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Zero Trust Architecture Leveraging AI-Driven Behavior Analytics for Industrial Control Systems in Energy Distribution Networks

Ugoaghalam Uche James[1], Chima Nwankwo Idika[2], Lawrence Anebi Enyejo[3]

[1]Department of Computer Information Systems. College of Engineering, Prairie View A&M University, Praire View , Texas, USA

[2]Department of Information Technology, De Meek Builders Ltd. Umuahia, Nigeria.

[3]Department of Telecommunications, Enforcement Ancillary and Maintenance, National Broadcasting Commission, Aso-Villa, Abuja, Nigeria

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ABSTRACT

The growing digitization and interconnectivity of energy distribution networks have increased their vulnerability to sophisticated cyber threats, particularly within Industrial Control Systems (ICS). Traditional perimeter-based security approaches are no longer sufficient to address the evolving threat landscape. This review explores the integration of Zero Trust Architecture (ZTA) with AI-driven behavior analytics to enhance cybersecurity in ICS across energy distribution networks. ZTA, built on the principle of "never trust, always verify," requires rigorous identity verification, least privilege access, and continuous monitoring. When paired with artificial intelligence, behavior analytics can autonomously identify deviations from baseline operational behavior, detect anomalies, and preemptively respond to insider threats or advanced persistent threats (APTs) without manual intervention. This paper analyzes the challenges of legacy ICS integration, models for AI-driven behavioral profiling, trust scoring, real-time authentication, and policy enforcement mechanisms. Additionally, it examines use cases in power grids, substations, and SCADA systems, emphasizing regulatory compliance and resilience strategies. By synthesizing current literature, standards, and technological advancements, this review outlines a comprehensive framework for deploying intelligent Zero Trust solutions in the critical infrastructure sector. The study also identifies open challenges and future directions for scalable, AI-enhanced Zero Trust deployments tailored to operational technologies (OT).

Keywords : Zero Trust Architecture (ZTA); Industrial Control Systems (ICS); AI-Driven Behavior Analytics; Energy Distribution Networks; Cybersecurity for Operational Technology

1.Introduction

1.1 Overview of Energy Distribution Networks and ICS

Energy distribution networks are increasingly transitioning toward intelligent, data-driven infrastructures to accommodate the dynamic demands of modern society. These networks—comprising substations, smart meters, distribution management systems (DMS), and renewable integrations—are vital for the stable delivery of electricity from generation to end-users. Underpinning this operational chain is a complex suite of Industrial Control Systems (ICS), including Supervisory Control and Data Acquisition (SCADA) systems and Programmable Logic Controllers (PLCs), which facilitate real-time monitoring and automated control over physical assets (Moreno Escobar, et al., 2021). The primary role of ICS in energy distribution networks is to manage load balancing, voltage regulation, fault detection, and remote device communication. However, the tight integration of IT and OT domains has exposed ICS to novel cyber risks. Traditional ICS were designed with assumptions of network isolation and minimal security mechanisms, rendering them particularly vulnerable in contemporary networked environments (Amin, Cárdenas, & Sastry, 2013). This vulnerability is exacerbated by the increasing convergence of edge devices, cloud-based analytics, and IoT-enabled sensors in distributed energy resources (DERs).

Moreover, the shift toward decentralized grid architectures necessitates highly resilient control mechanisms capable of addressing latency-sensitive and safety-critical functions. In this context, understanding the foundational architecture of energy distribution networks and ICS is pivotal for evaluating how Zero Trust models and AI-driven behavior analytics can be contextually applied to safeguard mission-critical operations.

1.2 Rising Cyber Threats and Security Gaps in OT Systems

The convergence of cyber and physical domains in operational technology (OT) environments has dramatically expanded the threat surface of energy distribution networks. Unlike traditional IT systems, OT systems prioritize availability and deterministic control over data confidentiality, making them inherently more susceptible to disruption-based cyberattacks. Recent threat vectors target control logic manipulation, unauthorized command execution, and firmware alterations, leading to physical damage or operational paralysis (Humayed, Lin, Li, & Luo, 2017).

Attackers increasingly leverage advanced persistent threats (APTs), ransomware, and zero-day exploits tailored to bypass proprietary communication protocols and legacy ICS components. These vulnerabilities are often exacerbated by outdated hardware, weak authentication mechanisms, and the lack of encryption within many ICS communication channels. For example, the attack vectors observed in industrial incidents such as Stuxnet or the Triton malware underscore the capacity of cyber adversaries to disrupt critical processes via subtle manipulation rather than brute-force sabotage (Krotofil & Larsen, 2015).

Moreover, many OT systems operate under static trust models and flat network architectures, making lateral movement within ICS environments trivial for adversaries once initial access is gained. This fragility, combined with poor visibility into device behavior, limits incident detection and response times. Consequently, there is an urgent need for integrating intelligent, adaptive security frameworks like Zero Trust architectures underpinned by AI-based behavioral analytics to mitigate emerging cyber threats targeting OT infrastructures.

1.3 Concept and Principles of Zero Trust Architecture

Zero Trust Architecture (ZTA) redefines the foundational paradigm of network security by eliminating implicit trust within digital systems, thereby enforcing continuous verification of all entities—users, devices, and applications—regardless of their location within or outside the network perimeter. Rooted in the principle of "never trust, always verify," ZTA advocates for granular access control, micro-segmentation, and real-time contextual policy enforcement to mitigate lateral movement and privilege escalation risks (Rose, Borchert, Mitchell, & Connelly, 2020). Unlike traditional perimeter-based defense mechanisms, ZTA decouples authentication from network topology, ensuring that every access request is dynamically evaluated based on identity attributes, device posture, geolocation, and behavioral history. This approach leverages mechanisms such as just-in-time (JIT) access, least privilege principles, and policy decision points (PDPs) that continuously authenticate and authorize access transactions. ZTA is particularly relevant in hybrid cloud-OT environments where static trust zones expose critical systems to APTs and insider threats.

The shift to ZTA is not merely technical but architectural, requiring a comprehensive integration of security policies across all layers—data, users, devices, and workloads. As Kindervag and Burbank (2021) assert, Zero Trust models foster cybersecurity resilience by creating dynamic perimeters around every user and asset, enabling real-time threat containment and enhancing trust evaluation mechanisms across distributed energy infrastructure systems.

1.4 Role of AI and Behavior Analytics in Modern Cybersecurity

Artificial intelligence (AI), particularly when paired with behavioral analytics, plays a transformative role in modern cybersecurity by enabling intelligent, adaptive defenses that can autonomously detect and respond to anomalies in real time. AI algorithms, such as supervised and unsupervised learning models, process high-dimensional data from network traffic, user activity, and system logs to establish behavioral baselines and flag deviations indicative of potential threats (Buczak & Guven, 2016). These systems move beyond traditional rule-based detection mechanisms by continuously learning from evolving threat landscapes, thereby improving accuracy and reducing false positives over time.

Behavioral analytics, integrated within AI frameworks, evaluates patterns such as access times, device usage, command sequences, and geographical movement to detect subtle indicators of compromise that may elude conventional signature-based systems. For example, an AI-powered behavioral engine can identify credential misuse by detecting a legitimate user performing atypical actions—such as accessing SCADA terminals at odd hours or issuing unfamiliar control commands (Sangkatsanee, Wattanapongsakorn, & Charnsripinyo, 2011).

These intelligent systems are particularly crucial in securing Industrial Control Systems (ICS) and energy distribution networks, where latency tolerance is low and real-time decisions are critical. By augmenting Zero Trust Architecture with AI-driven behavioral insights, organizations can implement dynamic policy enforcement and contextual authentication that adapts to evolving operational risks with minimal human intervention.

1.5 Objectives and Scope of the Study

The primary objective of this study is to explore how ZTA, enhanced by AI-driven behavior analytics, can be effectively integrated into Industrial Control Systems (ICS) within energy distribution networks to fortify cybersecurity defenses. The study aims to evaluate the limitations of traditional perimeter-based security approaches and demonstrate how continuous verification, dynamic access controls, and intelligent anomaly

detection can mitigate advanced cyber threats. The scope of the research encompasses the conceptual foundations of Zero Trust, its technical implementation in operational technology environments, and the application of machine learning models for behavioral profiling and threat detection. Additionally, the study addresses real-world use cases involving SCADA systems, substations, and smart grids, focusing on architectural frameworks that ensure resilience, operational continuity, and regulatory compliance. It also identifies critical gaps, such as the integration of legacy systems and AI explainability, offering strategic recommendations to support the secure digital transformation of energy infrastructure.

1.6 Structure of the Paper

This paper is structured into seven core sections to provide a comprehensive analysis of the integration of ZTA with AI-driven behavior analytics in energy distribution networks. Following the introduction, Section 2 examines the limitations of conventional ICS security models, highlighting the vulnerabilities inherent in legacy systems. Section 3 discusses the foundational components of ZTA tailored for ICS environments, including identity management, micro-segmentation, and policy enforcement. Section 4 delves into the role of AI and behavioral analytics, exploring algorithms and techniques used to detect anomalies and automate threat response. Section 5 presents implementation frameworks and real-world use cases across various energy infrastructure components such as substations and SCADA systems. Section 6 identifies current challenges and outlines future research directions, including scalability, adversarial AI, and system interoperability. Finally, Section 7 concludes with key insights and strategic recommendations to enhance the cybersecurity posture of critical energy distribution networks.

2. Limitations of Traditional ICS Security Models

2.1 Perimeter-Based Security and Its Failures

Perimeter-based security, once the cornerstone of industrial cybersecurity, operates under the assumption that threats originate primarily from outside the network and that entities within the perimeter are inherently trustworthy. In the context of ICS used in energy distribution, this model proves increasingly inadequate due to the growing complexity and interconnectivity of cyber-physical infrastructures as shown in table 1. The proliferation of smart sensors, remote access channels, and third-party vendor integrations in energy networks has blurred traditional network boundaries, rendering perimeter defenses porous and obsolete (Liao, 2018). One of the key failures of perimeter-based approaches lies in their static trust assumptions. an attacker breaches the external firewall—often through phishing, misconfigured remote access, or compromised credentials—they encounter minimal resistance within the internal network. This facilitates lateral movement, privilege escalation, and undetected manipulation of critical systems, such as SCADA components controlling substation automation. Furthermore, many ICS environments lack deep visibility or contextual awareness beyond the perimeter, making it difficult to detect insider threats or anomalies that mimic legitimate user behavior (Kimani, Oduol, & Langat, 2019). As smart grid systems increasingly rely on IoT technologies and decentralized architectures, the inadequacy of perimeter security becomes more pronounced. These evolving attack surfaces necessitate a paradigm shift toward Zero Trust Architecture, which focuses on identity-based access controls, continuous authentication, and behavioral verification rather than static boundary enforcement.

Table 1: Summary of Perimeter-Based Security and Its Failures

Aspect	Description	Examples	Implication
Security Model	Assumes trust within the network and defends only at the perimeter	Firewalls, DMZs, VPNs	Internal threats or compromised nodes can move laterally without detection
Limitations	Inadequate against modern threats; lacks continuous verification	Insider attacks, APTs, credential theft	Threat actors can exploit implicit trust and static policies
Technological Gaps	Legacy ICS lack native security features like encryption or identity enforcement	Modbus, DNP3 protocols without authentication	Weak segmentation and poor visibility into traffic increase risk
Need for Transformation	Transition toward Zero Trust principles with identity-based, context-aware access and continuous monitoring	Micro-segmentation, real-time authentication, policy enforcement	Enhances resilience by minimizing trust zones and enforcing least privilege across all users, devices, and services

2.2 Insider Threats and Advanced Persistent Threats (APTs)

Insider threats and Advanced Persistent Threats (APTs) represent two of the most insidious and complex challenges to the security of ICS within energy distribution networks. Insider threats emerge from individuals with legitimate access—such as employees, contractors, or third-party vendors—who intentionally or inadvertently compromise system integrity. Unlike external actors, insiders exploit their trusted status and often bypass traditional perimeter defenses, making detection significantly more difficult. Behavioral deviations, such as accessing sensitive control systems outside of operational hours or unauthorized file transfers, are frequently precursors to insider breaches (Greitzer et al., 2012).

APTs, on the other hand, are long-term, stealthy operations often executed by well-funded and highly skilled adversaries. These campaigns involve multiple phases—reconnaissance, initial compromise, lateral movement, privilege escalation, and exfiltration or sabotage—all while remaining undetected. APTs targeting ICS typically leverage zero-day vulnerabilities and spear-phishing to establish footholds in the network before slowly infiltrating high-value systems like SCADA servers or protection relays. The Stuxnet attack is a notable example, illustrating how nation-state-level APTs can induce physical consequences by manipulating ICS firmware (Tankard, 2011). Both insider threats and APTs exploit implicit trust models and lack of contextual monitoring in OT environments. Their convergence underscores the necessity of continuous authentication, behavioral profiling, and identity-based micro-segmentation, as offered by Zero Trust Architecture combined with AI-driven analytics.

2.3 Incompatibility of Legacy ICS with Modern Protocols

Legacy ICS deployed in energy distribution networks were originally engineered for reliability and longevity, not for integration with modern communication protocols or cybersecurity standards. These systems often operate on proprietary protocols such as Modbus, DNP3, or Profibus—many of which lack inherent encryption, authentication, or data integrity mechanisms—rendering them ill-suited for today's threat environment where Internet Protocol (IP)-based connectivity is ubiquitous (Knowles et al., 2015) as shown in figure 1. As organizations transition toward smart grids and cloud-integrated infrastructure, the interoperability between legacy devices and modern technologies becomes a critical bottleneck.

The challenge is compounded by the deterministic nature of legacy ICS, which are highly sensitive to latency and unexpected data payloads. When these systems are retrofitted or interfaced with TCP/IP networks, protocol conversion layers may introduce vulnerabilities or disrupt timing constraints critical for real-time operations. Furthermore, updating legacy firmware or patching outdated operating systems is often infeasible due to vendor dependencies, operational downtime risks, or lack of hardware support (Bhamare et al., 2020).

This architectural rigidity hinders the adoption of modern security practices such as Zero Trust Architecture, which relies on dynamic identity management, behavior-based access controls, and encrypted data exchanges. The technological and operational friction between old and new underscores the urgency for protocol-aware security solutions and AI-enhanced middleware to bridge the divide while safeguarding critical infrastructure.

Figure 1 illustrates the multifaceted barriers that prevent seamless integration between traditional ICS and contemporary cybersecurity frameworks. The central node represents legacy ICS, from which three primary branches extend. The first branch, Communication Protocol Limitations, highlights the use of outdated and proprietary protocols like Modbus and Profibus, which lack essential security features such as encryption, authentication, and data integrity mechanisms, rendering them incompatible with IP-based architectures used in modern networks. The second branch, System Constraints and Operational Risks, addresses the physical and architectural limitations of legacy devices, including low processing capacity, unpatchable firmware, and high sensitivity to latency—factors that inhibit the deployment of real-time security solutions or AI-based threat detection. The third branch, Integration Challenges with Modern Systems, focuses on the practical difficulties in bridging old and new environments. This includes the need for protocol translation via gateways, increased attack surfaces due to insecure connectivity, and the operational risks of introducing agentless monitoring tools to mitigate incompatibility. Collectively, the diagram underscores why a strategic, layered approach is necessary to modernize legacy ICS environments without compromising safety, performance, or security.

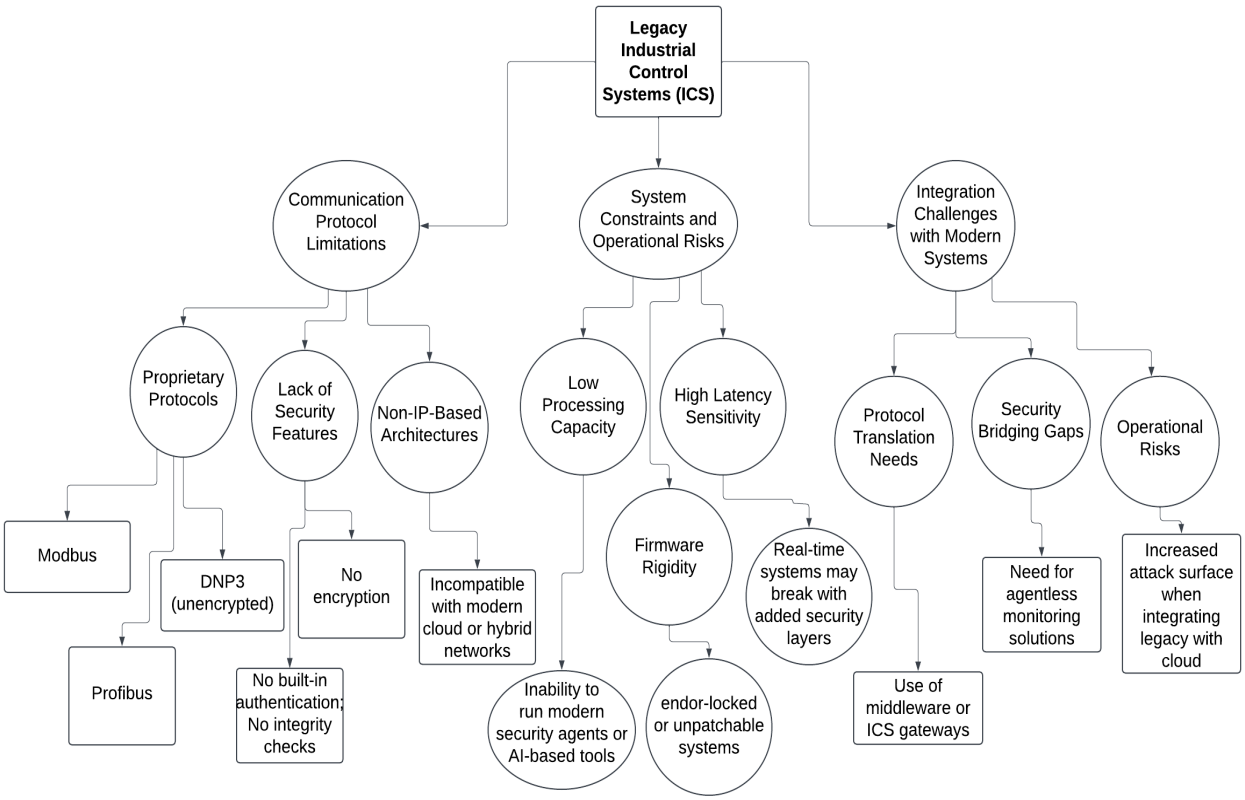

Figure 1: Diagram Illustration of Structural Barriers to Integrating Legacy Industrial Control Systems with Modern Security Protocols in Zero Trust Architectures.

2.4 Regulatory Challenges and Risk Exposure

The fragmented nature of cybersecurity regulations across jurisdictions presents a significant barrier to the unified protection of ICS in energy distribution networks. Multiple regulatory bodies—including national governments, industry-specific authorities, and regional energy commissions—often impose overlapping or conflicting security standards. This regulatory dissonance leads to compliance fatigue, resource misallocation, and inconsistencies in the adoption of baseline protections across critical infrastructure sectors (Schuett & Santillan, 2021). For example, while some jurisdictions mandate the implementation of intrusion detection systems (IDS) and network segmentation, others may lack enforcement capabilities or only recommend voluntary cybersecurity practices.

Further complicating this landscape is the dynamic and evolving nature of cyber threats. Regulatory frameworks often lag behind technological advancements, leaving ICS operators exposed to zero-day vulnerabilities, supply chain risks, and AI-enabled threat actors. Moreover, the compliance-driven model typically prioritizes checklist adherence over adaptive risk management, making it ill-suited for the high-stakes, real-time requirements of operational technology environments (Johnson et al., 2016).

Inadequate integration of risk-based approaches within these frameworks limits the ability of energy providers to prioritize mitigation strategies based on asset criticality or threat likelihood. Consequently, the lack of harmonized, forward-looking regulations exacerbates exposure to cyber incidents and inhibits the deployment of agile, intelligent security paradigms such as Zero Trust Architecture tailored to ICS environments.

3. Core Components of Zero Trust for ICS

3.1 Identity and Access Management (IAM)

Identity and Access Management (IAM) is a foundational pillar of ZTA, particularly within the cybersecurity frameworks of ICS in energy distribution networks. IAM ensures that only authenticated and authorized entities—whether users, devices, applications, or processes—can access specific network resources based on strict policy enforcement as represented in figure 2. Unlike traditional static role-based access models, modern IAM solutions incorporate contextual parameters such as device type, time of access, and geolocation to facilitate dynamic and adaptive authorization (Kayes, et al., 2020).

In operational technology environments, IAM becomes even more critical due to the deterministic and safety-critical nature of ICS. Unauthorized or misconfigured access to control components like PLCs or SCADA terminals can result in operational disruption or physical damage. Therefore, Zero Trust-compliant IAM frameworks integrate multifactor authentication (MFA), just-in-time access provisioning, and attribute-based access control (ABAC) to reduce the attack surface and enforce least privilege principles. IAM systems must also ensure interoperability with legacy protocols while providing visibility into access behavior through audit trails and continuous monitoring. Moreover, federated identity management and credential vaulting are increasingly being employed to prevent credential sprawl and eliminate hardcoded secrets in automation scripts (Fernandez & Mujica, 2017). Effective IAM design not only strengthens authentication but also acts as a behavioral boundary, enforcing trust through verifiable and adaptive identity constructs in critical infrastructure systems.

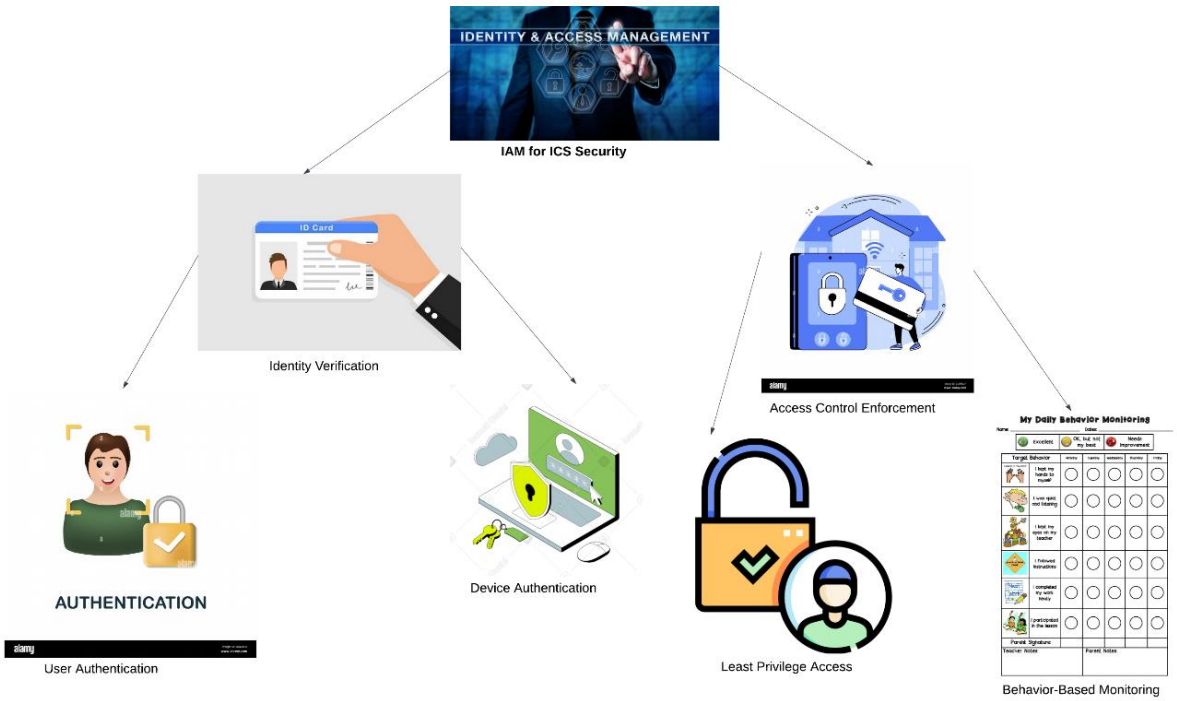

Figure 2: Diagram Illustration of Core Components of Identity and Access Management (IAM) in Zero Trust Architecture for Industrial Control Systems.

Figure 2 provides a simplified visualization of how IAM functions as a foundational component of Zero Trust Architecture within Industrial Control Systems. The central node represents IAM, branching into two main components: Identity Verification and Access Control Enforcement. Under Identity Verification, two sub-

branches illustrate the mechanisms for validating both users and devices. User Authentication involves methods such as Multi-Factor Authentication (MFA) and role-based access to ensure only authorized personnel can initiate critical functions. Device Authentication includes certificate-based identity validation and health checks to confirm that devices accessing the network are trusted and uncompromised. The second branch, Access Control Enforcement, includes Least Privilege Access, which ensures that users and devices are granted only the minimal level of access required, governed by time-bound and task-specific rules. Additionally, Behavior-Based Monitoring continuously tracks access patterns through real-time logs and anomaly detection systems to dynamically adjust permissions based on context. The diagram highlights how IAM not only authenticates and authorizes access but also adapts to changing risk conditions, thereby reinforcing Zero Trust principles in energy-critical infrastructure.

3.2 Micro-Segmentation of Control Systems

Micro-segmentation is a critical cybersecurity strategy in ZTA, designed to compartmentalize industrial control networks into smaller, isolated zones to limit the blast radius of potential cyberattacks. In contrast to traditional flat networks that allow lateral movement once perimeter defenses are breached, micro-segmentation creates granular security boundaries that tightly control east-west traffic within and across operational technology (OT) environments (Scott-Hayward, Natarajan, & Sezer, 2016). Each segment enforces its own set of policies, and communications between zones are mediated through authenticated and authorized pathways.

Within ICS for energy distribution networks—such as SCADA systems, intelligent electronic devices (IEDs), and substation automation systems—micro-segmentation enables functional isolation between safety-critical and non-critical assets. For instance, engineering workstations used for configuration should not have unfettered access to real-time process control segments unless explicitly permitted. This limits the spread of malware, mitigates privilege escalation, and enables real-time monitoring of unauthorized communication attempts.

Furthermore, segmentation policies can be dynamically enforced through software-defined networking (SDN) and firewall automation, enabling adaptive response to evolving threats. As demonstrated by Matheu-García, Garcia, and Jacob (2019), applying fine-grained segmentation in ICS significantly reduces the attack surface and improves forensic visibility. These outcomes underscore the value of micro-segmentation as a key enabler for Zero Trust implementation in distributed energy infrastructures.

3.3 Continuous Authentication and Authorization

Continuous authentication and authorization are central to enforcing the Zero Trust security paradigm within ICS that support energy distribution networks. Unlike static credential-based access control mechanisms, continuous models evaluate trust dynamically, using contextual signals such as device integrity, user behavior, location, and network activity to assess whether access should be granted, denied, or escalated. This approach is particularly crucial in real-time operational environments where cyber threats can emerge rapidly and unpredictably (Alrawais, Alhothaily, Hu, & Cheng, 2017). In ICS environments, continuous authentication ensures that even after a user or machine is initially verified, their interactions are constantly monitored and reevaluated. An operator controlling a SCADA interface may be prompted to reauthenticate if their access pattern deviates from established norms—such as unusual command input frequency, access from a new subnet, or atypical system calls. Meanwhile, authorization is not a one-time event but enforced at every request, minimizing the risk of privilege abuse and lateral movement. This granular, adaptive model aligns with Zero Trust principles

by promoting real-time enforcement of least privilege access. Trust management frameworks, particularly those that incorporate machine learning to model and predict identity behavior, are instrumental in supporting these mechanisms. As Yan, Zhang, and Vasilakos (2014) argue, such systems significantly enhance decision-making accuracy while reducing false positives, contributing to stronger cyber resilience in critical infrastructure.

3.4 Policy Enforcement and Trust Evaluation

Policy enforcement and trust evaluation are fundamental components of ZTA that ensure only legitimate, contextually verified interactions are permitted across Industrial Control Systems (ICS) in energy distribution networks. Policy enforcement defines how access decisions are dynamically applied in response to real-time identity and environmental signals, while trust evaluation determines the level of confidence in an entity's behavior, credentials, and system posture at any given moment (Chandramouli, Coyne, & Orebaugh, 2019) as presented in table 2.

In a Zero Trust ICS framework, every access request—whether from a human operator, software agent, or remote device—is subject to inspection against fine-grained policies encoded in Policy Decision Points (PDPs). These policies consider various attributes, including user role, geolocation, device health, time of request, and historical activity patterns. For example, a technician requesting access to substation control logic may be granted temporary, limited access only if their device meets compliance criteria and their trust score exceeds a dynamic threshold.

Trust evaluation mechanisms typically leverage continuous monitoring and AI-enhanced telemetry to assign risk scores, which can be used to trigger adaptive security responses such as multifactor authentication, session termination, or policy reevaluation. As Grandison, Spanoudakis, and Shaikh (2017) note, the use of real-time policy enforcement engines integrated with trust scoring systems significantly enhances visibility, responsiveness, and risk containment in complex, high-stakes infrastructures like energy distribution networks.

Table 2: Summary of Policy Enforcement and Trust Evaluation

Aspect	Description	Examples	Implications
Policy Enforcement	Real-time enforcement of access rules based on predefined security policies	Blocking access to SCADA terminals from unauthorized IPs	Prevents unauthorized access and reduces attack surface
Trust Evaluation	Dynamic assessment of user or device trustworthiness using contextual and behavioral attributes	Assigning trust scores based on location, device health, and usage history	Enables adaptive access control and supports continuous authentication
Integration with ZTA	Combines behavioral analytics and telemetry with policy decision points (PDPs) for identity-	Allowing access only if user's behavioral pattern aligns with historical norms	Reinforces Zero Trust principles and provides granular, identity-driven access governance

	and risk-based enforcement		
Operational Impact	Enhances decision-making, visibility, and control across distributed and sensitive ICS environments	Automatically revoking access when trust score drops below threshold	Strengthens resilience, enables rapid incident containment, and aligns with compliance and governance requirements

4. AI-Driven Behavior Analytics in ICS Environments

4.1 Behavioral Profiling and Baseline Generation

Behavioral profiling and baseline generation are foundational techniques in AI-driven cybersecurity frameworks, particularly in the context of Zero Trust security for ICS. These techniques involve capturing, modeling, and continuously updating normal patterns of user, device, and process behavior over time. By establishing statistical baselines that reflect routine operational activity, such systems can detect even subtle anomalies that may indicate malicious actions or system compromise (Sommer & Paxson, 2010).

For example, in an energy distribution network, behavioral baselines might track how often operators access SCADA terminals, issue specific control commands, or interact with programmable logic controllers (PLCs) during routine maintenance. Once this behavioral fingerprint is established, deviations such as off-hour logins, irregular command sequences, or connections from atypical IP addresses can be flagged for further inspection. These insights enable real-time threat detection with higher precision and lower false positive rates than signature-based methods. Advanced techniques such as clustering algorithms, hidden Markov models, and unsupervised deep learning models are commonly employed to differentiate between benign variations and suspicious anomalies. As Shon and Moon (2007) demonstrate, hybrid machine learning systems combining supervised and unsupervised learning offer robust detection capabilities for both known and novel threats. Behavioral profiling and baselining thus serve as the cognitive backbone for adaptive security enforcement in Zero Trust ICS environments.

4.2 Machine Learning Models for Anomaly Detection

Machine learning (ML) models are pivotal in modern anomaly detection systems, especially within Zero Trust frameworks for ICS used in energy distribution networks. These models analyze vast volumes of network traffic, user activity, and device behavior to differentiate between benign operational fluctuations and malicious anomalies as shown in table 3. By leveraging both historical data and real-time telemetry, ML-based systems can dynamically adapt to evolving threat landscapes and detect previously unseen attack patterns (Ahmed, Mahmood, & Hu, 2016).

Supervised learning algorithms such as Support Vector Machines (SVM) and Random Forests are effective when labeled datasets of attack and normal behavior are available. These models learn discriminative features that distinguish malicious events—such as command injection or unauthorized access—from regular operations. However, given the scarcity of labeled ICS attack data, unsupervised techniques like k-means clustering, autoencoders, and Isolation Forests are often preferred. These models identify anomalies as outliers based on deviations from learned normal patterns. In ICS environments, the temporal dimension is critical. Recurrent

Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) models, are well-suited for capturing sequential dependencies in control system telemetry. As Chandola, Banerjee, and Kumar (2009) emphasize, anomaly detection models that incorporate contextual, spatial, and temporal attributes are more robust against stealthy intrusions. These ML techniques thus enhance real-time anomaly detection, forming a core pillar of Zero Trust enforcement in critical energy infrastructures.

Table 3: Summary of Machine Learning Models for Anomaly Detection

Aspect	Description	Examples	Implications
Model Types	Uses supervised, unsupervised, and deep learning models to identify abnormal behavior in ICS environments	Support Vector Machines (SVM), K-means clustering, Autoencoders, LSTM networks	Enables detection of both known threats and previously unseen anomalies
Detection Capabilities	Learns baseline behavior from historical data and flags deviations from the norm	Identifying unusual login times or unauthorized access to control systems	Enhances real-time threat detection and reduces false positives
Temporal Relevance	Models capture time-series dependencies to detect sequential anomalies common in industrial processes	LSTM detecting abnormal control signal patterns in SCADA logs	Supports early detection of stealthy attacks and multi-stage intrusion attempts
Deployment Considerations	Requires high-quality telemetry data and computational resources; models must be tuned for operational constraints	Lightweight anomaly models deployed on edge devices or gateways in substations	Improves scalability and responsiveness of anomaly detection in resource-constrained energy distribution networks

4.3 Threat Prediction and Response Automation

Threat prediction and response automation are vital components of Zero Trust security architecture, enabling proactive and adaptive defenses across ICS in energy distribution networks. By leveraging AI and machine learning algorithms, these systems analyze telemetry, event logs, and behavioral trends to forecast potential attacks before they manifest. This capability shifts cybersecurity from reactive mitigation to anticipatory risk management, enhancing the resilience of real-time operational technologies (Bridges et al., 2020).

Predictive models use pattern recognition, temporal analytics, and probabilistic inference to detect early indicators of compromise—such as gradual privilege escalation, low-and-slow reconnaissance, or anomalous

command sequences (Abiodun, et al., 2023). For instance, Bayesian networks or recurrent neural networks (RNNs) can model complex dependencies in ICS environments, enabling the early identification of multi-stage attacks. Once threats are predicted, response automation platforms can initiate pre-approved actions, such as isolating affected network segments, revoking access tokens, or initiating forensic data capture. These systems rely on a closed-loop feedback mechanism to continuously refine detection and response strategies based on new threat intelligence and incident outcomes. As Buczak and Guven (2016) note, this automation not only reduces response latency but also compensates for the shortage of skilled cybersecurity personnel in critical infrastructure sectors. By embedding threat anticipation and autonomous response into Zero Trust frameworks, organizations can reduce dwell time, contain breaches rapidly, and protect high-value ICS assets from sophisticated cyberattacks.

4.4 Integration with ZTA Policy Engines

The integration of behavior analytics and AI-driven anomaly detection systems with ZTA policy engines plays a pivotal role in dynamically enforcing access control across ICS in energy distribution networks. Policy engines are central to Zero Trust by functioning as policy decision points (PDPs) that evaluate access requests in real-time based on pre-defined rules and adaptive context signals as represented in figure 3. These engines incorporate data such as user identity, device health, historical behavior, and threat scores to decide whether access should be granted, limited, or denied (Pritchard & Ekelhart, 2020).

Behavior analytics systems serve as critical inputs to these engines by continuously updating risk postures and providing situational awareness. For example, if a control engineer's behavior deviates from their established access pattern—such as attempting to reprogram substations from an untrusted device—the policy engine can trigger enforcement protocols that block access or escalate authentication requirements. These decisions are executed through policy enforcement points (PEPs) at the edge of each system zone.

Additionally, privacy-aware policy generation and enforcement are essential in ICS, where legal and operational constraints must be balanced. As Colesky, Hoepman, and Hillen (2016) highlight, integrating privacy and trust principles within policy engines enhances transparency and compliance without compromising resilience. In a Zero Trust framework, the synergy between AI-driven behavior analytics and responsive policy logic ensures that only verified, authorized, and trusted actions are allowed across distributed infrastructure layers.

Figure 3: Picture of Zero Trust Architecture with Integrated Policy Engines for Adaptive Access Control (Bloomfield, R. 2023).

Figure 3 visually represents Integration with ZTA Policy Engines through a fortified digital castle metaphor, symbolizing a tightly governed perimeter with continuous internal monitoring and adaptive control mechanisms. At the center, the fortified castle labeled "Zero Trust Architecture" embodies the core enforcement zone—housing critical infrastructure components like servers, access control systems, and telemetry processors. Surrounding the castle are interconnected icons representing policy decision points (PDPs), policy enforcement points (PEPs), and real-time monitoring systems, all of which feed into and receive commands from the central trust engine. The interconnected lines and circular layers illustrate a context-aware enforcement loop, where each request—whether user-based or machine-originated—is authenticated and evaluated against dynamic security policies in real time. Trust is never assumed; instead, it is calculated based on behavioral analytics, device posture, identity verification, and access context. The presence of security shields, biometric authentication icons, and encrypted communication nodes further reinforces the concept of granular access control and trust validation at each architectural layer. The layered architecture mirrors how ZTA integrates with AI-powered engines to adaptively authorize, isolate, or deny access, ensuring that even entities inside the network must prove trustworthiness continuously before interacting with sensitive operational resources.

5. Implementation Frameworks and Use Cases

5.1 ZTA in Power Grid Monitoring Systems

ZTA offers a transformative security model for power grid monitoring systems, where real-time operational integrity is critical and attack surfaces are expansive due to increased digitalization. Power grids are composed of diverse, distributed assets—including phasor measurement units (PMUs), remote terminal units (RTUs), and advanced metering infrastructure (AMI)—which generate high-frequency telemetry used for stability, load balancing, and fault detection. Traditional perimeter-based security approaches cannot protect this complex ecosystem from sophisticated threats such as state-sponsored attacks or coordinated ransomware campaigns (Liu, Liu, & Wang, 2019).

By implementing ZTA, each data flow and device interaction within the power grid is subject to dynamic authentication, authorization, and trust evaluation, regardless of network location. Behavior analytics and contextual telemetry feed into Policy Decision Points (PDPs) to assess access based on real-time data, such as anomalous frequency changes, voltage instability, or suspicious login attempts (Atalor, 2019). Micro-segmentation further ensures that a compromise in one sensor node does not propagate to high-value control layers. Software-defined networking (SDN) enhances ZTA deployment by enabling programmable policy enforcement across grid components, ensuring resilience and adaptability (Ghosh & Chaturvedi, 2018). The convergence of ZTA with AI-driven analytics not only mitigates lateral threat movement but also supports proactive grid management, ultimately strengthening cyber-physical resilience in national power infrastructures.

5.2 AI-Enhanced Security in Substations and Smart Meters

The integration of artificial intelligence (AI) into substations and smart meter infrastructures is reshaping the cybersecurity posture of modern energy distribution systems. Substations, serving as critical nodes for voltage transformation and power flow regulation, and smart meters, deployed ubiquitously at consumer endpoints, both face heightened exposure to cyber threats due to their digital interfaces and networked environments. AI-enhanced security models enable real-time threat detection, risk scoring, and adaptive response mechanisms tailored to the operational characteristics of these assets (Sulaiman, et al., 2023).

In substations, AI-driven intrusion detection systems (IDS) can monitor communication protocols such as IEC 61850 and DNP3 for unusual traffic patterns or control commands inconsistent with baseline behavior. For example, unauthorized switching signals or anomalous relay configurations can be flagged for immediate isolation and forensic analysis. Machine learning models such as support vector machines (SVM) and convolutional neural networks (CNNs) are trained on historical control data to recognize signatures of spoofing or command injection. In smart meters, AI supports device-level authentication, demand anomaly detection, and fraud prevention. Edge AI can process consumption patterns locally to identify outliers, such as reverse energy flow or tampered calibration, and alert central monitoring hubs (Atalor, et al., 2023). These intelligent capabilities, when fused with Zero Trust Architecture principles, ensure that each device, whether in a substation or residential premise, is continuously validated and contextually authorized, thereby reducing systemic risk across the energy distribution network.

5.3 SCADA System Protection with Zero Trust Principles

Supervisory Control and Data Acquisition (SCADA) systems serve as the operational backbone for monitoring and controlling critical functions in energy distribution networks, yet they remain prime targets for cyberattacks due to their historically implicit trust models and weak authentication layers as presented in table 4. Traditional SCADA architectures were not designed for today's dynamic and interconnected threat landscape, making them especially vulnerable to remote code execution, man-in-the-middle attacks, and insider threats. Integrating ZTA into SCADA systems addresses these gaps by enforcing continuous identity validation, granular access policies, and dynamic trust assessments at every communication point (Khurana, Hadley, Lu, & Frincke, 2010).

In practice, ZTA redefines SCADA communication by requiring strict segmentation between Human-Machine Interfaces (HMIs), Remote Terminal Units (RTUs), Programmable Logic Controllers (PLCs), and data historians. Access to each functional module is governed by a policy decision point (PDP) that considers contextual attributes such as user behavior, device health, geolocation, and time-based restrictions (Atalor, et al., 2023). For example, even a legitimate operator requesting control over a substation breaker may be denied if the request originates from a non-whitelisted network or violates established temporal access patterns.

Furthermore, SCADA telemetry—such as voltage trends, breaker statuses, and command frequencies—is continuously fed into AI-driven behavioral models to update trust scores and flag anomalies in real-time. This convergence of ZTA with adaptive analytics significantly elevates SCADA resilience against multi-stage cyberattacks in critical energy infrastructures.

Table 4: Summary of SCADA System Protection with Zero Trust Principles

Aspect	Description	Examples	Implications
ZTA Application in SCADA	Implements continuous authentication, least-privilege access, and real-time trust evaluation in SCADA systems	Verifying user access to HMI or PLC based on behavioral and contextual parameters	Eliminates implicit trust, reducing susceptibility to insider threats and unauthorized access

Access Control Mechanism	Utilizes Policy Decision Points (PDPs) to evaluate requests using device health, user behavior, and time-based constraints	Blocking access if a login originates from a non-whitelisted IP or during unauthorized time windows	Enhances adaptive security posture and prevents policy violations in critical environments
Telemetry Integration	SCADA command logs and operational metrics are continuously analyzed to detect abnormal patterns and update trust scores	Real-time flagging of anomalous switching commands or irregular control frequency	Enables proactive threat detection and real-time remediation in operational workflows
Security Enhancement	Ensures micro-segmentation and secure communications between SCADA components like RTUs, PLCs, and data historians	Restricting direct communication between field devices and control center without verification	Improves system integrity, limits lateral movement, and aligns SCADA architecture with modern Zero Trust security models

5.4 Case Studies of ICS Breaches and ZTA Successes

Historical breaches within ICS have underscored the systemic vulnerabilities caused by flat network architectures, implicit trust models, and outdated authentication mechanisms. One of the most notable examples is the 2015 Ukraine power grid attack, where attackers used stolen credentials and spear-phishing techniques to manipulate SCADA systems, causing widespread outages and highlighting the fragility of perimeter-based security models. This incident, among others, has catalyzed the adoption of ZTA to enhance ICS resilience (Humayed, Lin, Li, & Luo, 2017) as shown in figure 4.

In contrast, emerging case studies have demonstrated the efficacy of ZTA in defending ICS against multi-stage cyberattacks. For instance, a U.S.-based electric utility piloted a ZTA deployment incorporating continuous behavioral monitoring, micro-segmentation, and real-time identity validation across its substations (Imoh, 2023). When a rogue device attempted lateral movement through the OT network, the system's policy engine flagged the activity as anomalous, dynamically revoked access privileges, and quarantined the endpoint without human intervention.

Such successes highlight ZTA's core advantage—eliminating implicit trust and replacing it with context-aware, identity-driven policies that adapt in real time (Ononiwu, et al., 2023). When paired with AI-based telemetry

analysis, ZTA prevents breach escalation, improves visibility, and supports operational continuity. These case studies reinforce ZTA's strategic value in securing critical energy infrastructures against both external adversaries and insider threats.

Figure 4: Picture of Visual Depiction of ICS Cyber Breach Highlighting the Need for Zero Trust Architecture in Critical Infrastructure Security (Yetushenko, A. N.D.)

Figure 4 vividly depicts a high-stakes ICS environment under cyber siege, aligning with the context of Section 5.4: Case Studies of ICS Breaches and ZTA Successes. The control room, equipped with numerous operator terminals and real-time monitoring displays, is overlaid with alarm indicators such as "CYBER ATTACK", "SECURITY BREACHES", and a digital padlock symbolizing compromised access control. The visual chaos, including system sparks and flashing alerts, underscores the real-world consequences of security lapses in legacy ICS infrastructures—similar to historical incidents like the 2015 Ukraine grid attack, where attackers leveraged trusted access and lateral movement to disrupt national power systems. This image also metaphorically supports the argument for adopting ZTA, which replaces static perimeter defenses with continuous identity validation, behavioral analytics, and dynamic access control. In successful ZTA deployments, such threats are detected early via anomaly detection engines, and unauthorized actions are contained through automated policy enforcement and real-time trust scoring. The high-tech industrial setting shown in the image represents both the vulnerability and complexity of modern cyber-physical systems, illustrating the urgent need for ZTA's adaptive and identity-driven approach to secure critical infrastructure against escalating cyber threats.

6. Challenges and Future Directions

6.1 AI Model Explainability and Trustworthiness

As AI becomes increasingly integrated into cybersecurity operations within ICS, the explainability and trustworthiness of machine learning models are critical to ensuring reliable decision-making and user confidence. In energy distribution networks governed by ZTA, AI models often drive behavioral analytics, threat scoring, and access control decisions. However, the opaque nature of many high-performing models—especially deep neural

networks—poses a challenge for operators who must understand, verify, and audit system behavior in real-time (Doshi-Velez & Kim, 2017). Explainability refers to the extent to which the internal mechanics or outputs of an AI system can be interpreted by humans. In ICS, where operational safety and compliance are paramount, stakeholders must be able to trace how an AI system arrived at a particular anomaly classification, access denial, or incident prioritization (Ihimoyan, et al., 2022). Trustworthiness, on the other hand, involves the system's reliability under diverse operational conditions, its resilience to adversarial manipulation, and its alignment with established safety norms.

Techniques such as Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) offer post-hoc interpretability, allowing operators to evaluate feature importance and decision rationale. Embedding explainable AI (XAI) principles into ZTA ecosystems not only improves transparency and regulatory compliance but also enables better human-AI collaboration in protecting critical infrastructure.

6.2 Scalability in Distributed Energy Networks

Scalability is a critical consideration in deploying ZTA and AI-enhanced cybersecurity mechanisms across distributed energy networks, which are increasingly characterized by a high density of interconnected devices, substations, and edge computing nodes. Distributed energy systems—including microgrids, smart meters, and distributed generation units—require security solutions that can adapt to large-scale deployment without compromising performance, visibility, or policy enforcement (Fang, Misra, Xue, & Yang, 2012).

ZTA implementation at scale introduces challenges in managing thousands of identity profiles, real-time telemetry streams, and dynamically changing access policies (Ononiwu, et al., 2023). Traditional perimeter defenses become untenable in such a fragmented environment, necessitating the use of decentralized trust evaluation mechanisms and edge-deployed policy enforcement points (PEPs). AI plays a pivotal role in managing this complexity by automating anomaly detection, threat prediction, and behavioral adaptation across vast device ecosystems.

However, ensuring horizontal scalability of trust engines and vertical scalability of AI inference models requires efficient orchestration, lightweight computing, and reliable communication protocols. Federated learning and hierarchical trust propagation are promising strategies that can help scale AI-driven ZTA across layered architectures without overwhelming central control systems. As distributed energy infrastructures continue to expand with increasing heterogeneity, achieving seamless and scalable Zero Trust enforcement will be essential for operational resilience and cybersecurity sustainability.

6.3 Adversarial AI and Evasion Tactics

As machine learning models become more deeply embedded in ZTA and industrial cybersecurity workflows, adversarial AI and evasion tactics pose a significant threat to the reliability and integrity of intelligent security systems. Adversarial attacks involve the intentional manipulation of input data to deceive AI models into making incorrect predictions—such as misclassifying malicious activity as benign—without triggering alarms. In the context of ICS, these subtle perturbations can allow unauthorized access, command injection, or data tampering to go undetected (Biggio & Roli, 2018).

Common evasion techniques include adversarial examples, gradient masking, and model inversion, which exploit vulnerabilities in neural networks or statistical classifiers by introducing minimally altered, yet strategically crafted, inputs. In a distributed energy network, a malicious actor could slightly modify network traffic patterns

or command syntax to remain within behavioral baselines and evade anomaly detectors powered by AI. Furthermore, poisoning attacks—where corrupted data is introduced during training—can bias models toward misclassifying specific types of attacks as normal.

Mitigating these threats requires integrating robust adversarial training, employing defensive distillation, and applying explainable AI to continuously audit model decisions. In Zero Trust environments, where policy decisions are increasingly influenced by AI-generated trust scores, safeguarding these algorithms against adversarial manipulation is essential to preserving the integrity of cybersecurity enforcement and ensuring the resilience of energy infrastructure.

6.4 Interoperability Across Legacy and Modern Systems

Achieving interoperability between legacy ICS and modern cybersecurity frameworks remains a persistent challenge in the deployment of ZTA across energy distribution networks. Legacy systems—often decades old—were not designed with modern networking, encryption, or authentication standards in mind. They typically use proprietary protocols, lack built-in security features, and operate on hardware with limited processing capacity, creating significant integration barriers when aligning with modern ZTA-based security architectures (Hahn, Ashok, Sridhar, & Govindarasu, 2013) as presented in table 5.

In contrast, modern systems leverage virtualized infrastructures, cloud connectivity, and real-time data exchange, requiring adaptable interfaces and middleware to communicate securely with older components. The disparity in capabilities complicates policy enforcement, behavioral telemetry collection, and trust score computation—core elements of ZTA (Ononiwu, et al., 2023). Without careful engineering, attempts to modernize may introduce latency, reduce availability, or break deterministic control functions critical to operational safety.

Bridging this gap necessitates the use of secure protocol translators, modular gateways, and cybersecurity testbeds to simulate integration scenarios before field deployment. Additionally, layered security models that accommodate legacy constraints—such as agentless monitoring, passive traffic analysis, and out-of-band access control—can offer interim solutions while long-term infrastructure upgrades are phased in. Interoperability is thus not merely a technical requirement but a foundational condition for implementing scalable and secure ZTA in mixed-technology environments.

Table 5: Summary of Interoperability Across Legacy and Modern Systems

Aspect	Description	Examples	Implications
System Disparity	Legacy ICS lack modern security features, making integration with advanced ZTA components challenging	Legacy PLCs using unencrypted Modbus protocols unable to interface directly with cloud-native controls	Requires specialized integration strategies and secure middleware to bridge functionality gaps
Integration Challenges	Differences in communication protocols, processing	Real-time data exchange between IEC 60870-5-104-	Risk of performance degradation, incompatibility, or

	capabilities, and security expectations hinder seamless interoperability	based legacy devices and modern IEC 61850 platforms	security compromise if not properly managed
Transitional Solutions	Use of protocol converters, secure gateways, and agentless monitoring for compatibility without disrupting legacy operations	Deploying ICS security gateways that translate and encrypt traffic between old RTUs and new controllers	Enables incremental security upgrades and ZTA policy enforcement without complete infrastructure overhaul
Strategic Importance	Ensuring legacy-modern interoperability is essential for scalable and resilient Zero Trust implementation in hybrid environments	Integrating ZTA with both old substations and new cloud-based energy analytics systems	Facilitates cohesive security posture, operational continuity, and long-term modernization of critical infrastructure assets

7. Conclusion and Recommendations

7.1 Summary of Findings

This study reveals that integrating ZTA with AI-driven behavior analytics significantly strengthens cybersecurity resilience across ICS in energy distribution networks. The traditional perimeter-based security model has proven inadequate due to its implicit trust assumptions and limited visibility into lateral movements within operational technology (OT) environments. Through continuous identity verification, contextual policy enforcement, and micro-segmentation, ZTA ensures that every access request is independently authenticated and authorized. Furthermore, AI-enhanced behavior analytics enables real-time anomaly detection, predictive threat modeling, and dynamic access control adjustments based on evolving risk profiles. The application of ZTA across substations, smart meters, and SCADA systems demonstrates notable improvements in incident detection speed and breach containment. Use cases highlight how policy engines powered by behavioral baselining and anomaly detection can thwart sophisticated attacks such as unauthorized substation reprogramming or lateral command propagation. However, challenges persist, particularly in integrating legacy systems with modern security protocols and ensuring AI model explainability in high-assurance contexts. Scalability, interoperability, and adversarial resilience remain critical focus areas for future Zero Trust deployments. Collectively, these findings underscore the importance of a holistic, intelligence-driven approach to securing energy infrastructure, where ZTA and AI work in tandem to protect against both known and unknown cyber threats in real time.

7.2 Strategic Recommendations for Practitioners

To effectively implement ZTA in ICS for energy distribution networks, practitioners must adopt a phased and context-aware strategy. First, establish asset visibility and identity baselines for all users, devices, and applications across the operational technology (OT) environment. This includes integrating multi-factor authentication (MFA), certificate-based device identity, and contextual access control policies that dynamically adapt to user behavior and network conditions.

Second, segment critical ICS zones using micro-segmentation and enforce least-privilege principles to restrict lateral movement. For example, engineering workstations should not have unrestricted access to substations or protection relays unless explicitly required and monitored. Behavioral analytics engines should be deployed to generate real-time trust scores and detect deviations from established operational baselines.

Third, ensure all access requests pass through Policy Decision Points (PDPs) that leverage AI-enhanced telemetry, threat intelligence, and real-time risk scoring to authorize or deny access. Furthermore, integrate edge-based anomaly detection with central policy enforcement systems to support distributed decision-making.

Lastly, invest in AI model transparency tools and adversarial resilience techniques to ensure that predictive analytics remain trustworthy and auditable. These strategic measures enable secure interoperability between legacy and modern systems while enhancing detection, response, and recovery capabilities within mission-critical energy infrastructures.

7.3 Policy Implications for Critical Infrastructure Security

The implementation of ZTA and AI-driven behavioral analytics in energy distribution systems presents significant policy implications for critical infrastructure security. Policymakers must revise legacy regulatory frameworks that rely on perimeter-based controls and shift toward mandates that support continuous authentication, micro-segmentation, and real-time trust evaluation. This includes enforcing identity-centric security standards, where every user and device must be verified regardless of network location, and requiring operators to adopt least-privilege access controls backed by behavioral baselines.

National cybersecurity strategies should also prioritize interoperability standards that allow secure integration of legacy ICS with modern ZTA frameworks. For example, policies must encourage the use of protocol-agnostic gateways and middleware that support secure data exchange without compromising operational continuity. Additionally, AI accountability regulations must be established to ensure that predictive models used in access decisions are explainable, auditable, and resilient to adversarial inputs.

Furthermore, incident reporting policies should incorporate AI-generated alerts and behavior-based threat assessments as formal elements of compliance. Governments and regulatory bodies must also incentivize investment in testbeds for ZTA deployment in simulated OT environments. These policy shifts are essential to aligning industrial cybersecurity practices with the evolving threat landscape and ensuring that critical energy infrastructure remains resilient, intelligent, and secure in the face of increasingly sophisticated cyber adversaries.

7.4 Opportunities for Future Research

Future research should explore advanced methodologies for integrating explainable AI (XAI) into ZTA frameworks tailored for ICS. There is a critical need for developing lightweight, real-time explainability models that can operate efficiently on constrained devices at the edge, such as programmable logic controllers and smart

meters. Research can also expand on adaptive trust scoring algorithms that incorporate temporal-spatial awareness and can evolve based on operator behavior, threat intelligence feeds, and anomaly feedback loops.

Another promising area lies in the co-design of ZTA with federated learning to support privacy-preserving analytics across decentralized energy assets without centralizing sensitive operational data. This is particularly important for safeguarding data confidentiality in geographically distributed grids. Research is also needed to evaluate the resilience of ZTA components against adversarial machine learning attacks, including evasion, poisoning, and inference attacks, especially in high-stakes real-time environments.

Furthermore, simulation-based testbeds that model hybrid IT/OT infrastructure at scale could enable empirical validation of ZTA policies and AI responses in realistic cyber-physical scenarios. Lastly, future studies should address how regulatory frameworks can incorporate AI-governed trust decisions, and assess ethical implications of automated access control in critical infrastructures, ensuring the balance between security, transparency, and human oversight.

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