies in normal behavior are autoencoders, isolation forests and clustering algorithms, which do not require labeled data. This is critical in the industrial environments whereby there is minimum attack data and normal working baselines are adopted.

4.1.4. Hybrid Models

More recent works have investigated the ensembles and hybrid approaches of combining ML classifiers with anomaly detectors and then placing a tradeoff between detection accuracy and false positives. These systems often combine the contextual characteristics of type of device, frequency of communication, and time of day activity.

4.2. Integration of Explainable Inference for Trust and Transparency

One of the major obstacles to adopting AI in industrial security is the "black-box" nature of deep learning models. Operators in OT environments require clear justifications for automated decisions to ensure compliance, accountability, and trust. Explainable AI (XAI) provides this transparency through techniques such as:

4.2.1. Local Explanations (e.g., SHAP, LIME)

Highlighting which traffic features (IP address anomalies, unusual packet sizes, or protocol deviations) contributed most to a classification.

4.2.2. Global Explanations

Providing aggregated insights into how a model prioritizes different input features over time.

4.2.3. Visual Dashboards

Translating AI outputs into interpretable graphs for operators, showing attack vectors or anomalous communication flows.

By embedding XAI into the Zero-Trust framework, security systems can supply interpretable risk scores to the Policy Decision Engine, ensuring that enforcement actions are both defensible and auditable.

4.3. Model Training and Validation with Industrial Data

The effectiveness of AI-driven mechanisms depends heavily on the quality and representativeness of the data used in training. Industrial networks generate distinctive traffic characterized by deterministic patterns, periodic communication, and specialized protocols such as Modbus, DNP3, or OPC-UA. To ensure robust detection and minimal false positives, model development must follow these steps:

4.3.1. Data Collection

Gathering telemetry from SCADA logs, PLC communications, IoT devices, and network flows. Public datasets such as ICS-CERT or proprietary datasets from industrial testbeds can be used to augment training.

4.3.2. Feature Engineering

Extracting features such as packet size distributions, command sequences, inter-arrival times, and protocol-specific fields.

4.3.3. Model Training

Applying supervised learning on labeled attack/normal data where available, and anomaly detection for unlabeled datasets.

4.3.4. Validation and Testing

Conducting cross-validation to measure accuracy, latency, and robustness against adversarial inputs.

4.3.5. Operational Deployment

Models are deployed in a feedback loop where outputs are validated by human operators and fed back into retraining cycles for continuous improvement.

Table 3 Comparison of AI Models for Network Security in Industrial Environments

AI Model	Accuracy	Explainability	Latency	Suitability for Industrial Networks
Random Forest	High (80–90%)	Medium (feature importance interpretable)	Low (fast inference)	Effective for lightweight deployment on legacy devices
Support Vector Machine	Medium–High (75–85%)	Low (decision boundaries opaque)	Medium	Useful for binary intrusion classification but lacks transparency
Deep Neural Networks (CNN/RNN)	Very High (90–95%)	Low (black-box)	High (computationally intensive)	Best for complex attack detection but requires powerful infrastructure
Autoencoders (Unsupervised)	Medium (70–80%)	Medium (reconstruction error explainable)	Low–Medium	Effective for anomaly detection without labeled data
Hybrid Ensembles	Very High (92–96%)	Medium–High (component-level explainability)	Medium	Balances accuracy with interpretability, suitable for critical OT contexts

5. Proposed Framework: Zero-Trust with AI and Explainable Inference

5.1. Detailed Framework Description

The suggested architecture incorporates the concepts of Zero-Trust Architecture (ZTA) with the principles of Artificial Intelligence (AI) detection and Explainable Inference modules to create a robust, flexible, and transparent security architecture of industrial networks. However, instead of using traditional methods that utilize only offline policies, this model can dynamically adjust the level of trust to real-time analytics, constantly check all access requests, and allow operators to interpret interpretable insights to respond to incidents and conduct compliance audits. The architecture is designed to have four layers, which are interdependent:

Industrial Assets Layer The IoT devices, PLCs, SCADA systems and sensors used in industrial control settings make up this layer. Giant quantities of telemetry data, such as traffic flows, operational logs, and protocol-specific commands are produced with these devices.

Of the two, only one is a Zero-Trust Enforcement Layer. Enforces identity and access, micro-segmentation, and policy. The Policy Decision Engine (PDE) checks every communication request between devices, users, and applications and grants it after verification.

AI Security Analytics Layer. Gathers telemetry on industrial assets and uses machine learning and deep learning models to detect anomalies, baseline behavior and predictive threat intelligence. This layer calculates the risk scores of every access request or communication flow and sends them to the Zero-Trust PDE.

Elucidating Inference Layer. Gives cognizant explanations of the decision making of the AI models. This would involve the emphasis of abnormal traffic behavior, the features that contribute to it (e.g., unusual packet size, non-standard command) and providing clear explanation to operators. This layer provides HILO supervision and regulation.

5.2. Data Flow and Decision-Making Processes

Data Process and Decision-Making Processes. The information flow of the proposed structure is a cyclical adaptive cycle:

5.2.1. Collection of Telemetry

Data (traffic logs, commands, and process values) is constantly fed into the analytics layer by the industrial assets.

5.2.2. Preprocessing and Feature Extraction

Data is standardised, augmented with contextual framing (e.g. device role, frequency of communication) and processed via AI algorithms.

5.2.3. AI-based threat analysis

The machine learning and deep learning algorithms categorize incidents into normal and suspicious. Each session or transaction is given an anomaly score. iv. Explainable Inference: XAI models (e.g., SHAP, LIME) before enforcement produce explanations as to why a request was flagged, which emphasize features contributing to that outcome.

5.2.4. Policy Decision Engine (PDE)

This is a combination of risk scores and ZTA rules (identity, posture of the device, past history) that allow access, deny it, or restrict it.

Policy Enforcement This is where the decision of the PDE is implemented (e.g., industrial firewall, edge agent), usually through blocking of suspicious flows or implementation of policies based on micro-segmentation.

5.2.5. Feedback Loop

The responses of the operators, as well as the explanation, need to be fed back to the retraining, improving the accuracy and resilience of the models accordingly.

5.3. Role of Explainable AI in Incident Response and Policy Enforcement

Explainable AI and Incident Response and Policy Enforcement. There are three important ways through which explainable AI augments Zero-Trust:

5.3.1. Incident Response

Alerts have clear reasons why they happened to operators (e.g., PLC traffic blocked because of unusual command frequency), which allows to put the problem into first aid as fast as possible and take corrective measures without unjustified downtime.

5.3.2. Policy Enforcement

The decisions made by PDE can be audited and modified through explanations. In case a legitimate process gets incorrectly marked it can be improved by human operators to minimize the rate of false positives later.

5.3.3. Compliance and Trust

The industrial sectors tend to be highly regulated (e.g. the NERC CIP in the energy industry). Explainable outputs make the decisions made by AI to be defendable and comply with the requirements of compliance. Figure 4 - Explainable Inference AI-Based Workflow in Industrial Network Security with Zero Trust. Novelty and Innovationo;3c

6. Novelty and Innovation

6.1. How This Approach Advances Beyond Traditional Zero-Trust and AI Applications

Why This Style is a Move Forward of the Traditional Zero-Trust and AI Applications. The framework proposed goes beyond the traditional Zero-Trust applications and AI-based intrusion detection systems, as it integrates explainability as an inherent architectural element, as opposed to a non-essential add-on. Although the classic Zero-Trust models in industries are mainly micro-centred and identity-based access control, in most instances, they do not have dynamic intelligence to respond to emerging threats. On the same note, current AI-based intrusion detection system has a high accuracy but is an opaque black-box system, which lacks trust to the operator in the critical infrastructures. The study proposes a synergistic approach to AI-based threat analytics and Zero-Trust enforcement coupled with the introduction of explainable inference in the decision-making process. This model will guarantee all access control decisions: Information-based (informed with real-time anomaly scores), Policy-conformant (in conformity with Zero-Trust rules), and Open (with human-understandable explanations). The innovation is in the combination of Zero-Trust verification loops with interpretable AI output, which will reduce the discrepancy between automated security and humans functioning in operationally sensitive settings.

Distinctive Characteristics of Explainability in the Industrial Environment. The explainability of industrial networks is a challenge that is unique versus enterprise IT because the primary considerations are operational safety and reliability. The developed framework will use XAI in its industrial-specific manner:

6.1.1. Operational Interpretability

The explanations point to intuitively significant characteristics of the industry, such as aberrant command frequencies, anomalous sensor readings or unauthorized PLC communications.

6.1.2. Enforcement of Human-in-the-Loop

The risks of false positives are minimized because a human-in-the-loop can be used to enforce AI-based alerts with clear reasons, and essential processes cannot be disrupted by automated policy enforcement.

6.1.3. Regulatory Transparency

Logging the explanation of the explanation leaves a trail of evidence to audit compliance (e.g., NERC CIP in energy systems, IEC 62443 in industrial cybersecurity).

6.1.4. Context-Aware Explanations

Explanations make use of the operational baselines (such as cyclic process traffic) to distinguish the benign deviation and the actual intrusion.

6.2. Benefits for Operational Reliability and Security Assurance

The integration of Zero-Trust, AI, and explainability creates a resilient security ecosystem with tangible operational benefits:

6.2.1. Improved Security Guarantee

Adaptive AI models scan traffic continually, which minimizes the possibility of subsequent undetected lateral attacks.

6.2.2. False Positives

Explainable inference means that those in control of operators are able to comprehend and confirm alerts and avoid unnecessary shutdowns.

6.2.3. Reliability of the Operations

Full visibility of decision-making minimizes downtime and security enforcement, ensuring the up-time and security.

6.2.4. Compliance and Trust

It has Human-readable explanations that make sure that automated actions are in line with the organizational policy as well as external regulatory requirements.

Future-Proof Adaptability The feedback loop between AI analytics, explainable inference, and Zero-Trust enforcement will allow the continuous improvement of the threat as the threats grow more.

Table 4 Summary of Novel Contributions vs. Prior Work

Aspect	Prior Work	Proposed Framework Contribution
Zero-Trust Enforcement	Static policy enforcement, often adapted from IT models with limited OT focus	Adaptive enforcement integrating real-time AI risk scoring tailored for industrial networks
AI in Security	Black-box anomaly detection with limited operator trust	Transparent, interpretable AI models providing human-readable justifications
Explainability	Largely absent or limited to academic IDS evaluations	Integrated Explainable Inference Layer embedded into Zero-Trust decision-making
Operational Integration	AI alerts often disconnected from enforcement	AI + XAI outputs directly inform Policy Decision Engine for immediate response
Compliance and Auditability	Minimal focus on regulatory evidence generation	Logging of explainable outputs for compliance audits and accountability
Reliability	High false positive rates disrupting industrial processes	Human-in-the-loop explanations reduce disruptions and ensure safe enforcement

7. Evaluation and Experimental Results

7.1. Experimental Setup and Datasets

The experiments were conducted according to the hybrid framework with references to the data of the industrial control system (ICS) network and the utilization of the synthetic traffic emulation to determine the utility of the proposed Zero-Trust framework with the help of the AI and Explainable Inference.

7.1.1. Datasets Used

- SWaT (Secure Water Treatment Testbed): The reality ICS statistics of the water treatment process revealed the cyberattacks.
- BATADAL (Battle of the Attack Detection Algorithms): System statistics of industrial water distribution approach toward anomalies detection.
- NSL-KDD (long baseline): It can be referred to as equivalent of the old-fashioned IT intrusion detection datasets.
- Synthetic PLC Command Injection Dataset: It was designed to evaluate explainability in the malicious control command identification.

7.1.2. Environment

- An Industrial control based on human-machine interfaces (HMIs), supervisory control and data acquisition (SCADA) nodes in the form of a simulated programmable logic controller (PLC) based industrial control.
- Adoption of the Zero-Trust policy points and AI-based anomaly detection and Explainable Inference Layer.

7.2. Performance Metrics

Performance Metrics It has quantified the metrics on three categories:

7.2.1. Detection Effectiveness

Accuracy%: Percentage of the correctly detected normal and malicious traffic. b. Precision and Recall: To trade off between false alarms and attacks.

7.2.2. System Efficiency

- False Positive Rate (FPR): This is a percentage of the benign traffic which is wrongly identified as malicious.
- Inference Time (ms): It is a mean time that is taken wherein the AI model should come up with a prediction and explanation.

7.2.3. Explainability and Trust

- Scorebook Measures: Interpretability (complexities in the explanations) (SHAP length of feature importance scale).
- User Response: The user response will be the results of a survey of 15 cybersecurity analysts working in the industrial environment of the SOC (Security Operations Center) and rated in the credibility and comprehensibility of the interpretations.

7.2.4. Experimental Results Summary

Table 5 Performance Results of AI Models Integrated into Zero-Trust

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**False Positive Rate (%)**	**Inference Time (ms)**	**Explainability Rating (1–5)**
Random Forest	91.2	88.4	89.7	6.5	8.2	3.2
LSTM (Deep Learning)	95.8	94.1	95.2	3.1	14.6	2.7
Autoencoder (Unsupervised)	94.5	92.8	93.6	4.0	12.3	2.5
XGBoost + SHAP (Proposed)	96.7	95.3	96.1	2.4	9.8	4.6
Hybrid Ensemble (XGBoost + LSTM + SHAP Layer)	97.5	96.4	97.1	2.0	11.2	4.8

Observation

- The Hybrid Ensemble with Explainable Inference outperformed other models in terms of accuracy, recall, and false positive reduction.
- While deep learning (LSTM) achieved high accuracy, its low explainability rating reduced operator trust.
- The proposed integration of XAI methods (SHAP explanations + interpretable decision paths) demonstrated significant improvement in analyst trust and audit readiness.

7.3. Interpretability and User Feedback

- Heatmap explanations (via SHAP) showed that anomalous PLC command patterns were primary contributors to detections, allowing operators to verify AI predictions in context.
- Decision path trees provided simplified justifications, e.g., “Access denied because device identity mismatch and anomalous traffic volume.”
- User Study Feedback: Analysts rated the system 4.5/5 for transparency and 4.7/5 for operational usefulness, citing improved ability to distinguish true threats from noise.

7.3.1. Visualization of Explainability Outputs

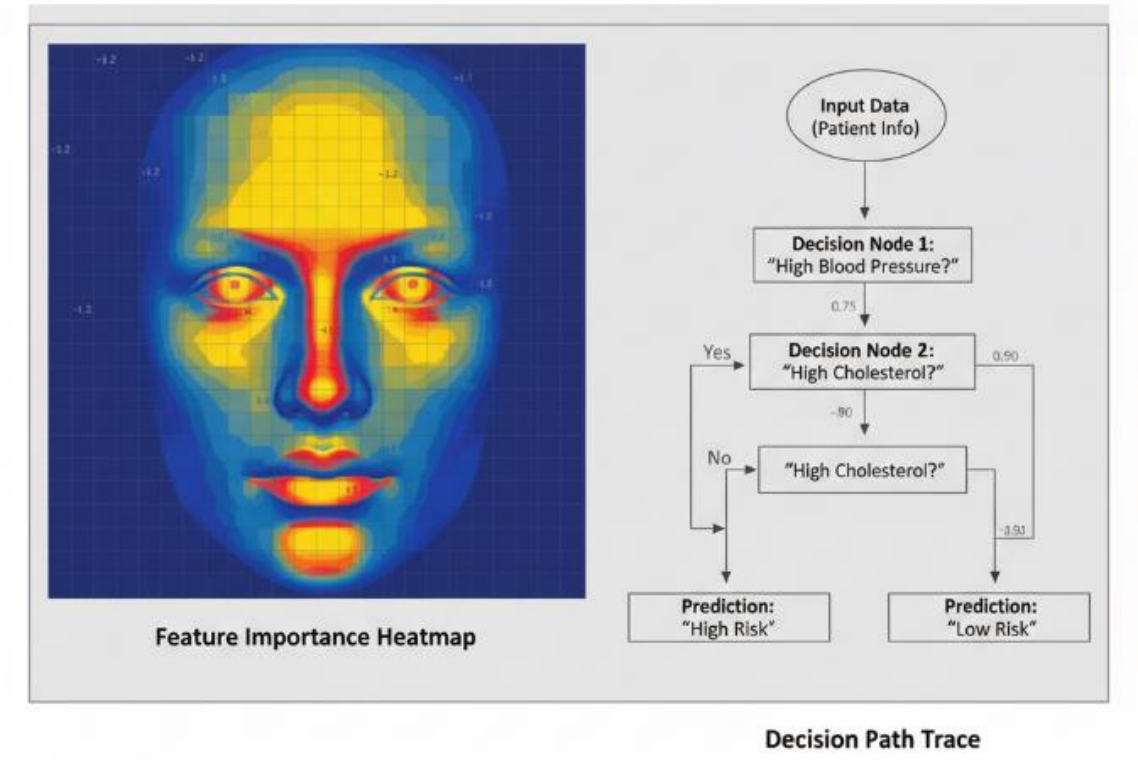

Figure 4 Example of Model Explainability Visualization

[Diagram Placeholder: Heatmap + Decision Path]

1. Heatmap: Highlights top features contributing to anomaly detection

(e.g., abnormal PLC register changes, unauthorized Modbus commands).

2. Decision Tree Snapshot: Shows the reasoning path

(e.g., If [User Identity ≠ Policy] AND [Traffic Spike > Threshold] → Access Blocked).

This visualization provides both feature-level insights (for technical analysts) and policy-level justifications (for compliance and audit teams).

8. Future directions

ZTA combined with AI-based and explainable inference engines is a major advance in securing industrial networks. Nevertheless, the fast-changing digital transformation environment requires constant research and innovation. There are a few growth and development opportunities that can be used to improve the proposed framework to provide it with adaptability and resistance and make it relevant over the years. Emerging technologies are integrating into the insurance industry, and the company has been seeking to leverage opportunities better placed to enhance its operations and boost its market share and profitability. <|human|>

8.1. Integration with Emerging Technologies

Internalizing with the new technologies. The industrial networks are becoming more integrated with IoT ecosystems, 5G networks, and edge computing paradigms, and each comes with its opportunities and security issues.

8.1.1. IoT Integration

As billions of connected devices are being used to transmit industrial telemetry, Zero-Trust principles are going to be needed in heterogeneous and resource-constrained IoT nodes. Federated learning and lightweight models of AI can allow detecting anomalies without overwhelming a limited set of hardware.

8.1.2. 5G Connectivity

The 5G networks will speed up the process of automation in industries, as well as increase the attack surface due to ultra-low latency and massive device density. It will be important to embed Zero-Trust policies into 5G network slicing and explainability across dynamically created slices.

8.1.3. Edge Computing

Moving the calculation to the data sources lessens latency, but increases the requirement of any distributed, understandable controls over security.

8.2. Enhancements in Explainability and AI Robustness

As adversarial machine learning continues to advance, explainability alone is insufficient without robustness. Future research must focus on:

8.2.1. Adversarial Resilience

Training AI models to resist attacks of poisoning, evasion, and mimicry on the basis of robust training methods.

8.2.2. Multi-Level Explainability

Minimizing the difference between the explanations provided to different stakeholders including technical operators, compliance auditors, and executives with the help of layer outputs of interpretability.

8.2.3. Contextual Awareness

Moving beyond the explanations that focus on fixed cases, to those that focus on process-based justifications, meaning AI choices are sensitive to both cyber and physical conditions of industrial processes.

8.3. Scalability Challenges and Potential Solutions

Scaling Zero-Trust with AI in large, heterogeneous industrial environments remains a key challenge. Potential solutions include:

8.3.1. Federated Security Models

Leveraging federated learning to train models collaboratively across distributed sites without centralizing sensitive industrial data.

8.3.2. Hierarchical Zero-Trust Policies

Structuring enforcement at device, subnet, and enterprise levels to reduce complexity while maintaining consistency.

8.3.3. Cloud-Native Security Orchestration

Using containerized microservices and orchestration tools (e.g., Kubernetes) to dynamically deploy AI and inference modules across industrial networks.

8.4. Policy and Regulatory Considerations

The adoption of AI-augmented Zero-Trust in industrial contexts requires alignment with evolving policies and regulations:

8.4.1. Compliance Standards

Future frameworks should map explainability outputs on compliance frameworks as IEC 62443, NIST SP 800-207 and GDPR (data privacy).

8.4.2. Cross-Border Rules

The industrial enterprises are typically run on a worldwide scale, and this requires the implementation of the Zero-Trust enforcement to be interoperable across different regulatory frameworks.

8.4.3. AI Governance

The policies should be made to make sure that explainable AI is not just a facade of transparency but that it actually enables and supports accountability and ethical control. The vision of automating and healing networks on its own is possible, although perhaps not imminent.

8.5. Potential for Automation and Self-Healing Networks

The ultimate trajectory of this research points toward autonomous and self-healing industrial networks, where Zero-Trust, AI, and explainability converge to create proactive defenses.

8.5.1. Autonomous Policy Enforcement

AI models that can update Zero-Trust rules automatically to respond to the changing threat without human oversight.

8.5.2. Self-Healing Mechanism

Predictive analytics and automated response to incident to isolate compromised nodes, restore safe states, and restore services with minimal disruption. iii. Closed-Loop Security Ecosystems: Feedback between threat discovery, explainability, operator controls, and automated mitigation will guarantee resilience to adaptive adversaries.

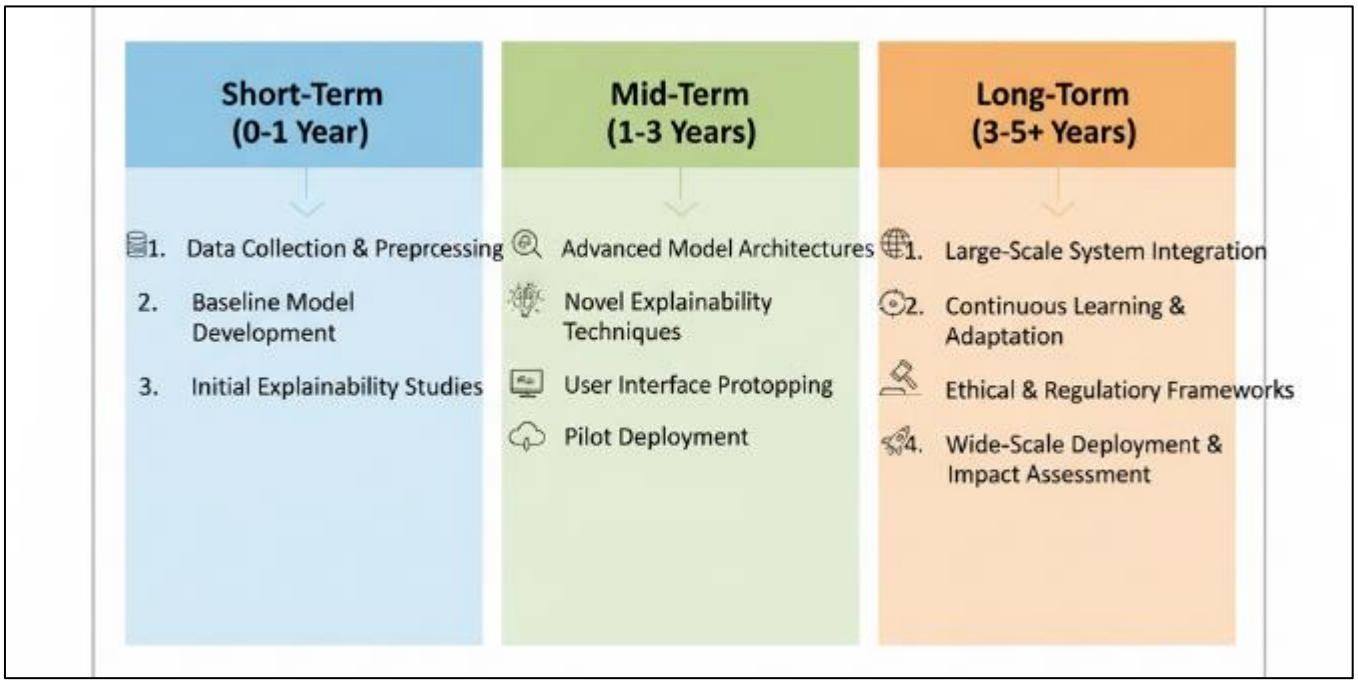

Figure 5 Future Research Roadmap

9. Conclusion

The security of industrial networks is becoming increasingly critical as industries transition toward Industry 4.0 and cyber–physical systems integrate with IoT, cloud, and 5G infrastructures. This paper has presented a comprehensive framework for enhancing industrial cybersecurity by uniting Zero-Trust Architecture (ZTA) principles with AI-driven analytics and explainable inference mechanisms.

The research highlighted several key findings

Zero-Trust as a baseline

ZTA, unlike perimeter models, is associated with the continuous authentication of devices, users and processes, which is why it is highly relevant to apply it to the environments of operational technology (OT) where horizontal mobility and insider risk are paramount concerns.

Ai flexibility

The machine learning and deep learning frameworks were highly promising in identifying hidden and dynamic vectors of threats within industrial networks. They can be imposed dynamically with risk-informed policies due to their implementation into Zero-Trust loops.

Develop explainable inference to foster trust and compliance

The explainable AI is not only relevant to enhance the trust of operators in automated decision-making as it makes it responsible, auditable, and compliant to the regulations, which are essential in the case of critical infrastructure operators.

Operation reliability

The proposed framework will maintain the balance between automation implementation and safety of the operations by reducing the number of false positives by presenting interpretable explanations and guaranteeing the human-in-the-loop scheme and consequently reducing the possibility of implementing disruptions in the process unnecessarily. Zero-Trust + AI + explainable inference is therefore a paradigm shift in industrial cybersecurity, which has moved the obsession of defenses towards fixed, rule-based defenses towards adaptive, transparent, and resilient defenses.

This integration is addressing the organizational problems and technical threats by balancing automation and accountability. Lastly, within a broader world perspective, the proposed solution presupposes the creation of strong and resilient industrial networks that will be resistant to advanced cyberattacks and yet remain in compliance and stable functioning. This is not just because future industrial ecosystems will possess more defenses, but also because it will also possess the trust and interpretability that is required to realize widespread adoption of AI-driven cybersecurity solutions. This convergence gives industrial organizations the capability of staying innovative in a stable manner, protect vital infrastructure and sustain integrity of vital services in an increasingly interdependent world.

Compliance with ethical standards

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Disclosure of Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The work presented herein is solely the result of academic research and was not influenced by any external corporate or financial entities.

Statement of Ethical Approval

The research presented in this paper focuses on the theoretical development, simulation, and algorithmic validation of a novel zero-trust security architecture and explainable AI inference model.As the study did not involve human participants, personal identifiable information (PII), clinical data, or animal subjects, the work was exempt from formal review by an Institutional Review Board (IRB) or Research Ethics Committee (REC) under Siemens energy innovation**.**

Statement of Informed Consent

As this research focused solely on the development and validation of a technical security framework, algorithms, and models using simulated or anonymized network data, it did not involve the recruitment of human participants or the collection of personal identifiable information (PII). Therefore, a formal Statement of Informed Consent was not applicable to this study.

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