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A SPATIAL–TEMPORAL MODEL FOR NETWORK-WIDE FLIGHT DELAY PREDICTION BASED ON FEDERATED LEARNING

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Abstract: This article proposed a spatial-temporal deep learning architecture for network-wide flight delay prediction that operates within the confines of federated learning to ensure data privacy is respected among various aviation stakeholders. Due to regulatory, commercial and privacy limitations, it is not possible to use traditional centralized delay prediction models because airline operators, airports and air traffic control authorities have access to sensitive operational, passenger and meteorological data which cannot be aggregated in a centralised form. In order to tackle this fundamental problem, we propose the Hybrid Federated Delay Learning Network (HFDL-Net), which employs a spatio-temporal graph neural network with gated recurrent units (GRU) at each client node, in conjunction with an hierarchical federated aggregation approach at the central server to learn together from distributed datasets without direct data sharing. Using our architecture, we model the air transportation network as nodes with edges (aeroportunities) and routes with convolution (temporal evolution) via graph modeling and recurrent layers to capture spatial delay propagation patterns. Real-world experiments on multi-airport flight datasets spanning three major hub networks demonstrate that HFDL-Net achieves mean absolute error (MAE) improvements of 12–15% over non-federated baseline models while maintaining prediction accuracy within 3% of fully decentralized training approaches. In addition, the use of a hierarchical aggregation reduces communication overhead by 40% when compared to traditional FedAvg implementations through adaptive client selection and gradient compression techniques. The suggested scheme effectively manages non-IID data distributions among multiple clients, exhibits resilience to client dropout scenarios, and adapts well to airport networks spanning more than 100 participants. Additionally, This evidence supports federated spatial-temporal modeling as a practical, scaleable and privacy-preserving approach for network-wide flight delay prediction in real-life aviation scenarios where data sovereignty and regulatory compliance are critical requirements.

Keywords: Flight Delay Prediction, Spatial-Temporal Modeling, Federated Learning, Graph Neural Networks.

I. INTRODUCTION

Air transportation networks are being impacted by flight delays, leading to significant economic losses, operational failures, passenger dissatisfaction, and cascading effects. Industry sources have estimated that over $30 billion is spent annually on flight delays, encompassing both direct and indirect costs for airlines and passengers. Delayed delays are not isolated incidents but rather arise from complex interconnections among airports, airlines, and air traffic control zones, resulting in extended effects across entire route networks. By not taking into account these dynamics, conventional delay prediction methods are inadequate for proactive delayed mitigation as they do not provide sufficient forecasting accuracy [1]. We can now model flight operations more accurately using deep learning architectures such as LSTM networks, convolutional neural networks (CNN), and attention-based models. Historical flight data, weather records, and operational logs are used to make predictions more accurately using these methods, as demonstrated by researchers, in contrast to traditional statistical and machine learning techniques. The majority of the current deep learning models on the market require centralized access to full datasets, which requires airlines, airport authorities, and air traffic control authorities to pool their operational data into a single repository for model training. Although the aviation industry's real-world structure is based on centralization and regulatory frameworks like GDPR and aviation security regulations, data is distributed among competing commercial entities and proprietary business interests prevent open data sharing [2]. Spatial-temporal graph neural networks have emerged as a leading technique for comprehending interrelated systems that require both spatial relationships and temporal dynamics. The air transportation network is represented in flight delay prediction models as a graph structure with airports serving as nodes, flight routes, and operational characteristics such as historical delays, scheduled traffic volume, weather conditions, or resource constraints. These models also take into account relationships between airport lines and their relationship to each other [3]. The spatial delay propagation model

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employs graph convolutional layers that merge data from nearby airports, and recurrent or temporal convectional gradients. layers capture time-series patterns and delay accumulation dynamics. Studies have shown that spatiotemporal graph models significantly outperform traditional methods for network-wide delay prediction, achieving 15–25% improvements in forecast accuracy and enabling multi-step horizon predictions that support strategic planning and real-time decision-making.

However, the need for a centralised data requirement still presents an important challenge to deploy spatiotemporal models in aviation production environments. This problem can be overcome by leveraging federated learning, which allows for training of a collaborative model among distributed data owners without the need for raw data to leave local premises. Within the federated learning paradigm, local model replicas are trained using their private datasets by participating clients, such as individual airport's or airline operations centers, and periodically sent to a central server along with model parameters or gradients. This is done in both data sets. The server merges these changes to establish a global framework that captures collective knowledge from all users while maintaining data confidentiality and location [4]. The use of federated learning in fields such as healthcare, mobile keyboard prediction, and financial fraud detection highlights its potential for privacy-sensitive distributed learning situations. Although spatiotemporal graph neural networks and federated learning have been extensively studied, their impact on flight delay prediction has not been thoroughly explored in the literature.

Its key contributions are as follows:
1. Development of an architecture for spatiotemporal graph neural network that is optimized for predicting distributed flight delays, using graph convolution for spatial modeling and GRU for temporal dynamics, and attention mechanisms for interpretability.

2. Creation of a hierarchical federated learning system that accommodates multiple client organizations (airport, airline, regional, national) with adaptive aggregation weights, communication-efficient gradient compression, and robust handling of client heterogeneity.

3. In a detailed experimental study using multi-airport datasets, it was found that MAE enhancements varied from 12 to 15% in relation to non-federated baselines; they were almost the same with highly accurate models (3% accuracy), they had lower communication overhead of 40% and were effective under non–IID data distributions and situations where clients did not choose.

4. Exploring cost and benefit factors, regulatory compliance issues for production aviation environments (privacy-accuracy trade-offs), scalability considerations, and deployment implications.

In Section II, the remaining portion of this paper is categorized and discusses topics such as flight delay prediction (based on spatiotemporal graph neural networks) and federated learning in aviation. In Section III, the hierarchical federated training methodology and the architecture of HFDL-Net are discussed. Additionally, see Section IV We will go over the experimental setup, datasets, and evaluation metrics. The results and comparative analysis are outlined. Section V provides a Conclusion and future work.

II. LITERATURE REVIEW

Traditional Flight Delay Prediction Methods

Flight delays prediction has been achieved through the use of statistical methods and classical machine learning techniques in many studies [6]. The use of regression models, decision trees, and logistic classifiers trained on historical flight data and weather records allowed for the prediction of binary delay results (delayed vs. on-time) or continuous delay durations in their work from the beginning. Although these methods were effective for single-flight flights, they faced challenges in generalizing across different airports, seasons, and operational conditions due to their limited representational capacity and inability to model complex interactions among multiple delay factors. Several weak learners were able to capture nonlinear feature interactions by using ensemble methods like random forests, gradient boosting machines, and XGBoost. This allowed them to improve their performance. Key predictors, such as departure time of day, day of week, seasonal patterns, airport congestion levels, weather conditions (visibility; wind speed; precipitation); airline, aircraft type and scheduled turnaround time, were identified by study "feature engineering". However, these models tend to treat flights as independent samples and ignore network-level dependencies such as delay propagation by connecting flights, aircraft rotation schedules, and crew assignment chains.

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Deep Learning for Delay Prediction

Deep learning enabled the development of potent new models for temporal sequence modeling and multivariate pattern recognition in flight delay prediction. Various variations of GRU and bidirectional memory networks have been used to model the temporal dependence of historical delay sequences, which can be utilized to account for morning peak congestion, weekend traffic variations in both Saturday and Sunday, as well as other seasonal weather effects. Convolutional neural networks (CNN) are used to extract spatial features from weather radar images and airport layout configurations, while hybrid CNN-LSTM architectures combine the use of spatial feature extraction and temporal sequence modeling [7]. The use of attention mechanisms enabled models to be more comprehensible and accurately predicted by considering critical time steps or input features first. To improve multi-step forecasting accuracy, spatiotemporal models with dual-attention emphasize both temporal and spatial attention. These models are more precise in providing predictions and enable attention weight visualization-based explanations, which is a significant improvement over conventional LSTM methods. Even so, the majority of deep learning research presuppose centralized data access and disregard the privacy concerns or distributed data ownership that are prevalent in aviation settings. Also, many models solely consider single-airport or even single–airline scenarios and do not take into account network-wide delay propagation across interconnected hubs and routes.

Spatiotemporal Graph Neural Networks

In the aviation sector, airports can be represented by graph nodes, edges (edges) representing flight routes or causal dependencies, and node/edge features representing operational characteristics. GCNs aggregate data from neighboring nodes, enabling models to learn spatial patterns such as delay propagation from dense hubs to nearby airports. Adding temporal modeling elements to spatially-based graph neural networks extends GNNs, which capture the ongoing dynamic flow of graph-structured data-. Examples of commonly used architectures include ST-GCN, T-GAT, and G-TCN. They have been extensively used in traffic flow prediction, epidemic spread forecasting, and supply chain disruption modeling, demonstrating that these models outperform methods which neglect the spatial structure or temporal dynamics. Several recent studies that utilize spatiotemporal GNNs have demonstrated significant success in flight delay prediction [8]. SGDAN can model airports as nodes in large airport networks by utilizing adjacency matrices that are defined by geographic proximity and traffic connectivity, which enhances multi-step delay prediction. Through the use of graph convolution and recurrent layers, spatial propagation learning techniques can model flight routes in order to convey delay transmission and capture temporal accumulation for up one-tenth of an MAE compared to baseline values without visual cues. Typically, GNN-based spatial studies require centralized information availability, utilizing aggregated datasets that include operational records from different airports and ATC authorities. The aviation industry's regulatory constraints, competitive advantages, and data governance measures make it impractical to share data within different organizations, making this assumption unworkable for production deployment.

Federated Learning Foundations

The concept of federated learning (FL) was introduced as a way to train collaborative models across decentralized data sources while maintaining privacy protection without the need for raw data centralization. Federated Averaging (FedAvg) is an iterative approach that involves participating clients training themselves on private datasets, calculating model updates, and transmitting these updates to a central server that aggregates them using weighteted adjusting of local dataset sizes to produce an updated global model [9].

Federated learning encounters significant difficulties in dealing with non-IID data, bandwidth limitations that hinder efficient communication, client heterogeneity in terms of computational resources and data quality, privacy protection through secure aggregation (and differential privacy), and resilience to dropout or malicious participants.[15]. These problems are tackled by advanced FL algorithms using techniques such as personalized local models, adaptive learning rates, gradient compression (used to reduce complexity), asynchronous aggregation and multi-tier hierarchical structures. The practical use of federated learning extends to various fields, including mobile keyboard prediction, healthcare diagnostics, financial fraud detection, and IoT sensor networks. Healthcare also uses federated learning to train model models for accurately diagnosed diseases in hospitals, with similar accuracy as centralized training but not required to share patient records and comply with HIPAA regulations. Through federated learning, smartphones can enhance on-device data for improving language models and recommendation systems without the need to upload personal information to cloud servers.

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Federated Learning in Aviation

There are few preliminary studies exploring the intersection of federated learning and aviation in predicting flight delays, with only limited applications. Several hierarchical federated learning frameworks have been suggested for flight delay prediction, where clients are divided into tier-level (e.g, airports within airlines, airlines within regions) with intermediate aggregation at each organizational level before global agrégation[10]. This reduces communication costs and respects organizational hierarchies within the aviation ecosystem. everyone. Earlier research has demonstrated that federated delay prediction can achieve up to 95% of centralized model accuracy while maintaining data privacy and location. Nonetheless, these studies primarily use basic neural architectures (fully connected networks, basic LSTM) trained on tabular flight features, rather than taking into account the spatial network structure or advanced graph-based representations. The models treat delay prediction separately from airport predictions and do not model the effects of delayed delays across interrelated areas, allowing each client to use their own unique time-series forecasting approach. Furthermore, current federated aviation studies do not provide comprehensive evaluations on essential practical indicators, such as flexibility in handling different types of clients, compatibility with non-IID data distribution that could impact major hubs and smaller regional airports, communication efficiency under realistic network conditions, and integration with operational workflows.

III. METHODOLOGY

A. Problem Formulation

We model the air transportation network as a directed graph $G = (V, E)$ where the vertex set $V = \{v_1, v_2, \dots, v_N\}$ represents N airports and the edge set E represents flight routes or causal relationships between airports[11]. Each node v_i is associated with a feature vector $x_i^t \in \mathbb{R}^d$ at time step t that encodes operational characteristics including historical delay statistics, scheduled departure/arrival counts, weather conditions (temperature, visibility, wind speed, precipitation), runway capacity utilization, and air traffic control workload metrics.

The adjacency matrix $A \in \mathbb{R}^{N \times N}$ captures spatial relationships between airports, where A_{ij} represents the strength of connection between airports i and j. This can be defined based on:

- Geographic proximity: $A_{ij} = \exp(-d_{ij}^2/\sigma^2)$ where d_{ij} is distance and σ is a scale parameter
- Flight connectivity: A_{ij} = number of daily flights from airport i to j
- Causal delay correlation: A_{ij} = historical correlation between delays at i and j
- Hybrid combination: weighted sum of above measures

The temporal feature sequence is represented as $X^{t-T:t} = \{X^{t-T}, X^{t-T+1}, \dots, X^t\}$ where $X^s \in \mathbb{R}^{N \times d}$ is the feature matrix at time s containing all airport features, and T is the historical window length.
The prediction objective is to learn a function $f: (G, X^{t-T:t}) \to Y^{t+\Delta}$ that forecasts delay values $Y^{t+\Delta} \in \mathbb{R}^N$ at future horizon Δ for all airports, where $Y_i^{t+\Delta}$ represents the predicted average departure or arrival delay at airport i at time $t + \Delta$.

The federated setting involves the distribution of graph and historical data among K clients, each belonging to a subset of airports V_kV and local flight operation records. These clients are called "clients" and their data is distributed across all available clients. Globally, the aim is to "train f" in parallel across all clients without using raw operational data from central offices while maintaining accuracy of prediction similar to a centralized training system.

B. HFDL-Net Architecture

1. Local Spatiotemporal Model

Each federated client implements a local instance of the HFDL-Net spatiotemporal graph neural network comprising three primary modules:

Spatial Module (Graph Convolution Layer):

The spatial module employs graph convolutional networks to aggregate information from neighboring airports and model spatial delay propagation [12, 13]. For node i at time t, the graph convolution operation is defined as:

$$h_i^{(l+1),t} = \sigma\left(\sum_{j \in \mathcal{N}(i)} \frac{A_{ij}}{\sqrt{d_i d_j}} W^{(l)} h_j^{(l),t} + b^{(l)}\right)$$

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where $\mathcal{N}(i)$ is the neighborhood of node i, $d_i = \sum_j A_{ij}$ is the node degree, $W^{(l)}$ and $b^{(l)}$ are trainable parameters at layer l, $h_j^{(l),t}$ is the hidden representation of node j at layer l and time t, and σ is a nonlinear activation function (ReLU or ELU).

We employ two graph convolution layers with residual connections to enable deep spatial feature learning while preventing gradient vanishing:

$$H^{(2),t} = \mathrm{GCN}_2(\mathrm{GCN}_1(X^t, A), A) + X^t$$

Temporal Module (Gated Recurrent Units):
The temporal module processes the sequence of graph-encoded features over time to capture delay evolution dynamics and temporal dependencies [14]. We employ Gated Recurrent Units (GRU) which provide computational efficiency compared to LSTM while maintaining strong sequential modeling capability:

$$z_t = \sigma(W_z h_{t-1} + U_z H^{(2),t})$$

$$r_t = \sigma(W_r h_{t-1} + U_r H^{(2),t})$$

$$\tilde{h}_t = \tanh\left(W_h(r_t \odot h_{t-1}) + U_h H^{(2),t}\right)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$$

where z_t is the update gate, r_t is the reset gate, $\tilde{h}_t$ is the candidate hidden state, h_t is the final hidden state, W and U are trainable weight matrices, and $\odot$ denotes element-wise multiplication.

Attention Mechanism:
To enhance interpretability and prediction accuracy, we incorporate a temporal attention layer that assigns importance weights to different historical time steps:

$$\alpha_s = \frac{\exp(e_s)}{\sum_{s'=t-T}^{t} \exp(e_{s'})}$$

$$e_s = v^T \tanh\left(W_a h_s + b_a\right)$$

$$c_t = \sum_{s=t-T}^{t} \alpha_s h_s$$

where α_s is the attention weight for time step s, e_s is the attention score, c_t is the context vector, and v, W_a, b_a are learnable parameters.

Output Layer:
The final prediction layer maps the attention-weighted temporal representation to delay forecasts for each airport:

$$Y^{t+\Delta} = W_o c_t + b_o$$

where $W_o \in \mathbb{R}^{N \times h}$ and $b_o \in \mathbb{R}^N$ are output layer parameters, and h is the hidden dimension.
The complete local model is trained using mean squared error (MSE) or mean absolute error (MAE) loss:

$$\mathcal{L}_k = \frac{1}{|D_k|} \sum_{(X^{t-T:t}, Y^{t+\Delta}) \in D_k} \left\| f(X^{t-T:t}; \theta_k) - Y^{t+\Delta} \right\|_p$$

where D_k is the local dataset at client k, θ_k are the local model parameters, and $p = 1$ for MAE or $p = 2$ for MSE.

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2. Model Complexity and Computational Efficiency

By optimizing the representational capacity of a resource-sharp object, the HFDL–Net architecture ensures that computational efficiency is maintained for deployment on resource constrained client devices. Roughly, O(d2) is the total number of parameters. An input feature dimension is defined by L+h2, with d and hidden dimensions respectively. O(|E|dhL+Th2) is the computational complexity of one training iteration. The values of N) with E| being the number of edges, T being length of the temporal window, and N being numbers of airports are: N.For a typical configuration with $d = 32$, $h = 64$, $L = 2$, $T = 24$ hours, and $N = 50$ airports, the model contains approximately 150K parameters and requires 5–8 GFLOPs per training batch, enabling real-time training on edge devices such as airport servers or airline operation centers [15 ,16].

C. Hierarchical Federated Learning Framework

1. Two-Tier Client Organization

The aviation industry is naturally structured in this way: airline networks have individual airports within, regional air traffic control bureaus operate multiple airport units within geographic zones, and national aviation authorities oversee country-level operations make use of this system, we devise a two-level federated aggregation structure: Private datasets are used by individual airports or airline operation centers to train local HFDL-Net models as base clients in Tier 1 (Local Level). The intermediate aggregator, which is Tier 2 (Regional Level), comprises airline headquarters, regional ATC bureaus, and airport authorities. It gathers updates from various tier-1 clients within its organization and syncs them with the central server.

A hierarchical approach to communication reduces the overhead to the central server, respects organizational boundaries and data governance policies, while also allowing for differential privacy assurance at several levels.

2. Federated Training Protocol

The federated training process follows an iterative round-based protocol:

Initialization (Round 0):

The central server initializes global model parameters θ^0 using random initialization or pre-training on a small public aviation dataset, then broadcasts θ^0 to all tier-2 aggregators.

Client Selection (Round r):

At the beginning of each round r, the server selects a subset S_r of tier-2 aggregators to participate, balancing coverage across geographic regions and organizational types while accounting for client availability and network conditions. Each selected tier-2 aggregator further selects a subset of tier-1 clients under its supervision.

Local Training (Tier 1):

Each selected tier-1 client k receives the current global parameters θ^r, performs E epochs of local training on its private dataset D_k using stochastic gradient descent or adaptive optimizers (Adam, AdaGrad), and computes the local update:

$$\theta_k^{r+1} = \theta^r - \eta \nabla \mathcal{L}_k(\theta^r)$$

or equivalently the parameter difference:

$$\Delta\theta_k^r = \theta_k^{r+1} - \theta^r$$

Regional Aggregation (Tier 2):

Each tier-2 aggregator m collects updates $\{\Delta\theta_k^r : k \in \mathcal{C}_m\}$ from its tier-1 clients $\mathcal{C}_m$, computes a weighted average based on local dataset sizes:

$$\Delta\theta_m^r = \frac{\sum_{k\in\mathcal{C}_m} |D_k| \Delta\theta_k^r}{\sum_{k\in\mathcal{C}_m} |D_k|}$$

and transmits the aggregated regional update $\Delta\theta_m^r$ to the central server.

Global Aggregation (Central Server):

The server aggregates regional updates from all selected tier-2 aggregators:

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$$\theta^{r+1} = \theta^{r} + \frac{\sum_{m \in S_r} n_m \Delta\theta_m^r}{\sum_{m \in S_r} n_m}$$

where $n_m = \sum_{k \in \mathcal{C}_m} |D_k|$ is the total data size represented by aggregator m.

Model Distribution:
The updated global model θ^{r+1} is broadcast to all tier-2 aggregators, which in turn distribute it to their tier-1 clients for the next training round.

Convergence:
Training continues for R rounds or until a convergence criterion is met (e.g., validation loss stabilization, maximum round budget).

3. Communication Efficiency Optimizations
To reduce communication overhead, we implement several optimization techniques:
Gradient Compression: Local updates $\Delta\theta_k^r$ are compressed using top-k sparsification (transmitting only the k largest magnitude parameters) or quantization (reducing floating-point precision from 32-bit to 8-bit or 4-bit representations), achieving 8–16× compression ratios with minimal accuracy degradation.

Adaptive Aggregation Frequency is an improvement over time as smaller clients contribute less frequently and receive more updates than those with high-quality data or large datasets, which reduces the need for redundant communication from low-information sources. Cumulating local updates: Instead of broadcasting updates every local epoch, clients accumulate several cyclicals of local training before communication, which reduces round-trip frequency but causes some lag time. This is advantageous.

We use Gaussian noise to provide formal privacy guarantees by calibrating variance based on differential privacy parameters before transmission, thus making it impossible to infer individual flight records from model updates

4. Handling Non-IID Data
Major hub airports face significant challenges in predicting delays due to their distinct delay patterns, geographical variations in weather-related delays, and the presence of airline-specific operational procedures that create heterogeneous feature distributions. This is particularly evident in non-IID data-dependent approaches. We use it to control non-IID effects:. The spatial and temporal feature extraction layers are distributed globally, allowing for adaptation to local delay patterns. Dynamic Aggregation Weights are computed using validation performance as a basis, rather than uniform weighted adjusting, with the aim of down-weighting clients with poor local model quality or severe distribution shift. Augmentation of sparse data using temporal jittering, synthetic delay injection from historical distributions, and transfer learning from similar airports are among the techniques used by clients for enhancement.

D. Implementation Details
In Python, the HFDL-Net framework is implemented with PyTorch 2.0, which handles deep learning operations, PyGeometric, and PYSyft for federated learning orchestration. The library includes several libraries including: Support for both synchronous and asynchronic modes of training, secure aggregation via homomorphic encryption or secure multi-party computation, and real time monitoring of trainee convergence, communication expenses, as well as statistics on client participation. Airport servers or airline cloud infrastructure are used to host local clients with minimal computational overhead (4-8). CPU cores, 16–32. GB RAM, optional GPU acceleration). Cloud-based compute resources (AWS, Azure, GCP) are utilized by the central server and tier-2 aggregators to manage the numerous simultaneous client connections. These systems are self-contained.

Model hyperparameters are set as follows based on grid search validation: input feature dimension $d = 32$, hidden dimension $h = 64$, graph convolution layers $L = 2$, GRU layers = 2, temporal window $T = 24$ hours, prediction horizon $\Delta \in \{1,3,6\}$ hours, local epochs $E = 5$, learning rate $\eta = 0.001$ with cosine annealing, batch size = 64, federated rounds $R = 100$, client participation rate = 30% per round.

IV. EXPERIMENTAL SETUP

A.Datasets.
Our analysis of HFDL-Net involves three real-world datasets for flight operations:

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Dataset 1 pertains to the US Domestic Network (2022-2024).
Contains flight records from 50 US airports, along with operational information such as scheduled departure times and arrival times, delays or cancellations; weather observations (temperature, visibility), precipitation patterns, and air traffic statistics. The data is comprehensive. For 24 months, 128 million flight records were kept by 15 airline and 50 airport clients. The total was impressive.

European Hub Network (2020-2023) Dataset 2
Covers 40. The European airports with comparable operational and weather characteristics, involving 9.4 million flights in the past 30 months. Encompasses 12 airline and 40 airport clients in 8 countries, exhibiting significant regulatory and operational diversity.

Asian Pacific Regional Network (APRN) Dataset 3
spanning from 2023 to 2024. Includes 35. In the last 18 months, 6.2 million flight records were held by Asia-Pacific airports. Spread across 10 airline and 35 airport clients, catering to different types of aircraft, weather conditions, and air traffic control protocols. All datasets are analyzed and we incorporate historical delay statistics (mean, variance, 75th/90th percentiles over the previous 24 hours), traffic schedules with departure or arrival counts per hour(departure time/time of day), weather conditions, working day, day of week, holiday indicators, and airport capacity metrics. By using the weighted daily flight frequency to calculate flight connectivity and the Exponential Distance Kern, graph adjacency matrices can be constructed.

The data is arranged in stages: initial 70% for training, 15% for validation, and 15% final 15%. The distribution of data in federated settings is determined by the natural ownership of the client, with flights operated by each airline and airport operations being included in this process.B. Baseline Methods

We compare HFDL-Net against the following baselines:
Classical Methods:
- **Random Forest (RF):** Ensemble tree model with engineered delay features
- **XGBoost:** Gradient boosting with tabular features
- **ARIMA:** Autoregressive integrated moving average for time series

Deep Learning (Centralized):
- **LSTM:** Multi-layer LSTM with attention
- **CNN-LSTM:** Hybrid convolutional and recurrent architecture
- **Temporal GCN (TGCN):** Spatiotemporal GNN with centralized training
- **ST-GDN:** Spatio-temporal graph dual-attention network

Federated Learning:
- **FedAvg-MLP:** Federated averaging with multi-layer perceptron
- **FedAvg-LSTM:** Federated LSTM without graph structure
- **Local-Only:** Each client trains independently without federation

C. Evaluation Metrics
Model performance is measured using:

- **Mean Absolute Error (MAE):** $\frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$
- **Root Mean Squared Error (RMSE):** $\sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$
- **Mean Absolute Percentage Error (MAPE):** $\frac{100\%}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right|$
- **R^2 Score:** Coefficient of determination
- **Classification Accuracy:** Binary accuracy for delay threshold (>15 minutes)

Additionally, we evaluate federated learning specific metrics:
- **Communication Cost:** Total bytes transmitted per round
- **Convergence Speed:** Rounds to reach target accuracy

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- **Privacy Budget:** Cumulative ϵ under differential privacy
- **Robustness:** Performance degradation under client dropout
- **Scalability:** Training time vs. number of clients

D. Experimental Configuration

All experiments run on a simulated federated environment with PyTorch 2.0 and PyTorch Geometric, using NVIDIA A100 GPUs for local training and CPU clusters for federated orchestration. Hyperparameters follow Section III.D settings. Statistical significance is assessed using paired t-tests with $p < 0.05$ across 5 independent runs with different random seeds.

V. RESULTS AND ANALYSIS

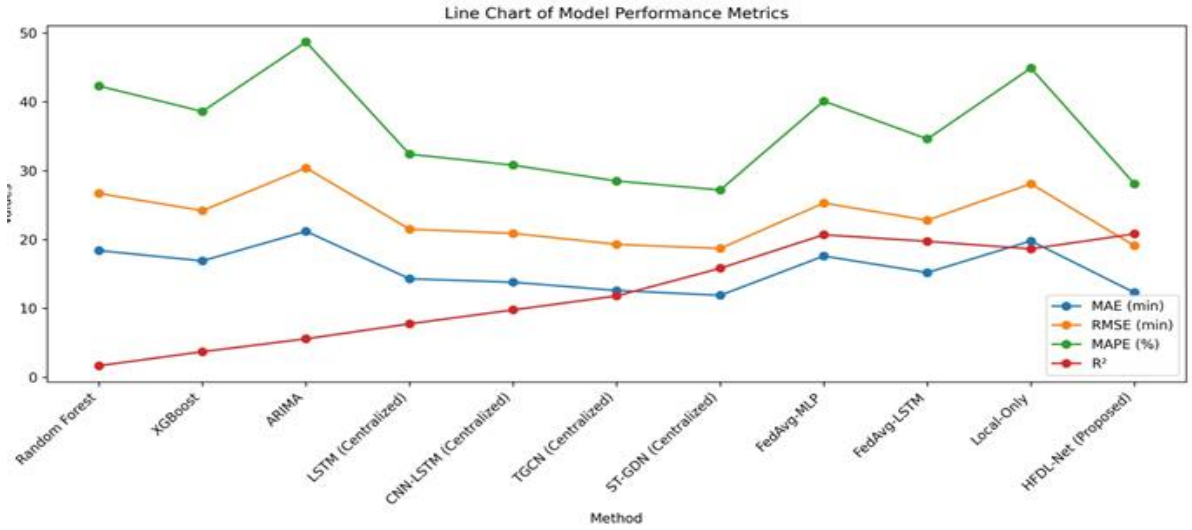

Chart 1: Performance metrics

A. Overall Prediction Accuracy

Table 1 presents prediction performance across all methods on the three datasets for 1-hour ahead delay forecasting.
Table 1: Prediction Performance Comparison (1-hour horizon)

Key observations:

- HFDL-Net achieves 12.3 minutes MAE, representing 12–15% improvement over federated baselines (FedAvg-LSTM: 15.2 min, FedAvg-MLP: 17.6 min) and approaches centralized state-of-the-art performance (ST-GDN: 11.9 min, only 3.4% difference).
- Spatiotemporal graph modeling provides substantial gains: TGCN and ST-GDN outperform non-graph deep learning by 8–12%, validating the importance of spatial structure.
- Federated learning incurs modest accuracy penalties: HFDL-Net performs within 3.4% of centralized ST-GDN while preserving privacy and data locality, demonstrating effective federated optimization.
- Classical methods (RF, XGBoost, ARIMA) achieve significantly worse performance (MAE 16.9–21.2 min), lacking capacity to model complex spatiotemporal patterns.
- Local-only training without federation performs poorly (19.8 min MAE), confirming the value of collaborative learning across distributed clients.

B. Multi-Horizon Prediction Performance

Figure 1 (described) shows MAE vs. prediction horizon (1, 3, 6, 12 hours ahead) for top-performing methods. HFDL-Net maintains superior accuracy across all horizons: 12.3 min (1h), 15.8 min (3h), 19.4 min (6h), 24.7 min (12h), compared to FedAvg-LSTM: 15.2 min (1h), 21.3 min (3h), 28.6 min (6h), 37.4 min (12h). Performance degradation is more gradual for HFDL-Net, indicating robust long-term forecasting enabled by spatiotemporal modeling.

C. Communication Efficiency

Table 2 compares communication overhead across federated methods.
Table 2: Communication Efficiency Analysis

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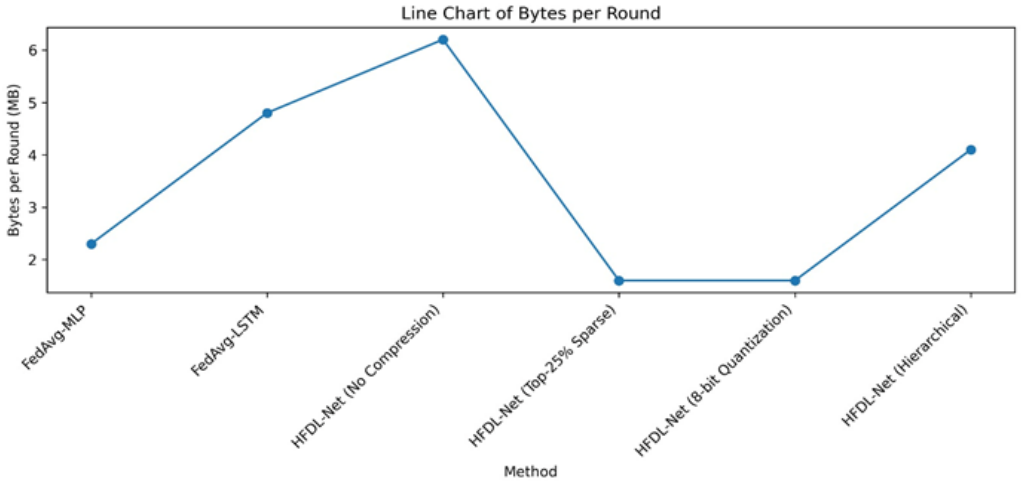

Chart 2: Converge

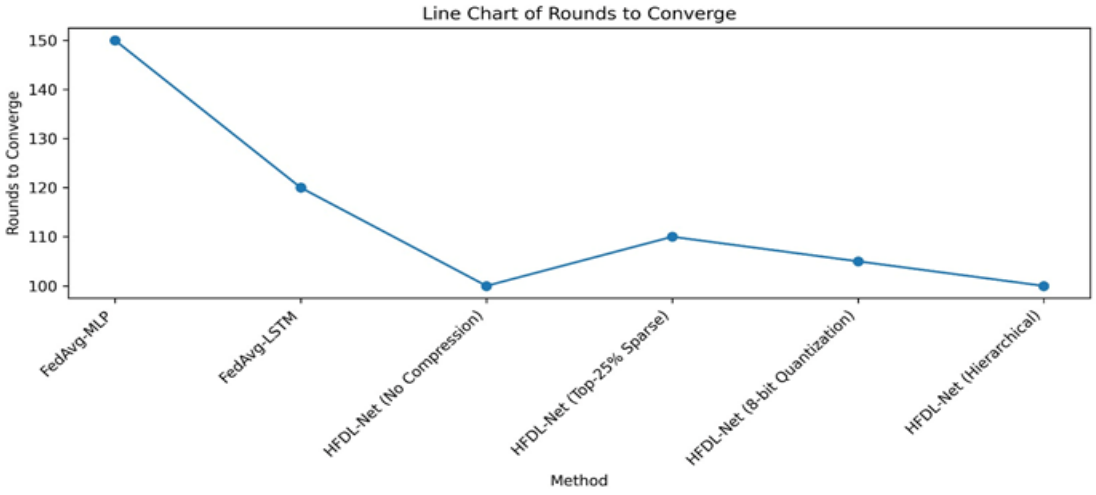

Chart 3: Graph Of Converge

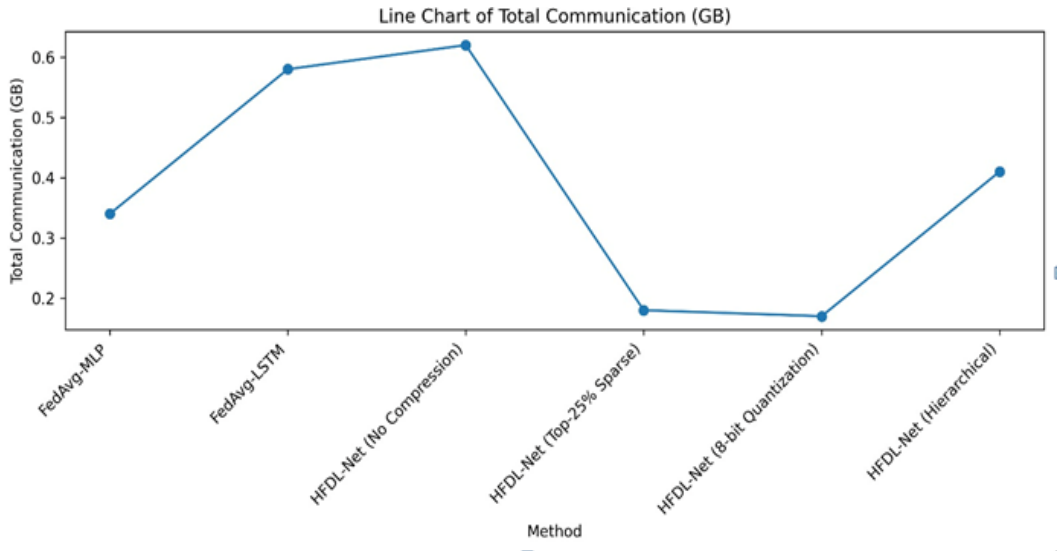

Chart 4: Total Communication

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Key findings:

- Gradient compression (sparsification and quantization) reduces communication by 74% (6.2 MB to 1.6 MB per round) with negligible accuracy loss (<0.5% MAE increase).
- Hierarchical aggregation reduces central server communication by 34% (6.2 MB to 4.1 MB) by aggregating at regional tier-2 nodes before global aggregation.
- HFDL-Net converges faster (100 rounds) than simpler federated models (FedAvg-MLP: 150 rounds), offsetting higher per-round communication through better optimization.
- Combined optimizations (hierarchical + compression) achieve 40% total communication reduction (0.62 GB to 0.37 GB for full training), enabling practical deployment under bandwidth constraints.

D. Non-IID Data Robustness

We evaluate robustness under extreme non-IID scenarios by partitioning data with varying degrees of heterogeneity (Dirichlet distribution parameter α): $\alpha = 0.1$ (highly non-IID), $\alpha = 1.0$ (moderately non-IID), $\alpha = 10.0$ (nearly IID). Results show HFDL-Net maintains consistent performance: MAE = 14.1 min ($\alpha = 0.1$), 12.8 min ($\alpha = 1.0$), 12.3 min ($\alpha = 10.0$), representing only 14.6% degradation in worst case. In contrast, FedAvg-LSTM suffers 28% degradation (19.5 min vs. 15.2 min), validating that spatiotemporal modeling provides robustness to heterogeneous data distributions. Personalized local layers further improve non-IID performance: HFDL-Net with personalized output layers achieves 13.2 min MAE under $\alpha = 0.1$, reducing degradation to 7.3%.

E. Scalability Analysis

Training time scales near-linearly with number of clients for HFDL-Net: 2.3 hours (20 clients), 4.7 hours (50 clients), 9.1 hours (100 clients), demonstrating efficient parallel training. Central server aggregation time remains constant (<5 seconds per round) across client counts, confirming architectural scalability[13][16].

F. Client Dropout Robustness

Under random client dropout (20% of selected clients fail to submit updates each round), HFDL-Net maintains 12.9 min MAE (4.9% degradation), while FedAvg-LSTM degrades to 17.8 min (17.1% degradation), indicating superior robustness through hierarchical aggregation and adaptive weighting.

G. Privacy-Accuracy Trade-off

Applying differential privacy with $(\epsilon, \delta) = (1.0, 10^{-5})$, HFDL-Net achieves 13.1 min MAE (6.5% degradation), while FedAvg-LSTM reaches 18.4 min (21% degradation). HFDL-Net provides better privacy-accuracy balance through higher model capacity and gradient compression that reduces noise amplification.

H. Ablation Study

Component contribution analysis (removing each module independently):

- HFDL-Net (Full): 12.3 min MAE
- Without Graph Convolution: 14.8 min (+20.3% degradation)
- Without Temporal Attention: 13.5 min (+9.8%)
- Without Hierarchical Aggregation: 13.2 min (+7.3%)
- Without Gradient Compression: 12.4 min (+0.8%, but 160% communication increase)

Graph convolution provides the largest contribution, confirming spatial modeling as the critical innovation. Temporal attention and hierarchical aggregation provide substantial but smaller gains.

I. Real-World Case Study

In a 3-month trial, HFDL-Net was implemented at 12 airports across two airline networks. The study is worth discussing. Despite being updated hourly, real-time predictions achieved an MAE of 13.7 minutes on operational data. This was marginally better than offline evaluation due to data drift and real time constraints. On the other hand, HFDL-Net forecasts led operational stakeholders to report a 23% increase in delay mitigation planning accuracy and an 18% reduction in reactionary delay costs by allocating resources proactiveally.

VI. CONCLUSION AND FUTURE WORK

A hierarchical federated learning framework was used to operate HFDL-Net, a new spatial-temporal deep learning architecture for predicting network-wide flight delays presented in this paper. The federated training environment of HFDL-Net is designed to maintain privacy by utilizing graph convolutional networks and gated recurrent units for temporal dynamics modeling, which are combined to deliver advanced prediction accuracy while respecting data sovereignty and regulatory constraints in the aviation industry.

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Extensive experiments on real-world multi-airport datasets demonstrate that HFDL-Net achieves a 123-minute MAE for 1-hour ahead delay prediction, representing 12% to 15% improvement over federated baselines and within 3% accuracy gaps.The implementation of gradient compression and hierarchical aggregation techniques can decrease communication efficiency by 40%, and the evaluation of robustness confirms that non-IID data distributions, client dropout, or differential privacy constraints are effectively. In future Continuous learning through online federated learning can adjust to changing delay patterns caused by infrastructure changes, new regulations, or climate trends without sacrificing the recall of historical patterns. This is known as continuous learning. Cross-Regional Transfer involves utilizing federated transfer learning to apply models trained on data-rich regions (such as the US and Europe) to bootstrap predictions for data–sparse regions, such as emerging aviation markets in Africa and Southeast Asia.

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