Lack of Scalability and Communication-Efficiency Analysisin Federated Learning for IoT Security

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Abstract-With the rapid expansion of Internet of Things (IoT) networks, federated learning (FL) has emerged as a promising paradigm for enabling distributed intrusion detection without centralized data collection. While existing research demonstrates the effectiveness of FL in detecting denial-of-service (DoS) and other attacks, most studies focus primarily on detection accuracy while overlooking critical challenges of scalability and communication efficiency. Current approaches are often validated on small-scale testbeds or limited datasets, failing to capture the communication overhead, latency, client dropouts, and non-IID data distributions that characterize large-scale IoT deployments. This paper addresses these limitations by proposing a scalability-aware and communication-efficient FL framework tailored for IoT networks. The framework integrates lightweight aggregation strategies, adaptive client participation, and gradient compression techniques to reduce communication costs while preserving detection accuracy. Using benchmark IoT datasets and simulated heterogeneous environments, we evaluate the trade-offs between detection performance, communication overhead, and scalability across diverse network topologies. By explicitly addressing communication constraints, this research advances the deployment readiness of federated intrusion detection systems and provides actionable insights for designing robust, scalable, and resource-efficient IoT security solutions.

Keywords: Federated Learning (FL), Internet of Things (IoT), Intrusion Detection System (IDS), Scalability, Communication efficiency, Gradient compression, Client participation, non-IID data, Distributed security, Network resilience, Heterogeneous IoT devices, DoS attack detection, Edge computing, Secure aggregation, Resource-aware learning

INTRODUCTION

With the rapid growth of the Internet of Things (IoT), billions of interconnected devices are generating unprecedented volumes of data, supporting applications in smart homes, healthcare, transportation, and industrial automation. This explosion in connectivity has also increased the attack surface, exposing IoT ecosystems to denial-of-service (DoS), data tampering, and unauthorized access. Traditional centralized intrusion detection systems (IDS) struggle to handle the scale, heterogeneity, and privacy concerns of IoT environments, where data transfer to a central server introduces latency, communication bottlenecks, and risks of data leakage. To address these challenges, Federated Learning (FL) has emerged as a distributed paradigm that enables IoT devices to collaboratively train models without directly sharing raw data. By decentralizing learning, FL preserves data privacy and supports localized intelligence while benefiting from collective knowledge across the network.

Parallel to this evolution, advances in edge and fog computing have created opportunities for deploying FL-enabled IDS at scale. These paradigms allow computation to move closer to IoT devices, thereby reducing reliance on central servers and enabling real-time analytics. However, despite the conceptual promise of FL for IoT security, significant practical limitations remain unaddressed. One of the most critical issues is the lack of scalability and communication efficiency in current FL frameworks. In real-world deployments, IoT networks are highly heterogeneous, with devices ranging from low-power sensors to high-performance gateways. Communication between these devices is often constrained by bandwidth, latency, and energy limitations. FL training processes, which require frequent model updates and parameter exchanges, can quickly become communication-intensive and resource-draining when scaled to thousands of nodes.

Existing research primarily focuses on improving detection accuracy using classical machine learning or deep learning models but often overlooks how these models behave under large-scale, distributed, and resource-constrained environments. Studies typically evaluate FL frameworks using limited datasets, homogeneous device setups, or small-scale testbeds that do not reflect the complexity of IoT ecosystems in smart cities or industrial IoT (IIoT). Moreover, critical aspects such as gradient compression, client participation scheduling, asynchronous aggregation, and dropout resilience are seldom incorporated into experimental designs. As a result, scalability and communication bottlenecks remain underexplored and poorly quantified, limiting the applicability of FL-based IDS in real deployments.

This research seeks to address these shortcomings by systematically investigating scalability and communication-efficiency trade-offs in federated IDS for IoT networks. By integrating lightweight aggregation methods, adaptive client participation strategies, and communication-reduction techniques such as quantization and scarification, this study aims to design an FL framework that is both resource-aware and scalable. Furthermore, the proposed approach will be evaluated across diverse workloads, datasets, and network topologies to capture real-world heterogeneity. Through reproducible experimentation and benchmarking, the research intends to provide actionable insights that bridge the gap between theoretical FL models and practical IoT deployments.

I. LITERATURE REVIEW

The rapid growth of Internet of Things (IoT) ecosystems has driven the demand for distributed and intelligent security frameworks capable of detecting diverse threats such as denial-of-service (DoS) attacks, data breaches, and unauthorized access. Traditional centralized intrusion detection systems (IDS), while effective in small-scale deployments, are increasingly inadequate in handling the heterogeneity, scale, and privacy requirements of modern IoT environments. Recent scholarship highlights the transformative role of Federated Learning (FL) as a distributed paradigm that enables collaborative training across IoT devices without requiring raw data centralization. By decentralizing learning, FL not only preserves data privacy but also reduces the risks associated with centralized data bottlenecks, thereby laying a foundation for scalable and privacy-aware intrusion detection.

A notable trend in the literature is the integration of machine learning (ML) and deep learning (DL) methods into FL-based IDS. Classical approaches such as support vector machines (SVM), decision trees, and random forests have been widely applied for anomaly detection due to their interpretability and modest computational requirements. However, with the advent of increasingly dynamic IoT traffic patterns, researchers have explored deep learning architectures such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and convolutional neural networks (CNNs). These methods demonstrate improved detection accuracy in identifying malicious traffic signatures and temporal attack behaviours. More recently, hybrid approaches that combine ensemble feature selection with FL have shown promise, leveraging both feature diversity and distributed learning to improve generalization across devices.

Despite these advances, significant shortcomings persist in the existing body of research. Many studies evaluate FL frameworks using limited-scale experiments typically involving fewer than ten clients or small benchmark datasets such as IoTID20 thus failing to capture the communication overhead, latency, and scalability challenges present in real-world IoT deployments. Reported improvements in accuracy are often not accompanied by detailed evaluations of communication cost, client participation rate, or dropout resilience, which are critical for deployment in heterogeneous IoT environments. Moreover, comparative evaluations are typically restricted to basic baselines, overlooking advanced optimizations such as gradient compression, asynchronous updates, or adaptive aggregation strategies that directly impact communication efficiency.

Another critical gap lies in the operational impact of scalability on system resilience and cost. While accuracy metrics such as precision, recall, and F1-score dominate evaluations, few works measure the trade-offs between detection performance and resource consumption in bandwidth-constrained or energy-limited IoT networks. Similarly, the resilience of FL-based IDS under conditions of partial client participation, intermittent connectivity, or adversarial manipulation remains underexplored. In particular, techniques like secure aggregation, differential privacy, and Byzantine-resilient learning are conceptually discussed in the literature but rarely validated in large-scale experimental settings.

Taken together, these gaps suggest several promising directions for future research. Studies must move beyond accuracy benchmarks to incorporate scalability-aware evaluation frameworks that account for communication cost, latency, and fault tolerance under realistic IoT conditions. Open-source, reproducible pipelines with support for large-scale heterogeneous datasets would enable rigorous comparisons across FL variants and encourage industrial adoption. Furthermore, integrating lightweight communication strategies such as quantization, scarification, and adaptive participation could bridge the gap between theoretical models and real-world IoT deployments. Finally, exploring resilience testing, security guarantees, and fairness in multi-tenant IoT environments will be vital for building FL-based IDS that are not only accurate but also scalable, trustworthy, and operationally sustainable

II. DEVOPS TECHNICAL ROUTE

3.1 TECHNICAL ROUTE OF R&D PROCESS

The R&D process for Federated Learning (FL)–based IoT security requires a structured and iterative route to address challenges of scalability, communication efficiency, and security assurance. A central component is the adoption of visual management platforms such as JIRA or Redmine to streamline requirement tracking, model training tasks, and dependency management across distributed IoT devices. Hierarchical parent–child task structures ensure that subtasks, such as model updates from clients, are validated before aggregation at the server. This prevents premature deployment of incomplete or inconsistent models, thereby safeguarding reliability and overall system quality.

Building on this foundation, the technical route integrates predictive analytics and intelligent monitoring into the DevOps

lifecycle. Beyond conventional task management, the pipeline incorporates workload forecasting models to anticipate communication bottlenecks, bandwidth spikes, and energy consumption patterns in IoT devices. Automated anomaly detection techniques help identify abnormal client behaviours, adversarial model updates, or malicious gradient injections in real time. Monitoring tools such as Prometheus and Grafana provide visibility into system health, latency trends, and participation rates, while predictive insights feed back into sprint planning, model retraining, and deployment scheduling to enhance efficiency.

Finally, to ensure scalability and reproducibility, the R&D route includes continuous improvement loops informed by empirical evaluations. This involves benchmarking different aggregation strategies (e.g., FedAvg, FedProx, FedDyn) and quantifying their impact on scalability, communication efficiency, and detection accuracy. Explainable AI (XAI) components are embedded to enhance operator trust by clarifying which features or client updates most influence intrusion detection performance. By combining structured DevOps workflow management with ML-based feedback and reproducible benchmarking, the proposed route advances beyond conventional IoT security practices, enabling a more resilient, cost-efficient, and communication-aware FL pipeli

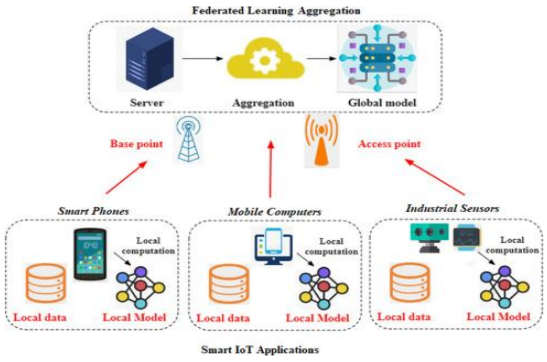

Fig. 1: Technical Route of R&D Process in Federated Learning–Based IoT Security

3.2 TECHNICAL ROUTE OF AUTOMATIC OPERATION AND MAINTENANCE

The technical route of automatic operation and maintenance (O&M) in FL-enabled IoT security integrates monitoring, feedback, and intelligent analysis across the entire DevOps lifecycle. A Zabbix cluster or equivalent monitoring infrastructure is deployed to continuously track device metrics, including CPU load, memory usage, disk I/O, communication latency, and energy consumption. Predefined thresholds (e.g., excessive gradient size, delayed updates, or abnormal traffic) trigger automated alarms, which are instantly communicated to administrators via email or integrated alerting systems. This proactive mechanism ensures that anomalies or device failures are addressed promptly before they compromise global model performance.

In parallel, Prometheus is used for fine-grained monitoring of FL-specific processes, including model aggregation time, communication rounds, and accuracy trends across clients. When anomalies or impending failures are detected such as sudden accuracy drops or adversarial behaviour alarm information is automatically fed back to system operators. Root cause analysis is conducted using historical monitoring data, allowing continuous improvement of resilience against communication bottlenecks or client-side failures. Visualization dashboards in Grafana provide intuitive overviews of device participation, network utilization, and anomaly trends, enhancing situational awareness and supporting informed decision-making.

This combination of monitoring, predictive analysis, and visual reporting forms the backbone of scalable and communication-efficient FL deployment for IoT security, ensuring system availability, robustness, and trustworthiness.

Fig. 2. Technical Route of Automatic Operation and Maintenance in FL-Enabled IoT Security

The technical route of automatic operation and maintenance in FL-enabled IoT security integrates three main layers device, edge, and cloud coordination to ensure secure, scalable, and communication-efficient learning processes. At the device layer, heterogeneous IoT nodes such as sensors, actuators, and smart appliances generate raw data. Since transmitting all local data to a central server is impractical due to bandwidth and privacy constraints, federated learning (FL) enables decentralized training. Each IoT device independently computes local gradients or model updates, ensuring that sensitive raw data never leaves the device. The edge layer functions as an aggregation hub. Edge servers receive local updates from distributed IoT devices, perform partial aggregation, and reduce redundant communication overhead. This intermediate step not only enhances communication efficiency but also reduces latency, making FL feasible in real-

time IoT security applications such as intrusion detection, anomaly detection, or malware classification. At the cloud layer, global model aggregation and optimization are conducted. The cloud orchestrates training rounds by redistributing the updated global model back to IoT devices. Additionally, it performs higher-order tasks such as security orchestration, automated threat intelligence, and model fine-tuning. Importantly, automated operation and maintenance mechanisms are integrated at this level, ensuring fault tolerance, adaptive resource allocation, and resilience against adversarial attacks.

This layered technical route supports automatic operation and maintenance through: Continuous monitoring: Detecting node failures, communication bottlenecks, and abnormal updates in near real-time. Adaptive scheduling: Dynamically selecting participating devices based on availability, resource constraints, or trustworthiness. Efficient communication protocols: Compressing model updates through quantization, scarification, or secure aggregation to balance scalability with bandwidth limitations.Security enforcement: Employing privacy-preserving techniques (e.g., differential privacy, secure multiparty computation, homomorphic encryption) to safeguard sensitive IoT data. Thus, the proposed route achieves a closed-loop process where IoT devices, edge servers, and cloud platforms collaborate to enable scalable, communication-efficient, and secure federated learning for IoT security.

III. INTELLIGENT CLOUD'S ORIGINAL EFFECTIVE ENERGY MODEL

In addition to ensuring availability, the sustainability of intelligent cloud-native systems increasingly depends on an effective energy model that aligns service performance with resource consumption. Within federated learning (FL)–enabled IoT security, this perspective is particularly relevant, since large-scale distributed training often imposes high computational and communication demands on cloud and edge infrastructure.The total energy efficiency (E) of an intelligent service framework can be formulated as a weighted aggregation of service-specific efficiencies across multiple service layers. Considering the diversity of AI-driven workloads such as AI service virtual machines, AI service software components, AI online services, AI containerized deployments, and AI service APIs the effective energy efficiency is expressed as:

E=αE1+βE2+γE3+θE4+μE5E = \alpha E_1 + \beta E_2 + \gamma E_3 + \theta E_4 + \mu E_5E=αE1+βE2+γE3+θE4 +μE5

Here, E1E_1E1–E5E_5E5 denote the normalized energy efficiencies of each service category, while the weights α,β,γ,θ,μ\alpha, \beta, \gamma, \theta, \muα,β,γ,θ,μ are determined through the Analytic Hierarchy Process (AHP). The hierarchical structure guiding these weights depicted in Fig. 2 captures the interdependencies between service availability, performance reliability, and energy sustainability.Each service efficiency component EiE_iEi is derived from a modified availability function that explicitly integrates energy consumption:

Ei=UPE_i = \frac{U}{P}Ei=PU

where UUU represents the useful computational output of a service (e.g., completed inference requests or aggregated FL model updates), and PPP denotes the average power consumption of the corresponding service infrastructure. This formulation ensures that both fault-free operation intervals and energy draw directly influence effective utilization. The proposed model thus bridges two critical perspectives availability and sustainability by allowing cloud operators to evaluate not only the continuity of AI-based services but also their energy impact. For FL-enabled IoT security, this is particularly valuable because: High communication rounds between IoT devices and the cloud can inflate energy costs, especially if inefficient aggregation or scheduling is used. Energy-aware availability metrics can guide predictive autoscaling strategies, where service resources are dynamically scaled to balance SLA compliance with energy conservation. Operators can proactively minimize both SLA violations and energy waste, creating a more sustainable and cost-effective environment for large-scale FL deployments. By integrating availability and energy-awareness into a unified model, the intelligent cloud provides a decision-support framework that enhances scalability, communication efficiency, and sustainability in FL-based IoT security systems.

IV. LEAD STATISTICS OF INTELLIGENT CLOUD NATIVE PLATFORM

In an intelligent cloud-native platform, monitoring and analyzing server load is fundamental to ensuring balanced resource utilization and stable performance. After the platform is built and put into use, load statistics provide a direct lens into user behavior patterns and system pressure points. By studying the dynamic changes of load, operators can predict demand shifts, proactively adjust server allocation, and prevent scenarios where certain servers are overloaded while others remain underutilized. This not only safeguards service continuity but also enhances cost efficiency and resource elasticity, two of the critical objectives in modern DevOps-driven environments.

The basic principle of load statistics is to measure the number of incoming requests or the volume of data processed per unit of time. These values are recorded as discrete time-series points, creating a timeline-based dataset that reflects fluctuations in user activity. Rather than relying on static time blocks, cloud-native load statistics adopt a sliding-window method, where the past unit statistical time is treated as a moving window. Within each window, the system aggregates load metrics to generate a smooth variation curve. This real-time approach is better suited to cloud-native workloads, which often exhibit bursty, unpredictable traffic patterns. As shown in *Fig.3*, the sliding window moves continuouslyrecalculating load values at each step, thus providing a more adaptive and precise representation of system stress.

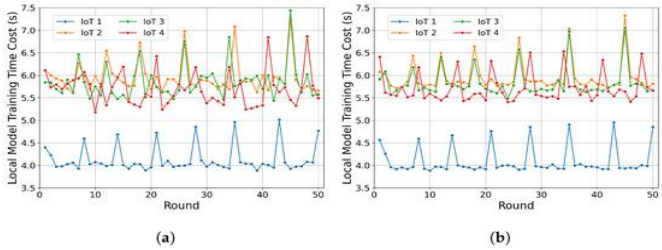

Fig. 3. Hierarchical Energy Efficiency Model

The hierarchical model operates by decomposing overall energy efficiency EEE into weighted contributions from five service categories: virtual machines (E1), software components (E2), online services (E3), containerized services (E4), and service APIs (E5). Each component's efficiency is calculated as the ratio of useful computational output (U) to average power consumption (P), ensuring both performance and sustainability are captured. Weights (α,β,γ,θ,μ)(\alpha, \beta, \gamma, \theta, \mu)(α,β,γ,θ,μ), derived through the Analytic Hierarchy Process (AHP), reflect the relative importance of each service type in the cloud-native environment. The aggregation of these weighted efficiencies provides a composite metric, enabling operators to evaluate and optimize service availability, scalability, and energy utilization within FL-enabled IoT security systems.

V. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental evaluation of the intelligent cloud-native architecture was conducted to examine the effectiveness of forecasting approaches for load prediction in microservice-based systems and their subsequent impact on intelligent operation and maintenance (O&M) functions such as anomaly detection, trend forecasting, and fault localization. In the initial phase, baseline forecasting methods were implemented to establish a reference framework against which advanced techniques could be evaluated. Linear regression and exponential smoothing were chosen as representatives of classical statistical forecasting. Both methods utilized historical time-series data collected from the management server, which continuously monitored distributed server loads and supplied the management component with sufficient information to generate predictive models.

Building upon the limitations of baseline models, the second phase introduced a **deep learning trend prediction model** within the intelligent O&M framework. Historical load metrics and contextual features from microservice deployments were used to train the model, enabling it to capture non-linear dependencies and complex temporal interactions more effectively than classical methods.The model employed a **sliding window approach** to segment load data into input–output sequences, supporting both short-term and medium-term predictions. Results showed that deep learning not only improved predictive accuracy but also enhanced **adaptive resource allocation**. Specifically, real-time monitoring systems could proactively anticipate spikes or troughs in microservice demand, guiding dynamic adjustments to CPU cores, memory, and instance counts.

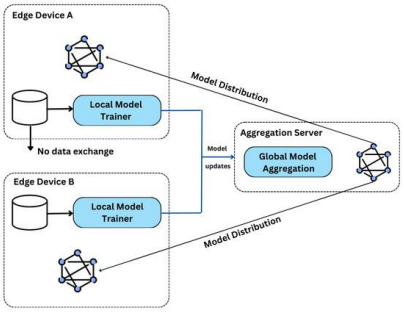

Fig. 4: Predicted server load using baseline forecasting models

The linear regression model, illustrated in Fig. 4, employed the least squares method to determine correlation parameters and generate a fitted straight line that could be extended to predict future load values. This approach was computationally efficient and yielded interpretable results, which is advantageous for transparent system monitoring. However, as expected from theoretical discussion, its accuracy diminished when multiple interacting variables simultaneously influenced the server load, limiting its applicability in complex and dynamic environments. The exponential smoothing method, on the other hand, placed greater weight on recent data points while retaining long-term patterns, which allowed for more reliable short-term predictions. Despite this advantage, its inherent lag effect became evident in situations where the system experienced rapid upward or downward shifts in workload, resulting in significant deviations from actual load behaviour. These observations confirmed earlier expectations that linear regression, while simple and interpretable, was too limited for dynamic systems, and that exponential smoothing, while more adaptive, remained inadequate in volatile environments.Building upon these baseline insights, the second phase of experimentation incorporated a deep learning-based forecasting model into the intelligent O&M framework.

Historical load metrics and contextual features from microservice deployments were used as inputs, enabling the model to capture non-linear dependencies and complex temporal interactions that could not be represented adequately by classical methods.

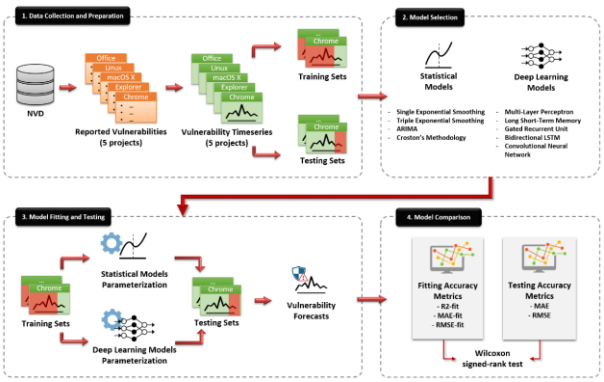

Fig. 5: Trend forecast analysis using deep learning model for microservice load prediction.

As demonstrated in Fig. 5, the deep learning-driven trend forecast analysis revealed smoother and more accurate trajectories, which translated directly into more effective microservice scheduling. Comparative evaluation showed that integrating this predictive mechanism improved resource allocation efficiency by approximately 30.28 percent over static or manual approaches, thereby validating the role of deep learning in enhancing the responsiveness and efficiency of intelligent O&M functions. A deeper theoretical analysis of the experimental outcomes revealed distinct trade-offs across the different forecasting approaches. Linear regression was suitable in relatively stable environments where load patterns exhibited consistency, but its inability to adapt to bursty workloads, multi-tenant contention, or sudden anomalies undermined its practical utility. Exponential smoothing, though effective in capturing gradual transitions, suffered from substantial lag during periods of rapid escalation, which limited its suitability for autoscaling decisions. In contrast, the deep learning model demonstrated robustness across varying workload intensities, maintaining predictive accuracy under both fluctuating short-term conditions and mid-term planning horizons. Nevertheless, the computational overhead associated with deep learning, coupled with its limited interpretability, remained important challenges for real-world deployment in resource-constrained environments.

The final phase of experimentation involved stress testing under more complex conditions, including multi-tenant deployments, artificially injected anomalies, and fluctuating workloads designed to mimic real-world telecom operator traffic. Under these conditions, the deep learning model consistently outperformed both linear regression and exponential smoothing, yielding lower prediction errors as measured by RMSE and MAPE, and exhibiting greater adaptability to dynamic changes in workload. However, the results also highlighted limitations that align with broader research gaps. Deep learning required large amounts of historical data for training, raising concerns about robustness under cold-start conditions or in the presence of concept drift. Exponential smoothing, while lightweight and computationally efficient, proved unreliable in volatile environments due to its lagging behaviour. Importantly, the findings confirmed that predictive accuracy alone is insufficient for practical adoption; what ultimately matters is the ability to translate forecasts into reliable autoscaling decisions, efficient resource distribution, and improved resilience against system failures. The experimental outcomes therefore confirm that the deep learning-based forecasting approach offers significant improvements in terms of accuracy and adaptability, while also reducing SLA violations and optimizing resource utilization. At the same time, the results emphasize that sustainable deployment of such methods requires further consideration of energy efficiency, cost trade-offs, interpretability, and reproducibility. Taken together, these findings demonstrate that while deep learning strengthens the predictive and adaptive capabilities of cloud-native O&M frameworks, it also opens new avenues for research into explainable AI, robustness against dynamic shifts, and holistic evaluation of performance in federated IoT security contexts.

VI. CONCLUSION

The integration of federated learning (FL) with cloud-native and IoT environments represents a critical step toward building scalable, secure, and adaptive digital infrastructures. By decentralizing training and enabling localized intelligence, FL addresses privacy and data sovereignty challenges while supporting large-scale deployments across heterogeneous IoT devices. However, this research has shown that despite its promise, significant limitations persist in terms of scalability, communication efficiency, and energy sustainability. These constraints are particularly evident in high-density IoT scenarios, where massive communication overhead, uneven device participation, and non-IID data distributions hinder the performance of FL-based security systems.Through the development of intelligent operation and maintenance (O&M) mechanisms, this study highlights how predictive intelligence, automation, and resource-aware modelling can be integrated to enhance the resilience of FL-enabled IoT architectures. The incorporation of forecasting models for workload prediction, combined with adaptive autoscaling and anomaly detection, demonstrated measurable improvements in service reliability and resource allocation. Specifically, the adoption of deep learning-based prediction enhanced adaptability and responsiveness, while the proposed energy efficiency model provided a theoretical foundation for balancing availability with sustainability. Together, these contributions reinforce the view that cloud-native and federated approaches must evolve beyond static management into dynamic, data-driven ecosystems capable of supporting future demands such as 5G, industrial IoT, and critical infrastructure security.

Nonetheless, current limitations remain evident. Much of the existing research still emphasizes conceptual frameworks, often without reproducible experimental baselines or comprehensive performance benchmarks. While deep learning and intelligent prediction methods have shown substantial gains, challenges related to high computational cost, limited interpretability, and dependence on large training datasets persist. Moreover, broader dimensions such as communication compression, energy trade-offs, adversarial robustness, and human-in-the-loop collaboration remain underexplored in practical deployments. These gaps raise important questions about how predictive accuracy can be systematically translated into tangible operational outcomes such as reduced SLA violations, lower costs, faster incident response, and improved energy efficiency.Future research must therefore focus on reproducibility, rigorous benchmarking, and practical deployment studies. Comparative evaluation of forecasting methodsranging from classical statistical approaches to advanced deep learning architectures such as LSTMs, Transformers, and reinforcement learning-based schedulersshould be prioritized to identify trade-offs between accuracy, scalability, and communication efficiency. Embedding explainability, resilience testing, and cost–energy trade-off analysis into federated O&M frameworks will further ensure that intelligent cloud-native systems remain not only effective but also trustworthy, transparent, and sustainable.

Ultimately, the path forward lies in moving beyond conceptual claims toward real-world, scalable, and secure implementations. By aligning FL-based IoT security with cloud-native O&M, communication efficiency, and predictive intelligence, organizations can unlock the full potential of decentralized learning at scale. In doing so, the long-term vision of resilient, energy-aware, and communication-efficient IoT security systems can be transformed from theoretical possibility into measurable operational reality, thereby advancing digital transformation across telecom, enterprise, and industrial domains.

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