A Novel Predictive Maintenance Methodology for Improving Defence Logistics Processes

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ABSTRACT

Emerging Machine Learning (ML) solutions aimed at predicting and anticipating the likelihood of asset failures by improving MTBF are enabling new maintenance strategies to reduce integrated logistic support costs. This paper describes a novel predictive maintenance methodology that optimizes maintenance schedules and, consequently, the overall system life cycle cost.

Moreover, with the increasing involvement of NATO in deployment operations, there is today the need to focus the attention on availability and mission reliability where the aircraft operational availability during missions represents an important aspect of overall availability.

Here we present a hybrid ML approach that allows increasing the reliability of the prediction and improving the total life cycle cost by maximizing aircraft availability and minimizing the need for maintenance and the related downtime. This innovative methodology optimizes major operational gaps in NATO logistics affecting the logistic footprint and the maintenance processes by improving the overall system performance and by enhancing the system reliability throughout in-service life. Furthermore, this approach allows Customers to estimate the real residual operating hours of the assets with a significant reduction of unplanned downtime, by managing their reliability risks and anomalies ahead of time.

In conclusion, the application of this strategy provides the decision makers with a more reliable and real time logistics situational awareness for the military assets on field.

Keywords: Predictive Maintenance, Machine Learning, Situational Awareness, Decision Making, Logistics, Availability

1.0 INTRODUCTION

Nowadays that large amount of in-service logistic data, coming from sensors or legacy info-logistic systems, are available also in the Defence sector, learning model techniques can be applied to them with interesting results from a Life Cycle Cost perspective.

In the aviation domain, artificial intelligence has laid the foundations to guarantee both resources optimization and logistic capabilities improvement by reducing the maintenance working time with a direct impact on maintenance costs.

In fact, building the optimal maintenance scheduling requires fundamental parameters information that comes from modules and submodules (and their combinations), overtime.

A novel Predictive Maintenance Methodology based on Machine Learning techniques for improving military aircraft in-service logistics support processes is described with the main objectives to:

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

In particular, in this paper three different Predictive Maintenance approaches based on Supervised Machine Learning algorithms are presented, each derived from real issues experienced by Maintenance Repair and Overhaul (MRO) units of the Italian Air Force (ITAF):

Use Case 1: Smart Aircraft Anomalies Analysis focused to support maintainers in solving newly raised anomalies using a Natural Language Processing (NLP) approach

Use Case 2: Aircraft Fleet Availability Improvement focused on the estimation of the aircrafts remaining flight time in order to improve aircraft fleet availability

Use Case 3: Engine Test Stand (ETS) Digital Twins also known as a Digital Replica, has brought technology to new interesting scenarios. This use case is focused on the reduction of the number of ETS that a specific engine could be subjected to using Deep Learning approach on a simulation environment.

2.0 SMART AIRCRAFT ANOMALIES ANALYSIS

2.1 Use Case description

During day by day maintenance activities descriptions of anomalies related to the execution of different maintenance tasks are expressed by the operators into natural language and recorded into the info-logistics system. Operators are likely to have different technical skills and to work in highly variable contexts, so the information recorded can vary from an operator to another one.

Sophisticated Natural Language Analysis systems can be applied to this data on the Big Data platform to extract the nuances of the context in which they are written.

Natural Language Processing (NLP) is a subfield of linguistics, computer science, and artificial intelligence that deals with the interaction of computers with human languages. The goal is a computer that can "understand" the content of the document, including distinction of the context of the language. This technology can accurately extract information and ideas contained in documents, classify and organize them.

The information has proved to be very useful into two different scenarios:

1. given a new anomaly to be fixed, by automatically extracting knowledge and information from other available anomalies descriptions, it is possible to understand, in a timely manner, what corrective actions can be taken to fix the one under analysis. This approach allows the unexperienced maintainers to leverage the skills and competences acquired by the experienced maintainers. while saving the maintenance time in fixing the issues as well.

2. to forecast possible anomalies that can be generated starting from an existing one. In real environments, classify similar types of anomalies turns out to be a non-trivial challenge because of different operators enter the different description of the same anomalies in the database by using a natural language model.

We are facing a human-noise problem in the dataset in which standard *ML* algorithms are not able to discriminate anomalies. Neural networks have achieved the *State-Of-The-Art* in classification problems in *Natural Language Processing* (*NLP*), reason for which we propose a *Transformers Neural Network* able to classify anomalies using the semantic similarity.

The process is composed of the following steps: the operator enters the specific anomalies in the system, via a web application. The proposed ML solution shows a list of similar anomalies. The operators can navigate through the history of the anomalies proposed. Moreover, the solution suggests corrective actions to fix the anomalies. Finally, the ML solution proposes the list and quantity of spare parts available for the maintenance operation. The above-mentioned process shows an important innovation key role of composed *ML* algorithms and Big Data platforms, in the Predictive Maintenance field thanks to its hybrid and scalable architecture to merge artificial intelligence with logistics features.

2.2 Implementation Details

The implementation of the solution involves the semantic analysis of anomalies that are entered the Big Data platform. The anomalies entered by the operators in the platform are in an unstructured format, i.e. information that either does not have a pre-defined data model or is not organized in a pre-defined manner. With *Natural Language Processing* (*NLP*), it is possible to produce robust models for textual inputs in natural language that are unfamiliar, for instance, containing words or structures that have never been seen before.

The approach used involves Semantic Text Similarity. Semantic textual similarity deals with determining how similar two pieces of texts are. Related tasks are paraphrase or duplicate identification. A lot of the recent success in *NLP* has been driven by vector representations of words trained on large amounts of text in an unsupervised manner. Vector representations of sentences allow clusterization based on anomalies similarity. This allows us to construct a similarity matrix between anomalies in the dataset, such as the one shown in Figure 1

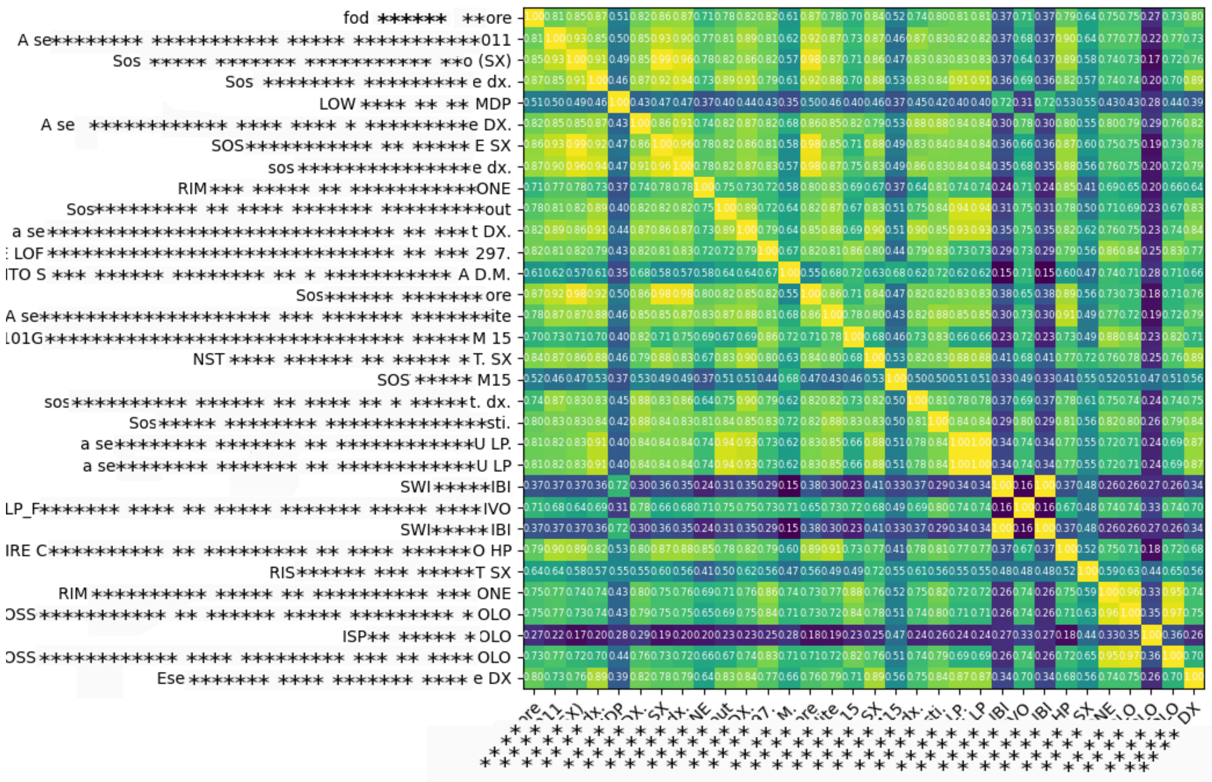

Figure 1: Anomalies Similarity Matrix: Similarity correspondences with high scores are represented by warm colours

A transformer encoder encodes text into high dimensional vectors that can be used for text classification, semantic similarity, clustering, and other natural language tasks. The transformer-based sentence encoding model constructs sentence embeddings using the encoding sub-graph of the transformer architecture. The models take as input English strings and produce as output a fixed dimensional embedding representation of the string. A classifier module is developed to process the similarity matrix and return the list of candidate anomalies and the system suggests the corrective actions to solve the anomalies.

3.0 AIRCRAFT FLEET AVAILABILITY IMPROVEMENT

3.1 Use Case Description

One of the main issues that affects aircraft fleet availability is the capability to accurately estimate the remaining flight time available for each aircraft of the fleet itself. Thus, understanding with 96% accuracy when an aircraft, or its modules, are at risk of failures, allows maintainers to modify accordingly the maintenance plan. These changes will affect the related logistic processes (such as skills schedule, tools and workshops schedules, or supply chain configuration, etc …) leading to direct costs reduction.

The developed ML approach, a deep learning one, exploits the past flight mission information, available from the in-service database, to predict failure risk and then define the residual available flight hours, merging both statistical/non-deterministic data, i.e., external unforeseen outputs, and on-board sensors parameters, as depicted in Figure 2. Hence, the developed system predicts, for each aircraft, its next six months flight availability (starting from the last flight mission), as well as the probability of encountering three different levels of anomalies overtime: mild, moderate, severe.

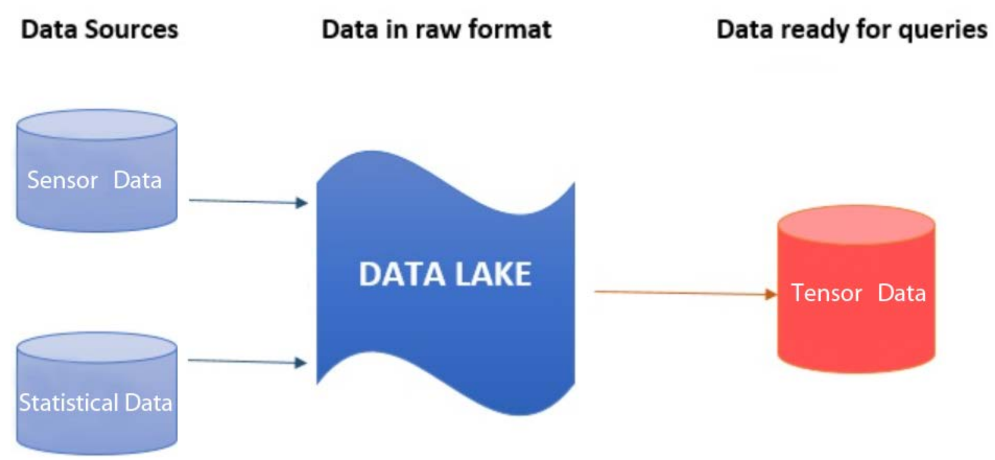

Figure 2 : Data Fusion flow: The data from sensors are integrated with the data relating to the mission history. The final tensor will take into account the data fusion useful as input to the neural network.

Finally, still for each aircraft, the Neural Network automatically creates an optimized Maintenance Scheduler, as depicted in Figure 3. This procedure optimizes the correct timeframe useful for maintenance execution, thus reducing maintainers working time, avoiding planning and managing manually all the aircraft-fleet maintenance.

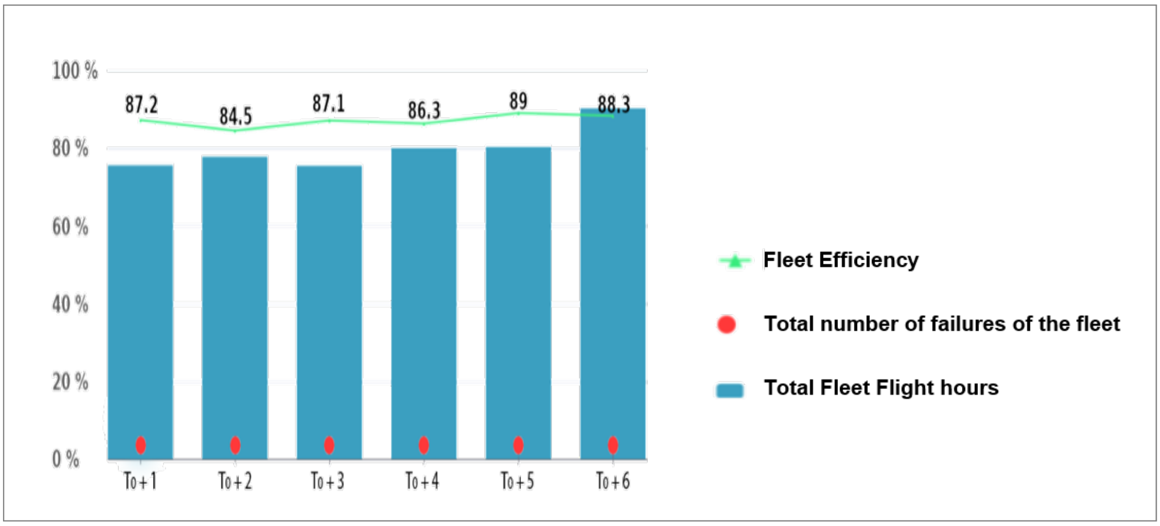

Figure 3: Availability Fleet Indices: The next 6 months network predictions for Fleet efficiency, Aircraft Failures, and Flight Hours parameters

3.2 Implementation Details

The core of the solution lies in the *Robust Statistical-Sensory Data* (RSSD) Neural Network, a sophisticated system capable of merging data of different nature. The network consists of convolutional layers concatenated with *LSTM* layers and, finally, fully-connected layers. While the convolutional and *LSTM* layers are responsible for extracting features from the data, the fully-connected layers use this information to estimate the Fleet Availability Index, which measures the availability for each aircraft over the next six months, starting from the last flight mission, and to report any anomalies that may occur.

Different nature of data are used: *engineering-type* data, such as data from sensors on the aircraft, and *non-deterministic statistical-type* data, such as bird strikes. As regarding engineering-type data, data from phatic meters, vibrations, as well as various other sensor parameters on the aircraft are used. Other inputs concern the sensors installed on the left and right engines. A data fusion of this information is performed and encapsulated in a tensor with a size of 6 rows, the months to be predicted, and more than 40 columns. The resulting output contains the stress index and the presence of any data on anomalies that might occur with their severity.

4.0 ETS DIGITAL TWINS

4.1 Use Case Description

Engine Test Stand (*ETS*) is the final process that allows engines to pass the performance check through rigorous tests. Once the tests have been passed, the engine is once again installed on an aircraft, ready for the next mission. Due to the effort, in terms of time and costs, that stands upon the execution of an ETS, the objective is to reduce, through appropriate software simulations, the overall number of possible *ETS* that a specific engine could be subjected to.

Digital Twin is a combination of two components: data and a representation of the given system. Using digital twin technology, industry, research units, and universities can build augmented reality (*AR*) software for engineers and maintenance technicians. For example, Tablet devices or *AR* glasses are exploited by operators to visualize the most up-to-date models of the machine laid over the one in front of them. This ensures the operators always have the right specs as they need them.

Given an aircraft engine SN, the proposed simulation pipeline allows the maintainer to compare different engine components by simulating their installation on the chosen engine. Hence, the resulting calculated parameters are used as input of the Neural Network to emulate the result of a performance check in the similar way as a real *ETS* performance check pipeline. This process results in the reduction of test execution time and costs, due to the fewer number of real resulting needed tests.

4.2 Implementation Details

The proposed network works by exploiting a 3-channel input tensor. Each channel contains data including properties that come from different physical nature:

1. Vibrometer and stress values
2. Values of the electronics sensors inside the motor
3. Pressure and temperature values

Predictions are made on certain parameters that must fall within certain ranges: if one of these falls outside the range, the bench test has failed. The parameters that are estimated are: engine rpm test, pressures, temperatures, and voltage values. In particular, during the simulation, the operator can select specific components in order to evaluate different possible module combinations. In this way, it is possible to compare multiple engine performance as depicted in Figure 4.

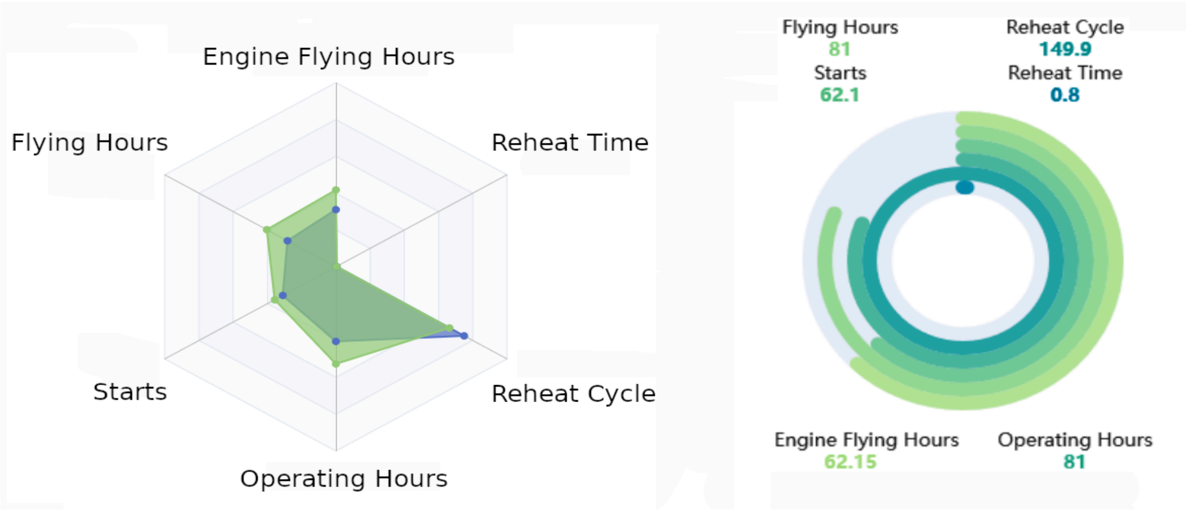

Figure 4: Engines Components Setup Comparison: In the left: The radar chart of a performance engines setup, chosen by the operator; In the right: The final candidate modules setup, chosen by the Neural Network

The network developed is a multi-branch convolutional neural network consisting of two inputs: the physical parameters, which are sent to a convolutional layer, and the parameters with the serial numbers of the engine components, which are sent to the fully connected cascade layers (*FCC*). The output of both layers flows into a final *FCC* layer to predict the bench test parameter as a regression problem.

4.0 CONCLUSIONS

The use cases described in this paper have been developed in collaboration with Italian Air Force that kindly provided the data collected during the life time of the aircrafts. In particular, these use cases are connected to key logistics processes for Italian Air Force where the aircraft platform availability is a fundamental parameter of military capability and represents an important measure of the readiness and effectiveness of a military force.

With the increasing involvement of NATO in deployment operations, there is today the need to increase the operational availability and mission reliability. To do that, it is necessary to minimise the need for maintenance and the related downtime.

If insufficient aircrafts are available to deliver a given capability, the force will be only partially ready or effective. Therefore, aircraft availability is a key parameter of both effectiveness and readiness in relation to a capability that requires aircraft to accomplish the desired mission.

The use of quantitative analytical methods based on Machine Learning (ML) techniques as applied in the 3 real-life use cases, provides an insight of how to maximise the aircraft operational availability by increasing the reliability of the prediction and improving the total true-life cycle cost.

The significant results achieved allowed to define a roadmap to developing further use cases in synergy with Italian Air Force with the goal to integrate the ML-based approach in the military organization.