Federated approaches for Remaining Useful Life prognosis

Raúl Llasag Rosero
rosero@dei.uc.pt
Catarina Silva
catarina@dei.uc.pt
Bernardete Ribeiro
bribeiro@dei.uc.pt

Universidade de Coimbra,
CISUC - Centro de Informática e Sistemas,
FCTUC-DEI - Departamento de Engenharia Informática,
Portugal

Abstract

Condition-Based Maintenance (CBM) using intelligent prognostic strategies that estimate Remaining Useful Life (RUL) has been applied in real scenarios to reduce maintenance costs and down times of machinery. When applied to aircraft maintenance, these models have also been developed in collaborative platforms that make use of data from similar components both in the same and different aircraft.

Even though RUL predictors have been presenting potential opportunities for developing federated scenarios after aggregating machine learning models, accuracy improvements of these models have not been evaluated yet, mainly due to absence of aircraft data.

In this work, we propose two collaborative federated approaches to determine RUL prognosis. The first approach aggregates models of equivalent subsystems located in the same airplane, while the second approach aggregates equivalent subsystems on different airplanes. We analyse 2 different systems from the aircraft: Integrated Cooling System (ICS) and Cabin Air Conditioning and Temperature Control System (CACTCS). We present the study of possible sensor data combinations according to the two proposed collaborative approaches.

After analysing the datasets description and failures, we determine that there are 19 models which can be integrated under the first federated approach, while for the second approach, there are 40 models which can be used to evaluate performance improvements in terms of distance.

1 Introduction

Prognostic is a very promising paradigm that permits strategies as Condition Based Maintenance (CBM) for reducing maintenance costs and downtimes of machinery such as aircraft systems [1]. CBM uses Prognostics and Health Management (PHM) techniques and metrics as Remaining Useful Life (RUL) to schedule maintenance tasks which are based in the duration left for a system before it fails [4].

RUL estimators are categorized into three types: model-based approaches, data-driven approaches, and fusion approaches [7]. Model-based approaches require physics machinery knowledge, while data-driven approaches analyze data using statistics and maths [1].

Strategies for developing data-driven approaches are based on the use of Artificial Intelligence techniques which have been deeply explored in the context of time series forecasting [4]. On the other hand, in order to reduce the distance between the estimation and the theoretical RUL, a recent collaborative paradigm named Federated Learning has been integrating machine learning models based on neural networks [6]. These evaluations have been done using virtual data engines as Turbofan but the aggregation of other equivalent airplanes subsystems has not been evaluated yet. Thus, in the present document, the aggregation of subsystems of the same airplane and different airplanes is considered.

2 State of the Art

The distance between RUL estimations and theoretical RUL for Turbofan engines has been reducing using direct computation approaches [6]. These approaches have been applied because degradation trends have been identified in specific time sensor data [5]. Nevertheless, due to the noise of sensors, finding a tren degradation requires of feature selection processes and the use of Health Indicator (HI) measures as the input for RUL computation [2, 3, 4].

The computation of virtual HI based on-flight phases aggregation [2] and feature selection under 3σ rule [4] has been presenting promising results for RUL computation of Boeing 787 Systems. However, the integration of HI estimators of equivalent subsystems of different airplanes has not to be done because federated scenarios on Boeing 787 datasets have not been identified yet.

3 Proposed Approach

Health estimator based in physics models have been limiting the scalability of PHM systems because collaborative scenarios have been depending on centralized processing architectures. So, estimators based in data-driven approaches through the use of neural networks have been gaining interest after collaboratively improving the accuracy of prognostic models under a newfangled parading named Federated Learning [6, 8]. Using the global loss function of the Equation 1, federated techniques based on Gradient Descent minimization improve the accuracy of equivalent prognostics systems in private aggregations of machine learning models [8].

$$F(w) \triangleq \frac{\sum_{j=1}^{N} n_j F_j(w)}{n} \tag{1}$$

Accuracy improvements in terms of distance between theoretical RUL and RUL estimations have done after iteratively averaging prognostic models (F_j) on a Federated Server, obtaining a central model ($F(w)$) which contains the knowledge of a defined number of federation participants (n) [6].

4 Experimental Setup

4.1 Datasets

For this work, data collected from the Cabin Air Conditioning and Temperature Control System (CACTCS) pack and the Integrated Cooling System (ICS) pack of Boeing 787 airplanes have been available as two datasets. The CACTCS pack is part of the Environmental Control System (ECS) and provides cabin temperature management and control, while the ICS pack is one of the three main packages which provide cooling flow to the primary electronics, the galley, and the forward cargo air conditioning system.

4.1.1 Cabin Air Conditioning and Temperature Control System

This dataset comprises data extracted from 13 different airplanes, in which data of sensors, faults and removals are useful for *a posteriori* RUL computation. Sensor data were extracted from 2 Packs systems using a sampling rate of 1Hz (sample per second). For each CACTCS pack, the data were retrieved from 45 different anonymized sensors. Here 23 sensors catch pack general information, while the other 22 sensors catch information of 2 equivalent Cabin Air Condition (CAC) components.

The faults data contains three types of failure reports that have been occurred during flights. Flight Deck Events (FDE) faults have been automatically generated during flights after presenting anomalies in sensors, while Aircraft Technical Log (ATL) and Predictive Maintenance (PM) faults have been identified by the maintenance team. Due to PM faults present removal/replacements dates given by technicians, we consider using these faults for HI prognosis.

4.1.2 Integrated Cooling System

This dataset comprises information collected of 17 Boeing 787 airplanes during 21 months. Similarly to CACTCS, ICS is composed of sensor data, failures and removals. However, FDEs are not reported over time, closing to use failure information provided by technicians.

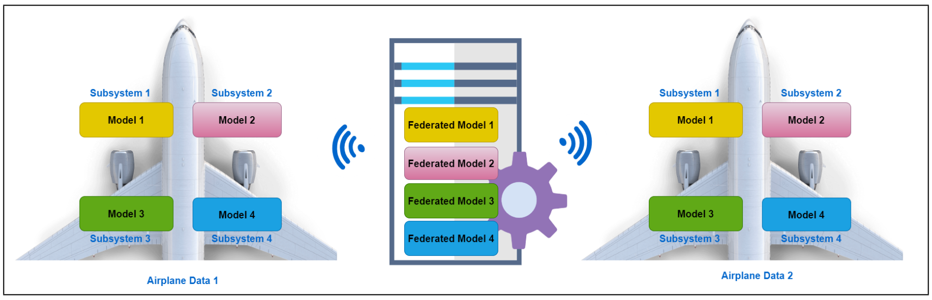

Figure 1: 1st Federated approach: Subsystems of different airplanes

ICS sensor data was retrieved from 70 anonymized sensors, which include 4 equivalent Supplemental Cooling Unit's (SCU), 2 SCU Motor Controllers (SCU-MC) and 2 PUMPs. However, as failures and removals are known only for SCUs, we propose to use only 9 sensors as input of an SCU RUL predictor and reuse the four of them in collaborative approaches.

4.2 Dataset equivalent terminology

To aggregate HI estimators of equivalent components of CACTCS and ICS with federated techniques, Boeing 787 systems terminology of the Table 1 has to be generalized to describe the identified approaches.

Federated Learning	CACTCS	ICS
Subsystem	Component	Unit
Model	Comp. HI predictor	Unit HI predictor
Federated Model	Fed. HI predictor	Fed. HI predictor

Table 1: Generalized terminology used in collaborative approaches

CACTCS dataset is composed of sensor data obtained by different components, while ICS dataset contains units. Thus, in order to adopt the same terminology in a Federated context, systems correspond to the dataset and subsystems correspond to components or units, respectively.

5 Proposed Implementation

5.1 Federating subsystems of the same airplane

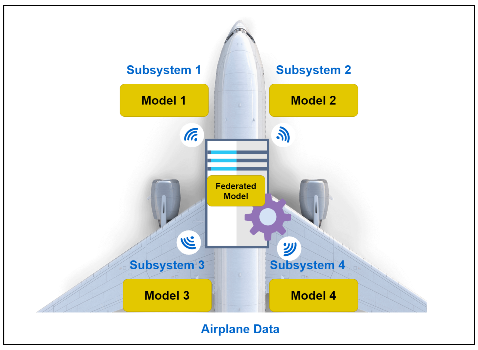

Figure 2: 2nd Federated approach: Subsystems of the same airplane

The approach illustrated in the Figure 2 assumes that some subsystems (same color boxes) per airplane are equivalent. In other words, the Remaining Useful Life of the 4 CAC components of CACTCS or 4 SCU units of ICS can be prognosticated using the same model.

Federation of equivalent subsystems does not require sharing models of different airplanes, but doing that, the prognosis accuracy of the federated model could be already improved.

5.2 Federating subsystems of different airplanes

In the Figure 1, the federation of equivalent subsystems (same color boxes) of different airplanes is illustrated. This approach generates one Federated Model per subsystem after aggregating models of different airplanes.

In the case of CACTCS, is assumed that the RUL of the 4 CACs of the left and the right packs can not be foreseen with the same model, i.e., the input sensors' data could be different for each subsystem. For ICS, this approach assumes that both SCU and PUMP are different.

6 Conclusions and Future Work

Due that the number of airplanes and failures are different for each dataset subsystem, the number of nodes for the both federated approaches are detailed in the Table 2. For the first federated approach, 10 CACTCS models and 9 ICS models contains the information of a same subsystem but located indifferent airplanes, while for the second federated approach, the number of federated constituents varies according each L-*th* and SCU-*th* subsystem. So, after developing and federating RUL predictors, improvements of federated approaches will be evaluated in future work.

Dataset	CACTCS	ICS
Subsystems	CAC (L1,L2,L3,L4)	SCU(1,2,3,4)
Airplanes	13	17
Failures	24	22
1st Fed. Approach	10	9
2nd Fed. Approach	6, 6, 4, 5	7, 4, 6, 2

Table 2: Federated cases for CACTCS ans ICS datasets

Acknowledgements

This work is part of a funded project from the European Union's Horizon 2020 research and innovation programme under grant agreement No769288.

References

[1] V. Atamuradov, K. Medjaher, P. Dersin, B. Lamoureux, and N. Zerhouni. Prognostics and health management for maintenance practitioners-review, implementation and tools evaluation. *International Journal of Prognostics and Health Management*, 8:31, 2017.

[2] D. Azevedo, A. Cardoso, and B. Ribeiro. Estimation of health indicators using advanced analytics for prediction of aircraft systems remaining useful lifetime. *Proceedings of the European Conference of the PHM Society*, 5(1):1–10, 2020.

[3] L. Guo, Y. Lei, N. Li, T. Yan, and N. Li. Machinery health indicator construction based on convolutional neural networks considering trend burr. *Neurocomputing*, 292:142–150, 2018.

[4] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin. Machinery health prognostics: A systematic review from data acquisition to rul prediction. *Mechanical Systems and Signal Processing*, 104:799–834, 2018.

[5] E. Ramasso and A. Saxena. Benchmarking and analysis of prognostic methods for cmapss datasets. *Prognostics and Health Management Conference*, 2(5):1–15, 2014.

[6] R. LLasag Rosero, C. Silva, and B. Ribeiro. Remaining useful life estimation in aircraft components with federated learning. *Proceedings of the European Conference of the PHM Society*, 5(1):1–9, 2020.

[7] K. Tidriri, N. Chatti, S. Verron, and T. Tiplica. Bridging data-driven and model-based approaches for process fault diagnosis and health monitoring: A review of researches and future challenges. *Annual Reviews in Control*, 42, 2016.

[8] Q. Yang, L. Yang, T. Chen, and Y. Tong. Federated machine learning: Concept and applications, 2019.