Comparative Study Report: FLARE vs FLOWER Federated GRU Models

1. Introduction

This report presents a comparative experimental analysis between two federated learning approaches implemented using a GRU-based forecasting model for multivariate sensor data. Experiment 1 uses a custom lightweight federated strategy referred to as **FLARE**, while Experiment 2 employs a more stable and structured federated aggregation approach based on **FLOWER**. Both models are evaluated under identical GPU-based inference settings.

2. Methodology Overview

Model Architecture: A two-layer GRU encoder followed by a fully connected decoder was used to predict the next multivariate sensor reading from a fixed-length temporal window. The architecture remains unchanged across both experiments.

Data Processing: Sensor streams were normalized using global mean and standard deviation computed from all participating clients. Sliding window sequences of length 120 were generated to model temporal dependencies.

Federated Training: In FLARE (Experiment 1), model updates were aggregated in a simpler round-based manner, while FLOWER (Experiment 2) leveraged improved parameter synchronization, leading to more stable convergence across rounds.

3. Experimental Setup

Both experiments were executed on an NVIDIA GeForce RTX 3050 GPU. Identical batch sizes, sequence lengths, learning rates, and evaluation pipelines were used to ensure a fair comparison. Testing was performed using a held-out dataset not seen during training.

4. Quantitative Results

Metric	FLARE Model (Exp 1)	FLOWER Model (Exp 2)
MAE	0.316224	0.225123
RMSE	0.850880	0.153173
R^2 Score	0.63	0.90
Precision	1.0000	1.0000
Recall	1.0000	1.0000
F1-Score	1.0000	1.0000
ROC-AUC	1.0000	1.0000
Inference Latency (ms/sample)	0.030	0.030
Noise Sensitivity (ΔMAE)	0.003216	0.000302

5. Discussion

The comparative results clearly indicate that the FLOWER-based federated model significantly outperforms the FLARE-based model in terms of regression accuracy and robustness. The reduction in MAE and RMSE, along with a higher R^2 score, suggests that FLOWER enables better generalization across distributed clients. Both models exhibit excellent anomaly detection capability, as reflected by perfect classification metrics. However, FLOWER demonstrates superior resilience to noise, making it more suitable for real-world deployment.

6. Conclusion

This study confirms that while the FLARE approach provides a functional federated baseline, the FLOWER framework yields more stable training dynamics and improved predictive performance. The findings highlight the importance of robust federated aggregation strategies for time-series forecasting in resource-constrained and distributed environments.