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FLARE – Federated Learning for Aircraft Reliability Enhancement

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***Abstract*— Modern aircraft engines are equipped with multiple sensors that continuously record data over time in a complicated environmental setting. Using these measurements, predictive maintenance applications to estimate the Remaining Useful Life (RUL) to predict the engine's failure and decide when maintenance should be performed. This article introduces a secure federated learning framework for collaborative aircraft engine RUL prediction system development named FLARE (Federated Learning for Aircraft Reliability Enhancement), that preserves user data confidentiality. The framework compares centralized learning, local-only learning, and federated learning using multiple machine learning models like Linear Regression, Random Forest, Gradient Boosting, Support Vector Regression and XGBoost along with a federated LSTM architecture. Furthermore, four federated optimization strategies, namely FedAvg, FedProx, FedNova, and a quality- weighted dynamic aggregation method (FedDWA), are implemented and analyzed to improve performance under varying data distributions using NASA C-MAPSS turbofan engine dataset.**

***Keywords*— Federated learning, Remaining Useful Life (RUL), Predictive maintenance, Aircraft engine prognostics, NASA C-MAPSS dataset, Distributed machine learning, Privacy-preserving learning, Long short-term memory (LSTM), Model aggregation, Turbofan engine degradation.**

I. INTRODUCTION

Distributed computing and machine learning play an important role in developing algorithms for processing complex data and supporting decision-making. In aircraft engine predictive maintenance systems, continuous sensor data streams are used to monitor engine performance and estimate the Remaining Useful Life (RUL) of critical components [1]. Accurate RUL prediction helps maintenance teams schedule maintenance activities in advance, which can improve safety and reduce unexpected maintenance events [2].

In practice, airlines perform maintenance before engine failures occur, resulting in limited run-to-failure data and labelled degradation paths in operational datasets [1],[5]. This shortage of failure data restricts the effectiveness of machine learning models for predicting critical events. Collaborative learning among airlines can improve forecasting by utilizing distributed datasets; however, privacy regulations, competition, and operational constraints often limit data sharing [4],[5].

This challenge highlights the need for privacy-preserving distributed learning algorithms. Federated Learning (FL) addresses this issue by enabling clients to collaboratively train a global model while keeping data local [2],[5].

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As a result, FL provides an effective approach for learning from distributed datasets without data centralization.
To address these challenges, this work proposes FLARE (Federated Learning for Aircraft Reliability Enhancement), a federated framework for aircraft engine RUL prediction. FLARE evaluates centralized, local-only, and federated learning approaches using traditional machine learning and LSTM-based models. The framework incorporates FedAvg, FedProx, FedNova, and FedDWA optimization strategies to handle heterogeneous client data while preserving privacy through local data retention. Experimental evaluation on the NASA C-MAPSS dataset demonstrates that federated learning outperforms isolated local models and achieves performance comparable to centralized approaches.

II. RELATED WORKS

A. Deep Learning for Prognostics and RUL Prediction

Deep learning methods have significantly improved Remaining Useful Life (RUL) prediction in aircraft engine prognostics. Fink et al. [1] showed that deep learning models effectively learn degradation patterns from high-dimensional sensor data. de Pater and Mitici [2] proposed an LSTM-based framework for engine degradation monitoring under varying operating conditions. Tian et al. [16] introduced a spatial-temporal LSTM model that improved sequential degradation learning and prediction accuracy. However, most existing deep learning approaches rely on centralized training where all operational data must be stored on a central server, creating privacy and security concerns in aviation systems.

B. Federated Learning for Distributed Industrial Applications

Federated Learning (FL) enables collaborative model training without sharing raw data. Landau et al. [2] developed a federated learning framework for aircraft engine prognostics using the NASA C-MAPSS dataset and achieved performance close to centralized learning. Sun et al. [3] proposed personalized federated learning for handling heterogeneous client data distributions. Chen et al. [13] introduced a federated RUL prediction framework using global degradation representations to improve distributed learning efficiency. Recent studies have also explored federated transfer learning, lightweight federated architectures, and adaptive aggregation techniques for industrial prognostics applications [14], [17], [20].

C. Research Gap and Limitations

Existing studies primarily focus on either centralized deep learning approaches for RUL prediction or federated learning for industrial fault diagnosis. Limited research has compared centralized, local-only, and federated learning approaches for aircraft engine RUL prediction within a unified experimental framework. In addition, the performance trade-offs among federated aggregation strategies such as FedAvg, FedProx, FedNova, and FedDWA remain insufficiently explored. To address these gaps, the proposed FLARE framework integrates multiple machine learning models, a federated LSTM architecture, and advanced aggregation methods within a privacy-preserving environment for aircraft reliability enhancement.

III. PROPOSED SYSTEM

FLARE (Federated Learning for Aircraft Reliability Enhancement) is a privacy-preserving framework for aircraft engine Remaining Useful Life (RUL) prediction. The framework combines traditional machine learning models, deep learning techniques, and federated aggregation strategies to enable collaborative learning without sharing raw data.
Key Contributions of the Proposed FLARE Framework
This approach comes with a few key benefits:

- A privacy-preserving distributed learning framework tailored for aircraft prognostics.
- Direct comparison of centralized, local-only, and federated learning paradigms.
- Integration of classical machine learning and sequence-based deep learning (LSTM).
- Implementation of advanced federated aggregation strategies
- A scalable architecture supporting multiple engine clients

A. System Workflow

The FLARE workflow begins with NASA C-MAPSS sensor data preprocessing, including RUL computation, Min–Max normalization, and engine-wise train–test splitting. The processed data are evaluated using centralized, local-only, and federated learning paradigms with Linear Regression, Random Forest, Gradient Boosting, XGBoost, and SVR models. A federated LSTM model is further employed to capture temporal degradation patterns through local training and global parameter aggregation. Model performance is assessed using RMSE.

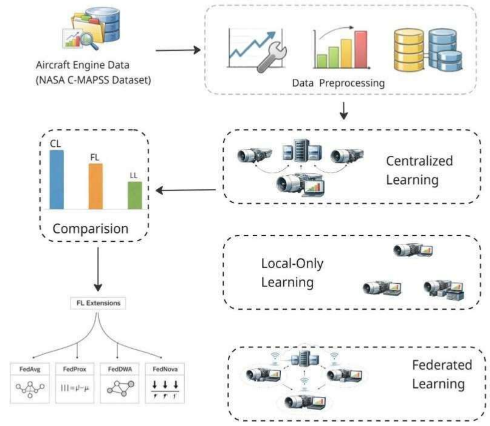

Fig.1. System workflow of the proposed FLARE framework.

B. System Architecture Description

Deep learning has led to significant empirical advances in prognostics and health management (PHM) have emerged across recent years. Given that the findings demonstrate considerable theoretical scope, Fink et al. [1] might reasonably indicate that deep learning methods could possibly demonstrate both important potential and critical challenges within PHM applications.

C. Data Layer for Dataset

The framework uses multi-engine sensor data from the NASA C-MAPSS turbofan engine dataset. Each engine generates time-series degradation data and is treated as an independent unit. In the federated configuration, each engine can function as a separate client, allowing distributed model training without centralized raw data collection.

D. Preprocessing Layer for Preparation

The preprocessing stage prepares the raw sensor signals for machine learning. In light of the significant methodological requirements, the important layered design could plausibly demonstrate that Remaining Useful Life (RUL) computation based on cycle information, feature scaling using Min–Max normalization, and engine-wise train–test splitting provide a structured and standardized dataset suitable for both classical machine learning models and deep learning architectures

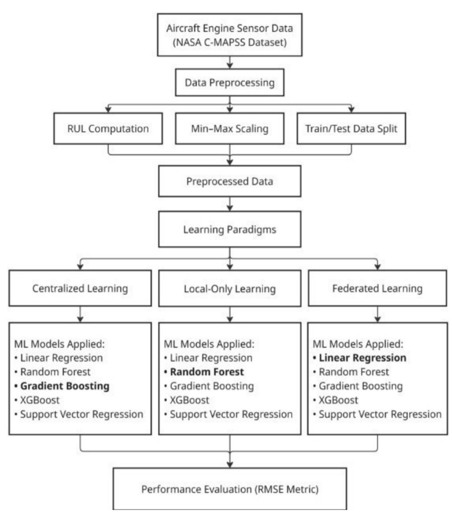

Fig. 2. Proposed Methodology for RUL Prediction Using Multiple Learning Paradigm

C. Learning Paradigm Layer for Training

To make systematic comparisons possible, the framework enables the selection of three different learning setups:

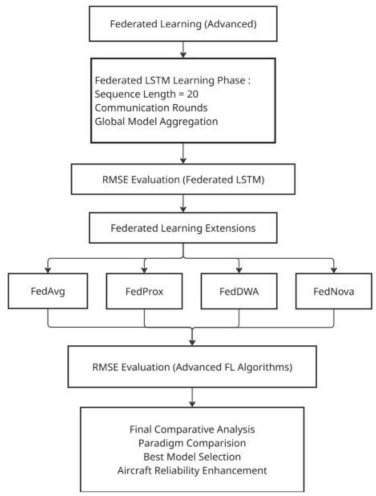

Fig.3. Architecture of the Advanced Federated Learning Framework for RUL Prediction

- Centralized Learning, which pools all engine data together into one dataset.
- Local-Only Learning, where each engine trains a model independently without sharing information.
- Federated Learning, where engines train locally and share only model updates with a central aggregation server.

D. Federated System Layer for Aggregation

Each engine performs local training and transmits only model parameters or gradients to a central server which aggregates these important updates to construct a global model that substantially preserves privacy. Nevertheless, the important results might indicate that multiple aggregation strategies including FedAvg, FedProx, FedNova, and FedDWA could demonstrate improved robustness and convergence behavior across critical configurations. Moreover, evidence might indicate privacy aligns with decentralized principles.

E. Evaluation and Analysis Layer for Assessment

The final layer could demonstrate that RMSE as the performance metric provides critical cross-paradigm benchmarking, important comparison of aggregation strategies, and identification of the key best-performing configuration.

IV. Results and Discussion

A. Performance Analysis under Centralized Learning

In the centralized learning configuration, all client datasets were merged into a single global dataset for model training. This setup provided the highest data availability and served as the upper-bound performance reference.

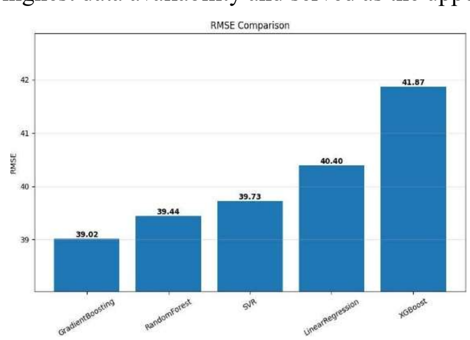

Fig. 4. Performance comparison of centralized learning models based on RMSE.

As shown in Fig. 4, Gradient Boosting achieved the lowest RMSE among all evaluated models, demonstrating superior prediction capability for aircraft engine RUL estimation. Random Forest and XGBoost also produced competitive results due to their ensemble learning capabilities. Linear Regression showed moderate performance, while SVR produced comparatively higher prediction errors.
The results indicate that centralized learning achieves strong prediction accuracy because the model has access to complete degradation information from all engines.

B. Performance Analysis under Local-Only Learning

The local-only learning configuration could indicate that separate model development demonstrate significant methodological implications, as each engine required its dedicated local data for training without sharing important information with other engines, suggesting critical privacy- preserving advantages across the relevant experimental condition. According to Fig. 5, Random Forest achieved the best RMSE performance among the evaluated local models. Ensemble-based methods demonstrated better adaptability to limited local datasets compared to linear approaches. However, overall prediction accuracy was lower than centralized learning because isolated engines lacked access to broader degradation patterns. These findings highlight the limitations of isolated learning in practical aviation environments where operational data is fragmented across multiple organizations

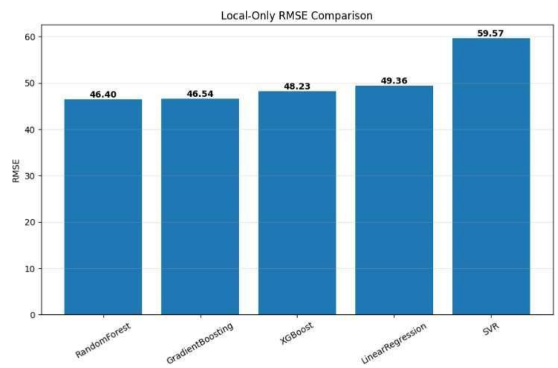

Fig. 5. Performance comparison of local-only learning models based on RMSE.

C. Performance Analysis under Federated Learning

In the federated learning configuration, each engine acted as an independent client performing local training while sharing only model updates with the aggregation server. Raw sensor data remained private throughout the training process.

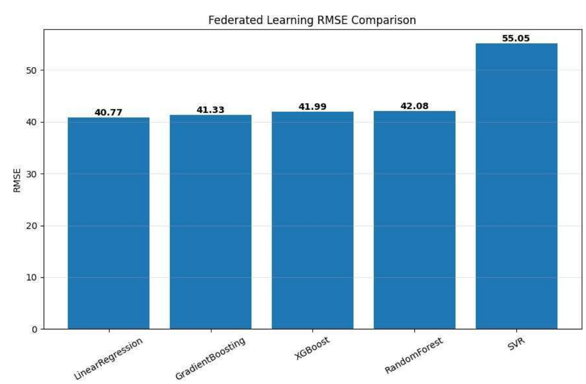

Fig. 6. Performance comparison of federated learning models based on RMSE.

Fig. 6 demonstrates that federated learning achieved prediction performance close to centralized learning while preserving data confidentiality. Linear Regression produced the lowest RMSE among the federated models, followed closely by Gradient Boosting. The results confirm that collaborative distributed learning significantly improves prediction accuracy compared to local-only learning. Federated learning successfully balances privacy preservation and predictive performance without requiring centralized data collection.

D. Comparative Analysis of Learning Paradigms

The comparative results presented in Fig. 7 illustrate the overall RMSE performance of centralized, local-only, and federated learning paradigms. Centralized learning achieved the best overall accuracy because the model had access to the complete dataset. Local-only learning showed the weakest performance due to data isolation and limited training diversity. Federated learning demonstrated performance very close to centralized learning while maintaining decentralized data ownership.

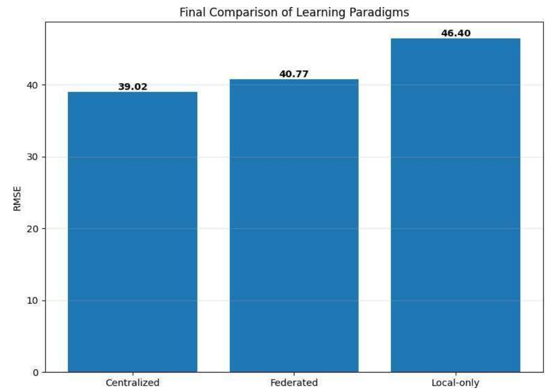

Fig. 7. Performance comparison of learning paradigms using RMSE.

This comparison validates the effectiveness of the proposed FLARE framework for privacy-preserving collaborative aircraft prognostic.

E. Federated LSTM Convergence Analysis

To analyze sequential degradation learning in distributed environments, a Federated LSTM architecture was implemented. The model was trained over multiple communication rounds using distributed engine clients.

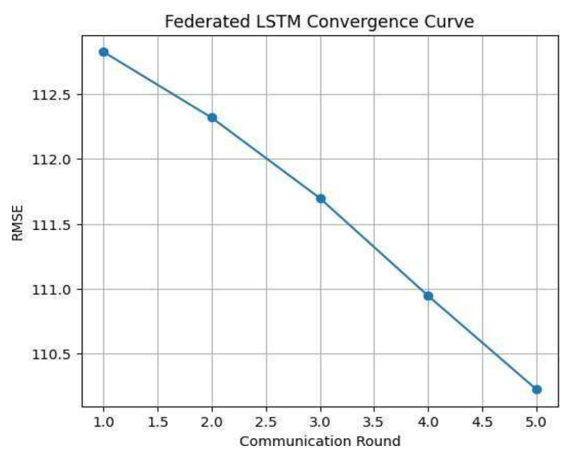

Fig. 8. Convergence behavior of the federated LSTM model across communication rounds.

As illustrated in Fig. 8, the global RMSE consistently decreased with increasing communication rounds. This behavior demonstrates stable convergence of the federated LSTM model and effective aggregation of knowledge from distributed clients. The gradual reduction in prediction error confirms that the model successfully learned temporal degradation patterns from multiple engines while preserving data privacy.

F. Performance Analysis of Federated Aggregation Algorithms

The FLARE framework additionally evaluated advanced federated aggregation algorithms including FedAvg, FedProx, FedNova, and FedDWA under identical experimental conditions. Among the evaluated methods, FedNova achieved the lowest RMSE and demonstrated the best convergence behaviour as shown in Fig. 9. FedProx and FedDWA also outperformed the baseline FedAvg method by improving robustness against heterogeneous client data distributions.

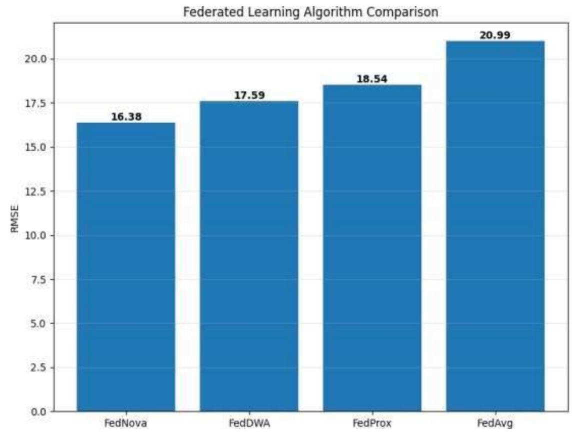

Fig. 9. Performance comparison of advanced federated aggregation algorithms based on RMSE.

The results indicate that advanced federated optimization strategies can significantly enhance global model stability and prediction accuracy in distributed aircraft maintenance systems.

V. Conclusion and Future Enhancement

FLARE (Federated Learning for Aircraft Reliability Enhancement) functions as a confidentiality-protecting distributed learning system which scientists built to forecast the remaining operational life of aircraft engines. The NASA C-MAPSS dataset evaluation demonstrates that researchers can perform effective performance assessments between three different learning methods which include centralized learning and local-only learning and federated learning by using different data-sharing methods. The results show how standardized machine learning models together with a federated LSTM system operate under various privacy requirements and distribution conditions while federated methods provide stable performance with competitive accuracy.

The federated LSTM model showed stable convergence results throughout all communication rounds which demonstrated that distributed deep learning can be used for sequential degradation modeling. Advanced aggregation strategies improved system performance through better security and faster system performance in federated environments. The FLARE framework demonstrates that aircraft maintenance teams can use federated learning to protect their sensitive operational information while achieving accurate predictions which enables secure joint forecasting activities in aviation systems. Future research will study how to enhance communication performance through model update compression methods which adapt to changing conditions together with aggregation techniques that consider available bandwidth and the development of secure aggregation methods which will provide better privacy protection and the assessment of hybrid federated- edge learning systems which will enhance operational readiness for massive aircraft maintenance networks.

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