

Leonardo Electronics

A Novel Predictive Maintenance Methodology for improving Defence Logistics Processes

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Authors : L. Monorchio, A. Garritano, E. Luciani, L. Ciolli, M. Santini



Machine Learning Solutions for New Maintenance Strategies

A novel Predictive Maintenance Methodology that uses Machine Learning techniques for improving

military aircraft in-service logistics support processes

OBJECTIVES:

- To improve Mean Time Between Failures (MTBF);
- To increase logistics KPI predictions reliability,
- To reduce maintenance support costs/working time.





>Summary

- > Use Case 1: Smart Aircraft Anomalies Analysis
- > Use Case 2: Aircraft Fleet Availability Improvement
- > Use Case 3: Engine Test Stand (ETS) Optimization via Digital Twin

Use Case 1: Smart Aircraft Anomalies Analysis

Objective: to support maintainers in solving newly raised anomalies using a **Natural Language Processing** (NLP) approach.



- · Pilots and maintainers record aircraft detected anomalies into the info-logistic system,
- Their skills and the operative contexts in which they act are highly heterogenous,
- Useful information resides all over the different types of meta data records (structured and not, free text).

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Natural Language Processing (NLP) approach

The proposed system provides the maintainer with a list of past anomalies, ranked by

similarity, that helps him understand how they have been solved and find out which

spares and ground support equipment have been used.

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He can easily perform anomaly diagnosis, reducing the related MTTR (Mean Time To Repair).



NLP has been used to process information contained in *Incident* or *Health Reports* with the aim of understanding, at semantic level, the anomalies entered by the operator.

The final objective is to analyze, understand and generate human languages

information, just like humans do.

USE Network Easy-To-Read Architecture

UNIVERSAL SENTENCE ENCODER (USE)

NEURAL NETWORK





NLP: Semantic Text Similarity Approach

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Inference Examples



Oil Filter

Similarity Accuracy Level	Similar Anomalies	Maintenance	ID_TASK	\backslash
1	REPLACE THE OIL FILTER ON R_ENGINE_OIL_FLTR_BLOCK	OIL FILTER CHANGED FOR ENG RIGHT WITH NEW OIL, OK	6XXXXX4	
2	REPLACE THE OIL FILTER ON ENGINE LEFT.	DONE, OK	3XXXXX1	
3	REPLACE THE OIL FILTER ON ENGINE LEFT.	DONE, OK	2XXXXX2	
4	REPLACE THE OIL FILTER ON ENGINE LEFT.	DONE, OK	1XXXXX9	

Bird Strike Event - Foreign Object Debris (FOD)

Similarity Accuracy Level	Similar Anomalies	Maintenance	ID_TASK
1	UNLOAD ENGINE - BIRD STRIKE EVENT	FOD CHECKING ON ENGINE S/N 1XXXX2	3XXXXX7
2	UNDERSTAND FOD IMPACT	PERFORM ETS	3XXXXX3
3	FOUNDED BIRD STRIKE EVENT	ENGINE REPLACED	2XXXXX9
4	FOD ON 4° STAGE XXXX OUT-OF-TOLERANCE	Check ok, no further damages	5XXXXX1



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Use Case 2: Aircraft Fleet Availability Improvement

Objective: To estimate the aircrafts remaining flight time in order to improve aircraft fleet availability.

Knowing accurately when aircrafts will be available or not has great impact on maintenance organization processes and associated costs.

In this scenario, failure predictions play a decisive role when combined with in-service real data.





Robust Statistical Sensory Data (RSSD) Network for Aircraft Availability prediction

- A RSSD network has been developed and trained with **data fusion** approach.
- For a single aircraft (**Input**), the output (**Prediction**) is compared with the historical data stored into the legacy repository (**Ground truth**) to calculate the **improved potential aircraft availability**.



- Tail Number Mission data (landings, touch & go, maneuvers, etc ..)
- Mission & Sensor Right Engine Data (es: vibrometers)
- Mission & Sensor Left Engine Data

The similarity trend between the predicted data and the historical data confirms the correct accuracy of the Neural Network.

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RSSD Fleet Flight Hours overtime Prediction

Single Tail Number



Robust Statistical-Sensory Data (RSSD) Neural Network

Exploiting Data Fusion, composed by statistical and sensorial data, to predict Fleet availability and optimize Maintenance Schedule.

Fleet Availability Index

Optimization Algorithm for readiness improvement

Use Case 3: Engine Test Stand (ETS) Optimization via Digital Twin

- ETS execution is the final process that allows engines to pass the performance check through rigorous tests.
- ETS are extremely time-consuming and costly.
- The objective is to reduce the number of ETS that a specific engine could be subjected to using Deep Learning approach on a simulation environment.

Photo credit: Pratt & Whitney

• KPI of Engine Test Stand (ETS)

Digital Twin – ETS Simulations Comparison

The comparison between perfomances of 2 different asset configurations provides best ETS benchmark results.

Maintainer supervised asset configurations provides high flexibility of the proposed solution.

The operator chooses an engine parameters configuration setup depending on its maintenance impact.

Engine Flying Hours

Flying Hours

Starts

62.1

Operating Hours 81 Reheat Cycle

149.9

Reheat Time

0.8

Engine Flying Hours

Flying Hour

Starts 71.5 Operating Hours 105.45 Reheat Cycle

132.75

Reheat Time

Conclusion

The use cases have been developed in collaboration with Italian Air Force that provided the data. The results achieved by the **applications of ML methods on both statistical and sensorial data** have provided an insight of how to **maximise the aircraft operational availability** by

- increasing the reliability of the prediction
- minimising the need for maintenance
- improving the total true-life cycle cost

Future steps include the extension of the use cases and the definition of additional operational scenarios as further demonstration of the benefits that such applications can bring to military logistics.