

# Bringing together Data and Physics to detect and predict gear failures

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## Abstract

Complex machinery such as aviation vehicles require well planned servicing, inspections, and maintenance to reduce faults and/or failures and improve availability. The severe consequences of ignoring maintenance related hazards in the aviation industry highlights the importance of a rigorous and pro-active maintenance approach in the lifecycle of these vehicles. A system to assure the safe and reliable operation of an aviation vehicle requires both a good complement of technical and management disciplines. The advancement in computer systems has played a major assistant role in empowering these disciplines in the recent times. From electronic data storage to advanced multi-physics simulation software, engineering fields have benefited from improvements in computing hardware, software, and networking. Now with recent developments in Machine Learning (ML) algorithms-equipped with strong computation devices and cloud services-the journey toward the application of data science methods in engineering and maintenance is enabling a shift from descriptive analytics with a focus on historical trends to real time or sensor driven predictive analysis capability. This paper looks at one of the potential applications of data analytics and Artificial Intelligence (AI) in the monitoring, prediction, and preventative maintenance of the helicopter gearbox. It analyses the generated vibration dataset of the seeded-fault test on the thin-rim helicopter planet gears and feeds them into an ML model to detect (and predict) the formation of a crack and its progression path. It also compares the result with a physical simulation of the phenomena, using Finite Element Method (FEM). The matching results from these three sources (i.e., the lab test, ML model, and FEM) will support future lab tests and ultimately strengthen the AI models to effectively inform and guide the technical and management teams in their efforts to detect failures early, reduce the cost of maintenance and save lives.

**Keywords:** Machine Learning, Finite Element Method, Maintenance, Asset Management, Aviation Industry

## Introduction

When designing aircraft, safety and operational reliability are paramount and are largely facilitated by the incorporation of redundancy. This redundancy is achieved either through duplicate systems (e.g., multiple engines or parallel hydraulic systems) or via substantial engineering tolerance from the expected component operating limits (e.g., wing loading failure limit vs max operating limit). In helicopters or rotary wing aircraft, the main gearbox is a single point of failure where any catastrophic issue will result in a total loss of the aircraft [1]. For this reason, civil airworthiness authorities require commercial helicopter main gearboxes (MGBs) to be certified to a 30-min “run dry” standard [2] where the gearbox will continue to operate in flight following a total loss of lubrication. This component is so critical that some manufacturers are now pursuing 50, and even 60 min, run dry capabilities [3].

The primary consequences of a catastrophic MGB failure are devastating for the survival of the passengers and crew, but there are also secondary consequences beyond the subsequent crash. Following the multiple incidents involving the Super Puma helicopter crashes, the manufacturer Airbus suffered initial costs to investigate and remediate the issues that lead to the MGB failures, before facing revenue loss from cancelled future sales of the aircraft type. The oil and gas industry, that relied on the type to provide rig-to-shore transfers of personnel, ceased

operating the Super Puma, with some countries such as Norway going so far as to ban the aircraft. In a military context, there have been recent cases of similar circumstances where after discovering or suspecting a fault, an entire aircraft fleet has been grounded due to safety concerns. This results in a loss of operational readiness and a risk to national security that could have been averted with superior system health monitoring.

Until the recent developments in ML and AI technology, the prevention of component failure depended on operators adhering to time-based maintenance servicing schedules. These are prescribed by the aircraft manufacturer and derived from test data during certification. Correction factors applied to flight time that recognize operations in abnormal environments (such as high all up weight, high G-loading or a corrosive saline environment) and vary the service or inspections schedule, are useful but imprecise in accounting for component fatigue and wear. Concurrently, onboard sensors act in real time during operation to detect and alert the crew of any limit exceedances, but they remain reactionary in nature and are unable to conduct analysis and predict failures. ML and AI are now making it possible to unlock the value of existing sensor data recorded during flight by deriving insights beyond simple limit adherence. During fleet planning, this change will allow for more accurate on-condition maintenance where components are serviced or inspected based on their actual rather than predicted wear, resulting in increased asset availability, and decreased operating costs. While during the day of operation, possible faults (such as the MGB crack in this study) can be detected and the asset withdrawn from operation for an unscheduled safety inspection, preventing catastrophic failure and saving lives.

### Methodology

Input data includes 526 .mat files, each includes [4 channels- one for each sensors X 405405 reading points] from the accelerometers. The data length for each of these files is 6.1 seconds. Collected data from the lab test on the gearbox and the accelerometer readings were provided as MATLAB files (.mat). The roadmap in Figure 1 shows the data preparation for this analysis:

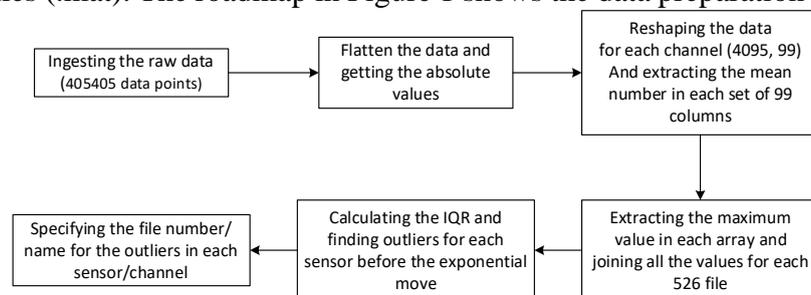


Figure 1. Data pre-processing for the analysis of one channel of one file

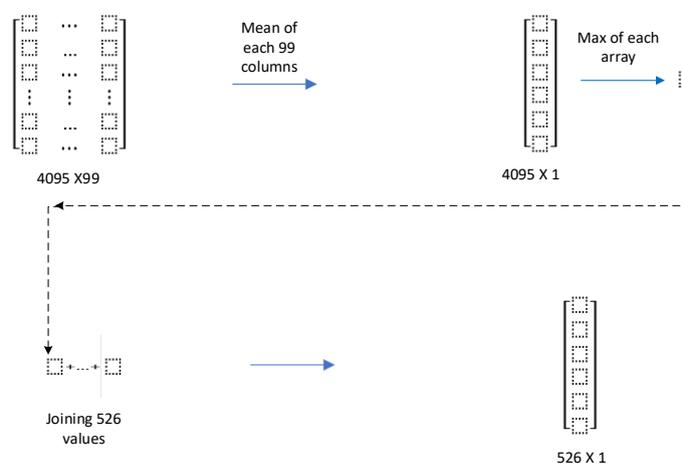


Figure 2. Data preparation for one channel of one file

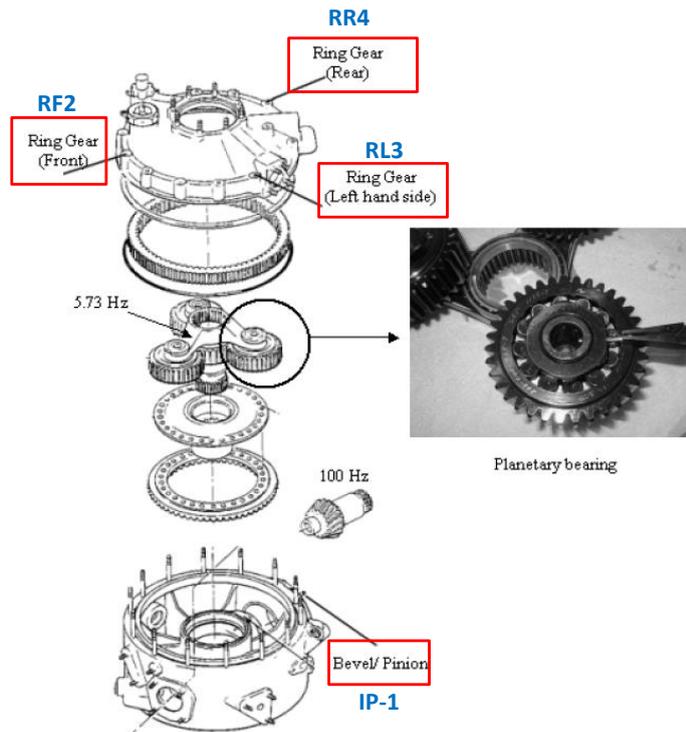


Figure 3. Bell 206B-1 (OH-58) main rotor gearbox (three-planet version). The four-planet version was used in the test. Four sensor locations are indicated in the figure.

Figure 2 shows the details of steps 1 to 4 in Figure 1 roadmap and Figure 3 illustrates the sensor locations on the gearbox.

As shown in this Figure 2, the data is first merged into a 3D matrix (for 526 files and 405405 readings X 4 channels). Then it is divided into 4 sections, for each channel. The absolute value of each 2D matrix of each channel is then kept for the next steps. The data is flattened and then reshaped to (4095 X 99) for the planet gear analysis. Getting the mean of 99 columns (one planet gear revolution) results in a 4095 X 1 array. Figure 4 shows the timeseries graph for the whole data and for all channels. The maximum value of each 4095 X 1 array is extracted for each 526 file which results in a final 526 X 1 array for each channel/sensor. Figure 5 shows the max of revolution mean for each file, for all channels.

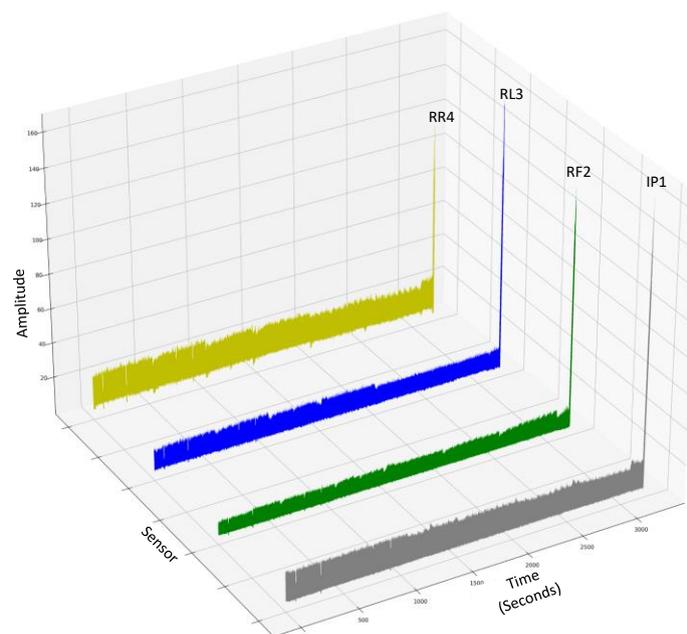


Figure 4. Timeseries graph for the mean of planet gear revolutions

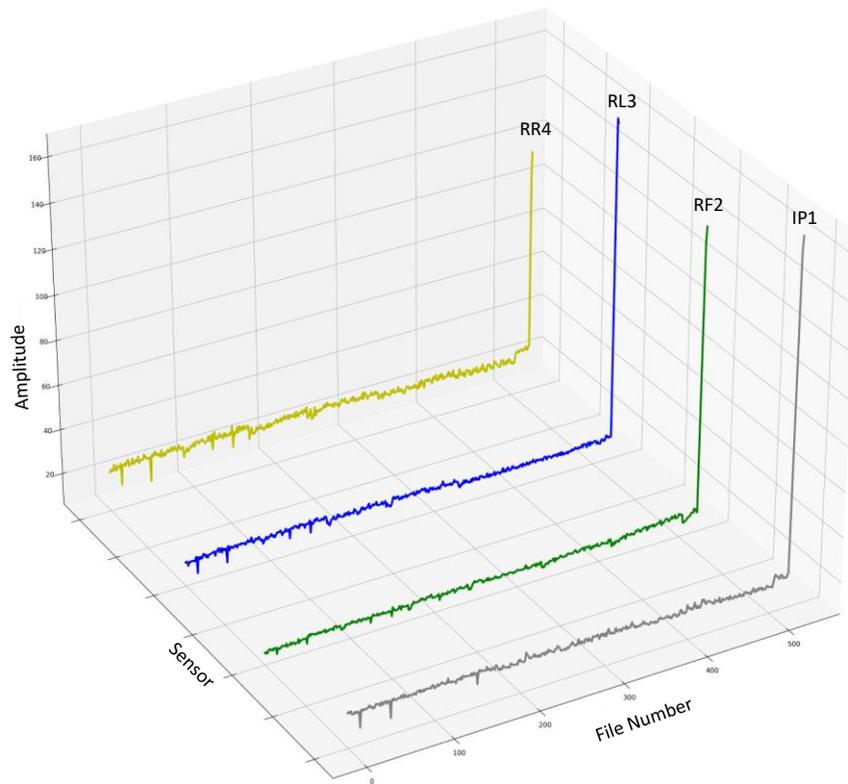


Figure 5. Max of revolution means of each file

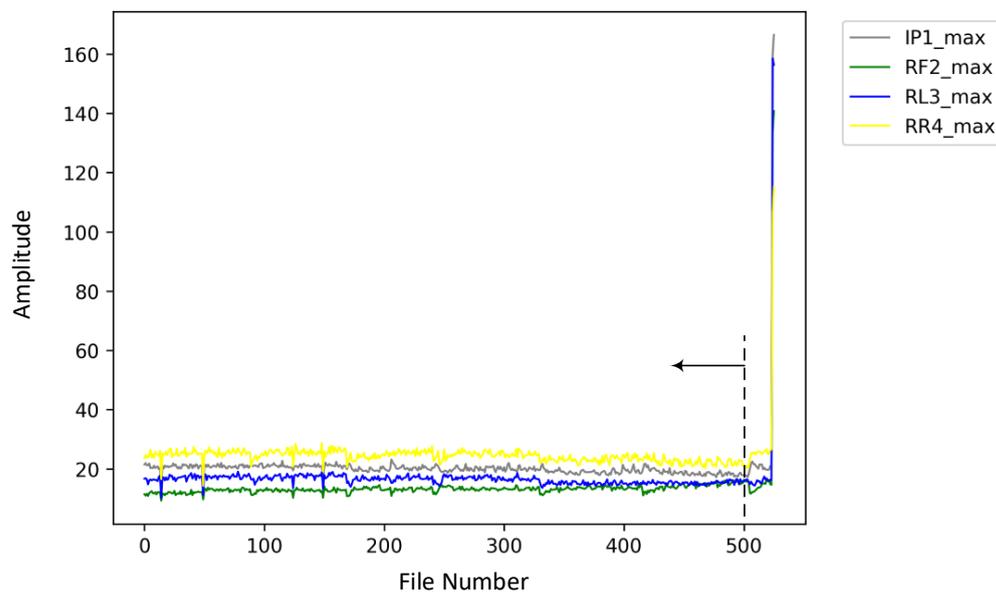


Figure 6. Flat view of the overlaid graphs of the max of revolution means for all channels

Figure 6 shows the flat view of the overlaid graphs of the max of revolution means for all channels. From this graph, the sharp increase (exponential move) in the amplitude happens after file 500. To have a clear picture of the data distribution-without being affected by extreme values after file 500- the final dataset is split between two parts: data before file 500 and after 500. The Interquartile range (IQR), as well as the lower and upper quartiles are calculated for the files before file 500 and these data, along with the specified outliers for each channel/sensor is used for the analysis in the next steps. Figure 7 illustrates the result for each sensor.

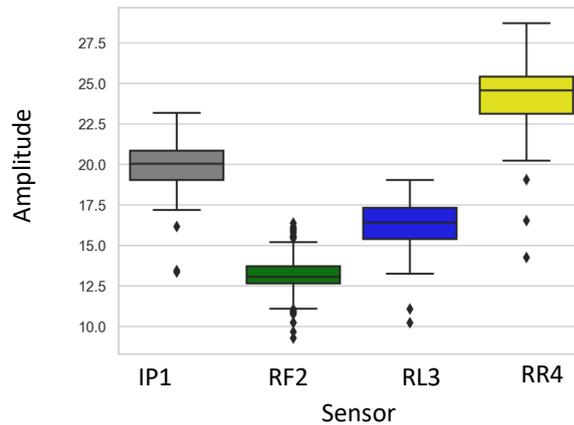


Figure 7. Box plots of the max of revolution means for all channels before file 500

### Description of fault detection method

Figure 7 illustrates the density plot view on box plots along with the outliers. The outliers on each channel/sensor reflects the amplitudes on each channel where the fault is located on the specific channel. By cross-referencing these outlier values with the filename-associated with the outlier amplitude-the specific filename can be detected. In other words, the algorithm will go through the list of filenames and their max of revolution mean, and extract the filenames associated with the outlier value.

The first fault is detected solely on the RF2 sensor on the fourth file-as shown on Figure 8 . The next fault on the 15<sup>th</sup> file is detected simultaneously on all sensors-as shown on Figure 9.

### Description of fault trending method

The algorithm will proceed with looking at the total values and point to where the amplitude of the max of the revolution mean reaches to a point where there is a consistent increase in it. This value can be different for each sensor, but the similar fact for all the cases is that this phenomenon happens after 500<sup>th</sup> file. The exponential change in the max of revolution mean is then visible from Figure 5.

The method described above uses the planet gear by reshaping the data to 4095 X 99 for each channel on each of the 526 files. The same method was used by reshaping the data to 11852 X 35-to cover the ring gear-and the same result (i.e., file number of earliest fault detection, simultaneous fault detection, and consistent increase and exponential change) were achieved.

## Results

Table 1 shows the summary of results for each part of the challenge:

Table 1. Summary of Analysis Results

#	Detection & Trending	Data file name/number
1	Consistent detection on at least one signal channel, i.e., the fault indicators remain consistently above the threshold.	Day021_Hunting_SSA_20211208_105651.mat/4
2	Confirmed detection on at least two signal channels, i.e., the fault indicators remain consistently above the threshold.	Day021_Hunting_SSA_20211208_113917.mat/15 Day021_Hunting_SSA_20211208_135820.mat/50 Day022_Hunting_SSA_20211209_124241.mat/125 Day022_Hunting_SSA_20211209_141330.mat/150
3	Clear multi-channel indication of the characteristic fault features, i.e., faulty planet gear meshing with both the ring and sun gears.	Day021_Hunting_SSA_20211208_113917.mat/15 Day021_Hunting_SSA_20211208_135820.mat/50 Day022_Hunting_SSA_20211209_141330.mat/150
4	Confirmed trend of fault progression, i.e., a consistent increasing trend started from which file number/name.	Day026_Hunting_SSA_20220114_140718.mat/495
5	Confirmed trend of accelerated fault progression, i.e., a consistent exponential increasing trend started from which file number/name	Day027_Hunting_SSA_20220118_111018.mat/525

### Characteristic Fault Signatures of Early Detection

Figure 8 shows the earliest detection on RL3 on the 5<sup>th</sup> file. There is no simultaneous fault detection-on the same file number-on other channels/sensors. Figure 9 shows the case of the earliest simultaneous fault detection on multiple channels/sensors on the 15<sup>th</sup> file. These fault detections are based on the outliers, and the outliers are calculated-for each channel/sensor-based on the interquartile range and the upper and lower ranges. Figure 10 shows the box plot for each sensor for the range of files before the 500<sup>th</sup> file (where the increase in the amplitude is about to start). Finally, in the early detection part, the simultaneous fault detections can be extended to the other files, as illustrated in Figure 11 where the fault is detected simultaneously on files 50 and 150.

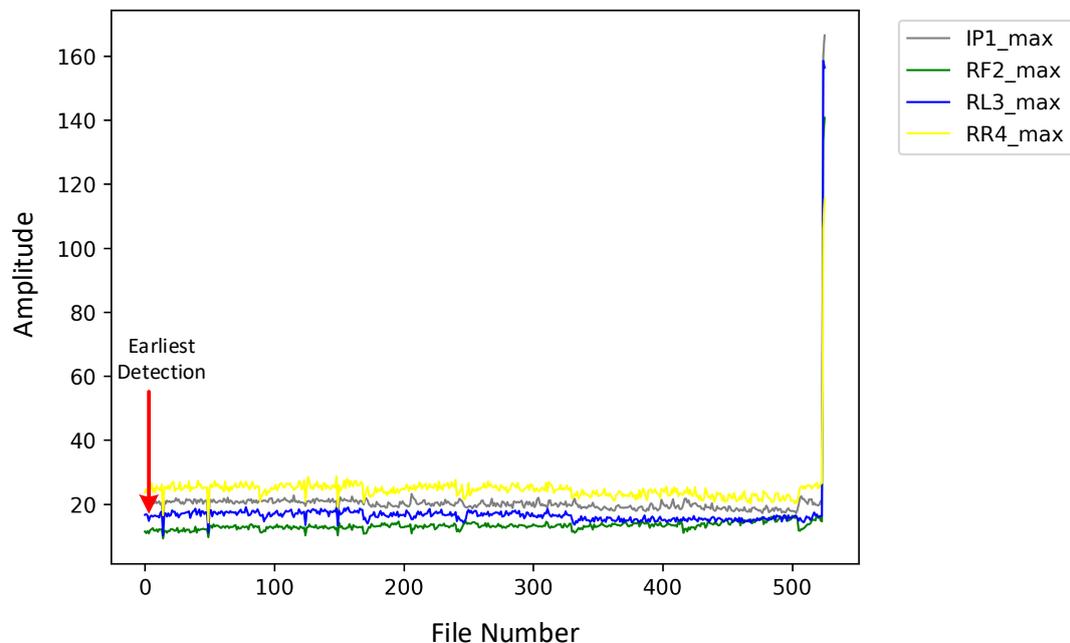


Figure 8. The earliest fault detected; it is on sensor RF2

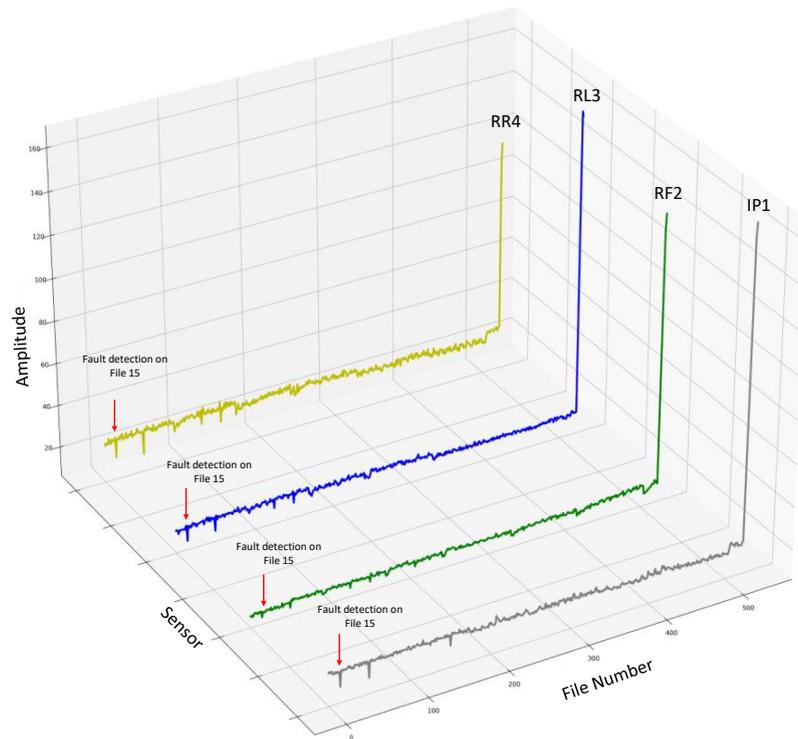


Figure 9. The earliest simultaneous fault detection on multiple sensors IP1, RF2, RL3, RR4

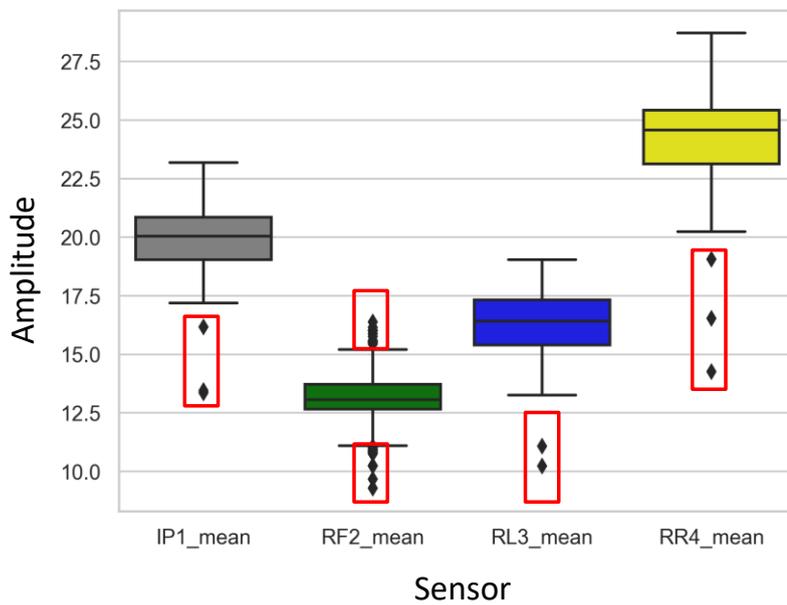


Figure 10. The box plots for the max of mean amplitude values and the outliers for fault detection

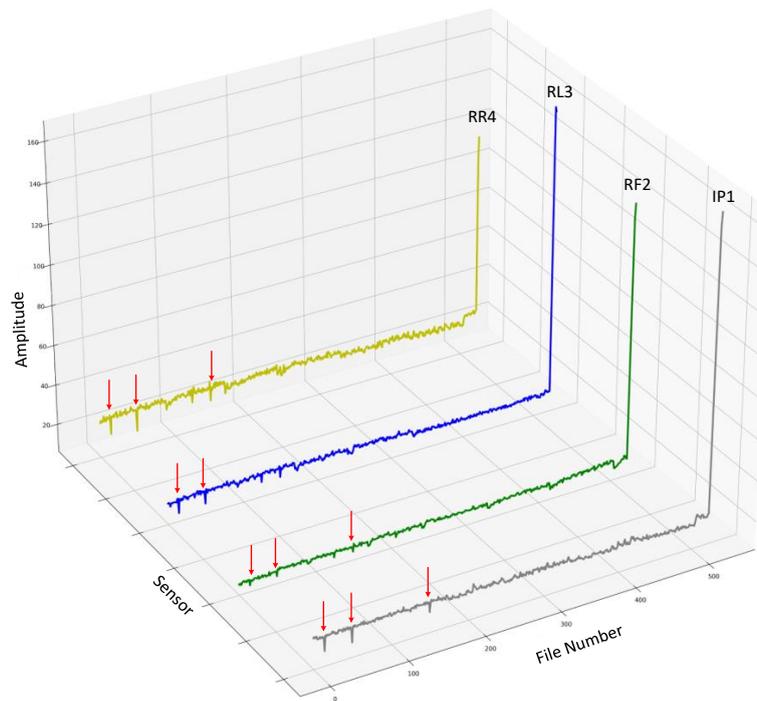


Figure 11. Simultaneous fault detection on multiple sensors

### Fault Progression Trending Curve

The other two parts of interest in this analysis are the consistent increase and the exponential increase in the amplitude. The focus of the algorithm is now shifted from the outliers and it looks at the whole dataset. The algorithm looks at each data point (out of 526 values) and compares it with the rest of following values; if there is no decrease, it picks that point as the start point for the consistent increase. Figure 12 illustrates such starting points on RF2 and RR4 charts. The exponential point of increase can be seen in Figure 13 on all the sensors. Although it is obvious by looking at the graphs, mathematically speaking, the algorithm looks at each value (from the 526 values) and checks the difference with its next coming value (e.g., difference between file 500 and 501), and check if the difference is within the upper and lower range for the IQR of differences. If the value is an outlier, then that's the point of exponential shift in the amplitudes and illustrates the collapse of the gears because of the crack opening.

The final observation from the results is the limited number of faults detected between the initial fault and the final exponential increase and collapse. This is a sign that the ultimate collapse, as the result of mechanical fatigue failure, comes without many warning signs before it happens. This is of high significance that the alarming signals (i.e., faults) need to be detected, monitored, and the proper action being taken accordingly before the collapse.

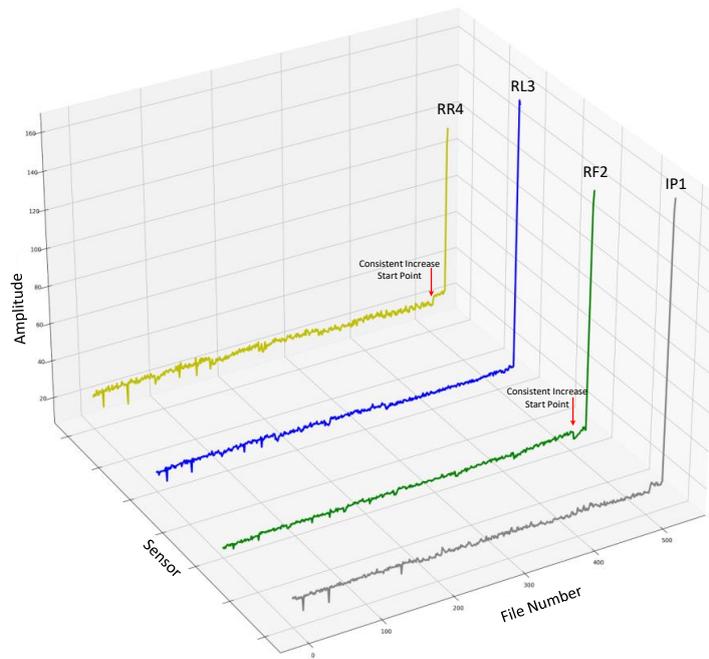


Figure 12. Consistent increase in the fault indicator on RF2 and RR4

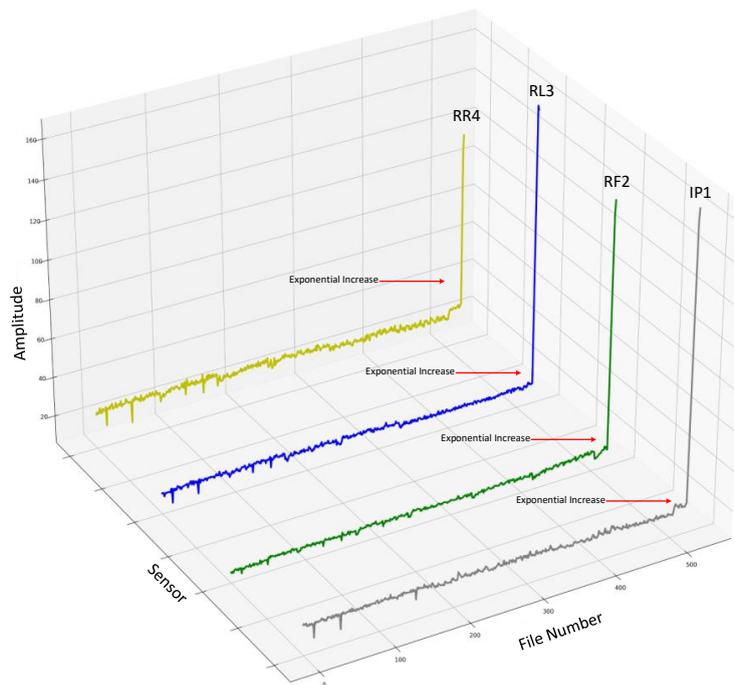


Figure 13. Exponential Increase in all sensors-possible collapse detection

## Concluding Remarks

The data analysis method was applied on a set of test data for a helicopter gearbox. The aim was to detect the fault in the reading points from multiple sensors and to trace the crack progression and final collapse of the gearbox. Several analytical approaches were tested, and the max of revolution mean were selected as a suitable method. The results from this method revealed the points in time where the failure points were detected and cross-checked for pinpointing the simultaneous fault on multiple sensors. This method has the capability to be implemented in a software product where the batch data is fed and analyzed. The type of sensors (i.e., accelerometer) and its ease of installation and the non-destructive form of data collection makes this a feasible method to be deployed in real scenarios. Collecting similar data in future (either from lab or from the flying helicopter) can assist in developing machine learning models to detect the crack progression on both stream and batch data. The nature of fatigue failure in the mechanical components and its sudden collapse, requires analytical methods such as this to predict the possible collapse and to take preventative action in a timely manner. The progression results-between the initial fault detection to the exponential increase and collapse point-showed the limited number of failure points. In real-case applications, it is critical to pick up on these limited number of failure points; missing the initial failure points may result in missing the most-significant alarms-and the chance to take action-before the catastrophic failure that may take the crew by surprise.

This analysis method and the potential machine learning models to detect the crack initiation and progression is a scalable and feasible method in many areas where the mechanical components are going through stress and/or strain circles. These circles are the major causes of mechanical fatigue failures, and they are famous for their sudden failure without any significant alarms and with the loads that are within the design load for the system. Finding cracks and their progression through traditional methods can be a time-consuming and expensive practice and the alternative non-destructive methods that use data from inexpensive and reliable sensors can find a valuable place in all engineering fields.

## References

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