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USING DEEP LEARNING BASED CLASSIFICATION ALGORITHM TO DETECT FAULTS IN TURBINE ENGINES

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Abstract

In this paper We propose a comprehensive fault-domain-driven (FDD) approach for hydraulic systems to circumvent the constraints of supervised diagnostic tools in identifying atypical and beyond-label failures. This approach requires the inclusion of a categorization phase step prior to the diagnosis. Thus, the limits of supervised diagnostic procedures may be circumvented. In this part, we avoid the problem at hand by doing detection and diagnosis independently. Long Short-Term Memory (LSTM) autoencoders are used during the fault detection phase. In the subsequent phase, known as diagnostic, ML and DL classifiers are employed to identify the nature of the discovered defects. Even though there is evidence in the research pointing to the existence of this strategy, our work surpasses the previous art in the following respects: (1) The information collected from hydraulic test rigs has never been employed in conjunction with this specific schema. Two exhaustive trials demonstrated how this strategy may be used to resolve sensor and component difficulties. We used a unique LSTM autoencoder design in the third step, which was the detection phase. (4) During the autoencoder's detection phase, we devised a unique criterion for calculating the divergence between the anticipated signal and the input signal. It has been proved that this technique is superior to the conventional way for determining more exact diagnostic thresholds. (5) We gave a comprehensive examination of the performance of a wide variety of ML and DL classifiers that vary in their functionality and technique. These classifiers are proposed for usage during the classification's fault diagnosis phase. In addition, we analyzed the behavior of each machine learning and deep learning classifier using a range of time-domain feature selection techniques. This was done to aid future study by mapping each classifier to its most or least suitable time-domain feature in order to implement component or sensor FDD in hydraulic systems.

Keywords: FDD, LSTM, ML, DL.

TÜRBİN MOTORLARINDAKİ HATALARI TESPİT ETMEK İÇİN DERİN ÖĞRENME TABANLI SINIFLANDIRMA ALGORİTMASI KULLANIMI

Özet

Bu yazıda, atipik ve etiket dışı arızaları belirlemede denetimli teşhis araçlarının kısıtlamalarını aşmak için hidrolik sistemler için kapsamlı bir hata alanı güdümlü (FDD) yaklaşımı öneriyoruz. Bu yaklaşım, teşhisten önce bir sınıflandırma aşaması adımının dahil edilmesini gerektirir. Böylece denetimli teşhis prosedürlerinin sınırları aşılabilir. Bu kısımda, bağımsız olarak tespit ve teşhis yaparak eldeki sorunu önlüyoruz. Uzun Kısa Süreli Bellek (LSTM) otomatik kodlayıcılar, arıza algılama aşamasında kullanılır. Teşhis olarak bilinen sonraki aşamada, keşfedilen kusurların doğasını belirlemek için ML ve DL sınıflandırıcıları kullanılır. Araştırmada bu stratejinin varlığına işaret eden kanıtlar olmasına rağmen, çalışmamız aşağıdaki açılardan

önceki tekniği aşmaktadır: (1) Hidrolik test teçhizatlarından toplanan bilgiler hiçbir zaman bu özel şema ile bağlantılı olarak kullanılmamıştır. İki kapsamlı deneme, bu stratejinin sensör ve bileşen zorluklarını çözmek için nasıl kullanılabileceğini gösterdi. Algılama aşaması olan üçüncü adımda benzersiz bir LSTM otomatik kodlayıcı tasarımı kullandık. (4) Otomatik kodlayıcının algılama aşamasında, beklenen sinyal ile giriş sinyali arasındaki sapmayı hesaplamak için benzersiz bir kriter geliştirdik. Bu tekniğin, daha kesin teşhis eşikleri belirlemek için geleneksel yoldan daha üstün olduğu kanıtlanmıştır. (5) İşlevsellikleri ve teknikleri bakımından farklılık gösteren çok çeşitli ML ve DL sınıflandırıcılarının performansının kapsamlı bir incelemesini yaptık. Bu sınıflandırıcılar, sınıflandırmanın hata teşhis aşamasında kullanım için önerilir. Ek olarak, bir dizi zaman alanı özelliği seçme tekniği kullanarak her bir makine öğrenimi ve derin öğrenme sınıflandırıcısının davranışını analiz ettik. Bu, hidrolik sistemlerde bileşen veya sensör FDD'yi uygulamak için her sınıflandırıcıyı en uygun veya en az uygun zaman alanı özelliğine eşleyerek gelecekteki çalışmalara yardımcı olmak için yapıldı..
Anahtar kelimeler: FDD, LSTM, ML, DL.

1. INTRODUCTION

Gas turbines, often known as GTs, are a kind of mechanical device that utilizes air as its working fluid and operates on the basis of a thermodynamic cycle. When air is compressed, fuel is added, and the mixture is burned in a combustor, a hot, pressured gas is produced. The expansion of this gas by a turbine result in the creation of energy. This acts not only as the push for the compressor, but also as its resistance to environmental difficulties (that is, for thrust or shaft power). A generic definition of a motor would include the following components and pieces of machinery:

1) Compressors, burners, and turbines are a few examples of the gas stream's constituent parts.

2) Among the several movable components of engines are bearings, rotors, and gear trains.

3) The fuel regulation, the fuel pump, and the control system are all regarded as accessories.

The systems that regulate the engine's air-bleed, ignition, and lubrication. In contrast, the GT is often seen as solely consisting of gas route components in its most elementary form. GTs have an increasing variety of applications, including mechanical drives in the oil and gas business, energy generation in the power sector, and propulsion systems in the aerospace and maritime sectors. All of these applications have a direct effect on people's day-to-day lives and their eventual consumption patterns. Due to advances in design, aerothermodynamics, and materials/cooling technologies, GTs are becoming more economically feasible. These innovations improve GTs in a number of ways, including better overall performance levels, greater thermal/component efficiency, and longer periods between overhauls (TBOs). GTs were first used for stationary applications in the early 1950s. These turbines were based on the concept of steam turbines and used the aerothermodynamic technology seen in military aircraft GTs. These GTs were built with pressure ratios between 12 and 1, firing temperatures between 649 and 816 degrees Celsius, and thermal efficiencies between 23 and 27%. As a consequence of advancements in design, aerothermodynamics, and material and cooling technologies, the efficiency of current systems exceeds 45 percent even at the highest possible operating temperatures and pressures. Greater than ever, gas turbines are employed in combination cycles, mixed cycles (in which gas turbines are used upstream and steam turbines are used downstream), and even combined cycles that do not include the production of heat. As a consequence of these actions, engagement in the system has considerably grown. Moreover, GTs may run on a variety of fuels, such as coal and gases with a low heating value, resulting in less pollution than other sources of power production.

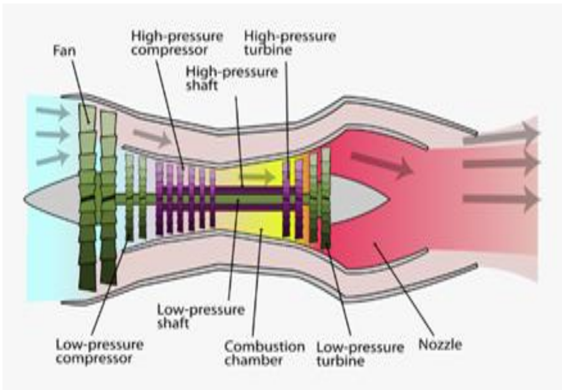

Figure 1. Schematic view of a gas turbine

Several sensors are coupled to diverse industrial machinery and equipment in order to train and automatically assess FDD algorithms and systems on a computer. These sensors continually provide signals that may be evaluated to detect the present state of the moving components of the machine. The sensor readings, sometimes referred to as modalities, are the source of the essential data used by automated FDD systems. If the sensors used to monitor these components are not in perfect operating condition, accurate monitoring of these components will not be possible. These sensors, which are attached to the piece of equipment, are necessary for computer-aided diagnostics; nevertheless, despite their importance, they are often absurdly inexpensive and continue to function even under extreme weather conditions. Therefore, sensors employed in mechanical systems cannot be relied upon and often become faulty for a number of reasons. As part of an intelligent FDD system, the health of the sensors responsible for reporting the condition of mechanical components must be checked.

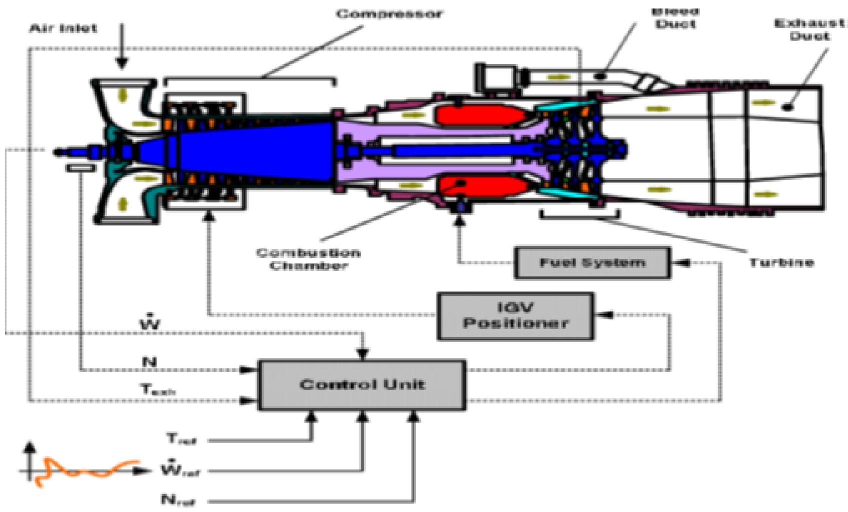

Figure 2. FDD system in a turbine engine

It is required to install component FDD systems in addition to sensor FDD systems in order to keep a close eye on all activities in the industrial sector. Hydraulic systems are some of the most crucial pieces of equipment when it comes to the production of goods. A hydraulic test rig was used in order to collect the required data for the study's hydraulic system. A test rig is a piece of mechanical equipment used to measure, analyze, and evaluate the functionality and efficiency of another piece of mechanical equipment or system, or a subset of the item being tested. The gear used for conducting tests is referred to alternately as a "test bench," "test pay," and "testing station." However, each of these names refers to the same thing. From the hydraulics sector to the aerospace business, test rigs are used in almost every area of the manufacturing industry. They have access to a vast array of analytical parameters and testing procedures, including, to mention a few, manual, cyclical, brake, and burst testing. This research focuses on hydraulic systems derived via a hydraulic test rig, which include a full FDD system of component and sensor issues. This is a result of the significance of hydraulic systems and the limited availability of FDD resources during the last decade.

Despite the recent rise in popularity of machine learning, researchers have barely scratched the surface of the potential of a hybrid model for defect identification and diagnosis leveraging artificial neural networks. Approaches based on hybrid ANNs may be able to significantly improve diagnostic skills in industrial contexts. This is because more and more information about processes is becoming accessible. This paper offers two hybrid strategies for fault detection and classification using supervised neural networks in an effort to further this area of inquiry. These methods use both unsupervised and supervised learning. The primary purpose of this thesis is to develop a hybrid strategy for problem detection in the chemical industry that combines traditional techniques with machine learning. This strategy will use both conventional techniques and machine learning. The precision of diagnostic processes will be one of the primary focuses of this investigation. This technique also aims to reduce the amount of time and resources necessary for model training and testing. This may be done with the aid of the following secondary objectives:

- Utilize the existing process data for identifying and investigating problems.
- Remove the noise from your data to improve the accuracy and efficiency of training a neural network.
- Utilize all visual information available when diagnosing difficulties.
- It is suggested that techniques be developed that permit the modification of network settings with little involvement from subject matter experts.

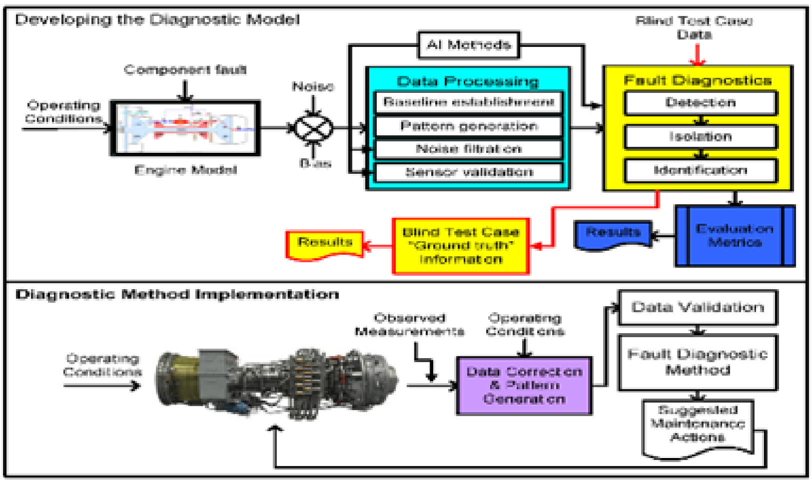

Figure 3. ANN system in fault detection

2. FAULT DETECTION FOR MAINTAINANCE

2.1. Definition of Industrial Maintenance

According to the AFNOR standard (NF X 60 010), maintenance is a “set of actions allowing to maintain or restore an item in a specified state or capable of providing a specific service”. Proper maintenance means ensuring these operations at the optimum cost. Indeed, whatever the field of activity, manufacturers must not neglect the costs and the various impacts that a sudden failure could cause. Their productivity relies heavily on their maintenance processes.

2.2. The Different Types of İndustrial Maintenance

There are three types of industrial maintenance. The first type is corrective maintenance. It is used to repair the failure of any equipment as soon as it arrives. It aims to restore the faulty equipment to working order after the breakdown. It is a corrective maintenance or also called curative maintenance. The second type of maintenance is preventive maintenance. The latter aims to detect and solve problems before they arise. It is usually carried out in the form of regular and planned inspections. The third type is that of predictive maintenance. According to the Cambridge Dictionary (Cambridge University Press, 2021), the adjective predictive is defined as "to say that an event or action will occur in the future". Maintenance is defined as “the work necessary to keep a machine in good condition”. In other words, predictive maintenance can be defined as a tool, which makes it possible to predict the future point of failure of a machine or system component before it fails. In fact, corrective maintenance is applied after the failure, while preventive maintenance uses precautionary measures to avoid possible problems. Predictive maintenance assesses the condition of existing equipment and, based on a projected trend of the deterioration process, failures are predicted and appropriate action taken (Matthew P. which predicts the future point of failure of a machine or system component before it fails. In fact, corrective maintenance is applied after the failure, while preventive maintenance uses precautionary measures to avoid possible problems. Predictive maintenance assesses the condition of existing equipment and, based on a projected trend of the deterioration process, failures are predicted and appropriate action taken (Matthew P. which predicts the future point of failure of a machine or system component before it fails. In fact, corrective maintenance is applied after the failure, while preventive maintenance uses precautionary measures to avoid possible problems. Predictive maintenance assesses the condition of existing equipment and, based on a projected trend of the deterioration process, failures are predicted and appropriate action taken.

2.3. Approach to a Predictive Maintenance Approach Based on Data

To be able to implement a predictive maintenance strategy, we must first have connected sensors that continuously measure the operating parameters of the equipment concerned. This data is massively collected and then transmitted using the IoT to an intelligence engine This engine analyzes the big data and cross-references them with the intervention reports carried out on the same equipment. The predictive model will thus gradually highlight correlations between certain information transmitted and breakdowns. He will therefore be able to learn that such measured values precede such type of failure. Thus, as soon as these values are measured again, he will be able to plan a maintenance action and avoid the occurrence of the failure.

For this, several tools are available for each phase of construction, and each tool is adapted to very precise characteristics which depend on the equipment and the field of activity of the industry. In this context, Radhya, John, & Muhammad Intizar (2020) have proposed a set of guidelines for decision makers to guide them in selecting the most appropriate technologies to meet their needs. Once the different technologies to be used have been selected, it is necessary to move on to the next step, which is the development of the predictive maintenance model. For this, four key steps have been identified. Indeed, the first step consists in collecting the data relating to the equipment, then analyzing them to classify them in normal state and non-normal state. Next, the second phase results in the modeling of failure patterns using algorithms for identifying anomalies on the one hand and, on the other hand, being able to classify them into several categories based on a history of failures. The next step is to develop the predictive model by teaching it to recognize new events and failures as they occur. Finally, what is interesting is to be able to adapt the system so that it can update its database according to the new information collected on the hardware. The next step is to develop the predictive model by teaching it to recognize new events and failures as they occur. Finally, what is interesting is to be able to adapt the system so that it can update its database according to the new information collected on the hardware. The next step is to develop the predictive model by teaching it to recognize new events and failures as they occur. Finally, what is interesting is to be able to adapt the system so that it can update its database according to the new information collected on the hardware.

IoT systems make it possible to refine the data collected which offers new value to the operator of the IoT system. To obtain new information, the process that is detected must be modeled. This process of modeling and extracting knowledge from datasets is called machine learning (Kapil & Kiran, 2018). This can be done, if enough data is available. In addition to the raw data, depending on the use case, a detailed description of the data may be required. If, for example, a model predicting faults is desired, it is necessary to train the model to detect faults from both faultless and faulty operation data. The model can then be trained with the data and detect the current state of the device (Kapil & Kiran, 2018). Model development can be divided into five (5) stages as shown in the diagram in Figure 4

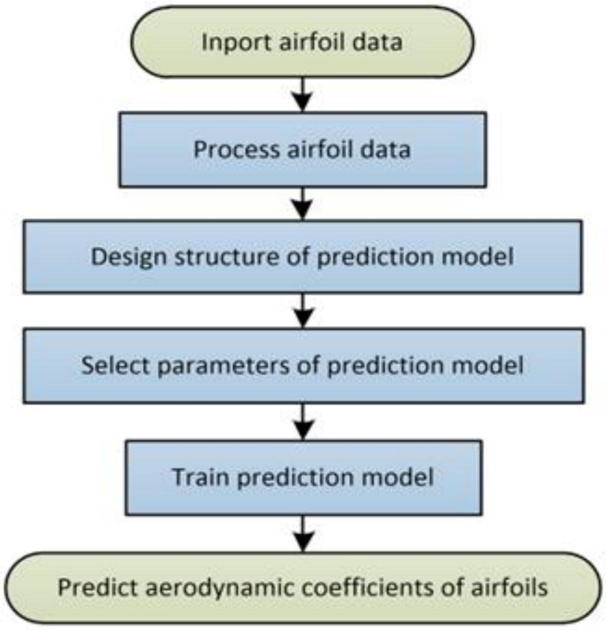

Figure 4. Steps in Creating a Prediction Model

Before the model is created with a machine learning algorithm in the model building phase, the dataset is usually split into two subsets: "training data" and test "data". Only the training subset is used to create a model. The subset, test data, is then used to test the operation of the created model. The workflow for creating a machine learning model is shown in Figure 5 below.

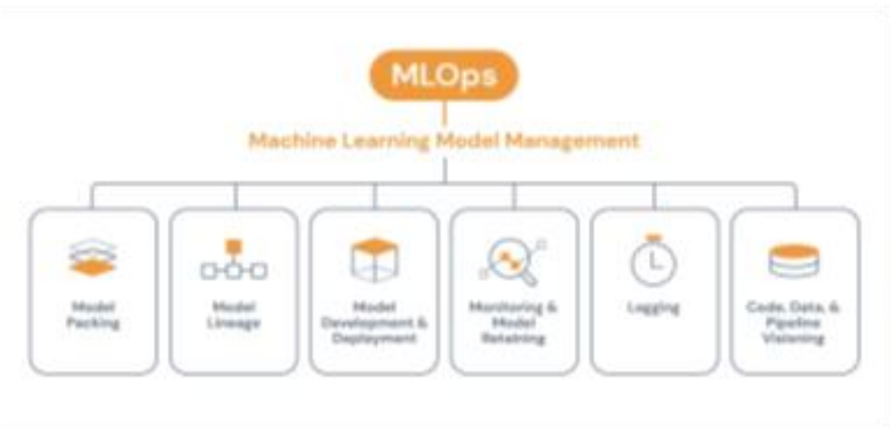

Figure 5. Creation of a machine learning model

2.4. Data Preprocessing and Feature Extraction

A crucial requirement for modeling is data. They must be collected before any analysis can be implemented. The next step is to process the data and extract the features needed for the learning phase. This pre-processing step processes and transforms the data so that it can be efficiently processed by the ML model. It includes data transformation for example, normalization, data cleaning, treatment of missing data, removal of outliers and data reduction (Thyago P et al., 2019). Thereafter, a phase of data analysis is necessary. The purpose of this step is to uncover possible trends,

2.5. Machine Learning Model

Depending on the type of data available during the model creation phase, machine learning is qualified in different ways. Indeed, after becoming familiar with the data, the next step is to apply a model to predict the type of defect. Most of the models applied to predictive maintenance are based on statistics or on artificial intelligence. These models are able to process and capture complex relationships between data. A key point of machine learning models is their learning process and depends on the application, the objective and the data available for the system (Russel & Norvig, 2012).

We speak of supervised learning when the data used in the training of a machine is labelled. That is to say, data that has already been labeled with the right "label", also called class. This learning, already knowing the class, makes it possible to subsequently predict the label of new unlabeled data. Indeed, the models are trained by putting training data as input, and the result of interest is known. Most of the papers categorize regression and classification in this learning approach. In regression, the result is numeric, whereas for classification, the result is a categorical, “yes” or “no” example. Possible algorithms are Bayesian statistics, decision tree learning, or random forest (M. Mohri, 2018).

Unlike supervised learning which attempts to find a pattern from labeled data, unsupervised learning uses unlabeled data. It must automatically bring out the categories to be associated with the data submitted to it in order to recognize them by trying to find patterns that characterize them. So here the outcome of interest is unknown or unlabeled for the given dataset. The main methods used are “aggregation” and “dimensionality reduction”.

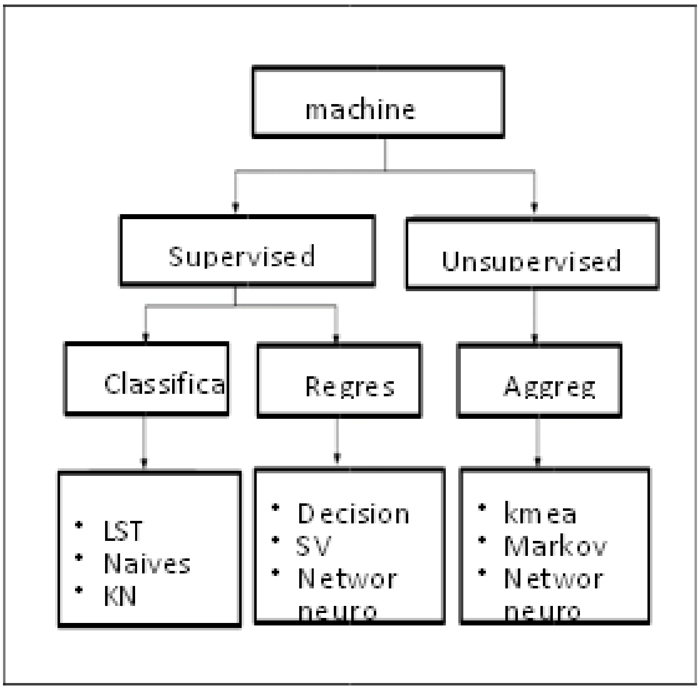

Figure 6. Taxonomy of machine learning models

2.6. Model Analysis and Validation

After obtaining the results of the algorithmic models, data-based techniques are combined with knowledge-based techniques to make better decisions and strategies (Sufiyan et al., 2021). Experienced industry experts review models and results, leading to improvements in operating, maintenance, monitoring, testing and auditing procedures to ensure safer and more efficient actions. Then, a deployment phase can be done which represents the last step of the workflow to design a classification system. It represents the commissioning of the system.

2.7. Machine Studied

The studied machine is an industrial axial flow gas turbine in the 6-7 MW power band. It is a proven unit for power generation, including cogeneration and mechanical load drive, compression and pumping for use in the oil and gas industrial power generation sectors (Siemens Industrial, 2005).

Figure 7. Gas turbine from Siemens Industrial (2005)

3. DESCRIPTION OF DATA

As mentioned in Chapter 3, the data used in this study is provided by Siemens Energy and was collected directly from the SGT-200 machine. All measurements were taken by displacement sensors. The data acquired is the amplitude of the vibration (in µm) as a function of time (in seconds). In fact, the rotating system studied includes a gas generator, a power turbine and the gas generator/power turbine coupling. To take the necessary measurements in this work, displacement sensors were placed at the inlet and outlet of the gas generator (Sensor 10 and 11) and at the inlet and outlet of the turbine (12 and 13). Figure 4 illustrates the locations of the sensors used.

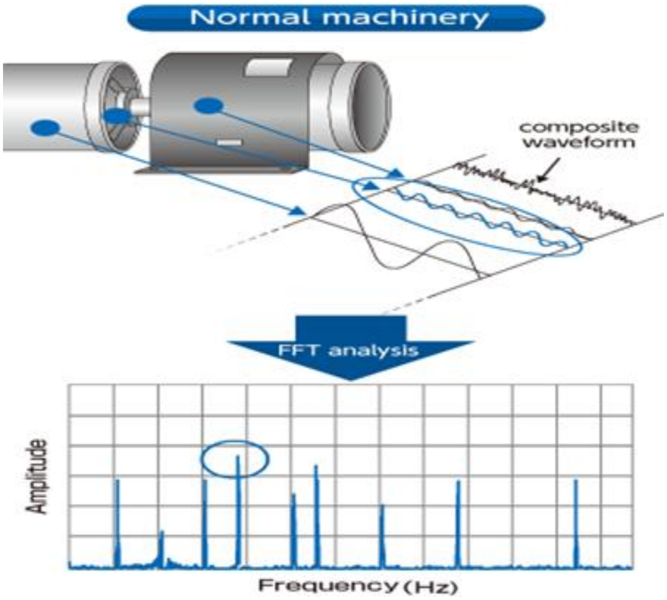

Figure 8. Measurement points vibration data

The tables below describe the displacement probes used as well as their positions on either side of the machine. Table 1 corresponds to the probes at the generator gas level. Table 2 corresponds to the probes at the turbine level.

Table 1. Sensors used at the gas generator

	gas generator		
Channel	**Last name**	**Probe**	**Position**
1	UD10X	GG Inlet X	45° left
2	UD10Y	GG Inlet Y	45° right
3	UD11X	GG Exit X	127° right
4	UD11Y	GG Exit Y	143° left

Table 2. Sensors used at the power turbine

	power turbine		
Channel	**Last name**	**Probe**	**Position**
5	UD12X	PT Inlet X	45° left
6	UD12Y	PT Inlet Y	45° right

7	UD13X	PT Exit X	35° left
8	UD13Y	PT Exit Y	55° right

During data acquisition, consecutive vibration signals were recorded before balancing and after balancing the machine at a rotational speed equal to 11067.5 RPM. Each signal lasts T=84 seconds and is recorded with a sampling frequency of 12.5 kHz and we have 8 sensors that we mentioned previously.

Thus, the total number of points analyzed is equal to 83.88576*12,500 =1,048,572*8 points.

4. PROPOSED METHODOLOGY

4.1. Identification Data Module BITE

The BITE module of the Boeing 767 aircraft pneumatic system delivers 64 variables contained in an individual Excel file for each flight, where they are recorded during each second of aircraft operation, and can be classified according to their origin and representation.

Table (3) shows a summary of those variables related to flight information, such as: Date, time zone, origin, destination, flight phase, altitude, wing tilt and turbine speed. These data are unrelated to the pneumatic system of the turbine, but may have an indirect effect on its operation, especially in cases where weather conditions vary according to the origins and destinations of the flights, or according to the time of year in which the flight took place. The latter escapes from the objectives of the title work, so from Table (3) only those data related to the functioning and operation of the flight are considered, which in this case correspond to the chronological time and the phase of flight.

Table (4) shows a second group of variables, corresponding to the continuous measurements of the most relevant data on the state of the pneumatic system, considering the temperatures measured by the FATS sensors, as well as the pressures measured for the PRV valves. in real time. Given that the PRV valve must regulate the inlet air coming from the eighth or fourteenth stage, the pressure in the inlet duct can take on a wide range of values, since the air passes directly and without regulation through the HPSOV or the check valve from the turbine (see Figure (5)), so the behavior of this variable is not essential for the study of the system.

On the other hand, given that the data provided by the company corresponds to flights related to the failure of the PRV valve, the main variables of the problem are considered to be the pressure at the outlet of the PRV valve and the temperature measured by the FATS sensor at the precooler outlet.

Table 3. Flight information data structure.

Description	Units	Type
Flight Date		Discreet
local time zone		Continuous
Local time, minutes and seconds		
Hometown		String
Destination city		String
flight phase		String
Altitude above ground level	feet	Continuous
Altitude above sea level	feet	Continuous
Engine 1 Angle Leveler	SDR	Continuous
Engine 2 Angle Leveler	SDR	Continuous
Engine 1 speed primary indicator	%	Continuous
Secondary engine speed indicator 1	%	Continuous
Engine 2 speed primary indicator	%	Continuous
Engine 2 secondary speed indicator	%	Continuous

Table 4. General flight data structure.

Description	Units	Type
Engine 1 outlet temperature	deg C	Continuous
Engine 2 outlet temperature	deg C	Continuous
Engine 1 bleeding system activation		Discreet
Engine 2 bleeding system activation		Discreet
Bleeding duct pressure Engine 1	PSI	Continuous
Bleeding duct pressure Engine 2	PSI	Continuous
Left PRV Pressure	PSI	Continuous
Right PRV Pressure	PSI	Continuous
Left FAMV temperature	deg C	Continuous
Right FAMV temperature	deg C	Continuous

Temperature, respectively, throughout an entire flight. The data used for these graphs correspond to a flight in which the pneumatic system of both turbines functioned correctly throughout the entire journey. It is observed that in both Figures ((3) and (4)), the operating range of the measured variables are within the normal range, however there are fluctuations that are associated with the different flight phases through which the aircraft passes., or that can eventually be studied for the possible degradation of the valves.

Table (5) lists the different variables related to the high-pressure controller (HPC), where it can be seen that one of them corresponds to the component failure alert. According to the data provided, the possible values that the variables associated with the pressure switches can take can be two. The first value indicates whether the

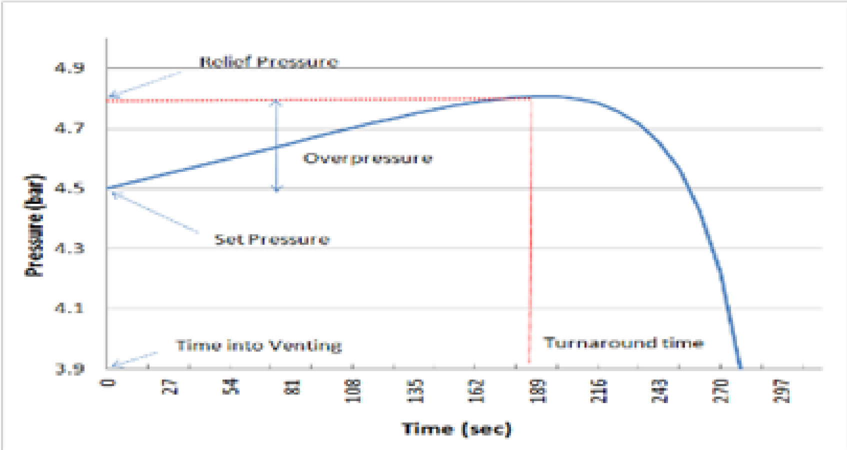

Figure 9. Pressure at the PRV valve outlet during flight time

Source: Prepared by the author based on company data

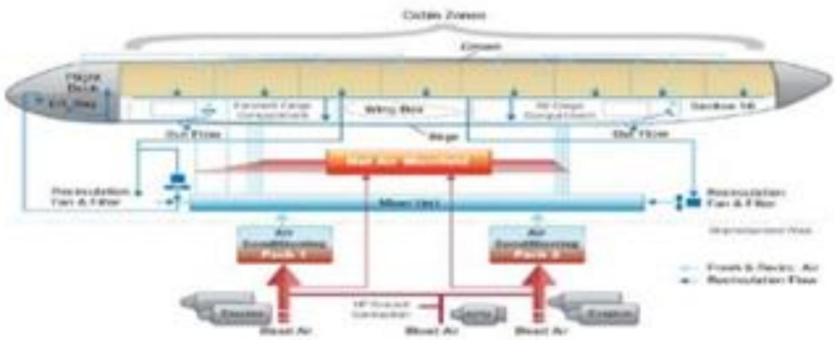

Figure 10. Temperature at the precooler outlet during the flight time

Source: Prepared by the author based on company data.

pressure is above or below its critical value (for example: <127 psig for the HPC high pressure switch), while the second possible value only shows the string “- - - - -”.

Like the HPC, the variables related to the HPSOV, PRV and FATS components. The values of the switches also have binary values, and, since the system is constantly comparing the servo pressures or the differential pressures of the switches, it is possible to see how they behave according to the fluctuations of the main variables of the system (pressure and temperature).

Finally, based on the information presented above for each variable.

Table 5. HPC sensor data structure.

Description	Type
Left HPC Fault Alert	Discreet
Right HPC failure alert	Discreet
Left HPC servo pressure switch	Discreet
Right HPC servo pressure switch	Discreet
Left HPC differential pressure switch	Discreet
Differential pressure switch HPC right	Discreet
Left HPC high pressure switch	Discreet
Right HPC high pressure switch	Discreet
Left HPC Low Pressure Switch	Discreet
Right HPC low pressure switch	Discreet

4.2. Classification

Considering that the pneumatic system is made up of various components, we seek to study the operation of one of the critical elements of the system.[1], the PRV valve. For this, the airline delivers two separate groups of flights. The first group corresponds to data collected from seventeen flights of a single aircraft, which operates in airports in South America. On the other hand, the second group of data is made up of eighteen flights made by four different aircraft, at airports located in both America and Europe. That is, there is a total of 35 flights, of which some have failures in at least one of the PRV valves that it has either reported by the BITE system or the crew in charge of the aircraft.

Now, although there are several flights, it is necessary to establish a criterion to select those that are suitable to develop the diagnostic analysis of the system, for which the following procedure is established

1) Search for a flight where a PRV valve failure is detected and classify it as "Flight Failed"
2) Considering the "Failed Flight" found, search for the flight immediately prior to this one that does not present a fault, classifying it as "Impaired Flight".

3) Search for a new flight, which in the following four operations does not present a fault, and which also operates during the entire cruise phase in the ideal operating ranges. This flight is classified as “Ok Flight” or “Operational Flight”.

4) Repeat the previous steps until exhausting the available flights.

In the case of the selection of the "Operational Flight" (point "b" of the previous list), it is used

the aforementioned criterion given that the data provided by the company are of flights in failure or very close to it, so there are no ideal cases such as the operation of a new or recently repaired valve. This is why it is decided to use those flights in which there are no failures for the list of flights available for work.

According to the procedure presented, it is possible to select five flights from each group, naming them as A and B respectively, which are listed in Table (6).

Table 6. Flights selected for separate analyses in two groups A and B.

Cluster	Name	Condition
A	Flight A1	Okay
	Flight A2	Failure
	Flight A3	Deterioration
	Flight A4	Failure
	Flight A5	Deterioration
B	Flight B1	Okay
	Flight B2	Failure
	Flight B3	Deterioration
	Flight B4	Okay
	Flight B5	Deterioration

Those variables that are directly related to the operation of the PRV are considered for the analysis, which in this case corresponds to the pressure at the valve outlet, as well as the temperature. measured at cooler outlet by FATS sensor. The values given for these variables in the Cruise Phase of the flight are used, given that, as also mentioned above, for other phases of the flight such as takeoff or landing, the PRV is inoperative, so the sensor records for the temperature and pressure of the system are not a consequence of its operation.

On the other hand, given that there are two groups of flights, Group A and Group B, different LSTMs are trained for each of these, as well as a final LSTM that uses all the data from both groups. Each of the trainings is carried out according to the following methodology:

1) Using the code presented in Annex A.1, the data of the PRV and FATS variables are extracted during the Cruise Phase for each flight of the group, creating a matrix of two columns, corresponding to the pressure and temperature respectively, and a number of rows equal to the number of data found during the Cruise Phase.

   The rows of this matrix are then randomly ordered in order to eliminate the temporal bias of the data. In the same way, a vector is created whose length is equal to the number of extracted data, which in each entry contains a string indicating the class to which the flight corresponds (Operational, Failure or Impaired).

2) The LSTM training is carried out using 70% of the data obtained for the Impaired and Operational Flights of each group, using the code presented in Annex A.2. Here, a graph is obtained that allows observing the classification obtained by the LSTM together with its respective decision curve, also providing the essential parameters of the model such as the Support Vectors, scale parameter, adjustment parameter, etc.

3) In the same way, and using all the data extracted for the studied group, a multiple LSTM is trained, which delivers as a result a graph representing the separation of the three defined classes in zones.

4) Finally, the code responsible for performing the previous steps automatically, measuring the time it takes to perform the iterations. In addition, the remaining 30% of the originally obtained data is used to classify them through the two-class LSTM. The results of this classification are compared with the real assigned classes, thus providing a validation percentage for the model.

In order to understand the behavior over time of the relevant variables of the problem, the pressure and temperature are plotted for each of the five flights chosen for Group A during the Cruise Phase.

the decision function delivered by the LSTM (data1) is illustrated, where the training data considered as impaired is shown in red, and the data for the operational PRV is shown in green. For the training, a total of 34,103 data from the Cruise Phase is used, with a successful classification of 100% when validating with 30% of the data that was not used in the training, which is to be expected considering that the class separation does not show overlapping classes and these, moreover, are distant from the decision function delivered by the LSTM

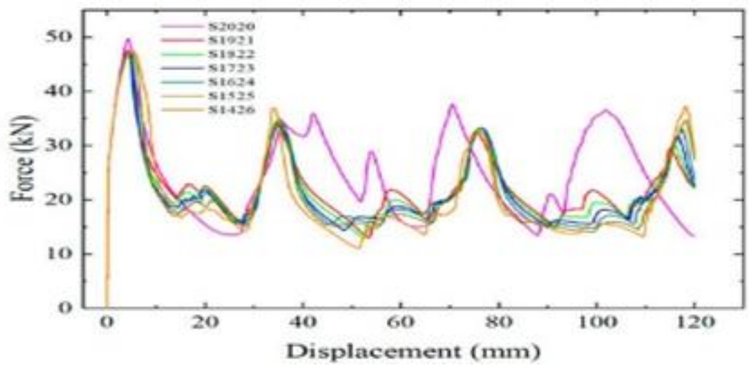

Figure 11. Pressure in PRV and temperature in FATS for operational Flight A1 in Phase Cruise.

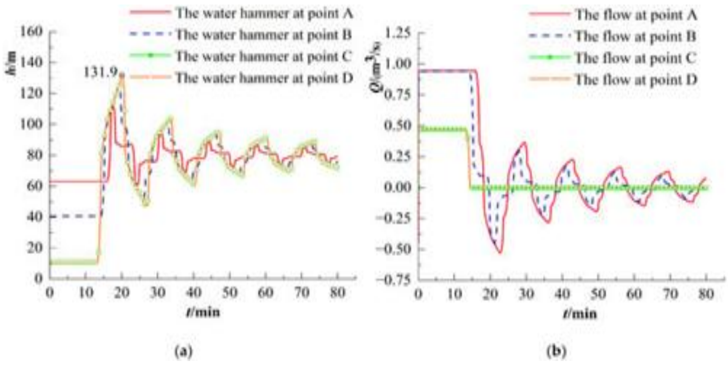

Figure 12. Pressure in PRV and temperature in FATS for flights with failure during Phase Cruise.

5. CONCLUSIONS

Thanks to the structure of the data delivered by the bite system, together with the flexibility provided by the MATLAB software for reading data in "csv" and "xls" formats, it is possible to obtain the relevant variables for the diagnosis of PRV for any file of the flights studied, delivering these in a vector for later use, along with a graph that illustrates the behavior of these variables over time. considering that the pneumatic system detects by itself the malfunction of the different components that comprise it, taking pertinent actions in case this happens, it does not make sense to detect failures with the data delivered after a flight, since this would not be useful any. taking this into account, given that most of the data delivered by the bite system correspond to fault detection signals or signals related to them, the variables that can be related to the correct operation of the valve are those that are continuous in time. since these can take various values depending on the operating state of the valve, as well as the phase of flight in which the aircraft is, it is possible to use support vector machine techniques for classification, seeking to identify three possible states for the valve: impaired, failed, operational. it is determined that the most important variables when diagnosing or studying PRV are those that directly depend on its functioning. thus, for the construction of the PRV diagnostic model, the pressure measured at the outlet of this valve is chosen as input variables to the LSTM, together with the temperature measured at the outlet of the chiller located downstream of the PRV. these variables are continuous in time, in the sense that they are measured and stored by the control system every one second of operation, thus providing crucial information on the operation of the PRV valve during an entire flight. now, although there is information for all phases of the flight, for the diagnostic analysis only those data measured during the cruise phase should be used, since this is where the main role of the valve is carried out. using a total of 90,487 data, corresponding to 70% of the data in the cruise phase obtained from the flights available for groups a and b, it is possible to develop a model for the diagnosis of prv status through lstm, trained with a normalized gaussian kernel, and using parameters σ = 1, 5, fit [-39.56 -158.24] 1 and scale [0.05 0.03].

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