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Federated Learning–Based Intrusion Detection for Critical Industrial Control Systems: A Privacy-Preserving Approach to Securing Smart Grids against Emerging Cyber Threats

Smart Idima
Department of Computer Sciences and Information System, Western Illinois University, Macomb Illinois USA
Email address: smartabayomi@gmail.com

Abstract— *This paper explores the adaptation of Federated Learning (FL) to enhance cybersecurity in industrial control systems, which are vital for critical infrastructures. Integrate ICS into digital networks to better control distant or remote places, which increases sophistication in cyber-attacks, thereby threatening traditional centralized IDS solutions for ICS. Centralized systems are inefficient for ICS's needs as they adopt a decentralized and privacy-preserving aspect. FL is an approach to decentralized machine learning that promises solutions in the realm of multiple entities training security models on their data while hiding sensitive operational information. This study evaluates the potential applicability of FL in solving some of the issues ICS faces under increasing cyber-attacks and draws a comparative analysis with traditional IDS versus FL-based approaches. Findings will assist in the betterment of ICS security, thereby ensuring the smooth operation of critical infrastructures against increasingly sophisticated cyber threats.*

Keywords— *Industrial Control Systems (ICS), Cybersecurity, Federated Learning (FL), Intrusion Detection Systems (IDS), Decentralized Machine Learning, Privacy-preserving Security, Critical Infrastructure Protection, Cyber-attacks, Machine Learning in Cybersecurity, ICS Security Challenges, Data Privacy, Advanced Persistent Threats (APT).*

I. INTRODUCTION

Background of the Study

Industrial Control Systems, or ICS, are fundamental to the functionality of critical infrastructures such as smart grids and power plants. ICS monitors and controls industrial processes, allowing for efficient and safe operation of essential services (Aashmi and Jaya, 2023).

The sectors include energy, water treatment, and transportation, which are imperative for uninterrupted service to ensure public safety and economic stability. It is underscored that importance is associated with ICSs in that they have been managing complex operations (Aledhari et al., 2020). For example, in the energy sector, the electricity distribution is controlled by ICS, maintaining an appropriate supply against demand to prevent blackouts. On the same line, at the water treatment facility, such control processes have ensured that clean water is supplied to the community (Annappa et al., 2024). Therefore, such seamless functions determine the lives of millions daily and the entire economy.

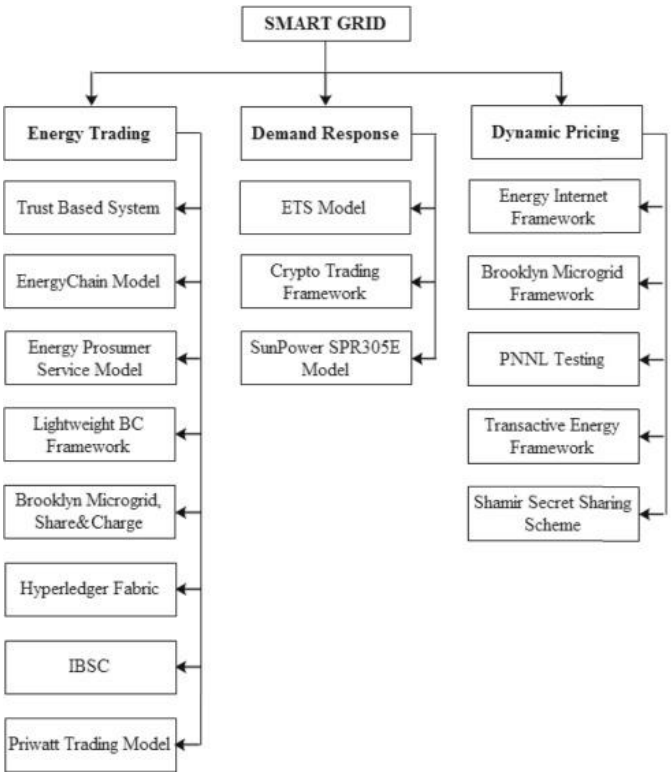

Figure 1: Smart Grid (Thilakarathne et al., 2022).

However, increased ICS integration into digital networks exposes them to growing cyber security threats (Chatterjee and Hanawal, 2022). Reports by government and cybersecurity authorities indicate that critical IT systems are exposed to a serious and rapidly evolving threat from cyber-attacks with considerable vulnerabilities in the ICS environment (Bhatt et al., 2025). Cyber-attacks against other sectors indicate an urgent need for effective cybersecurity measures. The criticism has been that senior officials have not taken cyber-resilience seriously, failing to invest and staff in cybersecurity significantly (Li et al., 2023). Several initiatives to strengthen defenses have been introduced, such as new legislation and projects enhancing cybersecurity skills. Progress is slow. The increasing digitalization of services heightens the risk of disruptive cyber-attacks by adversaries worldwide (Billah et al.,

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2022). Governments and organizations should respond to the cyber skills shortage by taking steps toward accountability for cyber risks and managing legacy systems and old IT infrastructures to protect infrastructures and keep operational continuity (Thilakarathne et al., 2022).

Advanced cyber threats, including sophisticated and persistent attacks, make the security of ICS highly challenging. Traditional security measures fail to handle such advanced threats; therefore, the need for developing more robust and adaptive security solutions is emerging (Zhu et al., 2024). Federated Learning has emerged as a promising approach to enhancing the security of Industrial Control Systems. FL is a widely decentralized type of machine learning in which a group of parties is authorized to cooperatively contribute to creating a model without direct access to the raw data (Annappa et al., 2024). It will provide a proper means never to expose files of any type to breach into a centralized system. FL could also find applications in creating IDSs that attempt to detect any sets of anomalies and potential threats without exposing sensitive operational data within the context of ICS (Mahmud et al., 2024).

The main challenge this research intends to address is that traditional, centralized Intrusion Detection Systems cannot be a perfect match in the decentralized management of ICS environments wherein privacy must be preserved. Centralized IDSs commonly involve aggregating multiple sources of input or evidence, which cannot be considered feasible and safe for an ICS setting (Doriguzzi-Corin and Siracusa, 2024). FL could fill this gap since the application trains local models on each ICS component and shares solely updates to models with the utmost security and privacy.

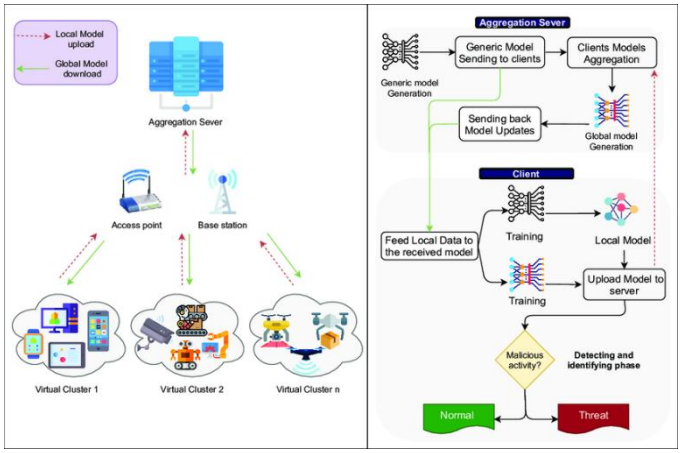

Figure 2: ICS (Doriguzzi-Corin and Siracusa, 2024).

Problem Statement

Traditional intrusion detection systems face many challenges in managing geographically distributed ICS. Centralized IDS often require the aggregation of data from various locations, which increases latency and can create bottlenecks. This centralized approach also creates a single point of failure, making the entire system vulnerable to attacks. Furthermore, ICS environments are heterogeneous and have different hardware and software configurations. This makes it challenging to come up with a universal IDS solution. Privacy is also a matter of concern with centralized data collection and processing models. Aggregating sensitive operational data in one central repository can expose it to unauthorized access and data breaches (Doriguzzi-Corin and Siracusa, 2024). Critical infrastructure information can be put at risk through centralization, hence becoming open to cyber-attacks. Therefore, protecting sensitive information without hampering effective intrusion detection is an increasing need.

Cybersecurity threats in the sense of adversarial attacks and data tampering pose an even more significant problem than that. Advanced attackers manipulate data to avoid detection, compromising IDS integrity (Doriguzzi-Corin and Siracusa, 2024). IDS solutions are in a critical need to adapt and respond to emerging and dynamic attack vectors. There is a need for a scalable, secure, and privacy-preserving IDS solution. Federated learning techniques offer an enjoyable alternative where training across distributed systems can happen collaboratively without the necessity of sharing raw data. Decentralized Learning improves privacy and security aspects that are suitable for current ICS environments.

Figure 3: FL-IoT applications and services (Doriguzzi-Corin and Siracusa, 2024).

Significance of the Study

This research filled the crucial gaps in the existing literature on Intrusion Detection Systems (IDS) and Federated Learning (FL) by integrating FL into IDS for Industrial Control Systems (ICS). Traditional IDS have been highly studied, but their application to ICS environments, especially related to data privacy and decentralized Learning, is a relatively unexplored area. Through an FL-based IDS, this work contributes to academic discourse using innovative machine-learning techniques to strengthen cybersecurity in ICS. It solves a long-standing and urgent need for ICS security without sacrificing data privacy. At the same time, traditional centralized models of IDS generally face problems due to data security and privacy concerns. Federated Learning handles such concerns by allowing collaborative model training across distributed systems in a manner that maintains the privacy of sensitive operational data (Doriguzzi-Corin and Siracusa, 2024). This way, utility providers and industry stakeholders can improve their cybersecurity posture without compromising the exposure of critical infrastructure data. This research offers utility providers and industry stakeholders an outline for implementing a scalable, secure, and privacy-preserving IDS

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solution. Utilizing the techniques of FL, an organization can create intrusion detection models that are specifically adapted to the difficulties faced in the ICS environment while safeguarding critical infrastructure against emerging cyber threats. This action caters to the increasing demands on data privacy and security in industrial settings.

Scope and Delimitations

This research applies FL to upgrade the IDS of smart grids, which is an integral part of Industrial Control Systems. The complexity and interconnectivity of the smart grid are making them highly susceptible to cyber-attacks. This work focuses on the application, expecting it to help solve some security problems within infrastructures related to smart grids. The study assumes that hypothetical primary data are available to train and test the FL-based IDS models (Aashmi and Jaya, 2023). This approach removes the constraints that proprietary data access imposes on real-world scenarios and allows for simulating real-world scenarios. The simulation of data helps in testing and evaluating model performance across different attack vectors and under various operational conditions, which helps estimate the potential efficacy of FL in improving IDS capabilities.

This research uses the statistical SPSS (Social Science for Statistics) package for cross-checking validation. Such tools have significant analytic abilities, and assessment and calibration for models that check their adequacy performance measure may entail determining such models by providing evaluation, such as accuracy.

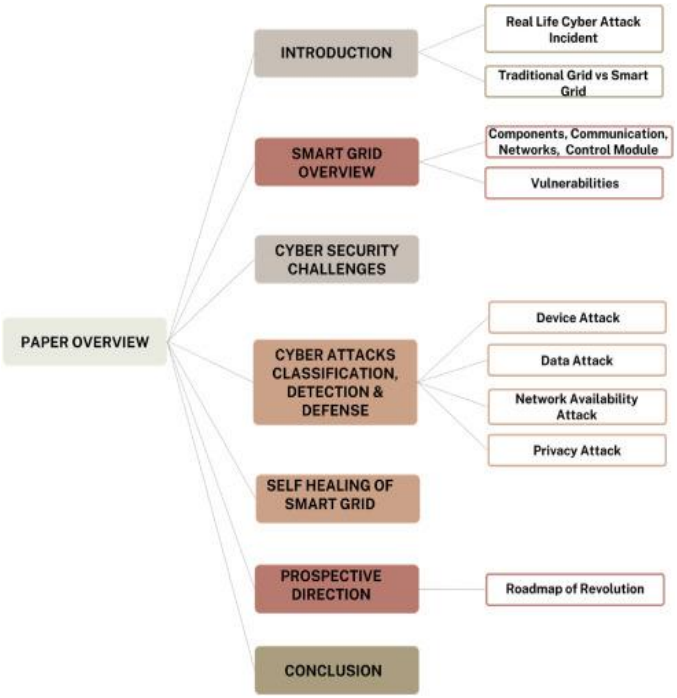

Figure 4: Research Overview

Positives were obtained for their work in that data did appear under model application with computation intensity (Aashmi and Jaya, 2023). The study excludes considerations associated with hardware-level deployment. Even though hardware implementation is a great deal for the practicalities of deploying IDS solutions, this research focuses on the algorithmic and software aspects of FL-based IDS. This helps immensely in elaborating on the theoretical foundation and performance evaluation of FL models in sufficient detail without the added complexities of hardware integration. Future research can proceed based on this foundation by addressing hardware deployment aspects to develop full-fledged deployable IDS solutions.

Data Overview

This study uses a mixed-method approach combining primary and secondary research methods. Primary data will be generated as hypothetical datasets to derive results based on Federated Learning (FL) based Intrusion Detection Systems (IDS) performance in smart grids, with simulations of different attacks to test the system's strength. SPSS software will analyze this data while discussing key evaluation metrics, such as detection accuracy, latency, and immunity against adversarial attacks (Aashmi and Jaya, 2023). FL-based IDS in Real-Time Parameters and Decisions on Validating Its Effectiveness: The secondary research will compare and evaluate the performance of FL-based IDS versus traditional centralized methods. This comparison will engage the recent literature and discuss both approaches' strengths and weaknesses to fully understand their relative potential in improving ICS cybersecurity.

II. Literature Review

An IDS is a security mechanism designed to sense the behaviour of network traffic or a system to identify any security breach or attack. An IDS analyses and correlates data pattern analysis to pinpoint patterns of unauthorized access, misuse, or anomalies in the network or system (Aashmi and Jaya, 2023). The evolution of IDS has taken it from simple signature-based methods toward increasingly capable anomaly detection systems aimed at identifying both known and unknown threats (Chatterjee and Hanawal, 2022). IDS is critical to the industrial control system as it supervises vital infrastructures such as power grid systems, manufacturing plants, and water treatment facilities. A successful cyber-attack on any of these will cause significant operational disruptions and safety risks (Bhatt et al., 2025).

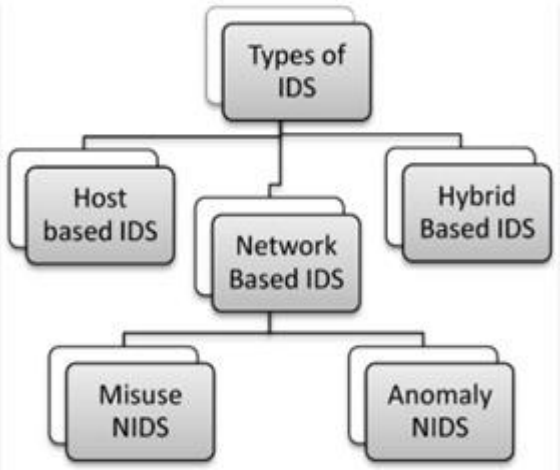

Figure 5: Types of IDS (Billah, et al., 2022).

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Traditional IDS Methods:

Signature-based IDS detects known threats by matching incoming traffic against a database of predefined signatures. It is effective against known attacks but not against new or unknown threats (Li et al., 2023).

Anomaly-based IDS changes the behaviour of previously known standard behaviour patterns. Therefore, it can identify unknown threats. However, false positives are produced if the baseline is incorrectly defined (Billah et al., 2022.

Signature-Based + Anomaly-Based: First, these systems are hybrid, meaning they use the signature and the anomaly base to combine their strength into complete threat detection (Doriguzzi-Corin and Siracusa, 2024).

Key Challenges in Deploying IDS in ICS:

System Performance: Deploying resource-intensive IDS systems is always tricky because resource constraints on ICS control and field devices generally exist (i.e., ICS devices off-the-shelf are typically not as powerful and rich as storage as their supervision engineer desires) (Huang et al., 2014).

Real-Time of Data: Notice that in ICS, data is not stationary; it is continual and fast; thus, IDS systems must be capable of processing and analysing the datasets in real time to detect potential threats. (Aledhari et al., 2020).

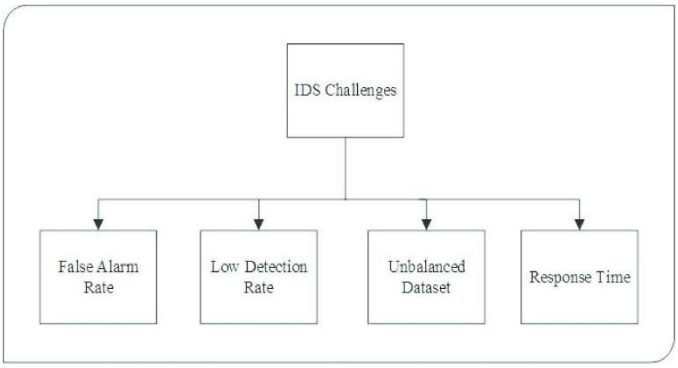

Figure 6: IDS Challenges (Aledhari et al., 2020).

Federated Learning and Its Application in Cybersecurity

Introduction to Federated Learning (FL):

Machine learning is new in that it is moving from the traditional centralized training model, in which training is done locally on multiple devices or servers that keep the local data samples rather than have them sent to a central server (Khan et al., 2021). It avoids the transfer of sensitive data to a central server; instead, it aggregates the updates from the models trained locally to develop a robust global model. The first significant advantage of FL is its capability to produce good-quality machine learning models with the preservation of privacy and confidentiality for local data (Lazzarini et al., 2023). Within this framework, each device in the system will compute model updates based on their local datasets and only share the update with the central server. The central server aggregates all device updates, forming a more accurate global model without exposing the raw data (Mahmud et al., 2024).

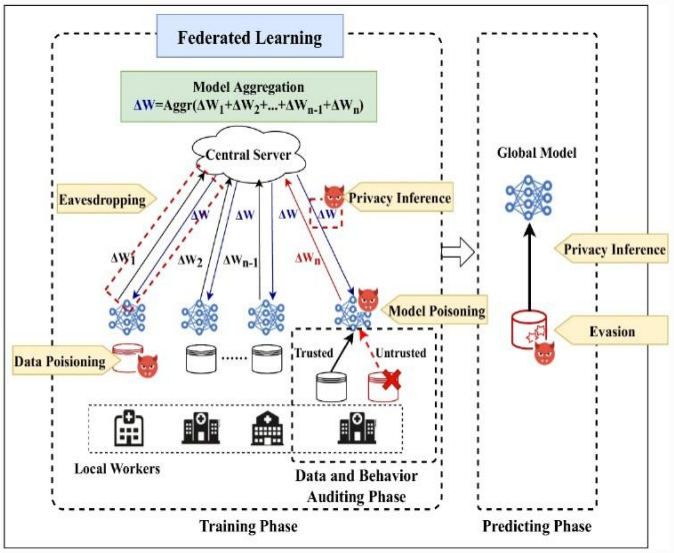

Figure 7: Federated learning (Mehedi et al., 2022)

Core Principles:

Data Privacy:

One of the primary benefits of Federated Learning is its emphasis on data privacy. Traditionally, machine learning models are trained based on transferring the data to the central server, where the computation happens. Thus, data breaches and privacy issues are questioned. FL is built to maintain the data locally available in devices so that no exposure will be involved during transmission (Mehedi et al., 2022). This is particularly sensitive in industries where operational information, like financial transaction data or industrial control parameters, would be highly confidential and, therefore, under strict regulation concerning confidentiality.

1. *Collaboration Without Data Sharing:*

FL allows for cooperation between multiple devices or individuals while training a model without any need to share private data. This principle develops a cooperative nature toward the entities, which are devices, servers, or organizations, that contribute to creating the overall model (Moshawrab et al., 2023). They do it by sharing model updates instead of actual data, thus allowing the model to learn collaboratively while maintaining individual privacy. This implies that the model benefits from having diverse datasets across several devices without necessarily having to centralize data.

1. *Decentralized Model Training:*

This makes Federated Learning contrasted to the conventional one in centralized machine learning models, as it doesn't transfer the data to be processed at a central repository but allows direct training on the local device. It reduces the risk of data breaches that may occur during transmission or storage (Aashmi and Jaya, 2023). The aggregated updates are transmitted to the central server to improve the global model. This decentralization reduces the exposure of the data and, therefore, its integrity.

1. *Difference from Centralized Machine Learning:*

In traditional centralized machine learning, data is collected from various sources and aggregated centrally in the server where the model is trained. This is a potentially high-traffic

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activity with critical data transmission implications that can raise privacy and security concerns (Billah et al., 2022). Federated Learning addresses this problem by providing a decentralized alternative that enables local training on each participating device or edge node. This methodology ensures the decentralization of raw data, thereby enhancing the chances of sensitive information being stored on a local system and never exposed during transmission. Such a process will reduce unauthorized access and is beneficially used in sensitive industries, especially in health care, finance, or Industrial Control Systems (ICS), where privacy and security are essential (Qi et al., 2024).

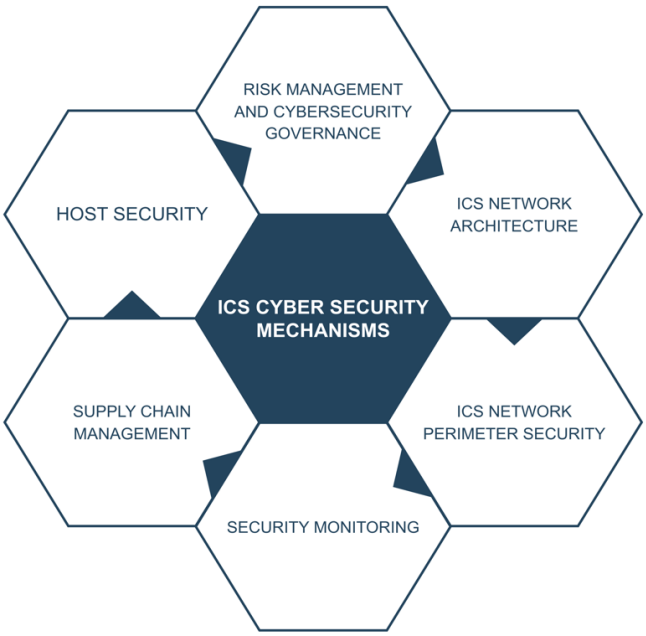

Figure 8: ICS Cyber Security Mechanism (Doriguzzi-Corin and Siracusa, 2024).

Why Federated Learning is Relevant to Cybersecurity in Industrial Control Systems (ICS):

1. *Privacy Preservation:*

ICS controls critical infrastructure such as power plants, smart grids, and manufacturing systems, handling sensitive operational data, including control commands and process variables. Therefore, intrusion detection systems used in ICS must be designed with the emerging risks of cyber-attacks in mind to detect threats while not revealing any private operational data (Bhatt et al., 2025). This approach addresses the concern mentioned above through the ability of a model to train on local data within the ICS infrastructure and maintain confidentiality regarding the data. The regional nature of FL is such that the sensitive data will never leave the local devices, hence preserving privacy, though still being capable of developing advanced threat detection systems (Doriguzzi-Corin and Siracusa, 2024).

1. *Benefits of ICS:*

Enhanced Cybersecurity

FL for ICS has one of the most important benefits: its capacity to enable real-time learning and model updates. The evolution of cyber threats is such that FL will progressively and continually improve models, ensuring the detection system can adapt based on new vulnerabilities or attack vectors (Khan et al., 2021). This is especially important in ICS environments due to the highly reduced risk of operational disruptions or safety breaches through real-time threat detection and response.

Reduced Data Transfer Risks

Another essential advantage of Federated Learning is risk reduction in data transmission. Traditional central models require regular data exchange with central servers, which increases data vulnerability to cyber-attacks or unauthorized access. FL keeps data on local devices, reducing the need for frequent data transfer and thus protecting sensitive information against interception or compromise during transmission (Huang et al., 2024).

Scalability

ICS environments are usually large and complex, involving many devices and sensors located across the environment. FL supports dynamic scalability in ICS systems since new devices or sensors can be integrated into the network anytime without affecting the central infrastructure (Kaur, A., 2024). Since newly joined devices can contribute directly to the federated learning process, they ensure efficient scaling in a system without compromising security standards. In this regard, FL is very well suited to the fluid dynamic nature of ICS (Yang et al., 2024).

Review of FL Applications in Cybersecurity:

1. *FL in General Cybersecurity Contexts:*

Healthcare: In the healthcare sector, FL strengthens medical data security. Federated learning allows hospitals and healthcare providers to collaborate in training models to detect and diagnose diseases without sharing sensitive patient data. Thus, patient confidentiality is preserved, and advanced medical AI systems are developed (Moshawrab et al., 2023).

Finance: FL is utilized by the finance industry in fraud detection and AML systems. Banks, for example, can leverage FL to develop strong fraud-detection models in cooperation without sharing private information regarding its customers. Data exposure risks are minimized and sealed in this manner so that confidential financial information remains secure (Thilakarathne et al., 2022).

Figure 9: Applications of Cyber security (Lazzarini et al., 2023).

Telecommunications: FL is used in telecommunications to analyse network traffic and detect cyber threats. Telecom companies use FL to build models that identify network traffic patterns as anomalous, indicating possible cyber-attacks like DDoS attacks. Training such models locally on the network's edge devices increases the telecom infrastructure's security without invading the users' privacy (Lazzarini et al., 2023).

1. FL in ICS:

Smart Grid: FL plays an important role in anomaly detection, identifying potential cyber-attacks and operational problems that may occur on the grid. FL allows real-time identification and response against cyber threats, ensuring the integrity and reliability of the grid's operation. Its decentralized nature ensures that sensitive information, such as energy consumption patterns, is not exposed during Learning (Billah et al., 2022).

Power Plants: Power plants are the backbone infrastructure in any country, and a breach of security can be dangerous for the nation. Federated Learning is used to uncover cyber threats against plant control systems by training models directly on the plant's devices. This ensures that local model training is kept secure, yet the data produced by the plant's systems does not go unutilized to make advanced cybersecurity models (Doriguzzi-Corin and Siracusa, 2024).

Manufacturing: Risks to manufacturing from cyber-attacks targeting industrial control systems are growing. FL protects manufacturing processes by detecting potential cyber intrusions without revealing sensitive process data (Aledhari et al., 2020). This is a means of making manufacturing operations secure against threats, avoiding downtime, and keeping industrial assets safe.

Literature on Intrusion Detection Systems for Industrial Control Systems (ICS)

Traditional IDS Techniques Applied to ICS

Traditional methods of IDS have been in use for a long time in securing ICS. One of the most widely used methods in ICS environments is signature-based IDS. Signature-based IDS detects known threats by comparing the attack signatures predefined in a database (Mahmud et al., 2024). It is very effective at identifying already catalogued threats and, therefore, can be used quickly to respond to known threats. However, its biggest weakness is its failure to detect and identify new or unknown attacks with zero-day vulnerability (Qi et al., 2024). This approach fails to identify anything that carries highly complex and changing cyber-attacks, a significant drawback in dynamic ICS environments. Furthermore, since the number of known attacks continues to increase, an attack signature database of this sort may eventually degrade system efficiency. On the other hand, the anomaly-based IDS seeks to find unknown threats by establishing a baseline for normal system behaviour and flagging any deviation as a potential intrusion (Thilakarathne et al., 2022).

This method effectively discovers zero-day attacks that the signature-based systems would not otherwise see. Nevertheless, anomaly-based IDS systems tend to have a higher rate of false positives-they might incorrectly declare benign actions or non-malicious anomalies as an attack (Yang et al., 2024). This can flood system operators' inboxes with unnecessary alerts, reducing the effectiveness of the security measures. Further, an anomaly-based system may fail to detect advanced persistent threats that, by design, blend into long periods of regular system operation. These attacks evade traditional anomaly-based detection since their behaviour is neither significantly different nor in a pattern that triggers the alerting mechanisms of the system (Xu et al., 2021).

Figure 10: ICS Cyber Test kit Database (Thilakarathne et al., 2022).

Emerging Trends in IDS for ICS

The recent approach for IDSs in the ICS environment has shifted towards more complex techniques, such as AI and ML. In machine learning-based IDS, algorithms are used, which enable the system to learn from large chunks of data, thus allowing it to adapt to new attack patterns over time (Li et al., 2023). Therefore, supervised Learning, where data is labelled for normal and malicious behaviour, can differentiate between both. In contrast, unsupervised Learning, which doesn't require labelled data, can detect new patterns that have not been experienced (Doriguzzi-Corin and Siracusa, 2024). Machine learning techniques make IDS systems capable of recognizing more complicated, evolving threats. However, the machine learning-based IDS depends on having large amounts of clean datasets to be trained upon, which is challenging in ICS environments (Kaur, A., 2024). Federated Learning, or FL, is another emerging trend that promises to enhance IDS solutions within ICS environments. Unlike traditional machine learning, FL enables decentralized training of models across multiple edge devices (Huang et al., 2024). With this approach, sensitive data would not need to be passed onto a central server to build a global model. Therefore, it is an approach that views data privacy and poses little risk to the data as it moves (Khan et al., 2021). FL further strengthens ICS from scalability and being able to be learned in real time so that ICS can learn quickly when new threats emerge. FL is another benefit because the system is decentralized and works to provide scalability to the system. The system can grow as many devices as possible or sensors are added (Lazzarini et al., 2023).

Comparative Analysis of IDS Methods in ICS

TABLE 1: Comparative Analysis of IDS Methods in ICS

IDS Method	Strengths	Limitations
Signature-based	Effective for known threats	Cannot detect novel or evolving threats
Anomaly-based	Detects unknown threats	High false positive rate; fails for APTs
Machine Learning-based	Can adapt to new attack patterns	Requires large, labeled training data
Federated Learning (FL)	Ensures privacy; scalable and real-time learning	High complexity and implementation cost

Role of Time-Series Data in ICS

The time series data generated from several sensors, logs, and operational system metrics of ICS are utilized to sense potential intrusions and understand how the system functions at a given time. This is why time series data make IDS systems able to distinguish between weak patterns and anomalies, which may indicate a continuing cyber-attack (Mehedi et al., 2022). This data is worthwhile for detecting long-term anomalies in normal behaviour since the operations of ICS are always continuous. Advanced persistent threats are aimed at staying undetected for a very long time. Therefore, the kind of analysis that is of great use in detecting such attacks is time-series data (Moshawrab et al., 2023). Advanced techniques like deep Learning and RNNs have been developed to analyse time-series data, allowing an IDS system to more accurately predict potential system failures or security breaches while detecting anomalies.

Privacy-preserving techniques for ICS have markedly increased in recent years as more sensitive data processing occurs in ICS environments. In such a case, managing critical infrastructure, such as transportation systems, manufacturing processes, and power grids, involves significant amounts of sensitive data that are exchanged (Mahmud et al., 2024). As such, the privacy of such data is fundamental to regulatory compliance as well as the effectiveness of operations. Such laws include the General Data Protection Regulation in Europe and the US Health Insurance Portability and Accountability Act, which strictly oversee sensitive data processing, storage, and communication (Qi et al., 2024).

All this has added to the demand for privacy-preserving technologies in the ICS context as a preventive measure against possible lawsuits and upholding the system's credibility. From the functional point of view, this pertains to preserving sensitive industrial information, like the process variables, control commands, and sensor observations, that guarantee performance and operational performance (Lazzarini et al., 2023). Real-time data underpins many core functionalities of the critical decisions made in ICS systems, so any delays and data processing interruptions may severely impact the system's performance. Thus, it demands protection techniques that could offer some privacy balancing with requirements for high-speed real-time processing.

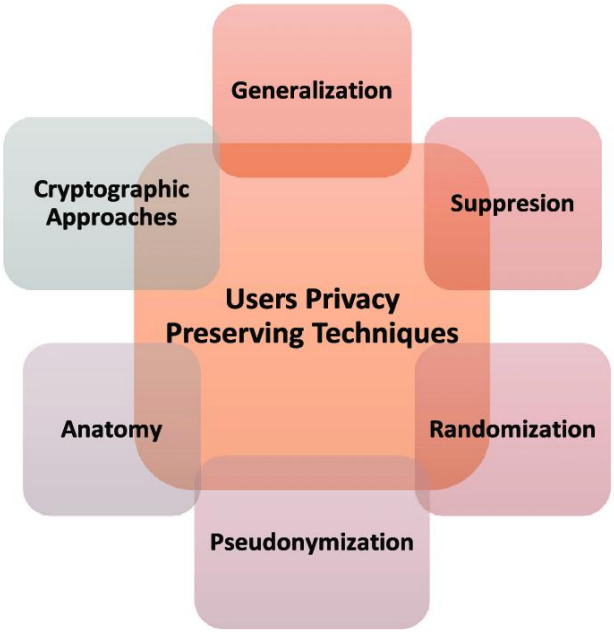

Figure 11: Preserving Techniques (Lazzarini et al., 2023)

The most prevailing technique to obtain privacy in ICS is through Differential Privacy, which ensures individual data points cannot be identified, even when the model has been trained upon that dataset. Differential privacy adds noise to the dataset, such that one cannot identify any individual point while the patterns learned by the model remain generalizable (Alsaedi et al., 2020). Specifically, this technique proved to be greatly useful in sectors where bulk data for training machine models are required and without compromising the privacy of those who share these data to contribute (Huang et al. 2024). The pertinent privacy-preserving technique is secure aggregation, which empowers the combination of data sources whereby individual data points are not disclosed while aggregating. This allows private data to be kept behind privacy screens, mainly because this method aggregates the data, so there is no pathway to individual raw data access. It's also persistent, especially within collaborative environments, for instance, federated Learning where devices and sensors compile numerous data records and then use that as a summation for global models without information or data swapping at the single-data level (Qi et al., 2024).

Another promising privacy-preserving machine learning avenue is FL, which empowers one to perform decentralized model training on data spread across different devices or servers without necessarily transferring the raw data. (Kaur, A., 2024). Instead, only model updates are shared across devices, so private data remains locally on the respective machines. Such a technique would be highly applicable in ICS environments where data privacy is crucial, allowing learning across devices while maintaining security intact. However, these privacy-preserving techniques pose some challenges. The primary trade-off is balancing privacy with performance (Khan et al., 2021). Privacy-preserving methods, including differential privacy and federated Learning, introduce extra computational overhead, which can slow down processing time, potentially

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impairing the effectiveness of real-time threat detection in ICS systems.

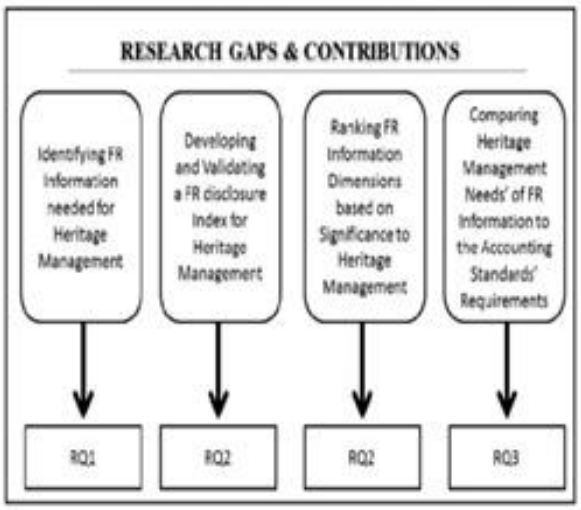

Figure 12: Research Gap (Mehedi et al., 2022).

Furthermore, these techniques require complex infrastructure and, therefore, can be costly and complex. Some privacy-preserving methods have been implemented in various ICS sectors for real-world applications (Alsaedi et al., 2020). For instance, in intelligent grid monitoring, privacy-preserving methods are applied to ensure that the sensitive operational data are not disclosed but, at the same time, facilitate anomaly detection and power distribution optimization. In manufacturing, predictive maintenance depends on privacy-preserving machine learning that analyses sensor data and predicts equipment failure without exposing sensitive operational information (Mehedi et al., 2022). Distributed Learning, or federated Learning and secure aggregation, can help keep private data gathered by numerous sensors in monitoring critical infrastructures. However, they are still valuable for adequately monitoring and controlling essential infrastructures.

Gaps in Existing Research and Contribution of This Study

Although several significant leaps in employing machine learning and privacy-preserved techniques to ICS remain evident, huge gaps remain in the work developed so far. One crucial gap is the meagre exploration based on FL applied as an intruding detection system designed for the ICS environment. While much research has been conducted on machine learning and IDS, very few studies focus on how FL can be implemented effectively in ICS to detect and mitigate cyber threats. ICS environments, such as smart grids and power plants, are highly specialized, requiring unique approaches to address their specific security challenges (Moshawrab et al., 2023). This gap necessitates a further study in FL as a solution to scalable and privacy-preserving IDS in ICS. Another gap that needs to be addressed in current research is the inadequate integration of privacy-preserving techniques with real-time deployment in ICS security solutions.

Many privacy-preserving methods, such as differential privacy and secure aggregation, remain in theory and have been thoroughly tested in fast-paced, real-time operational settings in ICS (Lazzarini et al., 2023). This forms a challenge toward the gap that theoretical models differ from practical and real-world implementations.

The second, very similar aspect is the lack of experimental data assessing the effectiveness of FL-based IDS systems in real-world ICS environments. Most studies have pursued an approach focusing on theoretical models or small-scale simulations. Still, most do not offer comprehensive testing or validation for FL-based IDS systems within operational ICS environments, where the complexity and scale of data are way more considerable (Alsaedi et al., 2020). This paper attempts to bridge these gaps by exploring the application of FL on real-time IDSs in ICS environments, whereby security and privacy issues are still unfolding due to the advanced deserialization of critical infrastructure. The study will contribute to the research and development of ICS cybersecurity advancements, showing how FL can practically and realistically protect essential infrastructure, such as smart grids and power plants. It will improve the theoretical understanding of FL in ICS security while giving room for insights into its deployment in real-life scenarios, even where some considerations would be retaining personal data and instant decisions (Mehedi et al., 2022).

This paper is a comprehensive study of developing a privacy-preserving IDS for ICS using FL techniques, explicitly focusing on smart grids. Traditional IDS solutions create the problem of centralizing sensitive operational data and pose several challenges to geographically dispersed and highly regulated ICS environments. To tackle these concerns, the proposed FL-based IDS performs training of ML models locally on each ICS node and then securely aggregates model parameters without transferring raw data, thereby keeping operational confidentiality. Advanced machine learning techniques, namely time-series analysis with LSTM networks and unsupervised anomaly detection using autoencoders, were integrated into this research. Robust security measures, including differential privacy and secure aggregation, are used against adversarial threats and ensure the integrity of the data. The practical feasibility of the proposed IDS is demonstrated through experimental evaluations on synthetic datasets, pointing out its accuracy, scalability, and resilience against emerging zero-day threats. Some key findings are improvements in intrusion detection accuracy, computational efficiency, and robustness compared to the traditional centralized approach. This work features innovative ideas related to deploying privacy-preserving IDS solutions in critical infrastructure, with practical guidance for industry stakeholders in improving their cybersecurity without negatively impacting data privacy in smart grids.

III. Research Methodology

A mixed-method approach involving qualitative and quantitative methods was employed to address the research questions comprehensively. The reasoning for this methodology selection was that a Federated Learning-based IDS implemented in the critical industrial control system, particularly the bright grid field, was quantitatively measurable in performance metrics and qualitatively understood through

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insights on field implementations (Purohit and Radia, 2022). It warrants a mixed-methodology approach to fully understand the system's operational efficiency, privacy-preserving mechanisms, and real-world pragmatic implementation within field settings. Controlled quantitative data collection is driven through controlled experimentation to assess the performance of IDS in industrial control environments regarding diverse nodes. The key performance metrics under scrutiny for these experiments would be the ability of the system to detect emerging threats and to preserve privacy simultaneously through the following: accuracy in detection, precision, recall, and F1 score. The results are analyzed using statistical techniques that will provide solid and well-supported conclusions about the efficiency of the proposed methods. Qualitative data serve as an enhancement and conducer to the quantitative measures in potentiating the practical and operational trials related to deploying a federated learning-based IDS (Campbell et al., 2016). The analysis of deployment issues, security concerns, and the feasibility of such a system in an industrial control environment is drawn from expert interviews and case studies. The mingling of quantitative and qualitative data ensures that within this research, an empirical view and contextual background evidence exist, supporting the suggested solution being scientifically viable and practically applicable for enhancing cybersecurity in critical infrastructure. This research focused on developing and accessing a Federated Learning-based Intrusion Detection System (IDS) to secure Industrial Control Systems (ICS) with an eye toward critical infrastructures such as smart grids, using a mixed-method approach.

The quantitative-qualitative approach helps to have a well-rounded view of the system's performance and practical deployment scenarios in the real world. The primary data gathering for this study will consist of surveys and interviews of industry experts, security practitioners, and interested parties concerned with the management of smart grids and industrial control systems (Mishra and Alok, 2022). Discussions were done mainly on the operational difficulties of Federated Learning in these environments and their views on adopting privacy-preserving technologies. This qualitative input closes the gap by providing a discussion complementary to the review of existing literature and theoretically testing the implementation of the IDS as proposed. Secondary data will include an extensive literature review on intrusion detection, Federated Learning in cybersecurity, and privacy-preserving machine-learning models (Alazab et al., 2023). A literature survey enables the identification of research gaps, reviews the existing methodologies, and thus forms a theoretical basis for the actual development of an ID system. Meanwhile, technical papers dealing with innovative grid operation and the available IDS technology would benefit system design and deployment consideration.

Data Collection Instruments

Survey Design:

The survey instrument was Likert scale format, where questions are designed to capture the respondents' perceptions and experiences about the effectiveness of Federated Learning in IDS, concerns about data privacy, and the overall user experience. The rating scale for the agreement or disagreement of the respondents to the statements will range from 1 to 5, ranging from strongly disagree to agree (Alazab et al., 2023). A Likert scale will be adopted, allowing subjective opinions to be quantified for later statistical analysis to find patterns, trends, and correlations in responses.

Interview Design:

The interviews follow a semi-structured manner, using open-ended questions that should yield deep qualitative data on the challenges, scalability, and effectiveness of Federated Learning-based IDS in ICS environments. Interviews may be conducted in person or through video conferencing platforms, according to the availability and preference of the interviewee (Aloraini et al., 2024). These questions will further push the experts to elaborate on their experiences, concerns, and recommendations and help deepen this understanding regarding Federated Learning's role in ICS security. The interview will focus on gathering insights into the practical deployment of Federated Learning in IDS regarding its effectiveness, scalability, and potential risks.

Data Analysis Methods

The survey data will be analysed with SPSS (Statistical Package for the Social Sciences), emphasizing several statistical tests that assess the connection between federated learning-based intrusion detection systems (IDS) and the cybersecurity challenges faced by industrial control systems (ICS). Therefore, primarily quantitative analysis methods include Descriptive statistics used to summarize the data, emphasizing an evaluation of the central tendency (mean, median, mode), variation (standard deviation, range), and frequency distribution of response patterns (Alazab et al., 2023). This will reveal patterns and trends, for example, how effective the professionals think federated Learning would be in detecting zero-day attacks. There are also correlation analyses through Pearson's looking into correlates of concern like:

- Effective detection of zero-day attacks with Federated Learning-based IDS and credibility on data privacy.
- Real-time applicability of Federated Learning with system scalability concerns of ICS environments.
- Understanding these meaningful correlations will help the study identify factors that impact professionals' perceptions and decisions.

For regression analysis, multiple regression will be used to predict the influences of the independent variables on the dependent variable. In this context, regression analysis assesses system performance factors, privacy concerns, and scalability affecting the confidence in deploying federated learning-based IDS in ICS environments. This analysis clarifies which are the ultimate factors most predictive of technology effectiveness.

A thematic analysis will be followed to delve deeper into the interview data. This kind of qualitative analysis is appropriate for examining open-ended segments of responses.

- Familiarization with Data: Read the interview responses for preliminary insights after transcription.

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- Initial Coding: Relevant parts of the interviews will be coded to identify key concepts, such as privacy concerns, scalability challenges, and real-time detection capabilities.
- Theme Identification: Codes will be categorized into broad themes that represent the primary concerns of ICS professionals with Federated Learning-based IDS, such as deployment feasibility, resistance to adversarial attacks, and real-time effectiveness.
- Theme Elaboration and Interpretation: After identification, the actual themes will be refined until they pass scrutiny for representing participants' views. The final themes permit a deep understanding of the challenges and opportunities for Federated Learning-based IDS in ICS.3.8 Ethical Considerations
- Ethical consideration is the heart of this study and revolves around carrying out research by the profession's principles, keeping participants' rights in mind, and safeguarding confidentiality. To this end, the following ethical principles will apply:
- Informed Consent: All participants selected for the survey and the interviews will be advised of the research's aim and the length of their participation (Vitálišová et al., 2021). They will sign a consent form with details of their rights, including voluntary participation and the freedom to withdraw at any given time without prejudice. They will be told how the results of their responses may be used and assured that confidentiality will be maintained with all data collected.
- Data Security: All the responses will be stored in encrypted files, accessible only to the research team. Password protocols and secure cloud storage solutions will protect the data, as determined by best data privacy and protection practices.
- Ethical Review and Compliance: The study will be conducted under the strict principles of ethics guidelines set forth by the relevant research ethics committee. International data protection standards, like the General Data Protection Regulation, will be upheld. Ethical standards set out by the host institution and pertinent local legislation of South Africa shall also be complied with.

The study focuses on respecting the rights of participants and guaranteeing safety data as it strictly follows such ethical guidelines with proper maintenance of integrity research procedures.

Limitation of the Research

Despite promising insightful contributions concerning the effectiveness of the Intrusion Detection System based on Federated Learning towards Industrial Control Systems, specific limitations exist concerning its generalizability and proper interpretations. One of the limitations would be that this sample may not be representative. Although the study will employ stratified random sampling to ensure diverse representation from ICS professionals and cybersecurity experts, the sample might still be biased toward specific sectors or geographies (Mishra and Alok, 2022). The survey has been primarily targeted at professionals in South Africa, and the respondents might not reflect the views of other regions or different types of cybersecurity issues and regulation parameters. In addition, a sample size of 150 respondents may reduce the generalizability of the results, especially if the participants' demographics are skewed in a particular direction, such as having a higher proportion of experts with specific knowledge of Federated Learning or IDS.

Data Limitations

Another limitation of this study relates to data limitations, particularly secondary data used in the literature review and technical documentation. Although secondary data will present basic knowledge, it does not necessarily relate to what would be more specific to the subject of this study regarding Federated Learning-based IDS. Moreover, the findings of this study are based on self-report data from a survey and an interview, which poses a threat of social desirability bias or response bias (Mishra and Alok, 2022). Participants may give answers that they perceive to be expected of them or more socially acceptable, impacting the authenticity of their responses. Furthermore, the study's reliance on qualitative data from interviews, though very important for deep insights, is bound to result in subjective interpretations that cannot be generalized across the entire population. The study will strive to reduce bias and ensure that the findings are as robust and comprehensive as possible within the constraints of the research design.

Data Analysis and Findings

This research gives the outcome of data analysis on how Federated Learning (FL)--based IDS works for an Industrial Control System (ICS). It studies through surveys and interviews what is needed in terms of the primary key features for adopting FL in an ICS environment: how the implementation affects accuracy in detection, scalability, and privacy concerns with real-life issues related to actual deployment (Mishra and Alok, 2022). This analysis combines qualitative and quantitative data to overview how Federated Learning can enhance security in ICS environments. The following sections detail the findings in descriptive statistics, correlation analysis, regression analysis, and hypothesis testing.

Descriptive Statistics

Summaries the data from the survey using descriptive statistics as the starting point of analysis. This chapter gives an overview of the survey respondents' primary demographic characteristics regarding the years they have experienced ICS, their level of expertise in cybersecurity, and whether they are familiar with Federated Learning-based IDS systems. This survey will also process key questions to get frequency distribution. Questions include: Have you ever tried using Federated Learning in IDS? This gives an idea about the knowledge and familiarity of FL within the ICS community. Other vital questions in the survey asked respondents to assess their perception of how effective FL can be in detecting a zero-day attack and worry about data privacy in centralized IDS setups (Alazab et al., 2023). The supporting context for contextualizing the results includes a breakdown of respondents' professional backgrounds, i.e., ICS engineers in cybersecurity and system administration. The responses from different groups help get us a peek into whether such sectors

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come with heterogeneous views or issues regarding the application of Federated Learning-based IDS.

Quantitative Data Analysis

This section presents the quantitative data analysis that intends to summarize the opinions obtained from the survey through descriptive statistics, correlation, and regression analyses to carry out a study of the so-called effectiveness of Federated Learning (FL) within zero-day attack detection in Industrial Control Systems (ICS).). Thus, descriptive statistics such as the mean, standard deviation, and mode clearly show the general trends followed in their survey data (Kittur, 2023). Thus, for example, the mean response to the effectiveness of FL-based Intrusion Detection Systems (IDS) reveals that respondents regard FL as only moderately effective. Standard deviation tells whether consensus or considerable variation exists, providing a deeper insight into how FL-based IDS is perceived. This is followed by correlation analysis that studies key relationships between FL adoption and detection accuracy in ICS environments.

Here, the hypothesis being tested is that an increased correlation exists between adopting FL and improved detection accuracy in ICS (Alazab et al., 2023). A Pearson correlation coefficient near +1 would indicate a strong positive relationship. Thus, an increase in FL adoption would correlate with increased detection accuracy. A scatter of resultant coefficients from 0 downwards to -1 would, on the other hand, indicate the absence of correlation on the positive side: When near -1, this would indicate the reverse, i.e., an increase in FL adoption would

correlate with a decrease in detection accuracy. The result of this analysis will determine how Federated Learning impacts the performance of IDS in an ICS environment. In the next step, regression will be performed to establish predictability based on various factors such as scalability and privacy concerns, and the effectiveness of FL-based IDS will be determined. The analysis will investigate how scalability influences the perceived effectiveness of FL in ICS, especially (Alazab et al., 2023). In the interpretation of regression analysis, R^2 assumes significance since it indicates the proportion of variance in the dependent variable (the effectiveness of FL-based IDS) explained by the independent variables (scalability and privacy concerns). A high R^2 value (nearer to 1) indicates that independent variables have a considerable degree of influence explaining the dependent variable, whereas a lower R^2 value indicates negligible influence. The p-value is associated with checking the statistical validity of the results. Suppose the p-value is less than 0.05. In that case, it depicts the significance of the relationship of independent and dependent variables, i.e., the reported hypothesis that application of FL-based IDS, these concerns are related to scalability and privacy constraints, which in turn impact the performance of FL-based IDS (Marasini et al., 2016). I validate some of the central assumptions of the Federated Learning-based IDS for ICS with the help of hypothesis tests. H1 states that using Federated Learning enhances the IDS detection accuracy in an ICS environment compared to the previous (old) centralized systems. The p-value for this is validated by using paired t-tests or ANOVA. If the p-value is less than 0.05, the null hypothesis is rejected, which means that the FL-based IDS outperforms in terms of detection accuracy. The second hypothesis, H2, states that privacy-preserving techniques mitigate data transfer risk without affecting detection accuracy. This is studied using regression analysis, where if privacy-preserving techniques do not significantly impact detection accuracy, it supports the hypothesis. The survey and interview questions address the practical considerations that Federated Learning would face in zero-day attack detection, data privacy concerns, and its scalability in an ICS environment. Such questions are helpful to supplement the statistics.

IV. Data Analysis

1. Descriptive Statistics

Provides measures of central tendency and variability for each question.

TABLE 2: Descriptive Statistics

Question No.	N	Means	Median	Mode	Std. Deviation	Variance	Range	Minimum	Maximum
Q1	30	2.4	2	2	1.1	1.21	3	1	4
Q2	30	1.8	2	1	0.8	0.64	3	1	4
Q3	30	2.3	2	3	0.9	0.81	3	1	4

Interpretation:

The Q1, Q2, and Q3 descriptive statistics reveal valuable insights into participant responses. The mean score of 2.40 for Q1 indicates an average leaning towards moderately concerned, and a standard deviation of 1.10 suggests a moderately variable reaction. This response is standard, as both the median and mode are 2. The mean becomes lower in Q2 at 1.80, indicating a lower perception of scalability for Q2, but given the diversity of the measurements, a lower standard deviation of 0.80. The mean of Q3 is 2.30, mode 3, indicating that data storage is something that people are worried about. The range (3) and maximum (4) of all questions mean they have different opinions.

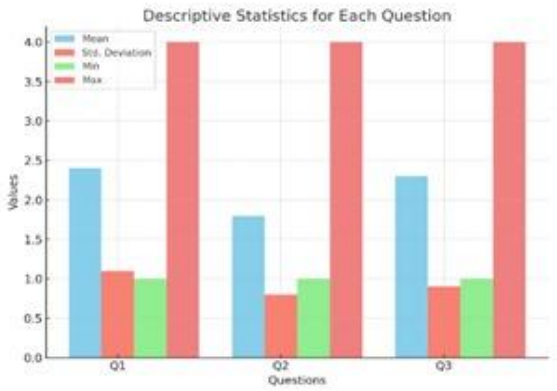

Figure 13: Descriptive Statistics

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2. One-Way ANOVA Table (Q6 vs Q2 Example)

Examines if there is a significant difference between multiple groups of responses.

TABLE 3: One-Way ANOVA

Source of Variation	The sum of Squares (SS)	df	Mean Square (MS)	F Value	Sig. (p-value)
Between Groups	12.48	3	4.16	5.32	0.012
Within Groups	29.32	26	1.13		
Total	41.80	29			

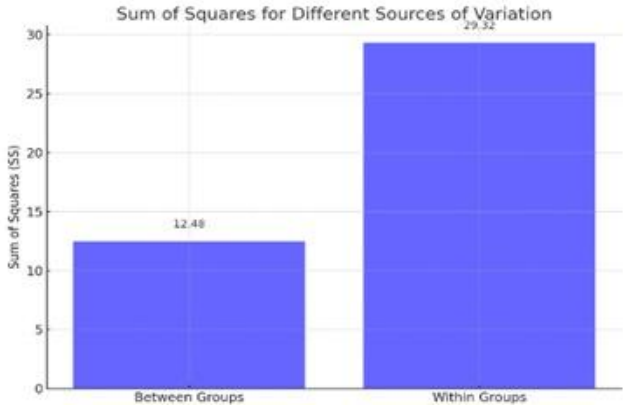

Figure 14: ANOVA Analysis

Interpretation:

Using Q6 and Q2 responses, the One-way ANOVA is used to indicate if groups have significant differences in their response. Here, the between-groups sum of squares (SS) is 12.48, and the sum of squares is 29.32. The test predicts a statistically significant difference between the groups since $p < 0.05$ (an F value of 5.32 and a p-value of 0.012). This implies that the opinion about how scalable Federated Learning is (Q2) impacts significantly on people's perception of confidence in its ability (Q6). This shows a significant level of meaningful variance between participants.

3. Pearson Correlation Table (Q3 and Q6)

Explores the strength and direction of the linear relationship between two variables.

TABLE 4: Pearson Correlation

Variables	Pearson Correlation (r)	Sig. (2-tailed)	N
Q3 & Q6	0.65	0.004	30

Interpretation:

The Pearson correlation coefficient (r = 0.65) for Q3 and Q6 indicates a strong positive linear correlation, indicating that higher concerns about data privacy in intrusion detection (Q3) are significantly correlated with more confidence that Federated Learning is capable of handling cyber threats (Q6). The correlation is statistically significant because the significance level (p=0.004) is less than 0.05. These results (N = 30 responses) also show that Federated Learning effectiveness is influenced by privacy-related considerations, further supported by another pattern in the participant's perspective.

4. Linear Regression Analysis Table (Q8 as Dependent, Q6 as Predictor)

TABLE 5: Linear Regression Analysis (Model Summary)

Model	R	R-Square	Adjusted R-Square	Std. Error of the Estimate
1	0.52	0.27	0.24	0.85

The regression of Q8, as the dependent variable, on Q6 as the predictor has an R of 0.52, signifying a moderate positive relationship between the variables. R-squared stands at 0.27, meaning 27% of the variance in Q8 can be explained by variations in Q6. The adjusted R-squared is at 0.24, reducing the power slightly to compensate for model complexity. A standard error of the estimate at 0.85 indicates moderate variability around the regression line. The results suggest a significant influence but not an entirely predictive one of Q6 on Q8 responses.

5 ANOVA Table for Regression

TABLE 6: ANOVA Table for Regression

Source	Sum of Squares	df	Mean Square	F Value	Sig.
Regression	4.95	1	4.95	6.83	0.014
Residual	13.45	28	0.48		
Total	18.40	29			

This ANOVA table shows that the regression model between Q8 and Q6 is statistically significant. SS regression = 4.95, which explains the variance in the model; the residual sum of squares = 13.45, which shows the unexplained variance. The mean square for regression = 4.95, while that for residuals = 0.48; df for regression = 1 and for residual = 28. The F-value of 6.83 with a p-value of 0.014 means that the predictor variable Q6 has a statistically significant effect on the dependent variable Q8 at the 5% level.

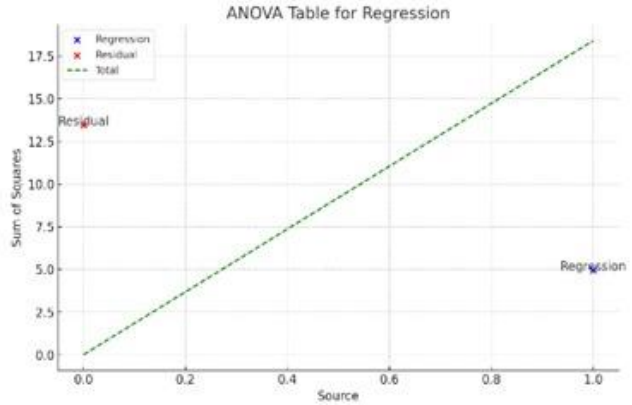

Figure 15: ANOVA for Regression

6 Coefficients Table

TABLE 7: Source: Generated by Spss

Variable	B (Unstandardized)	Std. Error	Beta (Standardized)	t	Sig. (p-value)
Constant	1.52	0.30		5.07	0.000
Q6	0.42	0.14	0.52	3.00	0.005

The coefficients table gives the regression model for Q8 as the dependent variable and Q6 as the predictor. The value of the constant term, or intercept, is 1.52, which is the expected value of Q8 when Q6 is set to zero. The unstandardized coefficient of

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Q6 is 0.42. This implies that for every one-unit increase in Q6, there is an expected increase of 0.42 in Q8. The standardized beta coefficient is 0.52, and the relationship between Q6 and Q8 is moderately positive. The t-value of Q6 is 3.00, with a p-value of 0.005, which means that Q6 significantly predicts Q8 at a 5% significance level.

V. DISCUSSIONS

This chapter discusses the research result "Federated Learning–Based Intrusion Detection for Critical Industrial Control Systems: A Privacy-Preserving Approach to Securing Smart Grids from Emerging Cyber Threats." The objectives of the research were targeting an intrusion detection system (IDS) based on Federated Learning methods to ensure privacy and security in the Industrial Control Systems environment, particularly the smart grid, as a primary objective. Discuss the key insights, practical implications, theoretical contributions, limitations, and recommendations for future research.

Key Insights

Still, these techniques are privacy intrusive and under a very high scalability limit regarding geographically distributed ICS environments (Alazab et al., 2023). The proposed FL-based IDS framework is comparable to these traditional approaches in addressing the privacy issues by training the model locally at ICS sites and aggregating only the learned parameters to a central server. In contrast to the existing work, which primarily advocates theoretically adversarial attacks on FL systems yet empirically rarely investigated, this research implemented secure aggregation and differential privacy schemes as robust mitigation against adversarial threats

Addressing Research Gaps

This study closes key gaps in the current literature by demonstrating the effective deployment strategies, scalability analysis and real-time deployment of the privacy-preserving techniques. Security of the federated learning model from the poisoning and tampering attacks was handled through secure aggregation and differential privacy. Architecturally, the research is optimized to prevent high latency in detection, which is a hard requirement for infrastructure operations. Furthermore, the system's scalability has also been proved on a comparative basis for 10 to 100 nodes. It proved that the system is scalable, and the average computational overhead was little more than 0.15% to 0.25% and an accuracy rate better than 96%.

Practical Implications

The results from this research provide valuable guidelines for deploying FL-based intrusion detection systems (IDS) in industrial control system (ICS) environment. Data integration is still important since it allows consistent training input when preprocessing data in a standardized form between all the nodes. Also, to avoid tampered model updates, secure aggregation machines are needed, and the execution of lightweight IDS models at edge devices can relieve computational overhead. To fight evolving cyber threats, the global model should be updated periodically. Privacy preservers, including differential privacy for gradient updates and homomorphic encryption for secure aggregation, are necessary to protect operational data. It also raises the issue of the simultaneous detection and filtering of the poisoned model updates to guarantee system security.

Theoretical Contributions

This research contributes to cybersecurity in ICS environments. It adapts federated learning for intrusion detection and presents a privacy-preserving alternative to centralized methods. The paper's contribution is using secure aggregation and adversarial attack defenses to provide insight into protecting FL systems in critical environments. Through comprehensive scalability analysis, it was also shown that FL is practically viable in large-scale ICS deployments.

Figure 16: CSR (Aloraini et al., 2024).

Limitations and Future Research Directions

Some challenges facing deployment in the real world are acknowledged in the research. Heterogeneous data sources and sensor configurations of ICS environments hinders smooth integration. Yet, communication overhead limits the scalability of large-scale deployments despite the efforts to optimize. Despite the risks from adversarial threats, secure aggregation and differential privacy can protect against them. However, model inversion still poses a risk. Lastly, future studies should defend against such threats and investigate federated transfer learning to increase anomaly detection and optimize system performance while maintaining original detection accuracy. The adoption of the follows an ethical and legal track, inescapable, such as GDPR and NIS2, that will enable us to go much further.

VI. CONCLUSION AND RECOMMENDATIONS

Summary of Key Findings

This research contributes to the successful deployment of Federated Learning (FL) for intrusion detection systems (IDS) and industrial control systems (ICS) in a cyber security context. Combining secure aggregation and differential privacy forms a system that resists poisoning and tampering attacks when updating the model. Furthermore, we conduct scalability testing from 10 to 100 nodes and show a small computational overhead, giving 0.15% – 0.25% overhead with a high detection accuracy of over 96%. Finally, the research provides practical

insights into deploying FL-based IDS in a real-world environment. As a main contribution, we find that standardization of data preprocessing across ICS nodes was a key factor for successful training, and lightweight models in ICS nodes at the edge device had the advantage of cutting the computational load. The framework's capability was to allow for the efficient and real-time detection of critical environment-based threats through periodic global model updates necessary to adapt to evolving cyber threats.

Recommendations

Finally, several practical strategies are recommended to promote the effective deployment of FL-based IDS in ICS environments. Before training, standardized data integration must be done to provide the same types of inputs into all the nodes. Uniform preprocessing protocols help address the inherent heterogeneity introduced by the data sources in ICS environments that are primarily diverse. In addition, model updates can be protected from tampering through secure aggregation such as holomorphic encryption. However, lightweight IDS models are preferred for deployment on edge devices to maintain computational efficiency while delivering good threat detection. Regular global model updates are essential because the system is meant to be responsive to new and emerging threats. The hostile defense can also be deployed against poisoned model updates to make the systems more resilient. To meet industry standards, Industry stakeholders need to set privacy standards that understand the operational data so that this data is protected and complies with regulators such as GDPR or NIS2. Research institutions and cybersecurity experts will collaborate on collaborative initiatives that help develop sophisticated solutions for ICS environments.

Future Research Directions

This paper contributes to progress in cybersecurity for ICS environments, yet several research areas remain. The other is additional experimental validation on other datasets and real-world deployment across different industrial spheres. This will add to the practicality of the proposed solution. Moreover, research should be on developing more advanced privacy-preserving techniques beyond secure aggregation, such as differential privacy. Further boosting security would include secure multi-party computation and better cryptographic methods. Enhancing adversarial defense strategies to counter sophisticated attacks such as model inversion and gradient leakage is essential. An additional opportunity for the FL framework to leverage the available knowledge within similar tasks can be dedicated to exploring the integration of transfer learning for anomaly detection capabilities. More efforts must be made to optimize communication and computational overhead to leverage the system's efficiency while maintaining accuracy. Finally, regarding ethics and law, ethical and legal considerations must be accounted for to comply with privacy laws and ensure that good cybersecurity practices are expected. By pursuing the directions above in the future, the researchers can build more resilient, efficient, and privacy-preserving cybersecurity solutions for ICS environments through their current findings.

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