Machine Learning Applied on Predictive Maintenance of Aircrafts: An experimental study

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Abstract

Maintenance is a constant for aircraft, and for this reason, it is well planned and scheduled with a proper timetable. The problem resides in unscheduled maintenance. Such event cause delays and considerable costs. In this context, predictive maintenance tools to support aircraft engineers to identify potential failures are gaining the attention of the airlines in the last few years.

In this project, we describe an approach using machine learning to analyze historical data of the aircraft and predict potential failures in order to support aviation engineers to take appropriate actions to avoid unscheduled maintenance. We apply ARIMA model to time series forecasting to detect anomalies. The anomaly scores are then determined based on the residual errors.

1. Introduction

The main objective of this project is to develop a machine learning approach that is capable of giving insights and alerts to help engineers to decide the best moment to proceed with the maintenance on the aircraft. In the project, we aim to use aircraft sensor values to identify unusual behaviour on the aircraft hydraulic system that can lead to a potential failure, so that maintenance can be planned in advance.

We first develop a general autoregression model using an open dataset available online and then we extend it and apply anomaly detection algorithms to discover operationally significant anomalies in the aircraft dataset.

As shown in Figure 1, utilizing the ARINC 429 DITS data busses, the behavior of the aircraft captured by thousands of sensors is stored in the black-box and in the Quick Access Recorder(QAR). In this work, we use QAR parsed data.

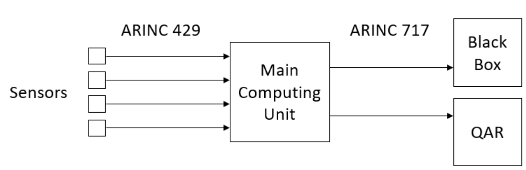

Fig. 1: Sensor data recording

2. Project description

2.1. Scientific

The main scientific aspect covered by this project is machine learning applied to predictive maintenance. Specifically, machine learning applied to time series forecasting.

2.2. Technical

The technical side of this project is related to developing a machine learning approach that is capable of giving insights and helping to determine when to proceed with the maintenance of the aircraft. We aim to develop a general time series autoregression model that could be then generalized to work with the time series data of the aircraft to predict when a failure of the aviation system might occur.

3. Introduction to Time Series (Scientific Deliverable 1)

3.1. Introduction to Time Series

A time series is a series or sequence of data points ordered in time. A time series can be represented by any data captured over time in sequential order. In a time series, time is the independent variable and the aim is to make a forecast for the future data points [1]. There are several important factors that we need to take into account when dealing with time series data, such as stationarity, seasonality and autocorrelation. Usuallly, we would like to have a stationary time series for modelling, however, it is possible to make time series stationary through transforming it. We see that the time series example below is stationary (the mean and variance do not vary over time):

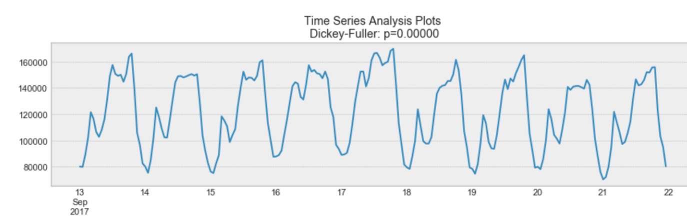

Fig. 2: Example of a stationary time series. Source: [1]

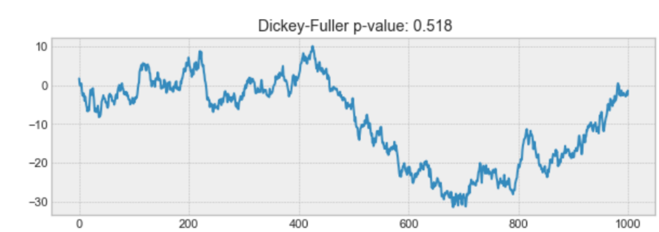

Fig. 3: Example of a non-stationary time series. Source: [1]

As an example, the time series above is not stationary as the mean is not constant over time.

3.2. Predicting Time Series

There are many ways to model a time series in order to make predictions, such as moving average, autoregression, ARIMA, Seasonal

ARIMA, and even Recurrent Neural Network (LSTM). In this project, we are focusing on ARIMA model, which is a class of statistical models for analyzing and forecasting time series data. ARIMA, is one of the most widely used forecasting methods for time series data forecasting.

4. Machine Learning Approach for Multi-Step Time Series Forecasting (Technical Deliverable)

The requirements of the deliverable are as follows:

- Develop a general time series forecasting model, that can be generalized to various use case scenarios.
- Next, we extend the general model described above to be able to detect anomalies with time series forecasting. The aim is to produce a robust data-driven anomaly detection model that will be able to find the discrepancy between predictions and real measurements over the time span of the specific event (i.e., aircraft failure).
- After implementing the models, we will discuss the results on how the models performed and what further improvements are possible.

We use Python and libraries, such as *Pandas*, *NumPy*, *matplotlib*, *statsmodels*, *sklearn*, *plotly* and *pyramid* for the implementation of the deliverable.

4.1. Autoregression Forecast Model for the Aircraft Engines Hydraulic Pressure

The case study presented in the project is concerned with the prediction of hydraulic pressure sensors data points. By our hypothesis, we want to investigate the anomalies *30 days* before and after the event, *60 days* before the event only, and *30 days* before the event only. This is due to the characteristics of the aircraft operation, as we want to see the behavioural trend before the event and after the event, when the maintenance has already occurred.

The Aircraft Engines Hydraulic Pressure is the dataset that describes the measures of hydraulic pressure sensors of the aircraft over almost *3* years. At a given day, each data point in the dataset is related to one flight.

5. Conclusion

In this project, we developed a machine learning approach that is capable of giving insights and alerts to help engineers to decide the best moment to proceed with the maintenance on the aircraft. We used aircraft sensor values to identify unusual behaviour on the aircraft hydraulic system that can lead to a potential failure, so that maintenance can be planned in advance.

References

[1] Peixeiro, M The Complete Guide to Time Series Analysis and Forecasting. https://towardsdatascience.com/the-complete-guide-to-time-series-analysis-and-forecasting-70d476bfe775

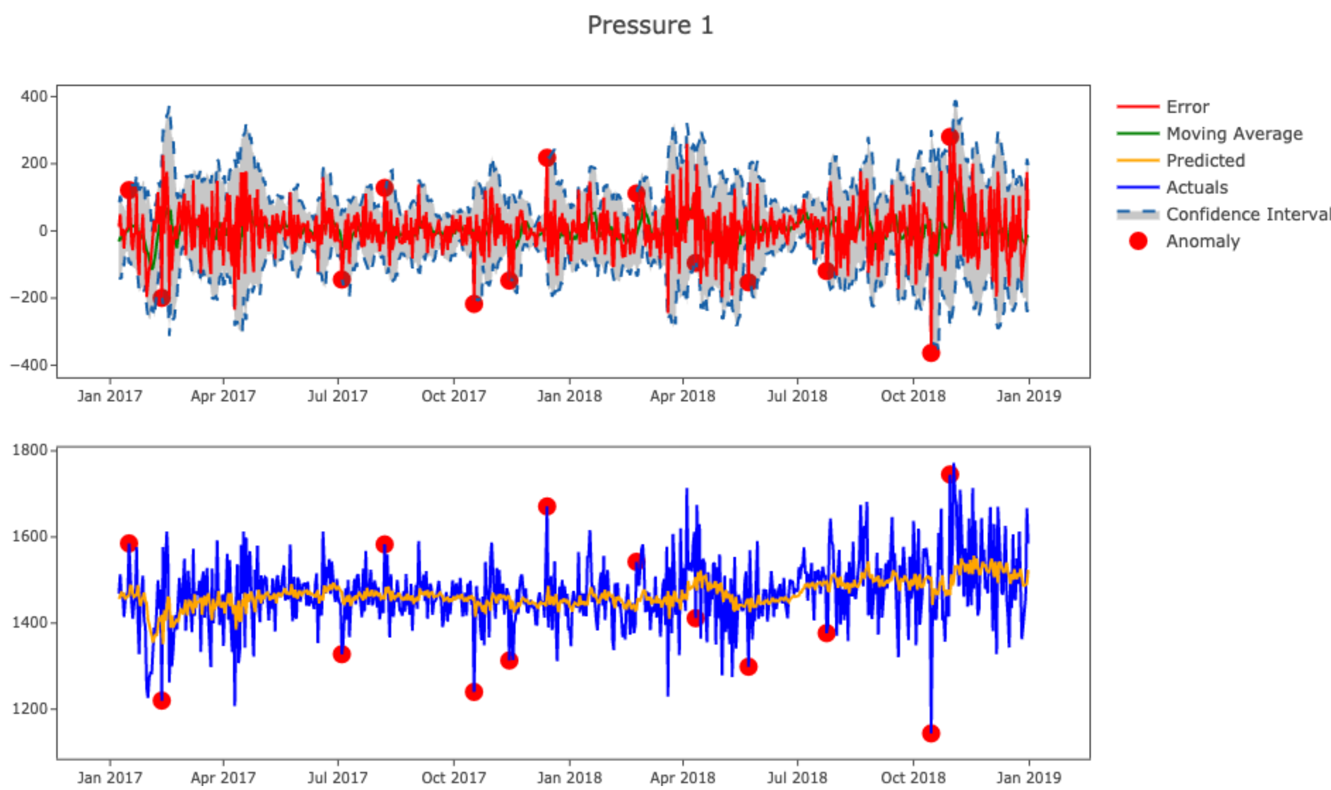

Fig. 4: The data from Hydraulic Pressure 1 for the first two years (*730* days). We split the selected time period on test and train dataset and take the first *730* dates from the dataset, as we have a total of *730* data points in the test dataset.