



Practice article

Acoustic monitoring of an aircraft auxiliary power unit

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ABSTRACT

In this paper, the development and implementation of a novel approach for fault detection of an aircraft auxiliary power unit (APU) has been demonstrated. The developed approach aims to target the proactive identification of faults, in order to streamline the required maintenance and maximize the aircraft's operational availability. The existing techniques rely heavily on the installation of multiple types of intrusive sensors throughout the APU and therefore present a limited potential for deployment on an actual aircraft due to space constraints, accessibility issues as well as associated development and certification requirements. To overcome these challenges, an innovative approach based on non-intrusive sensors i.e., microphones in conjunction with appropriate feature extraction, classification, and regression techniques, has been successfully demonstrated for online fault detection of an APU. The overall approach has been implemented and validated based on the experimental test data acquired from Cranfield University's Boeing 737-400 aircraft, including the quantification of sensor location sensitivities on the efficacy of the acquired models. The findings of the overall analysis suggest that the acoustic-based models can accurately enable near real-time detection of faulty conditions i.e., Inlet Guide Vane malfunction, reduced mass flows through the Load Compressor and Bleed Valve malfunction, using only two microphones installed in the periphery of the APU. This study constitutes an enabling technology for robust, cost-effective, and efficient in-situ monitoring of an aircraft APU and potentially other associated thermal systems i.e., environmental control system, fuel system, and engines.

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1. Introduction

The Auxiliary Power Unit (APU) is a key sub-system of the aircraft as it provides electrical and pneumatic power during ground operations and in-flight emergencies. Performance degradation, or failure in any of its sub-systems or components, can cause start-up failure, an abrupt shutdown, generation of excessive vibrations and noise, and may result in reduced power output [1]. Maintenance, Repair, and Overhaul (MRO) activities are in place to avoid such circumstances, however, the costs associated with these activities are significant [2,3]. Furthermore, in cases of unscheduled maintenance, the troubleshooting and rectification of faults can be both costly and disruptive. Legacy aircraft are particularly vulnerable, as they lack the appropriate sensors to support the implementation of a cost-effective and lean fault detection/identification solution. The aerospace industry is currently exploring innovative techniques that can aid the maintenance of key systems for legacy aircraft [4].

The existing techniques make use of aircraft state or engine parameters to assess the APU status by employing a model-based

or data-driven approach. Due to the complex nature of engine behavior, a data-driven approach is generally adopted to identify the fault(s) or degradation. The bibliography for data-driven methods is vast, and a comprehensive review of these methods has previously been provided [5]. One of the limitations associated with the data-driven approach is the unavailability of actual aircraft system data under healthy and faulty conditions, to support the training and testing of the appropriate machine learning models. To circumvent this limitation, a physics-based model can be used to simulate such data. Researchers [6] have trained and tested classifiers using simulated data to identify multiple co-existing faults and degraded conditions in an APU using a set of thermodynamic parameters that are acquired by conducting tests under healthy conditions with multiple intrusive sensors installed in an APU test rig. Another feasible approach is to develop regression models and compare their outcomes with the sensor data to detect fault(s). Modeling of EGT [7] and fuel flow [8], using Artificial Neural Networks (ANNs), fuzzy inference systems, and Deep Learning are among such approaches. Regression models have also been used to model the underlying engine faults (compressor/turbine efficiency losses) using simulated engine data [9]. Similarly, thermodynamic and vibration data have been combined to classify healthy and faulty engines [10]. The key shortfall

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associated with these approaches is their dependency on the system data acquired through intrusive sensors, specifically during the training and implementation stages, which may limit their application on an aerial platform. Furthermore, some of these sensors may not be practical to install, due to space and accessibility limitations, and their robustness may be compromised when subjected to the complex environment present inside an APU compartment. The intrusive sensor-based approaches may also impose significant testing, development, and certification requirements. Contrary to the intrusive sensor-based approach, one of the promising instrumentation techniques is the installation of microphones for fault detection and identification. The incorporation of microphones presents a convenient and robust approach due to their non-interfering and non-intrusive nature.

Considering the APU in-situ, the overall noise characteristics can be broadly categorized as (i) internal noise, noise characteristics that can be captured within the APU compartment (regarded as near-field acoustics in this study), and (ii) external noise, the noise characteristics radiated outside of the APU through its exhaust, more commonly referred to as the far-field noise. The existing literature has been found to primarily focus on the measurement of the far-field noise and its characterization to support the development of APU noise abatement solutions [11–13], whereas the research avenue to explore the potential of in-situ APU noise characteristics (near-field acoustics) remains unaddressed, specifically for APU fault diagnostics purpose.

The authors of the current paper have reported the development and validation of a far-field noise assessment model for a Boeing 737-400 [14]. The study reports spectral distortions of the APU far-field noise due to multipath propagation, ground reflections, and the acoustic characteristics of the reflecting surfaces. Furthermore, the noise characteristics at the receiving microphone were found to be sensitive to nearby noisy activities, occlusion, and other environmental factors that can render a monitoring solution ineffective based on an externally placed microphone. In contrast, the acoustic monitoring of the APU ignition system by utilizing a microphone inside the APU compartment has been identified to be a practically viable solution [15].

An acoustic-based fault detection system requires the identification of appropriate features to reduce signal dimensionality from several thousand samples per second down to a manageable number. The features can be based on time, frequency, time–frequency domain to high-order spectrum analysis and can include statistical features, Mel-frequency cepstral coefficients (MFCC), Spectrograms, Fast Fourier Transform (FFT), Bicoherence, Spectral Descriptors, Linear Predictive Coefficients, and Symmetric Dot Patterns. These features have already been applied to study gears [16–22], bearings [20], wind turbines [23], DC Motors [24], and ICE [25–27]. Most of the research has been based on the experimental work performed in a test rig while considering only a subset of a complete gas turbine. Moreover, the noise characteristics of an APU are quite different from that of an ICE due to their inherent design distinctions, hence the already developed approaches for an ICE are not valid for an in-situ aircraft APU. Also, due to the low signal-to-noise ratio (SNR) in the vicinity of a gas turbine, the Bicoherence analysis may not produce valid results [28]. To the best of the authors' knowledge, the near-field acoustic data of an in-situ aircraft APU has not been evaluated using signal processing and feature extraction techniques for condition monitoring or fault detection purposes.

In this paper, efforts have been made to address the research gaps by identifying the potential of employing microphones for fault detection in an aircraft APU. The impetus for this study stems from the need to develop a low-cost and readily deployable fault detection system for APUs with near real-time capability. To support this study, acoustic data has been acquired from Cranfield

University's Boeing 737-400 aircraft APU. The most salient contributions resulting from the successful implementation of this research study are as follows:

- (1) Development of acoustics-to-APU state identification models for detecting faults that restrict the APU in transitioning between different states.
- (2) Development of acoustics-to-thermodynamic parameter estimation models to detect fault/degradation in the APU lubrication and pneumatic system components.
- (3) Systematic verification and validation of the proposed models based on the implementation of multiple feature extraction, classification, and regression techniques at various sensor locations throughout the APU compartment.
- (4) Identification of best sensor locations for detecting potential faults in APU load compressor, IGVs, Bleed valve, and lubrication system components.

The paper is organized as shown in Fig. 1. Section 2 provides an overview of the reference APU, along with a description of the considered faults, noise characteristics, and application of signal processing techniques based on their theoretical background. The novel acoustic monitoring scheme is presented in Section 3. Description of the data collection, feature extraction, state classification, and regression analysis, are all covered in detail. The evaluation of its efficacy against the defined performance criterion is demonstrated in Section 4.

2. Problem description and background

2.1. Boeing 737-400 APU operation

For the experimental work, Cranfield University's Boeing 737-400 was used. The APU was instrumented, and the near-field acoustic data was acquired under a wide range of APU operating modes. In parallel, the APU thermodynamic data provided by the APU FADEC (Full Authority Digital Engine Controller) was recorded to supplement the overall data acquisition process. A high-level view of the installed APU is presented in Fig. 2. The power section (gas turbine) of the APU consists of a single-stage centrifugal compressor with 17 impellers, a reverse flow annular combustor, and a radial inflow turbine having 14 blades [29]. The compressor and turbine are mounted on the same shaft, which rotates at a constant speed of 63,830 rpm for all operating conditions. The APU is attached to the aircraft structure through vibration mounts, which inhibit unwanted vibrations from the gas turbine.

The load compressor is mounted on the same shaft as the gas turbine and generates pressurized air for the aircraft's pneumatic systems: Environmental Control System (ECS), wing anti-ice, and Main Engine Starter. The amount of air entering the load compressor is controlled by the inlet guide vanes (IGV) through an actuator. The Bleed Valve (BV) is located outside the shroud but inside the APU compartment and isolates the APU's output from the aircraft's pneumatic system. The Surge Control Valve (SCV) is another vital component of the APU's pneumatic system, it is controlled by the Surge Valve Torque Motor (SVTM) and allows pressurized air from the load compressor to be rejected into the exhaust system to avoid compressor surges.

The lubricating oil temperature is regulated by a cooling fan which forces air through the oil cooler. The cooling air takes excessive heat from the oil and then leaves the APU compartment via the cooling air outlet. The FADEC monitors the APU parameters (inlet temperature/pressure, IGV angle, load compressor output pressure, RPM, EGT, and oil temperature) using intrusive sensors and generates commands for the fuel torque motor, SVTM, and IGV actuator. The key APU parameters measured by

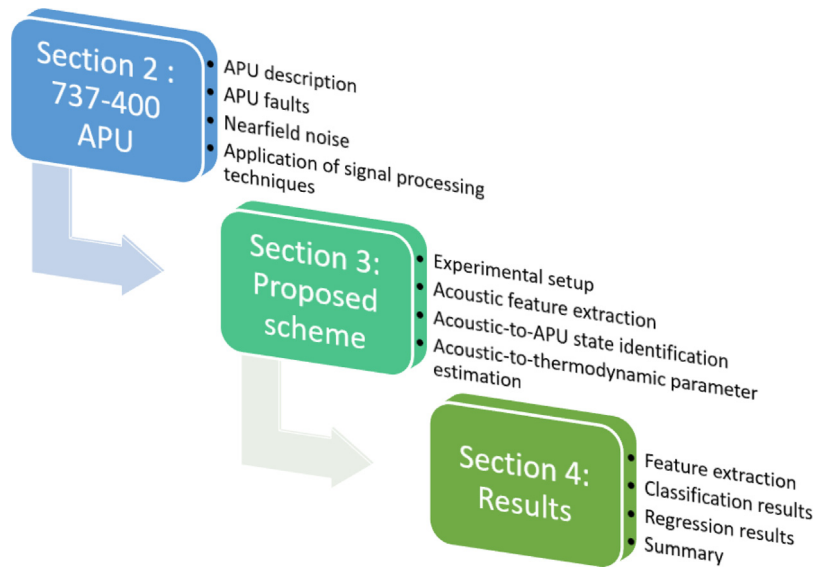


Fig. 1. Overview of the paper.

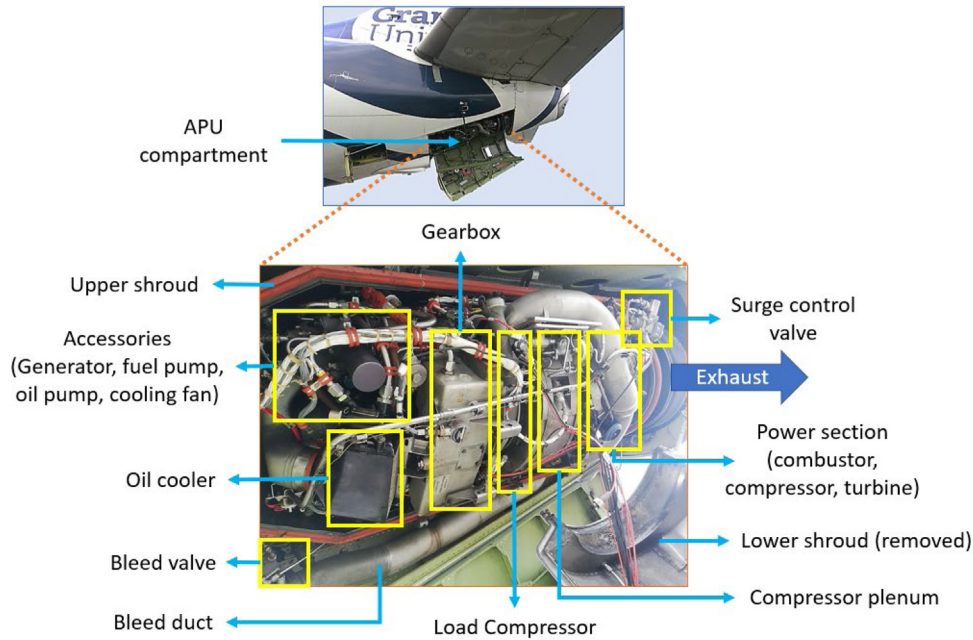


Fig. 2. Photographic overview of the APU.

the onboard intrusive sensors can be visualized using the FADEC display, the details of which are presented in Section 3.2.

The APU operating conditions can be segregated into three main states: Bleed system inactive (*BL OFF*), Bleed System activated without pneumatic load (*BL ON NL*) and Bleed System activated with pneumatic load (*BL ON LD*). From the perspective of the APU power setting, there is a considerable difference between the states *BL OFF* and *BL ON NL*. This is because, when the bleed system is activated to generate the required mass flow, the load compressor IGVs are fully opened. In such a situation, power is required to drive the load compressor, and the fuel rate increases to balance the energy of the system. However, there is no change in power between *BL ON NL* and *BL ON LD*. Only the SCV angles change. Under *BL ON NL* conditions, the surge valve allows all the flow from the load compressor to merge with the exhaust. Whereas, when the ECS or Wing Anti-ice system is turned on (*BL ON LD* conditions), the SCV closes to meet the

desired pneumatic demand. The SVTM current varies from 50 mA (*BL ON NL*) to 95 mA (*BL ON LD*) to control the SCV. The APU states, along with their effect on the APU thermodynamic parameters and the far-field noise, have been thoroughly reported and discussed by the authors as part of their preceding research conducted on the same APU [14].

2.2. APU near-field acoustics

The noise generated inside the APU compartment is shielded from the effects that are present in the surrounding environment. As such, a microphone placed inside the compartment is predominantly sensitive to the APU's internal noise characteristics. The aircraft skin thickness is close to 6 mm [30], and the sound transmission loss through a 6 mm aluminum panel can range linearly from 13–44 dB in the 63–8000 Hz frequency range [31]. Due to the proximity of the sensors to the APU, the effect of

Table 1
Description of APU Faults.

	Fault	Effect	Remarks
1	Faulty wiring	APU unable to transition between the states	Considered
2	Faulty Lubrication System	Increase in T_{Oil}	
3	Inlet Guide Vane Actuator Fault	Decrease in $\dot{m}_{LC}$ /IGV angles	
4	Load Compressor fouling	Decrease in $\dot{m}_{LC}$	
5	Bleed Valve Malfunction	Decrease in $\dot{m}_{Bleed}$ /APU unable to transition to <i>BL ON LD</i> state	
6	Surge Valve Malfunction	Variation in Gear Mesh Frequencies and Side Bands	Not Considered
7	Gearbox tooth wear/tooth crack		
8	Bearing Inner/Outer Race Defect		
9	Generator wiring fault	Appearance of Bearing frequencies	
10	Compressor/Turbine degradation	Mechanical power demanded by the generator increases Variation in thermodynamic parameters of the core	

external noise is negligible as compared to the noise generated by the APU components, and has been substantiated by a previous detailed analysis [32].

The APU internal noise characteristics can be described as having a convoluted combination of mechanical vibrations generated by the APU, the combustion process, and the tonal frequencies generated by the shaft, gears, bearing, compressor, and turbine [33]. Since the size of the radiating surface (APU) is large, compared to the distance between the source and the sensors, the acoustic near field is dominant. Within this field, the acoustic pressure at a given point is governed by the structural dynamics of a vibrating body and its effect on the acoustic pressure at a point in the three-dimensional space [34]. Also, due to the nearby reflecting sides, the audio measurements are sensitive to the distance from the source and the reflecting surfaces [35]. To add to this already complicated picture, flow noise due to turbulence in the ducts also contributes to the APU internal noise characteristics [36].

The lubricating oil temperature also has a direct effect on the vibration amplitude and thus the noise levels. In a study conducted on a long journal bearing, the acoustic pressure is proportional to the viscosity of the lubricant, which decreases with an increase in oil temperature [37]. This has been substantiated by other analyses [38], in which the vibration amplitude (and therefore the noise level) was found to decrease with an increase in oil temperature. Moreover, the temperature variation inside the APU compartment may also influence the acoustics during its propagation between the source and the receiver [39].

2.3. APU fault modes

A wide range of faults can potentially occur in an APU, resulting in performance degradation, automatic shutdown, or major failure [1]. To proceed with the development of the proposed scheme, it is important to understand these faults and evaluate their effect on the APU parameters. Table 1 presents faults that may occur in an APU like the one considered in this study. The foremost category of fault is a degradation in the electrical wiring that can affect the connectivity between the cockpit and the APU. Under such circumstances the APU would not respond as per the demand, for example, the APU remains in *BL OFF* state even if the *BL ON* switch is engaged from the cockpit.

Another category of fault relates to the degradation of the components of the lubrication cooling system which is designed to regulate the temperature of the lubrication oil. The cooling system comprises an oil cooler, cooling fan, and temperature-regulating assembly. Degradation in any of the components, like oil cooler fouling shown in Fig. 3(a), leads to an increase in the oil temperature that can eventually lead to the automatic

shutdown of the APU. The APU pneumatic system can be affected by a wide variety of faults. A faulty IGV actuator is not able to effectively control the Load Compressor IGVs (see Fig. 3(b)), which can lead to a reduction in the mass flow generated by the pneumatic system. Furthermore, fouling can occur in the load compressor (see Fig. 3(c)) because it is directly exposed to contact with airborne particles. Such degradation can cause a decrease in $\dot{m}_{LC}$ even if the IGVs are working flawlessly. Lastly, malfunction in the BV or the SCV can result in a decrease or fluctuation of the bleed mass flow ($\dot{m}_{Bleed}$).

Some of the other categories of fault include degradation of the electrical generator, and defects in the bearing/gearbox, compressor, and turbine. In this paper, only the faults which can lead to quantifiable variation in the acoustic characteristics inside the APU compartment during the steady-state operation are considered.

2.4. Application of signal processing techniques

Various signal processing techniques have been employed for machine fault diagnostics based on acoustics data. These techniques can separate signal sources that are localized in time, frequency, and space. However, they require several uniformly spaced sensors to perform beamforming, Direction-of-Arrival (DOA) estimation, or Blind Source Separation (BSS). The computational overhead and the hardware complexities associated with the installation of multiple sensors inside the APU compartment can also inhibit the use of several microphones for an aircraft condition monitoring application. Furthermore, the costs associated with the procurement, installation, and maintenance of such equipment for a complete aircraft fleet might render this approach unaffordable.

Due to the complex nature of near-field acoustics, the majority of the signal processing techniques have been applied in the far-field of a gas turbine [40], principally for noise characterization. Tracking of azimuthal shifts in the source position of a low Mach number jet [41], and noise source identification in the far-field of a turbo-fan engine using an array of microphones [42] are among such examples. During one of these experiments, acoustic barriers or anechoic chambers had to be used to further improve the results. In a particularly relevant study [43], a set of 13 microphones in a spherical configuration were used to perform angular estimation of noise sources and reflections in a large industrial hall with two machines generating broadband noise. By using the cross-correlation technique, the highly reflecting sources were identified. The assumption that the receivers were in the far-field of the sources had to be made for this analysis, which inhibits noise source separation at a granular level for each machine. Similar studies on the direction of arrival estimation include a 3-element acoustic vector sensor method [44], but its performance

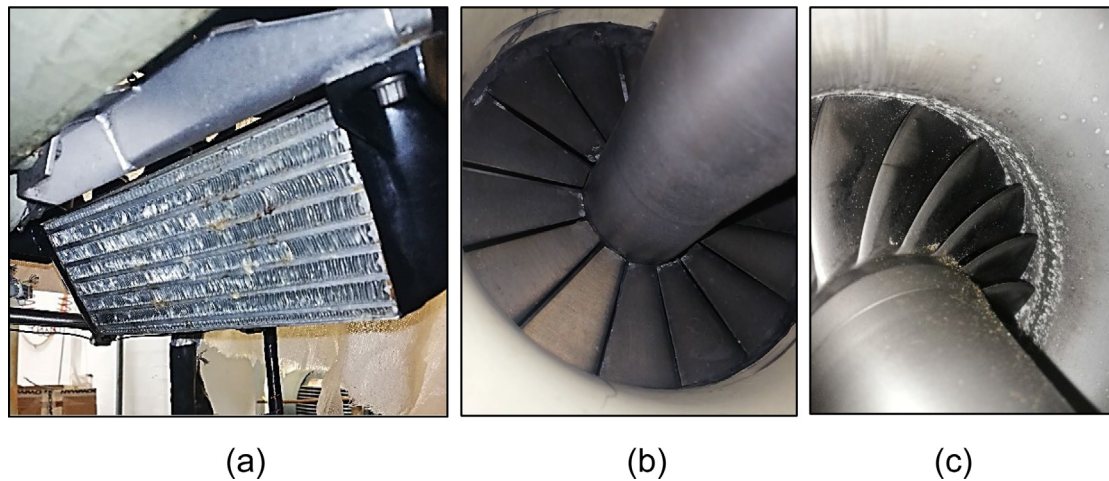


Fig. 3. Degradation of APU components: (a) Oil cooler fouling (b) IGVs closed (c) Wearing effects around the load compressor.

validation was done on simulated data without reverberation effects.

Due to their directional capabilities, sound intensity measurements using intensity probes could also be used for monitoring a system. These methods employ a pair of microphones to estimate the time-averaged rate of acoustic energy flow per unit area from a particular direction [45]. However, in an enclosed environment (the APU compartment), energy would be traveling back and forth due to acoustic reflections and hence net energy flow (and sound intensity) is zero. Due to these reasons, the studies undertaken on enhancing the performance of intensity probes are generally conducted in a controlled environment [43]. For example, Kalman Filtering was proposed to estimate the sound particle velocity and validate results in an anechoic chamber with an SNR as high as 40 dB [46]. Similarly, characterization of an airport acoustic environment has been done by using a 30 m tall 3-dimensional sound intensity probe, ensuring that the sensors are in the far-field of the sources [47].

The methodologies developed for the localization of near-field sources also have limitations in terms of their applicability for the desired purposes. Such techniques require a large number of microphones and require the source to be present inside an anechoic chamber. Some of the techniques have been evaluated on simulated data, and not for machine condition monitoring purposes. As an example, the Minimum Variance Distortionless Response (MVDR) technique [48] to separate radially aligned near-field sources was proposed, but the experiment was conducted on a smartphone speaker inside an anechoic chamber. In a similar vein, a radial filter technique was applied to an array of spherical microphones to attenuate an interfering source located in the same direction as the actual source [49]. The whole scheme was limited to analysis using synthetic data only. Likewise, an adaptive near-field beamforming technique that produced the desired results with a single loudspeaker in a room with negligible acoustic reflections was investigated [40].

Another set of signal processing methods, which may be relevant to condition monitoring, is termed Blind Source Separation (BSS) techniques. Given a series of observed signals, BSS uses multiple sensors and aims at recovering the underlying sources by exploiting the assumption of their mutual independence [50]. Due to the latter constraint, these techniques have been largely studied to separate speech signals [51]. The BSS technique has also found an application in mechanical systems. BSS algorithms have been proposed to determine the modal parameters of a uniform aluminum beam by using multiple vibration sensors [52]. Concerning the utilization of acoustic measurements, it has been

reported that implementing BSS on acoustic data for mechanical system monitoring is not suitable [53]. This is because the physical source contributions arise from a two-step mixing process: the first mixing of the mechanical sources occurs through the structure, and the second mixing step is created between the whole structure and the microphones through the air. Consequently, the hypothesis of source punctuality is not valid, and BSS cannot be easily used. To counter such limitations, a combination of multiple techniques with BSS might perform well in a constrained environment. A single microphone with TVF-EMD-Robust ICA (Time-Varying Filter–Empirical Mode Decomposition–Robust Independent Component Analysis) has been employed to separate combustion and piston slap noise in a diesel engine [54]. The tests were conducted in a large hall, and five out of the six cylinders had to be acoustically treated using lead covering so that their noise did not interfere with the noise of the cylinder under investigation. A similar analysis for noise source identification [55], using a combination of VMD (Variational Mode Decomposition) and Robust ICA on a gasoline engine in a similarly highly controlled environment, has been reported. These techniques are computationally intensive, and an embedded system may be needed for near real-time applications. The use of an FPGA has been proposed to provide the necessary resources to perform BSS-based noise cancellation [56], but the designed system can only function up to a sampling frequency of 16 kHz.

Considering the aforementioned literature, it can be seen that several signal-processing techniques are available for noise source identification, separation, and localization. However, most of these techniques require the object to be in an anechoic/semi-anechoic chamber, with the sensors being in the far-field of the device under test. None of the mentioned techniques are worth pursuing because of the hardware complexity and high computational resources, inhibiting practical implementation. Based on the above analysis, a data-driven approach may be adopted to ascertain the feasibility of utilizing microphones for APU fault detection.

3. Proposed scheme for fault detection

3.1. Overview

In this paper a novel system for monitoring an aircraft APU is presented; it is shown schematically in Fig. 4. The proposed system makes use of acoustic data acquired from microphones installed in the immediate vicinity of the APU and performs fault detection and isolation using classification and regression models,

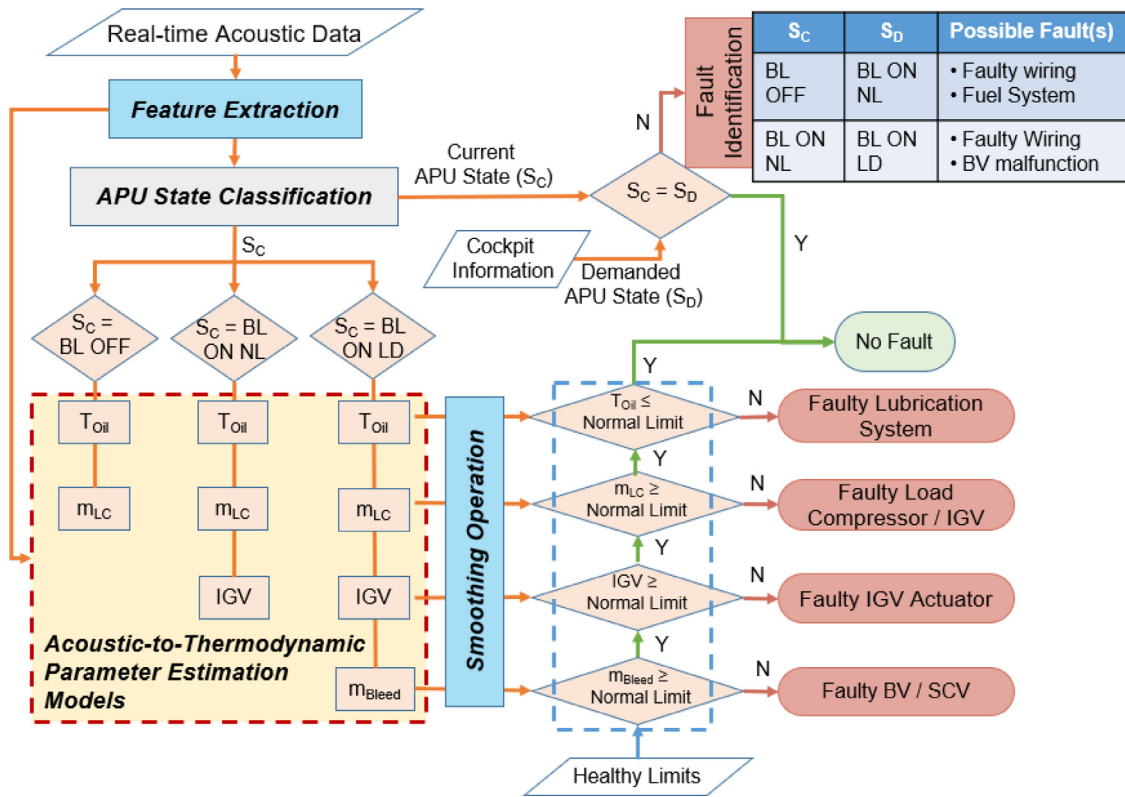


Fig. 4. Proposed novel system for APU fault detection and isolation using acoustics.

all integrated to work in near real-time. Based on the implementation of classification techniques, the model identifies the operating state of the APU and compares it with the demanded APU operating state from the cockpit. Any disagreement in the comparison can indicate a fault in the wiring, fuel system, or Bleed Valve. Furthermore, the regression models are trained to compute the key APU parameters (T_{oil} , IGv angle, $\dot{m}_{bleed}$, and $\dot{m}_{LC}$); they are termed acoustic-to-thermodynamic parameter estimation models. The first two parameters are directly readable from the FADEC display, whereas the remaining two have been derived from the known parameters for developing the requisite models. Output from the classification model selects the parameters that must be observed for fault detection under a given operating state. Due to the noisy nature of the acoustic data, the estimated parameters themselves are noisy, and hence require smoothing before being compared with the healthy limits. These limits are defined by examining the healthy system under different states and operating conditions. The purpose of this study is to ascertain the minimum set of microphones with appropriate feature extraction, classification, and regression techniques, for detecting a diverse set of APU faults by acoustically monitoring the state and parameters.

To evaluate the effectiveness of the proposed system, a detailed study has been undertaken to develop the desired classification and regression models and to assess their performance (Fig. 5). The overall aim is to exploit the acquired in-situ APU near-field acoustic data corresponding to various operating states and apply the most promising feature extraction and regression models for the estimation of APU health indicating parameters to support the implementation of online APU monitoring system. The overall procedure can be categorized into five stages: (i) Experimental data collection, (ii) Data Preparation, (iii) Feature Extraction, (iv) Training of classifiers, and (v) Application of regression models and identification of the best sensor locations.

The data collection is based on several microphones installed around the APU. The acquired near-field acoustic data is then segregated into the three distinct APU states based on the concurrently recorded FADEC data. Multiple feature extraction techniques are then applied to the near-field acoustic data and their performance is evaluated on the trained classifiers. Once the capability of noise to identify the APU states is proven, the methodology proceeds in estimating the key APU parameters using noise features as inputs and analyzing the trend of regression accuracies across the APU. In this paper, MATLAB has been selected as the computational environment for implementation. Demonstration of the proposed methodology is conducted by treating each microphone separately and their combination is not considered. The models have been shown to monitor the normal states and are also capable of detecting certain faulty conditions that have been noticed during the overall experimental data collection.

From the detailed analysis, the near-field acoustic data has been found to be capable of supporting the monitoring of the APU and detecting a faulty condition. Such a novel system makes use of microphones that do not interfere with the performance and safety of the equipment and therefore may not impose extensive efforts for development and certification. The acoustic-based predictive model can also provide the necessary information which can be fused with other sensors for accurate results and for enabling graceful degradation/uninterrupted operation in the case of built-in sensor failure. The proposed system can also enable the monitoring of similar systems for which access to sensor data is restricted, and the installation of additional sensors may not be feasible. Under such circumstances, the utilization of a non-intrusive sensor can be a very convenient approach.

3.2. Experimental data collection

This study focuses on near-field acoustic data collected from an in-situ aircraft APU. The data is collected by instrumenting

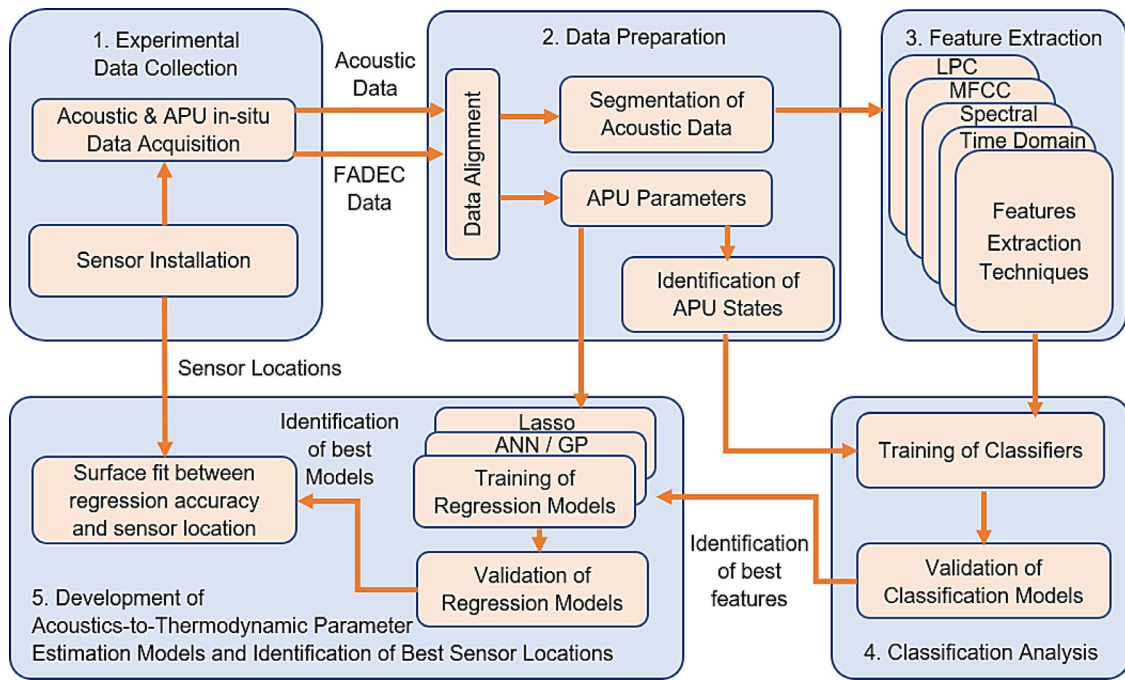


Fig. 5. Procedure followed for the development and evaluation of acoustic-to-thermodynamic parameter estimation models.

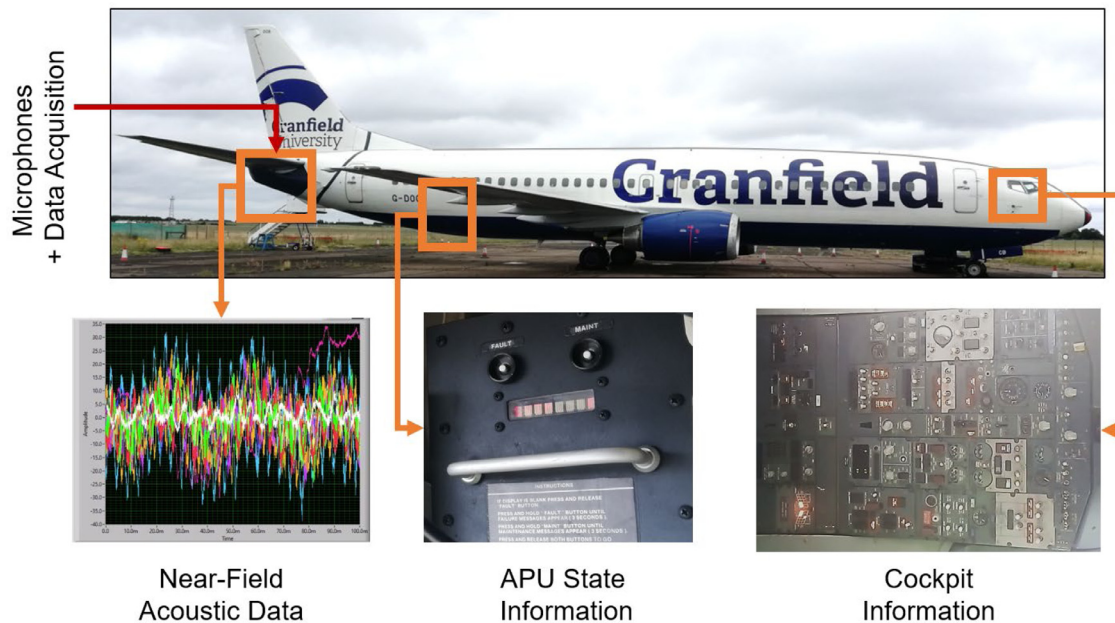


Fig. 6. Experimental setup for APU state and acoustic data collection.

Cranfield University's Boeing 737-400 aircraft (see Fig. 6). The testing for the data collection was performed at Cranfield airport with support from certified Boeing 737 maintenance and safety engineers based at Cranfield. The overall experimental setup involved acoustic data collection using eight 130F20 $\frac{1}{4}$ " IEPE microphones in combination with a National Instruments Data Acquisition (DAQ) System. The chosen sampling frequency for each channel is 51.2 kHz, nearly 2.5 times the frequency where the microphones provide a flat frequency response. The overall arrangement of the microphones is illustrated in Fig. 7. A total of eight microphones were installed, six were installed inside the APU shroud, and the remaining two (BV and BV2)

were placed within the APU compartment. The naming convention adopted for the sensors allows quick identification of the sensor locations. The locations are chosen in such a way that the noise characteristics around the key APU components (BV, SCV, Oil Cooler, Combustor, Load Compressor) can be monitored. Moreover, the sensors have been placed uniformly to capture any trend in the performance of the estimation models across the APU compartment.

In addition to the microphones, a camera is installed in the aircraft's cargo compartment, Fig. 8. This camera records the thermodynamic parameters shown in the FADEC display: T_{Oil} , IGV angle, output pressure from the Load Compressor, and SVTM

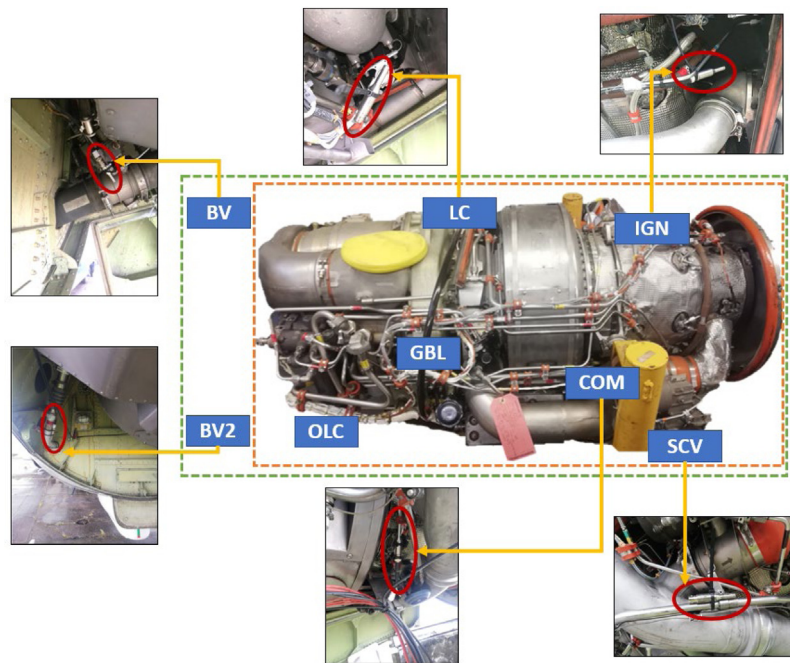


Fig. 7. Microphone placement in the APU compartment.



Fig. 8. Recording of the FADEC Display.

current. Another camera is installed inside the cockpit to monitor the state of the cockpit switches. The recorded videos are timestamped so that the cockpit and thermodynamic information can be synchronized with the acoustic data. Since $\dot{m}_{Bleed}$ and $\dot{m}_{LC}$ are not directly measured they are derived from known parameters, details of which have been previously reported [14]. The near-field acoustic and FADEC data have been gathered from the aircraft APU on nine different days over a period of five months. Table 2 presents the time duration of the data acquired each day under different load conditions. The time duration corresponds to the APU in steady state condition and excludes the data collected during transient states (startup, shutdown, and APU transitioning between various load states). In total, around 46 min of acoustic and APU data has been acquired under various states and load conditions. To generate the pneumatic loads, ECS or wing anti-ice systems have been activated from the cockpit panel.

3.3. Data preparation

Acoustic data from each sensor is divided into data segments of 51,200 samples, each lasting 1 s, with 80% overlap between them. This ensures that the number of samples is sufficient for computing the features while keeping the update rate of 0.2 s.

Such an update rate is chosen to match the highest rate reported in the literature for similar purposes [57].

Different features, detailed in Section 3.4, are then computed for each of the data segments containing the acoustic data. Simultaneously, the thermodynamic parameters from the FADEC are synchronized via time stamping. Throughout this analysis, only steady-state conditions are considered because of the limitation of visually observing the thermodynamic parameters through the FADEC display. Once the parameters are noted, three different APU states are defined based on the following conditions:

BL OFF: IGV angle = 22

BL ON NL: IGV angle > 22 and SVTM = 50

BL ON LD: IGV angle > 22 and SVTM > 50

To ensure that the classification and regression are not prone to overfitting, validation of the developed models is performed on unseen data. For this purpose, acoustic and APU state data from Day 8 is kept separate from training and is utilized for validation of the trained classifiers and the regression models. The number of data segments for training and testing the models is shown in Table 3. The total number of data segments acquired for this research is 13,789. For classification, around 85% of the data is used for training, while the remaining is used for testing, which corresponds to the data from Day 8. For regression analysis, the training data ranges from 79%–87% for the three APU states.

Table 2
Data collection duration during experimentation.

Day #	Duration (sec)			Total
	Bleed Sys OFF	Bleed Sys ON without Load	Bleed Sys ON with Load	
1	35	56	49 (Anti-ice ON)	140
2	42	65	74 (Anti-ice ON)	181
3	409	58	28 (Anti-ice ON)	495
4	133	137	25 (Anti-ice ON)	295
5	245	69	148 (Anti-ice/ECS ON)	462
6	53	20	71 (ECS ON)	144
7	91	207	126 (Anti-ice/ECS ON)	424
8	177	108	148 (Anti-ice/ECS ON)	433
9	78	104	35 (Anti-ice ON)	217
Total	1263	824	704	2791

Table 3
Data allocation for modeling and testing of models.

	Classification	Regression		
		BL OFF	BL ON NL	BL ON LD
Training Data	11,722 (84.4%)	5385 (86%)	3558 (87%)	2779 (79%)
Testing Data	2157 (15.6%)	880 (14%)	540 (13%)	737 (21%)
Total	13,879	6265	4098	3516

3.4. Feature extraction

The APU noise signals can be represented in multiple signal representation domains, but not all these techniques are relevant to the current application. For example, Spectrograms/Mel-Spectrograms are used for transient data analysis, whereas in this study only steady-state conditions are considered. The Spectrograms, as well as Symmetric Dot Patterns (SDP), generate a large dataset, which is not desirable. It was also found that the patterns produced by the applied SDP technique on the acoustic data were not significantly different among the different APU states and are therefore not relevant to the application. Furthermore, the Visibility graphs (Natural and Horizontal) are also not considered because of the inherent computational complexities which correspond to the time complexity of $O(n^2)$ [58]. Bicoherence analysis also requires considerable time for computation. Moreover, it was found to be producing bicoherence graphs that were inconsistent with the APU state, and varying (significantly) even between consecutive data segments. This is attributed to the highly noisy nature of the acoustic signal present inside the APU compartment.

The focus of this paper is on the identification of those features which can correctly capture the variation in the acoustic characteristics. As per the analysis, it has been found that the change in the APU parameters generates narrowband effects and therefore a group of tonal frequencies is not sufficient to describe the variations. Consequently, the selected categories of features in this study are the ones that represent the overall variation throughout the acquired audio spectral band (0–25.6 kHz). These include:

(a) Linear Predictive Coding Coefficients (LPC) with Error Term

These features comprise linear predictor coefficients (a_k) which minimizes the error between the linearly predicted signal $\hat{s}(n)$ and the actual signal $s(n)$, where

$$\hat{s}(n) = \sum_{k=1}^p a_k s(n-k), \quad (1)$$

and 'p' is the order of the linear predictor, which is selected to be 20 for this study. The standard deviation of the error between the actual and the estimated signal is also appended to the feature list making the total number of features 21. The coefficient terms (a_k) represent the spectral envelope of the signal, while the error

term is sensitive to the average difference between the envelope and the actual signal.

(b) Mel-Frequency Cepstral Coefficients (MFCC)

The MFCCs have been designed to capture the human perception of speech, and therefore adopt a non-uniform weighted scheme in the lower frequency band (Fig. 9(a)). In this study, since speech signals are not involved, the triangular filters used in the MFCC algorithm have been defined at 20 regular intervals with equal magnitude to capture noise variations between 0 and 25.6 kHz (Fig. 9(b)), where the upper limit is defined by the Nyquist criteria.

(c) Spectral Power in sub-bands (Spectral-Pow)

The power in each of the 20 equally divided non-overlapping sub-bands of the acoustic data is treated as another feature category. The power for each sub-band can be computed as follows:

$$P_{1,2} = \int_{f_1}^{f_2} P_{yy}(f) df \approx \sum_{i_1}^{i_2} P_{yy}[i], \quad (2)$$

Where, P_{yy} is the frequency transform computed using the 'pwelch' function and i_1 and i_2 correspond to the frequency limits for a sub-band.

(d) Time Domain Features

This set of features includes RMS, Kurtosis, Skewness, x_{peak} , ZCR, Negentropy [59], Impulse Factor, Crest Factor, and the Shape Factor of the time domain acoustic signal. They are defined by:

$$RMS = \sqrt{\frac{1}{N} \sum x^2}, \quad (3)$$

$$Kurtosis = \frac{1}{n} \sum \frac{(x - \mu)^4}{\sigma^4}, \quad (4)$$

$$Skewness = \frac{1}{n} \sum \frac{(x - \mu)^3}{\sigma^3}, \quad (5)$$

$$ZCR = \frac{1}{N} \sum |sgn[x(n)] - sgn[x(n-1)]|, \quad (6)$$

where $sgn(\cdot)$ is the sign function, that is:

$$sgn[x(n)] = \begin{cases} 1, & x(n) \geq 0 \\ -1, & x(n) < 0 \end{cases}$$

$$Negentropy = 33.67 \left(\frac{1}{N} \sum e^{-\frac{x_i^2}{2}} - 0.707 \right)^2, \quad (7)$$

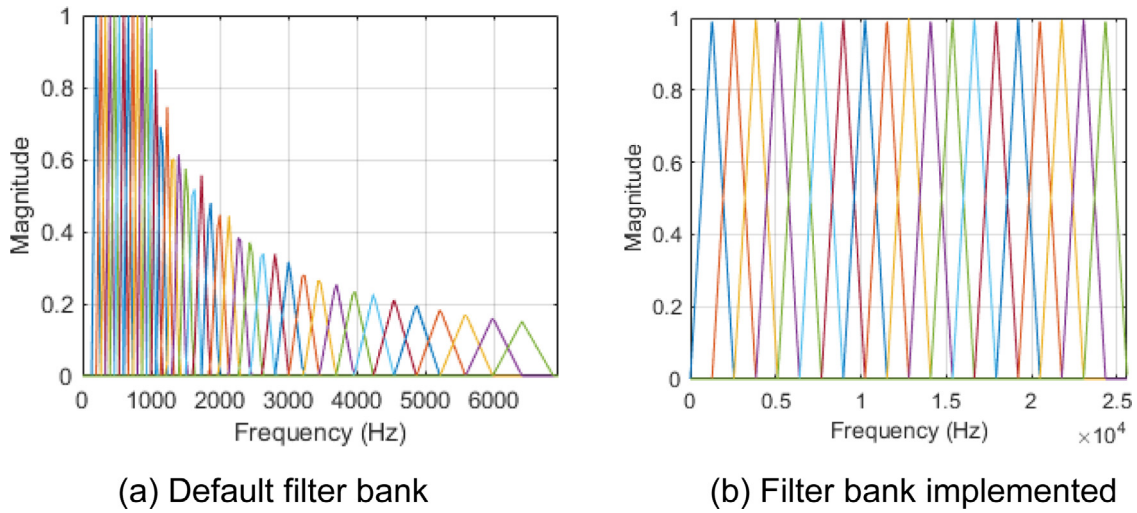


Fig. 9. MFCC filter bank.

$$\text{Shape Factor} = \text{RMS} / \frac{1}{N} \sum |x|, \quad (8)$$

$$\text{Impulse Factor} = x_{\text{peak}} / \frac{1}{N} \sum |x|, \quad (9)$$

$$\text{Shape Factor} = x_{\text{peak}} / \text{RMS}, \quad (10)$$

(e) Spectral-Descriptors

This category of features includes the characteristics derived from the audio frequency spectrum. These are computed using the audio signal processing toolbox in MATLAB and include skewness, spread, centroid, flatness, arithmetic mean, geometric mean, crest, spectral peak, flux, slope, decrease, and roll-off point. The expressions for these features are:

$$\text{Sp.Centroid} = \frac{\sum_{k=b_1}^{b_2} f_k s_k}{\sum_{k=b_1}^{b_2} s_k}, \quad (11)$$

$$\text{Sp.Spread} = \sqrt{\frac{\sum_{k=b_1}^{b_2} (f_k - \text{Sp.Centroid})^2 s_k}{\sum_{k=b_1}^{b_2} s_k}}, \quad (12)$$

$$\text{Sp.Skewness} = \frac{\sum_{k=b_1}^{b_2} (f_k - \text{Sp.Centroid})^3 s_k}{(\text{Sp.Spread})^3 \sum_{k=b_1}^{b_2} s_k}, \quad (13)$$

$$\text{Sp.AM} = \frac{1}{b_2 - b_1} \sum_{b_1}^{b_2} s_k, \quad (14)$$

$$\text{Sp.GM} = \left(\prod_{b_1}^{b_2} s_k \right)^{\frac{1}{b_2 - b_1}}, \quad (15)$$

$$\text{Sp.Flatness} = \text{Sp.GM} / \text{Sp.AM} \quad (16)$$

$$\text{Sp.Peak} = \max(s_k) \quad (17)$$

$$\text{Sp.Crest} = \text{Sp.Peak} / \text{Sp.AM} \quad (18)$$

$$\text{Sp.Flux} = \sqrt{\sum_{k=b_1}^{b_2} |s_k(t) - s_k(t-1)|^2}, \quad (19)$$

$$\text{Sp.Slope} = \frac{\sum_{k=b_1}^{b_2} (f_k - \mu_f)(s_k - \mu_s)}{\sum_{k=b_1}^{b_2} (f_k - \mu_f)^2}, \quad (20)$$

$$\text{Sp.Decrease} = \frac{\sum_{k=b_{1+1}}^{b_2} \frac{s_k - s_{b_1}}{k-1}}{\sum_{k=b_{1+1}}^{b_2} s_k}, \quad (21)$$

$$\text{Sp.Rolloff} = \left\{ i \mid \sum_{k=b_1}^i s_k = 0.5 \sum_{k=b_1}^{b_2} s_k \right\}, \quad (22)$$

Where, s_k is the spectral value at bin k , and b_1 and b_2 are the band edges.

3.5. APU state classification analysis

In this study, acoustic data is used to first identify the APU mode of operation. This is because, as mentioned in Section 3.1, the APU's failure to transition between the three different states can indicate a problem with the electrical wiring, fuel system, or bleed valve. Furthermore, the thermodynamic parameters to be monitored, and the applicable acoustic-to-thermodynamic model, also depend on the correct identification of the APU state. This approach has been proposed to improve the accuracy of the regression models because the acoustic features vary significantly with the change in the APU state even if the desired parameter (e.g., oil temperature) is not changing.

Several multi-class classifiers, available in MATLAB's Machine Learning Toolbox, have been trained using the five different categories of feature extraction techniques applied to the acoustic data acquired at each of the eight sensor locations. The classification techniques used are:

- k-Nearest Neighbor (KNN)
- Linear Discriminant Analysis (LDA)
- Decision Tree (TREE)
- Neural Network (NET)
- Ensemble of Learners (ENS)
- Error-Correcting Output Codes (ECOC)
- Multi-class Naive Bayes (MNB)

The performance of the trained classifiers has been evaluated on test data using the following metric:

$$\text{Accuracy (\%)} = \frac{TP + TN}{TP + FP + FN + TN} \times 100 \quad (23)$$

Where: TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative

The input to the classifiers is the raw features without applying a dimensional reduction technique. The Principal Component Analysis (PCA) is one such technique that translates m-dimensional data into another set of a low number of features containing most of the information/variance. Since PCA is an

unsupervised way of performing dimensional reduction, it does not account for the noise variance [60]. The derived principal components are sensitive to APU state information and unwanted variations and are not an exact representation of the system. Due to these reasons, classification results using the three principal components acquired from PCA have been found to be imperfect on the test data regardless of the feature extraction or classification technique used. In this paper, PCA has only been used for data visualization.

3.6. Regression analysis

In the proposed methodology, regression models are trained for acoustic-to-thermodynamic parameter estimation. There are several techniques available to build such models, each of which exhibits some strengths and weaknesses. The performance of each of the techniques is based on the Mean Absolute Percentage Error (MAPE):

$$MAPE (\%) = \frac{100}{n} \sum_{i=1}^n \left| \frac{A_i - E_i}{A_i} \right| \quad (24)$$

where 'n' corresponds to the total number of test data values, A_i are the actual values and E_i are the estimated ones. Lower MAPE values indicate that the corresponding model is free from overfitting and is therefore generalizable. MAPE is selected to compare the performance of the various combination of feature extraction and regression techniques amongst different sensor locations. The metric can be an indicator of the overall accuracy of the acoustic-to-thermodynamic parameter estimation approach if no smoothing operation is employed. However, with the application of a smoothing operator on N consecutive values, model accuracy can be increased. In this case, the effect of the last N values (corresponding to $0.2 \times N$ seconds) persists and sudden changes in the APU parameters cannot be registered. The final decision on the selection of the smoothing operator and the parameter N depends on the desired accuracy and how quickly the APU parameters can change for a particular system. Since only steady-state responses are considered, the trade-off between accuracy and update rate is not studied in detail. However, the effect of the application of a smoothing operator on MAPE values for a particular case is presented in Section 4.3.3.

The regression techniques evaluated in this study are described in Table 4. Three different methods were considered, these included Linear Regression, Artificial Neural Networks (ANNs), and Genetic Programming (GP). Linear Regression is a powerful tool for investigating the linear relationship between an outcome variable and multiple explanatory variables that are potentially correlated with each other. Linear Regression with L1 regularization (Lasso) is used to limit the number of parameters going into the model by placing a penalty on the coefficient values. Lasso aims to find the coefficients (β_0, β) of linear regression such that their sum and mean square error are minimized, that is:

$$\min_{\beta_0, \beta} \left(\frac{1}{2N} \sum_{i=1}^N (y_i - \beta_0 - x_i^T \beta)^2 + \lambda \sum_{j=1}^p |\beta_j| \right) \quad (25)$$

where λ is selected to be the highest value that gives a nonnull model.

The ANNs have been employed to identify the presence of non-linearities between the inputs and outputs for the current application. The simplest form of ANN structure has been chosen to avoid overfitting the models. Lastly, symbolic regression via GP is a non-parametric, nonlinear regression technique that looks for an appropriate model structure and model parameters as opposed to classic regression which assumes a certain model structure and

estimates the optimal parameters that best fit a given sample of data. A MATLAB toolbox supporting genetic programming [61] has been utilized with the parameter values defined in Table 4.

Regression models have been trained using acoustic features as inputs and the desired APU parameters (T_{Oil} , IGV angle, $\dot{m}_{Bleed}$, and $\dot{m}_{LC}$) as outputs. The models adjust the associated coefficients/hyperparameters to achieve a minimum error between the estimated and the actual output values. Since the desired APU parameters are state-dependent, they are termed as (see Fig. 4):

- T_{Oil} BL OFF, T_{Oil} BL ON NL, T_{Oil} BL ON LD
- $\dot{m}_{LC}$ BL OFF, $\dot{m}_{LC}$ BL ON NL, $\dot{m}_{LC}$ BL ON LD
- IGV BL ON NL, IGV BL ON LD
- $\dot{m}_{Bleed}$ BL ON LD

The last important aspect of the proposed methodology is the systematic identification of the optimum position for the microphones. Since dissimilar parameters are to be estimated, a single location might not be ideal for their correct estimation. Therefore, for each parameter, a surface curve between the x, y locations, and the corresponding error is fitted to assess the trend in variation in the overall accuracy of the models across the APU. This allows the generation of a heatmap for the swift identification of optimum sensor positions for the desired APU parameter.

4. Results and discussion

This section presents the results acquired based on the successful implementation of the proposed methodology presented in Fig. 5. Initially, some of the computed acoustic features, as they appear at different APU locations, are presented and discussed. This is followed by performance analysis and a discussion of the trained classification models and their possible utilization for fault detection. Subsequently, the fault detection capability of the acoustic-to-thermodynamic parameter estimation models is presented alongside the identified locations for best performance. Lastly, a summary of the results and the potential benefits of the proposed system are given.

4.1. Features extraction

A significant amount of near-field acoustic and FADEC data has been acquired for this study. Several features (mentioned in Section 3.4) have been computed for an initial assessment. The resulting feature set comprises $8 \times 5 \times 20$ dimensional data, where 8 is the number of sensors, 5 is the number of feature extraction techniques, and 20 is the approximate number of features computed by each technique corresponding to 1 s of acoustic data. The time required to compute the LPC, MFCC, and Time domain features for each 1 s of data is around 0.4 ms, while for the Spectral-Pow and Spectral-Descriptors, it is 3.5 ms when using a Core i5 computer with a 3 GHz processor. The former features, with a computation time of 0.4 ms, make them more suitable for real-time application.

In this section, only two of the extracted features (RMS from Time Domain features and the Fifth feature from the MFCC feature set) are qualitatively assessed for studying the variations due to the change in APU states and parameters at different sensor locations. The time-domain feature (RMS values) is considered first. Fig. 10 shows the distribution of this feature for the three different APU states (depicted by three colors) across the eight sensor locations. The figure displays the sensor locations in a cyclic manner (clockwise), as they appear on the APU (Fig. 7) from BV through COM and back to BV2. Several inferences can be drawn from Fig. 10. The sensor BV2 picks up the least noise as compared to the rest of the sensors, probably because this

Table 4
Parameters used in the selected regression techniques.

	Method	ID	Parameter name	Value
1	Linear Regression with L1 Regularization	Lasso	Cross-Validation	10-fold
2	Artificial Neural Network	ANN	Number of hidden layers	1
			Number of neurons	10
			Activation function	Tangent sigmoid
3	Genetic Programming	GP	Initial Population Size	100
			Function set	+, -, /, *
			Generation gap	90%
			Cross over probability	0.5
			Mutation probability	0.5

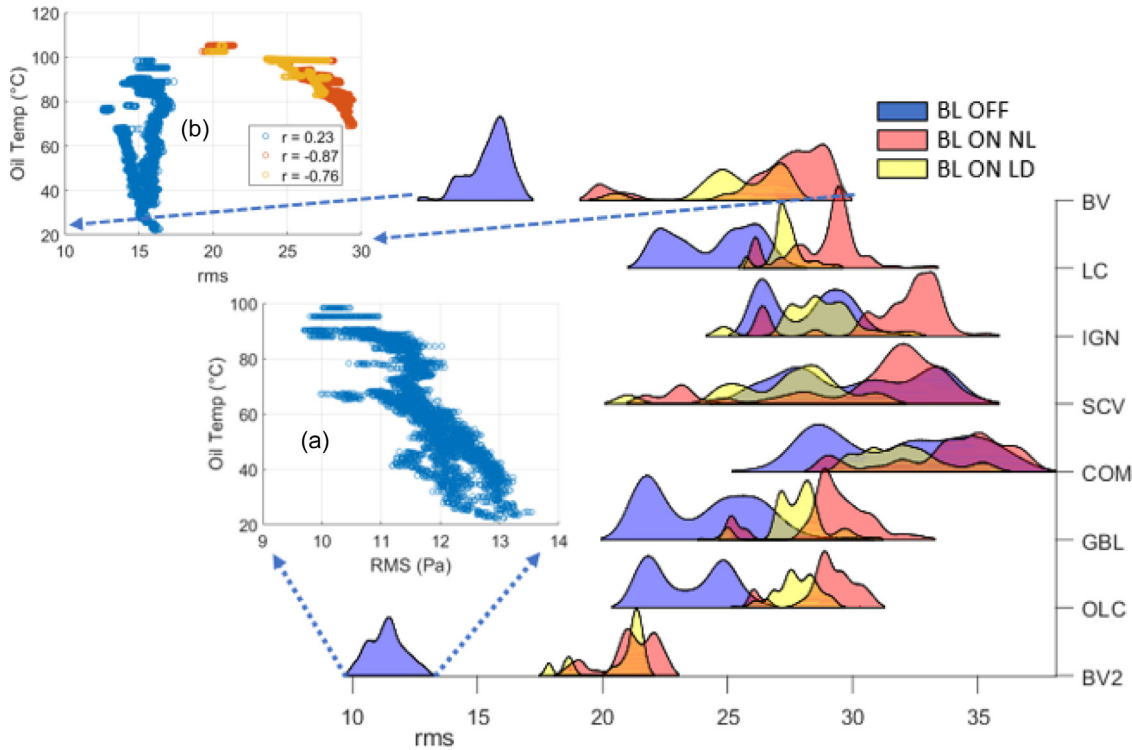


Fig. 10. Histogram of the RMS Time Domain Feature at different sensor locations.

location is the farthest from the main sources of noise. On the contrary, at the COM sensor, high noise levels are registered ($SPL \approx 125$ dB corresponding to $RMS \approx 37$ Pa). For the rest of the sensors, the noise levels go down with respect to their distance away from the combustor.

With regards to the APU states, the noise characteristics are mostly dissimilar for BL Off (blue) and BL ON (yellow or red). However, only some of the sensors (OLC, GBL, LC) exhibit distinct RMS values for BL ON LD state (yellow), which are not overlapping with the other two states. For these locations, RMS can be considered a suitable candidate for APU state classification. Another characteristic of the RMS feature at each of the APU states is its spread, which may be because of random noise, variations in oil temperatures, IGV/Surge Valve angles, and/or mass flows. As an example, a scatter plot of the RMS feature against the oil temperature at sensor location BV2 is shown (Fig. 10(a)). The strong negative correlation ($\rho = -0.82$) indicates a decrease in noise levels with an increase in the oil temperatures, thus making the RMS feature a suitable candidate to be used for regression at this location. There is also the presence of undesired variations in this feature, which warrants the requirement of using multiple correlated features for regression.

Another important characteristic of the features is their variation in response to the change in APU states. A scatter plot of RMS

features against oil temperatures at location BV2 is presented to explain this behavior, see Fig. 10(b). The plot shows three separate scatter plots corresponding to the three APU states. The RMS values are uncorrelated with the oil temperatures ($\rho = 0.23$) for the BL OFF state for this location. However, the correlation and the mean values significantly increase for the other two states ($\rho = -0.87$ for BL ON NL and $\rho = -0.76$ for BL ON LD). Under such circumstances, separate regression models are being proposed for each of the APU states for all the desired APU parameters. With this approach, the model accuracy increases because of the freedom to select the best model (category of features and regression techniques) against each APU state. However, this approach requires that the classification models be perfect in identifying the state, otherwise a wrong model is selected and the accuracy decreases.

As a further example, the distribution of the fifth MFCC feature is presented in Fig. 11. Like the RMS values, this feature follows a pattern across the sensor locations, with the outside shroud sensors (BV and BV2) as exceptions; the minimum values are around SCV, and they increase as the sensors move away from this location. From the classification perspective, this feature is well separated for all the APU states at two of the locations (IGN and SCV). For the remaining sensor locations segregating between

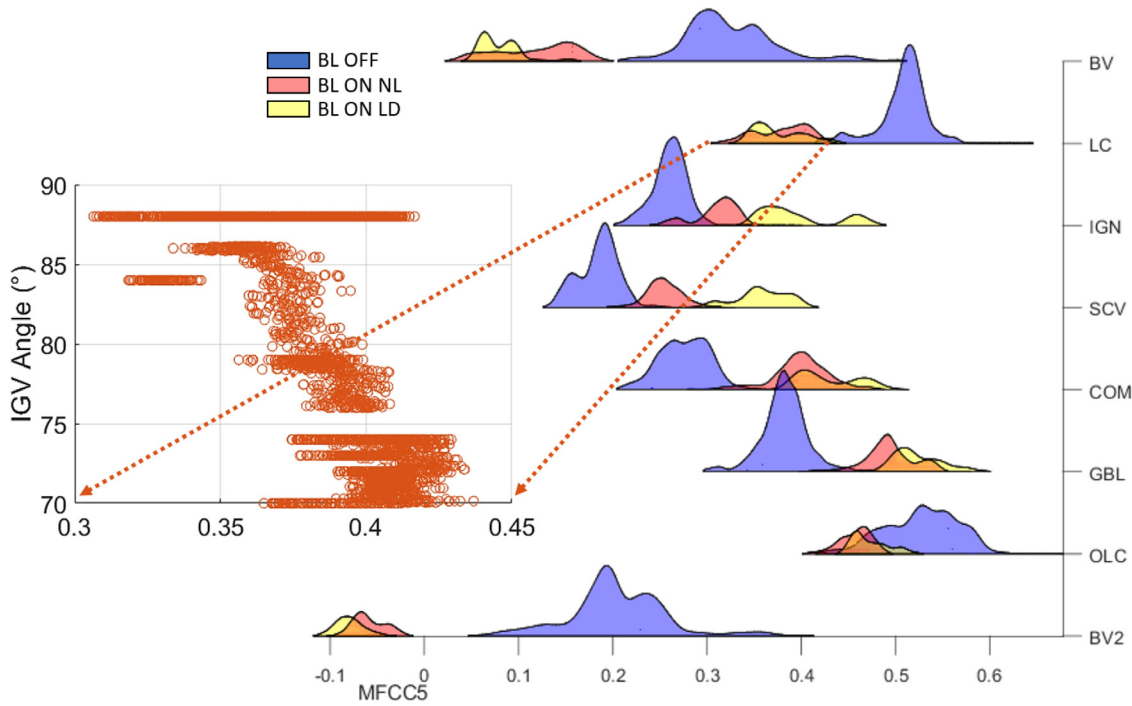


Fig. 11. Histogram of an MFCC Feature (F5) at different sensor locations.

the BL OFF and BL ON states can conveniently be done. With regards to the relationship between this feature and the APU parameters, a scatter plot between the feature and one of the parameters (IGV angles) in BL ON NL state is shown for location LC, see subfigure in Fig. 11. Although noisy, there exists a negative correlation ($\rho = -0.74$) between the two values, making this feature compatible with regression.

The complete analysis of the various categories of feature extraction techniques, their response with the APU states, and their correlations with the APU parameters have previously been carried out by the authors in comparison with vibration sensors and reported [32]. Hence, they are not covered here.

4.2. Classification results

The results of APU state classification on test data using different classifiers and features at all the sensor locations are shown in Table 5. The table has been color coded between ranges of green, white and red, where dark green color corresponds to perfect classification (100% accuracy), dark red color illustrates the worst classification condition (25% accuracy) and white color is for the median value (which is nearly 95%). The sensors are grouped based on their location with respect to the APU shroud, keeping BV and BV2 on the right side of the table. The first three categories of features outperform the remaining two by demonstrating 100% accuracy at multiple sensor locations. Employing Spectral-Pow features with the ECOC classifier can be regarded as the best combination for this application since it can achieve perfect classification at half of the sensor locations. Utilizing neural networks for classification is not recommended because, at certain locations, the accuracy drops down to 40%.

For the inside shroud sensors, perfect classification (with LC being an exception) can be achieved irrespective of the sensor location. However, outside the shroud, the accuracy drops to 99% (BV and BV2). This can be attributed to the fact that these locations are outside the noise-reducing casing (shroud) and at some distance from the APU itself; they are more susceptible to

True Class	BL OFF	880		
	BL ON NL		537	3
	BL ON LD		1	736
		BL OFF	BL ON NL	BL ON LD
		Predicted Class		

Fig. 12. Confusion Matrix for APU State classification using Spectral-Pow features.

external effects. Under such circumstances, small variations in the acoustic data due to the variation in APU state do not get registered by such distant sensors. For the remaining sensors, the output of the acoustic-to-APU state identification models can be compared with the desired APU state for detecting a fault. For example, if the demanded state is BL ON LD but the acoustic model is showing BL ON NL, a faulty condition is indicated. Such a condition can arise due to a fault in the electrical wiring or the fuel system. During the experimentation, such a fault could not be implemented for practical reasons, and therefore results have only been validated for healthy conditions.

Amongst the sensors installed inside the shroud, the LC location is not capable of perfect classification; the maximum achievable test accuracy is 99.8% with Spectral-Pow features and ECOC classifier. The confusion matrix for this location is shown in

Table 5
Classification results.

		Colour Code							
Accuracy (%)		100				95			25
Feature Category	Classifier	Sensor Location							
		LC	IGN	SCV	COM	GBL	OLC	BV2	BV
LPC	KNN	91.1	99.6	95.2	98.7	89.3	95.4	67.4	64.4
	LDA	97.5	100.0	99.8	99.9	100.0	99.8	94.9	97.7
	TREE	88.7	97.1	95.9	90.2	96.7	94.9	88.5	95.9
	NET	95.1	40.8	100.0	100.0	40.8	99.4	94.9	93.9
	ENS	98.1	100.0	100.0	99.9	99.9	98.7	85.3	96.0
	ECOC	90.1	100.0	100.0	99.6	99.0	99.0	94.1	99.1
	MNB	96.2	95.9	98.0	99.5	99.2	95.8	95.2	95.1
MFCC	KNN	85.1	91.4	98.7	96.0	87.3	91.9	74.2	62.4
	LDA	99.4	100.0	99.8	99.7	100.0	99.4	97.9	98.4
	TREE	77.4	99.7	100.0	96.8	92.3	96.0	85.2	74.2
	NET	99.8	100.0	100.0	99.1	99.9	99.9	95.7	91.0
	ENS	98.7	99.8	100.0	99.0	92.3	100.0	95.8	94.0
	ECOC	97.5	100.0	99.9	99.6	100.0	99.9	98.1	97.7
	MNB	97.7	100.0	98.8	97.8	78.2	98.3	99.2	95.3
Spectral Pow	KNN	76.6	99.8	96.9	92.9	96.9	95.5	73.9	77.0
	LDA	98.9	100.0	99.9	99.7	99.9	99.5	97.1	95.9
	TREE	96.8	99.8	99.1	86.5	90.4	96.6	93.4	94.9
	NET	96.6	100.0	99.9	99.6	40.8	40.8	96.7	94.9
	ENS	99.4	100.0	100.0	99.6	96.0	99.5	81.3	94.5
	ECOC	99.8	100.0	100.0	100.0	100.0	99.4	98.6	91.4
	MNB	83.2	97.5	85.7	85.7	93.4	84.1	95.1	64.5
Time Domain	KNN	69.4	68.9	69.5	67.7	64.3	75.7	63.2	65.0
	LDA	93.4	98.8	99.2	92.4	84.8	86.7	93.7	94.8
	TREE	94.8	97.6	70.2	73.0	92.0	87.1	70.0	94.4
	NET	96.4	96.9	40.8	99.2	90.3	40.8	82.8	89.1
	ENS	95.9	99.3	87.2	81.7	87.7	88.6	68.5	94.8
	ECOC	96.1	98.7	98.1	94.1	96.1	91.6	95.0	93.4
	MNB	92.5	90.3	95.0	67.2	95.4	87.9	96.2	94.9
Spectral Descr.	KNN	65.2	88.0	88.3	93.7	53.1	90.9	71.6	86.4
	LDA	98.7	92.1	99.2	93.3	76.9	90.8	88.9	95.5
	TREE	65.4	68.1	66.4	82.8	59.7	92.0	85.3	64.3
	NET	40.8	40.8	40.8	40.8	40.8	62.5	40.8	25.0
	ENS	66.4	68.7	93.4	86.8	61.9	93.0	83.4	82.4
	ECOC	57.0	38.4	71.4	29.0	25.3	61.7	94.7	45.9
	MNB	89.9	90.9	83.8	58.4	61.1	83.1	95.9	95.1

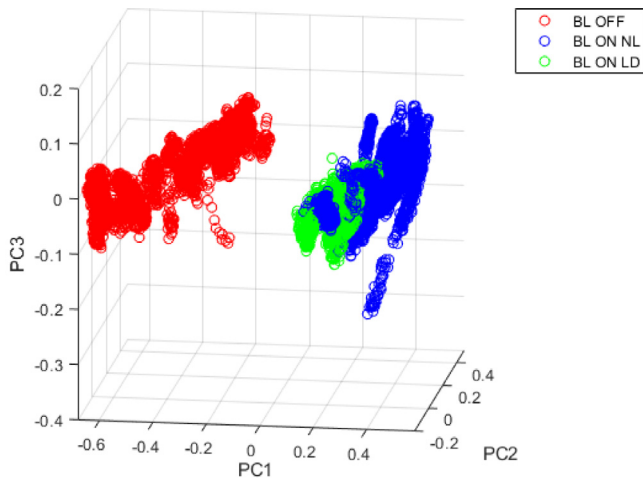


Fig. 13. MFCC feature visualization using PCA.

Fig. 12. The trained classifier can identify the BL OFF state accurately, however segregation between the other two states remains slightly ambiguous. The classifier wrongly predicts the other states 0.2% of the time. This is the consequence of the similarity that exists in the acoustic data between the BL ON states, within which only mass flow through the bleed and surge valves is varying while the rest of the parameters remain approximately constant, i.e., fuel flow, EGT, and IGV angles. Furthermore, as compared to the other in-shroud sensors, this location (LC) is further away from the surge control valve where acoustic variations are taking place (see Fig. 7). The sensor is close to the bleed duct, but the presence of a shroud might be restricting the desired acoustic characteristics reaching it. To appreciate the similarity in the acoustic data under the three different APU states, PCA is employed for visualization, Fig. 13. Here the variation of the three principal components are shown under different APU states. The acoustic data for the BL OFF case is unique, whereas, for the other two states, the principal components overlap. This is because the PCA is trying to retain the variance in the data that may not be completely originating from the flow variations.

The proposed system demands perfect classification not only for fault detection but also because incorrect identification of the APU state can lead to the incorrect selection of the regression model, adding to the overall inaccuracy of the acoustic-to-thermodynamic parameter estimation model. Since perfect classification has been achieved, the proposed approach can now be extended to regression modeling.

4.3. Regression results and fault detection

In this section, regression models, implemented to estimate various performance parameters of the APU, are evaluated. Each model is trained using the acoustic data acquired at each sensor location. The aim is to validate the models against the actual aircraft data acquired through the FADEC and demonstrate their ability to detect the presence of any possible faults/degradation using near-field acoustics. Initially, the trained models for five of the nine parameters mentioned in Section 3.6 are analyzed in detail to elaborate on the potential of acoustic-based models for APU monitoring, as well as their generalization and extrapolation capabilities. The selected parameters to support the analysis are: T_{Oil} , $\dot{m}_{LC}$, IGV angle, and $\dot{m}_{Bleed}$, under BL OFF, BL ON NL, and BL ON LD states. The detailed analysis of these parameters is followed by a summary of the regression results for all parameters from the aspect of test accuracies and how these vary across various locations. The overall analysis includes a combination of the five feature extraction techniques with three different regression methods. The resulting 15 models are designated using a combination of their acronyms, e.g., LPC+GP, MFCC+Lasso, TimeDomain+ANN, Spectral-Pow+GP, Spectral-Descriptors+Lasso.

4.3.1. Detailed analysis (T_{Oil} BL OFF)

During the BL OFF state, which includes the APU warmup, T_{Oil} starts to increase at a constant rate which reduces when T_{Oil} reaches around 60 °C. At this temperature a regulator assembly allows the lubrication oil to flow through the oil cooler, thus decreasing the rate of change of T_{Oil} . It is therefore important to be able to track T_{Oil} for monitoring the health of the regulator assembly, oil cooler, and cooling fan. The distributions of the oil temperature values for training and test data are shown in Fig. 14. These values range from 20–100 °C for the training data. Whereas, for the test data, there are two subsets of data, one in the 20–70 °C range (warmup) and another one at around 90 °C. The models have been trained at each of the eight different sensor locations using the training data, which are then employed to predict the oil temperature values on the unseen data.

The actual (FADEC) values at each data point and the predicted output from three of the fifteen models that produce the most accurate results at the GBL sensor location are shown in Fig. 15. The performance metric (MAPE) for each of the techniques is also shown against the labels. All the models closely follow the actual values, and a quantitative assessment of the results shows that accurate results are produced by employing Genetic Programming on the Spectral-Descriptors feature set (MAPE = 5.3%). The Spectral-Descriptors+GP model is produced by using symbolic regression via GP to find an appropriate model structure (comprising a function set) and a subset of Spectral-Descriptors features that best fit the training data. The generated model identifies two of the 12 features to accurately relate oil temperatures values with acoustics, resulting in:

$$T_{Oil} = 0.014 \text{ Sp.Centroid} - 229.7 \text{ Sp.ArithmeticMean} + 8.3 \quad (26)$$

At the same sensor location, similar accuracy can be achieved by employing seven of the nine time-domain features identified by the Lasso regression technique, which excluded crest factor

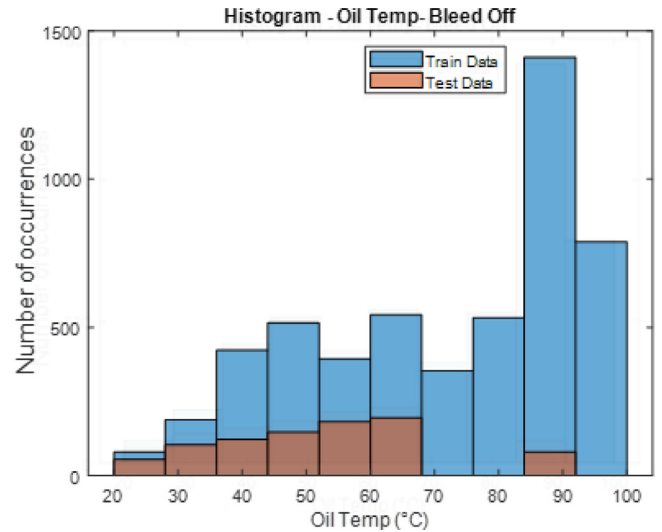


Fig. 14. Histogram of training and test data (T_{Oil} at BL OFF state).

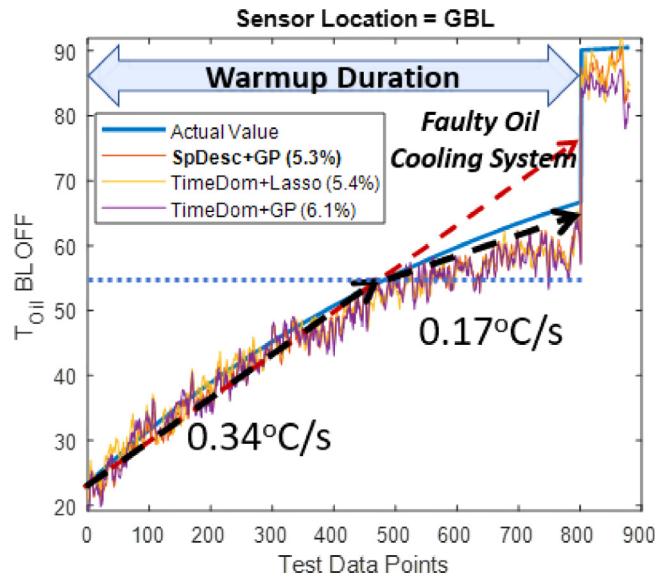


Fig. 15. Predicted vs actual T_{Oil} values at location GBL.

and shape factor features during the training phase. In contrast, GP further simplified the model at the expense of reduced accuracy (MAPE = 6.1%), giving:

$$T_{Oil} = 238 - 0.12 \frac{RMS^2}{ZCR} \quad (27)$$

The above-identified relationships can be utilized in detecting a faulty oil cooling system by observing the maximum oil temperatures or by monitoring the change in oil temperature during the warmup phase. A fault in the system results in the incorrect position of the inflection point (change in slopes) or the incorrect slope; a microphone at an optimum position can detect these.

The above analysis is repeated at all the sensor locations, and the best model, at each sensor location, with the corresponding MAPE is recorded (see Fig. 16). Amongst the sensor locations, GBL is found to be the best sensor location (MAPE = 5.3%) for predicting the oil temperature under the BL OFF state. This can be attributed to the proximity of the sensor to the oil cooler, Fig. 17. The oil temperature affects the characteristics of the air-flow (and thus the nearby acoustics) in the vicinity of the oil heat

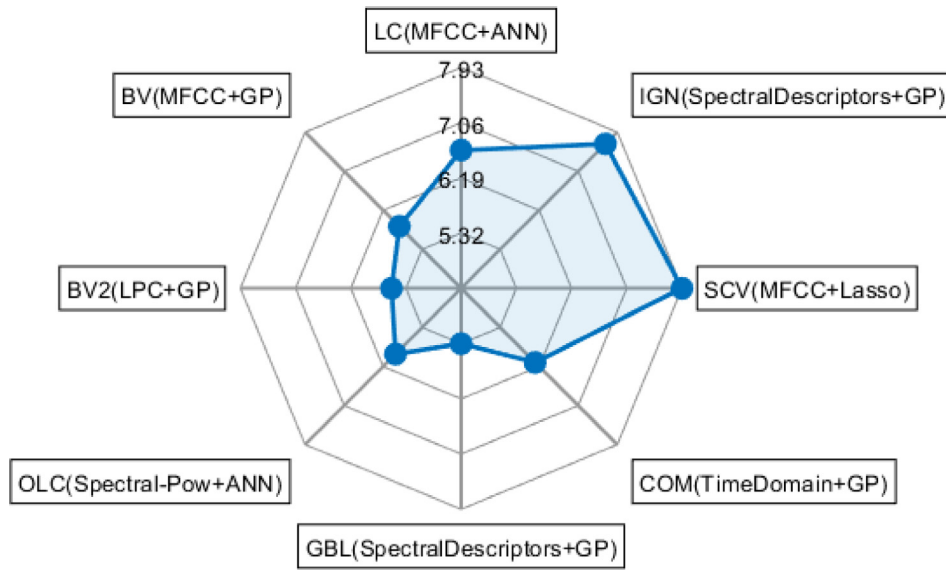


Fig. 16. Test data MAPE (%) and best models for estimating T_{oil} at various locations.

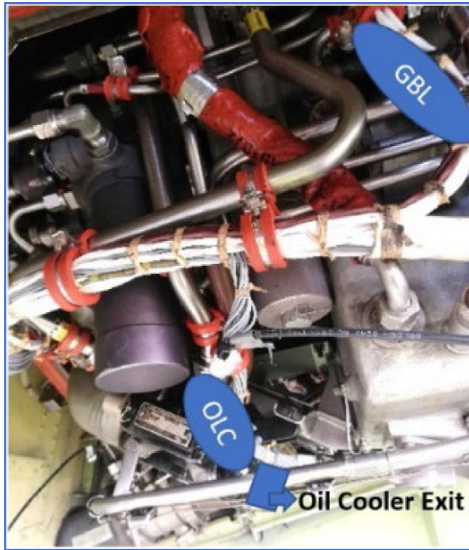


Fig. 17. Location of GBL and OLC sensors with respect to oil cooler.

exchanger, which can be expressed by the Spectral-Descriptors. The GBL sensor is also in proximity to the gearbox where the variations in the lubrication oil temperature can affect the vibroacoustic behavior around that region. The low error at GBL for the test data indicates generalization of the model, resistance to over-fitting, and negligible sensitivity to other parameters like load compressor mass flow, ambient temperature, and aircraft location.

There appears to be a linear trend between the MAPE value and the distance of the sensors from the oil cooler. The sensors BV, BV2, GBL, and OLC are closer to the oil cooler and have a low error, whereas LC, IGN, SCV, and COM are relatively far away and have slightly higher errors. For further visualization of the accuracy of the models across the APU, a 2-D surface plot is shown in Fig. 18. The x and y axes correspond to the axial and lateral coordinates of the APU, as in the diagram on the left of Fig. 18. The labels indicate the position of the sensors in 2-D space and the height/color indicates the error. The colors of the surface plot range from yellow (accurate) to blue (less accurate). The plots

show that the variation in the accuracy follows a trend across the APU, based on which a good position to place the microphone is a point around the oil cooler and the gearbox.

4.3.2. Detailed analysis (IGV and $\dot{m}_{LC}$ at BL ON NL State)

The IGV opening angles are important from the perspective of fault detection of the APU pneumatic system. Through experimentation, and in accordance with the AMM (Aircraft Maintenance Manual), it has been found that fully open IGVs (angle = 88°) lead to the desired ranges of $\dot{m}_{LC}$ and $\dot{m}_{Bleed}$ to satisfy the pneumatic loads, e.g., the air supply to the ECS. However, in part of the acquired experimental data, there are data segments in which the IGVs are not fully opening, and the IGV angles are as low as 70° (see Fig. 19). The data for the normal condition (IGV = 88°) is in the majority, while the remaining data shows the presence of lower IGV angles, which can be treated as faulty conditions. The test data has two separate regions:

First region: IGVs opening angles are varying between 72° – 75° .

Second region: IGVs finally settle at around 84° after 28 min of operation (data not acquired during the transition time). This is not a degraded condition and is not discussed in detail.

The first region can be treated as a degraded condition, and the test data has been utilized to validate the robustness of the trained regression models to detect such degradation at various sensor locations (see Fig. 20). According to the analysis, the sensors placed inside the shroud are appropriate for estimating the IGV angles ($MAPE = 1.4$ – 2.3%). Most of the best models utilize MFCC or Spectral-Pow features in conjunction with Lasso or ANN regression techniques. Outside of the APU shroud, the errors are high (3.1 – 4.7%) because the acoustic characteristics may be affected by external effects (ambient temperatures and aircraft location) making them unsuitable for this type of APU parameter estimation.

The capability of near-field acoustics to detect IGV degradation can be shown by the estimation of IGV angles from acoustic features on unseen data, Fig. 21(a). The figure shows the actual IGV values, displayed by the FADEC, along with the estimated ones at sensor location OLC using a linear combination of four of the LPC features identified using GP. The model can accurately compute the IGV angles during degraded, as well as under normal, conditions. As the data update rate was set to 0.2 s, the noisy element in the estimated results can be reduced by incorporating

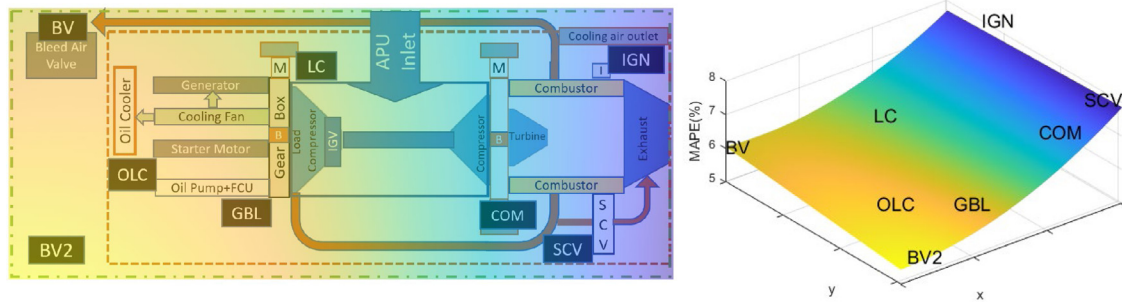


Fig. 18. Variation of oil temperature model accuracy across the APU.

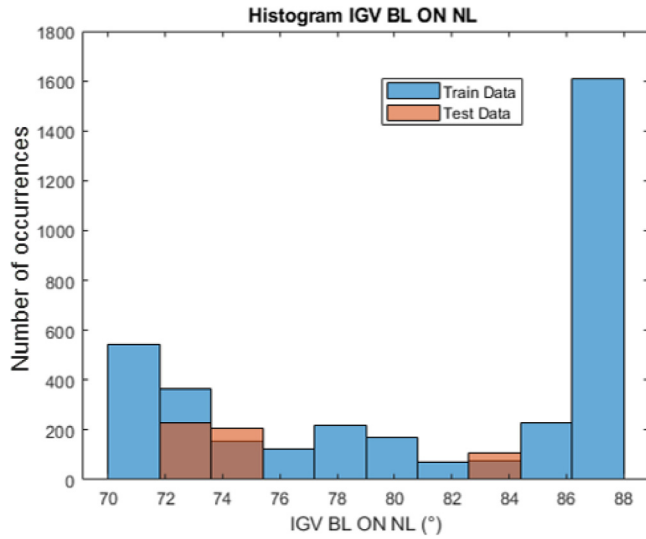


Fig. 19. Histogram of training and test data (IGV angles at BL ON NL state).

a suitable smoothing operation (moving average applied with a span of 30 samples), with the results shown in Fig. 21(a).

The direct effect of a reduced IGV angle, due to degraded conditions, is on $\dot{m}_{LC}$. Using the same acoustic-to-thermodynamic parameter estimation approach, the low values of $\dot{m}_{LC}$ can also be detected, Fig. 21(b). This graph shows how well the test data $\dot{m}_{LC}$ values can be estimated ($MAPE = 0.8\%$) under degraded and normal conditions from sensor location OLC. Using such acoustic-based models, fouling in the load compressor can also be detected by monitoring the $\dot{m}_{LC}$ values.

4.3.3. Detailed analysis (IGV BL ON LD)

In this section, results for the IGV angles during the BL ON LD state are presented from the point of view of generalizability of the acoustic-to-thermodynamic models. The dataset for this variable is peculiar in the sense that the corresponding test data do not coincide with the training data, see Fig. 22. The models are trained with data present at two separate ranges (72° – 76° and 86° – 88°), whereas the test data exists at 84° . The model trained at the location COM produced the best result on test data with a $MAPE$ value of 1.25%; Fig. 23 shows the values estimated by the model against the actual values of the IGV angle. This model utilizes a linear combination of all the Spectral-Pow features (determined by Lasso regression) and can be seen to center around the actual value, although it was not trained for this range of IGV values. The fluctuations in the estimated IGV values are due to the presence of unwanted variations in the acoustic features. These fluctuations are greater than the BL ON NL case because of the additional flow generated in the bleed duct due to the pneumatic

demand. Any smoothing operator (like moving average) could be employed to curtail this behavior at the expense of a slower update rate. In this case, a moving average filter with a span of 30 (corresponding to 6 s) has been applied, which reduced the error from 1.29% to 0.77%.

4.3.4. Detailed analysis ($\dot{m}_{Bleed}$ BL ON LD)

Mass flow through the BV ($\dot{m}_{Bleed}$) is another important parameter from the aspect of monitoring the performance of the APU. In this section, this parameter is shown to be estimated correctly, thus demonstrating the ability to detect a degraded condition. The test data for this parameter comprises instances where $\dot{m}_{Bleed}$ is found to be minimal during the ECS ON condition when compared with the rest of the dataset, see Fig. 24. During the entire ECS operations (excluding the test dataset), $\dot{m}_{Bleed}$ remained around 0.7–0.8 kg/s. However, on the test day, the values dropped below 0.6 kg/s resulting in degraded performance of the ECS. Using the acoustic-to-thermodynamic model, the decrease in $\dot{m}_{Bleed}$ can be detected (Fig. 25), which also demonstrates the extrapolation capability of the developed scheme. The figure shows the estimated values of $\dot{m}_{Bleed}$ (with $MAPE = 8.4\%$) from sensor location IGN using all the LPC features as input to the linear regression model. Similar accuracy ($MAPE = 9.3\%$) can also be achieved by placing the microphone close to the surge control valve and utilizing the time domain features (excluding crest factor and shape factor). These two locations are closest to the bleed duct and being inside the shroud are less susceptible to external effects. Fig. 26 illustrates the achieved accuracies at all the sensor locations. The outside shroud sensors (BV and BV2) and COM have been identified as the least-performing locations, likely due to external interference and the disturbances caused by the combustor. A surface fit between the error and the sensor locations is computed to visualize the trend in the accuracy of the models across the APU (Fig. 27). Accuracies are high toward the rear part of the APU where the bleed mass flow is originating (IGN, SCV). The remaining inside shroud sensors are either at a distance from the bleed duct (GBL, OLC) or suffers from shielding effects due to the presence of the shroud in between the duct and the sensor (location LC).

4.3.5. Summary of regression results

A complete analysis has been repeated for the remaining variables under all APU states. Results showing the best achievable test accuracy at each location for the desired parameters have been summarized and are presented in Table 6. Each cell in the table has been color-coded in the order they appear for each of the parameters (green for the lowest error, red for the highest error, and yellow for the intermediate error values). The following inferences can be drawn from the table:

- In a similar way to classification, the outside shroud sensors (BV & BV2) do not perform well in predicting most

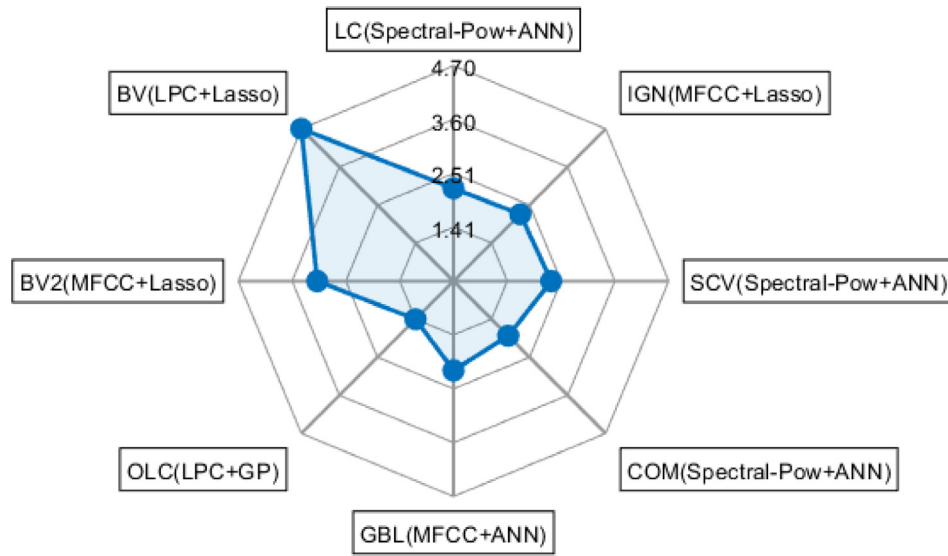


Fig. 20. Estimating IGV angles – MAPE (%) for best models at each location.

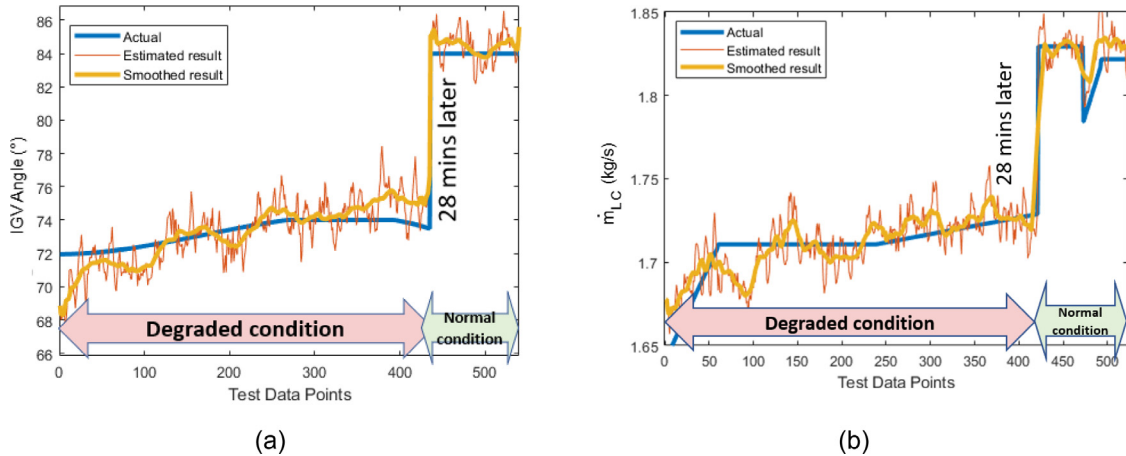
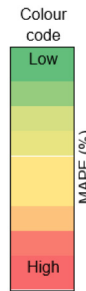


Fig. 21. Actual, estimated and smoothed values for IGV angles and $\dot{m}_{LC}$ at location OLC.

Table 6

The Minimum MAPE value for each parameter at each different sensor locations.

	LC	IGN	SCV	COM	GBL	OLC	BV2	BV
$T_{Oil} BL OFF$	6.6	7.7	7.9	6.1	5.3	5.9	5.5	5.8
$\dot{m}_{LC} BL OFF$	1.0	1.1	0.2	1.1	0.7	1.2	1.5	0.6
$T_{Oil} BL ON NL$	1.3	2.1	2.1	1.8	1.3	0.7	5.6	7.1
$IGV BL ON NL$	2.2	2.2	2.3	1.9	2.1	1.4	3.1	4.7
$\dot{m}_{LC} BL ON NL$	0.9	1.1	1.2	0.8	1.2	0.8	1.4	2.3
$T_{Oil} BL ON LD$	1.2	0.6	0.5	0.5	0.5	0.5	0.5	0.2
$IGV BL ON LD$	3.0	1.6	1.3	1.2	1.7	1.5	1.5	2.2
$\dot{m}_{Bleed} BL ON LD$	19.2	8.4	9.3	29.5	17.1	15.6	32.7	45.8
$\dot{m}_{LC} BL ON LD$	0.5	1.9	0.6	0.4	0.9	0.8	1.1	0.9



- of the parameters. They seem to be providing accurate readings for oil temperature under *BL ON LD* conditions, but the associated errors can compound due to inaccurate classifications. While their location is convenient from the perspective of sensor installation and routing of the cables, it is not the right choice for APU monitoring purposes.
- (b) Since the desired thermodynamic parameters are diverse in nature, their effect is not felt the same across the whole APU. Therefore, any single location might not be the best

for accurately determining all the parameters. Some locations are good for a certain subset, but not the whole parameter set.

- (c) OLC can be regarded as one of the best sensor locations because at this location all the desired parameters under *BL ON NL* state and $T_{Oil} BL OFF$ can be accurately determined. This location is not the right choice for predicting the parameters during the *BL ON LD* state, except for T_{Oil} for which the error is around 0.5%.

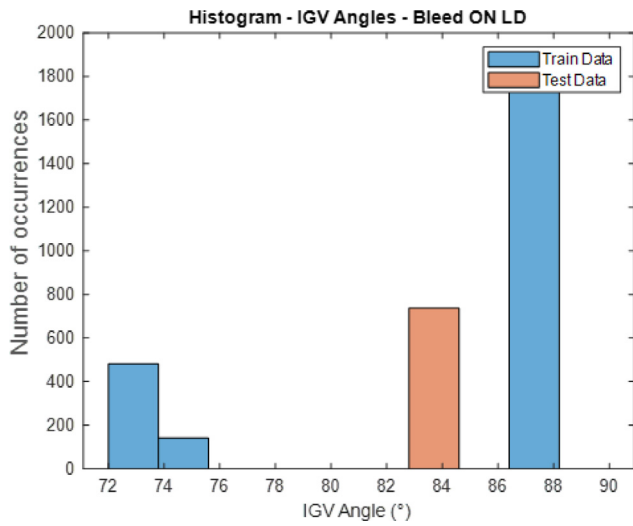


Fig. 22. Histogram of training and test data (IGV angles at BL ON LD state).

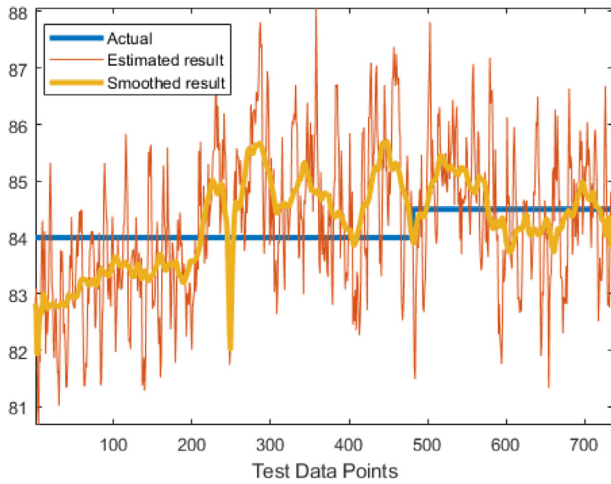


Fig. 23. Actual, estimated and smoothed values for IGV angles.

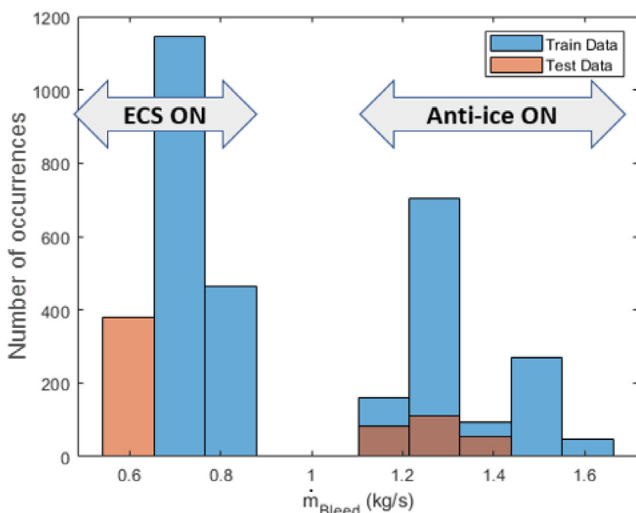


Fig. 24. Histogram of training and test data ($\dot{m}_{Bleed}$ at BL ON LD state).

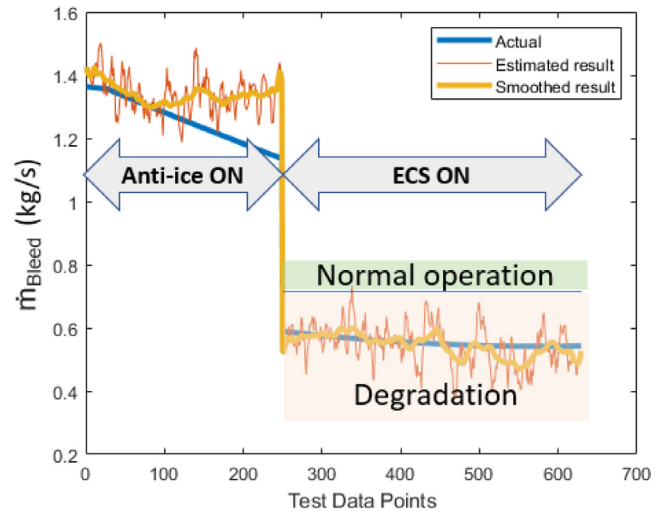


Fig. 25. Actual, estimated and smoothed values for $\dot{m}_{Bleed}$.

- (e) ANNs are recommended to develop a generalized model using noisy acoustic data. As per the complete analysis (not shown) ANNs have performed well for four of the nine APU parameters. This indicates non-linear relationships existing between the desired APU parameters and the acoustic features. Genetic programming, in conjunction with LPC and Spectral-Descriptors features, has also proved to be useful for the other three parameters, while Lasso has been identified to be the least favorable technique.
- (f) The LPC and Spectral-Descriptors features prove to be an appropriate choice for developing the regression models since they produce accurate results for six of the nine APU parameters.
- (g) The estimation of acoustic-to-thermodynamic parameters is accurate even on unseen data. The errors are less than 8.4%, and as low as 0.2% for the load compressor mass flows and oil temperatures. The accuracies can be increased by further extending the experiment to acquire a richer dataset for training.
- (h) The highest error has been recorded for $\dot{m}_{Bleed}$ BL ON LD (MAPE = 8.4%). This is because the test data exists in the extrapolated region for which it was not trained. The variation in $\dot{m}_{Bleed}$ is localized to a very small region (where the bleed duct is), and therefore leads to very small variations in the acoustic characteristics across the APU. Most importantly, the $\dot{m}_{Bleed}$ values are very low (as low as 0.55 kg/s). In this case, the denominator in the expression for MAPE is low, leading to high values even if the absolute error is small.

To conclude, two microphones placed near the oil cooler and surge control valve can provide the necessary parameter set for monitoring the APU. Either of them could be used for the accurate identification of the APU state. However, based on the results, it is suggested to utilize the latter one for predicting the desired parameters during BL ON LD state (except T_{Oil}) and $\dot{m}_{LC}$ under BL OFF state, and the former one for the remaining parameters.

5. Conclusion and future directions

In this paper, a novel approach has been proposed for the detection of various faults in an aircraft APU based on acoustic monitoring using non-intrusive sensors. To support its validation, a comprehensive dataset, under a wide range of operating

- (d) The remaining set of parameters can be estimated with reasonable accuracy by the sensor around SCV.

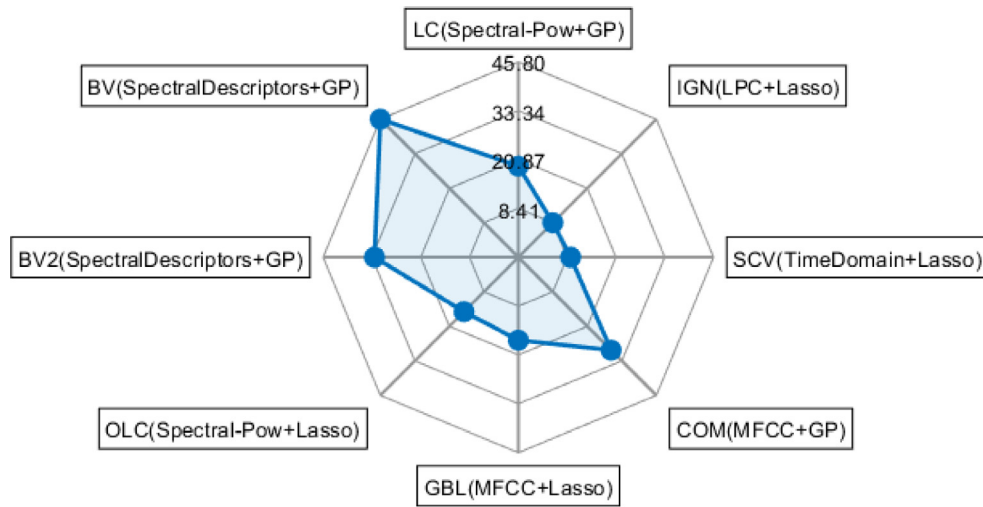


Fig. 26. Estimating $\dot{m}_{Bleed}$ - MAPE (%) for best models at each location.

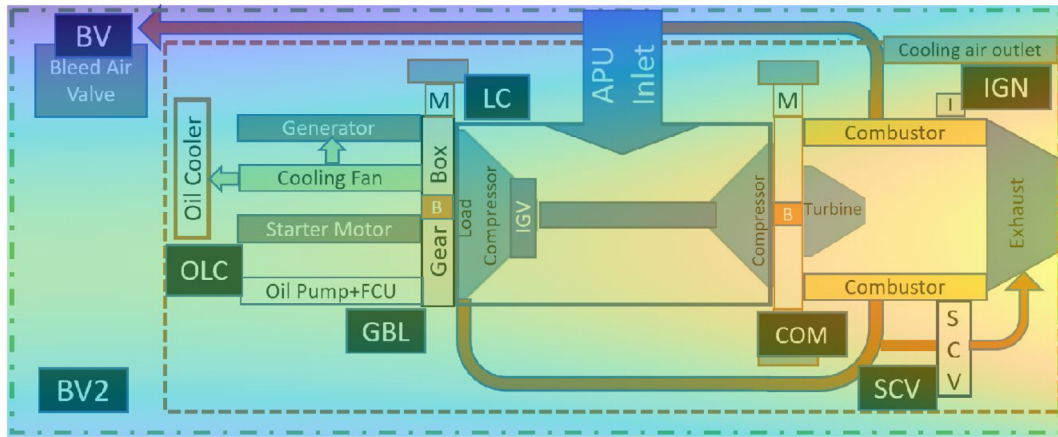


Fig. 27. Variation of $\dot{m}_{Bleed}$ model accuracy across the APU.

conditions, has been acquired on the APU of a Boeing 737-400 aircraft. Various acoustic features, classification, and regression techniques have been evaluated to develop and test appropriate models for enabling fault detection in an APU. The overall implementation initially deploys classification models to compare the desired and current APU state of operation to detect a faulty condition. Subsequently, acoustic-to-thermodynamic regression models compute the required parameters for detecting faults in the lubrication or pneumatic systems. Based on detailed analysis it has been found that data from the inside shroud microphones can accurately identify the APU states using LPC, MFCC, or Spectral-Pow features. The models can perform perfect classification, but performance deteriorates as the sensors are moved outside the APU shroud. Furthermore, the trained regression models have been found to be accurate (errors less than 8.4% without a smoothing operation for test data), making them appropriate for detecting a degraded condition. The overall analysis demonstrates that a set of only two well-placed microphones are sufficient for detecting multiple faults in an APU. The developed system is generalizable, and its ability to detect degradation in the target parameters has been successfully demonstrated.

Future research should focus on:

- Considering the effect of abnormal looseness of parts and components in the APU on the acoustic features and determining whether the noise generated would cause any

influence on the performance of the developed regression models.

- Evaluating the proposed methodology on other aircraft systems, e.g., ECS, engines, and hydraulics.
- Analyzing the acoustic data from the microphones for stability and reliability.
- Evaluation of advanced data-driven approaches (e.g., Fuzzy inference system, Ensemble Machine Learning, and Deep Neural Networks) to determine their performance for acoustics-to-thermodynamic parameter estimation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

Data is restricted due to agreement with the commercial partner.

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