A Flexible Data Management System for the Analysis of an Electro-Mechanical Actuator on a Test Bench

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ABSTRACT

The analysis of the behaviour of complex mechanical components to identify relevant patterns for health monitoring and diagnostics is a complex task. One example of this complexity is the data workflow that can be generated for analysis purposes when a new prototype of an electro-mechanical actuator (EMA) is being designed and experimented. The most accurate way of getting valuable insights during this analysis is by running tests in a controlled environment. Depending on the number and nature of the parameters to be obtained, the prototype's functionality under study, and the test frequencies and experiment duration, big data challenges may appear (volume, variety, and velocity). This work describes a data-driven information system developed for an electro-mechanical actuator on a test bench. It uses a multivariate statistical process control (MSPC) and a linear discriminant analysis (LDA) algorithm for detecting and evaluating the evolution of the actuator's health. The information system runs an automated data pipeline on a cloud platform with signals obtained on the test bench, leveraging data operations (DataOps) and machine learning techniques for a flexible and scalable data management.

1. INTRODUCTION

An electro-mechanical actuator (EMA) is a "power-by-wire" (PBW) device that uses an electrical source to generate mechanical motion (linear or rotary), instead of using hydraulic lines and pumps, or pneumatic circuits. The aircraft industry is pushing towards the use of these type of components as one of the aspects of the "More Electric Aircraft" (MEA) and "All Electric Aircraft" (AEA) paradigms.

The use of EMA components on aircrafts can bring numerous benefits (Qiao, Liu, Shi, Wang, Ma, Teik, 2018), for example:

- Weight savings, as the removal of hydraulic pumps means a reduction in weight.
- Higher engine efficiency and a reduction in fuel consumption, due to the removal of non-propulsive bleed air off-takes in engines.
- A better maintainability, because electrical systems are easier and faster to replace than most pneumatic and hydraulic systems.

Despite the advantages of EMA technology, there are still some technical, economical and safety challenges, which have restricted its use in the aviation industry to non-critical applications, or as a backup solution for hydraulic actuation. There has been a great effort at research level (Li J., Yu, Huang, Li Z., 2016) (Mazzoleni, Previdi, Scandella, and Pispola, 2019) to tackle these challenges, especially the problem of mechanical jamming. There are some approaches that can be followed to mitigate this, including a fault tolerant design, improved maintenance, and fault diagnosis (Hussain, Burrow, Henson, Keogh, 2018).

Fault diagnosis and condition monitoring techniques are widely spread in many industrial scenarios, but they are not a common practice in aeronautical actuators, where preventive maintenance is still a common practice (Zhang, Liu L., Peng, Liu D., 2018), and they are still in the early stages in EMA components (Ruiz-Carcel & Starr, 2018). Therefore, the use of health monitoring techniques can be a key strategy for improving the reliability of EMAs, thus moving from preventive to predictive maintenance (Todeschi & Baxerres, 2015).

The use of a test bench for the accelerated degradation of EMA components can be an efficient strategy to develop health monitoring algorithms for failure anticipation. A set of tests can be applied in this controlled environment to simulate the loads experienced by the actuator during its operational lifetime. Data is obtained from internal parameters in the control system and from sensors installed in the component (for example, accelerometers, or current sensors). This information can be taken through the whole life cycle of the actuator, and thus data driven algorithms can be developed.

The data management system needed to develop such data-driven algorithms must face several challenges. First, large amounts of data have to be acquired to detect patterns in signals where the behaviour is different from normality, as this may lead to conclusions about the condition of the EMA under study. Next, end-to-end automation is very important to obtain repeatable and reliable results. This can be applied at different levels, such as infrastructure provisioning, release management, workflow processing, quality assessment, and monitoring. Also, adapting to change and flexibility are desirable, due to the experimental nature of test bench activities. Finally, close cooperation in a multidisciplinary team is essential to enhance productivity and come up with a useful solution. This is the kind of scenario where data operations (DataOps) techniques can deliver good results and bring the data analytics project to a successful end.

DataOps is a methodology inspired in lean manufacturing, agile, and DevOps practices, that can be used to accelerate the development of data analytics solutions and ensure their quality (Ereth, 2018) (Munappy, Mattos, Bosch, Olsson, Dakkak, 2020). Putting the term "Ops" in the same level as "Data" emphasizes the importance of deploying data projects into production. The same way as lean principles can be applied to a production line, a data science project can take advantage of these methods to increase efficiency, provide consistent quality, foster collaboration between stakeholders, and continuously improve the processes. Agile practices, on the other hand, focus on adding business value to the outcome (Atwal, 2020). DevOps promotes more frequent software releases, automation strategies to ensure reproducibility of operations, and widespread testing to obtain reliable data insights (Capizzi, Distefano, Mazzara, 2019). Thus, many industries (Sahoo, 2019) (Atwal, 2020) can leverage this approach to bring data projects beyond the implementation of local applications and prototypes.

This paper presents a data management system that uses this methodology on a cloud platform for the analysis of the operational data coming from a fatigue test performed on an EMA prototype. The fatigue test has been conducted on a test bench designed and built specifically for this purpose at Tekniker research center. The system uses a data-driven multivariate statistical process control (MSPC) method for detecting anomalies during the EMA operation, and then executes a linear discriminant analysis (LDA) algorithm to identify the parameter that can lead to the source of the problem.

Data-driven approaches with different techniques have been proposed in the literature in recent years to devise health monitoring methods for EMAs. Data-driven semi-supervised algorithms have been used for anomaly detection to address the scarcity of anomalous data in this type of actuators. One example can be found in Pang, Liu, Peng Y., and Peng X. (2018) with the use of Gaussian process regression (GPR) and relevance vector machine (RVM) for anomaly detection in sensor data series. They developed a graphical indicator of the receiver operating characteristic curve of prediction interval (ROC-PI) to measure the model performance. Another example was presented by Zhang, Liu, Yu, Peng Y., and Peng X. (2017), where the estimation of the remaining useful life (RUL) was improved by ensemble learning with a weighted bagging Gaussian process regression (WB_GPR) method.

Yang, Guo, and Zhao (2019) presented in their work a recurrent neural network to consider the time dimension of EMA sensor data for fault detection and isolation. They proposed some improvements in a standard long short-term memory (LSTM) network to achieve a better classification accuracy and training performance in the model, and to allow for correlation between sensors.

Chirico and Kolodziej (2014) chose a data-driven fault classification technique based on frequency domain features extracted from EMA signals (motor current, position, and motor velocity data) and accelerometers (vibration data). PCA was used to choose the most effective features, which were the input for a Bayesian classifier, and the results were validated on an experimental setup.

Mazzoleni et al. (2019), within the European H2020 REPRISE project, obtained health monitoring indicators from the output of a Hotelling's mutivariate chart built with EMA controller signals (motor phase currents). Ruiz-Carcel and Starr (2018) generated a condition indicator based on features extracted from electric current and position measurement, and a comparison with normality was done through the Hotelling’s chart method. During the experiments, seeded faults were manually introduced in a test bench to simulate mechanical problems.

The approach followed in this work also uses a Hotelling's multivariate control chart for failure detection, using a higher number of signals due to the additional sensors added to the bench. In this respect, the approach of collecting and analysing data at large scale in a multisensor fusion environment, using the cloud as a supporting element, is what makes this proposal innovative.

The remainder of this document is organised as follows. Section 2 describes the experimental environment, the data acquisition hardware and sensors, and the test strategy. Section 3 explains the general approach to the solution. Section 4 focuses on the design of the data management system. Section 5 presents the data analysis results. Finally, section 6 summarises conclusions and suggests future work.

2. EXPERIMENTAL SETUP AND TEST PROCEDURES

2.1. Test Bench

The testbed used for the experiments with the EMA is shown in Figure 1. The actuator is mounted inside a metal housing and placed at the same operational angle as on the aircraft. The hydraulic system simulates the load exerted by a primary flight control surface, and the EMA must in turn apply a force to move it. The test bench response time is lower than 1 second, and the maximum force that can be applied by the hydraulic system exceeds 35 KN. This means that the system can simulate the different forces encountered during flight.

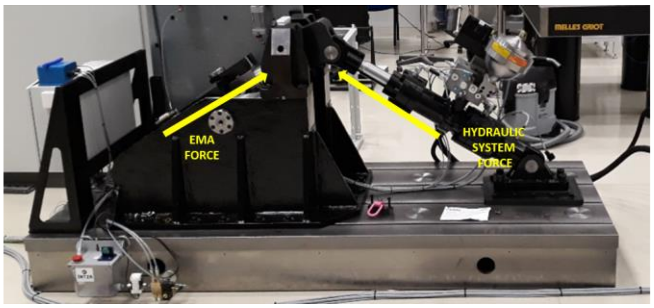

Figure 1. EMA test bench.

2.2. Data Acquisition System

The two acquisition devices used during the experiments are the following:

- A National Instruments CompactDAC system (cDAQ-9171 with a NI-9223 module), specifically aimed at reading data coming from acoustic sensors, due to the high frequency requirements for these readings.
- An Ingesys IC3 device, which is a general-purpose control system in charge of gathering information other than acoustic emissions.

The following sensors have been included on the bench:

- Thermocouples for registering the temperature in the room and in different critical positions on the actuator.
- A 3-axis high frequency accelerometer (CTC, AC230-2D/006M-F3C) with an acquisition rate of 25 KHz, and a measurement range from 0.6 Hz to 10 KHz, enough to cover the entire frequency spectrum in the test rig.
- An acoustic emission sensor (Kistler 8152B1), with an acquisition rate of 1 MHz, and a measurement range from 50 KHz to 400 KHz.
- A current sensor (LEM HTA 100S) installed in the electric cabinet to measure motor current consumption. The acquisition rate for this sensor is 25 KHz.

2.3. Test Procedures and Acquisition Process

The goal of the fatigue test is to wear down the EMA in an accelerated manner through a series of continuous movements simulating operating conditions, until the EMA has mechanical fault, or else reaches a point where degradation can be detected. During this experiment, information related to the EMA operation (such as speeds, positions, number of cycles, etc.) is acquired periodically (every 10 minutes) for a few seconds. In addition to this, specific condition tests are executed once a day to obtain information that can be used for health assessment. The fatigue test must be stopped to perform these condition tests, and then resumed when they are finished. The focus of this work, however, is the analysis of the fatigue test exclusively.

Figure 2 shows the acquisition steps and the main signals involved in the fatigue test (the acquisition frequencies can be seen in section 2.2). The configuration settings for the bench and the experiments are stored in a local database. Test results with electrical units are saved into MATLAB files, and metadata information is registered in database tables.

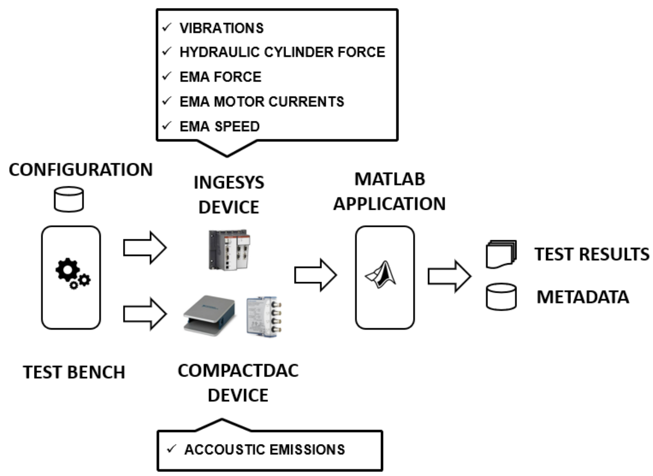

Figure 2. Acquisition process and test signals.

3. ANOMALY DETECTION AND DIAGNOSTICS STRATEGY

Data obtained during the experiment is not labelled, which means that an approach for anomaly detection must be applied without using supervised methods. In this respect, a good strategy for this analysis can be found in the work of López de Calle, Ferreiro, Arnaiz and Sierra (2019), where a fault detection method is presented during the real-time monitoring of a machine based on dimensionality reduction and statistical process control techniques.

This method assumes a monotonic degradation trend of the asset during the process, so that a health assessment can be made in the absence of previous experience in working conditions, or in the event of a non-labelled dataset, as is the case of the scenario considered in this work.

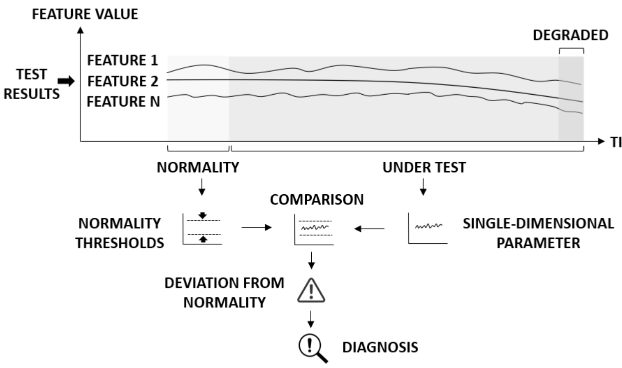

Figure 3. Anomaly detection and diagnosis.

Figure 3 shows that statistical thresholds representing normality are calculated from a set of features when the actuator is in a non-degraded state. These thresholds are compared with a single-dimensional parameter obtained in the section of the features where the EMA could be in a degraded condition. Thus, deviations from normality can be detected when the parameter goes beyond the limits. After this, a diagnosis is made to determine which feature has changed the most with the respect to normality, as this could provide clues for explaining the change in the EMA state.

This strategy is implemented as a pipeline in the data management system, which can be seen in Figure 4.

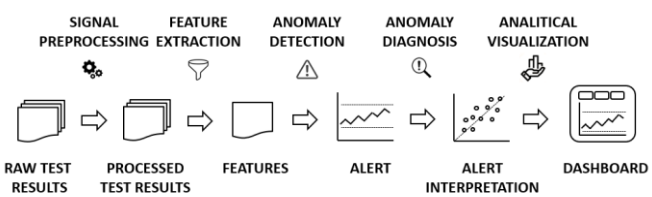

Figure 4. Steps of the data pipeline.

This pipeline is executed periodically as a batch process once a day with all the accumulated test results gathered during the experiment on that day. The details of every step of the pipeline are provided in the following sections.

3.1. Signal Preprocessing

Data acquired from the bench is stored in MATLAB (MAT) files in electrical units, and they must be converted to physical units. In addition to this, samples taken with the same trigger signal in both acquisition devices must be synchronised to a common time base. The metadata for this conversion can be read from the test bench database and from the MAT files.

3.2. Feature Extraction

During this step, a set of statistical features in the time domain are obtained for every cycle in the fatigue test (a cycle is each of the iterations which are repeated over and over, simulating the EMA operating conditions). These features are aggregations and calculations aimed at detecting problems from different perspectives. Some typical features in the time domain are described below (Lei, 2016):

- Mean value, root mean square (RMS), peak value. These values can be good fault indicators as they can be amplified by the presence of a mechanical fault in the EMA, and this change in the amplitude and energy can be proportional to the severity of the fault.
- Kurtosis value, crest factor, clearance factor, impulse factor. These calculations could be used for detecting the beginning of a fault, as they are more sensitive to peaks in the signal.

3.3. Anomaly Detection

Once the features are obtained from the signals, a multivariate statistical control chart is developed. A multivariate technique is preferred over univariate procedures (where variables are monitored individually) as we want to account for correlation between features. Among the different multivariate techniques, the Hotelling's control chart is a classic method (Montgomery, 2013), allowing observations to be plotted as a single statistical calculation (Q value) on a chart, together with two control limits. The application of this technique involves two phases:

- Phase I: a control chart is used to check the stability of the segment of the features taken as a reference for normality.
- Phase-II: another control chart is used to check if the process under test is in statistical control, using threshold limits created with the dataset used in Phase I.

To avoid potential computation overflows in chart calculations and decrease the influence of irrelevant data, a previous step of feature dimensionality reduction is applied with principal component analysis (PCA).

3.4. Anomaly Diagnosis

To determine which feature changes the most between the "non-degraded" state (normality) and the "degraded" state, a linear discriminant analysis (LDA) algorithm is used. As can be seen in Figure 5, the goal is to obtain a linear projection (LD1) maximising the separation between the groups of features representing the two states.

The samples with the "non-degraded" label are taken from the dataset created during phase I of the Hotelling's method. The samples with the "degraded" label are obtained from the first point in the chart where the process is considered out of control (and the number of elements is the same). The feature having the largest absolute coefficients in LD1 could provide clues for explaining the change in the EMA state.

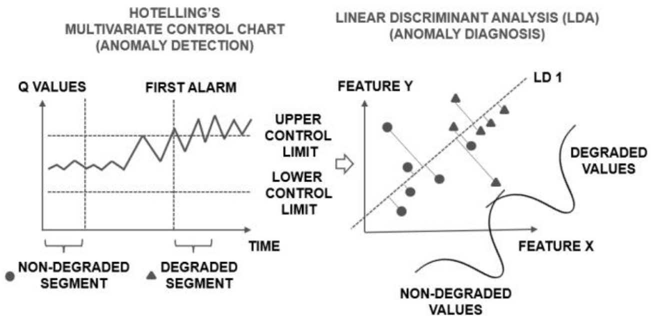

Figure 5: LDA analysis for diagnosis.

3.5. Analytical Visualization

An analytical dashboard is the last stage in the pipeline to get useful insights and metrics. The dashboard can be easily updated without requiring programmatic skills.

4. Data Management System

4.1. Design Principles

Several DataOps principles (The DataOps Manifesto) have been considered to implement the software platform:

- Reproducibility. All the steps are automated and orchestrated, which brings reproducibility and reliability to the results.
- Flexibility and collaboration. The core of the platform is a data lake where authorised stakeholders can access the data. This facilitates analytics, software engineering, and IT operations.
- Agility and speed. DevOps practices like infrastructure as code (IaC), continuous integration (CI), and continuous deployment (CD) facilitates integration of changes into production, as well as the quality of the process through testing.
- Adaptability and reusability. The platform can be adjusted and reused for new types of tests, or different versions of the EMA.

The cloud is a suitable option to meet these requirements, offering infrastructure, platform, and function as a service options (IaaS, PaaS, and FaaS), which can provide scalability for computation and storage, data governance, orchestration tools, and infrastructure provisioning resources. Leveraging these capabilities, the platform has been built using Azure cloud services.

4.2. Platform Implementation

Figure 6 shows the high-level architecture of the data management system. Data coming from the test bench is loaded periodically into the system through a scheduled task created with an Azure WebJob and an Azure Data Factory pipeline. An Azure Blob Storage account stores the raw information coming from ingestion, including the files generated during the analysis. Metadata is kept on an Azure SQL Database instance. This metadata is used in the preprocessing stage to parse the raw MAT files and generate the features for the analysis.

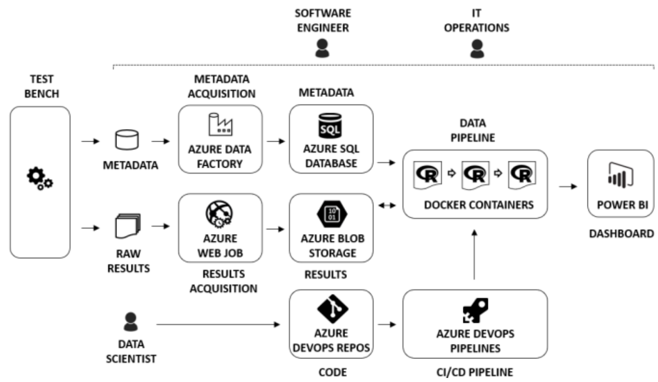

Figure 6: Implementation of the data processing pipeline.

Using a schema-on-read approach, an ELT (extract, load, transform) data pipeline is run periodically for data extraction, preparation, and analysis. These steps are executed as microservices inside their own docker container, and the output of each module is the input of the next. The intermediate results are stored in the Azure Blob Storage account. This strategy ensures decoupling of the modules, which improves the flexibility and adaptability of the system. The whole process is orchestrated so that the tasks are triggered sequentially at the right time. The workflow is efficient as it processes data incrementally (only new data is read in each execution). The dashboard is implemented with Power BI, and it is updated periodically with the results stored in the Azure Blob Storage account.

An infrastructure-as-code (IaC) template created with Azure Resource Manager (ARM) is used to define the platform resources in a declarative manner, and to create both a development and a production environment. The template is executed as part of an Azure Pipeline service for CI/CD.

5. Results and Discussion

During the execution of the fatigue experiment, a test bench component in the hydraulic system had to be changed. This component was causing the system not to work properly, and this incorrect behaviour was detected by the multivariate chart, as it is explained in the next section.

Given that a new component was introduced at some point in the system, it was considered that two independent analyses had to be performed on the data: the first one with samples before the test bench refurbishment, and the second one with samples after the component was replaced.

The following sections present the results of both analyses.

5.1. Analysis before the Test Bench Refurbishment

Figure 7 shows the multivariate control chart corresponding to the samples collected until the test bench component was replaced.

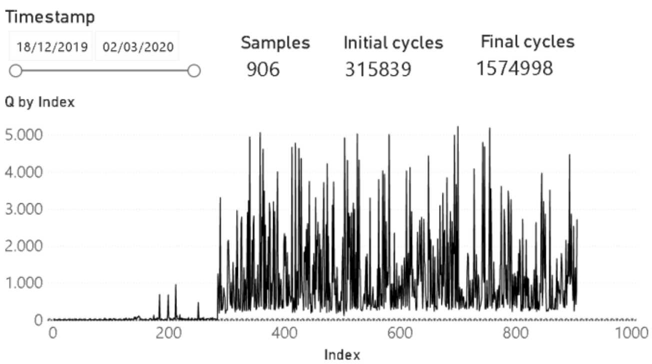

Figure 7: Chart before the test bench refurbishment.

The upper and lower control limits are situated very close to each other due to the comparatively higher values projected on the y axis. There is an initial period of stability in the chart, followed by a section with an increasing number of peaks above the upper limit, until reaching a point where the process went out of control. After doing some research, the cause of the problem was determined to be a faulty mechanical component in the hydraulic system of the test bench, which needed to be changed.

To confirm this diagnosis, a LDA algorithm was run to determine which features changed the most with respect to normality. The accuracy of the model for this analysis was 81,02%, which can be considered a good result in this scenario. The highest absolute coefficients in the linear discriminant (LD1) corresponded to features obtained from signal "Cylinder_force_filtered", which is the force applied by the hydraulic cylinder. This means that the algorithm was pointing to the right direction.

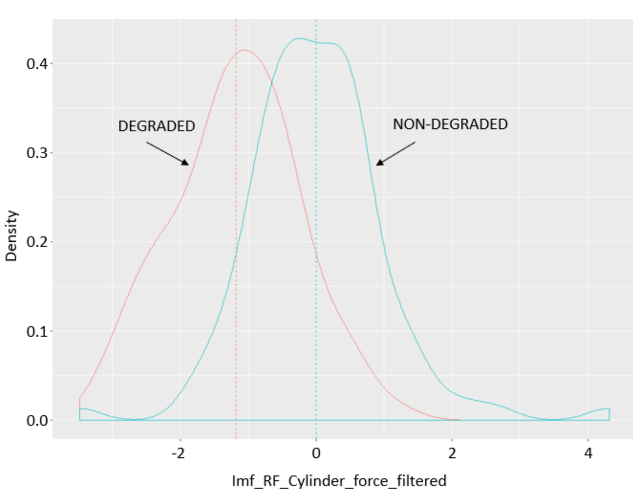

Figure 8: Density plot for LD1 highest coefficient feature.

Figure 8 shows the density plot for the feature with the highest absolute coefficient in LD1. As can be seen, the two sample types ("non-degraded" and "degraded") follow a normal distribution.

5.2. Analysis after the Test Bench Refurbishment

The second multivariate control chart presented in Figure 9 shows the evolution of the Q statistical values with the new mechanical component installed in the system.

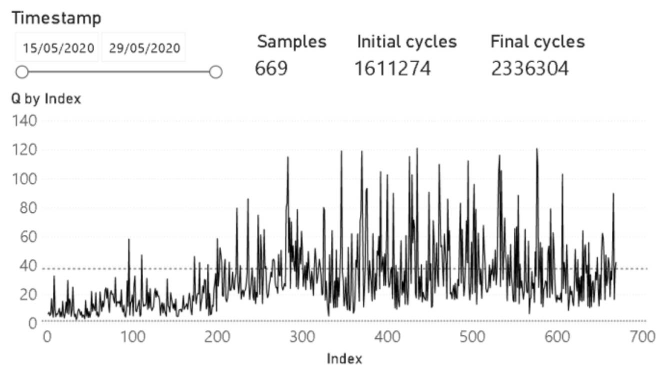

Figure 9: Chart after the test bench refurbishment.

The chart shows a raising trend in the Q statistical parameter towards the upper control limit, until a first critical point was reached. After this, the value went up and down around the limit, until it was decided to stop the experiment to check if the actuator was damaged (as it was confirmed later). As in the case of the first analysis, a LDA algorithm is executed to try to explain what happened. Here, the accuracy of the model was 48,09%. The accuracy is low, meaning that LDA cannot distinguish both classes, probably due to a lack of normality in the features. As can be seen in Figure 10, the two distributions in the density plot for the feature with the highest absolute coefficient in LD1 are non-normal.

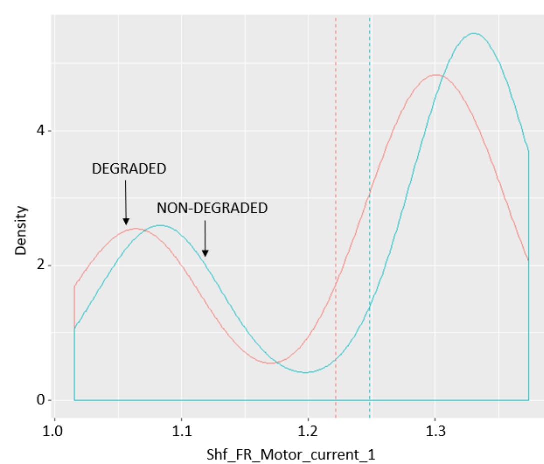

Figure 10: Density plot for LD1 highest coefficient feature.

6. CONCLUSIONS AND FUTURE WORK

6.1. Analysis Conclusions

The multivariate control chart worked well for both analyses, detecting that something wrong was happening in the system, and this was confirmed by the alarms raised in the test bench itself. Therefore, this automated platform provided useful information about the EMA state, helping in making decisions to prevent any problem that might occur to the EMA during the experiment. This is something important since the EMA prototype is an expensive system.

Regarding the explanation of the anomalies, the LDA algorithm worked well in the first analysis, pointing to the component in the hydraulic system as the cause of the problem. However, it could not explain the source of the failure during the second analysis. Therefore, it would be interesting to use other types of algorithms that do not rely on the normality assumption of the data to get a better result.

6.2. Data Management System Conclusions

The cloud has proven to be a very convenient environment to deploy this platform, providing the necessary processing and analytical infrastructure for a big data pipeline, without having to use the scarce resources of on-premises servers.

The use of DataOps principles facilitated the integration and orchestration of the activities:

- Changes in the data pipeline were deployed in production more rapidly through CI/CD practices.
- Data insights were automated and delivered periodically without the intervention of a software engineer.
- The platform was the central hub for collaboration between every role involved in the project (data analyst, software engineer, mechanical engineer).

Thanks to process decoupling, the data pipeline could quickly be readapted to perform a second analysis. Likewise, it could be extended for processing the condition tests, o for new versions of the EMA.

6.3. Future Work

As previously stated, a better alternative to the LDA algorithm for diagnosis should be found. Also, the analysis of EMA operational data can be complemented with the study of the condition tests performed in the same test bench. The goal would be to generate health features associated with specific functionalities in the actuator. Each of these tests is executed under the same conditions, so it would be possible to compare the features over time to make some conclusions about the EMA's health evolution. These features would have limits where the EMA health is considered safe, and these limits would be obtained through the analysis of the experiments similarly to other works in the literature (Ferreiro, Konde, Fernández, Prado, 2016).

NOMENCLATURE

AEA	all electric aircraft
CD	continuous deployment
CI	continuous integration
DataOps	data operations
DevOps	development and operations
ELT	extract, load, transform
EMA	electro-mechanical actuator
FaaS	function as a service
IaaS	infrastructure as a service
IaC	infrastructure as code
LDA	linear discriminant analysis
MEA	more electric aircraft
PaaS	platform as a service
PCA	principal component analysis
PBW	power by wire
MSPC	multivariate statistical process control

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