

CRANFIELD UNIVERSITY

UMAIR AHMED

INVESTIGATION OF AIRCRAFT AUXILIARY POWER UNIT
ACOUSTIC SIGNATURES FOR CONDITION MONITORING

SCHOOL OF AEROSPACE,
TRANSPORT AND MANUFACTURING
Integrated Vehicle Health Management

DOCTOR OF PHILOSOPHY
Academic Year: 2022- 2023

Supervisor: Professor Ian K Jennions
Associate Supervisor: Dr. Fakhre Ali
February 2023

CRANFIELD UNIVERSITY

SCHOOL OF AEROSPACE,
TRANSPORT AND MANUFACTURING
Integrated Vehicle Health Management

DOCTOR OF PHILOSOPHY

Academic Year 2022 - 2023

UMAIR AHMED

INVESTIGATION OF AIRCRAFT AUXILIARY POWER UNIT
ACOUSTIC SIGNATURES FOR CONDITION MONITORING

Supervisor: Professor Ian K Jennions
Associate Supervisor: Dr. Fakhre Ali
February 2023

This thesis is submitted in partial fulfilment of the requirements for
the degree of PhD

© Cranfield University 2023. All rights reserved. No part of this
publication may be reproduced without the written permission of the
copyright owner.

ABSTRACT

The auxiliary power unit (APU) of an aircraft is a key system responsible for providing electrical and pneumatic power during ground operations and in-flight emergencies. APU failures can result in delay or cancellation of a flight and fault diagnostic practices are in place to identify the cause of failure. The existing strategies generally require human intervention to identify the fault by traversing through a troubleshooting manual and examining the data acquired from multiple intrusive sensors. The complete process is cumbersome and prone to misjudgement; fault identification in its entirety may not be possible due to limited sensor coverage. Incorporating additional sensors may not be feasible due to accessibility issues, space constraints and certification requirements. However, incorporating microphones, which have previously been used for noise source characterization and verification of noise abatement solutions, is a promising non-intrusive approach. This PhD focuses on ascertaining the potential of microphones for fault detection / identification and condition monitoring of an aircraft APU. The research has been based on the far-field and near-field acoustic data acquired from Cranfield University's Boeing 737-400 aircraft and the aim has been to determine the degradation / faults that can be detected using microphones. While addressing this aim, a far-field noise model has been developed for sensitivity analysis, near-field data has been analysed, classification / regression models have been proposed and an acoustics-based scheme for ignition system monitoring has been conceived. The results suggest that the far-field acoustic data is not suitable for condition monitoring, and the near-field microphones are unable to monitor tonal frequencies for monitoring the gearbox and bearing. However, there is a huge potential in using microphones for monitoring the lubrication system, pneumatic system components and ignition system for faulty / degraded conditions. The proposed methodologies have online capability and require only a limited set of microphones inside the APU compartment.

Keywords:

Signal processing, Acoustics, vibration, Combustion noise, Jet Noise, Ignition system, condition monitoring, health management, fault detection, acoustic reflection, acoustic scattering, feature extraction, machine learning, classification, regression, genetic programming, data segmentation, igniter

ACKNOWLEDGEMENTS

All praise is due to Allah Almighty, the Lord of all worlds, the Greatest, the most Beneficent, the most Merciful, the Ever-providing, for His countless blessings. May His peace and blessings upon His Prophet Muhammad.

I express my sincere and deepest gratitude to my supervisor Professor Ian Jennions for his valuable feedback, support, and time. I appreciate his patience and encouragement in improving my research, presentation, and writing skills. His technical advice and feedback have been very helpful in the timely completion of the PhD. His insightful thinking helped me to become a better and more focused researcher. I have learned a lot from him, which will prove to be helpful during my future assignments and professional career.

I would also like to thank my co-supervisor Dr Fakhre Ali for being there with me during the ups and downs of the PhD and keeping me motivated. He kept on reminding me that every cloud has a silver lining. Special thanks to the Boeing Company for their financial support and technical feedback. The extensive assistance provided by Cengiz Turkuglo cannot go unnoticed. With his help, I was able to carry out the instrumentation of the aircraft and acquire the required set of vibroacoustic data within a short span of time.

Last, but most importantly, I would like to thank my wife for her unconditional love and patience during various phases of research. She ensured that I remain focused on my work by looking after the kids (even during the pandemic). I am eternally indebted to my mother for believing in me as I embarked on this perilous journey where there are several unknowns.

TABLE OF CONTENTS

ABSTRACT	i
ACKNOWLEDGEMENTS.....	iii
LIST OF FIGURES	viii
LIST OF TABLES	xiii
LIST OF EQUATIONS.....	xiv
LIST OF ABBREVIATIONS	xvii
LIST OF SYMBOLS	xxi
1 Introduction.....	1
1.1 Motivation behind this research	1
1.2 Aircraft Auxiliary Power Unit	2
1.3 Aim and Objectives	5
1.4 Methodology	6
1.5 Thesis Structure.....	8
1.5.1 Chapter 2 : A Review of Aircraft Auxiliary Power Unit Faults, Diagnostics and Acoustic Measurements.....	10
1.5.2 Chapter 3 : Development of a Far-Field Noise Estimation Model for an Aircraft Auxiliary Power Unit.....	11
1.5.3 Chapter 4 : Evaluation Of Aircraft Auxiliary Power Unit Near-Field Acoustics for Condition Monitoring.....	12
1.5.4 Chapter 5 : Acoustic Monitoring of an Aircraft Auxiliary Power Unit .	13
1.5.5 Chapter 6 : Signal processing of Acoustics Data for Aircraft APU Ignition System.....	13
1.5.6 Chapter 7 : Summary and Future Work.....	14
1.6 List of Publications	14
References	15
2 A Review of Aircraft Auxiliary Power Unit Faults, Diagnostics and Acoustic Measurements.....	17
2.1 Background to the Literature Survey.....	17
2.2 Aircraft Auxiliary Power Unit	19
2.2.1 APU Functions	20
2.2.2 APU Maintenance	21
2.2.3 Current and Future Trends in APUs	27
2.3 Fault Diagnostics	30
2.3.1 A Rudimentary form of fault Diagnostics	31
2.3.2 Performance-based diagnostics	32
2.3.3 Vibration-based diagnostics	33
2.3.4 Acoustics-based diagnostics	40
2.3.5 Other forms of diagnostics	45
2.3.6 Design Considerations in Aircraft Systems with Novel Architectures	47

2.4 Application of Acoustics in Airborne Gas Turbine Engines	49
2.4.1 Gas Turbine Noise Terminology	49
2.4.2 Significance of Engine Core Noise	52
2.4.3 Gas Turbine Noise Measurement and Characteristics	53
2.4.4 APU Noise Measurement and Characteristics	64
2.4.5 Engine Noise of Airborne Platforms with Novel Architectures	76
2.5 Acoustics for Fault Diagnostics of Aircraft Auxiliary Power Unit.....	77
2.5.1 Research Gaps	77
2.5.2 Opportunities	79
2.5.3 Challenges	80
2.6 Summary	81
References	82
3 Development of a Far-Field Noise Estimation Model for an Aircraft Auxiliary Power Unit.....	106
3.1 Introduction	106
3.1.1 Description of APU	108
3.1.2 Scope of Work.....	109
3.2 Proposed Methodology	110
3.2.1 Experimental Setup	111
3.2.2 APU Thermodynamic Model Development	113
3.2.3 Solver Implementation.....	115
3.2.4 Spectral Analysis of Far-field Noise.....	116
3.2.5 Noise Source Separation Using Similarity Spectrum	116
3.2.6 Component Level Noise Estimation Model Implementation	118
3.2.7 Modeling of Ground Reflections	122
3.3 Results and Discussion.....	124
3.3.1 APU Thermodynamic Model Results.....	125
3.3.2 Derived APU Thermodynamic Parameters	127
3.3.3 Component level noise separation results.....	130
3.3.4 Ground Reflection Effects	132
3.3.5 Noise Estimation Results	134
3.4 Study of Effect of Component Degradation on Far-Field	138
3.5 Conclusion	141
References	142
4 Evaluation Of Aircraft Auxiliary Power Unit Near-Field Acoustics for Condition Monitoring	147
4.1 Introduction	147
4.1.1 Background	147
4.1.2 Literature Review	148
4.1.3 Scope of Work.....	149
4.2 Boeing 737-400 APU Operation	150
4.3 Analyses Performed	151

4.3.1 Overview	151
4.3.2 Experimental Data Collection	152
4.3.3 Near-field and Far-field Noise Coherence Analysis.....	154
4.3.4 Tonal Analysis.....	154
4.3.5 Broadband Noise Analysis	155
4.4 Results and Discussion.....	160
4.4.1 Near-field and Far-field Noise Coherence Analysis.....	160
4.4.2 Tonal analysis	162
4.4.3 Broadband Noise Analysis	175
4.5 Summary and Conclusion.....	183
References	185
5 Acoustic Monitoring of an Aircraft Auxiliary Power Unit.....	190
5.1 Introduction	190
5.2 Problem Description and Background.....	194
5.2.1 Boeing 737-400 APU Operation.....	194
5.2.2 APU Near-Field Acoustics.....	196
5.2.3 APU Fault Modes	197
5.2.4 Application of Signal Processing Techniques.....	199
5.3 Proposed Scheme for Fault Detection	202
5.3.1 Overview	202
5.3.2 Experimental Data Collection	205
5.3.3 Data Preparation	208
5.3.4 Feature Extraction.....	209
5.3.5 APU State Classification Analysis	213
5.3.6 Regression Analysis.....	214
5.4 Results and Discussion.....	217
5.4.1 Features Extraction	217
5.4.2 Classification Results	220
5.4.3 Regression Results and Fault Detection	224
5.5 Conclusion and future directions.....	236
References	237
6 Signal processing of Acoustics Data for Aircraft APU Ignition System	245
6.1 Introduction	245
6.1.1 Boeing 737-400 APU.....	247
6.1.2 Literature Review	249
6.1.3 Scope of Research.....	251
6.2 Experimental Data Collection.....	251
6.2.1 Initial Analysis and Data Preparation.....	252
6.3 Employed Methodology	253
6.4 Results and Discussion.....	254
6.4.1 Implementation of High-Pass Filter	255
6.4.2 SRF estimation.....	257

6.4.3 Spark event segmentation.....	258
6.4.4 Performance Metric for Feature Evaluation.....	261
6.4.5 Selected Features for Evaluation	262
6.4.6 Feature Extraction Results	265
6.5 Conclusion	269
References	271
7 Summary and Future Work	275
7.1 Addressing the Research Aim and Objectives.....	275
7.2 Contribution to knowledge	278
7.3 Potential impacts of the findings	279
7.4 Future recommendations	280

LIST OF FIGURES

Figure 1-1 Cranfield University's B737-400 aircraft (a) Parked on taxiway (b) Parked inside a hanger	3
Figure 1-2 Schematics of the adopted APU	4
Figure 1-3 FADEC location inside the aircraft	5
Figure 1-4 PhD Methodology.....	7
Figure 1-5 Overview of thesis structure.....	9
Figure 2-1 Areas covered through the literature survey	19
Figure 2-2 Costs associated with aircraft APU	22
Figure 2-3 APU faults histogram	24
Figure 2-4 Causes and Effects of APU Failure.....	25
Figure 2-5 Engine Core Noise [139]	50
Figure 2-6 Baseline engine far-field noise and identified noise sources [151]..	54
Figure 2-7 Ratio of indirect to direct combustion noise (as a function of inlet and outlet Mach numbers at the flame zone and nozzle outlet respectively) [186]	75
Figure 3-1 Schematics of the adopted APU	110
Figure 3-2 Far-field noise model development methodology for an Aircraft APU	111
Figure 3-3 Acquisition of experimental data from Boeing 737-400 Auxiliary Power Unit.....	112
Figure 3-4 APU operating conditions and representation of experimental datasets	113
Figure 3-5 APU Model developed in T-MATS	114
Figure 3-6 Thermodynamic parameter estimation using T-MATS.....	116
Figure 3-7 Power Spectrum of far-field acoustic data with similarity spectrum superimposed	118
Figure 3-8 Measured EGT and estimated values of Turbine Inlet Temperature	125
Figure 3-9 Component efficiencies for different operating conditions.....	126
Figure 3-10 Comparison of mass flow through surge and the aircraft pneumatic system	126

Figure 3-11 Derived engine parameters (a) core mass flow (b) Fuel air ratio (c) Combustor inlet temperature	128
Figure 3-12 Estimated mass flow entering the muffler during various APU operating conditions	129
Figure 3-13 Estimated APU and Muffler exit parameters	130
Figure 3-14 Noise source separation results	131
Figure 3-15 Comparison of experimental data and synthetically generated noise data with reflections	133
Figure 3-16 Vertical arrangement of the experimental setup and synthetic data generation for simulating ground reflections	133
Figure 3-17 Estimated noise levels before offset correction	135
Figure 3-18 Comparison of estimated noise levels after offset corrections	136
Figure 3-19 Total Noise estimation results	137
Figure 3-20 Comparison between actual and estimated parameters (EGT and fuel flow rate) for various load conditions.....	139
Figure 3-21 Results of faults simulation on thermodynamic and noise parameters	141
Figure 4-1 The scheme adopted for APU Acoustic Data Analysis.....	152
Figure 4-2 Microphone and vibration sensors placement	153
Figure 4-3 Process followed for analysing feature response under the various APU States	157
Figure 4-4 Coherence analysis between far-field and near-field acoustic data	161
Figure 4-5 Coherence analysis between far-field acoustic and APU vibration data	162
Figure 4-6 Coherence analysis between Near-Field Acoustic Sensors and Vibration Data.....	164
Figure 4-7 Variation in the number of coherent tones across APU.....	164
Figure 4-8 Power spectrum of acoustic data from microphones at location (a) GBL and (b) BV	165
Figure 4-9 Power Spectrum of Gearbox Vibration Data	165
Figure 4-10 Power spectrum of the segmented versions of vibration and acoustic data	166
Figure 4-11 Deviation in tonal frequencies during BL OFF and BL ON states	167

Figure 4-12 Power Spectrum of $Sf12t$ for different levels of RPM fluctuations	170
Figure 4-13 Effect of variation in RPM fluctuations on SNR of tones at various orders	170
Figure 4-14 Experimental setup to study the effect of vibration on generated acoustic tones.....	171
Figure 4-15 Power Spectrum of acquired acoustic data from the microphone undergoing vibrations	172
Figure 4-16 Bicoherence analysis of vibration data.....	173
Figure 4-17 Bicoherence analysis of acoustic data	174
Figure 4-18 Result of bicoherence analysis on simulated data	175
Figure 4-19 Results of $\Delta BL OFFBL ON$ for RMS feature (Time domain feature category).....	177
Figure 4-20 Result of $\Delta BL ON NLBL ON LD$ for the fifth feature (MFCC feature category).....	177
Figure 4-21 Distributions of coefficients of overlap for different categories of acoustic and vibration features	178
Figure 4-22 Distributions of correlation coefficients for APU parameters and different categories of features	180
Figure 4-23 Analysis of external and internal microphone data (a) Time domain signal (b) Frequency Spectrum.....	182
Figure 5-1 Overview of the chapter	194
Figure 5-2 Schematics of the adopted APU	195
Figure 5-3 Degradation of APU components (a) Oil cooler fouling (b) IGVs closed (c) Wearing effects around the load compressor	199
Figure 5-4 Proposed novel system for APU fault detection and isolation using acoustics.....	203
Figure 5-5 Procedure followed for the development and evaluation of acoustic-to-thermodynamic parameter estimation models.....	204
Figure 5-6 Experimental setup for APU state and acoustic data collection. ...	206
Figure 5-7 Microphone placement in the APU compartment.....	207
Figure 5-8 Recording of FADEC Display.....	207
Figure 5-9 MFCC filter bank	211

Figure 5-10 Histogram of the RMS Time Domain Feature at different sensor locations.	218
Figure 5-11 Histogram of an MFCC Feature (F5) at different sensor locations	220
Figure 5-12 Confusion Matrix for APU State classification using Spectral-Pow features.....	223
Figure 5-13 MFCC Features visualization using PCA	223
Figure 5-14 Histogram of training and test data ($TOil$ at $BL OFF$ state)	225
Figure 5-15 Predicted vs actual $TOil$ values at location GBL	226
Figure 5-16 Test data MAPE (%) and best models for estimating $TOil$ at various locations	227
Figure 5-17 Location of GBL and OLC sensors with respect to oil cooler	227
Figure 5-18 Variation of oil temperature model accuracy across the APU	228
Figure 5-19 Histogram of training and test data (IGV Angles at $BL ON NL$ State)	229
Figure 5-20 Test data MAPE (%) and Best Models for estimating IGV angles at various locations.....	230
Figure 5-21 Actual, estimated and smoothed values for IGV angles and $\dot{m}LC$ at location OLC.....	230
Figure 5-22 Histogram of training and test data (IGV Angles at $BL ON LD$ state)	231
Figure 5-23 Actual, estimated and smoothed values for IGV angles.....	232
Figure 5-24 Histogram of training and test Data ($\dot{m}Bleed$ at $BL ON LD$ state)	232
Figure 5-25 Actual, estimated and smoothed values for $\dot{m}Bleed$	233
Figure 5-26 Estimating $\dot{m}Bleed$ - MAPE (%) for best models at each location	234
Figure 5-27 Variation of $\dot{m}Bleed$ model accuracy across the APU	234
Figure 6-1: The APU of a Boeing 737-400 (a) aircraft tail section and APU compartment (b) components of the APU.....	248
Figure 6-2 APU igniter and faults (a) Actual igniter with eroded tip (b) Nominal limit of erosion (c) Burnt outer shell fault, adapted from [10].....	248
Figure 6-3 Experimental setup (a) APU and sensor locations (b) IGN microphone location (c) SCV microphone location (d) Cross-sectional view of the APU combustor, adapted from [10].....	252

Figure 6-4 Flow chart of the employed methodology.....	254
Figure 6-5 Comparison between spark and no spark signal (a) Time domain representation (b) Frequency domain analysis and magnitude response of the high-pass filter	255
Figure 6-6 Results of application of high pass filtering on acquired data (a) Raw acoustic data (b) Filtered acoustic data (c) APU RPM.....	256
Figure 6-7 SRF computation (a) Envelope signal and envelope spectrum for acoustic data from Day#1 (b) Computed SRF and their fluctuations across all days of experimentation.	258
Figure 6-8 Time series data around a spark event.....	259
Figure 6-9 Moving average filter results (a) series of sparks (b) single spark with identified location of <i>tonset</i>	260
Figure 6-10 Rise times computed for the complete dataset at two sensor locations	261
Figure 6-11 Kurtosis values computed for spark and noise data at two sensor locations	264
Figure 6-12 Peak values computed for spark and noise data at two sensor locations	267
Figure 6-13 δRMS values computed for spark signals at two sensor locations	267
Figure 6-14 HVG values computed for spark and noise data at two sensor locations	268
Figure 6-15 Mean values computed for spark and noise data at two sensor locations	268

LIST OF TABLES

Table 1-1 List of thesis chapters aligned with research objectives and publication status	10
Table 2-1 Typical Usage of Aircraft APUs [1]	20
Table 2-2 Features of a good fault diagnostic method	31
Table 2-3 Categories of features for diagnosing gearbox faults [54]	35
Table 2-4 Summary of Experimentation done on Gas Turbine Noise	56
Table 2-5 Summary of Experimentation done on APU Noise	70
Table 3-1 Comparison of estimated and measured muffler exit temperature .	129
Table 3-2 RMS and Maximum error for combustion and jet noise estimates .	136
Table 3-3 Definition of faulty cases for simulation	140
Table 4-1 Number of tones with coherence greater than 0.5	164
Table 5-1 Description of APU Faults	198
Table 5-2 Data collection duration during experimentation.	208
Table 5-3 Data allocation for modeling and testing of models	209
Table 5-4 Parameters of the selected regression techniques	215
Table 5-5 Classification Results	221
Table 5-6 The Minimum MAPE value for each parameter at each different sensor locations	236
Table 6-1 Performance analysis of selected features.....	267

LIST OF EQUATIONS

(2-1)..... 52

(3-1)..... 117

(3-2)..... 117

(3-3)..... 117

(3-4)..... 119

(3-5)..... 119

(3-6)..... 119

(3-7)..... 120

(3-8)..... 120

(3-9)..... 120

(3-10)..... 120

(3-11)..... 121

(3-12)..... 121

(3-13)..... 121

(3-14)..... 122

(3-15)..... 122

(3-16)..... 123

(3-17)..... 123

(3-18)..... 124

(3-19)..... 124

(3-20)..... 124

(3-21)..... 137

(3-22)..... 137

(4-1)..... 157

(4-2)..... 158

(4-3)..... 158

(4-4)..... 159

(4-5)..... 159

(4-6).....	167
(4-7).....	168
(4-8).....	168
(4-9).....	168
(4-10).....	168
(4-11).....	168
(4-12).....	169
(4-13).....	169
(4-14).....	169
(4-15).....	169
(4-16).....	174
(4-17).....	174
(4-18).....	174
(5-1).....	210
(5-2).....	211
(5-3).....	211
(5-4).....	211
(5-5).....	211
(5-6).....	211
(5-7).....	212
(5-8).....	212
(5-9).....	212
(5-10).....	212
(5-11).....	212
(5-12).....	212
(5-13).....	212
(5-14).....	212
(5-15).....	212
(5-16).....	212

(5-17).....	212
(5-18).....	212
(5-19).....	213
(5-20).....	213
(5-21).....	213
(5-22).....	213
(5-23).....	214
(5-24).....	214
(5-25).....	216
(5-26).....	225
(5-27).....	226
(6-1).....	258
(6-2).....	261
(6-3).....	261
(6-4).....	262
(6-5).....	262
(6-6).....	263

LIST OF ABBREVIATIONS

ACARE	Advisory Council for Aeronautics Research in Europe
AFEWT	Adaptive Filtering Empirical Wavelet Transform
AMM	Aircraft Maintenance Manual
ANN	Artificial Neural Network
ANOPP	Aircraft Noise Prediction Program
ANTLE	Affordable, Near-Term Low Emissions
APU	Auxiliary Power Unit
BIT	Built-in Test
BL ON NL	Bleed System ON with No pneumatic Load
BL ON LD	Bleed system ON with pneumatic Load (ECS / Wing anti-ice system)
BP	Back Propagation
BPF	Blade Pass Frequency
BPM	Band-Pass Mesh
BSS	Blind Source Separation
COTS	Commercial off-the-shelf
CWT	Continuous Wavelet Transform
DAQ	Data Acquisition
DARTeC	Digital Aviation Research and Technology Centre
DOA	Direction-of-Arrival
DWT	Discrete Wavelet Transform
ECS	Environmental Control System
EEMD	Ensemble Empirical Mode Decomposition
EGT	Exhaust Gas Temperature
EPN	Effective Perceived Noise
ESDU	Engineering Sciences Data Unit
EVNERT	Engine Validation of Noise and Emission Reduction Technology

EWT	Empirical Wavelet Transform
FAA	Federal Aviation Administration
FADEC	Full Authority Digital Engine Control
FFT	Fast Fourier Transform
FMEA	Failure Modes and Effects Analysis
FTIR	Fourier Transform Infrared
GLCM	Gray Level Co-occurrence Matrix
GP	Genetic Programming
GPA	Gas Path Analysis
GPU	Ground Power Unit
IATA	International Air Transport Association
ICE	Internal Combustion Engine
IEPE	Integrated Electronics Piezo-Electric
IHHT	Improved Hilbert–Huang Transformation
IGV	Inlet Guide Vane
IMF	Intrinsic Mode Function
IP	Intellectual Property
IVHM	Integrated Vehicle Health Management
KDEMI	Kernel Density Estimator Mutual Information
LDA	Linear Discriminant Analysis
LPC	Linear predictive coding
LRU	Line Replaceable Unit
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
MED	Minimum Entropy Deconvolution
MES	Main Engine Start
MFCC	Mel-Frequency Cepstral Coefficients
MI	Mutual Information
MRO	Maintenance Repair and Overhaul

MVDR	Minimum Variance Distortionless Response
MW	Megawatt
NAH	Nearfield Acoustic Holography
NG	Next Generation
NI	National Instruments
OASPL	Overall Sound Pressure Level
OEM	Original Equipment Manufacturer
PCA	Principal component analysis
PDF	Probability Density Function
PSD	Power Spectral Density
RMS	Root Mean Square
ROC	Receiver operating characteristic
RPM	Revolutions per minute
RUL	Remaining Useful Life
SAE	Society of Automotive Engineers
SCV	Surge Control Valve
SDP	Symmetric Dot Patterns
SF	Shape Factor
SNR	Signal-to-Noise Ratio
SOFC	Solid Oxide Fuel Cell
SPL	Sound Pressure Level
SRF	Spark Repetition Frequency
STFT	Short-Time Fourier Transform
STOL	Short Take-Off and Landing
SVM	Support-Vector Machine
SVTM	Surge Valve Torque Motor
TEENI	Turboshaft Engine Exhaust Noise Identification
TKEO	Teager-Kaiser Energy Operator

T-MATS	Toolbox for the Modelling and Analysis of Thermodynamic Systems
TVF-EMD	Time Varying Filter–Empirical Mode Decomposition
TSA	Time Synchronous Averaging
VMD	Variational Mode Decomposition
VTOL	Vertical Take-off and Landing
WPT	Wavelet Packet Transform
WVD	Wigner-Ville Distribution
ZCR	Zero-Crossing Rate

LIST OF SYMBOLS

a_k	Linear predictor coefficients
A_b	Burner cross-sectional area
A_{jet}	Muffler cross-sectional area
c_0	Speed of sound in ambient condition
$c_{C/Jet-Model}$	Offset computed for Combustion/Jet Model
c_p	specific heat at constant pressure
c_{refl}	Sound reflection coefficient
DI	Directivity Index
D_{jet}	Exhaust jet diameter
$Eff_{Load\ Compressor}$	Load compressor efficiency
Eff_{Solver}	Component efficiency computed by solver
f_{shaker}	Shaker frequency
F_b	Burner fuel-to-air ratio
F_{st}	Stoichiometric fuel-to-air ratio
H_f	Fuel heating value
I	Sound Intensity
$\dot{m}_{Core}$	Mass flow through the engine core
$\dot{m}_{Bleed}$	Mass flow through aircraft bleed system
$\dot{m}_{LC}$	Mass flow generated by load compressor
$\dot{m}_{SV}$	Mass flow through the surge control valve
$\dot{m}_{APU\ Exit}$	Mass flow exiting the APU
$\dot{m}_{cold}$	Mass flow entering the muffler
$\dot{m}_{Muffler\ Exit}$	Mass flow exiting the muffler
η	Component efficiency
$\dot{N}$	Rate of change of rotor rpm
N_f	Number of fuel nozzles
ρ_{Jet}	Jet density

OASPL	Overall Sound Pressure Level
PR_{LC}	Pressure Ratio for Load Compressor
P_{Amb}	Ambient Pressure
$P_{Turbine\ Inlet}$	Combustor exit total pressure
P_3	Combustor inlet total pressure
$Q_{Combustion}$	Combustion noise propagation coefficient
Q_{Jet}	Jet noise propagation coefficient
R	Universal gas constant
r	The radial distance between APU exhaust and sensor M1
$SPL_{C/Jet-Model}^{Basic}$	SPL computed by the original form of Combustion / Jet noise model
$SPL_{C-model-i}$	Combustion noise estimated by Model i
$SPL_{Jet\ model\ i}$	Jet noise estimated by Model i
$SPL_{Measured}$	SPL of the far-field noise measured at sensor M1
T_{Amb}	Ambient temperature
T_{Jet}	Jet temperature
T_{Oil}	APU lubrication system oil temperature
$T_{Turbine\ Exit}$	Exhaust Gas Temperature
$T_{Turbine\ Inlet}$	Turbine Inlet temperature
T_3	Combustor inlet temperature
v_{Jet}	Jet velocity
v_{Mach}	Jet Mach number
Δ	Coefficient of overlap
ρ	Correlation Coefficient
$\bar{\sigma}_{RPM}$	Standard deviation of RPM fluctuations

1 Introduction

1.1 Motivation behind this research

A civil aircraft is a highly integrated platform, composed of multiple complex systems and sub-systems. Its functionality is strongly dependent on the safe operation of these systems within their design parameters. Maintenance, Repair, and Overhaul (MRO) activities are implemented to retain the functionality of systems, sub-systems, or components as they suffer from performance degradation. Maintenance overall is estimated to make up 10% of airline costs [1], with spending reported to be around US\$83 billion in 2019. These costs are anticipated to be US\$115 billion by 2030 [2]. Unscheduled maintenance activities have a substantial impact on these costs. In 2017 alone this amounted to more than US\$6.5 billion for wide-body jets and almost US\$5 billion for small regional jets, due to delays and cancellations [3]. The industry is currently exploring innovative health management solutions that aid the maintenance of aircraft key systems, based on prediction-based maintenance approaches using online near real-time condition monitoring techniques [4]. Legacy aircraft are particularly vulnerable, as they lack the appropriate sensors to support the implementation of a cost-effective and lean health management strategy.

Amongst others, the Auxiliary Power Unit (APU) is a key system of the aircraft and has been reported as a major driver of unscheduled maintenance in legacy aircraft [5]. Its primary purpose is to provide electrical and pneumatic power during ground operations and in-flight emergencies [6]. The APU is a gas turbine unit, a turboshaft engine [3], composed of several rotating components, valves, guide vanes, igniters, and other associated accessories to generate the required electrical and pneumatic power. Performance degradation/failure in any of its sub-systems/components can consequently result in main engine start-up failure, generation of excessive vibrations/noise, abrupt shutdown, and reduced power output [7]. The existing inbuilt test equipment provides limited technical data for supporting a robust condition monitoring system. In addition, the intrusive nature of the equipment imposes testing and certification requirements, which can add significant costs to the overall development of the system. For the same reason,

any retrofit condition monitoring solution, based on the implementation of intrusive sensors, would also incur significant development effort and implementation cost, and therefore cannot be easily deployed as an online monitoring system. For legacy aircraft, the OEM, operators, and academia have a profound interest in devising a robust condition monitoring solution that can be readily deployed with minimum development and implementation cost, without imposing any additional certification requirements.

The Boeing Company, the funding body of this study, has been interested in ascertaining the potential of utilizing microphones for condition monitoring or fault detection in an aircraft APU. Microphones can be conveniently installed in the APU compartment, and since they also do not interfere with the safety and performance of the equipment, they can be a suitable choice for legacy aircraft. If proven useful, their utilization on a newly built aircraft can also be considered in subsequent research. The available literature does not sufficiently explore the potential of using microphones on an aircraft system in situ. In order to address that, this PhD is focused on the systematic evaluation of acoustic data acquired from a Boeing 737-400 aircraft APU and the development of appropriate acoustic-based techniques for APU monitoring and fault detection.

1.2 Aircraft Auxiliary Power Unit

The aircraft APU is a gas-turbine engine that is typically installed in the tail section of the aircraft. The APU is responsible for providing pneumatic and electrical power during ground / aerial operations. The APU also serves as a backup source of power during emergencies in flight. APU noise, on the other hand, is an undesired by-product resulting from APU operation. Unlike the main engine, this noise is not regulated by regulating authorities such as the FAA (Federal Aviation Authority), however, it is of major concern for personnel working around the aircraft, as well as from the point of view of noise pollution at the airport terminal. Therefore, local authorities at the airport may restrict the duration of its operation.

This research has been conducted on APU of Cranfield University's B737-400 aircraft (Figure 1-1). During experimentation, the aircraft has been either on the taxiway of Cranfield airport or inside the hanger of the Digital Aviation Research

and Technology Centre (DARTeC) building. The duration of data collection from the aircraft's APU spans over a five-month period.



Figure 1-1 Cranfield University's B737-400 aircraft (a) Parked on taxiway (b) Parked inside a hanger

The APU of the referenced aircraft is installed in the rear-section within a fire enclosure (or shroud) {see Figure 1-2}. The APU is a turboshaft engine with a generator and a load compressor for delivering electrical and pneumatic power, respectively. The power section 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. The compressor and turbine are mounted on the same shaft which rotates at a constant speed of 63,830 rpm for all operating and loading conditions.

The APU shaft rotates the load compressor which generates pressurized air for the aircraft's pneumatic system as per the demand. The bleed air from the APU is delivered to the Environmental Control System (ECS), wing anti-ice system, or

the pneumatic starter of the main engines. A set of inlet guide vanes (IGV) control the amount of air entering the load compressor and hence the pneumatic system. During the initial phases of start-up, the IGV remains closed but is then allowed to open by 22° to prevent compressor surge. The surge control valve (SCV) is another important component of the APU's pneumatic system. The SCV is controlled by the surge valve torque motor (SVTM) and allows the pressurized air from the load compressor to be rejected into the exhaust system to avoid compressor surges.

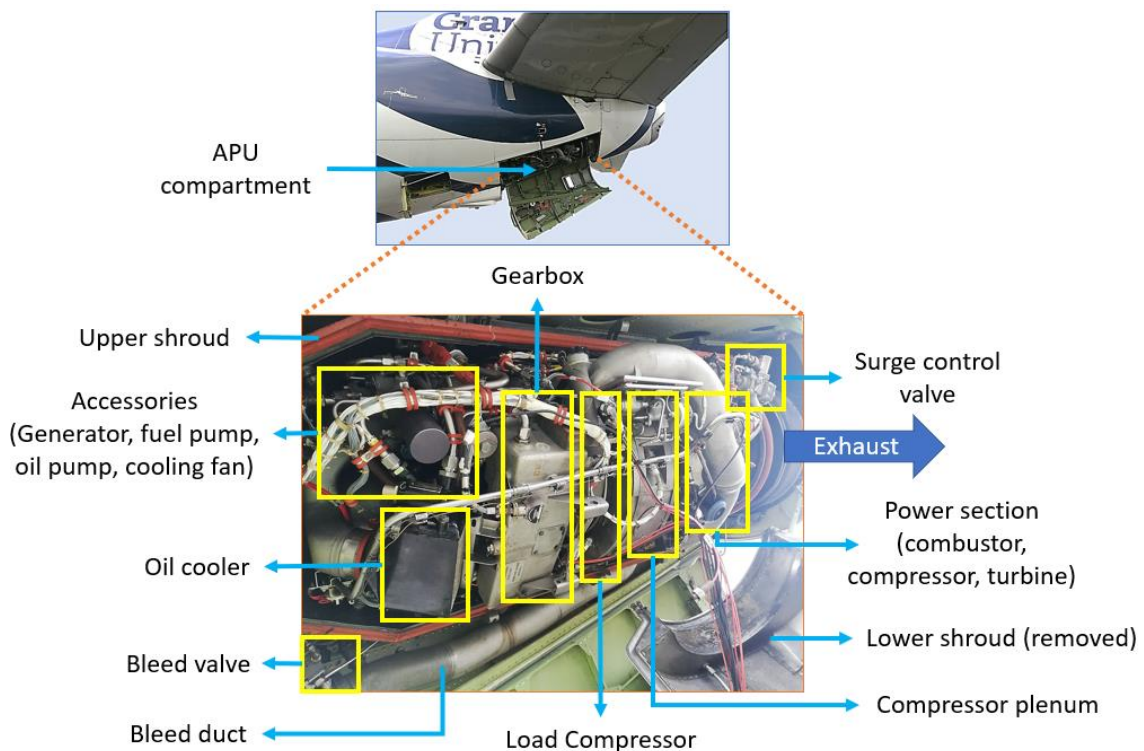


Figure 1-2 Schematics of the adopted APU

The APU is attached to the aircraft structure through vibration mounts, which inhibit the unwanted vibrations from the gas turbine traveling into the aircraft body. The complete APU assembly is enclosed inside the shroud which acts as a fire enclosure and attenuates the noise levels. The lubricating oil temperature is regulated by the cooling fan which forces air through the oil cooler. The cooling air takes excessive heat from the oil and then leaves the APU compartment from the cooling air outlet. The overall operation of the APU is controlled by a Full Authority Digital Engine Controller (FADEC) which is installed in the cargo

compartment (see Figure 1-3). This unit monitors the state of the system and generates commands for the fuel torque motor, SVTM, and IGV actuator.

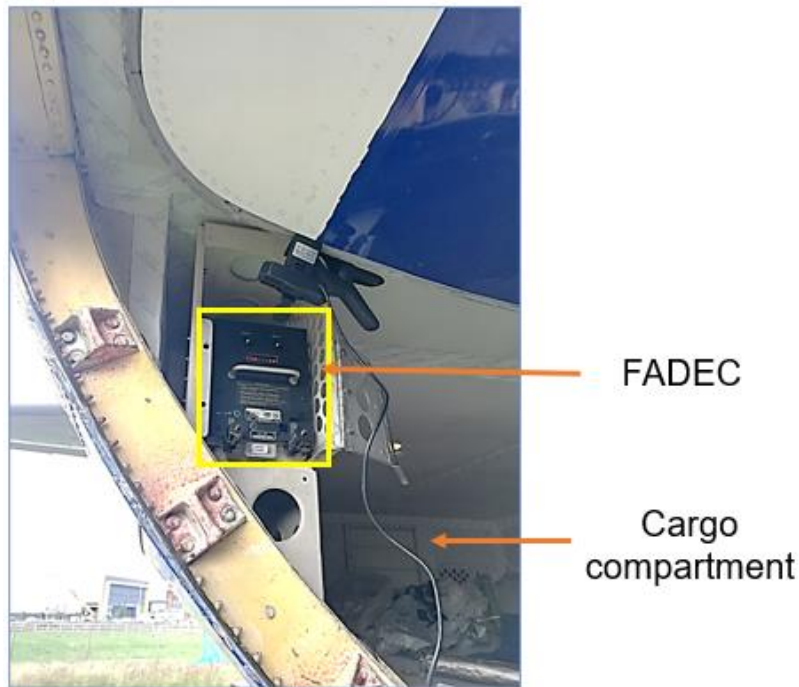


Figure 1-3 FADEC location inside the aircraft

The APU ignition system is also a key element that is responsible for generating high-energy sparks to initiate combustion during the APU startup. It consists of an ignition exciter, an igniter plug lead, and an igniter plug. The excitation circuit operates on aircraft DC power and generates high voltage to the igniter plug which is installed inside the combustor housing. The igniter plug lead provides a low resistance path between the exciter and igniter plug. The ignition system is energized during a certain duration of the startup sequence ($7\% < \text{RPM} < 95\%$) and generates a series of sparks inside the combustor.

1.3 Aim and Objectives

Aim

To evaluate the potential of utilizing acoustic signals for condition monitoring of an aircraft APU. The study should evaluate the far-field and the near-field noise using appropriate techniques to detect fault / degradation in the APU.

Objectives

- 1) Carry out a literature review covering aircraft auxiliary power units, their faults, acoustic measurements, and the available condition monitoring techniques.
- 2) Instrumentation of Boeing 737-400 aircraft with microphones (near-field / far-field), vibration sensors, data acquisition system, and associated co-axial cables. Acquisition of thermodynamic parameters from FADEC and cockpit synchronized with the vibroacoustic data. Experimental data collection from the APU under various load conditions.
- 3) Development and validation far-field noise estimation model for the APU and quantifying the effect of components' degradation on the noise components.
- 4) Analyse the behaviour of the acquired near-field noise data under various load conditions in order to evaluate it for condition monitoring.
- 5) Propose a methodology for APU monitoring using microphones installed within the APU compartment.
- 6) Identify the prospects of utilizing a microphone for monitoring the APU ignition system.

1.4 Methodology

To achieve the desired aim and objectives, a methodological approach has been adopted, which consists of five phases (see Figure 1-4). Phase 1 of the research comprises a literature review and identification of research gaps. The literature review implied that the noise data from an aircraft APU has not been extensively studied and evaluated particularly from the perspective of condition monitoring. In order to enhance research in this domain, experimental data from Cranfield University's Boeing 737-400 aircraft auxiliary power unit has been initially acquired (Phase 2). This has been achieved by installing multiple vibration sensors and microphones in the APU compartment and a microphone in the far-field of the APU exhaust. During experimentation, the APU thermodynamic parameters and other associated parameters (for example current drawn from the APU generator and state of cockpit switches) have also been acquired by

recording the FADEC display and cockpit overhead panel during APU operations. The data acquisition system for the vibration sensors and microphones has been powered by a rechargeable lithium polymer battery and placed onboard the aircraft next to the APU compartment. For practical purposes, the APU has been operated in its original configuration with the shroud and APU compartment door closed.

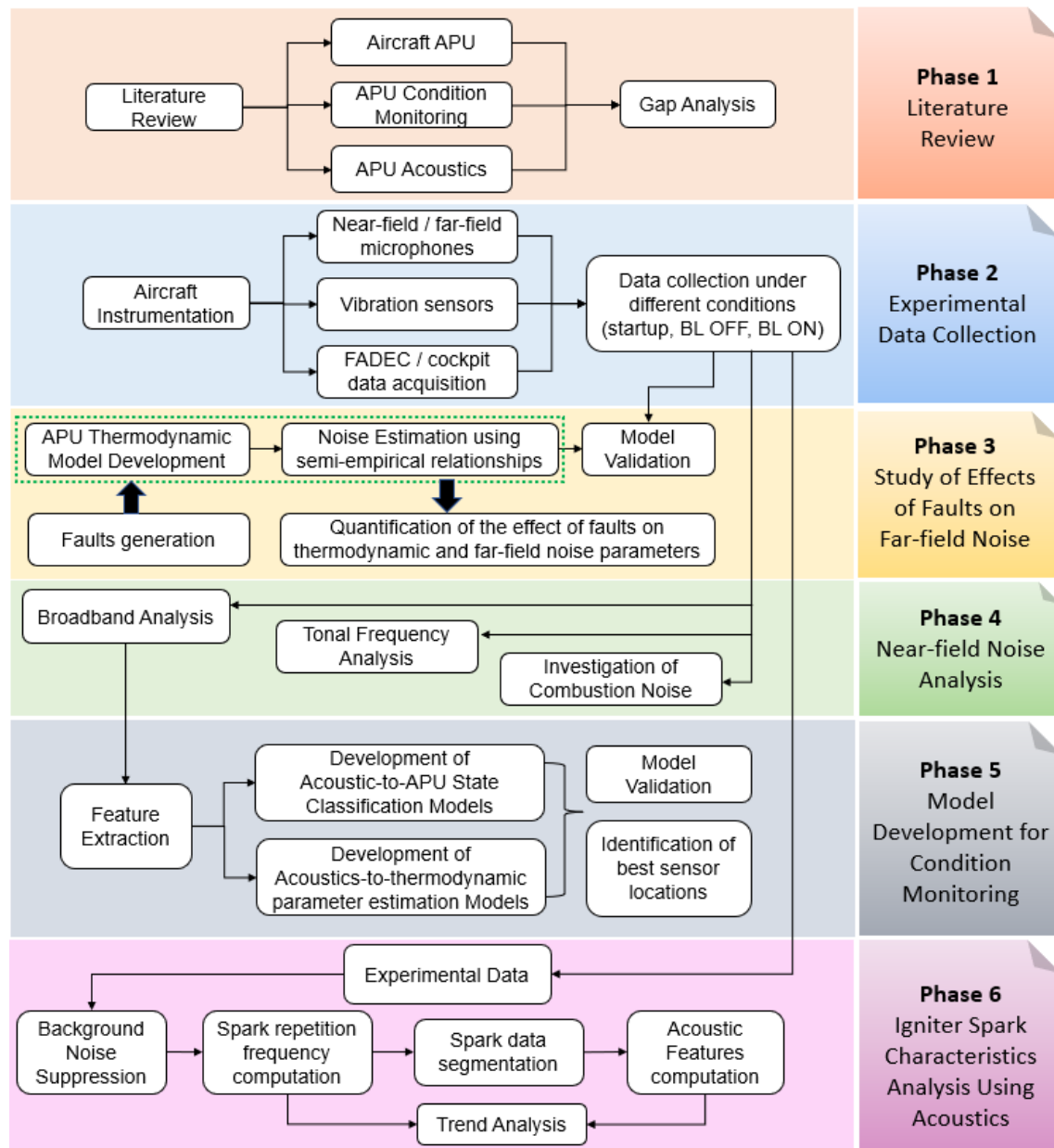


Figure 1-4 PhD Methodology

Phase 3 of the research systematically evaluates the far-field noise by first developing a noise estimation model and then quantifying the effect of components' degradation on the far-field noise parameters. Evaluation of the near-field noise begins in Phase 4 and culminates in Phase 5. In the former phase, extensive analysis has been carried out, and eventually, several findings have been reported. In Phase 5, the information derived from the previous phase has been utilized to develop appropriate models for APU condition monitoring. Lastly, in Phase 6, the prospects of utilizing a microphone for monitoring the APU ignition system have been identified by systematically processing and analysing the acquired experimental dataset during startup operations.

1.5 Thesis Structure

Figure 1-5 presents a graphical summary of the thesis structure. The thesis is written in a 'Paper-based' format, consisting of seven chapters, where each chapter [except Chapter 1 (Introduction) and Chapter 7 (Summary and Future Work)] has been written as a technical paper and corresponds to the outcomes made during different phases of this research. The technical papers corresponding to Chapters 2, 3, 4, 5, and 6 have been published in various journals. These chapters are the reformatted versions of the papers and are unchanged from their published forms. Chapter 3 has been modified to include the effect of components' degradation on the far-field noise parameters, which has not been discussed in the published version. Description of the work done corresponding to phase 2 of the methodology (Experimental Data Collection) is made part of Chapters 3, 4, 5, and 6. All the chapters are outcomes of different phases of the research methodology and are arranged cohesively to align with the research objectives, as listed in Table 1-1. A concise summary of the chapters is provided in the subsequent paragraphs.

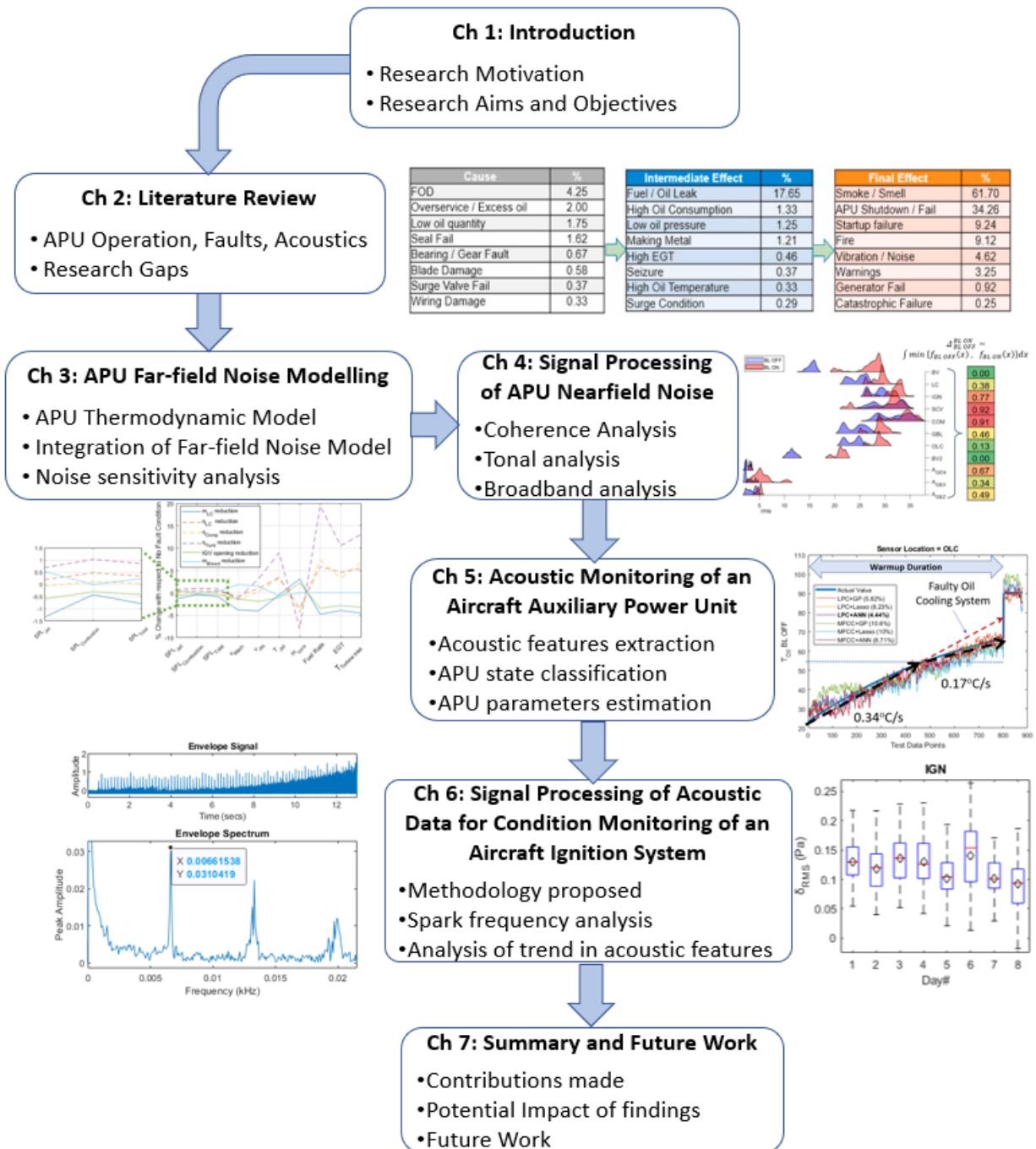


Figure 1-5 Overview of thesis structure

Table 1-1 List of thesis chapters aligned with research objectives and publication status

Chapter	Phase / Objective achieved	Publication status
Chapter 2	Phase 1 / Objective 1	Published in journal [7]
Chapter 3	Phase 2,3 / Objective 2,3	Published in journal [8]
Chapter 4	Phase 2,4 / Objective 2,4	Published in journal [9]
Chapter 5	Phase 2,5 / Objective 2,5	Published in journal [10]
Chapter 6	Phase 6 / Objective 6	Published in journal [11]

1.5.1 Chapter 2 : A Review of Aircraft Auxiliary Power Unit Faults, Diagnostics and Acoustic Measurements

A thorough review of the available information in the fields of auxiliary power units, their faults, diagnostics, and acoustic measurements is presented in this chapter. In doing so, the signal processing techniques commonly utilized for condition monitoring of turbomachinery faults and source separation for understanding the noise components in the far-field have also been reported. Other contributions made in this chapter include:

- 1) A thorough analysis of defect reports related to aircraft APUs that led to the identification of common causes of APU failures.
- 2) Summarized all kinds of research that have been performed on APUs involving acoustic measurements, noise source identifications, and evaluation of noise abatement technologies.
- 3) A comprehensive review of acoustics-based diagnostics strategies developed for various types of machinery.
- 4) Identification of research gaps in the domain of acoustics-based condition monitoring of aircraft auxiliary power units.

Outcomes of this chapter:

Failure-free functioning of APU is required to avoid disruptions in aircraft operations. The available condition monitoring / fault detection schemes require intrusive sensors which have hardware complexities associated with them. The research community has not extensively studied the APU noise for condition monitoring purposes, which can prove to be a convenient way to achieve the desired results with minimal hardware modifications.

1.5.2 Chapter 3 : Development of a Far-Field Noise Estimation Model for an Aircraft Auxiliary Power Unit

This chapter originates from the research activities undertaken during phase 3 of the adopted methodology. In this chapter, a far-field noise estimation model has been developed for the APU under consideration. The APU thermodynamic model, semi-empirical relationships for combustion and jet noise, and ground reflection model are the building blocks of the model. Model validation has been performed using an experimentally acquired dataset. The developed model has been employed to study the effect of components' degradation on the APU thermodynamic parameters and the far-field noise.

Outcomes of this chapter:

The APU far-field noise is dominated by combustion and jet noise which can be estimated by the semi-empirical relationships available in the literature. Thermodynamic parameters are required by these relationships, which have been estimated using FADEC data, APU geometrical information, a solver, and best engineering judgments. A certain level of scaling has to be applied in order for the relationships to match the experimental data, and in some cases, the relationships may not be suitable at all. Ground reflections affect the frequency spectrum as well as the level of received noise power, and therefore have to be incorporated into the noise estimation model. The developed model has proven to be accurate with a Root Mean Square Error of 0.73dB. Using the same model, sensitivity analysis has been carried out and the results indicate that the far-field noise levels are less affected as compared to the thermodynamic parameters if

components' efficiencies decrease, and therefore utilizing a far-field microphone for monitoring a degraded condition may not be practically feasible.

1.5.3 Chapter 4 : Evaluation Of Aircraft Auxiliary Power Unit Near-Field Acoustics for Condition Monitoring

This chapter captures the initial analysis that has been performed on the acquired near-field acoustic data from the aircraft APU. The chapter aims to assess the near-field data for condition monitoring purposes. It seeks to achieve answers to key questions: can a microphone installed inside the APU compartment sense the combustion noise, how consistent are the tonal frequencies in the acoustic data, and in a broadband sense how well correlated the data is with the APU states and parameters. For broadband analysis, various categories of feature extraction techniques have been evaluated to ascertain their usefulness for developing state classification and regression models. Lastly, the effect of external noise sources on the microphone installed inside the APU shroud has also been evaluated.

Outcomes of this chapter:

The nearfield microphones are not suitable to monitor the combustion noise and the tonal frequencies. Such behaviour is attributable to the high level of background noise that conceals the signal of interest. Other phenomena like fluctuations in the APU RPM and acoustic scattering are also responsible for disrupting the acquisition of tonal frequencies using microphones. Due to the same reasons, other techniques like Bicoherence fail to respond the way it does for the vibration sensors. In contrast to the above, certain feature extraction techniques exhibit strong correlations with the APU states and parameters using nearfield acoustic data and therefore can be used to develop models for APU condition monitoring. Furthermore, due to the presence of the aircraft structure and APU casing, the microphones are shielded from external effects, which makes an acoustics-based solution practically viable.

1.5.4 Chapter 5 : Acoustic Monitoring of an Aircraft Auxiliary Power Unit

This chapter is in line with Phase 5 of the research methodology, which aims to develop and validate APU state identification and parameter estimation models with acoustic data as input. The acoustics-to-state identification model can be utilized for detecting faults that restrict the APU to transition between different APU states. The acoustics-to-thermodynamic parameter estimation models can further enable a non-intrusive solution to detect a faulty or degraded lubrication oil cooling system or the APU pneumatic system. The effect of sensor location on the models' performance has also been made part of the research.

Outcomes of this chapter:

Near-perfect APU state classification can be done using microphones with multiple feature extraction techniques depending on the sensor located inside the APU shroud. However, the performance deteriorates if the sensors are moved outside the shroud. The utilization of microphones can also be extended to develop accurate acoustic-to-thermodynamic parameter estimation models. In total, two well-placed microphones can estimate multiple thermodynamic parameters in real-time, deviation of which from normal limits can indicate a faulty / degraded condition.

1.5.5 Chapter 6 : Signal processing of Acoustics Data for Aircraft APU Ignition System

This chapter studies the prospects of processing the acoustic signal during the APU startup sequence to monitor the ignition system. A methodology to estimate the spark signal characteristics has been proposed and evaluated on the experimental dataset using appropriate signal processing, data segmentation, and feature extraction techniques.

Outcomes of this chapter:

During APU startup, the ignition system is activated which generates a series of sparks. The sound generated by these sparks resembles a train of impulse signals that tend to get hidden behind the background noise. An appropriate high

pass filter on the acoustic data can suppress the background noise while retaining the impulse signals up to a certain RPM value. The envelope spectrum technique can then be used to estimate the spark repetition frequency and the associated fluctuations. The spark region can further be segregated to compute certain acoustic features that are robust against the background noise and variations in the acoustic measurement path. By analysing the trend in SRF, its fluctuations, and the features, certain trends can be observed that are related to faults or degradations in the system.

1.5.6 Chapter 7 : Summary and Future Work

A summary of the PhD is presented in this chapter highlighting the contributions made and the potential impact of the findings. The chapter also provides insight into the future course of action that can further substantiate or extend this research.

1.6 List of Publications

Published:

Journal Papers:

- i. U. Ahmed, F. Ali, I. Jennions, A review of aircraft auxiliary power unit faults, diagnostics and acoustic measurements, Prog. Aerosp. Sci. 124 (2021) 100721. <https://doi.org/10.1016/j.paerosci.2021.100721>.
- ii. U. Ahmed, F. Ali, I. Jennions, Development of a Far-Field Noise Estimation Model for an Aircraft Auxiliary Power Unit, IEEE Access. 9 (2021) 127703–127719. <https://doi.org/10.1109/ACCESS.2021.3112390>.
- iii. U Ahmed, F. Ali, I. Jennions, Evaluation of Aircraft Auxiliary Power Unit Near-Field Acoustics for Condition Monitoring, IEEE Access. (2022) [10.1109/ACCESS.2022.3213698](https://doi.org/10.1109/ACCESS.2022.3213698).
- iv. U Ahmed, F. Ali, I. Jennions, Signal Processing of Acoustic Data for Condition Monitoring of an Aircraft Ignition System, Machines. 2022; 10(9):822. <https://doi.org/10.3390/machines10090822>.

- v. U Ahmed, F. Ali, I. Jennions, Acoustic Monitoring of an Aircraft Auxiliary Power Unit, ISA Transactions (2023).
<https://doi.org/10.1016/j.isatra.2023.01.014>

References

- [1] P. Hollinger, Smarter aircraft create a wealth of data but it remains underexploited, *Financ. Times*. (n.d.). www.ft.com/content/3f956a92-0943-11e5-b643-00144feabdc0 (accessed February 25, 2022).
- [2] D. Costanza, B. Prentice, Recover and Rebuild - Toward a Leaner, More Agile MRO Industry, Oliver Wyman. (2021). <https://www.oliverwyman.com/our-expertise/insights/2021/apr/mro-maintenance-repair-overhaul-survey-2021.html> (accessed February 25, 2022).
- [3] A. Grous, Sky High Economics: Chapter Two: Evaluating the economic benefits, London Sch. Econ. (2018). <https://www.lse.ac.uk/business/consulting/assets/documents/sky-high-economics-chapter-two-evaluating-the-economic-benefits.pdf> (accessed February 25, 2022).
- [4] M. Esperon-Miguez, P. John, I.K. Jennions, A review of Integrated Vehicle Health Management tools for legacy platforms: Challenges and opportunities, *Prog. Aerosp. Sci.* 56 (2013) 19–34. <https://doi.org/10.1016/j.paerosci.2012.04.003>.
- [5] C. Skliros, F. Ali, I. Jennions, Experimental investigation and simulation of a Boeing 747 auxiliary power unit, *J. Eng. Gas Turbines Power.* 142 (2020). <https://doi.org/10.1115/1.4047771>.
- [6] C. Skliros, F. Ali, I. Jennions, Fault simulations and diagnostics for a Boeing 747 Auxiliary Power Unit, *Expert Syst. Appl.* 184 (2021) 115504. <https://doi.org/10.1016/j.eswa.2021.115504>.
- [7] U. Ahmed, F. Ali, I. Jennions, A review of aircraft auxiliary power unit faults, diagnostics and acoustic measurements, *Prog. Aerosp. Sci.* 124 (2021) 100721. <https://doi.org/10.1016/j.paerosci.2021.100721>.

- [8] U. Ahmed, F. Ali, I.K. Jennions, Development of a Far-Field Noise Estimation Model for an Aircraft Auxiliary Power Unit, IEEE Access. 9 (2021) 127703–127719. <https://doi.org/10.1109/ACCESS.2021.3112390>.
- [9] U Ahmed, F. Ali, I. Jennions, Evaluation of Aircraft Auxiliary Power Unit Near-Field Acoustics for Condition Monitoring, IEEE Access. (2022) [10.1109/ACCESS.2022.3213698](https://doi.org/10.1109/ACCESS.2022.3213698).
- [10] U Ahmed, F. Ali, I. Jennions, Acoustic Monitoring of an Aircraft Auxiliary Power Unit, ISA Transactions (2023). <https://doi.org/10.1016/j.isatra.2023.01.014>
- [11] U Ahmed, F. Ali, I. Jennions, Signal Processing of Acoustic Data for Condition Monitoring of an Aircraft Ignition System, Machines. 2022; 10(9):822. <https://doi.org/10.3390/machines10090822>.

2 A Review of Aircraft Auxiliary Power Unit Faults, Diagnostics and Acoustic Measurements

The Auxiliary Power Unit (APU) is an integral part of an aircraft, providing electrical and pneumatic power to various on-board sub-systems. APU failure results in delay or cancellation of a flight, accompanied by the imposition of hefty fines from the regional authorities. Such inadvertent situations can be avoided by continuously monitoring the health of the system and reporting any incipient fault to the MRO (Maintenance Repair and Overhaul) organization. Generally, enablers for such health monitoring techniques are embedded during a product's design. However, a situation may arise where only the critical components are regularly monitored, and their status presented to the operator. In such cases, efforts can be made during service to incorporate additional health monitoring features using the already installed sensing mechanisms supplemented by maintenance data or by instrumenting the system with appropriate sensors. Due to the inherently critical nature of aircraft systems, it is necessary that instrumentation does not interfere with a system's performance and does not pose any safety concerns. One such method is to install non-intrusive vibroacoustic sensors such that the system integrity is maintained while maximizing system fault diagnostic knowledge. To start such an approach, an in-depth literature survey is necessary as this has not been previously reported in a consolidated manner. Therefore, this chapter of the thesis concentrates on auxiliary power units, their failure modes, maintenance strategies, fault diagnostic methodologies, and their acoustic signature. The recent trend in APU design and requirements, and the need for innovative fault diagnostics techniques and acoustic measurements for future aircraft, have also been summarized. Finally, the shortcomings found during the survey, the challenges, and prospects, of utilizing sound as a source of diagnostics for aircraft auxiliary power units will be highlighted.

2.1 Background to the Literature Survey

In the current era, the world has no boundaries and people can travel across the globe within predetermined times. This has been achieved with modern aircraft

with very mature levels of aircraft operations, maintenance, and component reliability. Like all other aircraft sub-systems, the availability of the auxiliary power unit (APU) is of paramount importance to meet the desired operational demands in a timely manner. Regular maintenance ensures that the APU provides the desired performance and does not fail. Even if a failure occurs, diagnostic mechanisms are in place for the timely recovery of faulty equipment. Ultimately, a cost is associated with each segment of planned or unplanned maintenance activities. One way of reducing the cost is to automate the fault diagnostic process by deploying sensors that do not interfere with the aircraft functionality but are still able to acquire significant information about the system. Acoustic sensors fall into the category of such non-intrusive sensors, they can capture a wide range of information and assist in better fault diagnostics. The development of such diagnostic systems can expedite the recovery process, reduce the person-hours consumed during troubleshooting, provide accurate fault classification by excluding human interaction from the troubleshooting loop, and eventually reduce aircraft downtime.

To enable the above-mentioned approach, a comprehensive literature review was necessary to re-evaluate the work done by the research community in the appropriate domains. This led to the compilation of this review article, which aims to cover all the relevant domains needed to be understood before proceeding towards the development of an acoustics-based fault diagnostic framework for an aircraft APU. The areas touched in this review are shown in Figure 2-1. The major areas to be explored are shown as large circles. Section 2.2 will discuss APUs, their functions, fault modes, and currently adopted maintenance strategies. The section will also cover the technological advancements, made or suggested, for aircraft APUs. Section 2.3 will focus on all types of fault diagnostic methodologies explored by the research community. Some of the challenges associated with emerging technologies will also be discussed. Section 2.4 is dedicated towards understanding various aspects of gas turbine noise, and the kind of experiments performed for its characterization. State-of-the-art methods for noise reduction in novel / future aircraft will also be presented. The last section (Section 2.5) is built on the information gathered from the previous sections and summarizes the

research gaps, opportunities, and challenges involved when dealing with acoustics for engine health monitoring or fault diagnostics.

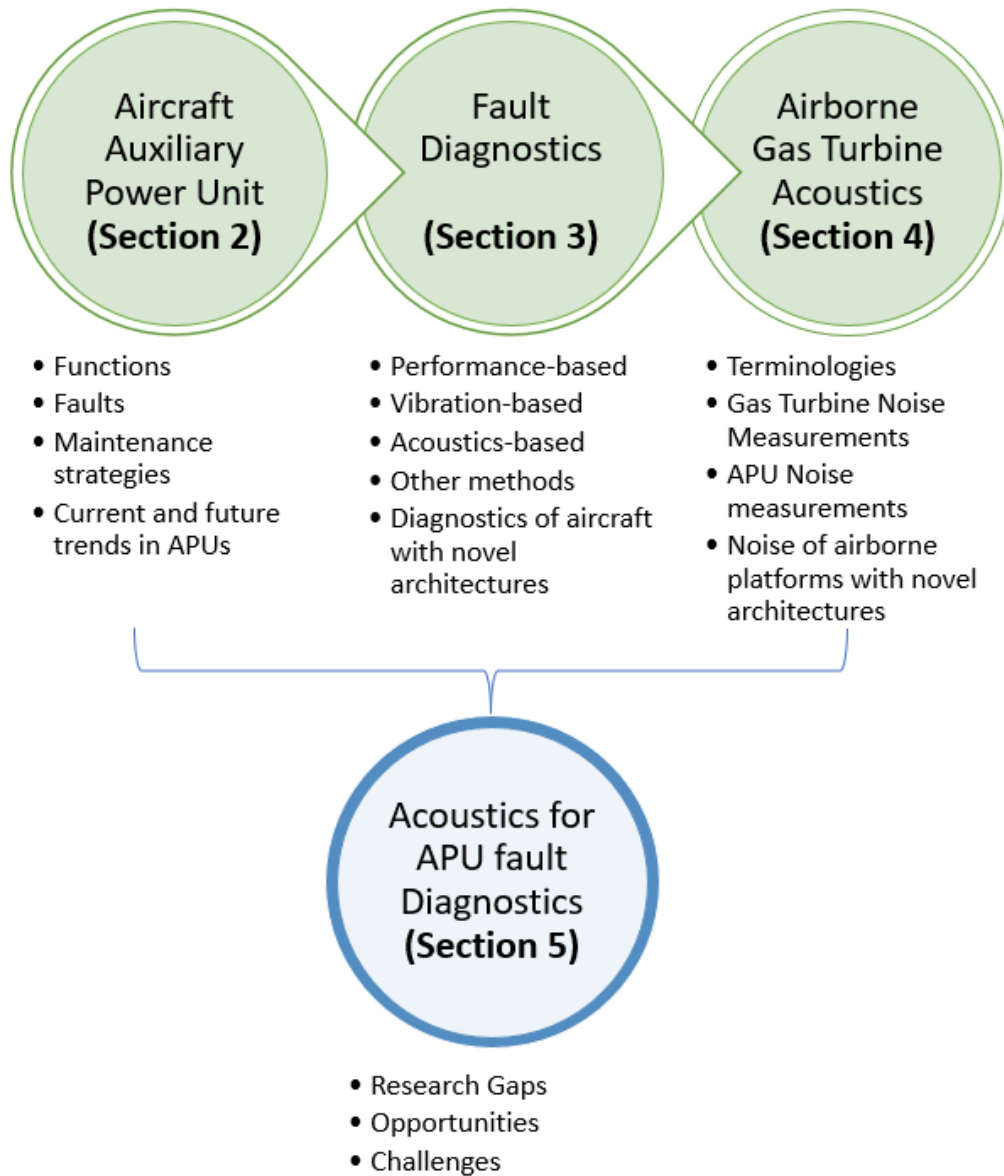


Figure 2-1 Areas covered through the literature survey

2.2 Aircraft Auxiliary Power Unit

Auxiliary Power Units are turboshaft engines mounted on an aircraft for fulfilling electrical and pneumatic needs for any given aircraft. Table 2-1 provides information about APU usage during various phases of flight or ground operations [1]. APUs are primarily used when the aircraft is on the ground and a Ground Power Unit (GPU) is not available. Emergency power may also be delivered by

the APU in case of main engine failure during flight. The idea behind integrating APUs into aircraft is to inhibit the use of main engines during ground operations to save fuel and to reduce emissions as well.

Table 2-1 Typical Usage of Aircraft APUs [1]

Phase of Flight	APU Usage	Usage frequency
Ground operation	Environmental control system (ECS) Main Engine Start AC Power (400 Hz)	Mostly
Taxi-out	Backup power	Sometimes
Taxi-in	Backup power for large aircraft	Sometimes
Take-off	Backup power	Sometimes
Landing	Nil	Mostly
In-Flight	Electrical & Pneumatic Power	In Emergencies

2.2.1 APU Functions

Unlike aircraft main engines which are primarily responsible for generating thrust, APUs are designed to generate shaft power which is generally used to drive an electrical generator. In addition to electrical power, the APU provides bleed air which is either taken from one of the compressor stages or a designated load compressor is designed for this purpose. This compressed air is required by the aircraft's Environmental Control System (ECS) which provides air conditioning and pressurized air to the cabin. The bleed air from the APU also drives the main engine's air turbine starter during startup. This excludes the need for a heavy and big electrical component for achieving the same purpose. Depending on the aircraft design, APUs may also be used to deliver compressed air to the wing anti-ice system to prevent the formation of ice due to atmospheric conditions. Unlike the main engines, APUs are designed to operate at lower altitudes as per the operational requirements. Another important characteristic of the APU is the handling of electrical and pneumatic load at the same time and the prioritization which takes place if an overloading condition is sensed.

Like any other aircraft system, APUs are desired to be fuel-efficient, light in weight, occupy minimum space, contribute less towards aircraft noise, and should be easy to maintain and operate [2]. APU usage can range from mere 25 minutes for passenger aircraft to several hours for cargo aircraft [3] at airports where Ground Power Units are not available. Generally, it is desirable to limit the use of APUs because they generate more noise as compared to their counterparts. Some airports put restrictions on the use of APU to minimize environmental effects. Depending on the required electrical and pneumatic power for each aircraft, manufacturers have developed a range of APUs based on similar technologies. There is a wide range of APUs (mostly from the same manufacturer) that have been in service for various categories of aircraft [4]. In some cases, the same model of APU is installed on different types of aircraft due to similar power requirements.

Auxiliary Power Unit is designed to operate with minimal effort from the aircraft operator so that the pilot can focus on primary tasks. Therefore, an electronic control unit (analog or digital) continuously monitors and regulates the operation of the APU. Some of the parameters being monitored are shaft speed, EGT, Oil temperature, differential pressures, and generator output. In response to the state of APU, the control unit modifies the fuel flow to keep the operation within desired limits. A complimentary surge control system is also part of the feedback system, which inhibits surge conditions for safe operation. Most critical parameters are displayed in the cockpit and the pilot has the option to react to a hazardous condition like fire.

2.2.2 APU Maintenance

Overall costs associated with an aircraft APU are pictorially represented in Figure 2-2. Maintenance is one of the main cost drivers for operating aircraft APU. Failure of an APU in air or ground results in cancellation or delay in flight departure, which inhibits flight operations. An aircraft APU that requires maintenance after 7000 flight hours, would require a maintenance cost of nearly \$0.4 Million [4]. In case of failure, costs are associated with its removal, disassembly, repair, and replacement. As per FAA's Service Difficulty Reporting

database, aircraft APUs are found to be replaced more than 50% of the time whenever a fault is reported. Aviation Week in its Biennial survey reported that the world fleet needed over \$4 Billion for MRO of all APUs in 2018.

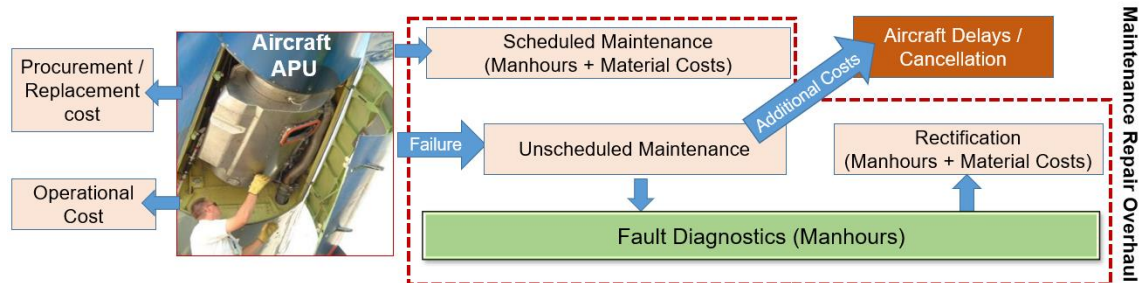


Figure 2-2 Costs associated with aircraft APU

Apart from the costs associated with unscheduled maintenance itself, regulatory authorities may also impose hefty fines if a scheduled flight is canceled or delayed for more than a certain time limit. The fine comes in the form of compensation which must be paid to each boarding entitled passenger or the airlines may be asked to pay for lodging costs of a passenger. As per European Union Flight Compensation Regulation 261/2004 [5], the compensation amount depends on the distance to be traveled by the scheduled flight and it can be €600 per passenger.

An aircraft is a complex combination of several sub-systems and APU is one of them. APU has equal importance like any other system on the aircraft because it provides electrical and pneumatic power when the main engines are not operating on the ground. Furthermore, in case of main engine failure, the aircraft is designed to acquire power from APU. Therefore, APU should be reliable and regularly maintained to meet the desired performance and failure-free operation. However, if a failure does occur, they result in in-flight emergencies which can lead to turnaround or diversions. In a study conducted on power plant-related occurrences between 2008 – 2012, APU failures were found to occur second most frequently after abnormal engine indications [6]. The study also shows that APUs are generally placed in the power plant category and assessed together with the main aircraft engines and are therefore an important part of an aircraft.

2.2.2.1 APU Failure Mechanisms

Several studies have been conducted on various failing mechanisms of aircraft APU. Validation of the Weibull model using APU oil pump failure data has been done [7] and correspondingly recommendations have been made for the optimum time for their replacement. In the study by [8], it was concluded that one of the reasons for APU failure is an uneven distribution of fuel from the nozzle which leads to wear of turbine disk. An independent study has been conducted on cracks in the APU exhaust duct which is a hazard to the structural integrity of the aircraft [9]. Potential causes of rotor seizure in 737 APU are discussed in [10] and the fault has been attributed to be initiated due to foreign object damage to compressor stage or a bearing fault. As per [4], failure of APU rotating parts result in high EGT, high oil consumption, and low power outputs. In [11], APU failure results have been categorized into two groups; those which can be fixed on-wing by replacing faulty Line Replaceable Units (LRU) and those which require APU removal accompanied with complex maintenance actions. The on-wing faults are rectified quickly because the LRUs are placed at convenient locations as per the design-for-maintenance approach. In the case of APU removal and visit to repair shops, the cost of material mainly contributes to the overall amount, whereas the costs associated with the manhours are between 20%-30% [4].

In [12], it is stated that 30% of gas turbine failures are due to turbine blade failures. These occur due to blade corrosion and erosion, hot start, compressor fouling, and operating the engine beyond its limits. [13] describes the interdependency which exists between components failures for an APU. An example of this type of interaction is provided which describes how turbine blade tip loss induces rotor unbalance, which eventually results in bearing failure. A summary of failure modes and their frequency of occurrence is also provided which shows that the turbine is more prone to failures than any other components in the APU power section [16]. A similar frequency of turbine blade failures is also reported in [14].

Detailed analysis of APU component failures was done in [15] to update the OEM-provided FMEA parameters. For this purpose, the OEM FMEA list and maintenance data were obtained, by the authors, from the airline operator for

subsequent analysis. During the study, which was focused on the inability to start failure, dissimilarity was observed when field data was compared to OEM data. As per the maintenance data, startup failure occurs due to failure in starter, igniter, fuel control assembly, fuel pump, fuel flow divider, low oil pressure switch, speed sensor, and thermocouple. The rank of each component had to be updated because they deviated substantially from the OEM provided ranks. The study concluded that it is difficult for the product designers to accurately determine failure(s) and their probabilities before the product has made it into service. Therefore, it would be advisable to re-evaluate the OEM-provided parameters using operational and maintenance data after sufficient data has been collected.

Other than the published literature, the Federal Aviation Administration's Service Difficulty Reporting database provides useful information about aircraft systems' failures (including APUs). The database contains defect reports submitted by airline operators starting from the year 1993 and these reports can be publicly accessed by using FAA's website. As per the database, APU reported defects continue to rise in the last few years with the highest number recorded in 2018 (Figure 2-3). Moreover, such instances have led to in-flight emergencies more than one hundred times during the last three decades.

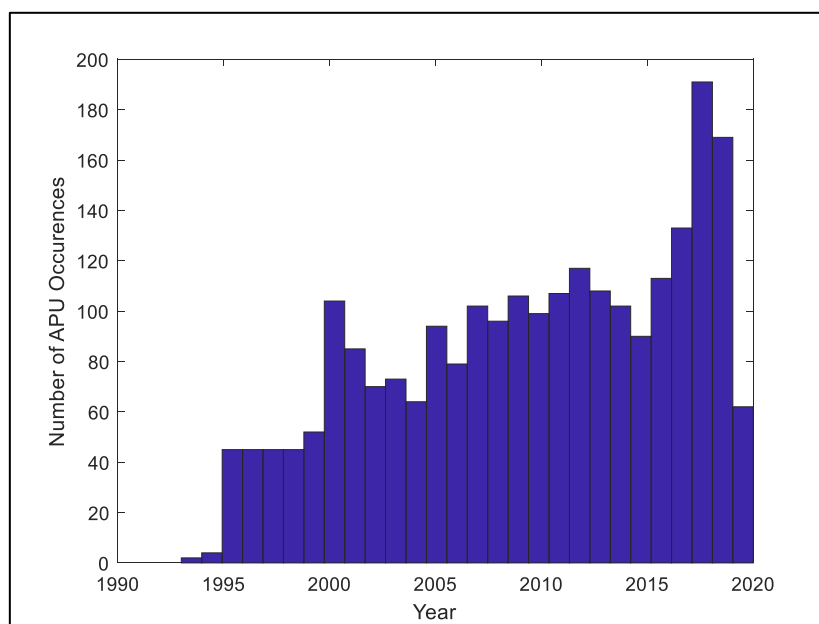


Figure 2-3 APU faults histogram

Further scrutiny of the extracted information from the FAA's repository gives considerable insight into the causes/nature of APU failures and the type of decision that is generally taken after fault diagnostics. Meaningful information has been gathered by searching for a combination of various keywords in the discrepancy column. It is found that the APUs are replaced more than 50% of the time whenever a defect/failure is reported. Figure 2-4 depicts the various kinds of defects/failures which have been reported by the airline operators and the maintenance personnel. The main problems associated with APUs are smoke/smell from the bleed system and unwanted shutdowns. The figure also puts together potential causes that lead to such failure conditions. It is to be noted that the root cause of a failure is not generally diagnosed at the first line of maintenance. Hence, a detailed level of information about the potential causes and their effects could not be gathered from the given defect reports. It is further observed that the underlying causes and the faults do not generally occur independently. Most of the time, multiple faults occur simultaneously and cannot be treated as mutually exclusive events. For instance, an APU warning light may appear in the cockpit which may or may not lead to APU shutdown, generator failure, or unwanted vibrations.

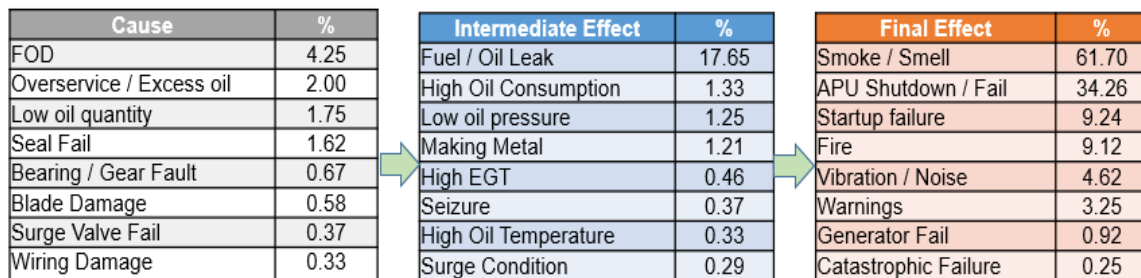


Figure 2-4 Causes and Effects of APU Failure

2.2.2.2 Maintenance Strategies for Aircraft APUs

Mechanical systems can range from small electric motors to huge turbomachines depending on the kind of output that is desired from them. In certain applications, the equipment could be producing Megawatts of energy and the components constituting these machines would be subjected to extreme pressures, temperatures, loads, and stresses. If there are no systems in place for monitoring

and reporting the apparent and incipient failures, then the outcome could be catastrophic. Owing to the severity of the situation, hazardous and safety-critical systems are equipped with sensors and associated hardware, which ensure that the system is operating within safe limits. Moreover, maintenance practices are in place to avoid accidents, ensure desired performance and system availability. The approaches range from preventive maintenance schemes to condition-based maintenance. The latter technique is an emerging field of research with huge potential in the industry because it addresses the key questions of maintenance engineers and eventually leads to decreased downtimes.

A range of maintenance strategies is adopted to keep APUs operational and avoid unnecessary downtimes. As per the study conducted on the 737-NG [8], APUs are initially subjected to mandatory scheduled maintenance practices which span from visual inspection and component replacement when the APU is in the aircraft to removal and installation of life-limited parts at the shop level. This activity is conducted at regular intervals regardless of the condition of the component(s) rendering the effort unnecessary in certain cases. However, even with the preventive maintenance strategies, an unexpected fault may appear in the system, and depending on the nature and severity of the fault, it must undergo unscheduled maintenance with added operational disruption costs.

In contrast to the above, a desirable way is to execute condition-based maintenance, which eliminates the need for resorting to unnecessary maintenance efforts. This is achieved by using condition monitoring data and failure prognostics models [16] materialized using data-driven or physics-based approaches. The former approach makes use of aircraft operation and maintenance data while the latter one generally relies on gas path analysis. However, [17] maintains that the airlines generally follow regular maintenance for APU, and they are not repaired until a failure occurs. Operating APU under such sub-health conditions can have undesirable economic and safety impacts, which must be mitigated using prognostics and health management strategies. The researchers who proposed failure prediction of aircraft APU relied greatly on its operational, maintenance, and repair data. For example, [18] utilized failure and

performance data from over fifty APUs to develop a Weibull-based method which is shown to perform well in predicting APU failure rates.

2.2.3 Current and Future Trends in APUs

A study on the importance of APUs is reported in [19], in which the potential advantages of removing APU from the existing aircraft are discussed. The study concluded with the finding that removing APU from aircraft can provide some economic and ecological benefits, only if those aircraft are operated for long ranges. Similarly, a detailed study has been reported in [20], which highlights the benefits of replacing fuel-powered systems (like APU / GPU) with hydrogen-solar-based energy networks for airport and aircraft electrification. The study shows that, although the upfront costs would be inhibitive, the energy costs and emissions can potentially be significantly reduced. Possible elimination of APUs from an electric aircraft is investigated in [21]. This is because the power for this kind of aircraft will be solely provided by technologically advanced batteries with a very high level of specific energy. However, at present, only short-range missions are possible with the less-advanced batteries. On a smaller scale, [22] investigates the possibility of using low-voltage power sources as a source of power for the aircraft's electrical needs. The proposed solution is said to provide voltage regulation and is robust against load fluctuations.

Numerous studies have been conducted which assess the shortcomings in the current APU design and suggest ways of improvement. In this regard, [23] presents a high-performance motor controller design for the starting system of an aircraft APU, that eliminates the need for a dedicated battery, the DC starter, and the clutch assembly. The effects of impulse load on an aircraft electric system are studied in [24] and the suggested modifications are made which will ensure that the APU or main engine's generator can withstand such loads. The study concludes that real-time compensating devices and a supervisory control system are necessary to maintain the electrical system's stability. [25] adopted Non-dominated Sorting Genetic Algorithm-II for choosing the parameters of a passive filter for an APU inverter. The response of the designed filter proved to be superior to the standard filters. [26] looked at the possibility of optimizing the rotor design

of an aircraft APU. The proposed method considered the rotor weight, the maximum unbalance response, and the response during the aircraft maneuvering phase for optimization. A Hybrid genetic algorithm was used for three-objective optimization, which resulted in a better design as compared to a reference APU. A design of a multi-level inverter for aircraft APUs is presented by [27], which comprises a smaller number of components and therefore is smaller in size and cost-effective. Development of an Auto Transformer Rectifier Unit for an aircraft APU is also needed to control the dc-powered electric motors when shifting towards a more electric design [28].

As the aircraft is becoming more electric, the need for electric systems is increasing, which would replace the existing hydraulic and pneumatic systems. [29] presents a novel design for an aircraft starter/generator system that allows electrical motoring of the aircraft engines. The developed system can start the aircraft engines through electrical power and therefore pneumatic power from the APUs would no longer be required. The benefits of a bleed-less architecture are discussed in [30]. The study reports that an APU designed for an aircraft with bleed-less architecture can save fuel up to 50 kg/hr for a 50-passenger aircraft.

Possible utilization of APU for futuristic and more electric aircraft will be of providing power to the electric motors that will drive the wheels of the aircraft [31],[32]. This capability would allow the main engines to remain off during the taxi phase, but it would increase the aircraft mass due to the presence of motors. The solution has also been tested through taxi trials of an Airbus A320 aircraft, which showed a reduction in fuel by 3% [33]. The current battery technologies do not provide the energy density for energizing a fully electric short-haul aircraft. However, the possibility of improving the existing APUs to provide higher levels of electrical energy is there [34]. There have been attempts of replacing BA-146 engines with electric motors and powering them with the electrical power generated by a Rolls-Royce AE 2100 APU. Furthermore, the predicted power density for future aircraft is expected to reach 40kVA/kg. The key enablers for this type of power would constitute non-conventional technologies like superconductivity. Some devices have already been developed with a power

density of 16kVA/kg. While designing a more-electric aircraft, [35] emphasizes the need for upgrading the APU generators to meet the desired electrical demands.

The researchers have been proposing innovative ideas to fulfill the requirements for an aircraft's auxiliary power needs. In [36], a novel design of an ICE engine is proposed that can find its application as an aircraft APU. The engine has no reciprocating components and hence has vibration-free characteristics. The invention's configuration, geometry, and operation are explained, and a prototype is built which has shown to achieve the desired outcomes under no-ignition conditions by driving it using an electric motor. The concept is in the early stages and has yet to satisfy all the criteria needed for an airborne application. Similarly, the feasibility of using the heat generated by a helicopter as a source of auxiliary power using the Organic Rankine Cycle has been carried out by [37]. However, the results showed that the power generated by this scheme was very reduced and thus this approach is not practically possible.

Lastly, there is a plethora of information available in the public domain literature which revolves around the possibilities of using fuel cells for airborne applications. In [38], an in-depth review is carried out on the existing SOFC technologies that can potentially replace conventional APUs. A symmetrical and planar SOFC design is studied by [39]. [40] designed a hybrid Fuel Cell / battery-based design for 767 as a replacement to APU. In [41], the key benefits of using SOFC-based APU are evaluated by simulating the performance of the fuel cell using proprietary library modules. The study employs a twin-engine aircraft designed for short-range missions. The simulation compares the performance of SOFC-based APU with a conventional gas-turbine-based APU and it is found that the former design performs better in terms of efficiency and fuel reduction. However, it is asserted that the findings are at a conceptual level and various aspects of safety and integration have to be considered before making it practical. The preliminary design of a fuel-cell-based aircraft is reported and the design is also tested on a 2-seater aircraft first time [42]. IATA, while considering the possible technological advancements needed to reduce fuel consumption, hints at the incorporation of

fuel cells as a replacement to conventional APUs is also under consideration [28]. However, it is asserted that hydrogen generation is currently not sufficient, and infrastructure is required to be developed on a global level for hydrogen generation.

2.3 Fault Diagnostics

For any given machine, maintenance strategy is incomplete without a comprehensive fault diagnostics method. Diagnostics aims to correctly identify faults that generally lead to warnings, performance degradation, and unsafe operation. Ideally, modern diagnostics methods should be all-encompassing and inherently possess the attributes mentioned in Table 2-2 (gathered from [43] and [44]). For any given system, the manufacturer or designer selects the optimum diagnostics method which can provide the maximum information about the system at the least possible costs and efforts.

Multiple types of diagnostics methods have been explored by the research community and most of them are in use by the industry. Any given type of diagnostics method can be uniquely identified by the adopted methodology and the type of capabilities it possesses. These are:

- (a) Type of fault(s) it can identify
- (b) Nature of sensing mechanism
- (c) Number of sensors employed
- (d) Signal Processing technique applied
- (e) Machine Learning algorithm used
- (f) Data / information fusion methodology
- (g) Performance of diagnostics method in terms of accuracy
- (h) Real-time / Offline capability
- (i) Ability to detect and identify faults during transient or steady-state

Table 2-2 Features of a good fault diagnostic method

Desirable attribute	Enabling features
Accurate	Exact amount of deterioration in the correct component
Low cost	Simple Low implementation cost Small number of sensors
Reliable	High probability of detection No False alarm Fail-safe
Quick	Online detection capability
Comprehensive	Able to detect multiple faults simultaneously Able to detect all possible faults

After decades of research, a considerable number of fault diagnostics methods have surfaced, each being capable of identifying a certain number of degraded or faulty components in a machine. Each method requires a unique sensor-set and a series of algorithms to convert the sensor data into useful information about machine conditions and fault locations. In the subsequent paragraphs, machine fault diagnostics methodologies are explained in detail, which have been categorized primarily based on the type of sensor used for processing.

2.3.1 A Rudimentary form of fault Diagnostics

Aircraft engines, including APUs, are complex systems, which require continuous monitoring for flight safety and timely maintenance. This may be achieved through the display of vital information through cockpit displays (engine RPM, EGT, oil quantity, oil temperature, etc.) [45]. Moreover, modern APUs are driven by a dedicated FADEC for feedback and control of the engine under various conditions. FADEC regulates fuel supply to meet desired performance, prevents compressor surge, initiate automatic shutdown in case of failure and record historical data into memory. FADEC also performs a built-in test (BIT) during startup and continuous operation. The outcome of the test is based on status monitoring of sensors and actuators based on electrical signals. BIT fails if

FADEC's connection with the component is found to be either open or short-circuited. Moreover, a failure is also detected if sensor data falls into an invalid range. Generally, BIT does not trigger a failure if the sensor data is noisy or biased or if the failure condition is momentary. In case a safety-critical failure is detected, FADEC initiates APU shutdown and records the information in memory for diagnostics purposes.

The seemingly decent approach mentioned in the previous paragraph does not help in diagnosing the complete range of failures that can occur in the system and are difficult to identify due to the intricately integrated nature of a gas turbine. Consequently, manufacturers must provide troubleshooting techniques through which the maintenance engineers have to traverse to single out the potential cause(s) of failure(s). Depending on the type and nature of failure, this process can be time-consuming and result in unwanted delays.

2.3.2 Performance-based diagnostics

Performance-based analysis of gas turbines is a prevalent approach towards engine health monitoring. The idea is to monitor measured variables such as temperature, pressure, and rotational speeds and relate them to engine health variables that are not directly measurable (like efficiency). Implementation of this approach requires an in-depth understanding of engine dynamics and the possible development of a digital twin. This will be accompanied by the selection and installation of correct types of sensors with added signal processing techniques for noise removal. In cases where sensor coverage is limited, various approaches like Kalman Filter and optimization / combinatorial techniques are proposed in the literature [46].

Performance-based monitoring (also called gas-path analysis) techniques give considerable insight into the degradation levels of compressors and turbines of a gas turbine [47]. The degradation could be the result of fouling, erosion, corrosion, or tip clearance. Aircraft engines, compared to industrial engines, are more susceptible to fouling because they do not have an air filtration system. However, this statement needs further assessment because in modern turbofan engines with a high bypass ratio, the particles are separated at the fan as they

are pushed outwards due to centrifugal forces acting on them. On the other hand, erosion in aviation is a frequently occurring phenomenon that greatly affects those engine components that are directly in contact with the atmosphere [48]. Numerous particles in the air deteriorate the component surfaces and lead to cracks and weight loss of the material. Nevertheless, the effect of degradation is the same regardless of the type and nature of the gas turbine. It is also highlighted that implementation of performance-based diagnostics and prognostics is a challenging task because it requires an in-depth understanding of the engine performance with inherent non-linearities and an elaborate set of sensor data that may be corrupted by noise and bias. Even in the presence of these complexities, performance-based health monitoring of gas turbines is considered a faster and reliable way of acquiring information and using it for maintenance.

Considerable importance is given to evaluating the degradation of compressors and turbines because they are the most expensive parts of an engine. Therefore, [49] discussed the cause and effect of compressor fouling and how it can be detected using performance deterioration. In the case of a combustor, it is stated that its performance deteriorates when carbon deposits start breaking off from the nozzles, and soot is produced as a result of incomplete fuel burning.

A practical realization of the model-based diagnostics approach has been presented in detail in [50], in which a turbofan engine is subjected to multiple faults, and data is collected in healthy and faulty states for model development, testing, and validation. Only those faults were selected and implemented which could not damage the engines. The model was eventually shown to accurately determine the cause of failure, however, the results were reliable during steady-state only.

2.3.3 Vibration-based diagnostics

Gas turbines, like rotatory machines, comprise mechanical components like bearings, rotors, and gears. Failures associated with these are rotor imbalance/misalignment, cracks, shaft rub, mechanical looseness, gear crack, gear tooth break, and defect in inner / outer race of bearing. Due to the mechanical nature of these faults, vibrations are induced which can be picked up

by appropriate sensors. In certain cases, mechanical and performance-based (or aerodynamic) faults may be coupled (like engine surge / corroded blades) which results in excessive vibrations. For each type of failure in rotating machines, vibration frequencies are associated with them [51], and vibration techniques aim to look for the presence of these emerging frequencies under the presence of background noise that relates to incipient failures. Vibration measurement can be in the form of displacement/velocity probes or accelerometers and the sensors are generally placed close to bearings, gearbox, engine shaft, and engine casing [44].

A two-step knowledge-based system for turbomachinery vibration diagnostics is proposed in [52], in which certainty factor is used to express the relationship between symptom and cause. The usefulness of fuzzy-based analysis of machine data for diagnostics has been presented in [53]. Fuzzy logic allows flexible threshold levels since the vibration amplitudes cannot have the same implications for the complete range of similar machines.

2.3.3.1 Gearbox fault diagnostics

Numerous studies have been performed on gearbox faults diagnostics alone. They are either based on data collected from test rigs operated in a controlled environment or from actual systems. This field has matured to an extent that there are metrics associated with gearbox deterioration. These metrics are in the form of features that are more stable as compared to raw data and help in data reduction as well. A survey was conducted by [54] on these features, who then classified them into 5 different categories (Table 2-3). The segregation is based on the type of pre-processing which is to be performed before calculating the features themselves. The categories start from virtually no pre-processing and end on a complicated approach in which Time Synchronous Averaging and band-pass filtering must be applied before the actual features are computed.

Table 2-3 Categories of features for diagnosing gearbox faults [54]

Category	Technique	Metric
RAW signal (RAW)	Features from the raw signal	RMS, Kurtosis, Delta RMS, Crest Factor, Enveloping and Demodulation.
TSA	Synchronous averaging of raw data (results affected by interpolation factor, number of revolutions concatenated during alignment, and number of averages)	FM0, Kurtosis
Residual signal (RES)	Removal of Primary meshing and shaft components along with their harmonics	NA4 and NA4*
Difference signal (DIF)	Removal of regular meshing components from the time-synchronous averaged signal	FM4, M6A, and M8A
Band-pass mesh signal (BPM)	TSA signal is band-pass filtered around the primary gear mesh frequency, including as many sidebands as possible	NB4

In an older study, [55] reviewed the vibration-based health and usage monitoring techniques developed for a helicopter. It included techniques like DWTs, STFT, Analog / Digital Neural Networks, neuro-fuzzy algorithms, WVD, and gear condition monitoring metrics like FM0, FM4, NA4, NA4*, NB4, and ND48*. The reviewer made greater emphasis on introducing the methods instead of comparing their results.

In [56], de-noising of weak fault signals was performed using the Donoho method with Morlet wavelet with a generalized soft-thresholding feature. Morlet mother wavelet was selected because it resembles an impulse that is generally produced in bearing and gearbox faults. The shape of the Morlet Wavelet can be optimally controlled using the minimal entropy method. The combination of Hilbert and wavelet packet transform was proposed for extracting modulating signals for detecting an early gear fault [57]. The results were analyzed using simulated and

real signals and it was found that the method was able to handle the time-varying situation and had better accuracy and efficiency as compared to WPT (wavelet packet transform) alone. The resulting transform was visually inspected for locating faults.

Improved HHT (iHHT) is also a method for machine fault diagnostics [58]. This method is HHT applied on sensitive IMFs calculated from the EEMD of the vibration signal. Comparison between time and frequency domain features for gear crack diagnostics is also available in [59]. Denoising of gear crack signal using Wavelet Transform with Gabor Wavelet has also been evaluated, where the threshold was selected using median absolute value [60].

Joint Time Frequency Analysis on vibration data is suggested for health monitoring of engine accessories like reduction gearbox [61]. A very robust method for gear crack de-noising is proposed using biorthogonal wavelet transform [62]. The method can identify gear damage at the level of an individual tooth. In the review by [63], it is stated that the vibration data varies with varying load and the only reliable data that can be captured is under no-load conditions. However, even under such circumstances, teeth lose contact and lead to random vibrations. While summarizing the effect of gear faults on the amplitude and frequency modulation, [63] wrote that shaft misalignment and eccentric gear lead to amplitude modulation, whereas local gear failure effect frequency modulation due to speed variation. In [64], possible locations of vibration sensors on a gas turbine are stated and the effect of compressor, combustor, and turbine failures on vibrations and performance parameters is summarized. However, only qualitative criteria for fault diagnostics are presented which may be insufficient for fault localization.

Machine rotor faults have been comprehensively studied using the physics-based approach and its validation using data collected from a Machine Fault Simulator [65], [66]. Efforts have been made to localize unbalance faults using vibration data collected from the simulator. Autoencoder technique is yet another way for system modeling and analyzing discrepancy signal for gear diagnostics under

varying load [67]. Adaptive morphological gradient lifting wavelet has also been applied for de-noising of signal and applying FFT to visualize the sidebands [68].

A recommendation is made in [69] to use Mel Cepstrum on vibration and acoustic data for diagnosing faults in a jet engine. During this study, a jet engine was operated under healthy and 02 faulty states to acquire vibroacoustic data and use it to model the fault classification algorithm. A time-domain technique is to use Dynamic Time Warping to generate a residual signal from raw and reference gear mesh signals and applied correlated kurtosis for diagnosing gear spalling [70]. Adaptive spectral kurtosis for denoising (extracting transients signals) using Morlet wavelet is another way of observing the transients in case of broken teeth gear [71]. In [14], RMS values of vibration are predicted based on a data-driven approach where data is collected from a 25 MW gas turbine at multiple instances for a span of 1 year. The developed ANN model is s Multi-layer perceptron-based and is shown to accurately predict vibration rates from known parameters. Sensitivity analysis of the input parameters reveals that the vibration rates are more sensitive to differential pressure across bearing, fuel consumption and rotor speed. The study was concluded without further analysis and a physical explanation of the results. A comprehensive review of time, frequency, and time-frequency domain condition indicators for gearbox fault detection is presented in [72].

Hilbert transform along with Wavelet packet transform has also been applied for localizing faults in the two-stage gearbox which was not possible using Wavelet Packet transform alone. The induced failures were gear pitting, chipped gear tooth, and spall on bearing outer race [73]. Similarly, [74] applied the Wavelet Bicoherence technique on vibration signals for diagnosing gear faults. TSA was done using up-sampled signal and mesh frequencies were removed before applying Wavelet transform. Finally, Wavelet Bicoherence processing was done, and Fisher Criteria was applied as a diagnostic feature. [75] proposes using spectral Kurtosis with envelope analysis for diagnosing bearing faults in wind turbine gearbox.

In [76], an explanation is made towards successful implementation of vibration monitoring which helped maintenance engineers in diagnosing failure in one of the bearings of a gas turbine using time-domain analysis. A model has been successfully developed for predicting the vibration behavior of gas turbines using the Neural Network approach [77]. In this approach, the state of the gas turbine is used as input to the model which predicts axial and radial vibration of the rotor. This information is compared with measured vibration data for diagnostics purposes. In another report [78], problems encountered during the vibration-based approach in gas turbines are discussed. It is stated that the desired health monitoring estimates from vibrations analysis are difficult to retrieve because they are masked by comparatively high levels of oscillations from the flow of air and combustion products. The situation is further deteriorated due to harmonics from various other sources as well; impellers, rotors, generators, gears, and other auxiliary accessories. A suggested way for diagnostics, which may not be practical in most cases, is to decouple the component(s) under study from the main engine and rotate in using an external drive.

2.3.3.2 Bearing fault diagnostics

Bearing faults have also been the object of study by the research community due to their significance in safe and reliable operations of turbomachinery. Resonance demodulation method for indicating gear tooth fault has been proposed in [79]. The method involves the removal of meshing harmonic frequencies and filtering the signal around structural resonance and employing Kurtosis as a fault indicator. The method was tested on numerically simulated data, test-rig data, and helicopter data.

The use of STFT with marginal time integration for extracting features in a ball bearing is mentioned in [80]. In [81], it is exhibited that the diagnostic features are susceptible to load conditions for ball bearings and have to be modeled as a function of load for better segregation of healthy and faulty data. Multi-fault diagnostics of simultaneously occurring gear and bearings faults can be performed using Hilbert Transform with Wavelet Multiresolution Transformation [82]. Cepstral pre-whitening on residual signal for detecting a fault in ball bearing

has been recommended in [83]. Application of various signal processing algorithms like minimum entropy deconvolution (MED), Teager-Kaiser Energy Operator (TKEO) followed by Genetic algorithm, and kurtosis computation is discussed in [84] for bearing fault diagnostics using vibrational analysis.

A novel technique for helicopter bearings diagnostics is described in [85], [86]. Usage of energy parameters of the multi-factor transfer function as a feature for fault detection is cited. This feature is computed from vibration signals, casing transfer function, bearing geometry, and rotation signal for onwards diagnostics. However, the experimental data was gathered in un-realistic conditions, since the engine was driven in 'cold' mode by a powerful electric motor. Feature vector computed from IMFs of vibration signals for diagnosing rotor and bearing faults has also received considerable attention [87]. It is claimed that adaptive filtering of EWT (Empirical wavelet transform) as a feature extraction tool produces better results for bearing fault diagnostics. It was followed by classification using a merger of KDE (kernel density estimator) and MI (mutual information). The method was termed AFEWT-KDEMI (Adaptive Filtering Empirical Wavelet Transform – Kernel Density Estimator Mutual Information) and was shown to perform better than SVM and BP techniques [88].

The combination of Adaptive Waveform decomposition for noise removal and Limper-Ziv Complexity as feature extraction method is another method of fault diagnostics [89]. An analytical model for pump bearing vibration using dimensional analysis is proposed and compared the results with experimental data for observing a trend in bearing deterioration [90]. The use of envelope spectrum of vibration signal and observed slice-spectrum for analyzing bearing faults is also mentioned [91]. Convolutional Neural Network with S-Transform for bearing fault detection is shown to outperform all other techniques [92]. For tackling distributed damages in bearings, a mathematical model has been developed for computing damage frequencies for the inner and outer ring of bearing. The model has also been successfully validated with experimental data [93]. Another feature extraction method is to compute the ratio of characteristic

frequency computed from EEMD of vibration signal for bearing fault diagnostics [94].

It can be concluded that there is a lot of work that has been done in the field of fault diagnostics of rotating machinery using vibration data. The majority of the research has been towards fault detection and identification using test-rigs or a subset of the whole system, thus rendering the performance of developed algorithms to be contentious for a complete system. Since the component faults are studied separately, it is rare to see a detailed analysis of engine noise and its effect on components' characteristic frequencies. Moreover, selection and performance analysis of sensors of different types and specifications have not been made part of the research, which can be of great significance to the maintenance engineers who would be practically implementing the research.

2.3.4 Acoustics-based diagnostics

Several attempts have been made to harness the potential of utilizing airborne sound for health monitoring of rotating machinery. This is because microphones are easily installable as opposed to accelerometers since the latter require rigid connectivity to the component which is intended to be monitored. This is generally not feasible when the surface is not flat and is potentially at high temperatures. Although many commercially available accelerometers can sense machinery vibrations at higher temperatures, a considerable cost is associated with them. The whole activity of installing vibration sensors is suitable if they are being considered for condition monitoring when the product is in the infancy stage of development. However, the same process may not hold good if sensors are to be installed on vintage machinery or a certified product. Other than the reasons already mentioned, any mechanical modification to a product, once it is through from its design cycle, will entail risks, redesign, and costs.

Microphones belong to the category of non-intrusive sensors and they can capture a wide range of acoustic signatures emitted by mechanical components in the vicinity. Also, their installation would not require major alteration to machine structure. An astounding feature of acoustics is its capability of capturing variations in fluid flow characteristics which is not much pronounced in the case

of vibration signals [95]. Nevertheless, the acoustics signals are proliferated by background noise, unwanted reflections, and reverberations which may cover the informative signal. This can, however, be evaded by using specialized signal processing techniques. Due to the inherent limitations, acoustics-based diagnostics has not received due attention and the studies that have been conducted are generally carried out in a controlled environment.

In [96], the effect of surface roughness on bearing noise was studied using microphones in an anechoic chamber and it was found that the produced noise has a proportional relationship with surface roughness. Smoothed pseudo Wigner-Ville distribution analysis of vibration and acoustic signals for gear faults diagnostics can achieve desirable results [97]. Moreover, it has been found that the acoustics-based technique performs better for detecting cracks. However, vibration signals can detect tooth defects at a much early stage. Comparison between vibration and acoustics signals is made using wavelet transform and it is concluded that acoustic signals can equally perform well in detecting faults in a gearbox. With regards to acoustic signals, they were found to be unaffected by small changes in position and orientation of the sensor [98].

Acoustic data can also be used to detect wearing and crack in gearbox by observing the trends in Power Spectral Density and Cepstrum results [99]. Comparison between the performance of using accelerometer, acoustic, and stator current data from an induction motor is made in [100]. It is concluded that the accelerometer signals outperformed the rest for diagnosing gear tooth wear if the Welch method is used for computing Welch Method. Near-field acoustic holography is a unique way of using acoustics for bearing fault diagnosis [101]. In this method, GLCM features are computed from NAH images and the optimal feature subset is selected based on F-score. The features are then used to train classifiers, and finally, diagnostics is done using multi-SVM. The results are promising but the dataset was collected in an anechoic chamber using several microphones. Empirical Mode Decomposition is a well-known technique that has been applied on vibration and acoustic data for fault diagnosis of ball bearing [102]. This method can also perform well in the absence of bearing specifications.

Tests are conducted in a lab setup with healthy and fault-induced ball bearing. FFT is then applied to IMFs of the acoustic signal and it is found that bearing fault leads to increased intensity of computed frequency levels. The same method also allows the estimation of bearing frequencies.

In [103], it is stated the turbomachinery blade faults like blade rubbing can be captured by using acoustics. Diagnoses faults in planetary gears can also be done using acoustic signals and their frequency spectrum [104]. In one of the case studies [105], the usefulness of installing vibration and microphones on a vacuum pump is studied. It is shown that the two installed microphones can capture operational frequencies of the whole system even in the presence of background reflections. Comparison between vibration and sound signals shows that the microphones can capture spectral content which is sensed by the accelerometers also. The study has been conducted using low-cost sensors and no further analysis is performed.

Similar activity has been undertaken by [106], in which accelerometer and microphone are installed on a pump for studying bearing faults in a pump. Time domain, frequency domain, and envelope spectrum analysis are done, and it is shown that bearing frequencies' amplitude and harmonics are visible in the acoustics data and RMS values of acoustic envelope signals are robust features for performing fault diagnostics. Several other features and algorithms have also been computed using acoustic signals for detecting damage in rotary machines [107]. This includes Spectrogram, Wavelet Transform, co-occurrence matrix, and AdaBoost classification algorithm. Work on detecting gear misalignments using vibration and acoustic signals is also presented [108]. For this purpose, an experimental setup is developed for inducing gear-pair misalignments acquiring corresponding vibration and noise data under various operating conditions. Multiple techniques are employed for estimating misalignment using regression models based on time-domain features computed from vibration and sound sensors.

Efforts have also been made to diagnose gears faults using low-cost acoustics-based solutions [109]. A test rig was developed which could generate acoustic

data from a gearbox in healthy and faulty states. Various time-domain and frequency-domain features were evaluated under different rotational speeds to detect a faulty condition. The proposed solution was based on a low-cost microcontroller and was shown to perform equally well when compared to COTS-based data acquisition systems.

Modulation Signal Bi-Spectrum is another technique applied on airborne sound for diagnosing failures in reciprocating compressors. A detailed study has been carried out on the planetary gearbox of wind turbines [110]. A fusion-based method is proposed which combines information sensors including electrical, acoustic, and vibration sensors. Features are computed from the energy of fault frequency computed from PSD estimation of signals. ROC curve is then used to compare results from various fusion parameters. Acoustics for wind turbine health monitoring has also been evaluated in [111]. It is stated that the installation of multiple microphones inside a wind turbine blade can be used to monitor cracks development. This study is conducted on a wind turbine blade that was undergoing fatigue testing. A total of 6 microphones are placed inside the blade and a subset of data is retrieved where the onset of cracks is noticed. Several signal processing techniques are applied for feature extraction. This includes time-domain parameters, cepstral coefficients, short-time energy, and zero crossings. Focus is given to Linear Predictor cepstral coefficients due to their popularity in audio signal processing. Dimensionality is further reduced using PCA and K-means clustering which is applied to the top 3 PCA components. Results are compared with features consisting of ZCR (Zero Crossing Rate), short-time energy, and first LPC coefficient only. The results show that the former set of features is robust in indicating deviation from a healthy state.

Very little information is available in the public domain literature that covers aspects of acoustics signal processing for gas turbine fault diagnostics. Nevertheless, an industrial gas turbine had been subjected to three different kinds of faults and acoustic data was collected for onward processing and fault diagnostics [112]. The sensors were installed around the compressor which had been subjected to rotor fouling, blade twisting, and mistuned stator vanes faults.

Wavelet transforms were used to analyze the differences in acoustics signals during healthy and faulty conditions. The microphone signals displayed a shift in energy to higher frequencies in the case where stator vanes were restaggered. Finally, the difference between wavelet coefficients from the healthy and faulty engine was declared to be a robust feature for fault diagnostics due to the reduction in the number of features as compared to Fourier analysis.

Acoustics have also been of interest in the automobile sector where the focus has been towards understanding the sound generation from engines and determining possible ways of noise reduction [113]. The same phenomena have been utilized by researchers for evaluating engine noise as a source of information for fault diagnostics. Combustion noise was found to be the dominant source of noise for a diesel engine and is proportional to cylinder pressure [95]. Furthermore, time-frequency domain analysis can provide useful information about the engine firing order and crank angles. Automobile engine signals belong to the category of cyclo-stationary processes due to their reciprocating nature. This type of signal comprises repetitive cycles and is best observed with the help of time-frequency domain analysis. This information was utilized in [114] in which faults were induced in the engines and sound signals were used to differentiate between healthy and faulty conditions using Continuous Wavelet Transform (CWT). During the experimentation, it was noted that the lower frequencies are greatly affected by environmental factors, whereas the higher frequencies are more stable and provide robust features. Considerable improvements were made in [115] in which various wavelet domain features were studied and the appropriate ones were selected using the correlation-based feature selection method. This method aims to provide a subset of features that are uncorrelated with each other but are correlated with the fault under study. This is achieved by searching for a subset of features using a best-first algorithm, which provides the maximum gain or mutual information. The overall approach was declared to be robust in detecting faulty combustion conditions of an automobile engine, even in the presence of environmental noise. In another approach [116], envelope spectrum was obtained from sound signals and a correlation coefficient was used to segregate between the healthy and damaged engine.

The literature survey conducted on acoustics-based diagnostics reveals that the research community has approached this problem using data-driven techniques and the underlying noise generating mechanisms have not been the object of their study. Experimental data is usually collected from healthy and faulty states and models are trained to classify the faults based on measured data. Furthermore, the tests are conducted in a very controlled environment where other sources of noise are generally not present. In certain situations, certain conditions are set which may render the developed strategy impractical. Conducting the tests in an anechoic or semi-anechoic chamber and experimenting on the only subset of the whole machine are examples of such unrealistic scenarios. It has also been learned that for achieving repeatability in the data, the microphone should be placed at a distance that is greater than the engine length [95]. This condition may get satisfied for land-based systems but may not be possible for airborne platforms in which the systems are compactly placed and there is very little room available for mounting additional sensors.

2.3.5 Other forms of diagnostics

Certain elements, other than performance parameters and vibration, can also be used to estimate the current health of gas turbines. Using spectrometric oil analysis to predict the RUL of aircraft engines is one such method [117]. Total metal concentration computed from oil analysis has been proposed for engine failure prognosis. Wear debris analysis of lubrication can also determine the amount of wear occurring due to sliding, rolling, rubbing, abrasion, etc [51]. In [118], the importance of electrically charged particles for engine health monitoring is described. It is shown that these particles can appear in exhaust flow due to turbulent flow the increase in these particles is related to failures like abnormal loss of blade coating material due to on-going damage. As per the comprehensive survey carried out by [119], several diagnostics techniques are available for identifying failures in turbine blades and combustion chambers which constitute hot components of a gas turbine. The foremost method is of using various types of tip-timing sensors (magnetic, optical, capacitive, etc) provides information about cracks, creep and wear of turbine blades. Strengths and limitations of using

temperature, pressure, vibration, mm-wave ultrasonic, and Acoustics Emissions for blades health monitoring have also been critically evaluated for various types of failure modes.

Another approach for engine health monitoring is to combine the results from various sensors to increase diagnostics coverage and making the results more robust and reliable. A practical example is discussed in [120], in which an information fusion system for the P&W F117 turbofan engine is developed using gas path measurement, accelerometer data, and oil debris analysis. The Fuzzy Logic method is another way of combining data from various sources for turbofan engine diagnostics [121]. Details of another fusion method are presented in [46] in which performance and vibration data are fused for gas turbine fault identification. The proposed GPA is based on a non-linear method that provides deviation from healthy conditions and the irrational results are leveraged by vibration measurements by fusing it using PDF integration followed by fusion using certainty factors. The vibration data used for validation was in terms of RMS values from 4 locations on the engine. Machine Learning techniques may also be applied for sensor data fusion. Neural Network techniques have been applied to performance and mechanical data acquired from engines in transient and steady-state fault diagnostics. A detailed survey has been carried out on sensor fusion techniques for condition monitoring of gas turbines using vibration data and GPA [122] which covers a comparison between different signal processing and probabilistic techniques. Another practical example of using multiple heterogeneous sensors for gas turbine fault diagnostics is presented in [123] in which data from 35 sensors were used to formulate a diagnostics model. The model was developed using hierarchical clustering and self-organizing map neural networks and was shown to perform well under steady and transient states.

Novelty detection framework development is yet another way of predicting failure in a system using information from multiple sources. The approach is to develop a high-dimensional system model using engine data in healthy states. This model is then used to monitor any significant departures from the normal state which

may be an indication of failure onset [124]. This technique may not be directly applicable towards fault classification, but it can be used for detecting excessive vibrations or any other abnormal conditions which can damage the engine. This is because in real-life applications complete dataset is not available for various states of engine operation. Therefore, it is convenient to resort to novelty detection instead of the classification approach. Models for novelty detection are generally data-driven, and one such method based on advanced Machine Learning is discussed in [125].

2.3.6 Design Considerations in Aircraft Systems with Novel Architectures

Airborne systems' reliability has been a cause of concern for all the stakeholders. Whether it is the design phase, or any other part of a product's life cycle, incorporating diagnostics capability into the system is desired. Even with technologically advanced systems, failure is inevitable. A failure can originate at a component level, triggered by foreign object damage, human error, or any other unforeseen circumstances. However, by carefully assessing the hazards and putting systems in place for risk mitigation, the frequency of occurrence of failures can be drastically reduced. To detect and respond to such failure conditions, a well-designed fault diagnostic system is integrated into an aircraft. The diagnostic capability is crucial for quickly responding to a failure condition by executing requisite measures. As the aircraft are being equipped with a greater number of systems, the overall complexity is increasing and therefore the importance of detecting and diagnosing failures cannot be ruled out.

With the significant projected increase in air travel [126], futuristic aircraft would be required to be greener, fuel-efficient, high performance, and less noisy. In this section, various novel aircraft architectures will be discussed from the aspect of their diagnostic capability. Starting with distributed propulsion technology, a detailed review is presented by [127] on the evolution and challenges associated with such technologies. Another review by [128] acts as a supplementary article and brings in military aircraft and UAVs within the scope as well. The distributed propulsion technology is said to cover a diverse range of aircraft, ranging from

VTOL-aircraft to supersonic aircraft. The authors revisited the historical advances which have been made towards the design or development of aircraft with distributed propulsion systems, that can operate in subsonic or supersonic flight regimes. By distributing the thrust generation, the key benefits include noise reduction and better performance. Increased reliability can also be achieved by adopting a fail-safe mechanism in case of a diagnosed failure. As per the author, since superconducts is becoming a reality now, using distributed fans instead of small gas turbines is a better option. A novel concept is proposed by [129], in which a series of multiple electrical fans are integrated within an aircraft wing to generate the necessary thrust. The design involved multiple ducts and nozzles within a split-wing and posed several challenges. As per [130], the research community benefited from the design which incorporated multiple ducted fans for propulsion and employed a similar concept when designing VTOL / STOL aircraft. The use of electric propulsion for such types of aircraft has also been explored. In this regard, NASA's Puffin electric tailsitter VTOL concept is identified to be a highly reliable and efficient design [131]. In the case of the UAVs, the propulsion system is the most critical and is found to be the most common cause of a UAV failure [132]. Therefore, various electric solutions have been explored and tested for reliability using Hardware-in-the-loop simulations [133].

As the trend in the aviation industry is moving towards a more electric architecture, it is envisaged that the hydraulic/mechanical linkages will be replaced by electronic components. This will result in the reduction of the number of moving parts and therefore maintenance costs will decrease [134],[135]. Using a high level of DC voltages on board the aircraft has also been proposed in [136], which will reduce the transmission losses through the aircraft electrical system. However, such a design would require the development of an advanced system for detecting faults in the aircraft power generation system. The turbofan engines are also being studied to incorporate electrical generators within the engine, as opposed to the generators are being driven by the low-pressure turbine through a mechanical drive [134],[135]. The standard diagnostic practices may not be applicable to such designs if they are made practical.

There are several technical challenges involved with the above-mentioned innovative aircraft architectures. For example, in the case of a distributed propulsion system, the common problems which have been identified are engine cooling and loss of airflow and thrust by the rear engines. Fabrication and manufacturing of unconventional aircraft structures along with the integration of a distributed propulsion system in the airframe are also considered high-risk tasks that should be overcome before proceeding with further development.

2.4 Application of Acoustics in Airborne Gas Turbine Engines

Acoustic power or sound energy from an aircraft originates from its engines, auxiliary power units, high-lift systems, landing gear, and propeller. Such unwanted Acoustic noise has been classified to be “annoying” for the people living around the airports [137]. It can even have adverse effects on the health of airline employees leading to partial or complete hearing loss [138]. Owing to such serious implications, aircraft regulating authorities have put restrictions on airline operators and airports to limit noise generation. This can be achieved by reducing noise at the source, modifying flight procedures, or by restricting flight operations. Ideally, technological improvements to existing and future aircraft and engines can help in reducing noise radiation from the source without hampering the operations. Thus, the research community has been considerably involved in developing methods to ascertain noise-producing mechanisms and their abatement. Since the object of this review is to appraise the reader about various aspects of airborne engines’ noise, so the following sub-sections will be limited to turbofan, turboshaft, turbojet engines, and auxiliary power units.

2.4.1 Gas Turbine Noise Terminology

To proceed further and learn more about airborne gas turbine noise and its characteristics, it is necessary to understand the terminology commonly used by the industry as well as the research community. These terminologies are associated with gas turbine noise and have been frequently used in the literature.

2.4.1.1 Engine Core noise

The term 'engine core noise' has been coined for the phenomena which contribute towards engine noise upstream of the nozzle exit (Figure 2-5) [139]. The core-noise mechanisms are engine specific and become dominant when the jet velocities are considerably low (for example a turbofan engine on idle when the aircraft is at approach). As per [140], core noise consists of combustion noise, low-frequency noise generated in the turbine as a result of interaction with upstream turbulence from the combustor, noise generated in the flow passage discontinuities (turbine exit struts), and turbulence level and swirl in mean flow upstream of the nozzle exit. In certain cases, jet-noise / jet-mixing noise is excluded from core-noise category [141].

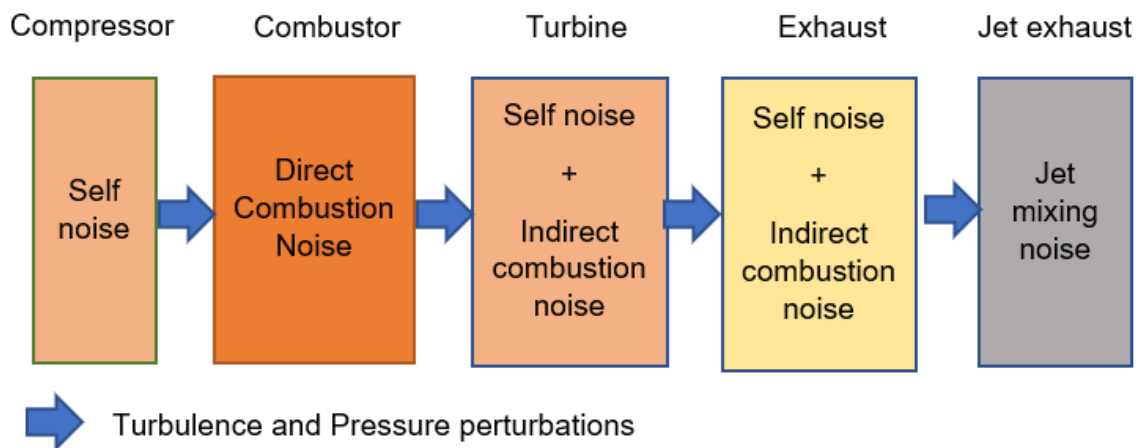


Figure 2-5 Engine Core Noise [139]

2.4.1.2 Direct combustion noise

It is related to the acoustic waves which are generated due to the turbulent combustion process and are propagated through the turbines.

2.4.1.3 Indirect combustion noise

This is the name given to acoustic waves which are induced by convection of combustion-generated heterogeneities like temperature fluctuations/turbulence through mean velocity gradients appearing through turbine blades or nozzles.

2.4.1.4 Tonal Noise.

It is produced by a regular rotation of turbomachinery blades (compressors and turbines). This tonal noise is mainly present at high frequency and radiates through the air intake in case of compressors and the exhaust in case of turbine stages. It is possible to characterize the sound pressure frequencies with the Blade Passing Frequency (BPF) which corresponds to the revolution rate per second times the number of compressor or turbine blades [142]. The compressor noise may be masked by fan noise in the case of turbofan engines [143].

2.4.1.5 Broadband noise.

This is the noise that has greater spectral content as compared to tonal noise. This is caused by pressure fluctuations associated with the turbulence in the flow field. Fans are a major contributor to this kind of noise because of the vortex shedding occurring at the blade trailing edges [144]. Jet noise is the noise generated from the high-velocity engine jet mixing with slower ambient air [145].

2.4.1.6 Casing-radiated Noise

The noise generated by internal components of a gas turbine may radiate through the casing of the gas turbine assembly. This noise leaves the engine and will be picked up in the near vicinity of the engine. This form of noise is termed the casing-radiated noise. This noise experiences sound reduction when it passes through the engine panels and is therefore an attenuated version of the actual noise present inside the engine [146]. In general, this type of noise depends on the internal noise, geometry, and stiffness of the casing [147].

2.4.1.7 Sound Power.

Any item of equipment that generates noise radiates acoustic energy. The total amount of acoustic energy it radiates is sound power. This is, generally, independent of the environment [146]. Sound Pressure Level is the sound pressure acting on the sensor or human ear. The sound pressure is very dependent on the environment and the distance from the noise source to the listener. SPL is the RMS value of sound pressure signals.

2.4.1.8 Sound intensity

It is the amount of sound energy radiated per second through a unit area. If a hypothetical surface, or envelope, is fitted around the noise source, then the sound intensity is the number of acoustic watts of energy passing through 1 m² of this envelope. The sound intensity, I , normal to the spherical envelope of radius, r , centered on a sound source of acoustic power, W , is given by:

$$I = W / 4 \pi r^2 \quad (2-1)$$

2.4.1.9 Overall Sound Pressure Level (OASPL)

It is the Sound power level obtained by integrating power in all the frequency bands. Let $S(f)$ be the power spectral density of sound, then:

$$OASPL = 10 \log_{10}(E) \text{ [units: dB]}, \text{ where } E = \int S(f) df$$

2.4.1.10 Metric for engine noise

Most of the acoustic parameters are expressed in terms of decibels because of the huge range of levels that are possible. During conversion to decibels, a reference pressure of 20×10^{-6} Pa is usually selected.

2.4.2 Significance of Engine Core Noise

Generally, gas turbine noise is studied to provide insight into its physics, develop empirical prediction models, separate noise sources for validating results, and eventually developing noise suppression methods. In literature, more emphasis is given to combustor noise because it dominates the lower frequencies and is thus difficult to curtail when dealing with noise abatement. In [139], the significance of core noise for turbofans in low-power settings and APUs is also explained. As per [148], jet noise was initially very high and its contribution towards overall noise was significant. As jet noise depends on the 8th power of jet speed – so increase by a factor of 2 will increase noise by 50 dB. Jet speed reduction was at the time not only a noise concern but also a performance requirement, since the propulsive efficiency increased significantly when the jet speed was reduced, increasing aircraft range and reducing cost. The turbofan engine used nowadays achieved these goals by reducing jet speed and

maintaining the total thrust by increasing the mass-flow using a by-pass design. Now the major source of noise is from fan and turbomachinery noise at higher power settings. Moreover, when the aircraft is in flight, the relative difference between jet velocity and the ambient velocity decreases and so does the jet mixing noise thus making direct and indirect combustion noise to be more prominent [149].

2.4.3 Gas Turbine Noise Measurement and Characteristics

Extensive measurements have been taken around engines of various sizes and configurations to construe noise-producing mechanisms and subsequently quantifying the effect of the noise suppressing arrangements. Owing to the massive size of turbofan engines, sound measurements are acquired using a large anechoic chamber or a ground with no obstructions for producing meaningful results. Also, the measurements are generally made with multiple microphones placed in the far-field of the inlet or exhaust. Table 2-4 presents a summary of different types of experiments that have been performed on airborne gas turbine engines. Each entry in the table gives information about the engines under study, the nature of the experiment, and the objective of that activity. The salient features of each activity are explained in the subsequent paragraphs.

In [150], the theory of the relationship between acoustic power and temperature fluctuations from combustor was validated using noise measurements from three aero-engines. The overall contribution from this source exceeded jet mixing noise at low jet speeds. By assuming temperature fluctuations to be 2 percent of the mean static temperature into the turbine, it was shown that the exhaust noise at low power settings was related to the average temperature fluctuations for all three engines.

In a detailed report by NASA-funded research on integrated technologies for aircraft noise reduction, a turbofan engine was used to establish baseline noise measurements [151]. Extensive measurements were taken at NASA Glenn Research Centre using the TECH977 turbofan engine with microphone arrays and acoustic barriers to separate inlet and exhaust noise. Case radiated noise was also studied and found to be in a lower frequency range caused by flow in c-

ducts. The analysis revealed that the combustion noise was present at 250 Hz and multiple resonating frequencies are also generated from the combustor. With respect to the jet noise, it was observed to be reduced with a decrease in power and appeared in the low frequencies. Effects of various acoustic treatments on engine noise levels and directivity were also studied. The noise sources identified by this program are presented in Figure 2-6. The combustion and jet noise are overlapping in the lower frequency range while fan noise is in the intermediate range and turbine noise is contributing to the end of the spectrum.

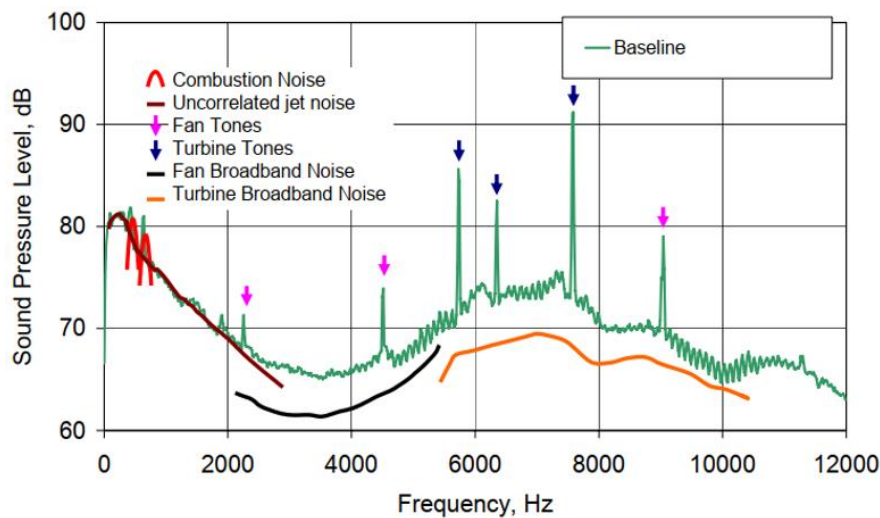


Figure 2-6 Baseline engine far-field noise and identified noise sources [151]

A separate study was conducted on a turbofan engine with and without the fan, with an aim to develop a better understanding of the combustion and turbine noise [152]. This was a sub-task of NASA's Engine Validation of Noise and Emissions Reduction Technologies (EVNERT) program. The engine had to be modified so that it could be operated without the fan. This removed the tonal and broadband frequency content which is generated from a fan. Moreover, internal pressure sensors were installed so that the internal dynamics of the combustor can be better understood. It was discovered that there were broadband peaks inside the combustor, which can be the result of resonance. However, these peaks were not present in the far-field data. In addition to this, very little change was observed in combustor noise spectra amplitude at different engine operating speeds but was accompanied by a slight change in frequencies. The combustion noise was found to be the dominant source in the 250-1000 Hz range, whereas

turbine noise was in between 5 – 10 kHz. Complete engine (with fan) acoustic response was also compared with prediction models and the major discrepancy was found in the 1250-4000 Hz range where the fan duct acoustic treatment was present. In the same study, case radiated noise was analyzed using phased array configuration of multiple microphones. The transition portion of the c-duct was found to be the prominent source of casing-radiated noise which was present between 100-700 Hz. This noise was considerably reduced at lower power settings.

In [153], various signal processing techniques were applied to determine the contribution of noise sources on the overall acoustic behavior of a turbofan engine in the far-field. The three-microphone method produced desirable results where the sources did not overlap in the frequency domain and only a single source was dominant.

A study on combustion noise from a large turbofan engine was undertaken as part of the EU Silencer(R) (Significantly Lower Exposure to Aircraft Noise) project [154]. The spectral coherence technique was used to study the relationship between data from data captured from internal sensors and far-field microphones installed around Rolls-Royce Trent 500 aero-engine. Experimental results support the presence of low-frequency direct combustion noise (below 100 Hz) which was not affected by the change in engine shaft speed. Furthermore, indirect combustion noise is found to be present in the 100 – 1000 Hz range. Eventually, two spectrums were defined to represent direct and indirect combustion noise, with peaks at 160 Hz and 200 Hz respectively. The results were compared with the SAE prediction model which predicted combustor peak at 400 Hz, but the noise levels and the directivities were similar.

Rigorous analysis of TECH977 turbofan acoustic data was done in order to characterize the core-noise [155]. Time delay analysis was performed to maximize coherence between combustion chamber signal and far-field acoustic data. For this specific engine, direct noise was present in the 200-400 Hz frequency range and indirect noise due to interaction of entropy fluctuations with downstream components lead to noise in the 0-200 Hz range.

Table 2-4 Summary of Experimentation done on Gas Turbine Noise

Year	Type of Engine	Acoustic Suppression	Acoustic Sensors	Other sensors	Experiment Location	Observed parameters	Operating Conditions	Target Objective	Prediction method compared with
1977 [150]	P&W JT8D-9 & Rolls Royce Spey 512 Turbofan engines + Olympus 593 Turbojet	Standard	Far-Field microphone array (placed on the ground)	Nil	Not mentioned	1/3 Octave band up to 1 kHz	Not mentioned	Study combustion and jet noise	Temperature fluctuations
1988 [164]	Turboshaft engine - 90k RPM, 8 kW, radial compressor and turbine	No	Nil	2 vibration sensors installed on combustor and compressor	Not mentioned	Frequency Spectrum up to 21kHz	Idle, 50%, 75%, Full Load	Effect of fuel type on induced vibrations	Nil

2008 [151]	TECH977 demonstration engine	Standard	32 Far Field Microphones (100 ft radius)	In-duct sensors	Open Environment	Frequency Spectrum up to 10kHz + Directivity	48%, 54%, 60%, 71%, 87%, and 91%	Study noise and noise reduction methods	ANOPP
2008 [152]	TECH977 demonstration engine	Standard	Far Field microphones array + 16 Internal sensors in Combustion chamber	Nil	Open Environment	Frequency spectrum up to 10 kHz	24%, 48%, 54%, 60%	Study turbofan noise engine by taking measurements with and without the fan	Nil
2008 [154]	ANTLE demonstrator engine (Rolls- Royce Trent 500)	Standard	6 Microphones (7.25 m from exhaust) + Internal sensors	Nil	Test Cell with acoustic treatment	Frequency spectrum up to 1kHz	35%, 40.5%, 43.6%, 46.1%	Study combustion noise	SAE 876D
2009 [155]	TECH977 demonstration engine	Standard	Far Field microphones array + 16	Nil	Not mentioned	Frequency spectrum up to 1 kHz	48%, 54%, 60%	Study Direct and Indirect combustion	Nil

			Internal sensors in Combustion chamber					noise based on time delay analysis	
2009 [156]	FJ44 Turbofan	Standard	3 Array of microphones (2 side, 1 front - Total 48 microphones - 16 ft distance)	Nil	Anechoic chamber	Order Spectrum up to 120 of N1	69%, 85%, 100%	Effect of acoustic line at inlet, dominant noise production mechanisms	Nil
2011 [141]	GE Turbofan engines	Standard	Not mentioned	Nil	Not mentioned	Frequency Spectrum up to 10 kHz + Directivity	Low Power, High Power	Study noise from components	ANOPP
2014 [154]	Ardiden 1H-1 Turboshaft engine	No	34 Internal, 18 in Far-field at 19.2m	Thermocouples in combustor and HP Turbine	Open Environment	Correlation + Frequency Spectrum	Low and high power	Identification of noise sources and contribution	Nil

						up to 4 kHz + Directivity		towards total noise emission	
2018 [143]	DGEN 380 turbofan engine	Standard	24 Microphone array (12 m from exhaust)	Internal pressure sensor in the core- nozzle exit	Anechoic chamber	Frequency spectrum up to 1.6 kHz	60%, 70%, 80%, 90%	Study combustion noise	Nil
2019 [165]	SR-80 Turbine Engine	No	2 microphones (1 meter from combustion chamber at 90° and 45° from exhaust)	Thermodynamic sensors, Triaxial Vibration sensor, MultiGas FTIR Spectrometer	Open Environment	Frequency spectrum up to 16 kHz	Fixed RPM	Comparison in noise, vibration and emission for 2 different types of fuel	Nil
2019 [160]	DGEN 380 turbofan engine	Standard	24 Microphone array (12 ft arc)	Internal pressure sensor in the core- nozzle exit	Anechoic chamber	1/3 Octave band up to 2 kHz + Directivity	50%, 60%, 70%, 80%	Study combustion noise	ANOPP

Microphone arrays have also been employed for turbofan engine's noise source identification [156]. A 48-microphone array system was installed at 60 – 193 inches from the FJ144 engine, which aided in specifying the region of interest and subsequently spatial filtering of inlet and exhaust noise. All the necessary analysis was done with the engine being operated inside an anechoic chamber. The principal observation that was made referred to the presence of multiple tones from the inlet in the exhaust noise spectrum, provided they were greater than the exhaust noise levels. Another peculiar behavior was the location of jet mixing noise, which moved closer to the nozzle exit with an increase in frequency. Moreover, as the jet flow speed was increased, the peak turbulent mixing noise moved further downstream of the nozzle exit. Towards the engine inlet, the noise was found to be emancipated from the edges of fan blades.

In another publication by NASA [141], the engine noise prediction model is iteratively developed, and its validation is made using multiple turbofan engines. Primarily, the attention is towards the broadband combustor noise which is corrupted by the jet noise in the same frequency range. The notion of single peak combustor noise is debunked in this study, due to the presence of four core-related peaks. However, since the fourth peak is masked by the turbomachinery noise towards higher frequencies, a three-peaks combustor model is proposed. The proposed method is said to be effective for the engines under study, however, improvements can be made by comparing the results with other engines using the same methodology.

In [157], a study was conducted to understand the relationship between combustor and turbine noise with far-field noise for a turboshaft engine. This activity was part of the EU-funded TEENI (Turboshaft Engine Exhaust Noise Identification) project. Various techniques like coherence, coherence output power, three and five microphone signal enhancement techniques were employed for better accuracy. The analysis showed that the sound power spectrum can be divided into 5 bands where noise from various engine zones is making contributions. The first band is of combustion zone ranging from 100 – 260 Hz, the second is designated for indirect combustion noise (260-600 Hz),

third for turbomachinery noise from a high-pressure turbine, and so on. This study does not deal with jet noise due to the assumption that the jet velocity is negligible for turboshaft engines.

In another study [158], the three-signal coherence method was applied to study the origin of broadband noise for turboshaft engine which had been instrumented with internal sensors and far-field microphones. With the aid of numerical simulation, it was shown that the three-signal method can extract narrowband sources corrupted with background noise. The method also outperformed the conventional signal processing techniques when applied to measured data. It was eventually concluded that the broadband component is developed due to multiple turbine stages and is a result of indirect combustion noise. Furthermore, combustion noise was identified at low frequencies (200 Hz). Another type of experimentation on turboshaft engine was undertaken by [159] in which three-dimensional evaluation of noise was done. It was found that the sound directivity was focused towards the sky and conventional methods of measuring sound directivity were not enough to pick up such response.

NASA's Glenn Research Centre houses Aero-Acoustic Propulsion Laboratory which has been used for noise measurement of several engines. As per [143], this facility was used to acquire a baseline dataset for a DGEN 380 turbofan engine. The tests were conducted inside an anechoic chamber with two internal and several far-field microphones. Using two-signal source separation, broadband combustion noise was found to be present in the 100-500 Hz range. The frequency range of the combustor-noise component was also observed to be increasing with the rise in power level.

Using the same engine, noise measurements in 1/3 Octave band were compared with ANOPP (Aircraft NOise Prediction Program) noise prediction model [160]. It was found the ANOPP model was not able to accurately predict the combustion noise. There was a shift in directivity and a presence of a second spectral peak was observed which is not modeled by the ANOPP subroutine for combustor noise. Emphasis was towards the understanding of combustor noise. In a similar study conducted on the TECH977 turbofan engine [161], it was observed that the

direct and indirect combustion noise share the same frequency spectrum, but their spectral shapes could be quite dissimilar.

Acoustics has also found its application in measuring gas turbine exhaust characteristics using sonic anemometry. In [162], the aim of the experiments was to map the temperature profile at the exhaust of a power generation gas turbine. Eight-channel transmitter-receiver pairs were placed around the exhaust and average temperatures were computed using flight-time, distance information, and gas properties. The received signals were corrupted by machine noise and had to be filtered out by disregarding highly noisy time-frequency bins and complementing the results with statistical models. However, the method led to several inaccuracies due to the presence of temperature and velocity gradients which affect sound propagation. For higher Mach numbers, the straight-line propagation model of sound is not valid and the flow velocity's effect on acoustic propagation has to be modeled [163]. This methodology produces many accurate results and utilized only two microphones.

Effect of fuel on gas turbine noise and vibrations have also been recorded in the literature. Effect of fuel type on combustion-induced vibrations was investigated for a turboshaft engine in [164]. It was noted that the vibration spectra were similar for compressor and combustion vibrations. Combustion was found to induce vibrations at higher frequencies (above 1 kHz) and vibration levels increased with an increase in RPM and load. Since the scope of this study was limited, the vibration spectra cannot be treated as a reference model for other gas turbines. Likewise, in [165], the effects of two different fuel types on noise, vibration, and emission were studied for a turbojet engine. Noise measurements were taken very close to the combustor (at 1m) and the exhaust. The engine was also equipped with thermodynamic sensors, a spectrometer, and a triaxial accelerometer for recording vibrations. Change in fuel type resulted in a slight variation of low-frequency noise which may be because of a variation in combustion characteristics. A detailed analysis was not performed, and the data acquired at two different instances were inconsistent. Therefore, the results cannot be treated as baseline measurements for the turbojet engine.

Independent studies have also been carried out to characterize the acoustic behavior of combustion processes only. In [166], various sizes of burners were used and were subjected to varying flow velocities and equivalence ratios. The results indicated that the acoustic spectrum was broadband in nature with its peak slightly changing with burner's diameter (proportional to $D^{-0.8}$) and there is a $f^{-5/3}$ decay in 800-3000 Hz range. Another peculiar behavior was of equally spaced local maxima which occurred after the peak frequency. Total flame noise was found to be a function of fuel ratio and flow velocity. Moreover, Flame tip reduction led to a drop in low-frequency energy. The analytically driven relationship for direct noise indicates that acoustic power varies proportionally (4th power) of flame speed but this phenomenon does not incorporate combustion noise radiation in the high-frequency range (indirect-combustion noise) [167].

An altogether different nature of the study has been undertaken by [168] which investigates the possibility of reducing the total noise radiated by an aircraft by modifying its landing trajectory. The study relies on the aircraft noise data that is simulated using a combination of semi-empirical relationships and physics-based models which consider the aircraft geometry, engine state, and flight mechanics. The simulations are then carried out for different glide slopes and it is found that there is the scope of noise reduction on landing by increasing the glide slope angle. However, this would require an extension of the runway by 450m and an assessment of this approach concerning flight safety. Moreover, the claim is also required to be substantiated by experimentally acquired measurements.

2.4.3.1 Discussion on Gas Turbine Noise Experiments

Several inferences can be made after conducting a literature survey in the field of gas turbine noise measurements. Firstly, relatively more information is available for turbofan engines, as compared to turboshaft and turbojet engines. This is clearly due to the huge demand for turbofan engines in the aviation industry because of their impressive performance and efficiency. With the increase in commercial aerial activities, overall noise levels will tend to rise which have to be curtailed with the advent of state-of-the-art noise reduction

technologies at an equivalent pace. Aircraft engine noise is complex to understand due to the inherent complexities of sound generation and propagation. Therefore, the overall scale of experimentation has been quite large because of the requirement of a large number of microphones, spacious anechoic chamber, engine modifications, and in some cases acoustic barriers between inlet and outlet. The engines have been mostly modified to incorporate internal sensors in the upstream of the exhaust nozzle till the combustor. The sensors must be ruggedized to withstand the heat at various engine stages. Due to the above-mentioned reasons, engine noise has not been studied extensively while it is installed on the aircraft. Moreover, the measurements are mostly made in the far-field. Even the aim of the installation of internal acoustic sensors has been to correlate their information with the far-field data. Lastly, since all engines had axial compressors, very less information is available for the acoustic response of centrifugal compressors. Moreover, no efforts are seen to be made in using the information gathered from acoustics for health monitoring purposes. It can be observed that this field is considerably complex and requires an in-depth understanding of noise-generating mechanisms, engine dynamics, sound propagation techniques, and sensor limitations. The overall resources needed for carrying out detailed analysis should not be underestimated also. These could be the reasons because of which, acoustics have not gained much attention for engine fault diagnostics or health monitoring.

2.4.4 APU Noise Measurement and Characteristics

Various forms of experimentation performed on APU noise are presented in Table 2-5 and similar to the gas turbine experiments, it is apparent that the focus has been towards the understanding of noise-generating sources and possible ways of their reduction. However, unlike the turbofan engines, APU noise has not been studied in greater detail and their levels have not been compared to any of the sound prediction models. In the following paragraphs, details of the experimentation or analysis performed on APU noise are presented.

A study on APU noise has been carried out in [169] to broadly the noise in order to develop attenuation methodologies. Major sources of noise were found to be

from turbine exhaust, body radiation, cooling fan, and compressor inlet. Acoustic treatment of inlet was suggested so that fan and compressor noise is suppressed. On the other hand, the exhaust noise can be attenuated by a silencer. The author also suggested the installation of vibration isolators and a titanium enclosure for treating high-frequency surface radiated noise.

Core noise was characterized for a specific APU by performing correlation analysis between internal and external microphones for a range of 0-1000 Hz [170]. The APU with 06 internally mounted acoustic sensors was placed inside a soundproof box while an array of far-field sensors was installed in a circular manner. It was inferred that direct combustion noise dominated the far-field spectrum till 400 Hz. Two additional noise sources were also located which constitute the exhaust noise. Noise generation occurs between combustor exit and turbine which is due to the interaction of noise from combustor with the turbine. Another indirect source of noise is due to the mixing of engine exhaust with cooling air in the secondary duct. The results gave insight into the noise generation mechanisms but variation in noise features with loading conditions were not experimented with and analyzed.

In [138], average noise from APU of different aircraft was acquired in order to substantiate concerns of airline employees regarding exposure to noise while servicing the aircraft. Microphones were placed around the aircraft and attached to personnel working on the aircraft for measuring occupational exposure to noise. SPL (93-124 dB) and 1/3 Octave levels were recorded for various aircraft and procedures were recommended for reducing harmful effects on people. This study did not involve in-depth study of APU noise directivity and variation of noise with operating conditions.

An elaborate study has also been done in [171], where APU noise data was gathered from 5 aircraft with and without ECS operation in order to characterize noise from ground operations. With the help of circularly placed microphones, spectra and directivities were obtained for each aircraft at 1m from the fuselage center. Broadband noise till 10 kHz was observed for all aircraft in all directions when the air conditions were not operational. The directivity pattern was

symmetric and exhibited minimum sound levels in the forward hemisphere while maximum levels were measured at 150° and 210°. Only A340 displayed slightly different results and had a non-symmetric pattern with a maximum level at 150° which is because of the off-centered placement of the exhaust outlet. It was also concluded that the APU operation with ECS did not produce a uniform change in noise features and no correlation was found between bleed air pressure and the measured noise.

Numerical analysis to predict the behavior of acoustically treated inlets and exhaust ducts of APU was performed in [172]. Experimental evaluation of the same was done by placing the APU in a soundproof room and it was found that the sound attenuation levels and directivities were in line with the predicted results. An experimental investigation was done in [173] to study the effect of different mufflers on noise reduction for a specific APU. Tests were conducted in an outdoor environment with far-field sensors placed in a semi-circle around the muffler exhaust while the APU was inside a wooden box. It was observed that Main Engine Start noise was more than for the ECS test which can be because of high flow rate and off-design operation. Moreover, noise attenuation for all the configurations was negligible for frequencies below 200 Hz which maybe because of the resonances induced by mufflers' geometry. Spatial directivities were also studied and found to be maximum at $\pm 60^\circ$ for higher frequencies and this deflection of sound occurs because of the shear layer between high-velocity jet with the surrounding airflow. [174] also claims to have designed mufflers for APU which perform well over a large range of frequencies. The cavities-based muffler design with bias flow has been proposed for better noise absorption.

An indoor activity with APU noise was performed in [175] where the APU was subjected to various loading conditions. The study was conducted in an enclosed chamber and noise measurements were taken very close to the exhaust. It was found that the overall noise level was mainly dominated by low-frequency broadband noise in the range of 20 – 300 Hz under all operating conditions. Moreover, maximum noise was observed at no-load condition because of the additional flow through the exhaust from the load compressor to avoid surge. The

effect of fuel on noise and vibration of an APU with can-combustor was evaluated in [176]. Tests were conducted in a test cell and some varied amplitudes of vibration signals were noted for different configurations of fuel. This study lacks an in-depth analysis of spectral content and directivity of APU noise.

A narrowband combustion noise model has been proposed in [177], which was validated using APU exhaust noise data. The model captures the modulating behavior of the base spectrum by using a transfer function that describes the frequency response of the path from the combustor to exhaust. An approximation of similarity spectrum is used as the base, while the modulation function caters for the variations occurring due to engine geometry and EGT. The relationship was further improved by introducing the frequency-dependent damping function into SAE ARP876 [178] directivity function. Broadband peaks in the combustion chamber of a turbofan engine have also been witnessed in [152]. Experiments were carried out on a turbofan engine (with and without its fan) and the spectral shape of combustion noise was in line with the narrowband model prediction proposed by [177]. However, this behavior was only observed at an angle of 120° from the inlet. This model is applicable to turboshaft, turboprop, turbofan, and APUs [137] for far-field measurements.

Analysis of sound levels from 3 different APUs was done in [179] and it was found that they exhibit a unique spectral shape that does not depend on engine design, power setting, and directivity. This shape was coincidentally like the similarity spectrum of high-speed jet noise. The peak frequency remained in the range of 250 – 350 Hz for all conditions while the peak sound level varied proportionally to the square of fuel consumption rate. However, this required a scaling factor to be computed for each APU and hence the same relationship may not be extended to another system. Additionally, the presence of a secondary source of noise is debunked by the author.

The presence of indirect combustion noise in APU was investigated by relating experimental results with the theoretical model [180]. Indirect noise is said to be generated when entropy waves interact with a constriction. It was eventually established that the experimental results did conform to the model's prediction of

indirect noise. However, it was suggested that further research should be undertaken to further substantiate the findings. Therefore, the claim of [179] was reevaluated using data from the same APUs [179], [180]. By subtracting the similarity spectra of direct combustion noise from far-field data, noise peaks were reported at the frequencies which were predicted by model theory. This led the authors to conclude that APUs do generate indirect combustion noise. The study was further expanded to a broader set of acoustic data including measurements from turbofan engines [181], [182] where the similarity spectra were again validated for combustion noise. It is also suggested that this method can be used to separate combustion noise from all other noise sources if the jet noise is low. Detailed numerical analysis was also performed to validate the presence of indirect combustion noise [183]. Simulations carried out by [184] for helicopter noise showed that the main constituent of turbine-exit noise is indirect combustion noise [148].

Engine core noise generating mechanisms were reviewed in [139] which also included a study on jet exhaust noise. It was argued that the assumption of direct and indirect combustion noise propagating directly to far-field neglects secondary noise generating mechanisms which are induced when the core noise exits the jet nozzle. Another relevant study is by [142], where it is argued that acoustic power due to jet noise follows the 6th power law and since the Mach number for turboshaft engines does not exceed 0.15, the contribution is negligible. According to [137], APU noise is not generally modeled together with aircraft noise because APU data is not sufficiently available and the noise radiating from APU undergoes interferences during propagation. However, SIMUL (German noise simulation program) implements combustor and jet models for predicting APU noise, and the combustion noise in APU peaks around 250 – 500 Hz. The writer in [144] posits that the APU noise is not generally modeled in the aircraft noise prediction software because of the scarcity of APU data. A standard by SAE (ARP1307) recommends procedures for conducting noise surveys around the aircraft. However, it comes with a disclaimer that it does not provide ways of predicting APU noise from basic engine characteristics [185].

Similar to noise measurements, vibration data have also been analyzed for APUs [125]. The purpose of this study was to observe variation in vibration data when operated with various fuel types. The data were acquired at a sampling rate of 2 kHz and the accelerometer was placed at the base of the gas turbine. When conventional fuel was used, the broadband vibration spectra were observed with no tonal components. However, some discrete frequency components appeared when fuel composition was altered.

A very detailed study is conducted by Dowling [186] on combustion noise in which all relevant aspects of combustion are highlighted and analytically evaluated. This includes an explanation of the broadband nature of the direct combustion noise, rationality behind the appearance of indirect combustion noise, rumble noise, and combustion instabilities. The latter two kinds of phenomena are associated with the feedback of noise due to reflection from the combustor walls. The study is equally valid for understanding noise from the APU combustion process as it covers the level of noise for all ranges of mass flows. As an example, Figure 2-7 shows the relationship between magnitudes of direct and indirect combustion noise as a function of Inlet Mach number (in the flame zone) and outlet Mach number (at combustor nozzle outlet). This relationship has been found using analytical studies which also revealed that indirect combustion noise is present at lower frequencies. Engine manufacturers can be commended in achieving a reduction of the indirect combustion noise, which has been the result of decreasing flow rates through the engines with the help of a high by-pass ratio design.

Table 2-5 Summary of Experimentation done on APU Noise

Year	Number / Type of APU	Acoustic Suppression	Acoustic Sensors	Other sensors	Experiment Location	Observed parameters	Operating Conditions	Target Objective	Prediction method compared with
1968 [169]	GTCP-36-4	Yes	Not mentioned	Nil	Not mentioned	Frequency spectrum up to 10 kHz	No Load + Full Load	Study noise sources and develop attenuation methods	Nil
1978 [170]	GTCP - 85 series APU	No	6 Internal, 8 Near-Field and 8 Far-Field (25 ft radius)	Nil	APU inside Acoustically isolated chamber	Frequency Spectrum up to 1 kHz	No Load + Full Load (Full bleed and electrical power)	Correlation between internal and external sensors in order to characterize noise sources	Nil

2005 [179]	3 Different APU's (GTCP-36-150, RE220, 321-600)	No	24 microphones (12 on pole + 12 on ground) at 25 ft from APU exhaust	Nil	APU inside Acoustically isolated chamber	Frequency spectrum up to 12 kHz	low, mid, high power	Study spectral shape of combustion noise	Similarity spectra
2007 [171]	APU of 5 Aircraft	Yes	8 circularly placed microphones	Nil	Aircraft	Frequency Spectra up to 10 kHz + Directivity	No Load - ECS	Develop reference dataset for APU noise	Nil
2010 [138]	Multiple Aircraft (10)	Yes	Multiple (around aircraft tail-sections + sensors worn by employees)	Nil	Aircraft	1/3 Octave band up to 20 kHz	All conditions	To study occupational noise due to APU operation	Nil

2010 [196]	Multiple Aircraft (767,747,A310)	Yes	1 Microphone (around 20 ft from APU Exhaust)	Nil	Aircraft	Average Sound Levels	Not mentioned	Assess effect of noise on employees	Nil
2011 [172]	1 APU (Specs not mentioned)	Yes	24 (25ft from exhaust) + 31 (3 ft radius from inlet)	Nil	APU inside Acoustically isolated chamber	Frequency spectrum up to 8 kHz + Directivity	Electric Load only - ECS and Electric loads	Measure attenuation of inlet and exhaust treatments	Numerical Analysis
2012 [197]	APU Compressor only	Yes	Microphone array around inlet only	Unsteady pressure sensors	APU inside Acoustically isolated chamber	Frequency spectrum up to 3 x BPF	90% - 100% RPM	Inlet noise prediction due to impeller shock wave	Numerical Analysis
2012[180], 2013[198]	RE-220 APU	No	10 internal sensors placed around combustor +	Nil	Room with no acoustic treatment	Frequency spectrum up to 6.5 kHz	Not mentioned	Identify the presence of indirect combustion noise	Numerical Analysis

			6 pressure sensors in the exhaust pipe						
2014 [173]	GTCP-36-300	Yes	25 Far Field sensors (25 ft radius)	Nil	APU inside Acoustically isolated chamber	1/3 Octave band up to 10 kHz + Directivity	ECS only and MES only	Effect of muffler design on noise attenuation	Nil
2017 [125]	GTCP-85-129	No	Nil	1 accelerometer (2 kHz) at engine support	Not mentioned	Frequency Spectrum up to 1 kHz	3 Modes	Effect of fuel type on vibrations	Nil
2017 [175]	APS3200	No	3 (0.6 m from exhaust) + 1 in the chamber	Thermodynamic sensors, Exhaust Gas analyzers	Room with no acoustic treatment	Frequency Spectrum up to 10 kHz	25 combinations of electric and pneumatic loads	Effect of loading conditions on exhaust noise	Nil

2018 [174]	GTCP-36-28	Yes	3 microphones around turbine exit + 15 inside exhaust	Temperature + Pressure sensors	Room with no acoustic treatment	Frequency spectrum up to 12 kHz	No Load, Bleed load only, Electric + Bleed load	Study Attenuation of different exhaust mufflers	Nil
2019 [199]	GTCP-85	No	2 Microphones (1 m from APU)	2 accelerometers (x, y direction)	Room with no acoustic treatment	Frequency spectrum up to 500 Hz	No Load + ECS + MES	Comparison in noise and vibration for different types of fuel	Nil

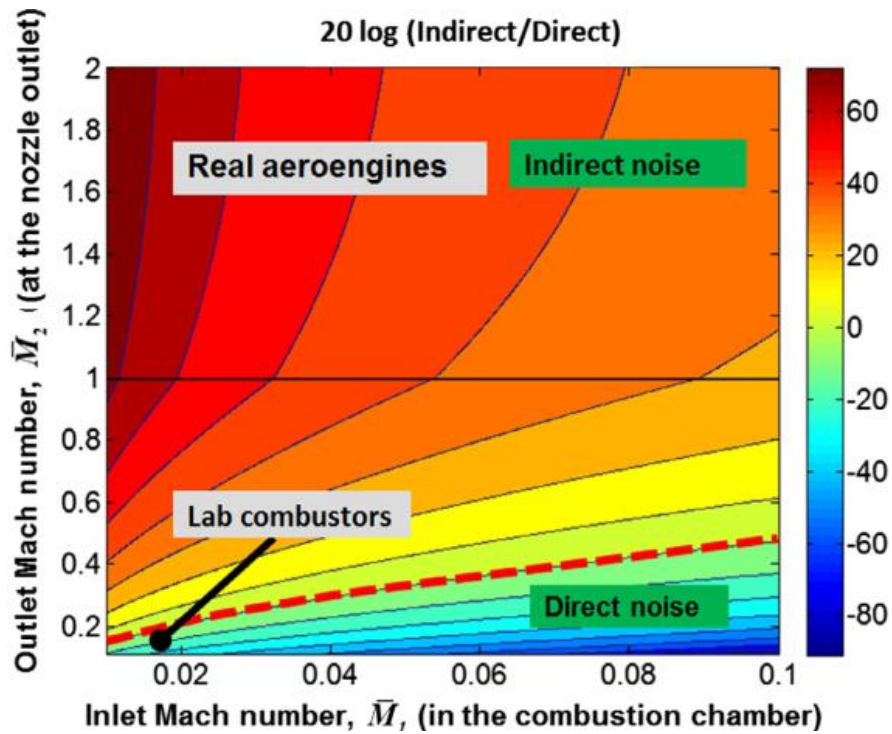


Figure 2-7 Ratio of indirect to direct combustion noise (as a function of inlet and outlet Mach numbers at the flame zone and nozzle outlet respectively) [186]

2.4.4.1 Discussion on APU Noise Experimentation

It is apparent from the literature survey that, with regards to the APU noise, efforts have been mainly made towards understanding noise generating sources and their attenuation. This is evident from the summary of experiments presented in Table 2-5. None of the activities have been targeted towards health monitoring and therefore no APU is subjected to failure(s) during acoustic data collection. Moreover, the number of instances where APU noise is measured in an acoustically treated room outnumber the occasions where experimentation is done on actual aircraft. Also, the literature is not rich with APU noise gathered very close to the whole engine, that too on the aircraft where all the associated systems are intact. Most importantly, the complete spectrum and directivity of noise have never been captured in the near-field and the results compared with any of the noise prediction models. The numerical simulations which have been performed focused on either performance analysis of external acoustic treatments or modeled a specific component of the complete system. In some of the cases, 1/3 Octave band results are presented which may be a requirement

for certification purposes but in this representation, the accuracy of spectral content is lost due to low resolution. Similarly, the selected frequency span for analysis has been mostly a few kilohertz because of more interest in understanding the combustion process rather than the whole APU noise. Lastly, there is a dearth in understanding noise under unsteady/transient states that may help in diagnosing faults in components that control overall APU operation.

2.4.5 Engine Noise of Airborne Platforms with Novel Architectures

Currently, all the conventional methods of engine noise reduction have been exhaustively studied, and, based on the envisaged requirements, novel techniques are needed to be explored. In [187], various options are discussed that have been explored for reducing noise from the aircraft including its engines. The study highlights the targets which have been set by ACARE 2020, FlightPath 2050, NASA's N+2 and N+3 goals. The target reduction in noise is set to be 50%, 65%, 42 EPNdB, and 71 EPNdB, respectively. Noise reduction by using various configurations of a blended-wing-body aircraft is studied in [188]. It is found that, by using multiple engines, the jet noise frequencies would be high and would be greatly attenuated by atmospheric attenuation. Similarly, the silent aircraft design suppresses the forward radiating engine noise by mounting the engines above the airframe and extending the engine exhaust ducts with acoustic liners [189]. Distributed exhaust nozzle arrangement is yet another way of reducing jet noise by dividing the flow into very small exhaust plumes [190]. An open rotor design with counter-rotating propellers is also proposed to reduce the jet noise by the high bypass ratio design, however, there would be an increase in the sound radiated due to the interactions between the blades and the airflow [187]. Apart from the complexities involved with the manufacturing of aircraft with novel designs, it is highlighted that the noise reduction techniques employed by the concept aircraft have been theoretically tested, and they need to be validated with experimental data once the designs are practically realized.

As the VTOLs and air taxis are becoming a reality now, their utilization is likely to grow and noise would become a concerning factor [191]. Although the noise radiated by electric-powered VTOL is expected to be quite less as compared to

helicopters [192], the number of air-taxis is likely to increase because of affordability. Therefore, it is prudent to design the aircraft for urban air mobility with low levels of noise. In this regard, various designs have been put forward keeping in view the performance, operational effectiveness, and noise emissions [193]. It is desired to have low rotor tip speeds so that the noise generated by the fan is minimum. Similarly, for reducing the noise generated due to the rotor-rotor interactions, the blade shape and spacing have to be optimized. The noise generated by the blade-vortex interactions is also annoying and can be controlled by adjusting the blade tip twist [194]. Out of the several designs for an air-taxi, the multi-rotor design is found to be the least noisy but has limited range and cruise speed [195].

2.5 Acoustics for Fault Diagnostics of Aircraft Auxiliary Power Unit

In the previous sections, all the necessary information has been covered in the subject domain. This assisted in understanding the research gaps, opportunities, and challenges involved in the field of acoustics-based fault diagnostics of an aircraft system like an auxiliary power unit.

2.5.1 Research Gaps

Certain areas have been identified to be either in the state of infancy or not covered in the public domain literature. It is believed that, if these spheres of knowledge are explored extensively, it would contribute towards the development of a comprehensive fault diagnostic methodology using sound measurements. The gaps have been identified to be the following:

- (a) Incomplete information about APU failure modes for legacy and state-of-the-art aircraft. This can be addressed by collecting information from the defect reports and the maintenance records.
- (b) There is no information about the possible list of APU faults that can be diagnosed with the help of acoustics.
- (c) Less information about the acoustic response of radial compressor and turbine is available as compared to their axial counterparts. Presently, literature

provides noise prediction models for axial systems, but such models are unavailable for the radial / centrifugal category.

(d) The dearth of acoustic measurements in the vicinity of APUs under various operating and ambient conditions has also been observed from the literature. Such data can provide useful information about the distribution of sound energy around an APU. Furthermore, it may also indicate the systems which contribute towards the overall noise at closer ranges.

(e) The optimum number and location of microphones for gaining maximum information about an APU has also not been identified.

(f) No aircraft have been reported to have been instrumented with acoustic sensors with an aim to acquire sound data for APUs. Mostly, acoustic data has been acquired in test-cells and anechoic conditions. In an actual configuration, the effects of associated components (intake, exhaust muffler, enclosures, oil cooler, vibration isolators, bleed flow) will be visible.

(g) Effects of Environmental Control System, Main Engine operation, and wing anti-ice system noise on APU compartment noise have not been studied. This study is necessary to evaluate the stationarity of the acoustics signals inside the APU compartment under all conditions.

(h) Acoustic analyses have not been performed during startup/shutdown stages. It is believed that these signals carry useful information about the system state and can be used for diagnostics.

(i) Due to obvious reasons, APUs (in actual configuration) have never been subjected to single/multiple faults for data collections and onward development of fault diagnostics methodologies.

(j) The complete spectrum of APU noise has not been predicted using any of the noise prediction models and validated with actual aircraft data.

(k) A detailed set of acoustic features have not been explored for APU fault diagnostics. The features should be such that they produce consistent results

under all operating conditions and would be unaffected due to the transients and background noise.

(l) Optimum and robust fusion methods for APU fault diagnostics are also non-existent. A fusion of thermodynamic, vibration, and acoustics features may assist in the correct identification and classification of faults in a system.

(m) Casing-radiated noise from an APU is not studied in detail and they have neither been correlated with the thermodynamic parameters. Such type of noise will be prominent at closer ranges to the engine and is important to understand for fault diagnostics.

2.5.2 Opportunities

Acoustics have a tremendous amount of potential which has not been harnessed properly for gas turbine health monitoring. It is believed that, by acquiring knowledge about prominent sources of noise in gas turbines and using it for engine health monitoring, a better judgment could be made about the engine condition. In the field of fault diagnostics and engine health monitoring, acoustics may outperform other sensors due to the following reasons:

(a) Ability to capture a wide range of information about engine operation. From engine startup until its shutdown, important information can be acquired using microphones, which can be used for developing fault diagnostic mechanisms.

(b) Installation of acoustic sensors is convenient. Since they are non-intrusive in nature, the microphones can be placed at an appropriate location without interfering with the safety and integrity of a system.

(c) Acoustics can detect variation in the flow, which is not reported by vibration sensors.

(d) Acoustic sensors can capture higher frequencies (up to 20 kHz). The frequency response of vibration sensors is reduced if the adhesive is used for installation.

(e) Vibration from components translates into sound energy which can be acquired by the microphones. If the strength of these signals is high, they can be used to monitor key components of an engine like bearing and gears.

2.5.3 Challenges

Acoustics is inherently a complex field that poses several challenges while dealing with them. The difficulties associated with auxiliary power unit acoustics are:

(a) Effects of background noise are fairly pronounced and are difficult to control. Such noise may be generated by rotating or vibrating components present in the vicinity of the subject-under-test.

(b) Like vibration analysis, component details are needed to ascertain the characteristic frequencies of bearing and gears in acoustic signals. This information may be proprietary to the manufacturer and may not be available.

(c) Acoustics suffer from reflections from the surfaces resulting in multipath propagation effects. This leads to variation in sound signals if the environment is changing (due to aircraft motion, etc.).

(d) Accessibility to aircraft with functional APU and using the same for research purposes is also considered to be a challenge. Due to the same reason, little or no information is available on APU acoustics response on actual aircraft with all necessary systems intact.

(e) In order to accurately characterize acoustic response, unsteady pressure sensors are required which are intrusive in nature. Furthermore, the acoustic response is highly affected by thermodynamic parameters in and around the APU, therefore a complete picture of thermodynamic parameters is needed within and outside the APU for accurate modeling. Such a detailed level of instrumentation is not feasible on actual aircraft and has not been performed. Engines have normally been instrumented while being on the ground, that too independently on a test cell. On an actual aircraft, installation of such sensors is unfeasible and is, therefore, a challenge.

2.6 Summary

After carrying out a detailed literature survey of the areas mentioned in Figure 2-1, the following represents a summary:

(a) Aircraft APUs are an important part of commercial aircraft and their operational readiness is paramount for airline activities. In legacy aircraft, where sensor coverage is limited, the operators resort to conventional maintenance practices. Therefore, scheduled maintenance can be carried out even if it is not needed. The APU controller (FADEC) performs basic diagnostics. For detailed fault analysis, manufacturers provide troubleshooting manuals. Traversing through the manual is generally a cumbersome process and may even require the removal of the APU from the aircraft for further scrutiny. A comprehensive view of the technical advancements made recently in APU design and requirements is also presented. As aircraft become more electric, APUs are also required to provide increased levels of power density efficiently and reliably (Section 2.2).

(b) Performance-based diagnostics is the classical way of assessing the cause of degradation in a gas turbine. The literature also suggests the fusion of information at various levels for robust results. Gas path analysis is a model-based approach and hence requires in-depth knowledge of system parameters, an approach that has been found to be productive when the engine is in steady-state. All types of turbomachinery have a gearbox and a set of bearings and the nature of their degradation is common. Therefore, there is a plethora of information in diagnosing such faults, especially using vibration analysis. The methods range from time-domain analysis to more complex signal processing techniques and even include machine learning approaches. Relatively more analysis has been done using test-rig data, which is generally not representative of a complete system. Furthermore, component specifications are a pre-requisite for any of the presented approaches. These specifications are important to compute the characteristic frequencies that indicate component degradation. In the absence of such specifications, it is difficult to isolate the frequency of interest in the presence of various undetermined sources. With the increasing demand

for air travel, the next generation of aircraft will be high performance, efficient and reliable. This reliability can only be achieved if innovative fault diagnostic techniques are incorporated in the design during the initial phases of development (Section 2.3).

(c) Airborne sound has also been evaluated for machine diagnostics, but not as rigorously as its counterpart (vibrations). Results are shown to be reliable, however, experimentation is generally done inside an anechoic chamber using a subset of the whole system. This completely excludes measurements and analysis done on a complete system like APU. Moreover, due to the complex nature of acoustics, the developed schemes are data-driven with no support from the physics of sound (Sub-section 2.3.4).

(d) The study of sound from gas turbines and APUs has been of great interest to the research community. A huge amount of work has been done in instrumenting engines, acquiring far-field noise data, performing source separating techniques, and analyzing the effect of engine power on noise levels. Moreover, it is envisaged that the interest in acoustic measurements is likely to increase with the increase in Urban Air Mobility (Section 2.4).

(e) The last section discusses the research gaps, opportunities, and challenges, of which there are many, involved in the field of fault diagnostics of aircraft APUs using sound measurements (Section 2.5).

References

- [1] E. Fleuti and P. Hofmann, "Aircraft APU Emissions at Zurich Airport," 2005. [Online]. Available: https://www.flughafen-zuerich.ch/~media/flughafenzh/dokumente/das_unternehmen/laerm_politik_und_umwelt/luft/2005_zrh_apu-emiscalcsmeth.pdf.
- [2] L. M. Stohlgren and L. D. Werner, "The GTCP36-300, a Gas Turbine Auxiliary Power Unit for Advanced Technology Transport Aircraft," 1986, doi: 10.1115/86-gt-285.

- [3] M. Harper-Bourne, A. Moore, and H. Siller, "A study of large aero-engine combustor noise," 14th AIAA/CEAS Aeroacoustics Conf. (29th AIAA Aeroacoustics Conf., no. April, 2008, doi: 10.2514/6.2008-2942.
- [4] S. Ackert, "Basics of Aircraft Maintenance Reserve Development and Management," *Aircr. Monit.*, vol. 249, no. 1, pp. 101–111, 2012, doi: 10.1016/0003-2670(91)87013-W.
- [5] T. E. Parliament and The European Council, "REGULATION (EC) No 261/2004," Regulation, no. 9, pp. 1–7, 2004.
- [6] ATSB Transport Safety Report, "Power plant failures in turbofan-powered aircraft," no. June, 2008, [Online]. Available: https://www.atsb.gov.au/media/4908943/ar-2013-002_final.pdf.
- [7] M. Tozan and A. Jamal, "Failure Data Analysis for Aircraft Maintenance Planning," no. 1, pp. 1–8.
- [8] A. Yabsley and Y. Ibrahim, "Study on maintenance contribution to life cycle costs: Aircraft auxiliary power unit example," *Proc. IEEE Int. Conf. Ind. Technol.*, 2008, doi: 10.1109/ICIT.2008.4608331.
- [9] G. ho Kim, B. won Lee, H. Lu, and J. hyun Park, "Failure analysis of an aircraft APU exhaust duct flange due to low cycle fatigue at high temperatures," *Eng. Fail. Anal.*, vol. 20, pp. 97–104, 2012, doi: 10.1016/j.engfailanal.2011.11.003.
- [10] A. Type, L. H. Airport, and A. Transport, "Boeing 737-4Y0, G-OBMM," pp. 0–3, 2001.
- [11] P. Lukas, N. Jan, and B. Heiner, "Aircraft APU Prognostic Health Monitoring Utilizing Physics-Based Model."
- [12] R. K. Mishra and D. Organisation, "Causes And Remedies Of High Jet Pipe Temperature In Turbo Shaft Engines : Case Studies," no. July, 2015.

- [13] P. Wang, S. Wang, and L. Wang, "Gas turbine APU reliability modeling and failure forecasting," *Proc. - Annu. Reliab. Maintainab. Symp.*, vol. 2015-May, pp. 2–6, 2015, doi: 10.1109/RAMS.2015.7105054.
- [14] A. Zadeh Shirazi, M. Hatami, M. Yaghoobi, and S. J. Seyyed Mahdavi Chabok, "An Intelligent Approach to Predict Vibration Rate in a Real Gas Turbine," *Intell. Ind. Syst.*, vol. 2, no. 3, pp. 253–267, 2016, doi: 10.1007/s40903-016-0057-6.
- [15] C. Yang, C. Canada, M. Zaluski, and C. Canada, "APU FMEA Validation using Operation and Maintenance Data," no. January 2009, 2014.
- [16] Y. Zhang, L. Wang, S. Wang, P. Wang, H. Liao, and Y. Peng, "Auxiliary power unit failure prediction using quantified generalized renewal process," *Microelectron. Reliab.*, vol. 84, no. April, pp. 215–225, 2018, doi: 10.1016/j.microrel.2018.03.002.
- [17] X. Liu, L. Liu, L. Wang, Q. Guo, and X. Peng, "Performance sensing data prediction for an aircraft auxiliary power unit using the optimized extreme learning machine†," *Sensors (Switzerland)*, vol. 19, no. 18, 2019, doi: 10.3390/s19183935.
- [18] Y. Zhang, Y. Peng, P. Wang, L. Wang, S. Wang, and H. Liao, "Aircraft APU failure rate prediction based on improved Weibull-based GRP," in *2017 Prognostics and System Health Management Conference, PHM-Harbin 2017 - Proceedings*, 2017, no. 61571160, doi: 10.1109/PHM.2017.8079158.
- [19] D. Scholz, "An Optional APU for Passenger Aircraft," in *The Council of European Aerospace Societies*, 2015, no. 177, pp. 1–14.
- [20] Y. Xiang, H. Cai, J. Liu, and X. Zhang, "Techno-economic design of energy systems for airport electrification: A hydrogen-solar-storage integrated microgrid solution," *Appl. Energy*, vol. 283, no. September 2020, p. 116374, 2021, doi: 10.1016/j.apenergy.2020.116374.

- [21] National Academies of Sciences Engineering and Medicine, "Commercial aircraft propulsion and energy systems research: Reducing global carbon emissions," 2016. doi: 10.17226/23490.
- [22] Z. Geng, D. Gu, and D. Czarkowski, "Novel control architecture for dual-output DC-DC converters driving DC-AC inversion system," ECCE 2016 - IEEE Energy Convers. Congr. Expo. Proc., 2016, doi: 10.1109/ECCE.2016.7855298.
- [23] C. Anghel, "A novel start system for an aircraft auxiliary power unit," SAE Tech. Pap., vol. 2000, no. 724, 2000, doi: 10.4271/2000-01-3624.
- [24] H. Ebrahimi, H. El-Kishky, M. Biswass, and M. Robinson, "Impact of pulsed power loads on advanced aircraft electric power systems with hybrid APU," 2016 IEEE Int. Power Modul. High Volt. Conf. IPMHVC 2016, no. i, pp. 434–437, 2017, doi: 10.1109/IPMHVC.2016.8012857.
- [25] H. Khaligh, H. Torkaman, and A. Ebrahimian, "Novel algorithm for optimum output passive filter design in 400 Hz inverter," 9th Annu. Int. Power Electron. Drive Syst. Technol. Conf. PEDSTC 2018, vol. 2018-Janua, pp. 335–340, 2018, doi: 10.1109/PEDSTC.2018.8343819.
- [26] J. Shibu K, K. Shankar, C. K. Babu, and G. K. Degaonkar, "Three-objective optimization of aircraft secondary power system rotor dynamics," Mech. Based Des. Struct. Mach., vol. 0, no. 0, pp. 1–17, 2020, doi: 10.1080/15397734.2020.1798781.
- [27] Y. Ye and K. W. E. Cheng, "Bootstrap gate driver and output filter of an SC-based multilevel inverter for aircraft APU," 2015 6th Int. Conf. Power Electron. Syst. Appl. Electr. Transp. - Automotive, Vessel Aircraft, PESA 2015, 2016, doi: 10.1109/PESA.2015.7398940.
- [28] IATA, "Aircraft Technology Roadmap to 2050," Iata, pp. 1–51, 2019, [Online]. Available: <https://www.iata.org/contentassets/8d19e716636a47c184e7221c77563c93/technology20roadmap20to20205020no20foreword.pdf>.

- [29] S. Bozhko et al., "Development of Aircraft Electric Starter-Generator System Based on Active Rectification Technology," *IEEE Trans. Transp. Electrification*, vol. 4, no. 4, pp. 985–996, 2018, doi: 10.1109/TTE.2018.2863031.
- [30] D. N. Mavris, I. Chakraborty, E. Garcia, C. A. Perullo, and D. R. Trawick, "Onboard Energy Management," *Encycl. Aerosp. Eng.*, pp. 1–10, 2015, doi: 10.1002/9780470686652.eae1029.
- [31] I. Chakraborty and D. N. Mavris, "Integrated assessment of aircraft and novel subsystem architectures in early design," *J. Aircr.*, vol. 54, no. 4, pp. 1268–1282, 2017, doi: 10.2514/1.C033976.
- [32] I. Chakraborty, "Subsystem Architecture Sizing and Analysis for Aircraft Conceptual Design," no. December, pp. 1–325, 2015, [Online]. Available: <https://smartech.gatech.edu/bitstream/handle/1853/54427/CHAKRABORTY-DISSERTATION-2015.pdf>.
- [33] Y. Nicolas, "eTaxi-Taxiing aircraft with engines stopped. Flight Airworthiness Support Technology (FAST)," *Airbus Tech. Mag.*, pp. 2–10, 2013.
- [34] V. Madonna, P. Giangrande, and M. Galea, "Electrical Power Generation in Aircraft: Review, Challenges, and Opportunities," *IEEE Trans. Transp. Electrification*, vol. 4, no. 3, pp. 646–659, 2018, doi: 10.1109/TTE.2018.2834142.
- [35] Y. Cai, I. Chakraborty, and D. N. Mavris, "Integrated assessment of vehicle-level performance of novel aircraft concepts and subsystem architectures in early design," *AIAA Aerosp. Sci. Meet.* 2018, no. 210059, 2018, doi: 10.2514/6.2018-1741.
- [36] Y. Ishino and T. Niwa, "A novel rotational internal combustion engine with a single-lobe peritrochoid rotor (Design fundamentals and motoring test of a prototype engine)," *Trans. Jpn. Soc. Aeronaut. Space Sci.*, vol. 15, pp. A117–A126, 2016, doi: 10.2322/tastj.15.a117.
- [37] E. M. Gallart, "Design of Auxiliary Power Unit (APU) for co-operation with a turboshaft engine," no. 900625, 2013.

- [38] M. D. Fernandes et al., "SOFC-APU systems for aircraft: A review," *Int. J. Hydrogen Energy*, vol. 43, no. 33, pp. 16311–16333, 2018, doi: 10.1016/j.ijhydene.2018.07.004.
- [39] T. L. Cable and S. W. Sofie, "A symmetrical, planar SOFC design for NASA's high specific power density requirements," *J. Power Sources*, vol. 174, no. 1, pp. 221–227, 2007, doi: 10.1016/j.jpowsour.2007.08.110.
- [40] H. Ebrahimi, J. R. Gatabi, and H. El-Kishky, "An auxiliary power unit for advanced aircraft electric power systems," *Electr. Power Syst. Res.*, vol. 119, pp. 393–406, 2015, doi: 10.1016/j.epsr.2014.10.023.
- [41] R. J. Braun, M. Gummalla, and J. Yamanis, "System architectures for solid oxide fuel cell-based auxiliary power units in future commercial aircraft applications," *J. Fuel Cell Sci. Technol.*, vol. 6, no. 3, pp. 0310151–03101510, 2009, doi: 10.1115/1.3008037.
- [42] G. Romeo, F. Borello, G. Correa, and E. Cestino, "ENFICA-FC: Design of transport aircraft powered by fuel cell & flight test of zero emission 2-seater aircraft powered by fuel cells fueled by hydrogen," *Int. J. Hydrogen Energy*, vol. 38, no. 1, pp. 469–479, 2013, doi: 10.1016/j.ijhydene.2012.09.064.
- [43] G. Bechini, *Performance Diagnostics and Measurement Selection for On0Line Monitoring Gas Turbine Engines*, vol. 369, no. 1. 2013.
- [44] M. Adamowicz and G. Zywicka, "Advanced gas turbines health monitoring systems," *Diagnostyka*, vol. 19, no. 2, pp. 77–87, 2018, doi: 10.29354/diag/89730.
- [45] I. Y. Tumer and A. Bajwa, "A survey of aircraft engine health monitoring systems," *35th Jt. Propuls. Conf. Exhib.*, no. February, 1999, doi: 10.2514/6.1999-2528.
- [46] A. Kyriazis, A. Tsalavoutas, K. Mathioudakis, M. Bauer, and O. Johanssen, "Gas turbine fault identification by fusing vibration trending and gas path analysis," *Proc. ASME Turbo Expo*, vol. 1, pp. 687–696, 2009, doi: 10.1115/GT2009-59942.

- [47] M. Tahan, E. Tsoutsanis, M. Muhammad, and Z. A. Abdul Karim, "Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: A review," *Appl. Energy*, vol. 198, pp. 122–144, 2017, doi: 10.1016/j.apenergy.2017.04.048.
- [48] O. Gohardani, "Impact of erosion testing aspects on current and future flight conditions," *Prog. Aerosp. Sci.*, vol. 47, no. 4, pp. 280–303, 2011, doi: 10.1016/j.paerosci.2011.04.001.
- [49] I. S. Diakunchak, "Performance deterioration in industrial gas turbines," *Proc. ASME Turbo Expo*, vol. 4, no. April, pp. 161–168, 1991, doi: 10.1115/91-gt-228.
- [50] A. W. Rinehart and D. L. Simon, "An integrated architecture for aircraft engine performance monitoring and fault diagnostics: Engine test results," *50th AIAA/ASME/SAE/ASEE Jt. Propuls. Conf. 2014*, pp. 1–11, 2014, doi: 10.2514/6.2014-3924.
- [51] N. Tandon and A. Parey, "Condition Monitoring of Rotary Machines," pp. 109–136, 2006, doi: 10.1007/1-84628-269-1_5.
- [52] J. H. Wang and L. J. Perng, "A knowledge-based expert system to diagnose turbomachinery vibration problems," *ASME 1993 Int. Gas Turbine Aeroengine Congr. Expo. GT 1993*, vol. 3C, 1993, doi: 10.1115/93-GT-383.
- [53] C. Siu, Q. Shen, and R. Milne, "TMDocor: A Fuzzy Rule- and Case-Based Expert System for Turbomachinery Diagnosis," *IFAC Proc. Vol.*, vol. 30, no. 18, pp. 537–544, 1997, doi: 10.1016/s1474-6670(17)42457-8.
- [54] M. Lebold, K. McClintic, R. Campbell, C. Byington, and K. Maynard, "Review of vibration analysis methods for gearbox diagnostics and prognostics," *54th Meet. Soc. Mach. Fail. Prev. Technol.*, no. November, pp. 623–634, 2000, doi: 10.1017/CBO9781107415324.004.
- [55] P. G. Victor Giurgiutiu, Adrian Cuc, "REVIEW OF VIBRATION-BASED HELICOPTERS HEALTH AND USAGE MONITORING METHODS," 2001, [Online]. Available: <http://www.dtic.mil/dtic/tr/fulltext/u2/p023723.pdf>.

- [56] J. Lin and L. Qu, "Feature extraction based on morlet wavelet and its application for mechanical fault diagnosis," *J. Sound Vib.*, vol. 234, no. 1, pp. 135–148, 2000, doi: 10.1006/jsvi.2000.2864.
- [57] X. Fan and M. J. Zuo, "Gearbox fault detection using Hilbert and wavelet packet transform," *Mech. Syst. Signal Process.*, vol. 20, no. 4, pp. 966–982, 2006, doi: 10.1016/j.ymssp.2005.08.032.
- [58] Y. Lei and M. J. Zuo, "Fault diagnosis of rotating machinery using an improved HHT based on EEMD and sensitive IMFs," *Meas. Sci. Technol.*, vol. 20, no. 12, 2009, doi: 10.1088/0957-0233/20/12/125701.
- [59] T. H. Loutas, G. Sotiriades, I. Kalaitzoglou, and V. Kostopoulos, "Condition monitoring of a single-stage gearbox with artificially induced gear cracks utilizing on-line vibration and acoustic emission measurements," *Appl. Acoust.*, vol. 70, no. 9, pp. 1148–1159, 2009, doi: 10.1016/j.apacoust.2009.04.007.
- [60] A. Belsak and J. Flaker, "Wavelet analysis for gear crack identification," *Eng. Fail. Anal.*, vol. 16, no. 6, pp. 1983–1990, 2009, doi: 10.1016/j.engfailanal.2008.12.002.
- [61] M. J. Watson, J. S. Sheldon, H. Lee, D. Ph, and C. S. Byington, "NOVEL JOINT TIME FREQUENCY VIBRATION DIAGNOSTICS OF TURBINE ENGINE ACCESSORIES," pp. 1–11, 2010.
- [62] A. Belsak and J. Flaker, "Determining cracks in gears using adaptive wavelet transform approach," *Eng. Fail. Anal.*, vol. 17, no. 3, pp. 664–671, 2010, doi: 10.1016/j.engfailanal.2009.09.006.
- [63] R. Bajrić, D. Sprečić, and N. Zuber, "Review of vibration signal processing techniques towards gear pairs damage identification," *Int. J. Eng. Technol. IJET-IJENS*, vol. 11, no. 04, pp. 124–128, 2011, [Online]. Available: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.418.9450&rep=rep1&type=pdf>.
- [64] M. P. Boyce, *Control Systems and Instrumentation*. 2012.

- [65] L. Common, F. For, I. Aero, and E. Maintenance, "LOCALIZING COMMON FAULTS FOR IMPROVED AERO ENGINE MAINTENANCE," pp. 1–11, 2012.
- [66] L. Unbalance, F. In, and R. Machinery, "GT2013-94455," no. 1994, pp. 1–12, 2013.
- [67] T. Heyns and S. Heyns, "Gear Fault Detection under Fluctuating Operating Conditions by Means of Discrepancy Analysis," *Cond. Monit. Mach. Non-Stationary Oper.*, pp. 81–88, 2012, doi: 10.1007/978-3-642-28768-8_9.
- [68] B. Li, P. L. Zhang, Q. Mao, S. S. Mi, and P. Y. Liu, "Gear fault detection using adaptive morphological gradient lifting wavelet," *JVC/Journal Vib. Control*, vol. 19, no. 11, pp. 1646–1657, 2013, doi: 10.1177/1077546312448502.
- [69] M. Gawecki, "A Signal Processing Approach to Robust Jet Engine Fault Detection and Diagnosis," no. August, 2014.
- [70] L. Hong and J. S. Dhupia, "A time domain approach to diagnose gearbox fault based on measured vibration signals," *J. Sound Vib.*, vol. 333, no. 7, pp. 2164–2180, 2014, doi: 10.1016/j.jsv.2013.11.033.
- [71] H. Liu, W. Huang, S. Wang, and Z. Zhu, "Adaptive spectral kurtosis filtering based on Morlet wavelet and its application for signal transients detection," *Signal Processing*, vol. 96, no. PART A, pp. 118–124, 2014, doi: 10.1016/j.sigpro.2013.05.013.
- [72] V. Sharma and A. Parey, "A Review of Gear Fault Diagnosis Using Various Condition Indicators," *Procedia Eng.*, vol. 144, pp. 253–263, 2016, doi: 10.1016/j.proeng.2016.05.131.
- [73] L. Cung, B. Minh Hien, and N. Thai Son, "Gear and Bearing Fault Detection Using Wavelet Packet and Hilbert Method Via Acoustic Signals," vol. 6, no. 2, pp. 5–13, 2016, [Online]. Available: <http://www.seed-net.org/wp-content/uploads/2015/12/GEAR-AND-BEARING-FAULT-DETECTION-USING-WAVELET-PACKET-AND-HILBERT-METHOD-VIA-ACOUSTIC-SIGNALS.pdf>.

- [74] L. Gelman, K. Solinski, B. Shaw, and M. Vaidhianathasamy, "Vibration diagnosis of a gearbox by wavelet bicoherence technology," 2017. doi: 10.1784/insi.2017.59.8.440.
- [75] S. Shanbr, F. Elasha, M. Elforjani, and J. A. Teixeira, "Bearing Fault Detection within Wind Turbine Gearbox," *Proc. - 2017 Int. Conf. Sensing, Diagnostics, Progn. Control. SDPC 2017*, vol. 2017-Decem, pp. 565–570, 2017, doi: 10.1109/SDPC.2017.112.
- [76] S. A. Naumov, A. V. Krymskii, M. A. Lipatov, and D. N. Skrabatun, "Experience in Use of Remote Access and Predictive Analytics for Power Equipment's Condition," *Therm. Eng.*, vol. 65, no. 4, pp. 189–199, 2018, doi: 10.1134/S0040601518040055.
- [77] M. Benrahmoune, A. Hafaifa, M. Guemana, and X. Q. Chen, "Detection and modeling vibrational behavior of a gas turbine based on dynamic neural networks approach," *Stroj. Cas.*, vol. 68, no. 3, pp. 143–166, 2018, doi: 10.2478/scjme-2018-0032.
- [78] N. Barkova, A. Barkov, and D. Grishchenko, "Vibration diagnostics of equipment units with gas turbine engines," *Vibroengineering Procedia*, vol. 25, pp. 89–94, 2019, doi: 10.21595/vp.2019.20723.
- [79] W. Wang, "Early detection of gear tooth cracking using the resonance demodulation technique," *Mech. Syst. Signal Process.*, vol. 15, no. 5, pp. 887–903, 2001, doi: 10.1006/mssp.2001.1416.
- [80] M. Cocconcelli, R. Zimroz, R. Rubini, and W. Bartelmus, "STFT Based Approach for Ball Bearing Fault Detection in a Varying Speed Motor," *Cond. Monit. Mach. Non-Stationary Oper.*, pp. 41–50, 2012, doi: 10.1007/978-3-642-28768-8_5.
- [81] W. Bartelmus, "Object and Operation Factor Oriented Diagnostics," *Cond. Monit. Mach. Non-Stationary Oper.*, pp. 13–23, 2012, doi: 10.1007/978-3-642-28768-8_2.

- [82] I. Moumene and N. Ouelaa, "Gears and Bearings Combined Faults Detection Using Hilbert Transform and Wavelet Multiresolution Analysis," *Cond. Monit. Mach. Non-Stationary Oper.*, pp. 319–328, 2012, doi: 10.1007/978-3-642-28768-8_34.
- [83] R. B. Randall, N. Sawalhi, and M. Coats, "Separation of Gear and Bearing Fault Signals from a Wind Turbine Transmission under Varying Speed and Load," *Cond. Monit. Mach. Non-Stationary Oper.*, pp. 3–12, 2012, doi: 10.1007/978-3-642-28768-8_1.
- [84] D. H. Kwak, D. H. Lee, J. H. Ahn, and B. H. Koh, "Fault detection of roller-bearings using signal processing and optimization algorithms," *Sensors (Switzerland)*, vol. 14, no. 1, pp. 283–298, 2013, doi: 10.3390/s140100283.
- [85] A. Mironov, P. Doronkin, and A. Priklonsky, "Advanced vibration technique for monitoring of helicopter bearings," *40th Eur. Rotorcr. Forum 2014*, vol. 1, pp. 149–158, 2014.
- [86] A. Mironov, P. Doronkin, A. Priklonskiy, and S. Yunusov, "Adaptive technology application for vibration-based diagnostics of roller bearings on industrial plants," *Transp. Telecommun.*, vol. 15, no. 3, pp. 233–242, 2014, doi: 10.2478/ttj-2014-0021.
- [87] L. Lu, J. Yan, and C. W. De Silva, "Dominant feature selection for the fault diagnosis of rotary machines using modified genetic algorithm and empirical mode decomposition," *J. Sound Vib.*, vol. 344, pp. 464–483, 2015, doi: 10.1016/j.jsv.2015.01.037.
- [88] M. Ge, J. Wang, F. Zhang, K. Bai, and X. Ren, "A novel fault diagnosis method of rolling bearings based on AFEWT-KDEMI," *Entropy*, vol. 20, no. 6, 2018, doi: 10.3390/e20060455.
- [89] Y. Tang, F. Lin, and Q. Zou, "Complexity Analysis of Time-Frequency Features for Vibration Signals of Rolling Bearings Based on Local Frequency," *Shock Vib.*, vol. 2019, 2019, doi: 10.1155/2019/7190568.

- [90] I. M. Jamadar, S. A. I. Bellary, R. A. Kanai, and A. A. Alrobaian, "Model-Based Condition Monitoring for the Detection of Failure of a Ball Bearing in a Centrifugal Pump," *J. Fail. Anal. Prev.*, vol. 19, no. 6, pp. 1556–1568, 2019, doi: 10.1007/s11668-019-00792-x.
- [91] Y. Zhu and J. Yao, "Bearing Fault Diagnosis Based on Slice Spectral Analysis," *Proc. - 2018 Progn. Syst. Heal. Manag. Conf. PHM-Chongqing 2018*, pp. 704–709, 2019, doi: 10.1109/PHM-Chongqing.2018.00126.
- [92] J. Wu, "Sensor data-driven bearing fault diagnosis based on deep convolutional neural networks and s-transform," *Sensors (Switzerland)*, vol. 19, no. 12, 2019, doi: 10.3390/s19122750.
- [93] M. Irfan, "Modeling of Fault Frequencies for Distributed Damages in Bearing Raceways," *J. Nondestruct. Eval.*, vol. 38, no. 4, pp. 1–10, 2019, doi: 10.1007/s10921-019-0635-0.
- [94] D. Wu et al., "An automatic bearing fault diagnosis method based on characteristics frequency ratio," *Sensors (Switzerland)*, vol. 20, no. 5, pp. 1–12, 2020, doi: 10.3390/s20051519.
- [95] F. Gu, W. Li, A. D. Ball, and A. Y. T. Leung, "The condition monitoring of diesel engines using acoustic measurements part 1: Acoustic characteristics of the engine and representation of the acoustic signals," *SAE Tech. Pap.*, no. 724, 2000, doi: 10.4271/2000-01-0730.
- [96] T. Ananthapadmanaban and V. Radhakrishnan, "An investigation of the role of surface irregularities in the noise spectrum of rolling and sliding contacts," *Wear*, vol. 83, no. 2, pp. 399–409, 1982, doi: 10.1016/0043-1648(82)90192-2.
- [97] N. Baydar and A. Ball, "A comparative study of acoustic and vibration signals in detection of gear failures using Wigner-Ville distribution," *Mech. Syst. Signal Process.*, vol. 15, no. 6, pp. 1091–1107, 2001, doi: 10.1006/mssp.2000.1338.

- [98] N. Baydar and A. Ball, "Detection of gear failures via vibration and acoustic signals using wavelet transform," *Mech. Syst. Signal Process.*, vol. 17, no. 4, pp. 787–804, 2003, doi: 10.1006/mssp.2001.1435.
- [99] H. Tian, L. Tang, and T. Yang, "Application of acoustic testing for gear wearing fault diagnosis," 2007 8th Int. Conf. Electron. Meas. Instruments, ICEMI, pp. 3635–3638, 2007, doi: 10.1109/ICEMI.2007.4350997.
- [100] S. H. Kia, H. Henao, and G. A. Capolino, "A comparative study of acoustic, vibration and stator current signatures for gear tooth fault diagnosis," *Proc. - 2012 20th Int. Conf. Electr. Mach. ICEM 2012*, no. 1, pp. 1514–1519, 2012, doi: 10.1109/ICEIMach.2012.6350079.
- [101] W. Lu, W. Jiang, H. Wu, and J. Hou, "A fault diagnosis scheme of rolling element bearing based on near-field acoustic holography and gray level co-occurrence matrix," *J. Sound Vib.*, vol. 331, no. 15, pp. 3663–3674, 2012, doi: 10.1016/j.jsv.2012.03.008.
- [102] S. Mohanty, K. K. Gupta, K. S. Raju, A. Singh, and S. Snigdha, "Vibro acoustic signal analysis in fault finding of bearing using empirical mode decomposition," *Proc. 2013 Int. Conf. Adv. Electron. Syst. ICAES 2013*, vol. 7, pp. 29–33, 2013, doi: 10.1109/ICAES.2013.6659355.
- [103] A. M. Abdelrhman, L. M. Hee, M. S. Leong, and S. Al-Obaidi, "Condition monitoring of blade in turbomachinery: A review," *Adv. Mech. Eng.*, vol. 2014, 2014, doi: 10.1155/2014/210717.
- [104] Z. Zhou and Z. Feng, "Planetary gearbox fault diagnosis via acoustic signal analysis," *Proc. - 2017 Int. Conf. Sensing, Diagnostics, Progn. Control. SDPC 2017*, vol. 2017-Decem, pp. 29–34, 2017, doi: 10.1109/SDPC.2017.16.
- [105] R. Appadoo, Y. Xu, F. Gu, and A. D. Ball, "Performance monitoring and fault diagnosis of vacuum pumps based on airborne sounds," *ICAC 2018 - 2018 24th IEEE Int. Conf. Autom. Comput. Improv. Product. through Autom. Comput.*, no. September, pp. 1–6, 2018, doi: 10.23919/IConAC.2018.8748969.

- [106] A. Daraz, S. Alabied, A. Smith, F. Gu, and A. D. Ball, "Detection and diagnosis of centrifugal pump bearing faults based on the envelope analysis of airborne sound signals," ICAC 2018 - 2018 24th IEEE Int. Conf. Autom. Comput. Improv. Product. through Autom. Comput., no. September, pp. 1–6, 2018, doi: 10.23919/IConAC.2018.8749053.
- [107] P. Vasilić, S. Vujnović, N. Popović, A. Marjanović, and Ž. Durović, "Adaboost algorithm in the frame of predictive maintenance tasks," 2018 23rd Int. Sci. Conf. Inf. Technol. IT 2018, vol. 2018-Janua, pp. 1–4, 2018, doi: 10.1109/SPIT.2018.8350846.
- [108] M. A. Khan et al., "Gear misalignment diagnosis using statistical features of vibration and airborne sound spectrums," Meas. J. Int. Meas. Confed., vol. 145, pp. 419–435, 2019, doi: 10.1016/j.measurement.2019.05.088.
- [109] Vanraj, R. Singh, S. S. Dhami, and B. S. Pabla, "Development of low-cost non-contact structural health monitoring system for rotating machinery," R. Soc. Open Sci., vol. 5, no. 6, 2018, doi: 10.1098/rsos.172430.
- [110] L. He, J. Unnikrishnan, L. Hao, B. Matthews, and W. Qiao, "Enhanced wind turbine main drivetrain gearbox and bearing monitoring and diagnostics via information fusion of acoustic, electrical, and vibration signatures," 2019 IEEE Int. Electr. Mach. Drives Conf. IEMDC 2019, pp. 51–56, 2019, doi: 10.1109/IEMDC.2019.8785271.
- [111] J. Solimine, C. Niezrecki, and M. Inalpolat, "An experimental investigation into passive acoustic damage detection for structural health monitoring of wind turbine blades," Struct. Heal. Monit., 2020, doi: 10.1177/1475921719895588.
- [112] N. Aretakis and K. Mathioudakis, "Wavelet analysis for gas turbine fault diagnostics," Am. Soc. Mech. Eng., vol. 119, no. October, pp. 870–876, 1996.
- [113] R. Haworth and M. F. Russell, "Combustion Noise from High Speed Direct Injection Diesel Engines," SAE Publ., 1985.

- [114] F. Gu, W. Li, A. D. Ball, and A. Y. T. Leung, "The Condition Monitoring of Diesel Engines Using Acoustic Measurements Part 2: Fault Detection and Diagnosis," SAE Tech. Pap., 2000.
- [115] H. Ghaderi and P. Kabiri, "Automobile engine condition monitoring using sound emission," Turkish J. Electr. Eng. Comput. Sci., vol. 25, no. 3, pp. 1807–1826, 2017, doi: 10.3906/elk-1605-77.
- [116] W. Prasetyo and M. Alaydrus, "The condition monitoring of diesel engines using acoustic signal analysis," Indones. J. Electr. Eng. Comput. Sci., vol. 13, no. 1, pp. 179–185, 2019, doi: 10.11591/ijeecs.v13.i1.pp179-185.
- [117] W. Wang and W. Zhang, "A model to predict the residual life of aircraft engines based upon oil analysis data," Nav. Res. Logist., vol. 52, no. 3, pp. 276–284, 2005, doi: 10.1002/nav.20072.
- [118] C. De Michelis, C. Rinaldi, C. Sampietri, and R. Vario, "Condition monitoring and assessment of power plant components," Power Plant Life Manag. Perform. Improv., pp. 38–109, 2011, doi: 10.1533/9780857093806.1.38.
- [119] F. Mevissen and M. Meo, "A review of NDT/structural health monitoring techniques for hot gas components in gas turbines," Sensors (Switzerland), vol. 19, no. 3, 2019, doi: 10.3390/s19030711.
- [120] A. J. Volponi, T. Brotherton, and R. Luppold, "Development of an information fusion system for engine diagnostics and health management," Collect. Tech. Pap. - AIAA 1st Intell. Syst. Tech. Conf., vol. 2, no. March 2004, pp. 873–886, 2004, doi: 10.2514/6.2004-6461.
- [121] J. A. Turso and J. S. Litt, "Data Fusion System for Turbofan Engines," no. August, 2004.
- [122] V. Zaccaria, M. Rahman, I. Aslanidou, and K. Kyprianidis, "A review of information fusion methods for gas turbine diagnostics," Sustain., vol. 11, no. 22, 2019, doi: 10.3390/su11226202.

- [123] Y. Zhang, C. Bingham, M. Garlick, and M. Gallimore, "Applied fault detection and diagnosis for industrial gas turbine systems," *Int. J. Autom. Comput.*, vol. 14, no. 4, pp. 463–473, 2017, doi: 10.1007/s11633-016-0967-5.
- [124] D. A. Clifton, P. R. Bannister, and L. Tarassenko, "A Framework for Novelty Detection in Jet Engine Vibration Data," *Key Eng. Mater.*, vol. 347, no. January, pp. 305–310, 2007, doi: 10.4028/www.scientific.net/kem.347.305.
- [125] I. Matthaïou, B. Khandelwal, and I. Antoniadou, "Vibration monitoring of gas turbine engines: Machine-learning approaches and their challenges," *Front. Built Environ.*, vol. 3, no. September, pp. 1–10, 2017, doi: 10.3389/fbuil.2017.00054.
- [126] Federal Aviation Administration, "FAA National Forecast 2019-2039," p. 105, 2019, [Online]. Available: https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2019-39_FAA_Aerospace_Forecast.pdf.
- [127] A. S. Gohardani, G. Doulgeris, and R. Singh, "Challenges of future aircraft propulsion: A review of distributed propulsion technology and its potential application for the all electric commercial aircraft," *Prog. Aerosp. Sci.*, vol. 47, no. 5, pp. 369–391, 2011, doi: 10.1016/j.paerosci.2010.09.001.
- [128] A. S. Gohardani, "A synergistic glance at the prospects of distributed propulsion technology and the electric aircraft concept for future unmanned air vehicles and commercial/military aviation," *Prog. Aerosp. Sci.*, vol. 57, pp. 25–70, 2013, doi: 10.1016/j.paerosci.2012.08.001.
- [129] A. Gibson, D. Hall, M. Waters, B. Schiltgen, T. Foster, and K. Papathakis, "Superconducting Electric Distributed Propulsion Structural Integration and Design in a Split-Wing Regional Airliner," no. January, pp. 1–15, 2011, doi: 10.2514/6.2011-223.
- [130] Eden P and M. S, *The complete encyclopedia of world aircraft*. London, United Kingdom: Barnes & Noble Books/Amber Books Ltd., 2002.

- [131] M. D. Moore, "NASA puffin electric tailsitter VTOL concept," 10th AIAA Aviat. Technol. Integr. Oper. Conf. 2010,ATIO 2010, vol. 3, pp. 1–12, 2010, doi: 10.2514/6.2010-9345.
- [132] K. Dalamagkidis, K. P. Valavanis, and L. A. Piegler, "On unmanned aircraft systems issues, challenges and operational restrictions preventing integration into the National Airspace System," *Prog. Aerosp. Sci.*, vol. 44, no. 7–8, pp. 503–519, 2008, doi: 10.1016/j.paerosci.2008.08.001.
- [133] R. Todd and A. J. Forsyth, "HIL emulation of all-electric UAV power systems," 2009 IEEE Energy Convers. Congr. Expo. ECCE 2009, pp. 411–416, 2009, doi: 10.1109/ECCE.2009.5316350.
- [134] T. R. Ensign, "Sensitivity studies of electric systems on business jet range," 46th AIAA Aerosp. Sci. Meet. Exhib., no. January, pp. 1–30, 2008, doi: 10.2514/6.2008-147.
- [135] P. Krammer, K. Rued, and J. Truebenbach, "AIAA 2003-2790 TITLE : TECHNOLOGY PREPARATION FOR GREEN AERO ENGINES Authors : MTU Aero Engines GmbH," no. July, pp. 1–11, 2003, doi: 10.2514/6.2003-2790.
- [136] P. Laskaridis, "Performance Investigation and Systems Architectures for the More Electric Aircraft," Cranfield University, 2004.
- [137] A. Filippone, "Aircraft noise prediction," *Prog. Aerosp. Sci.*, vol. 68, pp. 27–63, 2014, doi: 10.1016/j.paerosci.2014.02.001.
- [138] R. L. Tubbs, "Noise exposure to airline ramp employees," *Appl. Occup. Environ. Hyg.*, vol. 15, no. 9, pp. 657–663, 2000, doi: 10.1080/10473220050110022.
- [139] M. Ihme, "Combustion and Engine-Core Noise," *Annu. Rev. Fluid Mech.*, vol. 49, no. 1, pp. 277–310, 2017, doi: 10.1146/annurev-fluid-122414-034542.
- [140] E. GRANDE, "Core engine noise," 1973, doi: 10.2514/6.1973-1026.

- [141] E. a. Krejsa and J. R. Stone, "Enhanced Fan Noise Modeling for Turbofan Engines," no. June 2011, 2014, [Online]. Available: <http://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20150000884.pdf>.
- [142] T. Livebardon, "MODELING THE NOISE OF COMBUSTION IN HELICOPTER TURBINES," UNIVERSITÉ DE TOULOUSE, 2015.
- [143] D. K. Boyle, B. S. Henderson, and L. S. Hultgren, "Core/combustor-noise baseline measurements for the DGEN aeropropulsion research turbofan," 2018 AIAA/CEAS Aeroacoustics Conf., no. June, pp. 25–29, 2018, doi: 10.2514/6.2018-3281.
- [144] A. Filippone, "Aircraft noise prediction," Prog. Aerosp. Sci., vol. 68, pp. 27–63, 2014, doi: 10.1016/j.paerosci.2014.02.001.
- [145] E. M. Nolan, "Modeling Performance and Noise of Advanced Operational Procedures for Current and Future Aircraft," pp. 1–113, 2014.
- [146] C. Soares, Gas Turbines: A Handbook of Air, Land and Sea Application. Elsevier, 2015.
- [147] D. R. Mcauliffe, "What to do About Gas-Turbine Noise," ASME, 1964.
- [148] I. Duran, S. Moreau, F. Nicoud, T. Livebardon, E. Bouty, and T. Poinso, "Combustion Noise in Modern Aero-Engines Aeroacoustics Combustion Noise in Modern Aero-Engines," Combust. Noise Mod. Aero-Engines, no. 7, pp. 1–11, 2014, doi: 10.12762/2014.AL07-05.
- [149] N. A. Cumpsty, "Excess noise from gas turbine exhausts," Proc. ASME Turbo Expo, vol. 1A-1975, no. June, 1975, doi: 10.1115/75-GT-61.
- [150] N. A. Cumpsty, "Excess noise from gas turbine exhausts," Proc. ASME Turbo Expo, vol. 1A-1975, 1975, doi: 10.1115/75-GT-61.
- [151] D. Weir, "Engine Validation of Noise and Emission Reduction Technology Phase I," 2008.
- [152] C. M. Royalty and B. Schuster, "Noise from a turbofan engine without a fan from the engine validation of noise and emission reduction technology

(EVNERT) program,” 14th AIAA/CEAS Aeroacoustics Conf. (29th AIAA Aeroacoustics Conf., no. May, pp. 5–7, 2008, doi: 10.2514/6.2008-2810.

[153] J. M. Mendoza, D. K. Nance, and K. K. Ahuja, “Source separation from multiple microphone measurements in the far field of a full scale aero engine,” 14th AIAA/CEAS Aeroacoustics Conf. (29th AIAA Aeroacoustics Conf., no. May, pp. 5–7, 2008, doi: 10.2514/6.2008-2809.

[154] M. Harper-Bourne, A. Moore, and H. Siller, “A study of large aero-engine combustor noise,” 14th AIAA/CEAS Aeroacoustics Conf. (29th AIAA Aeroacoustics Conf., no. May 2008, 2008, doi: 10.2514/6.2008-2942.

[155] J. H. Miles, “Time delay analysis of turbofan engine direct and indirect combustion noise sources,” J. Propuls. Power, vol. 25, no. 1, pp. 218–227, 2009, doi: 10.2514/1.38030.

[156] G. G. Podboy and C. Horvath, “Phased array noise source localization measurements made on a Williams International FJ44 engine,” 15th AIAA/CEAS Aeroacoustics Conf. (30th AIAA Aeroacoustics Conf., no. May, pp. 11–13, 2009, doi: 10.2514/6.2009-3183.

[157] B. Pardowitz et al., “Core noise - Identification of broadband noise sources of a turbo-shaft engine,” no. June, 2014, doi: 10.2514/6.2014-3321.

[158] D. Blacodon and S. Lewy, “Source localization of turboshaft engine broadband noise using a three-sensor coherence method,” J. Sound Vib., vol. 338, pp. 250–262, 2015, doi: 10.1016/j.jsv.2014.10.019.

[159] H. Gounet and S. Lewy, “Three-dimensional sound directivity around a helicopter turboshaft engine,” J. Am. Helicopter Soc., vol. 57, no. 4, pp. 1–10, 2012, doi: 10.4050/JAHS.57.042002.

[160] L. S. Hultgren, D. K. Boyle, and B. S. Henderson, “1/3-Octave Analysis of Core/Combustor-Noise Measurements for the Dgen Aeropropulsion Research Turbofan With Application To Noise Prediction,” 25th AIAA/CEAS Aeroacoustics Conf. 2019, no. May, pp. 1–21, 2019, doi: 10.2514/6.2019-2642.

- [161] L. S. Hultgren, "Full-scale turbofan-engine turbine-transfer function determination using three internal sensors," 17th AIAA/CEAS Aeroacoustics Conf. 2011 (32nd AIAA Aeroacoustics Conf., no. June, pp. 5–8, 2011, doi: 10.2514/6.2011-2912.
- [162] U. DeSilva, R. H. Bunce, and H. Claussen, "Novel gas turbine exhaust temperature measurement system," Proc. ASME Turbo Expo, vol. 4, no. May, 2013, doi: 10.1115/GT2013-95152.
- [163] R. Otero, K. Todd Lowe, W. F. Ng, L. Ma, and C. Y. Kim, "Non-intrusive gas turbine engine exhaust characterization using acoustic measurements," 32nd AIAA Aerodyn. Meas. Technol. Gr. Test. Conf., no. June, pp. 1–13, 2016, doi: 10.2514/6.2016-4160.
- [164] M. Othman, Y. S. H. Najjar, and T. W. Abou-Arab, "Fuel effect on induced vibration in gas turbine engines," Fuel, vol. 67, no. 3, pp. 321–326, 1988, doi: 10.1016/0016-2361(88)90313-4.
- [165] M. Kilpatrick, "The Investigation of Noise, Vibrations and Emissions of Aero-Gas Turbine Combustion with Synthetic Kerosene Fuels," Georgia Southern University, 2019.
- [166] R. Rajaram and T. Lieuwen, "Parametric studies of acoustic radiation from premixed flames," Combust. Sci. Technol., vol. 175, no. 12, pp. 2269–2298, 2003, doi: 10.1080/714923281.
- [167] C. Bailly, C. Bogey, and S. Candel, "Modelling of Sound Generation by Turbulent Reacting Flows," Int. J. Aeroacoustics, vol. 9, no. 4–5, pp. 461–489, 2010, doi: 10.1260/1475-472x.9.4-5.461.
- [168] A. Filippone, "Options for aircraft noise reduction on arrival and landing," Aerosp. Sci. Technol., vol. 60, pp. 31–38, 2017, doi: 10.1016/j.ast.2016.10.027.
- [169] J. J. Dias, "Gas turbine auxiliary power unit noise and its attenuation," SAE Tech. Pap., 1967, doi: 10.4271/670155.

- [170] B. N. Shivashankara, "Gas turbine core noise source isolation by internal-to-far-field correlations," *J. Aircr.*, vol. 15, no. 9, pp. 597–600, 1978, doi: 10.2514/3.58412.
- [171] M. Pott-Pollenske, W. Dobrzynski, H. Buchholz, and D. Almoneit, "Characteristics of noise from aircraft ground operations," 13th AIAA/CEAS Aeroacoustics Conf. (28th AIAA Aeroacoustics Conf., pp. 1–14, 2007, doi: 10.2514/6.2007-3560.
- [172] M. Lavieille, D. Brown, and F. Vieuille, "Numerical modeling and experimental validation of the acoustic efficiency of treated ducts on an aircraft auxiliary power system," 17th AIAA/CEAS Aeroacoustics Conf. 2011 (32nd AIAA Aeroacoustics Conf., no. June 2011, 2011, doi: 10.2514/6.2011-2810.
- [173] S. Busse-Gerstengarbe, "FULL-SCALE TESTS ON APU NOISE REDUCTION," in *ASME Turbo Expo 2014: Turbine Technical Conference and Exposition*, 2014, vol. 5, pp. 1–9.
- [174] K. Knobloch, L. Enghardt, and F. Bake, "APU-noise reduction by novel muffler concepts," *Proc. ASME Turbo Expo*, vol. 2B-2018, pp. 1–11, 2018, doi: 10.1115/GT2018-76762.
- [175] I. Repository and C. Sheet, "American Society of Mechanical Engineers Experimental Investigation of Cycle Properties , Noise and Air Pollutant Emissions of an APS3200 Auxiliary Power Unit," vol. 140, no. 140, 2018, doi: 10.1115/1.4038159.
- [176] J. R. Stone, E. A. Krejsa, and B. J. Clark, "Progress in core/combustion noise prediction," 43rd AIAA Aerosp. Sci. Meet. Exhib. - Meet. Pap., no. January, pp. 10547–10563, 2005, doi: 10.2514/6.2005-1199.
- [177] B. Schuster and L. Lieber, "Narrowband model for gas turbine engine combustion noise prediction," *Collect. Tech. Pap. - 12th AIAA/CEAS Aeroacoustics Conf.*, vol. 6, no. May, pp. 3611–3623, 2006, doi: 10.2514/6.2006-2677.

- [178] SAE Aerospace, "Gas Turbine Jet Exhaust Noise Prediction ARP876D," SAE Tech. Pap., 1978.
- [179] C. K. W. Tam, S. A. Parrish, J. Xu, and B. Schuster, "Indirect combustion noise of auxiliary power units," *J. Sound Vib.*, vol. 332, no. 17, pp. 4004–4020, 2013, doi: 10.1016/j.jsv.2012.11.013.
- [180] J. Xu, C. K. W. Tam, and S. A. Parrish, "On indirect combustion noise," 50th AIAA Aerosp. Sci. Meet. Incl. New Horizons Forum Aerosp. Expo., no. January, pp. 1–16, 2012, doi: 10.2514/6.2012-543.
- [181] C. K. W. Tam, "The spectral shape of combustion noise," *Int. J. Aeroacoustics*, vol. 14, no. 3–4, pp. 431–456, 2015, doi: 10.1260/1475-472X.14.3-4.431.
- [182] C. K. W. Tam, "On the spectrum of combustion noise," 21st AIAA/CEAS Aeroacoustics Conf., no. June, 2015, doi: 10.2514/6.2015-2969.
- [183] C. K. W. Tam and S. A. Parrish, "The physical processes of indirect combustion noise generation," *Int. J. Aeroacoustics*, vol. 17, no. 1–2, pp. 22–35, 2018, doi: 10.1177/1475472X17743628.
- [184] T. Livebardon, S. Moreau, L. Gicquel, T. Poinso, and E. Bouty, "Combining LES of combustion chamber and an actuator disk theory to predict combustion noise in a helicopter engine," *Combust. Flame*, vol. 165, pp. 272–287, 2016, doi: 10.1016/j.combustflame.2015.12.012.
- [185] SAE Aerospace, "Measurement of Exterior Noise Produced by Aircraft Auxiliary Power Units (APUs) and Associated Aircraft Systems During Ground Operation. Aerospace Recommended Practice," SAE ARP1307 Rev.B, 2013.
- [186] A. P. Dowling and Y. Mahmoudi, "Combustion noise," *Proc. Combust. Inst.*, vol. 35, no. 1, pp. 65–100, 2015, doi: 10.1016/j.proci.2014.08.016.
- [187] W. R. Graham, C. A. Hall, and M. Vera Morales, "The potential of future aircraft technology for noise and pollutant emissions reduction," *Transp. Policy*, vol. 34, no. 2014, pp. 36–51, 2014, doi: 10.1016/j.tranpol.2014.02.017.

- [188] G. A. Hill, S. A. Brown, K. A. Geiselhart, and C. M. Burg, "Integration of propulsion-airframe-aeroacoustic technologies and design concepts for a quiet blended-wing-body transport," Collect. Tech. Pap. - AIAA 4th Aviat. Technol. Integr. Oper. Forum,ATIO, vol. 2, no. September, pp. 703–722, 2004, doi: 10.2514/6.2004-6403.
- [189] J. I. Hileman, Z. S. Spakovszky, M. Drela, and M. A. Sargeant, "Airframe design for 'Silent Aircraft,'" Collect. Tech. Pap. - 45th AIAA Aerosp. Sci. Meet., vol. 8, no. January, pp. 5403–5417, 2007, doi: 10.2514/6.2007-453.
- [190] R. J. Gaeta, K. K. Ahuja, B. Murdock, and R. Combier, "Noise reduction from a Distributed Exhaust Nozzle with forward velocity effects," Collect. Tech. Pap. - 10th AIAA/CEAS Aeroacoustics Conf., vol. 3, no. May, pp. 1911–1927, 2004, doi: 10.2514/6.2004-2970.
- [191] H. Eißfeldt, "Sustainable urban air mobility supported with participatory noise sensing," Sustain., vol. 12, no. 8, 2020, doi: 10.3390/SU12083320.
- [192] H. Kinjo, "Development Trends and Prospects for eVTOL: A new Mode of Air Mobility," Mitsui Co. Glob. Strateg. Stud. Inst. Mon. Rep., no. June, pp. 1–8, 2018, [Online]. Available: https://www.mitsui.com/mgssi/en/report/detail/___icsFiles/afieldfile/2019/07/18/1906m_kinjo_e.pdf.
- [193] W. Johnson, C. Silva, and E. Solis, "Concept vehicles for VTOL air taxi operations," Proc. AHS Int. Tech. Meet. Aeromechanics Des. Transform. Vert. Flight 2018, 2018.
- [194] U. T. Sou, "Investigation into the Effects of Blade Tip Twist on Noise Reduction for a NACA 0012 Rotor Blade," vol. 15, 2019.
- [195] W. N. Gianmarco SCALABRIN, "En-Route to Urban Air Mobility," 2020. [Online]. Available: <https://www.altran.com/tr/en/insight/en-route-to-urban-air-mobility-on-the-fast-track-to-viable-and-safe-on-demand-air-services/>.
- [196] F. Gugliermetti, F. Bisegna, A. C. Violante, and C. Aureli, "Noise exposure of the ramp's operators in airport apron," 20th Int. Congr. Acoust. 2010, ICA 2010

- Inc. Proc. 2010 Annu. Conf. Aust. Acoust. Soc., vol. 3, no. August, pp. 2051–2057, 2010.

[197] R. H. Schlinker et al., “Simulation and validation of centrifugal impeller shock wave and acoustic power prediction,” Proc. ASME Turbo Expo, vol. 8, no. PARTS A, B, AND C, pp. 1843–1851, 2012, doi: 10.1115/GT2012-70076.

[198] C. K. W. Tam, S. A. Parrish, J. Xu, and B. Schuster, “Indirect combustion noise of auxiliary power units,” J. Sound Vib., vol. 332, no. 17, pp. 4004–4020, 2013, doi: 10.1016/j.jsv.2012.11.013.

[199] C. J. Wijesinghe and B. Khandelwal, “Impact of alternative fuel on gas turbine noise, vibration and instability,” AIAA Scitech 2019 Forum, no. January, pp. 1–7, 2019, doi: 10.2514/6.2019-0240.

3 Development of a Far-Field Noise Estimation Model for an Aircraft Auxiliary Power Unit

Aircraft Auxiliary Power Unit (APU) is one of the major aircraft systems and is reported to be a key driver of unscheduled maintenance. So far, the research has been focused on the implementation of the APU thermodynamic state data to isolate and diagnose faults. To advance the available diagnostic techniques, research work has been initiated to explore the potential of employing far-field microphone data for the identification and isolation of APU faults. This chapter of the thesis aims to address the first step required in the overall effort and proposes a novel methodology for the development of a noise model that can be used for evaluating noise as a source of fault diagnostics. The methodology integrates experimentally acquired full-scale aircraft state and noise data, a physics-based APU thermodynamic model, and semi-empirical noise models to estimate the noise produced by an aircraft APU based on a limited parameter-set. The methodology leads to a model which works by estimating the unknown thermodynamic parameters from the limited dataset and then passes on the relevant parameters to noise estimation models (combustion/jet noise models). An inherent part of the model is the effect of multipath propagation and ground reflections for which a relationship has been analytically derived that considers all the necessary parameters. The developed model has been validated against experimental noise and thermodynamic data acquired from a Boeing 737-400 aircraft APU under several different operating conditions. The acquired noise estimates suggest that the proposed approach provides an accurate estimation of the far-field noise under a wide range of APU operating conditions, both at the sub-system and APU level. The model would act as an enabler to simulate APU noise data under degraded functional states and subsequently developing fault diagnostic schemes based on the far-field noise data.

3.1 Introduction

The aircraft is a highly complex and integrated system. Amongst, others, one of its major systems, the Auxiliary Power Unit (APU), has been reported as a key driver of unscheduled maintenance and therefore demands a robust

maintenance strategy [1]. The heart of maintenance and troubleshooting is a fault diagnostic scheme that comprises a sensor-set and a fault diagnostic algorithm. Generally, a diagnostic capability is embedded into the system during the design phase depending on the technologies (hardware, sensors, processing techniques) available at that time. Performance-based monitoring (also called gas-path analysis) is an example of the prevalent approach for a gas turbine's health monitoring or fault detection [1-7]. However, these methods require the installation of thermodynamic sensors which could be intrusive and may not be feasible if they were not considered during the product's design phase. Moreover, with the increasing demand for air travel, the desire to reduce aircraft downtime, and the technological advancements made in the relevant fields, the need for state-of-the-art fault diagnostic solutions is increasing. The proposed solutions should be readily deployable and assist in expediting the unscheduled maintenance activities.

In addition to the thermodynamic parameters, the noise generated by an aircraft APU may also contain useful information about the state of the system and, therefore, assist in detecting degradation or faults. To proceed with the assessment of the noise generated by the aircraft APU as a source of fault diagnostics, a noise estimation model is required. Such a model has been found to be missing from the literature. In this regard, research is being undertaken on a Boeing 737 (B737) aircraft to evaluate the noise radiated by its APU as an enabler for fault diagnostics. The focus is on the development of a far-field noise estimation model that would facilitate the characterization of noise when the APU is subjected to faults under various degradation severities.

Various types of experimentation which have been performed on APU have either been focussed on its thermodynamics aspects or the qualitative assessment of its far-field noise. Generally, a test rig is developed to gather information about thermodynamic parameters, acoustics, or exhaust emissions. Several test rigs [1]–[4] have been developed to understand the thermodynamic aspects of APUs. In other forms of experimental data collection, APUs are placed inside an anechoic chamber and their exhaust noise is studied with far-field microphones

[5]–[7]. These studies discussed the spectrum of combustion noise and the presence of indirect combustion noise. Another form of experimentation involves the development and testing of noise suppression mechanisms for aircraft APUs [8]. Other studies [9]–[11] have ascertained the average acoustic levels to which the service personnel is exposed while working on the aircraft. Towards the development of noise models for aircraft APUs, very little information is available and is said to be because of the scarcity of APU noise data. A German noise simulation program is reported to be developed for APUs [12], however, its results have not been compared with experimental data and thus its accuracy is questionable.

Contrary to acoustic analysis on APU, extensive work [13]–[18] has been done on turbofan engines, their noise, and the comparison of the performance of various noise estimation models. As per the regulations, the noise from the main engines has to be well within the prescribed limits set by the regulating authorities, which is not the case for aircraft APUs. Therefore, APU noise and its dependence on the underlying physical parameters need to be explored. Recently, we [19] have highlighted that APU far-field noise has not been studied at a full scale and under a wide range of operating conditions. Besides, none of the noise estimation models have been reported to be validated on an aircraft APU using experimental data.

3.1.1 Description of APU

The APU is a gas-turbine engine that is typically installed in the tail section of the aircraft. The APU is responsible for providing pneumatic and electrical power during ground / aerial operations. The APU also serves as a backup source of power during emergencies in flight. APU noise, on the other hand, is an undesired by-product resulting from APU operation. Unlike the main engine, this noise is not regulated by regulating authorities such as the FAA (Federal Aviation Authority), however, it is of major concern for personnel working around the aircraft, as well as from the point of view of noise pollution at the airport terminal. Therefore, local authorities at the airport may restrict the duration of its operation [20].

This study is conducted on Cranfield University's B737-400 aircraft APU which is a turboshaft engine (high-level schematic presented in Figure 3-1). The power section 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. The compressor and turbine are mounted on the same shaft which rotates at a constant speed of 63830 rpm for all operating and loading conditions. The APU shaft also rotates a load compressor which generates pressurized air for the aircraft pneumatic system as per the demand. The bleed air from the APU is delivered to the Environmental Control System (ECS), wing anti-ice system, or to the pneumatic starter of the main engines. A set of inlet guide vanes (IGV) control the amount of air entering the load compressor and hence to the pneumatic system. During the initial phases of start-up, the IGV remains closed but is then allowed to open by 22° to prevent compressor surge. The surge control valve (SCV) is another important component of the APU's pneumatic system. The SCV is controlled by the surge valve torque motor (SVTM) and allows the pressurized air from the load compressor to be rejected into the exhaust system to avoid compressor surges. The overall operation of the APU is controlled by a Full Authority Digital Engine Controller (FADEC) which is installed in the cargo compartment. This unit monitors the state of the system and generates commands for the fuel torque motor, SVTM, and IGV actuator.

3.1.2 Scope of Work

The focus is on the development of the far-field noise estimation model for an aircraft APU. At the heart of this model are the thermodynamic principles which govern the operation of a gas turbine and allows computation of the unknown thermodynamic parameters. The results are then coupled with appropriate component-level semi-empirical noise estimation relationships. The effect of ground reflections is analytically derived and embedded in the model. The overall model is developed in MATLAB's Simulink environment by using the approach described in Section 3.2. The model's accuracy is ascertained using the experimentally acquired dataset (Section 3.3). The overall approach allows the rapid development of a robust model that can accurately estimate the far-field

noise under a wide range of operating conditions. It can be further enhanced to perform fault injection in APU components, modelling transient response, and component-level noise sensitivity analyses (Section 3.4).

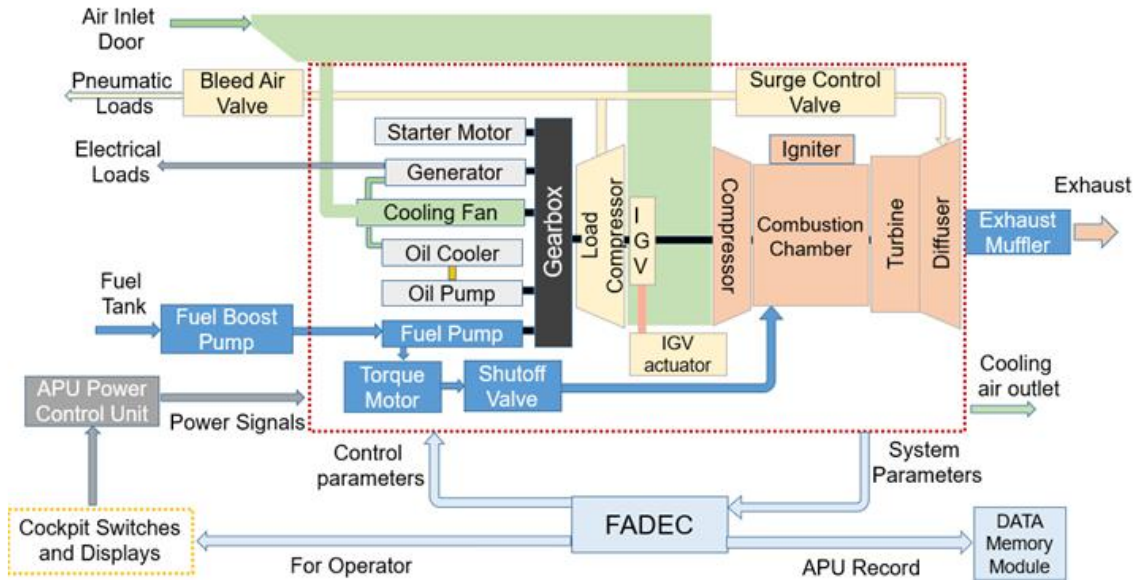


Figure 3-1 Schematics of the adopted APU

3.2 Proposed Methodology

The methodology for the development of a far-field noise estimation model is presented in Figure 3-2. This is a novel approach that systematically considers all necessary aspects of the far-field noise under a wide range of operating conditions. The process begins with the acquisition of far-field noise and thermodynamic data from the aircraft APU. The latter is processed using a custom-built thermodynamic model for estimating the unknown parameters. The model is build using Toolbox for the Modelling and Analysis of Thermodynamic Systems (T-MATS), which operates in MATLAB's Simulink environment. In parallel, frequency domain analysis is carried out on the noise data for identifying the prominent sources, enabling the selection of the appropriate noise models. Source separation technique using similarity spectrum is then applied to separate the component-level noise from the experimental far-field noise data. The acquired, separated noise levels serve as the reference values for the noise estimation models. Subsequently, component-level noise estimation models are implemented, which take thermodynamic parameters as input while also

accounting for the effect of ground reflections. Eventually, the deviation between the estimated component-level noise and the reference values is determined in order to estimate the total noise. In the subsequent paragraphs, a detailed description of the individual sections of the methodology is elaborated.

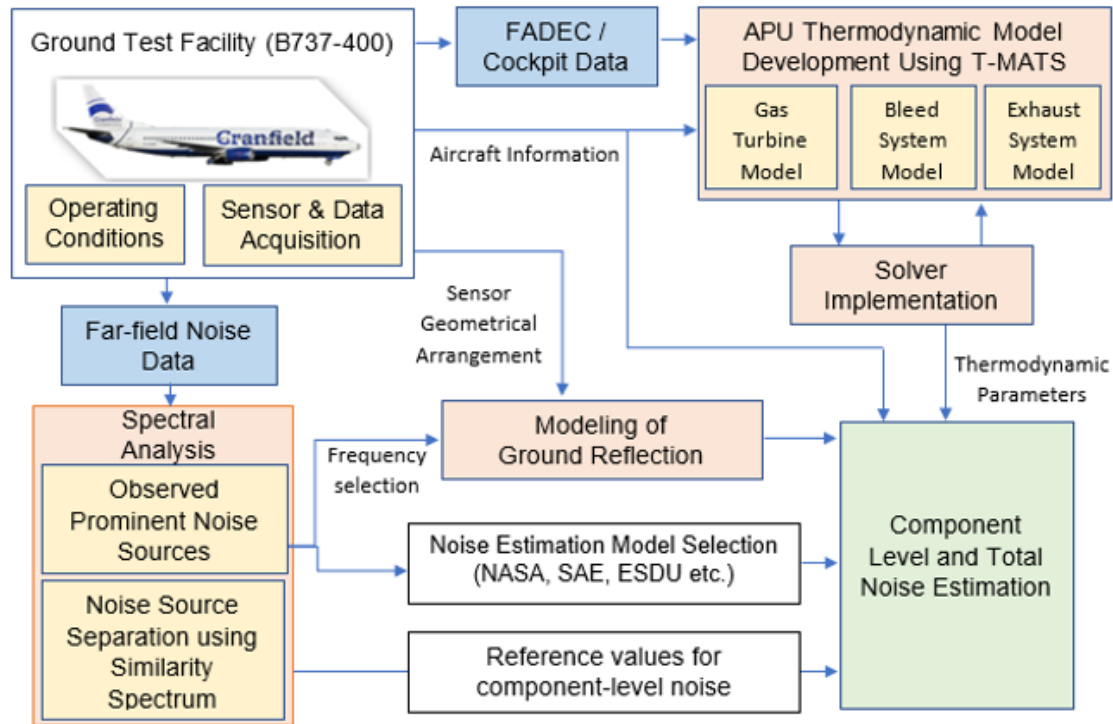


Figure 3-2 Far-field noise model development methodology for an Aircraft APU

3.2.1 Experimental Setup

The overall arrangement for acquiring the necessary data is depicted in Figure 3-3. The acoustic data is collected by a 130F20 ¼" microphone (M1) and is relayed to the Data Acquisition (DAQ) using the NI Integrated Electronics Piezo-Electric (IEPE) module. M1 is at a radial distance of 9.5m and is placed on the concrete taxiway. The figure also shows 3D arrangement of the sensor with respect to the jet axis. The position of the sensor is at an angle of 60° from the jet axes and is selected because it has been reported that the noise from gas-turbine engines has maximum directivity around this angle [20], [21]. Furthermore, the microphone is placed on the left side of the fuselage so that the inlet noise (if any) is masked by the fuselage structure. The microphone is covered with a windscreen to reduce the effects of wind on acoustic measurement. In addition

to the sensor, two cameras are installed in the aircraft (see Figure 3-3). One camera is placed in the cargo compartment, which records the thermodynamic parameters presented by the FADEC display. This display conveys information about the rpm, inlet pressure/temperature, EGT, and positions of IGV / SCV. Another camera monitors the activities inside the cockpit. The videos from both sources are timestamped for synchronization. During one of the test runs, a thermocouple was held at the exhaust to measure the temperature at the exit of the exhaust muffler.

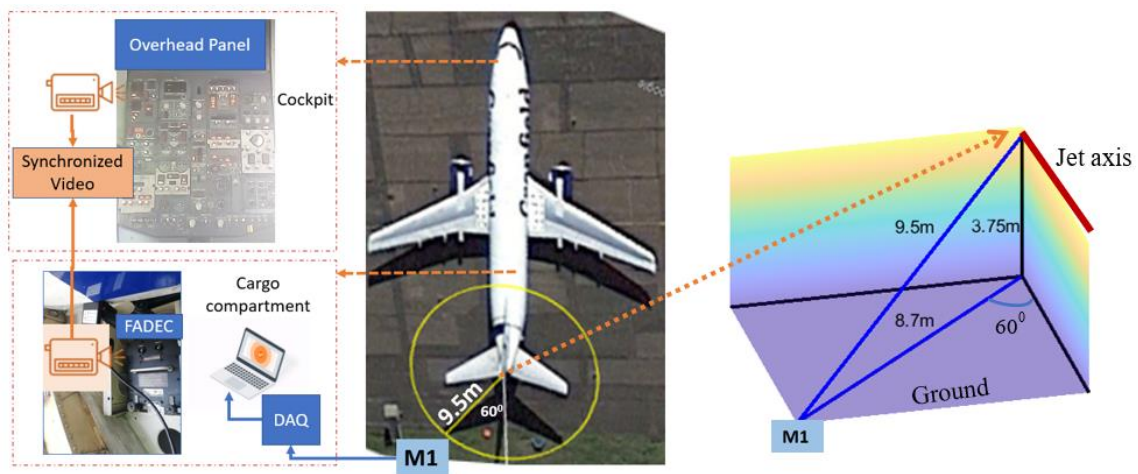


Figure 3-3 Acquisition of experimental data from Boeing 737-400 Auxiliary Power Unit

The methodology requires data collection under a wide range of APU operating conditions. For the successful implementation of this study, the overall data is acquired at 8 different APU operating conditions (C1, C2,...C8), and is repeated for 8 different days, resulting in a total of 64 datasets (see Figure 3-4). The test conditions represent various combinations of electrical and pneumatic load, some conditions have been intentionally duplicated (for example C4 and C7, both correspond to bleed on with no load). This is done so that any variation in the parameters due to the prolonged duration of APU operation can be captured within the data collection. For example, C2 and C8 are both no-load conditions (Bleed off and 0A electrical load), however, a slight change in oil temperatures is present between these two conditions, which can have a very small effect on the fuel consumption at these two conditions. Furthermore, by increasing the number

of data points, a certain trend in the unknown parameters can also be ascertained. Data collected at a particular condition on a specific day is termed as a Dataset (for example 1,9,17... represent the data collected on day 1). At each dataset, part of the thermodynamic parameters (observable through the FADEC) is acquired. With regards to the microphone data, a one-second interval is selected that is converted into SPL values (termed as $SPL_{Measured}$). All the values of the dataset at a given operating condition have been accumulated for boxplot analysis and for observing the overall trend in the data. However, the values at the dataset level have been used to compare the accuracy of the noise estimation model.

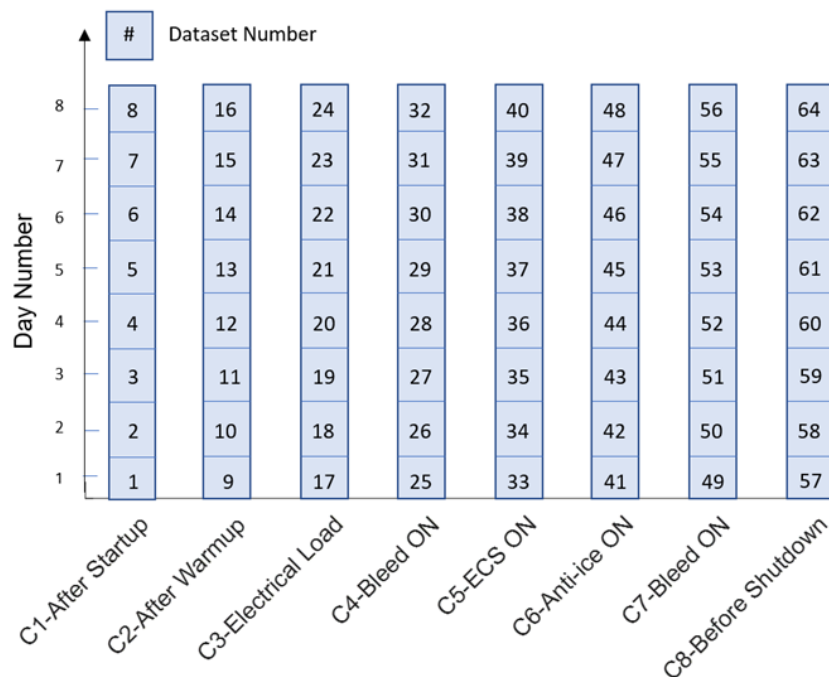


Figure 3-4 APU operating conditions and representation of experimental datasets

3.2.2 APU Thermodynamic Model Development

The onboard APU FADEC display provides limited technical data (e.g. thermodynamic data) to efficiently support the implementation of the adopted empirical noise estimation models. Therefore, a customized gas turbine simulation model is developed using Toolbox for the Modelling and Analysis of Thermodynamic Systems (T-MATS) turbomachinery components (compressor,

turbine, shaft, and a burner) (see Figure 3-5). The symbols used have been listed in the start of the thesis.

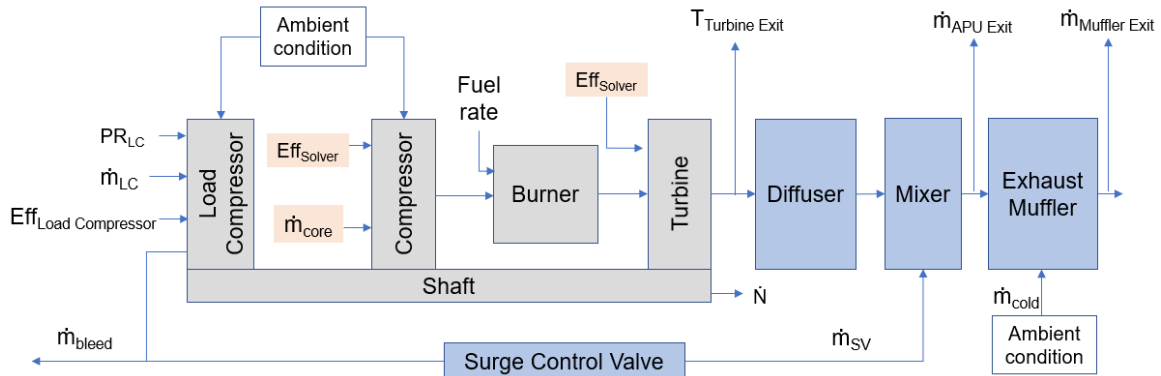


Figure 3-5 APU Model developed in T-MATS

T-MATS is an open-source Simulink-based plugin developed by NASA Glenn Research Centre, which can be utilized by industry personnel or academics without any restrictions. T-MATS allows the development of a customized gas turbine using modular turbomachinery components, which can be analyzed in detail by integrating the model with the software-provided iterative solvers. The research community has frequently used T-MATS for simulating the performance of gas turbines ([1], [22], and [23] are some of the examples), but it has not been adopted for noise modelling purposes.

Since T-MATS is a Simulink-based platform, it allows customized code to be integrated to compute other parameters as per the requirements and to execute the model under different operating conditions. The T-MATS component blocks can be altered to execute in the absence of performance maps that are proprietary to the manufacturer. The thermodynamic model is the core part of the overall methodology and mimics the behaviour of various sections of the APU, that can influence the far-field noise. So, customized code is integrated with the T-MATS blocks to model the Surge Control Valve, Mixer, and Exhaust Muffler.

To simplify the model, the following assumptions have been made:

- (a) The compressor and turbine (mounted on the same shaft) have the same pressure ratio under all operating conditions and are assumed to be equal to the

maximum pressure ratio acquired through FADEC corresponding to the load compressor.

- (b) Mixing is adiabatic at the mixer and the muffler.
- (c) The compressor and turbine operate on a similar isentropic efficiency for a given operating condition. The load compressor efficiency ($Eff_{Load\ Compressor}$) is assumed to be proportional to the IGV position.
- (d) The changes in the air temperature downstream of the surge valve are negligible.
- (e) The surge control valve linearly controls the mass flow as a function of SVTM current (I_{SVTM}) acquired from the FADEC readings ($\dot{m}_{SV} \propto I_{SVTM}$).
- (f) For Muffler, the value for $\dot{m}_{Cold}$ is a factor (F) of $\dot{m}_{APU\ Exit}$, such that the exit temperature matches the measured muffler exit temperature. This approach is based on the work performed in [24].
- (g) The total pressure at the muffler and diffuser exit is equal to ambient conditions.
- (h) The efficiency of the electrical generator is chosen to be 95%, whereas for the burner it is assumed to be 99% (supported by [25] and [26]).

3.2.3 Solver Implementation

This section will explain the process by which the unknown engine parameters are estimated using the T-MATS provided solver. At each operating condition, the parameters of the APU model are updated using experimental test data. The T-MATS solver is then implemented to iteratively update core mass flow, and component efficiencies in order to meet the following set of conditions (see Figure 3-6):

- (a) The computed EGT at the turbine outlet is equal to the value measured by the FADEC. Meeting this condition ensures that the solver meets the experimentally determined value for the EGT.

- (b) The total pressure at the output of the diffuser should be equal to the ambient pressure.
- (c) The net torque on the shaft is zero, which means that the torque produced by the turbine equals the sum of torques required by the compressors and the generator. This condition leads to no change in the rpm ($\dot{N} = 0$).

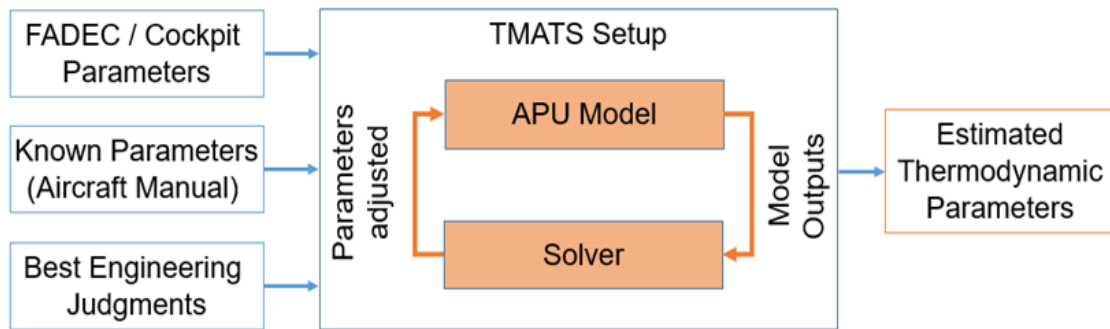


Figure 3-6 Thermodynamic parameter estimation using T-MATS

3.2.4 Spectral Analysis of Far-field Noise

This study identifies the optimum combination of noise models that can provide acceptable levels of accuracy for far-field noise estimation from an APU. Combustion (or core) noise models and jet noise models are considered since the combination of these two models provided meaningful results. The compressor noise generally propagates towards the inlet which is not the focus of this study. Moreover, compressor blade pass frequency is not present in the far-field noise spectra. Noise is also generated by the turbine, but it is assumed that it is attenuated by the exhaust muffler to an extent that it is overwhelmed by the broadband jet noise. This has been experimentally verified by observing the frequency content of the acquired far-field data [Figure 3-7(a) (frequency spectrum in blue colour) shows the non-existence of prominent noise around the turbine blade pass frequency of 14.89 kHz].

3.2.5 Noise Source Separation Using Similarity Spectrum

This section focuses on describing the methodology that has been adopted in separating the noise sources from experimental data. The approach relies on the assumption that the far-field noise from the APU consists of combustion and jet

noise only. With this assumption, spectral analysis has been carried out on the raw data. Initially, power spectrum $S(f)$ is acquired using MATLAB's *pspectrum* function, which is then converted in SPL values using the following relationship:

$$SPL(f) = 20 \log \left[\frac{S(f)}{20 \times 10^{-6}} \right] \quad (3-1)$$

The power spectrum is then compared with the similarity spectrum which has been specified to be the characteristic of combustion noise. This spectrum has been reported in the literature [21], [27] and shown to be significantly contributing towards the overall noise at low frequencies (<2 kHz). As per [22], the spectral shape $[SS(f)]$ can be reproduced by using the following relationship:

$$SS(f) = -16 \log [(0.003037 f)^{1.8509} + (0.002051 f)^{-1.8168}] \quad (3-2)$$

An offset value is then computed that would reduce the mean difference between $SPL(f)$ and $SS(f)$ for frequencies less than 2 kHz. The complete process would lead to a situation depicted in Figure 3-7(a) which shows the power spectrum of far-field acoustic data from APU in bleed-off condition with the similarity spectrum superimposed on it. The same process is shown for the bleed on condition and the results are shown in Figure 3-7(b).

From this analysis, combustion noise is estimated to be equal to the power contained in the similarity spectra if it is lower or equal to the spectral power of the acoustic data in the same frequency range. If the similarity spectrum becomes greater, only the power inside the raw acoustic data is taken. For computing the power, MATLAB's *pwelch* function is used which can provide the spectral power for a given range of frequencies [28]:

$$P_{1,2} = \int_{f_1}^{f_2} P_{yy}(f) df \approx \sum_{i_1}^{i_2} P_{yy}[i] \quad (3-3)$$

Where, P_{yy} is the frequency transform computed using *pwelch* function and i_1 and i_2 are the indexes of frequencies related to the combustion noise. $P_{1,2}$ is the RMS value of the required combustion noise. The remaining part of the noise (assumed to be the jet noise) is computed by subtracting the combustion noise

from the total power contained in the acoustic signal. The complete process is performed for all 64 instances and the results are presented in Section 3.3. The noise sources separated in this manner is termed as $SPL_{Jet(i)}^{experimental}$ and $SPL_{Combustion(i)}^{experimental}$, where 'i' is the dataset number at which they are calculated.

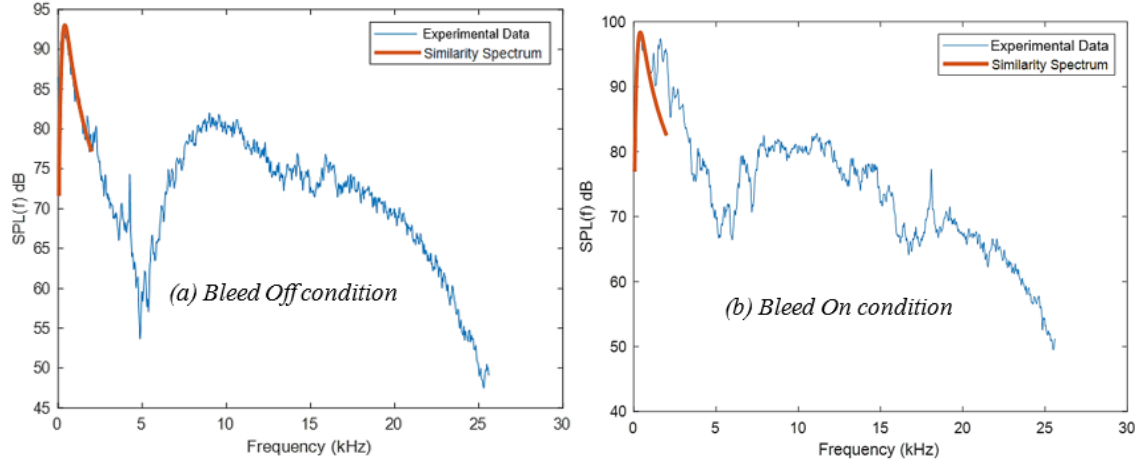


Figure 3-7 Power Spectrum of far-field acoustic data with similarity spectrum superimposed

3.2.6 Component Level Noise Estimation Model Implementation

Various noise estimation models are available which can estimate noise generated at the component level or by treating the gas turbine as a single component. These models can range from empirical / semi-empirical relationships to more complex physics-based numerical solutions. The latter approach is time-consuming, bears a high computational cost, and demands a detailed level of system design and geometry parameters, these are generally propriety information limited to the manufacturer only. On the other hand, the semi-empirical relationships provide a rapid computation of noise parameters from engine components based on thermodynamic and geometric parameters. These models are continuously evolving and being updated based on the acquired experimental data, however, specifically in the case of APU, they have not been reported to be validated against the actual aircraft data under various load conditions. As per the spectral analysis, combustion and jet noise are the

major constituents in the experimentally acquired far-field noise. Therefore, only these two components is estimated by adopting two different models.

3.2.6.1 Jet Noise Estimation Models

For jet noise estimation, the Engineering Sciences Data Unit (ESDU) model has been utilized because it is said to be valid for lower jet velocities, as in the case of an APU. The acoustic power is proportional to the jet density, velocity, and diameter, and is given by [29],

$$W_{Jet} \propto \frac{\rho_{Jet} v_{Jet}^8 D_{Jet}^2}{c_0^5} \quad (3-4)$$

This relationship incorporates the core variables on which the jet noise power is dependent. However, information about the proportionality constant and the Directivity Index is not provided in [30]. In order to convert W_{Jet} into SPL_{Jet} at a particular angle θ and distance 'r' Eq. (3-4) becomes,

Jet Model 1

$$SPL_{Jet-Model-1} = 10 \log \left[\frac{K_{Jet-model-1}^{empirical} \rho_{Jet} v_{Jet}^8 D_{Jet}^2}{c_0^5 10^{-12}} \right] + 10 \log \left[\frac{Q_{Jet}}{4 \pi r^2} \right] + DI(\theta)$$

Or,

$$\begin{aligned} SPL_{Jet-Model-1} &= 10 \log \left[\frac{\rho_{Jet} v_{Jet}^8 D_{Jet}^2}{c_0^5 10^{-12}} \right] \\ &+ 10 \log \left[\frac{Q_{Jet}}{4 \pi r^2} \right] + 10 \log [K_{Jet-model-1}^{empirical}] + DI(\theta) \end{aligned} \quad (3-5)$$

Let,

$$c_{Jet-Model-1} = 10 \log [K_{Jet-model-1}^{empirical}] + DI(\theta) \quad (3-6)$$

The term $c_{Jet-Model-1}$ would remain the same for all the conditions, since θ and the system under study will not be changing. Since the underlying values for

$c_{Jet-Model-1}$ are not known, initially, the SPL values are computed in the absence of $c_{Jet-Model-1}$:

$$SPL_{Jet-Model-1}^{Basic} = 10 \log \left[\frac{\rho_{Jet} v_{Jet}^8 D_{Jet}^2}{c_0^5 10^{-12}} \right] + 10 \log \left[\frac{Q_{Jet}}{4 \pi r^2} \right] \quad (3-7)$$

Once $SPL_{Jet-Model-1}^{Basic}$ values are obtained, $c_{Jet-Model-1}$ is estimated by computing the mean offset between $SPL_{Jet-Model-1}^{Basic}$ and $SPL_{Jet(i)}^{experimental}$, that is:

$$c_{Jet-Model-1} = \frac{1}{n} \sum_{i=1}^n [SPL_{Jet}^{experimental}(i) - SPL_{Jet-Model-1}^{Basic}(i)] \quad (3-8)$$

Where ‘i’ is the dataset number and ‘n’ is the total number of observations made during the experimentation (n=64). Eventually, Jet Model 1 response is computed by using the following relationship:

$$SPL_{Jet-Model-1} = SPL_{Jet-Model-1}^{Basic} + c_{Jet-Model-1} \quad (3-9)$$

Another model for jet noise estimation is also considered. This model is acquired from [21] which describes the acoustically radiated jet noise power to be dependent on the jet’s mechanical power and its simplified version is given by:

Jet Model 2

$$SPL_{Jet-Model-2}^{Basic} \quad (3-10)$$

$$= 10 \log \left[C \frac{T_{Jet}^9}{T_{Amb}^2} \frac{\dot{m}_{Muffler Exit}^8}{P_{Amb}^7} \right] + 10 \log \left[\frac{Q_{Jet}}{4 \pi r^2} \right] \\ + 10 \log [K_{Jet-model-2}^{empirical}] + DI(\theta)$$

Where the term C comprises of several constant parameters,

$$C = \frac{\pi D_{Jet}^2 R^7}{c_0^5 A_{Jet}^8 8 \times 10^{-12}}$$

And, $K_{Jet-model-2}^{empirical} = 5 \times 10^{-5}$ for subsonic jets [20]. Since this model is also being evaluated for an APU first time, its deviation from the reference values is recorded and corrections are made in the model's output, that is:

$$SPL_{Jet-Model-2} = SPL_{Jet-Model-2}^{Basic} + c_{Jet-Model-2} \quad (3-11)$$

Where, $c_{Jet-Model-2}$ is computed in the same manner as in Eq. (3-8). This constant will accommodate for the differences between the model results and the experimental data.

3.2.6.2 Combustion Noise Estimation Models

For the combustion noise estimation, SAE [21] and NASA [30] models are separately implemented. The SAE combustion model only relies on the thermodynamic parameters, whereas NASA's model also incorporates the geometrical parameters [Eq. (3-13) and (3-12)].

Combustion Model 1

$$SPL_{C-Model-1}^{Basic} = 10 \log \left[\frac{\dot{m}_{Core}^4 T_{Turbine Inlet}^2 F_b^2 4F}{A_b^2 P_3^2 N_f (1+F)^2} \left[1 + \frac{H_f F_{st}}{c_p T_3} \right]^2 \right] \quad (3-12)$$

$$+ 10 \log \left[\frac{Q_{Combustion}}{4 \pi r^2} \right] + DI(\theta) + 131.3$$

Where,

$$F = \frac{P_{Turbine Inlet}}{P_{Amb}} \sqrt{\frac{T_{Amb}}{T_{Turbine Inlet}}}$$

Combustion Model 2

$$SPL_{C-Model-2}^{Basic} = 10 \log \left[\frac{\dot{m}_{Core} c_0^2 \left(\frac{T_{Turbine Inlet} - T_3}{T_{Turbine Inlet}} \right)^2}{10^{-12}} \left(\frac{P_3}{P_{Amb}} \right)^2 \left(\frac{T_{Turbine Inlet} - T_{Turbine exit}}{T_{Amb}} \right)^{-4} \right] \quad (3-13)$$

$$+ DI(\theta) - 60.5 + 10 \log \left[\frac{Q_{Combustion}}{4 \pi r^2} \right]$$

The Directivity Index (DI) in the above equations covers the variation in sound levels due to the angular placement of the sensor with respect to the source. This index is generally presented in tabulated form and the value is noted for $\theta = 60$ degrees to the jet axis. Furthermore, 'r' is the radial distance between the exhaust and the microphone.

Similar to the approach adopted for the jet noise models, the original form of the combustion noise models is implemented and their results are compared against $SPL_{Combustion}^{experimental}$ for possible offset computation. The corrected SPL values would become:

$$SPL_{C-Model-X} = SPL_{C-Model-X}^{Basic} + c_{C-Model-X} \quad (3-14)$$

Where,

$$c_{C-Model-X} = \frac{1}{n} \sum_{i=1}^n [SPL_{Combustion}^{experimental}(i) - SPL_{C-Model-X}^{Basic}(i)] \quad (3-15)$$

$x = 1$ or 2 for Combustion noise model 1 and 2 respectively, 'i' is the dataset number and $n = 64$.

Ideally, the constants $c_{Jet-Model-2}$, $c_{C-Model-1}$ and $c_{C-Model-2}$ should be zero, which would mean that the predicted results exactly match the measured values for the exhaust noise. However, this situation is unlikely to occur since these models are being evaluated for an aircraft APU for the first time, and there can be various inaccuracies inherent with the models, the directivity index, and the estimated thermodynamic parameters.

3.2.7 Modeling of Ground Reflections

A term Q is also embedded in the noise estimation models, that relate to the change in the sound levels due to the multi-path propagation of the sound. This term should take into consideration a number of factors that can affect the acoustic noise levels reaching the sensor. To find a relationship between those

parameters, the reflection process is analytically studied, and an equation is subsequently derived.

Consider a source of noise $s(t)$ and its corresponding reflection reaching the microphone after Δt seconds,

$$s_{rec}(t) = s(t) + c_{refl} s(t - \Delta t) \quad (3-16)$$

Where, c_{refl} is the average value of the reflection coefficient of the surface. The frequency-domain representation would be:

$$\begin{aligned} s(t) + c_{refl} s(t - \Delta t) &\rightarrow X(f) + c_{refl} X(f) e^{-j2\pi f \Delta t} \\ X(f) + c_{refl} X(f) e^{-j2\pi f \Delta t} &= X(f) [1 + c_{refl} e^{-j2\pi f \Delta t}] \end{aligned}$$

The second term in the above equation will modify the amplitude of the $X(f)$, and is termed as Q ,

$$Q = E |1 + c_{refl} e^{-j2\pi f \Delta t}| \quad (3-17)$$

Where E is the expected value operator. The above equation and its corresponding time-domain signal becomes,

$$X(f) Q \rightarrow Q s(t)$$

This means that the addition of an indirect source of noise due to the ground reflection would modify the amplitude of the signal in the time domain. In order to compute the factor Q , the expected value of $|1 + c_{refl} e^{-j2\pi f \Delta t}|$ is computed in the following manner,

$$\begin{aligned} |1 + c_{refl} e^{-j2\pi f \Delta t}| &= |1 + c_{refl} \cos(2\pi f \Delta t) - j c_{refl} \sin(2\pi f \Delta t)| \\ &= \sqrt{(1 + c_{refl} \cos(2\pi f \Delta t))^2 + c_{refl}^2 \sin^2(2\pi f \Delta t)} \\ &= \sqrt{1 + c_{refl}^2 + 2 c_{refl} \cos(2\pi f \Delta t)} \end{aligned}$$

So, Eq. (3-17) becomes,

$$Q = \int_{f_1}^{f_2} \sqrt{1 + c_{refl}^2 + 2 c_{refl} \cos(2 \pi f \Delta t)} p(f) df$$

The probability density function $p(f)$ is uniform and is given by $p(f) = \frac{1}{f_2 - f_1}$, so

$$Q = \frac{1}{f_2 - f_1} \int_{f_1}^{f_2} \sqrt{1 + c_{refl}^2 + 2 c_{refl} \cos(2 \pi f \Delta t)} df \quad (3-18)$$

And,

$$s_{rec}(t) = s(t) \frac{1}{f_2 - f_1} \int_{f_1}^{f_2} \sqrt{1 + c_{refl}^2 + 2 c_{refl} \cos(2 \pi f \Delta t)} df \quad (3-19)$$

According to the above relationship, the received signal's amplitude is modified by a factor that is dependent on the value of the reflection coefficient, the time delay between the direct and indirect source of the sound, and the selected frequency range. This relationship has been utilized for estimating the term Q and the results have been presented in Section 3.3.3.

The total sound pressure level at location M1 is due to the contribution of the combustion and the jet noise. The addition of these noise sources is assumed to be non-coherent and is given by,

$$SPL_{Total} = 10 \log[10^{0.1 (SPL_{C-Model-X})} + 10^{0.1 (SPL_{Jet-Model-Y})}] \quad (3-20)$$

Where X and Y can be either 1 or 2 depending on the selected model.

3.3 Results and Discussion

This section presents the outcomes of the developed noise estimation methodology which has been successfully implemented for the assessment of the B737 APU far-field noise. The focus has been on the development of a thermodynamic model and its integration with the appropriate semi-empirical relationships for noise estimation. The former category of modelling can be treated independently and therefore its results is presented first. The rationality of the results have been discussed based on the available literature and physics-

based principles. The remaining part of the result section will present the outcomes of the noise estimation model. The acquired estimates are compared with the component level noise extracted using the frequency-domain technique. Finally, the total noise estimation models' results are presented and corroborated against the experimental data.

3.3.1 APU Thermodynamic Model Results

In this section, the acquired results from the thermodynamic simulation model are discussed which allow systematic assessment of the APU thermodynamics performance characteristics under a wide range of operating conditions (i.e. C1 – C8). To start with, the solver is converging to a point where all the constraints are met for all the 64 instances of the dataset. Convergence is reached as the solver iterates through various combinations of core mass flow and component efficiencies so that the measured EGT is reached, there is no shaft acceleration and the pressure at the diffuser exit equals the ambient pressure. The turbine inlet temperature is predicted to be a maximum at the bleed on conditions, shown in Figure 3-8, with the values reaching as high as 816 °C. As per [31], radial turbines can withstand such a level of temperatures for prolonged durations of operation. The acquired efficiency values (assumed to be maintained equal for both the compressor and the turbine) are estimated to be realistic for radial-type compressors and turbines [32] (Figure 3-9).

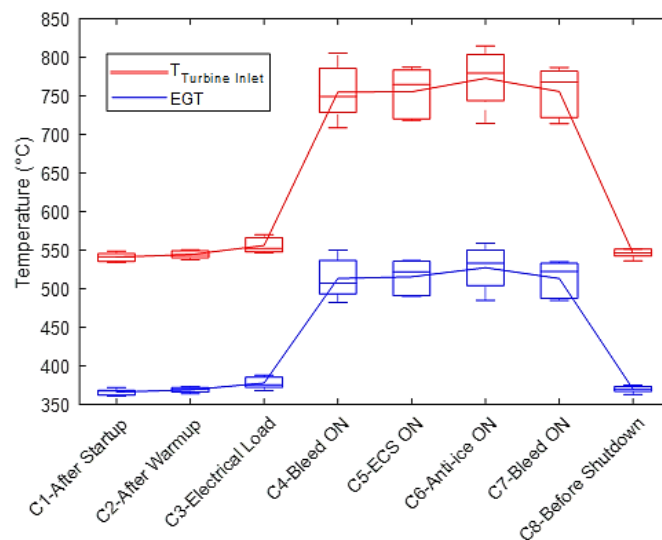


Figure 3-8 Measured EGT and estimated values of Turbine Inlet Temperature

The thermodynamic results presented so far have been focused on the validity of various parameters related to the core of the APU, and are found to be acceptable, as they adhere to the first principles and engineering of the APU design and operation. In addition to the core parameters, the mass flow values corresponding to the surge control valve and the aircraft pneumatic system must also be determined and assessed. These two parameters are presented in Figure 3-10.

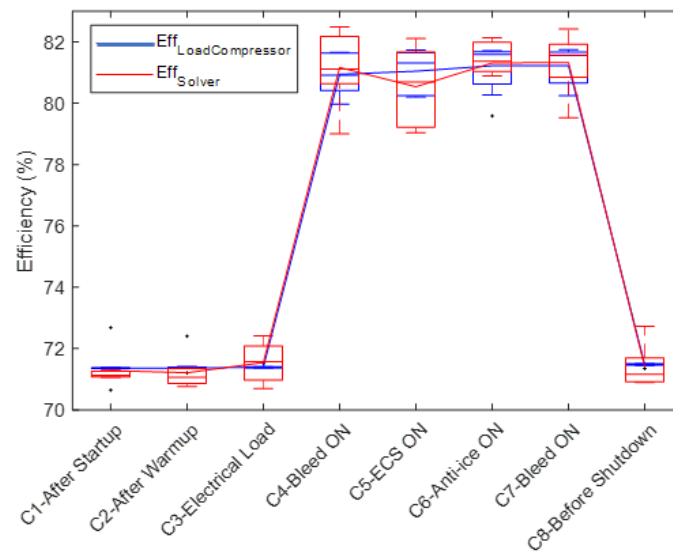


Figure 3-9 Component efficiencies for different operating conditions

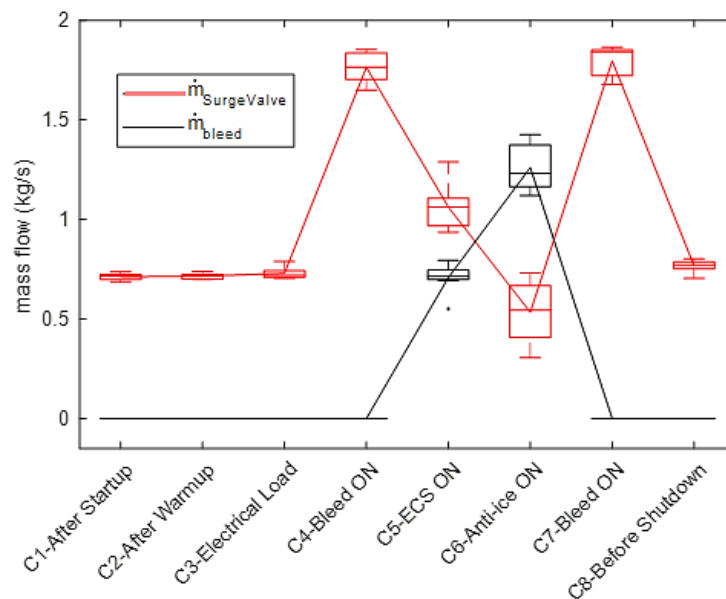


Figure 3-10 Comparison of mass flow through surge and the aircraft pneumatic system

The results for the conditions (C1-C4 and C7-C8) are well estimated by the model, as under these conditions there is no pneumatic load and the entire mass flow generated by the load compressor must flow through the surge control valve. For condition-5 which corresponds to ECS ON, the verification of the mass flow values is carried out based on the data collected from the same aircraft Environmental Control System as part of a sister project [33], [34]. Lastly, the values for C6 are based on the extrapolation of mass flow readings as a function of the surge control valve torque motor current. This produces a maximum flow rate of 1.42 kg/s through the aircraft pneumatic system when the anti-ice system is turned on. As per the aircraft manual, this reading is found to be less than the specified range of the APU bleed system and indicates that more mass flow can be provided by the APU by further closing the surge valve in case of higher pneumatic demand (e.g. main engine start).

3.3.2 Derived APU Thermodynamic Parameters

In this section, various derived thermodynamic parameters are presented that have been computed using thermodynamic principles. The focus is on those parameters that present a strong influence on combustion and jet noise as per the literature. These include core mass flow, combustion inlet temperature, fuel to air ratio, mass flow and temperature across the muffler, and jet exit velocity. Figure 3-11 presents the first three parameters. During the high load conditions, the core mass flow decreases while the fuel to air ratio increases by 58-90% depending on the opening angle of the load compressor IGV. Furthermore, the combustor inlet temperature drops down by 30°C [Figure 3-11(c)] during the full load conditions due to the increasing levels of isentropic efficiency.

With regards to the jet exit velocity, in terms of the APU, this requires an understanding of the mass flowing through the exhaust muffler. The APU exhaust flow is composed of (i) core mass flow, (ii) the flow coming through the surge control valve, and (iii) the cold mass flow added into the exhaust muffler through aspiration, (see Figure 3-5). To begin with, a value of the factor ' F ' has to be computed that controls the amount of the cold flow entering the muffler. The measured values of the muffler exit temperature have been chosen as a

reference to select an appropriate value of F , such that the estimated results closely resemble the measured exit temperature.

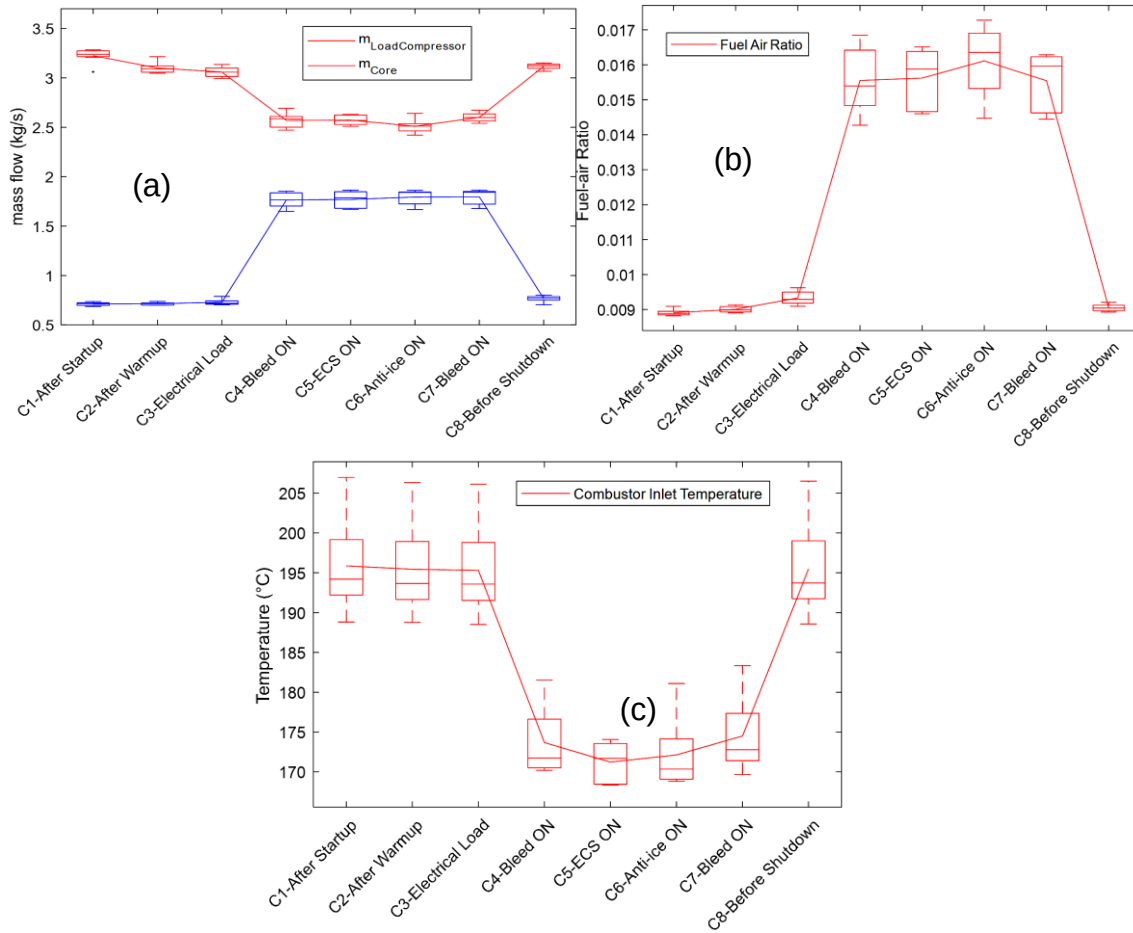


Figure 3-11 Derived engine parameters (a) core mass flow (b) Fuel air ratio (c) Combustor inlet temperature

The measurements of the exit temperature were taken during one of the test runs and are tabulated in Table 3-1. The estimated muffler exit temperature values correspond to 8% of the cold mass flow relative to the muffler inlet mass flow. Across all conditions, the cold mass flow is found to be varying between 0.24 – 0.36 kg/s, as shown in Figure 3-12. The lowest value of $\dot{m}_{core}$ occurs at C6 when there is a drop in $\dot{m}_{SV}$ and $\dot{m}_{core}$. In this condition, the dynamic pressure at the muffler entrance is reduced leading to a higher static pressure as compared to the other conditions. Consequently, the pressure difference across the muffler orifice is reduced, which controls the amount of $\dot{m}_{cold}$ entering the muffler. The

average temperature drop across the muffler due to the mixing of the cold mass flow with the APU hot exhaust flow is observed to be 26°C.

Table 3-1 Comparison of estimated and measured muffler exit temperature

Load Condition	Estimated Muffler Exit Temp (°C)	Measured Muffler Exit Temp (°C)
No Load	293.5	300
Bleed ON	365	360
Anti-ice ON	450.6	450

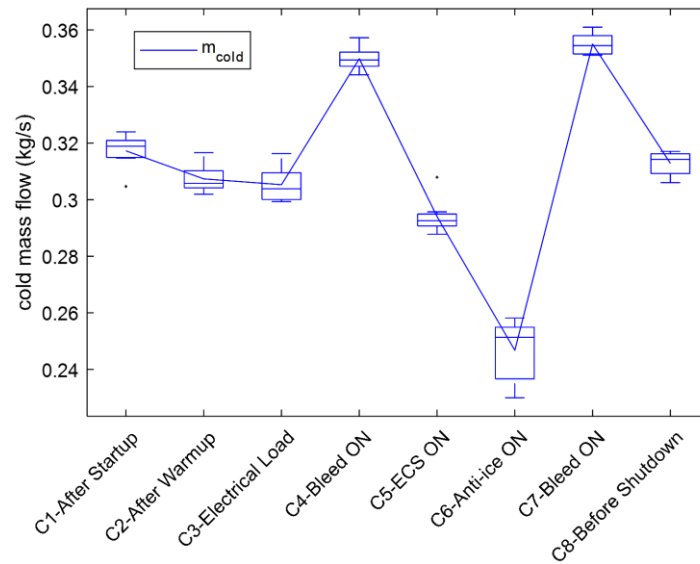


Figure 3-12 Estimated mass flow entering the muffler during various APU operating conditions

Under no-load conditions (C4 and C7), all the mass flow from the load compressor merges with the exhaust gases, thus lowering the temperature at the APU exit. The change in temperatures has an inverse effect on the flow densities. The performance parameters in terms of temperature, mass flow, density, and exit velocity for the APU exhaust and the muffler exit are presented in Figure 3-13. The APU exit temperature is estimated to have a maximum value of 485°C which corresponds to anti-ice on conditions, being the highest demand from the APU. This condition leads to a reduction of mass flow from the APU bleed system (which is at a lower temperature) merging with the APU exhaust

gases from the turbine (Figure 3-10), thus leading to higher values of temperature.

The highest values for the exhaust mass flow and the exit velocity occur for C4 and C7, due to the increased level of mass flow from the load compressor. However, they are reduced when there is pneumatic power demanded from the aircraft (C5 and C6). The addition of a muffler leads to a slight increase in the mass flow and density while reducing the temperature and velocity which is significantly reduced mainly because of the increase in the duct diameter by 25%.

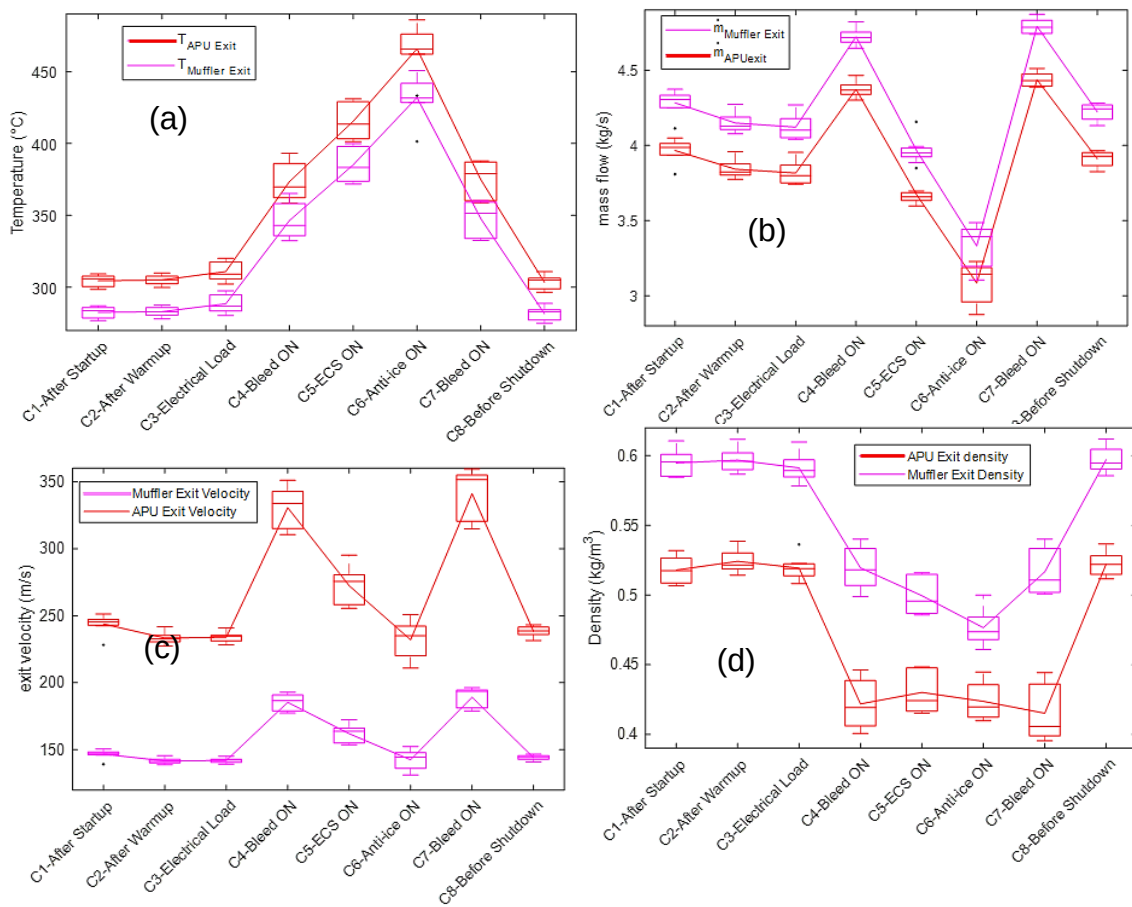


Figure 3-13 Estimated APU and Muffler exit parameters

3.3.3 Component level noise separation results

This section will present the outcomes of the source separation technique applied to the far-field noise data. The complete process has already been described in

Section 3.2.5. Figure 3-14 shows the combustion and jet noise levels obtained from the far-field noise against all the 64 instances.

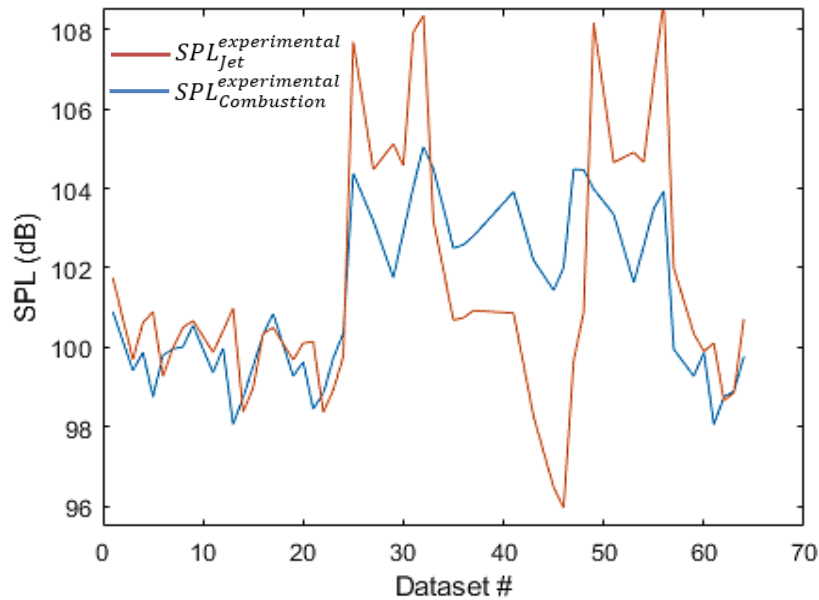


Figure 3-14 Noise source separation results

Following inferences can be made by observing the results:

- (a) The combustion and jet noise are approximately at the same levels when the bleed system is not operational.
- (b) The combustion noise increases when the bleed system is activated. The variation in this noise component within the bleed on conditions (dataset# 25-56) is because the IGVs behaved differently between different days of operation. For the cases where the IGV was fully opening, the fuel rate was observed to be high and correspondingly the combustion noise levels are also high.
- (c) The jet noise also increases with the bleed on conditions. This is because of the additional flow which is generated by the load compressor. This flow is proportional to the IGV opening angles and inversely proportional to the mass flow going through the surge valve. The conditions in which the aircraft pneumatic system is activated, there is a reduction in the flow exiting through the APU exhaust and therefore the jet noise decreases.

3.3.4 Ground Reflection Effects

In this section, the effect of ground reflections has been quantified based on the relationship derived in section 3.2.7. To begin with, an experimental investigation of the far-field showed the presence of multiple equidistant nulls in the frequency spectrum (see Figure 3-15). Such a situation arises when the same source of sound is reaching the receiver through different paths. The far-field microphone has been placed inside a 6.5 cm diameter windscreen which raises the sensor by 3.25 cm above the ground. This seemingly small difference creates a time difference (Δt) of 78 μ s between the direct and the indirect source of noise using the geometrical parameters computed from the experimental setup (see Figure 3-16). The time difference is computed after the values of distances 'a' and 'b' have been computed at which incidence and the reflected angles become equal. For validation of these results, the same Δt has been used to synthetically generate broadband noise and its delayed version for simulating reflections at the microphone. The results are shown in the frequency domain in Figure 3-15 where the location of the nulls for synthetic data coincides with that of experimental data. It can also be seen that for certain frequencies the amplitude increases, whereas around the nulls the effect is opposite. Since the total noise is treated to be a combination of the combustion and the jet noise, a single value of Q is not valid for both and must be dependent on the frequencies of interest and the value of Δt .

To address the effect of ground reflection on the estimates of Combustion and Jet noise, the value of Q is found by solving Eq. (3-18) for the desired set of parameters. The equation is solved numerically by using MATLAB's *integral* function. Two different frequency ranges have been selected to account for the change in amplitudes occurring due to the ground reflections in the radiated combustion and the jet noise. For the former category of noise, frequencies are selected up to 2 kHz since the combustion noise is dominant at those frequencies. For the jet noise, the integral is solved for the whole frequency range (0-25.6 kHz), where the upper limit is determined by the selected sampling frequency. Using these frequency ranges and $c_{refl} = 0.97$ for the frequencies <

2 kHz and $c_{refl} = 0.93$ for the complete frequency range (these values are taken from [35] for concrete surface), the value of Q is computed to be 1.88 and 1.27 for the combustion noise and the jet noise, respectively.

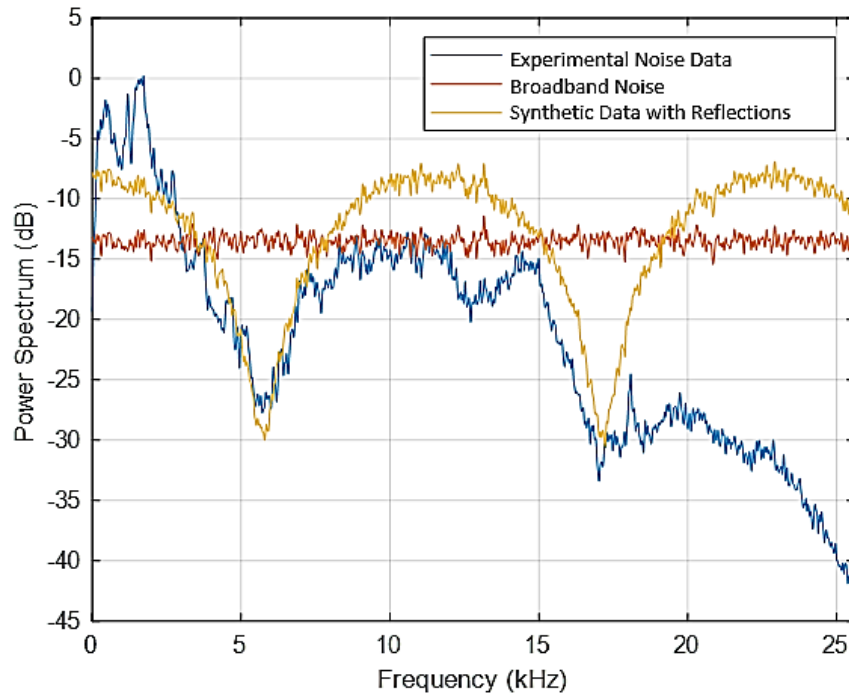


Figure 3-15 Comparison of experimental data and synthetically generated noise data with reflections

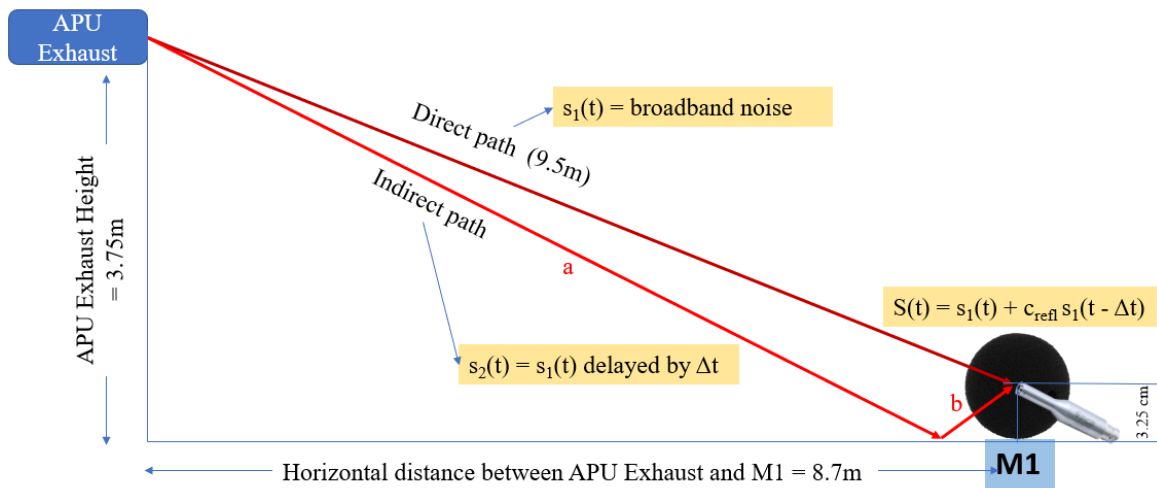


Figure 3-16 Vertical arrangement of the experimental setup and synthetic data generation for simulating ground reflections

3.3.5 Noise Estimation Results

This section presents the acquired results for the APU noise estimation based on the implementation of the approach described in section 3.2. The noise results in this section are presented for all the 64 datasets. Initially, the results of the individual noise estimation models (combustion and jet) are discussed without computing the coefficients $c_{C-Model}$ and $c_{Jet-Model}$ for each of the models. This is done to exclude any of the model(s) which does not corroborate well with the experimental data. Subsequently, those coefficients are computed and lead to the estimation of the total far-field noise.

Considering the combustion noise first, the predicted results are shown in Figure 3-17(a) for all the 64 instances of the dataset. These results are a direct outcome of the model's implementation, without applying the offset correction. As can be observed, the C-Model-2 demonstrates a very different behavior relative to C-Model-1 as well as $SPL_{Combustion}^{experimental}$ (see Figure 3-14), both of which suggest an increase in the combustion noise levels during the bleed on conditions (Dataset # 25-54). Due to the dissimilar behaviour of C-Model-2, it will not be considered for further analysis. One of the reasons for the inappropriate behavior of C-Model-2 can be attributed to the fact that the number of underlying parameters included in the C-Model-2 is limited, and therefore the model is not robust enough to capture the variations taking place inside the combustor under a wide range of APU operating conditions.

The SPL values estimated from the two jet noise models are shown in Figure 3-17(b). These values have been plotted without the offset correction. Both models behave similarly and follow the same pattern as in Figure 3-14. Therefore, both jet noise models have been considered for further analysis and total noise computation. The extremely high value of noise computed from the Jet-Model-1 is because of the lack of information about $K_{Jet-model-1}^{empirical}$ and $DI(\theta)$ for this model.

To align the models' result with the experimental data, Eq. (3-8) and (3-15) has been employed to compute the coefficients $c_{Jet-Model-1}$, $c_{Jet-Model-2}$ and $c_{C-Model-1}$. These offsets are then applied to the basic forms of Jet-Model-1,2

and C-Model-1 so that, on average, their output matches $SPL_{Jet}^{experimental}$ and $SPL_{Combustion}^{experimental}$. C-Model-1 has been found to require the minimum offset ($-0.48dB$). This indicates the overall accuracy of the estimated thermodynamic parameters and suitability of the C-Model-1 for an APU configuration presented in Figure 3-1.

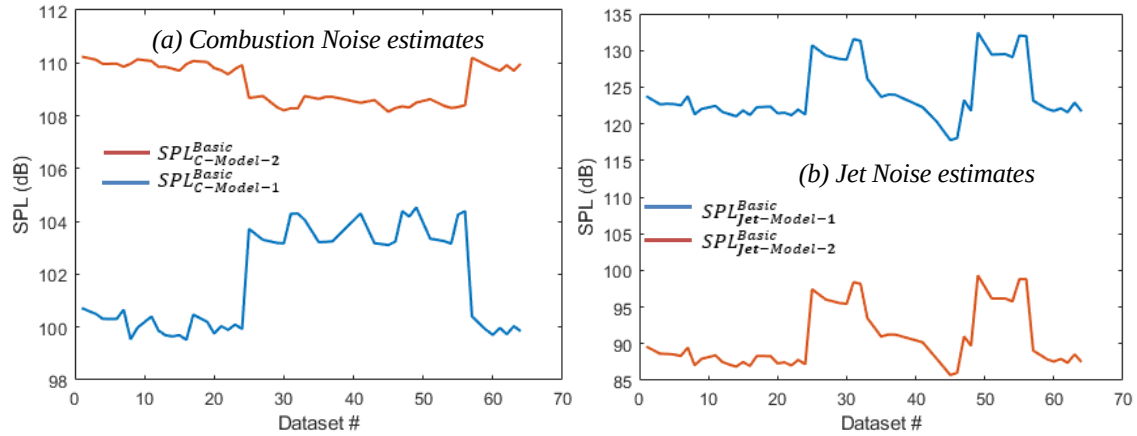


Figure 3-17 Estimated noise levels before offset correction

With regards to the jet noise models, a straightforward comparison between the computed offsets cannot be made. This is because for the Jet-Model-1, the computed offset ($c_{Jet-Model-1} = -23.6dB$ using Eq. (3-8)) covers the missing empirical coefficient and the Directivity Index. Whereas, for Jet-Model-2, the offset ($c_{Jet-Model-2} = 9.96dB$) is the correction to the original model. For comparison, all the empirical coefficients (including the offset for Jet-Model-2) can be combined in the following manner:

Jet-Model-1

$$Net\ effect\ of\ coefficients = c_{Jet-Model-1} = -23.6dB$$

Jet-Model-2

$$Net\ effect\ of\ coefficients =$$

$$10\log[K_{Jet-model-2}^{empirical}] + DI(\theta) + c_{Jet-Model-2} = -26.05dB$$

Where, $K_{Jet-model-2}^{empirical}$ and $DI(\theta)$ are taken from [21]. For both the models, the overall effect of empirical coefficients is similar, and they are within 2.45dB of each other. Figure 18 shows the results of component-level noise estimation after the computed corrections have been applied. The combustion noise estimate can be seen to perform well under all the conditions [Figure 3-18 (a)]. However, for the jet noise, there are discrepancies observed during certain conditions [Figure 3-18 (b)]. The results for the considered models are summarized in Table 3-2. The combustion model produces the most accurate reading with an RMS error of 0.69 dB. However, the jet noise estimates have RMS errors of 1.2dB and 1.52dB for models 1 and 2, respectively. The reason for the slightly higher level of inaccuracy for the jet noise can be attributed to the fact that a very large frequency spectrum (up to 25.6 kHz) is considered where minor contributions can also be taking place from other components which have not been considered. Amongst the jet noise models, Jet-Model-1 performs well than the other.

Table 3-2 RMS and Maximum error for combustion and jet noise estimates

Parameter (dB)	C-Model-1	Jet-Model-1	Jet-Model-2
Max Error	1.44	2.67	3.00
RMS Error	0.69	1.20	1.52

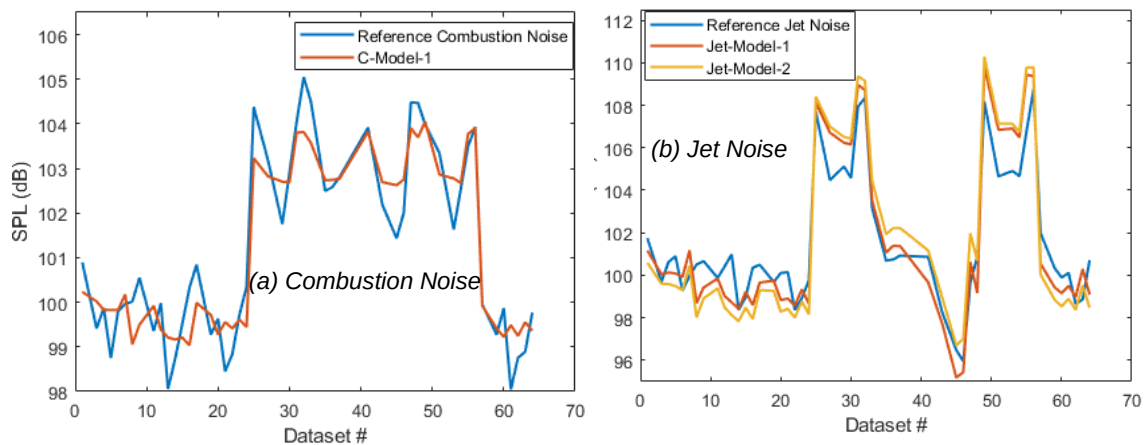


Figure 3-18 Comparison of estimated noise levels after offset corrections

Finally, two sets of models are available for computing the total noise and validating their performance with the experimental data. These models employ Eq. (3-20) and are given by:

Total Noise Model 1 (TNM-1)

$$SPL_{TNM-1} = SPL_{C-Model-1} (+) SPL_{Jet-Model-1} \quad (3-21)$$

Total Noise Model 2 (TNM-2)

$$SPL_{TNM-2} = SPL_{C-Model-1} (+) SPL_{Jet-Model-2} \quad (3-22)$$

Where, (+) represents addition in dB scale.

In Figure 3-19 the total noise level estimates from the (TNM-1 and TNM-2) are presented. The acquired estimated correlate well against the measured noise data ($SPL_{Measured}$) throughout the 64 instances, with the TNM-1 (RMS error = 0.73 dB) being slightly better than its counterpart (RMS error = 0.85 dB). As per the analysis, the maximum deviation for the total noise estimation can be 1.30 dB and 1.56 dB for TNM-1 and TNM-2 respectively.

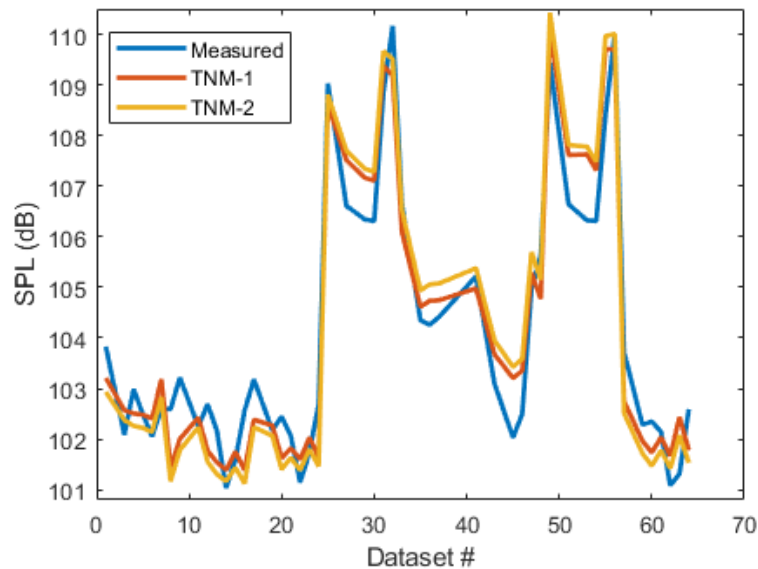


Figure 3-19 Total Noise estimation results

Following inferences can be drawn after observing the results:

- (a) Far-field noise from aircraft APU is dominated by combustion and jet noise. Correct estimation of these two components can allow accurate estimation of the total far-field noise.
- (b) There are a number of semi-empirical noise estimation models available in the literature. However, not all of them could be suitable for the desired category of a gas turbine. Some of these models are either restricted to turbofan engines or they could be applicable to only one state of operation (like take-off condition). Careful selection of these models is needed by comparing the results from various models.
- (c) Accurate modeling of noise propagation is needed along with the estimation models. This model should cater to the decrease in noise power due to spherical divergence, ground reflections (or any other reflections taking place), and the effects of the selected frequency range on the reflections.
- (d) The gathering of a diverse set of APU noise and thermodynamic data by operating the APU in a range of different load conditions, allows the deviation between the model results and experimental data to be detected. This deviation can be used to compute the average value of offset that can bring the model output closer to the experimental data.
- (e) The correctness of the results indicates that the proposed framework is performing well under a wide range of conditions. This also ensures that the various assumptions made during the whole process are acting well within the overall integrated approach.

3.4 Study of Effect of Component Degradation on Far-Field

The developed far-field model has been leveraged to quantify the effect of faults on the APU far-field noise components characteristics. The model makes use of the APU thermodynamic model (developed in T-MATS) and semi-empirical relationships for combustion and jet noise to estimate the SPL value in the far-field for a given operating state. The thermodynamic model is responsible for

estimating the additional set of parameters ($\dot{m}_{core}$, $T_{\text{Turbine Inlet}}$, v_{Jet} , T_{Jet}) from the known parameters (EGT, $\dot{m}_{LC}$, T_{amb} , P_{amb} , APU geometric data, generator current, IGV angle, and FTM value) so that the following developed relationships can be utilized for estimating noise 9.5 m away from the APU exhaust at an angle of 60°.

Further tweaking of the APU thermodynamic model has been done so that it can estimate the desired set of parameters (Fuel flow, EGT, $T_{\text{Turbine Inlet}}$) at a given load condition (which is determined by the IGV angle, demanded pneumatic load ($\dot{m}_{\text{Bleed}}$) and Generator current) and component efficiencies. To achieve this, the components' performance maps have been synthetically generated by deriving relationships for the components' parameters. The developed model has been found to be sufficiently accurate for faults' sensitivity analysis. Figure 3-20 illustrates the accuracy of the model in estimating two of the desired parameters (EGT and Fuel flow rate) for various load conditions. The estimated values correspond well with the true values determined and hence indicate that the model has accounted for the variations taking place due to the change in the operating regimes of the components.

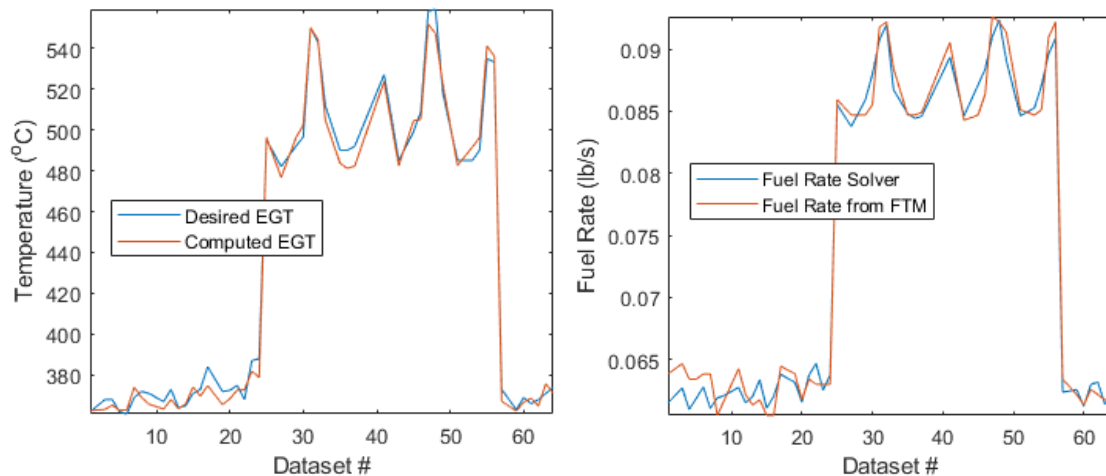


Figure 3-20 Comparison between actual and estimated parameters (EGT and fuel flow rate) for various load conditions

In order to draw a comparison between the thermodynamic and far-field noise parameters in terms of their sensitivity to faults, initially, a healthy baseline is defined (IGV=88°, Generator Current = 70 A, $\dot{m}_{\text{Bleed}} = 0.7$ kg/s at standard

atmospheric conditions without degradations in components efficiencies and load compressor mass flow rate). The model is then executed to compute the reference thermodynamic parameters ($\dot{m}_{Core}$, fuel rate, v_{Jet} , v_{Mach} , T_{Jet} , EGT and $T_{Turbine\ Inlet}$) and noise values (SPL_C , SPL_{Jet} and SPL_{Total}). For this study, several faulty conditions have been simulated, a summary of which is presented in Table 3-3. The considered faulty components include the compressors (load and main), turbine, IGVs and SCV. Case-1 represents 10% reduction in load compressor mass flow as compared to the ideal mass flow, that can arise due to fowling. Cases 2-3 corresponds to 10% reduction in the efficiencies of load compressor, compressor, and turbine respectively. Reduction in IGVs opening angle by 10% (angle = 79.2° instead of 88°) is covered in Case-5, whereas a fault in the SCV is simulated by assuming that the SCV opening angle is not optimum leading to a reduction of $\dot{m}_{Bleed}$ by 10% (0.63 kg/s instead of 0.7 kg/s). A high value of degradation has been selected so that deviation in the noise parameters may be discernible by being more than the error of the developed model (which is around 1%).

Table 3-3 Definition of faulty cases for simulation

Case	Degraded component / fault	Degradation factor (%)
1	Load Compressor mass flow	10
2	Load Compressor Efficiency	
3	Compressor Efficiency	
4	Turbine Efficiency	
5	IGVs	
6	$\dot{m}_{Bleed}$ Reduction	

The results have been accumulated for all the cases and are presented in Figure 3-21. The noise parameters vary slightly ($\sim -1.5\%$ to 1%) even at a high degradation level of 10%, whereas the thermodynamic parameters exhibit a higher value for the same cases (except for case 6 in which only few of the parameters are affected). The highest deviation ($\sim 20\%$) is found to be in the fuel

rate for 10% reduction in the turbine efficiency. EGT and $T_{\text{Turbine Inlet}}$ also display a similar behaviour ($|\text{percentage change}| > 5\%$), however for the remaining parameters ($\dot{m}_{\text{Core}}$, v_{Jet} , v_{Mach} , and T_{Jet}) the change is less than 5%.

Amongst the noise parameters, SPL_{Jet} has been found to be greatly affected by reduction in the $\dot{m}_{\text{LC}}$, because it has a direct effect on the jet velocity and Mach number. IGV reduction also leads to a similar scenario but the SPL_{Jet} is less affected by such a degradation. The increase in the jet noise level can also be observed when $\dot{m}_{\text{Bleed}}$ reduces (Case-6) due to an increase in the mass flow through the surge valve. The combustion noise level is greatly affected by reduction in turbine efficiency, while for the remaining case it is negligible (less than 1%). The overall effect on the total noise levels is also less than 1% for all the cases.

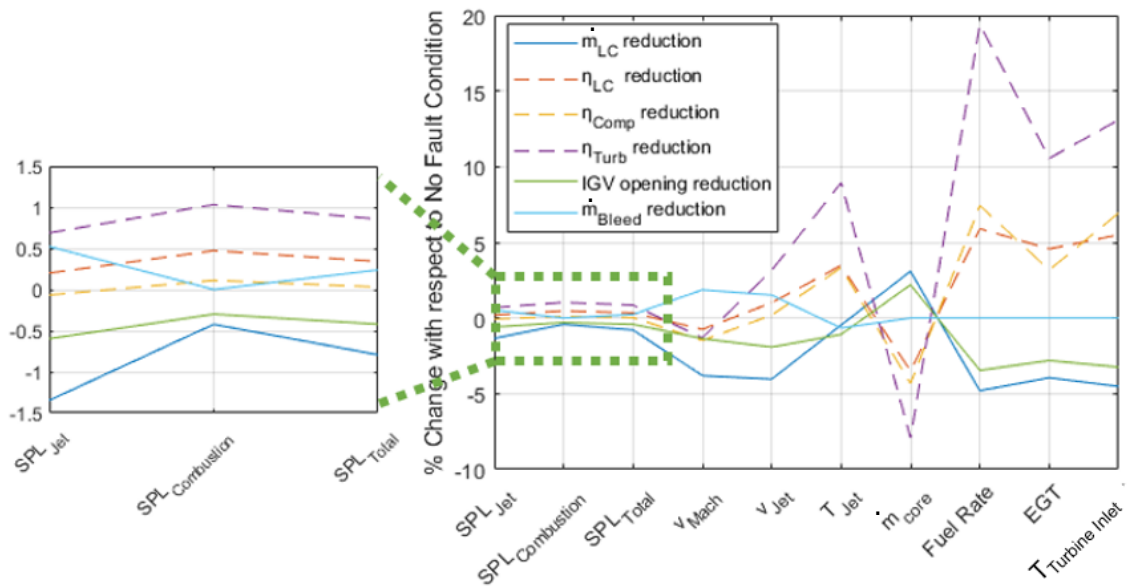


Figure 3-21 Results of faults simulation on thermodynamic and noise parameters

3.5 Conclusion

In this thesis, a methodology for the development of a far-field noise estimation model has been proposed and implemented on a Boeing 737-400 aircraft Auxiliary Power Unit (APU) during steady-state operations. The approach makes use of the open-source thermodynamic modelling package (Toolbox for the Modeling and Analysis of Thermodynamic Systems [T-MATS]) and recommends

modification of its turbomachinery blocks to operate in the absence of the components' performance characteristics. The resultant thermodynamic parameters have been shown to exhibit logical behaviour under a wide range of operating conditions. Another contribution of this study is the evaluation of various noise estimation models for an aircraft APU, which have not been reported in the literature so far. Two combustion noise models and two jet noise models are considered for evaluation. These models have been integrated with the outputs of the thermodynamic model for examination. For comparing the noise models results, reference values of the combustion and jet noise are found by applying the source separation technique on the experimental far-field noise data. An immediate analysis reveals that one of the combustion estimation models is not in agreement with the experimental data and is therefore excluded from further analysis. In the case of jet noise, the models' output has to be scaled by a constant offset. After applying the corrections, the total noise estimation model can predict the far-field noise levels with a Root Mean Square Error of 0.73 dB.

The overall approach compiled is innovative and is useful for rapid estimation of thermodynamic parameters and the far-field noise from a limited parameter set. The approach has been further capitalized to carry out a sensitivity analysis between the APU component degradations and the far-field noise components. The results suggest the far-field noise is less sensitive to such degradations as compared to the thermodynamic parameters, and hence a far-field microphone may not appropriate to detect any potential fault.

References

- [1] C. Skliros, F. Ali, and I. Jennions, "Experimental investigation and simulation of a Boeing 747 auxiliary power unit," *J. Eng. Gas Turbines Power*, vol. 142, no. 8, 2020, doi: 10.1115/1.4047771.
- [2] T. Siebel, J. Zanger, A. Huber, M. Aigner, K. Knobloch, and F. Bake, "Experimental investigation of cycle properties, noise, and air pollutant emissions

of an APS3200 auxiliary power unit,” *J. Eng. Gas Turbines Power*, vol. 140, no. 6, pp. 1–9, 2018, doi: 10.1115/1.4038159.

[3] J. Zanger, T. Krummrein, T. Siebel, and J. Roth, “Characterization of an Aircraft Auxiliary Power Unit Test Rig for Cycle Optimization Studies,” *J. Eng. Gas Turbines Power*, vol. 141, no. 1, pp. 1–9, 2019, doi: 10.1115/1.4041119.

[4] S. Aus Der Wiesche, “A mobile test rig for micro gas turbines based on a thermal power measurement approach,” *Proc. ASME Turbo Expo*, vol. 5, pp. 467–477, 2012, doi: 10.1115/GT2012-68095.

[5] C. K. W. Tam, “On the spectrum of combustion noise,” *21st AIAA/CEAS Aeroacoustics Conf.*, no. June, 2015, doi: 10.2514/6.2015-2969.

[6] C. K. W. Tam, S. A. Parrish, J. Xu, and B. Schuster, “Indirect combustion noise of auxiliary power units,” *J. Sound Vib.*, vol. 332, no. 17, pp. 4004–4020, 2013, doi: 10.1016/j.jsv.2012.11.013.

[7] B. N. Shivashankara, “Gas turbine core noise source isolation by internal-to-far-field correlations,” *J. Aircr.*, vol. 15, no. 9, pp. 597–600, 1978, doi: 10.2514/3.58412.

[8] K. Knobloch, L. Enghardt, and F. Bake, “APU-noise reduction by novel muffler concepts,” *Proc. ASME Turbo Expo*, vol. 2B-2018, pp. 1–11, 2018, doi: 10.1115/GT2018-76762.

[9] M. Pott-Pollenske, W. Dobrzynski, H. Buchholz, and D. Almoneit, “Characteristics of noise from aircraft ground operations,” *13th AIAA/CEAS Aeroacoustics Conf. (28th AIAA Aeroacoustics Conf.)*, pp. 1–14, 2007, doi: 10.2514/6.2007-3560.

[10] R. L. Tubbs, “Noise exposure to airline ramp employees,” *Appl. Occup. Environ. Hyg.*, vol. 15, no. 9, pp. 657–663, 2000, doi: 10.1080/10473220050110022.

[11] F. Gugliermetti, F. Bisegna, A. C. Violante, and C. Aureli, “Noise exposure of the ramp’s operators in airport apron,” *20th Int. Congr. Acoust. 2010, ICA 2010*

- *Inc. Proc. 2010 Annu. Conf. Aust. Acoust. Soc.*, vol. 3, no. August, pp. 2051–2057, 2010.

[12] A. Filippone, “Aircraft noise prediction,” *Prog. Aerosp. Sci.*, vol. 68, pp. 27–63, 2014, doi: 10.1016/j.paerosci.2014.02.001.

[13] M. Harper-Bourne, A. Moore, and H. Siller, “A study of large aero-engine combustor noise,” *14th AIAA/CEAS Aeroacoustics Conf. (29th AIAA Aeroacoustics Conf.)*, no. May 2008, 2008, doi: 10.2514/6.2008-2942.

[14] G. G. Podboy and C. Horvath, “Phased array noise source localization measurements made on a Williams International FJ44 engine,” *15th AIAA/CEAS Aeroacoustics Conf. (30th AIAA Aeroacoustics Conf.)*, no. May, pp. 11–13, 2009, doi: 10.2514/6.2009-3183.

[15] D. K. Boyle, B. S. Henderson, and L. S. Hultgren, “Core/combustor-noise baseline measurements for the DGEN aeropropulsion research turbofan,” *2018 AIAA/CEAS Aeroacoustics Conf.*, no. June, pp. 25–29, 2018, doi: 10.2514/6.2018-3281.

[16] H. Gounet and S. Lewy, “Three-dimensional sound directivity around a helicopter turboshaft engine,” *J. Am. Helicopter Soc.*, vol. 57, no. 4, pp. 1–10, 2012, doi: 10.4050/JAHS.57.042002.

[17] J. M. Mendoza, D. K. Nance, and K. K. Ahuja, “Source separation from multiple microphone measurements in the far field of a full scale aero engine,” *14th AIAA/CEAS Aeroacoustics Conf. (29th AIAA Aeroacoustics Conf.)*, no. May, pp. 5–7, 2008, doi: 10.2514/6.2008-2809.

[18] R. Otero, K. Todd Lowe, W. F. Ng, L. Ma, and C. Y. Kim, “Non-intrusive gas turbine engine exhaust characterization using acoustic measurements,” *32nd AIAA Aerodyn. Meas. Technol. Gr. Test. Conf.*, no. June, pp. 1–13, 2016, doi: 10.2514/6.2016-4160.

[19] U. Ahmed, F. Ali, and I. Jennions, “Progress in Aerospace Sciences A review of aircraft auxiliary power unit faults, diagnostics and acoustic

measurements,” *Prog. Aerosp. Sci.*, vol. 124, no. December 2020, p. 100721, 2021, doi: 10.1016/j.paerosci.2021.100721.

[20] M. Munjal, “Noise Control Strategies,” in *IISc Lecture Notes Series, Volume 3 - Noise and Vibration Control*, 2013, pp. 221–266.

[21] SAE International, “Gas Turbine Jet Exhaust Prediction,” SAE ARP876F Rev. F 2013.

[22] B. Yu, C. Cao, W. Shu, and Z. Hu, “A New Method for the Design of Optimal Control in the Transient State of a Gas Turbine Engine,” *IEEE Access*, vol. 5, pp. 23848–23857, 2017, doi: 10.1109/ACCESS.2017.2764056.

[23] J. W. Chapman, T. M. Lavelle, R. D. May, J. S. Litt, and T. H. Guo, “Propulsion system simulation using the toolbox for the modeling and analysis of thermodynamic systems (T-MATS),” *50th AIAA/ASME/SAE/ASEE Jt. Propuls. Conf. 2014*, no. March 2015, 2014, doi: 10.2514/6.2014-3929.

[24] A. Baylar, F. Ozkan, and M. Unsal, “Effect of air inlet hole diameter of venturi tube on air injection rate,” *KSCE J. Civ. Eng.*, vol. 14, no. 4, pp. 489–492, 2010, doi: 10.1007/s12205-010-0489-6.

[25] B. Khandelwal, “Development Of Gas Turbine Combustor Preliminary Design Methodologies And Preliminary Assessments Of Advanced Low Emission Combustor Concepts,” Cranfield University, 2012.

[26] B. SCHLEIN, “Gas Turbine Combustion Efficiency,” *ASME Paper No 85-IGT-121*. 1985.

[27] B. Schuster and L. Lieber, “Narrowband model for gas turbine engine combustion noise prediction,” *Collect. Tech. Pap. - 12th AIAA/CEAS Aeroacoustics Conf.*, vol. 6, no. May, pp. 3611–3623, 2006, doi: 10.2514/6.2006-2677.

[28] H. Schmid, “How to use the FFT and MATLAB’s pwelch function for signal and noise simulations and measurements,” Univ. Appl. Sci., Cham, Switzerland, Tech. Rep. FHNW/IME, Aug. 2012.

- [29] J. R. Barbosa and D. J. Dezan, "Single-stream jet noise prediction using empirical methodology for a newly designed turbojet engine," *Proc. ASME Turbo Expo*, vol. 2, no. November 2014, 2013, doi: 10.1115/GT2013-95199.
- [30] J. W. Rawls and J. C. Yeager, "High Speed Research Noise Prediction Code (HSRNOISE) User's and Theoretical Manual," *Nasa/Cr-2004-213014*, no. November, 2004.
- [31] A. F. El-Sayed, "Fundamentals of aircraft and rocket propulsion," Blackwell Sci., London, U.K., Tech. Rep., 2016, doi: 10.1007/978-1-4471-6796-9.
- [32] P. Fletcher and P. P. Walsh, "Gas Turbine Performance, Chapter 5: Gas Turbine Engine Components," *Gas Turbine Perform.*, no. 1, pp. 159–291, 2004.
- [33] I. Jennions and F. Ali, "Assessment of heat exchanger degradation in a boeing 737-800 environmental control system," *J. Thermal Sci. Eng. Appl.*, vol. 13, no. 6, pp. 1–13, Dec. 2021, doi: 10.1115/1.4050324.
- [34] S. H. Chowdhury, F. Ali, and I. K. Jennions, "A methodology for the experimental validation of an aircraft ECS digital twin targeting system level diagnostics," *Proc. Annu. Conf. Progn. Heal. Manag. Soc.*, vol. 11, no. 1, pp. 21–26, 2019, doi: 10.36001/phmconf.2019.v11i1.888.
- [35] M. Vorlander. (2007). Material Data Absorption. [Online]. Available: https://cds.cern.ch/record/1251519/files/978-3-540-48830-9_BookBackMatter.pdf

4 Evaluation Of Aircraft Auxiliary Power Unit Near-Field Acoustics for Condition Monitoring

This thesis presents a comprehensive evaluation of the near-field acoustics of an aircraft auxiliary power unit (APU), based on experimental data acquired from an in-situ APU. The aim is to establish whether near-field acoustics can be implemented for online condition monitoring. The APU of Cranfield University's demonstrator aircraft, a Boeing 737-400, has been instrumented to acquire acoustics (near-field and far-field) and vibration data in synchronization with aircraft state parameters under a wide range of operating conditions. The acquired data is first implemented to determine the efficacy of employing near-field / far-field microphones, and vibration sensors, to monitor the combustion noise and tonal frequency levels from the APU components. Subsequently, an evaluation of the broadband characteristics of the vibroacoustic data and its variations against APU states and performance parameters is conducted based on several categories of feature extraction techniques. The findings suggest that nearfield acoustics lacks the ability to capture the combustion noise process. In addition, the tonal frequencies are also lost due to the level of background noise, fluctuations in the APU speeds, and scattering effects. For the same reasons, the phase couplings occurring between the signals generated by the APU components cannot be detected using acoustic data. Nevertheless, the overall analysis substantiates that the near-field acoustic data can be used to predict the APU operating states and has the potential to be implemented for developing APU performance parameter estimation models to enable condition monitoring.

4.1 Introduction

4.1.1 Background

Monitoring of system parameters is essential for a feedback control system, ensuring system operation within the required performance and safety limits, and for condition monitoring purposes. The complexities associated with designing, integrating, and installing such a monitoring system depend primarily on the type of sensing mechanisms employed. Generally, the sensor required for a particular

application depends on its capability to sense the desired variations in the system parameters or faults. The sensor-fault pairs (like vibration sensors for bearing faults, and pressure transducers for mass flow measurements) are well-established and are being used for a wide range of applications. However, the intrusive nature of most of these sensors can make them unsuitable for legacy aircraft due to hardware complexity and the associated cost, including certification, which escalates when developing retrofit solutions.

The aircraft auxiliary power unit (APU) is a turboshaft engine [1], composed of several rotating components, valves, guide vanes, igniters, and other associated accessories to generate the required electrical and pneumatic power for aircraft systems. An APU is a complex piece of machinery that requires continuous monitoring to ensure its performance and reliability. Due to accessibility issues, space, power, and weight constraints, installation of an elaborate sensor-set may be prohibitive, and the desired condition monitoring capability may not be possible. On the contrary, the acquisition of noise data using microphones may prove to be useful for such applications. A microphone-based solution could be readily deployed, non-intrusive, and cost-effective.

The authors have initiated research on the development of a microphone-based condition monitoring solution by first considering the far-field noise as a probable source of information about the health of the system. This led to the development of a far-field noise estimation model [2]. Sensitivity analysis has been performed using the developed model to quantify the effect of APU component degradation on the far-field noise. The effects, essentially negligible, have not led to any practical solution. Moreover, the solution employing far-field microphones is prone to interference from external effects and cannot be used for onboard condition monitoring. Therefore, in this study, the research has been extended to the near-field acoustic data to ascertain the feasibility of its utilization for onboard condition monitoring purposes.

4.1.2 Literature Review

Microphones have been used to study the sources of noise in the far-field of an aircraft APU. Coherence analysis is generally employed along with a set of

multiple external and internal microphones to study the sources of direct and indirect combustion noise [3,4]. The use of microphones is also common for noise measurements [5], its effect on airline employees [6], and the design of noise abatement solutions [7]. A recent study employed far-field microphone data to develop and validate a far-field noise estimation model for the complete range of APU operating conditions [2].

From the perspective of condition monitoring, microphones have been shown to detect faults in bearings, gears, and rotors using statistical features [8–10], frequency transform [11–14], Bicoherence analysis [11,14], spectral sub-bands [15] and symmetric dot patterns [16]. The proposed methodologies have been shown to be useful on individual components placed in a controlled environment to minimize acoustic reflections. The efficacy of these methods on an actual system in its original configuration is not known, and therefore the usual approach for condition monitoring of aircraft APUs is to use thermodynamic data acquired from a set of intrusive sensors [17].

The noise data acquired from a machine may also have broadband characteristics peculiar to the state in which the machine is operating. Several techniques can be used to transform broadband characteristics into useful features for further processing; such analysis has been widely used for speech-related applications. The use of Linear Predictive Coefficients (LPC) [18–23] and spectral descriptors [24–27] are among such applications. The same feature extraction techniques have not been evaluated on the noise generated by an aircraft APU and their usefulness for APU state and parameter estimation is yet to be ascertained.

4.1.3 Scope of Work

Although the use of microphones for condition monitoring purposes seems to be an attractive solution, the literature has been found to be lacking a detailed analysis of APU noise data (captured through microphones) to determine its potential utilization. In this research, a thorough examination of the noise generated by an in-situ aircraft APU is conducted in order to determine the usefulness of the microphone data for condition monitoring purposes. For this

study, experimental data has been acquired from Cranfield University's Boeing 737-400 demonstrator aircraft [Section 4.2], which has been systematically processed using appropriate techniques [Section 4.3]. The results and discussion [Section 4.4] present the scientific understanding associated with:

- (a) Detecting combustion noise along the periphery of the APU using microphones and vibration sensors.
- (b) The possibility of examining tonal frequencies generated by the APU components (shaft, gears, bearing) through acoustics.
- (c) Segregation between APU states using vibroacoustic (near-field microphones and vibration) sensors.
- (d) Establishing relationships between various features extracted from vibroacoustic data and APU thermodynamic parameters.

The APU nearfield acoustic and vibration signatures, and their signal processing techniques, will be examined for application to condition monitoring. The findings are indicated where they occur {Finding #} and then referenced, in total, in the Conclusions. It is to be noted that, the primary focus is on analyzing the acoustic data, while the vibration sensor data is considered for comparison purposes.

4.2 Boeing 737-400 APU Operation

The Boeing 737-400 APU is a single-shaft gas turbine engine with a load compressor and a generator to support pneumatic and electrical loads (see Figure 3-1). The APU has two centrifugal compressors (one for the power section and one for APU pneumatic system) with 17 impellers each, while the radial turbine has 14 blades. The APU operates at 63,830 rpm for all operating and load conditions. A set of Inlet Guide Vanes (IGVs) control the flow through the load compressor when demanded by the aircraft systems: Environmental Control System (ECS), wing anti-ice, and Main Engine Starter. A bleed valve (located outside the shroud) isolates the APU's output from the aircraft pneumatic system and is put to a fully open position during bleed-on conditions. The surge control valve, controlled by the surge valve torque motor (SVTM), splits the flow

produced by the load compressor towards the aircraft pneumatic system and the APU exhaust to prevent a surge condition.

The APU accessories (generator, fuel pump, cooling fan, and oil pump) are driven by the gearbox. Lubricating oil passes through the gearbox to reduce friction and gear wear. The oil temperature is regulated by an oil cooler which acts as a heat exchanger and the cooling air eventually leaves the APU through the cooling air outlet. The APU assembly is enclosed inside a shroud for noise reduction and safety against fire. A Full Authority Digital Electronic Controller (FADEC) controls the APU operation by varying the IGVs, SCV, and fuel flow to the combustor, based on the input from multiple sensors (RPM, EGT, etc.) which can be viewed through the FADEC display.

The APU states can be divided into three categories:

- (a) Bleed system inactive (BL OFF)
 - (b) Bleed System activated with no pneumatic load (BL ON NL)
 - (c) Bleed System activated with pneumatic load (BL ON LD)
- 

There are major variations taking place when the APU transitions from BL OFF to BL ON states and vice versa. In the latter state, the IGVs are fully open and there is a considerable rise in fuel flow. Whereas, between BL ON NL and BL ON LD, only mass flow through the bleed valve varies depending on the load. This is achieved by varying the SCV angles by changing the current through the SVTM; from 50 mA for BL ON NL to a maximum of 95 mA for BL ON LD conditions. The effects of load conditions on the APU thermodynamic parameters and the far-field noise have already been discussed [2].

4.3 Analyses Performed

4.3.1 Overview

This thesis systematically analyses the noise generated by an in-situ aircraft APU using appropriate signal processing techniques to address the research gaps found in the literature. The overall scheme adopted to perform the necessary set

of analyses is presented in Figure 4-1. Acoustic (far-field and near-field), Vibration and FADEC data form the basis of the analysis, these have been acquired from the aircraft APU in its original configuration (APU installed on vibration mounts with shroud and exhaust muffler). The complete analysis is divided into three categories:

- (1) Coherence analysis between near-field and far-field noise to establish the existence of combustion noise inside the APU compartment.
- (2) Tonal Frequency analysis evaluates the efficacy of utilizing near-field acoustic data for shaft, gearbox, and bearing condition monitoring. In this analysis, vibration data is treated as a reference and a comparison between the performance of commonly applied signal processing techniques using vibration and acoustic sensors has been carried out.
- (3) Broadband noise analysis evaluates various features from the acquired vibroacoustic data for segregating between the APU states and utilizing them for APU parameter estimation.

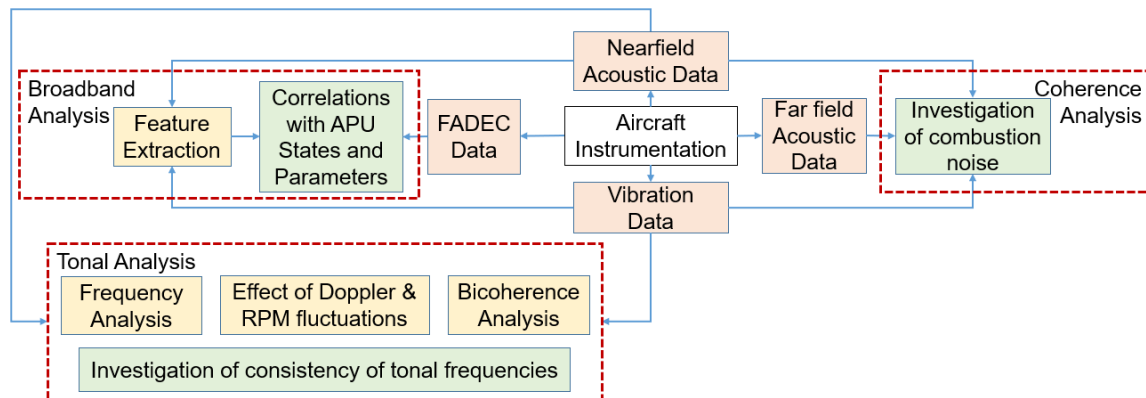


Figure 4-1 The scheme adopted for APU Acoustic Data Analysis

4.3.2 Experimental Data Collection

The data collection is conducted by instrumenting Cranfield University's Boeing 737-400 aircraft APU in-situ. The overall experimental setup involved nine 130F20 ¼" IEPE microphones and 6 vibration sensors in combination with a National Instruments Data Acquisition (DAQ) System, allowing data sampling at

51.2 kHz. The overall arrangement of the microphones is illustrated in Figure 4-2. Six microphones have been installed inside the APU shroud, while two (BV and BV2) were placed outside the shroud but within the APU compartment. The installation is made by attaching the microphones to the APU cables / wires that run across the APU. 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 microphones have been placed uniformly to capture any trend in the acoustic characteristics across the APU compartment. One microphone is installed on the outside of the aircraft body (near the cooling air outlet) and is denoted by CAO. It will be utilized to study the effects of external noise sources on the near-field microphone data.

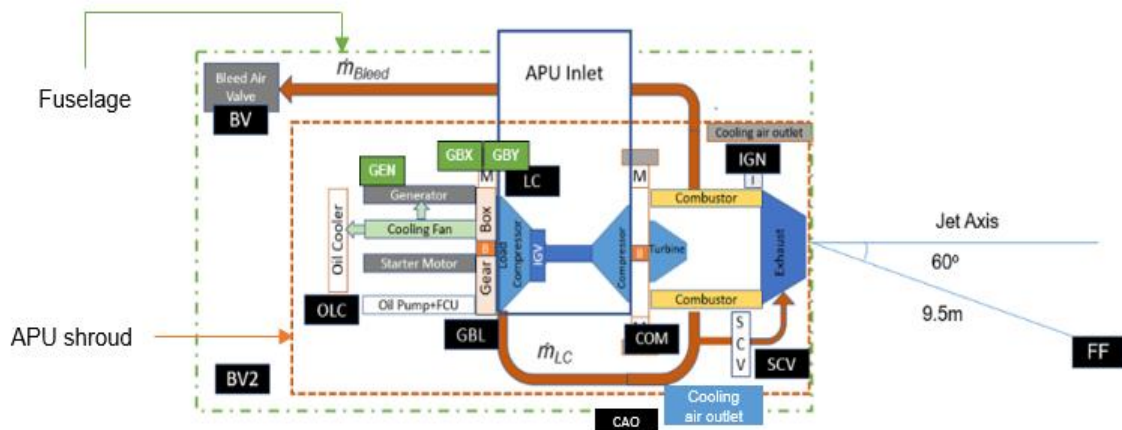


Figure 4-2 Microphone ■ and vibration ■ sensors placement

Another microphone (FF) of the same specifications is placed in the far field of the exhaust. This microphone is on the left side of the jet axes so that the effect of noise from the APU inlet is minimized. The APU has also been instrumented with six CTC AC102 vibration sensors (using adhesive mounts) which have a dynamic range of 50 g. These sensors are integrated with the same DAQ to ensure synchronized data acquisition. It should be noted that three out of the six vibration sensors did not provide readable data during the experimentation and were excluded from the analysis. For the remaining three sensors, sufficient data has been acquired, and only their locations are mentioned in Figure 4-2. The

setup also includes a camera facing the FADEC display for recording T_{oil} , IGV angle, output pressure from the Load Compressor, and SVTM current. For mass flow through the bleed valve ($\dot{m}_{Bleed}$) and load compressor ($\dot{m}_{LC}$), appropriate relationships have been used, details of which have been previously reported [2]. The complete dataset has been acquired over a period of five months.

4.3.3 Near-field and Far-field Noise Coherence Analysis

Combustion noise levels can provide useful information about the state and health of an APU. These levels can be measured in the far-field of the APU exhaust due to the distinct nature of the combustion spectra at lower frequencies [7,28,29]. Moreover, they can also be predicted by using semi-empirical relationships, with APU geometric and thermodynamic data [30]. For exact measurements, highly specialized acoustic sensors have to be installed intrusive in the combustor to withstand the harsh environment. To avoid hardware complexities associated with the intrusive sensors, it is desired that have the same information using ordinary measurement microphones.

To detect the presence of combustion noise along the periphery of the APU structure, coherence analysis has been performed to ascertain the extent to which the low frequency (combustion) noise is related between the far-field and near-field acoustic / vibration sensors. The analysis also establishes a relationship (if any) between the tonal noise components of the far-field microphones and the vibration sensor. MATLAB's 'mscohere' function has been utilized for this analysis with a window size of 51200 samples (1 second) with 95% overlap and an FFT size of 2^{18} . The resultant magnitude-squared (Mag. Sq.) coherence estimate is in the range [0,1] for each of the frequency bins, where a value of 1 at a certain frequency indicates a linear relationship, and nonlinear otherwise. The analysis has been done separately for BL OFF and BL ON to evaluate the effect of activation of the APU's pneumatic system on coherence.

4.3.4 Tonal Analysis

The use of vibration sensors for observing the tonal frequencies generated by a gas turbine (or an APU) for condition monitoring purposes has been well-

established and is widely employed. The amplitude and the location of the tones generated by shafts, bearing, and gearbox can be used for fault detection and identification. For example, the amplitude of the sidebands in the gear mesh frequency corresponds to the gear tooth breakage [31] for a gearbox. During the early stages of the fault, the sideband amplitudes are very low and are further deteriorated by the background noise. The situation may become worse if acoustic sensors are employed due to the increase in the background noise levels. For accurate results, the signal (or tonal) amplitudes should be higher than the noise levels (i.e., high SNR), so that they are observable in the frequency domain.

In this study, the efficacy of utilizing microphones for monitoring tonal frequencies is established. Since faults have not been injected into the aircraft APU due to operational and safety concerns, the vibration data is treated as a reference. The exact source of the tones is also not discussed, due to the unavailability of the gearbox / bearing geometry details which are proprietary to the OEM. The aim is to determine the extent to which the acoustic sensors can capture the same number of tonal frequencies which are being captured by the vibration sensors.

First, coherence between a vibration sensor and the near-field microphones is carried out to determine the possibility of acquiring the tonal frequencies using either of the sensing mechanisms. The coherence estimates have been computed in the same manner as mentioned in section 4.3.3 while considering one of the three installed vibration sensors as a reference. In the analysis, each microphone has been treated separately to identify the locations where a greater number of coherent tones can be acquired. The effect of change in the APU load conditions on the tonal amplitudes and overall noise levels is also discussed, and the possible explanation for such variations is presented. Lastly, the usefulness of Bicoherence analysis on acoustic data using experimental and simulated data is presented.

4.3.5 Broadband Noise Analysis

In this analysis, the vibroacoustic response with the variation in APU states and parameters is studied. This analysis aims to determine the usefulness of using

nearfield acoustic and vibration data for APU state identification and parameter estimation. To achieve this, several feature extraction techniques are employed on the vibroacoustic data, and eventually, the performance of the resultant features is evaluated against a defined performance metric. Comparison between the performance of acoustic and vibration data is an inherent part of the analysis. This analysis comprises the description of the various categories of features employed, performance analysis of features against different APU states using the coefficient of overlap as a metric, and lastly, studying the correlation of the features with various APU parameters.

4.3.5.1 Data Preparation and Feature Extraction

For computing the requisite sets of features, the time series data from the vibroacoustic sensors is divided into segments of one second with 80% overlap. For each segment, five different categories of features are computed, which are:

- (a) A set of 20 linear predictor coefficients (LPC) with the error term, which are computed using MATLAB '*lpc*' function.
- (b) Mel-Frequency Cepstral Coefficients (MFCC), keeping the 20 triangular filters regularly spaced between 0 and 25.6 kHz.
- (c) Spectral Power in sub-bands (BandPower) corresponding to the average power in the 20 sub-bands computed using MATLAB's '*bandpower*' function.
- (d) The time-domain feature set includes RMS, Kurtosis, Skewness, Max, Zero Crossing Rate, Negentropy [32, eq. (81)], Impulse Factor, Crest Factor, and the Shape Factor.
- (e) Spectral Descriptors include 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 thermodynamic parameters corresponding to the data segments are also noted, and the segments are labelled as per the APU states:

BL OFF → IGV angle = 22°

BL ON NL → IGV angle > 22° and SVTM = 50

BL ON LD → IGV angle > 22° and SVTM > 50

4.3.5.2 Evaluation of Feature Response against the APU States

From the perspective of condition monitoring, it is important to ascertain the current state in which the APU is operating. Any disparity between the current and the desired state of operation can indicate the presence of a faulty condition. In this study, the features extracted from the vibroacoustic data have been evaluated to ascertain the potential of the use of microphones and vibration sensors for condition monitoring purposes. The overall approach followed is presented in Figure 4-3.

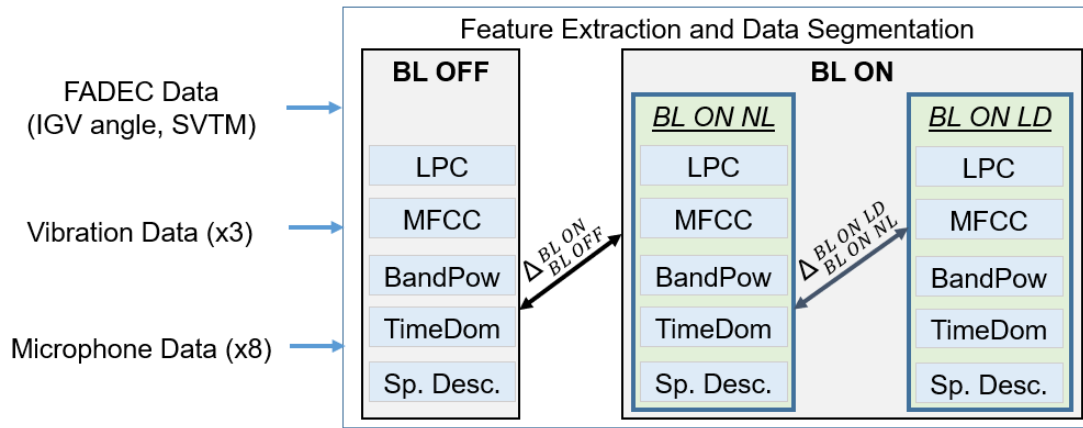


Figure 4-3 Process followed for analysing feature response under the various APU States

The five different categories of features are computed for the vibroacoustic data using the approach mentioned in section 4.3.5.1. The computed features are then segregated into three categories depending on the APU State determined from the FADEC Data. For each of the features, coefficients of overlap ($\Delta_{BL OFF}^{BL ON}$ and $\Delta_{BL ON NL}^{BL ON LD}$) [33] are then computed to evaluate performance, where:

$$\Delta_{BL OFF}^{BL ON} = \int \min \{f_{BL OFF}(x), f_{BL ON}(x)\} dx \quad (4-1)$$

and:

$$\Delta_{BL\ ON\ NL}^{BL\ ON\ LD} = \int \min \{f_{BL\ ON\ NL}(x), f_{BL\ ON\ LD}(x)\} dx \quad (4-2)$$

In the above equations, $f_{BL\ OFF}(x)$, $f_{BL\ ON}(x)$, $f_{BL\ ON\ NL}(x)$, and $f_{BL\ ON\ LD}(x)$ correspond to the probability density functions of a feature for BL OFF, BL ON, BL ON NL, and BL ON LD conditions respectively. MATLAB's '*ksdensity*' function has been used to estimate the probability density function of a feature for a particular APU state, and '*trapz*' function is employed to perform the required numerical integration after the '*min*' operation. The values of coefficient of overlap for a particular feature can range between [0,1], with lower values indicating that the feature changes significantly between different APU states, thus leading to a lower overlap between the feature values between those two states. This would be a desirable condition, as opposed to a situation in which the feature values do not alter significantly even if the states are changing. The above-mentioned coefficients of overlap are computed for each category of feature resulting in a dataset containing the values of Δ for each category of feature using acoustic and vibration data. The resultant dataset includes 20 vectors which are labelled as follows:

$$[\Delta_{BL\ OFF}^{BL\ ON}, \Delta_{BL\ ON\ NL}^{BL\ ON\ LD}]_{Acoustic, Vibration}^{LPC, MFCC, BandPower, TimeDomain, Spectral Descriptors} \quad (4-3)$$

The subscript refers to the sensor type, while the superscript represents the feature extraction technique used for each category of the sensor. For example, $[\Delta_{BL\ OFF}^{BL\ ON}]_{Acoustic}^{MFCC}$ is a vector comprising 160 values of coefficients of overlap between BL OFF and BL ON conditions corresponding to each of the 20 MFCC features for all the eight microphones:

$$[\Delta_{BL\ OFF}^{BL\ ON}]_{Acoustic}^{MFCC} = [\Delta_{BL\ OFF\ S1}^{BL\ ON\ MFCC1} \dots \Delta_{BL\ OFF\ S1}^{BL\ ON\ MFCC20} \dots \Delta_{BL\ OFF\ S1}^{BL\ ON\ MFCC1} \dots \Delta_{BL\ OFF\ S8}^{BL\ ON\ MFCC20}]$$

Here, $S1 - S8$ correspond to eight of the microphone locations, and $MFCC1 - MFCC20$ are the 20 MFCC features computed at each of those sensor locations. The distributions of the resultant dataset (expression 4-3) are eventually analyzed

to ascertain the potential of using vibroacoustic data for the desired condition monitoring purposes.

4.3.5.3 Features' Response with APU Parameters

Continuous monitoring of APU parameters, like mass flows, oil temperatures, and IGV angles, can also give insight into the health of the system. Generally, several intrusive sensors are employed, however, in this study, the capability of using microphones for the same purpose is explored. The results are also compared with that of using vibration sensors. Similar to the process followed in section 4.3.5.2, the variation in the feature responses to the various APU parameters is analyzed. The correlation coefficient (ρ) is utilized to act as a metric to establish a relationship (if any) between an APU parameter (P) and a feature (F) for a specific sensor (S_i):

$$\rho_{P_{S_i}}^F = \frac{1}{N-1} \sum_{i=1}^N \left(\frac{F_i - \mu_F}{\sigma_F} \right) \left(\frac{P_i - \mu_P}{\sigma_P} \right) \quad (4-4)$$

Where ' N ' is the number of datapoints, ' F_i ' and ' P_i ' are the feature and the parameter values at datapoint ' i ', and σ and μ represent the standard deviation and mean. Four of the APU parameters are considered, which include $\dot{m}_{Bleed}$, $\dot{m}_{LC}$, IGV angles, and T_{Oil} . By observing these parameters, the state of APU pneumatic system components (IGVs, SCV, and BV) and lubrication oil cooling system can be monitored, and deviations from the nominal limits will indicate the presence of a faulty condition. The result of this analysis is a dataset containing 40 vectors comprising four sets of correlation coefficients corresponding to the four APU parameters, two types of sensors, and five categories of features:

$$\begin{bmatrix} \rho_{TOil}, \rho_{mLC} \\ \rho_{IGV}, \rho_{mBleed} \end{bmatrix} \begin{matrix} LPC, MFCC, BandPower, TimeDomain, Spectral Descriptors \\ Acoustic, Vibration \end{matrix} \quad (4-5)$$

As an example, $[\rho_{TOil}]_{Acoustic}^{LPC}$ is a vector containing 168 values corresponding to the correlation coefficients between each of the 21 features from eight microphones and T_{Oil} , that is,

$$[\rho_{TOil}]_{Acoustic}^{LPC} = [\rho_{TOil_{S1}}^{LPC1} \quad \dots \quad \rho_{TOil_{S1}}^{LPC21} \quad \dots \quad \rho_{TOil_{S8}}^{LPC1} \quad \dots \quad \rho_{TOil_{S8}}^{LPC21}]$$

Here, $S1 - S8$ corresponds to eight of the microphone locations, and $LPC1 - LPC21$ are the 21 LCP features computed at each of those sensor locations. In this study, the distributions of each of the 40 vectors ($[\rho_{TOil}]_{Acoustic}^{LPC}$, $[\rho_{mLC}]_{Acoustic}^{MFCC}$, $[\rho_{mBleed}]_{Vibration}^{BandPower}$, etc.) are visualized to assess the range of correlation values existing between features and APU parameters for acoustic and vibration sensors.

It is to be noted that, since the IGV angles are only modulating during BL ON states, the correlation coefficients for the IGV angles have been computed for those durations only. Similarly, the correlation coefficients for $\dot{m}_{Bleed}$ include the data from BL ON LD state only because it is zero otherwise. Whereas, for T_{oil} and $\dot{m}_{LC}$, the data from all the states have been considered.

4.4 Results and Discussion

This section presents a detailed picture of the three independent analyses that have been performed on the APU noise. Initially, the coherence analysis between the far field and nearfield acoustic is presented. This is followed by the analysis of the tones present in the acquired vibration and acoustic data. The disparity between the results is then explained using engineering and physics principles. The practicality of using Bicoherence analysis on APU acoustic data is also presented, and validation of the results is done using synthetically generated data. Lastly, a thorough analysis of several features extracted from the vibroacoustic data is carried out and the results of coefficients of overlap and correlation coefficients are presented in a summarized form.

4.4.1 Near-field and Far-field Noise Coherence Analysis

Coherence estimates have been computed by choosing the far-field microphone as a reference using 20 seconds of data, and the results are presented in Figure 4-4. Apart from the outside shroud sensors (BV and BV2), there is a common trend for all the sensors. Only a few tones [generator shaft rpm of 100 Hz, shaft frequency of 1 kHz and its harmonics, and compressor blade pass frequency (BPF) of 18 kHz] are slightly coherent with the far-field microphone data, with the coherence levels reducing further under BL ON conditions.

Furthermore, the low frequency (combustion) noise has not been found to be coherent with any of the inside shroud sensors. BV and BV2 sensors show a certain level of coherence at low frequencies, being slightly distant to the APU as compared to the remaining sensors, but coherence levels are not sustained under BL ON conditions where APU noise due to vibrations becomes dominant (see the zoomed-in figure for sensor BV2).

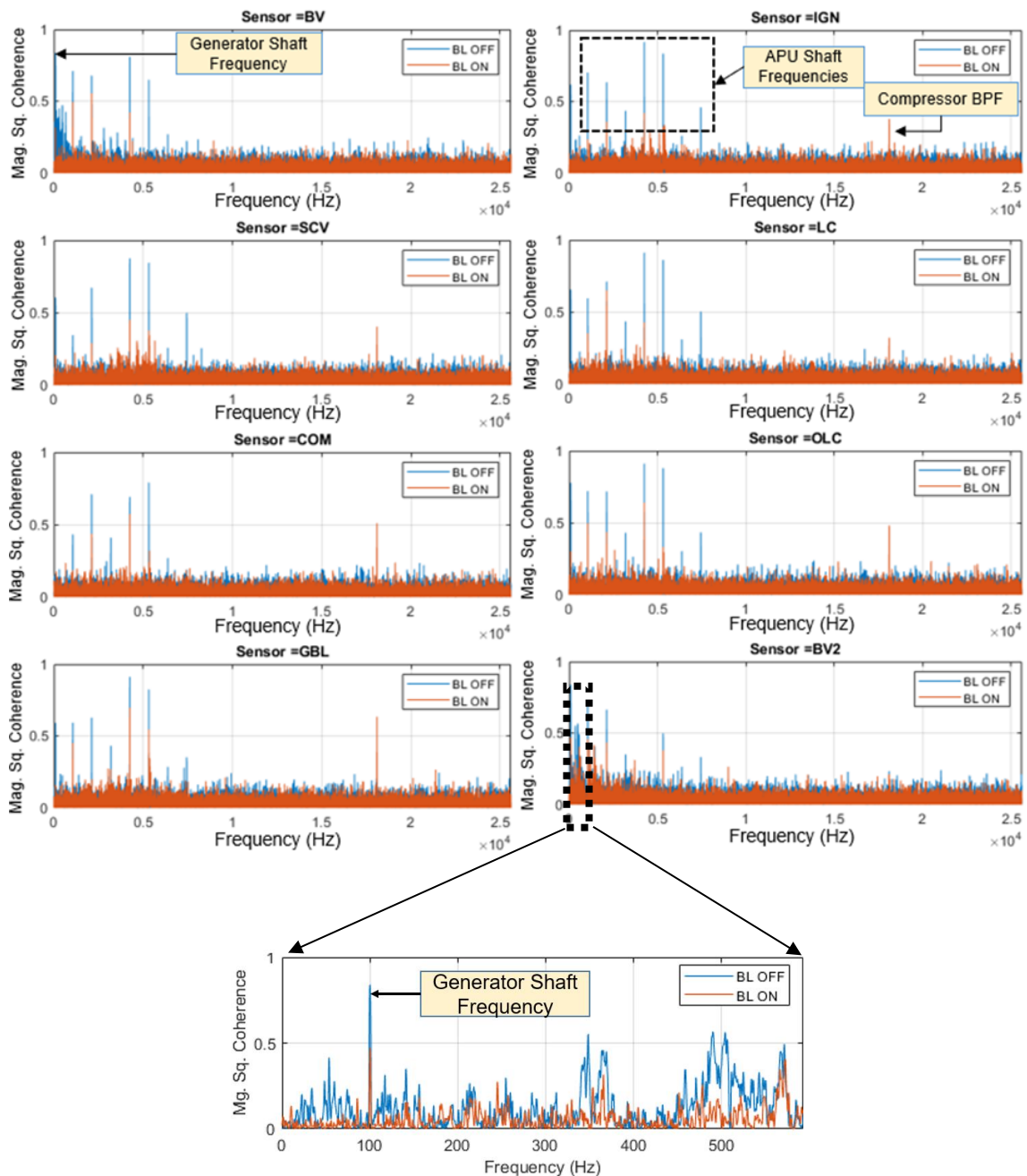


Figure 4-4 Coherence analysis between far-field and near-field acoustic data

Based on the analysis, it can be concluded that the near-field microphones close to the APU are overwhelmed by the noise generated by engine vibration and pneumatic flows inside the APU compartment and are therefore unable to sense the variations in the combustion noise taking place in the far-field of the APU. Moreover, the combustion noise from the far-field may also be getting attenuated while traversing through the aircraft structure and the APU shroud. The absence of the typical combustion spectra at any of the sensor locations (analysis not shown) further substantiates this outcome. The analysis has been expanded to include coherence of the far-field microphone data with the vibration sensor [GBX] (Figure 4-5). The results are similar to the ones with the microphone data and show that the vibration sensor also cannot sense the combustion noise. This can be because of the design of the APU combustor and structure which restricts the induction of low-frequency acoustic waves into the structure to avoid acoustic fatigue. This suggests that combustion noise levels cannot be estimated by microphones and vibration sensors inside the APU compartment *{Finding # 1}*. On the other hand, the shaft frequencies are coherent with the far-field microphone data, thus making an external microphone suitable for monitoring the APU shaft faults *{Finding # 2}*.

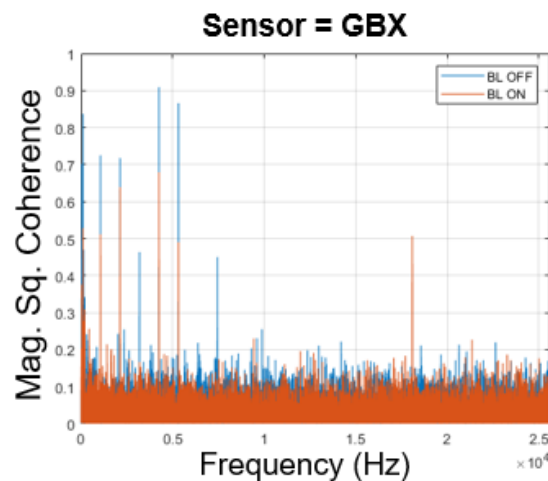


Figure 4-5 Coherence analysis between far-field acoustic and APU vibration data

4.4.2 Tonal analysis

In this section, a detailed analysis of the tonal frequencies acquired by the near-field microphones is presented. Initially, the outcomes of the coherence analysis

between the microphone and a reference vibration sensor are discussed. The effect of sensor locations on coherence estimates is also presented. Secondly, an in-depth analysis of the frequency response of the acoustic data is performed. Lastly, the performance of Bicoherence analysis on acoustic data is presented, for which the Higher-Order Spectral Analysis Toolbox, developed for MATLAB [34], has been utilized.

4.4.2.1 Coherence Analysis between acoustic and vibration sensors

Coherence analysis has been performed between the vibration sensor installed on the APU gearbox and the near-field microphones under BL OFF and BL ON states (two of the results are shown in Figure 4-6). Under the BL OFF state, a large number of tones display a certain level of coherence, however, under the BL ON case the tones are no longer coherent. Table 4-1 provides a summary of the number of tones that have coherence greater than 0.5 at various sensor locations. The drastic reduction in the number of coherent tones is visible across all the sensor locations under BL ON conditions, with the GBL microphone being able to retain 23 coherent tones due to its proximity to the source. On the contrary, the microphones farthest from the gearbox show a downward trend. Figure 4-7 shows this information overlaid on the APU schematics using a surface plot, where the colour represents the number of coherent tones (brighter colour indicates a greater number of coherent tones and vice versa). It can be concluded that the region around the gearbox can be an appropriate choice to observe some of the tonal frequencies. However, as per the analysis (not shown), only the shaft frequencies are in a majority amongst the coherent tones while the remaining ones get hidden behind the background noise (especially under BL ON conditions) *{Finding # 3}*. Possible reasons for the deterioration in the coherence results under the BL ON state are explained in subsequent paragraphs.

Consider the power spectrum of the acoustic data from two of the sensor locations (GBL and BV) under BL OFF and BL ON states (Figure 4-8). The clear distinction between the two states is visible from the figure in terms of reduction in the amplitudes / weakening of certain tones and the increase in the overall noise levels for BL ON states. These effects (some of which have been

highlighted in the figure) are more pronounced at sensor location BV which is outside the shroud. This sensor is only able to retain four tones corresponding to shaft frequencies and the compressor blade-pass-frequency. All the other tones are overwhelmed by the background noise.

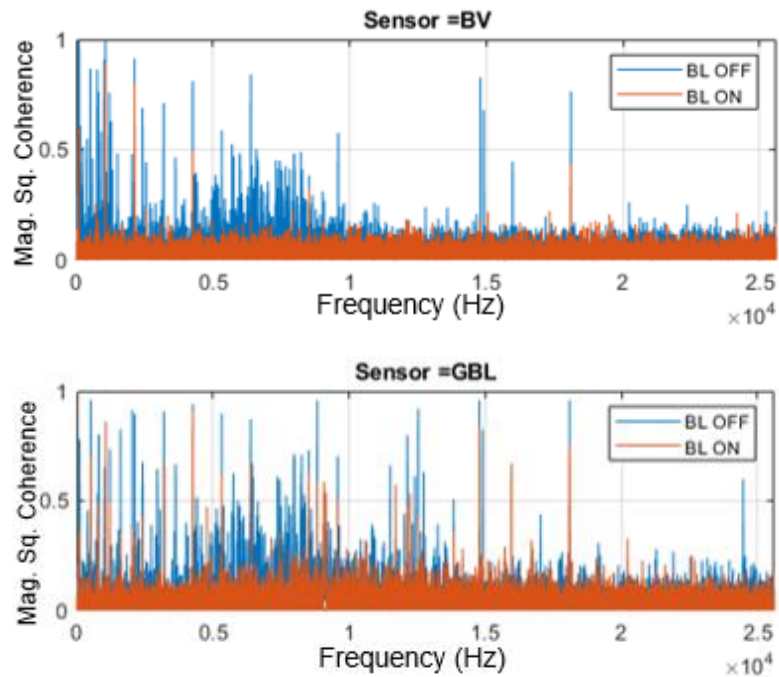


Figure 4-6 Coherence analysis between Near-Field Acoustic Sensors and Vibration Data

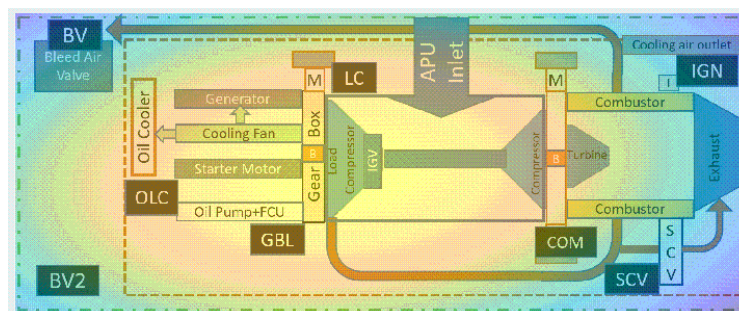


Figure 4-7 Variation in the number of coherent tones across APU

Table 4-1 Number of tones with coherence greater than 0.5

	BV	LC	IGN	SCV	COM	GBL	OLC	BV2
<i>BL OFF</i>	27	82	19	22	17	83	61	35
<i>BL ON</i>	3	14	11	12	11	23	18	5

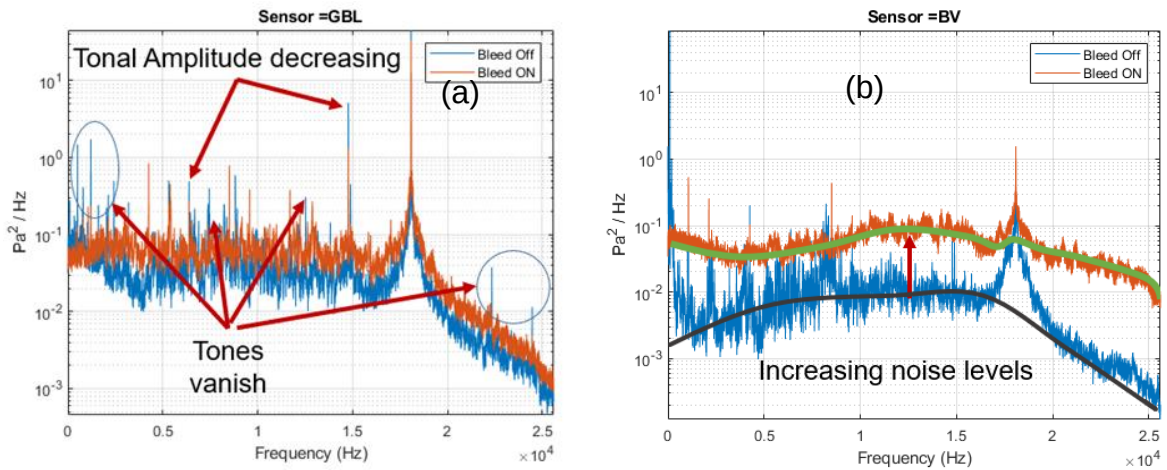


Figure 4-8 Power spectrum of acoustic data from microphones at location (a) GBL and (b) BV

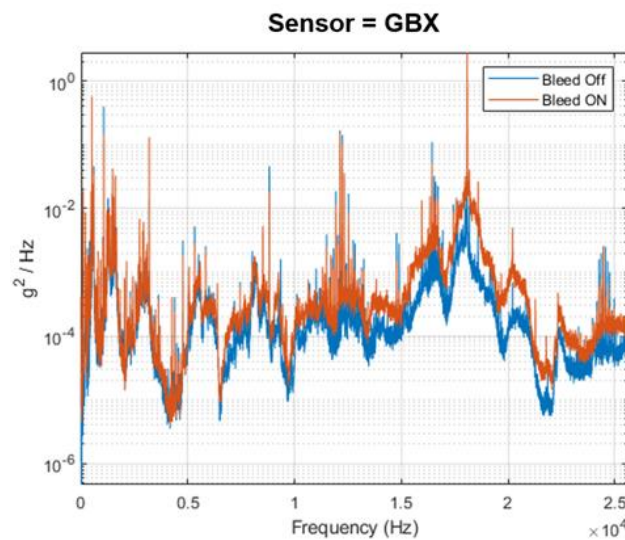


Figure 4-9 Power Spectrum of Gearbox Vibration Data

In order to identify the possible source of these effects, the frequency power spectrum of the vibration data corresponding to the same APU states is presented in Figure 4-9. Firstly, it is evident that the vibration sensor is less affected by the change in the APU state as it only shows a very slight reduction in some tonal amplitudes. There is, however, some increase in the vibration levels for frequencies above 7 kHz, but the increase is still small enough not to completely conceal the tones. The vibration characteristics remain unaffected by the combustion noise (which is present at low frequencies) {Finding # 4}. After

conducting this analysis, the disparity between the vibration and acoustic sensors (in terms of the degradation of tones amplitudes under BL ON conditions for acoustic sensors) can be explained to be because of the combined effect of the increase in the overall noise levels and decrease in tonal amplitudes. The increase in the overall noise floor can be because of the microphones being sensitive to the variations in the flow noise. For the reduction in tonal amplitudes, two phenomena have been identified which may be causing this effect: RPM fluctuations and the Doppler effect.

4.4.2.1.1 Effect of RPM fluctuations on tonal frequencies

In the absence of the raw RPM signal from the APU to determine the extent of RPM fluctuations, the power spectrum has been used to ascertain the extent of fluctuations. Figure 4-10 shows the power spectrum of the vibration and acoustic data by dividing the data into one-second segments, which have been zoomed into the tone at 12.53 kHz. The tone appears to be quite stable (not fluctuating its position in terms of frequency) under BL OFF conditions for both the vibration and acoustic data. Whereas the same tone is shifting back and forth under BL ON conditions for vibration data. This, in turn, distorts the tone in the acoustic data which is evident from the figure. The net effect is the reduction in the amplitude and increase in the spread of tones for both types of sensors.

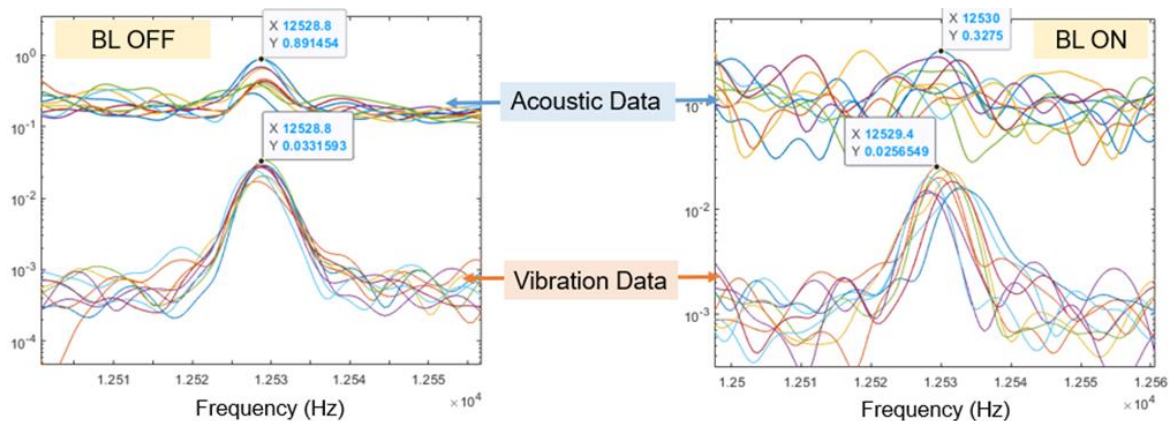


Figure 4-10 Power spectrum of the segmented versions of vibration and acoustic data

In order to quantify the degree of RPM fluctuations under BL OFF and BL ON conditions using experimentally acquired data, certain tones (for example 12.53 kHz) in the vibration data have been chosen for analysis. For each of the one-second data segment, the location of the tones (f_i) is noted using MATLAB's 'findpeaks' function, and eventually, the deviation for each frequency (σ_{fi}) is computed. The process is carried out for both the cases (five tones for BL OFF and nine tones for BL ON) and the results are presented in Figure 4-11. There is a distinct difference between both states. Under low load conditions, the deviation in the frequencies is low (maximum σ_{fi} of 0.5 Hz), whereas for high load conditions the deviations are high. Moreover, for high frequencies, the deviations are high as well, which confirms that the fluctuations are related to the variations in the RPM because the higher-order tones are affected more as compared to the ones with lower orders.

Consider a tonal frequency generated by a component that is rotating at a multiple of n_i with respect to the APU RPM, that is,

$$f_i = n_i \text{ RPM}/60 \quad (4-6)$$

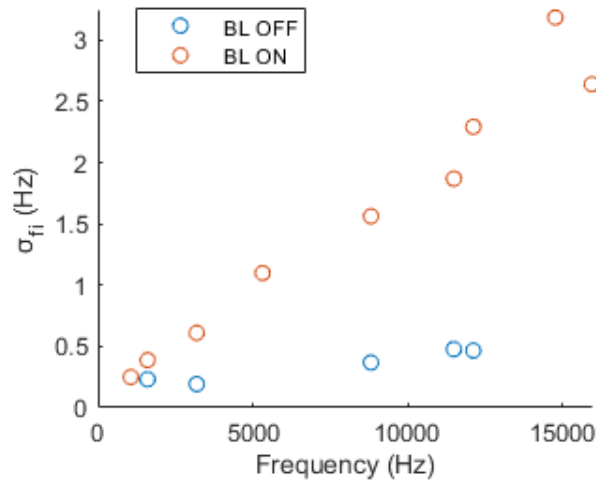


Figure 4-11 Deviation in tonal frequencies during BL OFF and BL ON states

Conversely, the term n_i can be computed if the average RPM ($\overline{RPM}$) and average frequency ($\overline{f_i}$) are known:

$$n_i = 60 \bar{f}_i / \overline{RPM} \quad (4-7)$$

If the RPM is fluctuating with σ_{RPM} , there is equivalent fluctuation in the tonal frequencies (σ_{fi}) which is given by:

$$\sigma_{fi} = n_i \sigma_{RPM} / 60 \quad (4-8)$$

Or,

$$\sigma_{fi} = n_i \sigma_{RPM} / 60 \quad (4-9)$$

Combining 7 and 9 give,

$$\sigma_{RPM} = \sigma_{fi} \overline{RPM} / f_i \quad (4-10)$$

Since there are multiple tonal frequencies generated by the APU, σ_{RPM} computed from the individual tones (f_i) can be averaged to provide an accurate estimation of RPM fluctuations ($\bar{\sigma}_{RPM}$),

$$\bar{\sigma}_{RPM} = \frac{\overline{RPM}}{N} \sum_i \frac{\sigma_{fi}}{f_i} \quad (4-11)$$

Where 'N' is the number of tones used for the analysis.

The analysis reveals that the average deviation in APU RPM ($\bar{\sigma}_{RPM}$) is 2.64 under lower load conditions which increases to 11.77 when the APU pneumatic system is activated. This, in turn, fluctuates the tones, and the variation is more for higher frequencies where n_i is high [Eq. (4-8)]. These fluctuating tones generated by the engine vibrations are translated into sound and superposition of sinusoidal tones with varying amplitude, phase, and fluctuating frequencies takes place. The resultant effect is a decrease in acoustic tonal amplitudes spread over a wider range of frequencies. The tones which display an opposite trend in their amplitudes are the resonating frequencies of the APU structure and are not affected by the change in RPM (see tone at 20 kHz in Figure 4-9).

To illustrate the effect of RPM fluctuations on SNR of tones, the relationship between σ_{RPM} , n_i and SNR for a signal with a tone at f_i is studied using synthetically generated data. Consider a signal in which the tone f_i is varying due to RPM fluctuations,

$$S_{f_i}(t) = \sin(2\pi \int f_i(t)dt) + n(t) \quad (4-12)$$

Where $n(t)$ is additive Gaussian noise, and f_i is related to RPM using relationship (6),

$$S_{f_i}(t) = \sin(2\pi n_i / 60 \int RPM(t)dt) + n(t) \quad (4-13)$$

$RPM(t)$ is simulated as a triangular wave with amplitude $A = \sqrt{3} \sigma_{RPM}$ [35] to generate the desired σ_{RPM} . The frequency of the triangular wave has been arbitrarily chosen to be 0.25 Hz. MATLAB's '*sawtooth*' function has been used to generate the desired triangular wave [$tri(t)$],

$$RPM(t) = \overline{RPM} + \sqrt{3} \sigma_{RPM} tri(t) \quad (4-14)$$

Where $tri(t)$ is a triangular wave that spans in the range [-1,1]. Combining (12) and (13),

$$S_{f_i}(t) = \sin\{2\pi n_i / 60 (\overline{RPM} + \sqrt{3} \sigma_{RPM} \int tri(t)dt)\} + n(t) \quad (4-15)$$

Using the above relationship, a set of signals [$S_{f_1}(t)$, $S_{f_4}(t)$, $S_{f_8}(t)$ and $S_{f_{12}}(t)$] have been derived corresponding to $n_i = [1, 4, 8 \text{ and } 12]$ for $0 \leq \sigma_{RPM} \leq 12.5$ with $\overline{RPM} = 63,830$ (1063.8 Hz). For the required numerical integration, MATLAB's '*cumtrapz*' function has been used. Figure 4-12 shows the effect of varying σ_{RPM} on the tonal amplitude of the signal $S_{f_{12}}(t)$ in the frequency domain. The amplitude can be seen to be decreasing as the RPM fluctuation increases. The tone also spreads in the frequency domain the same way it has been noticed in the experimental data. Figure 4-13 shows a summary of the analysis for all the considered tones. It can be seen that the SNR of the tones decreases with the increase in σ_{RPM} , and the effect is more pronounced for higher-order tones. This

behaviour will reciprocate in the acoustic data to an extent that the tones may totally disappear [see the vanishing tones highlighted in Figure 4-8(a)].

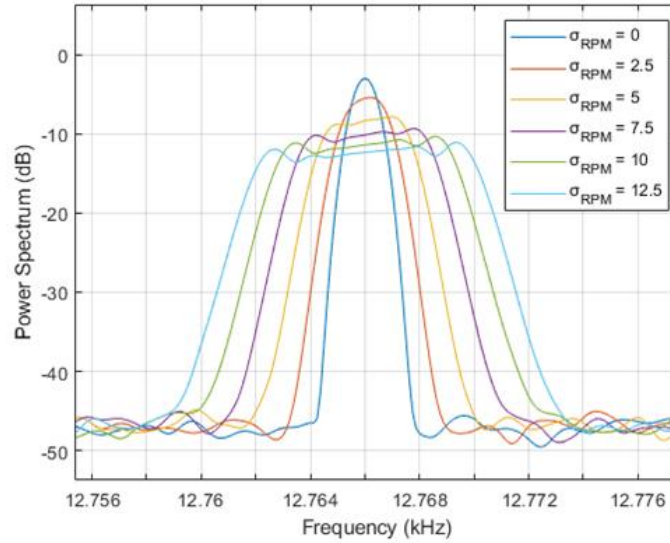


Figure 4-12 Power Spectrum of $S_{f12}(t)$ for different levels of RPM fluctuations

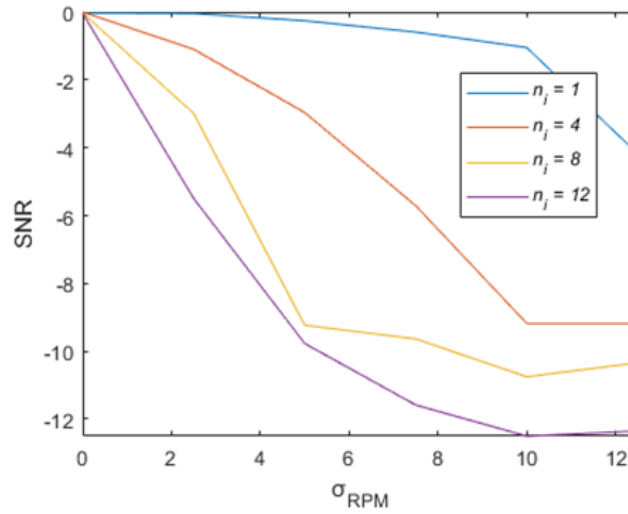


Figure 4-13 Effect of variation in RPM fluctuations on SNR of tones at various orders

4.4.2.1.2 Doppler Effect on data collection

The tones produced by the APU undergo reflections by various surfaces inside the APU compartment and eventually reach the microphones. Some of these surfaces are under continuous oscillations, and the acoustic waves propagating inside the compartment are incident on those vibrating surfaces. Moreover, since

the microphones are installed on wires / cables, they also experience a certain level of shaking. Under such circumstances, the acoustic waves encounter a Doppler effect due to the vibrations of surfaces / microphones with a multitude of frequencies. To study this phenomenon, an experiment has been set up that includes a tone-generating instrument, which is kept stationary, and a microphone installed on a shaker to generate vibrations (Figure 4-14).

Acoustic data from the microphone is sampled at 11.025 kHz and a 1 kHz tone is transmitted from the speaker. Five sets of data are acquired by varying the shaker vibration frequencies (0-40 Hz with an interval of 10 Hz). Figure 4-15 shows the frequency power spectrum of the acquired acoustic data. Apart from the tones and harmonics corresponding to the selected vibration frequency (not shown in the figure), modulation of the transmitted 1 kHz tone is taking place, which leads to sidebands corresponding to $1 \text{ kHz} \pm n f_{shaker}$, with the amplitude of the sidebands diminishing for higher values of n . For example, with $f_{shaker} = 30 \text{ Hz}$, the sidebands occur at around 1.03 kHz and 0.97 kHz for $n = 1$. The slight reduction in the 1 kHz tonal amplitude is also visible when compared with the shaker in a stationary condition. These results are in agreement with previous work [36], where a slightly different experiment was set up and a very high frequency (225 kHz) was used.

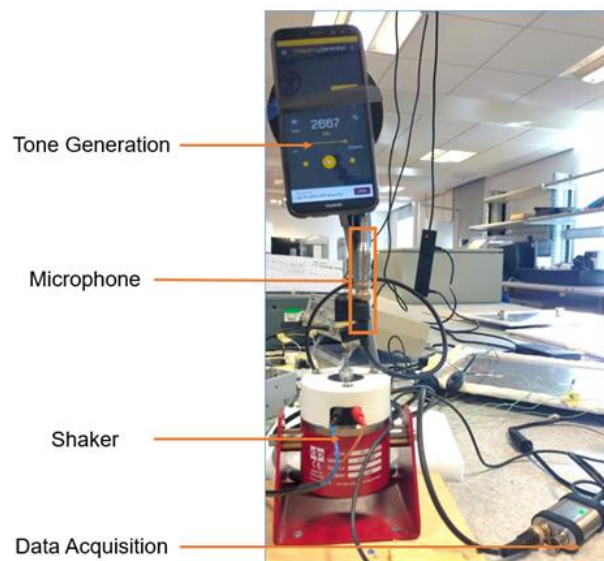


Figure 4-14 Experimental setup to study the effect of vibration on generated acoustic tones

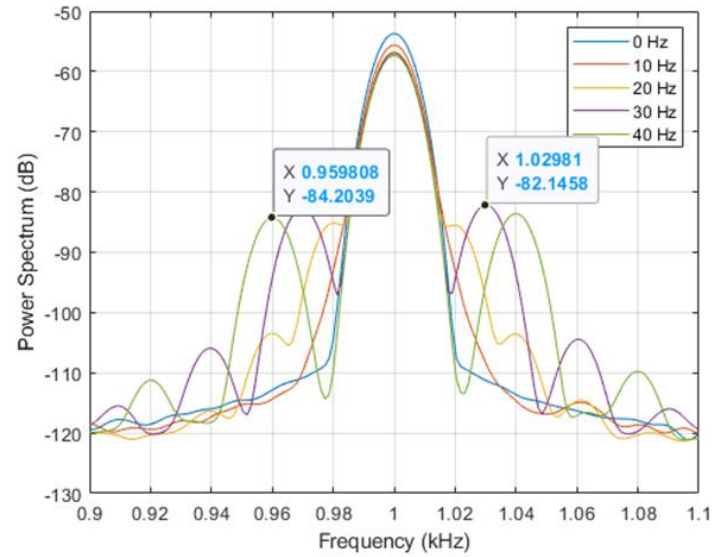


Figure 4-15 Power Spectrum of acquired acoustic data from the microphone undergoing vibrations

The combined effect of RPM fluctuations and the Doppler effect is the superposition of multiple tones generated by the components and sidebands due to the acoustic reflections from vibrating surfaces. The sidebands can also interfere with the frequencies of interest and thus render them ineffective for condition monitoring purposes. Moreover, as the tones move back and forth, due to RPM fluctuations, their superposition may lead to a reduction in their amplitude due to phase mismatch during propagation inside the APU compartment. Furthermore, since the vibrations are taking place at multiple frequencies, a clear separation between the tone and the sidebands will not be present, and the tonal frequency will spread over a wider range. Under such circumstances, the appearance of any new tonal frequency or an increase in the amplitudes of the already existing frequencies (which has not been detected under healthy conditions using microphones) due to a faulty condition cannot be captured through the deployment of microphones in the APU compartment.

4.4.2.2 Bicoherence Analysis

Vibration signals measured from a rotary machine can have many forms of amplitude and phase modulations which can indicate a large range of failure conditions [37,38]. High-order spectral techniques (like Bicoherence) can detect such modulations which are otherwise not visible in the frequency spectrums. In

this study, the possible utilization of Bicoherence analysis on near-field acoustic data is assessed. In the absence of detailed information about the system parameters, Bicoherence graphs of the vibration data have been considered as a reference, and the possibility of those graphs getting reciprocated in the acoustic data is ascertained. The parameters selected for Bicoherence analysis are similar to the ones for coherence (described in Section 4.3.3), however, the FFT size is chosen to be 512 to reduce the computational requirements.

The Squared Bicoherence values for vibration data from sensor GBX during BL OFF and BL ON states are shown in Figure 4-16. Phase coupling can be seen to be occurring between 100 Hz and 12.1 kHz. The Bicoherence at this pair of frequencies remains almost constant and has been found to exist at locations GEN and GBY (results not shown). The Bicoherence value for GBX decreases slightly (0.6 to 0.5) under the BL ON state, which is attributable to the increase in the overall vibration levels and decreasing tonal amplitudes (SNR decreasing). Treating the identified phase coupled frequency pair as a reference, the same analysis is repeated for acoustic data [sensor = GBL] (Figure 4-17). The resultant graphs do not reproduce similar results regardless of the APU state. Moreover, any other phase coupled frequency pairs do not surface across the whole spectrum, which renders Bicoherence analysis on highly noisy (acoustic) data completely ineffective to generate any useful information about the system {Finding # 5}.

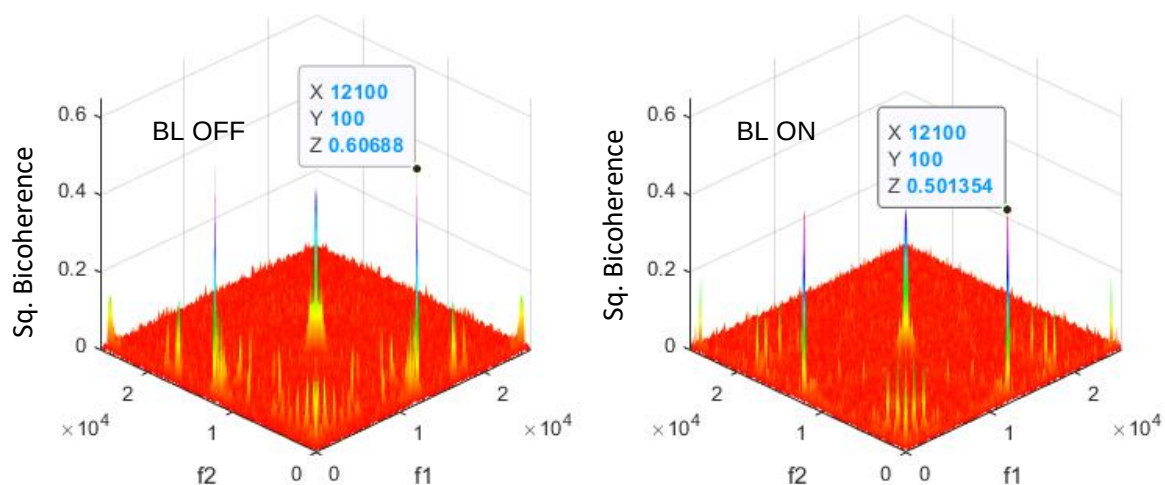


Figure 4-16 Bicoherence analysis of vibration data

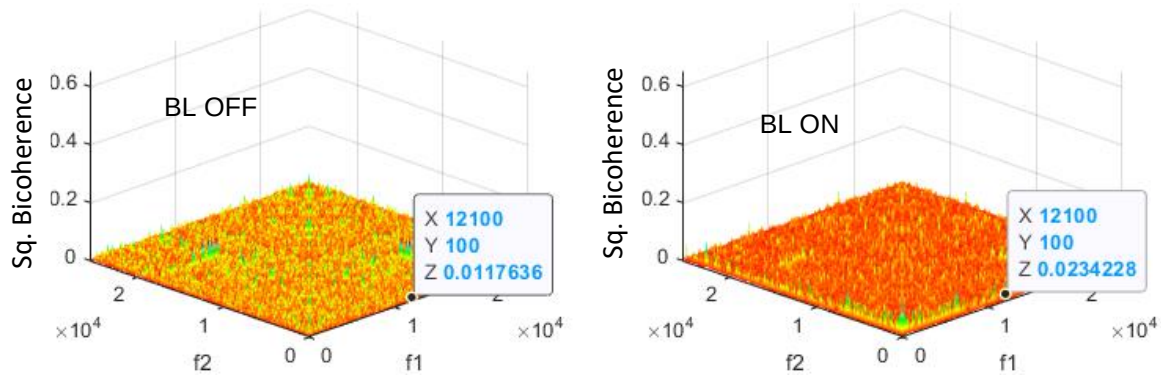


Figure 4-17 Bicoherence analysis of acoustic data

To observe the effect of SNR on Bicoherence results, the process is repeated on synthetically generated data with known phase coupling and varying SNR. A phase-modulated signal is created with a sinusoidal carrier ($f_c = 1300 \text{ Hz}$) and sinusoidal signal ($f_m = 5100 \text{ Hz}$) with the sampling frequency of 51.2 kHz using the following relationship:

$$S(t) = S_{pure}(t) + n(t) \quad (4-16)$$

Where,

$$S_{pure}(t) = \sin(2\pi f_m t + \varphi_m) + \sin[2\pi f_c t + \sin(2\pi f_m t)] \quad (4-17)$$

The noise power $[\sigma_{n(t)}^2]$ of the added normally distributed noise $[n(t)]$ is varied to produce three sets of signals with different SNRs [0dB, -15dB, and -20dB]. SNR is computed using the following relationship:

$$SNR = 10 \log \left(\frac{\sigma_{S_{pure}(t)}^2}{\sigma_{n(t)}^2} \right) \quad (4-18)$$

The results of Bicoherence estimates on the simulated signals are shown in Figure 4-18. At 0dB SNR, the phase coupling between 1300 Hz and 5100 Hz is visible with a high value of Bicoherence. The estimated Bicoherence value reduces to 0.26 at SNR = -15dB and eventually diminishes to almost zero at SNR of -20dB. The results are similar to [39] where a different phase coupling model was used to report that Bicoherence fails to reliably detect phase coupling when SNR is less than -16 dB (or S/N = 0.158). As per their analysis [39, Figure-3], for

a sq. bicoherence of 0.6 [computed for the vibration sensor – Figure 4-16(a)], SNR of -4 dB (or $S/N = 0.63$) is required. Since no phase coupling is detected in the acoustic data, it implies that, during vibration to acoustic conversion, SNR reduces by at least $0.158 / 0.63 = 1/4$ to produce a signal which has an $SNR \leq -16dB$ at which bicoherence does not produce useful results. The reduction in SNR can be because of the combined effect of the decrease in the tonal amplitudes and increase in the noise floor for microphone data (the effects have been shown in Figure 4-8).

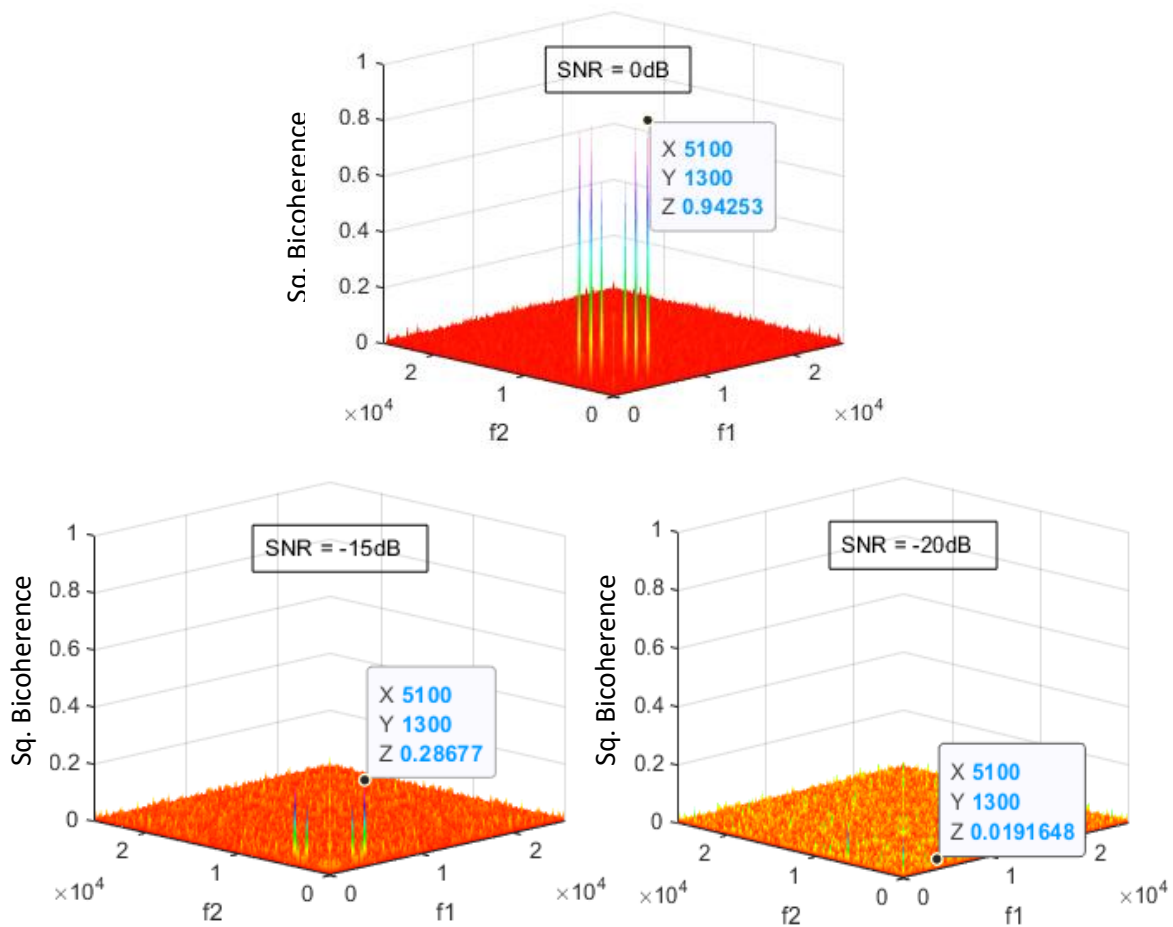


Figure 4-18 Result of bicoherence analysis on simulated data

4.4.3 Broadband Noise Analysis

This section presents the results acquired based on the analysis described in section 4.3.5. Initially, the results for coefficients of overlap for calculated features are presented and discussed. This is followed by a detailed discussion of the computed correlation coefficients between vibroacoustic data and the considered

APU parameters. Lastly, the possibility of external sources affecting the near-field acoustics is presented.

4.4.3.1 Coefficients of Overlap

A significant amount of near-field acoustic, vibration and FADEC data has been acquired for this study. Several categories of features (mentioned in section 4.3.5.1) have been computed in order to proceed with the desired analysis. The acquired dataset consists of 13,879 data points (corresponding to one-second data segments), out of which 6,265, 4,098, and 3,516 correspond to BL OFF, BL ON NL, and BL ON LD conditions, respectively. For any data point, there are 8x5x20 features from eight microphones and 3x5x20 from vibration sensors, where there are 5 feature categories and the approximate number of features in each category is 20. For computing the coefficients of overlap ($\Delta_{BL\ OFF}^{BL\ ON}$, $\Delta_{BL\ ON\ NL}^{BL\ ON\ LD}$), the kernel density for each of the features is computed separately for BL OFF, BL ON, BL ON NL, and BL ON LD states, and then expressions (1) and (2) are employed.

Figure 4-19 illustrates the process of computing $\Delta_{BL\ OFF}^{BL\ ON}$ for a time-domain feature (RMS value) for each of the acoustic and vibration sensors. The figure shows that the RMS value is a good feature to separate between BL OFF and BL ON conditions for acoustic sensors BV and BV2, both of which are outside the APU shroud. OLC is the only sensor inside the shroud which exhibits a similar behavior and provides a lower overlap (0.13). Apart from these sensors, the RMS values have overlapping distributions for the remaining sensors, including the vibration sensors. Figure 4-20 shows the same procedure repeated for $\Delta_{BL\ ON\ NL}^{BL\ ON\ LD}$ but with a different feature (the fifth feature of MFCC). It is evident from the figure that the two APU states (BL ON NL and BL ON LD) cannot be distinguished using this feature. However, the microphones installed near the igniter and the surge control valve demonstrate better performance. These two locations are closest to the bleed duct and therefore have a better chance of acquiring any change in acoustic characteristics due to flow variations.

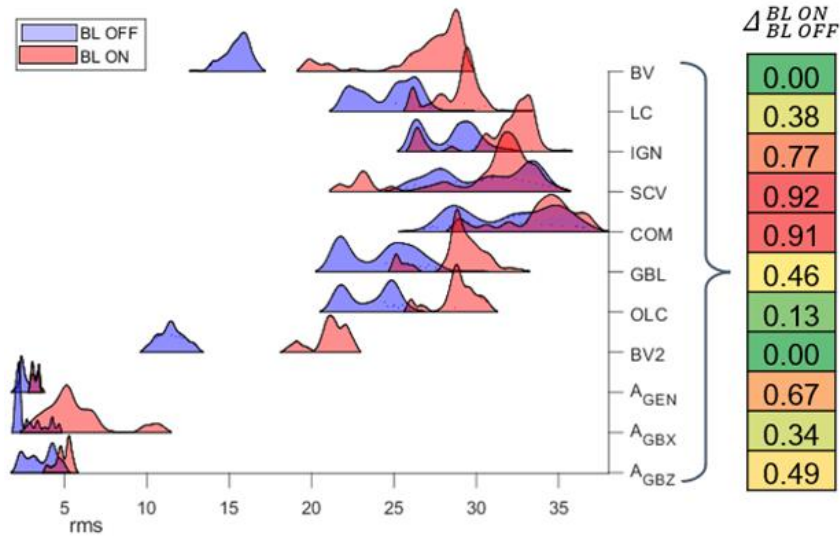


Figure 4-19 Results of $\Delta_{BL OFF}^{BL ON}$ for RMS feature (Time domain feature category)

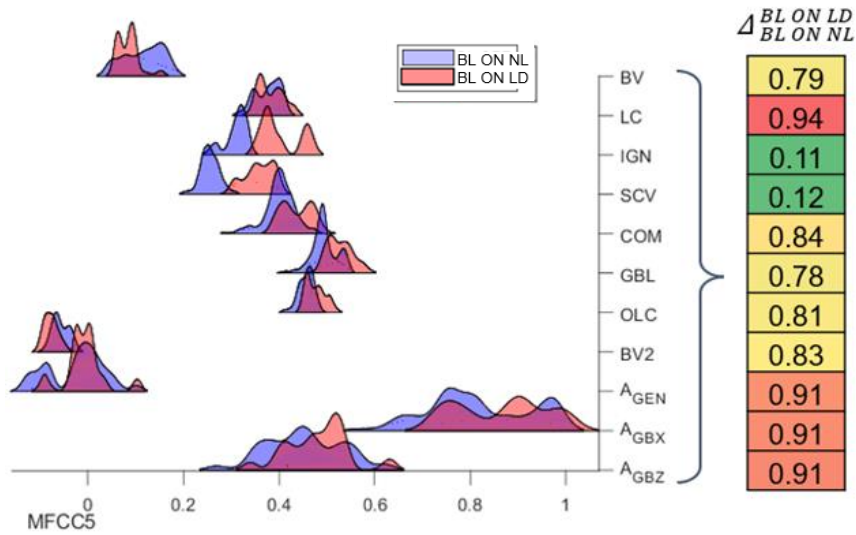


Figure 4-20 Result of $\Delta_{BL ON NL}^{BL ON LD}$ for the fifth feature (MFCC feature category)

Figure 4-19 and Figure 4-20 have considered each microphone and vibration sensor separately to illustrate the employed scheme for computing the coefficients of overlap, each for a single feature. However, in order to provide a summarized version of the results, the two coefficients ($\Delta_{BL OFF}^{BL ON}$, $\Delta_{BL ON NL}^{BL ON LD}$) have been accumulated while keeping segregation between feature categories and sensor type. Figure 4-21 shows the distributions of the overlap coefficients for each of the five categories of features, separately for acoustic and vibration sensors. Considering $\Delta_{BL OFF}^{BL ON}$ first, the results show that a clear separation

between BL OFF and BL ON states can be made (i.e., several features demonstrate zero values of overlap coefficients) regardless of the sensor and the category of feature extraction technique used [Figure 4-21(a)] *{Finding # 6}*. The acoustic data, however, offers a larger number of features (32%) with zero overlaps as compared to the vibration data where only 10% of the features can reliably separate the two states using a given feature category. Furthermore, the ‘BandPowers’ have the highest number of lower $\Delta_{BL\ OFF}^{BL\ ON}$ values for both sensor types and may prove to be a better choice for developing classification models if all the sensors are concurrently considered. The ability of the vibroacoustic sensors to be able to segregate between the BL OFF and BL ON states stems from the fact that numerous changes take place when the APU’s pneumatic system is activated, which can be easily picked up by these sensors. In BL ON states (BL ON NL / NL ON LD), IGVs open increasing the mass flow through the Load Compressor, Surge Valve and Bleed Valve. This increases the torque required by the load compressor. To keep the APU RPM constant under such conditions, the fuel flow to the combustor increases thus increasing the combustion noise. The combined effect is the increase in vibrations and noise across the whole APU, which can be picked up by vibroacoustic sensors with appropriate feature extraction techniques.

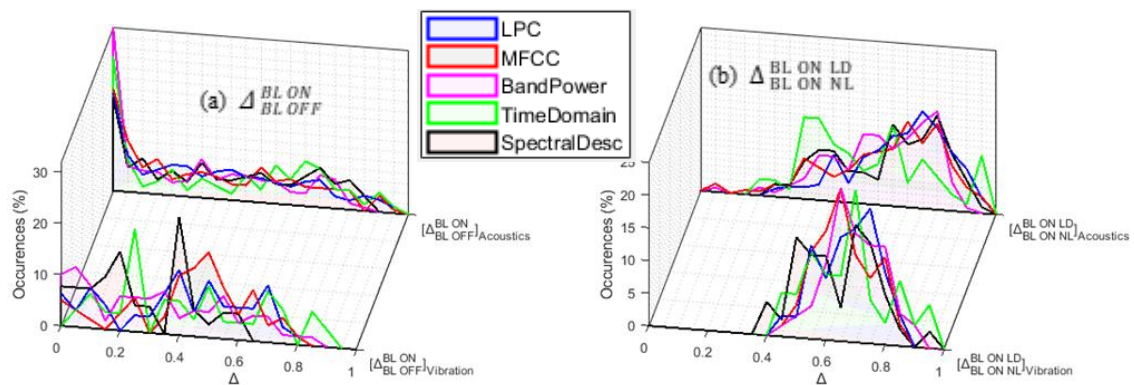


Figure 4-21 Distributions of coefficients of overlap for different categories of acoustic and vibration features

The situation is considerably different when segregating between BL ON NL and BL ON LD states, which is evident from Figure 4-21(b). There is a distinct difference between the response of the acoustic and vibration sensors, as the

latter does not show promising results. The values of $\Delta_{BL\ ON\ NL}^{BL\ ON\ LD}$ for the vibration sensors are high ($\Delta > 0.3$) regardless of the technique used, while for the acoustic data there are some features for which the values of coefficients are close to zero which is desirable {*Finding # 7*}. This behaviour can be attributed to the fact that, between the two APU states, only the mass flow through the surge valve and the bleed valve varies, while everything else remains the same. The flow variations lead to changes in acoustic characteristics around the bleed duct, which may not get induced as vibrations and picked up by the vibration sensors. Amongst the feature categories, certain features from MFCC and BandPower exhibit better performance on acoustic data, where the former slightly outperforms the latter using acoustic data {*Finding # 8*}.

4.4.3.2 Correlation Coefficients

In this section, the distribution of the correlation coefficients accumulated using: different categories of features; microphone and vibration data; and various APU parameters, is presented. The distributions depict the number of features that are correlated / uncorrelated with a specific APU parameter. The desired response of a distribution is to have a minimum number of features exhibiting zero correlations, while the maximum is highly correlated (i.e. $|\rho| \approx 1$). Such a distribution will imply that the majority of the features in that category change linearly with an APU parameter, or in other words, most of the features are directly affected by only that parameter and uninfluenced by any other variation taking place in the APU.

The amount of data utilized for this analysis consists of: 13,897 data points (corresponding to all APU states) to compute ρ_{TOil} and $\rho_{m_{LC}}$, 7,614 data points (corresponding to BL ON states) to compute ρ_{IGV} , and 3,516 data points (corresponding to all BL ON LD states) to compute $\rho_{m_{Bleed}}$. The result of the complete analysis is presented in Figure 4-22 which gives the complete picture of the distributions of the computed correlation coefficients while segregating between acoustic and vibration data for all the five categories of feature extraction techniques [refer to expression (4-5)].

Considering T_{oil} first [Figure 4-22(a)], the superiority of vibration sensor over acoustic sensor can be clearly observed. The values of $[\rho_{T_{oil}}]_{vibration}$ range between -1 and 0.9, whereas for $[\rho_{T_{oil}}]_{acoustic}$ the values are between -0.9 and 0.8. Moreover, the ratio of features exhibiting higher correlations is also high for the vibration sensors. This makes the vibration sensors a better choice utilizing them to estimate the oil temperature *{Finding # 9}*. MFCC features using vibration sensors have been identified as the best feature extraction technique for this purpose. The situation is different for the other three APU Parameters ($\dot{m}_{LC}$, IGV angles, and $\dot{m}_{Bleed}$), with the acoustic sensors showing better correlations as compared to their counterpart. The values of $[\rho_{\dot{m}_{LC}}]_{acoustic}$ have been found to be nearly ± 1 using any of the feature extraction techniques [Figure 4-22(b)] which makes the acoustic sensors a suitable candidate for developing a regression model for monitoring the performance of the load compressor *{Finding # 10}*.

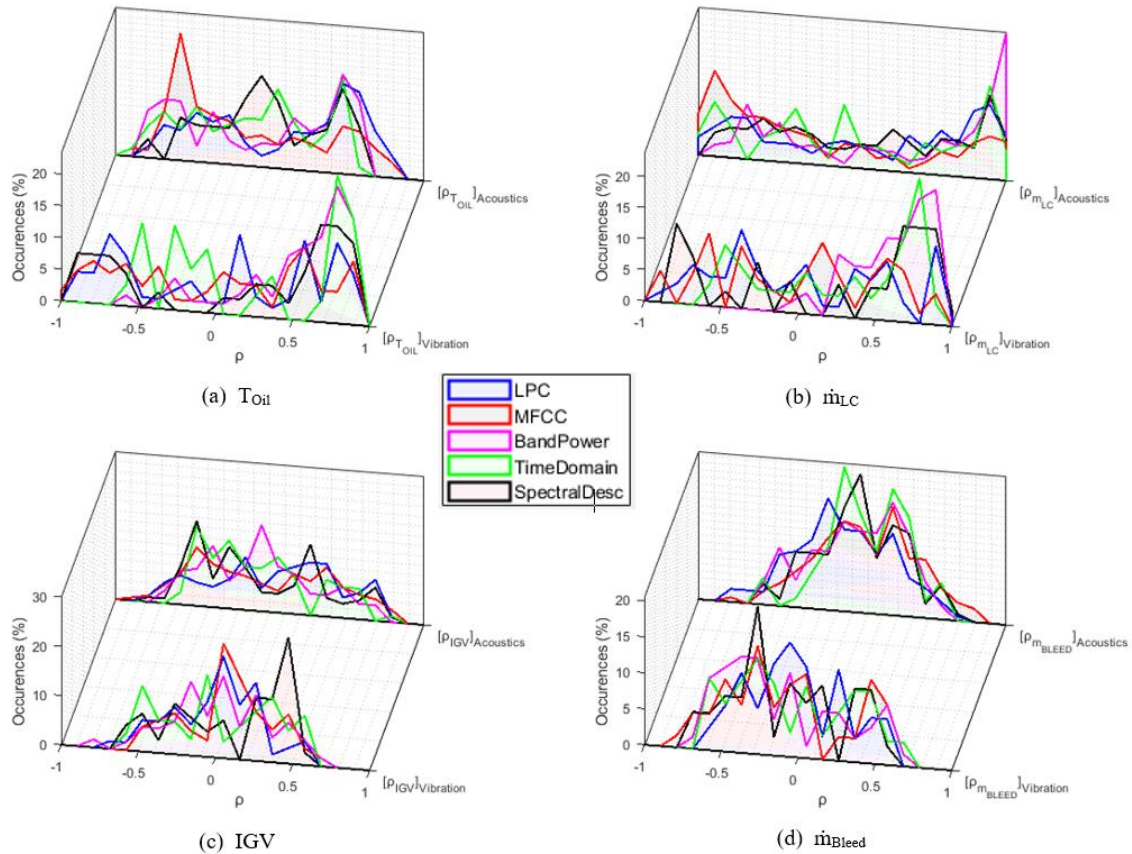


Figure 4-22 Distributions of correlation coefficients for APU parameters and different categories of features

A greater deviation between the two types of sensors can be observed when computing correlations with IGV angles [Figure 4-22(c)]. With the acoustic sensors, $|\rho_{IGV}|$ values can be as high as 0.85 with certain MFCC features, while they are below 0.75 with the vibration sensors regardless of the feature extraction technique used. This may be attributed to the vibration sensor being sensitive to localized variations in the vibrations and therefore not being able to capture a wide range of variations taking place due to the change in APU operating characteristics. Within the acoustic sensors, it can be observed that the Time Domain and BandPower features are not the most desirable set of inputs for regression since most of the features are uncorrelated. Lastly, acoustic sensors have also been found to be better in terms of higher values of correlations between the derived features and mass flow through the bleed valve $[\rho_{\dot{m}_{Bleed}}]_{acoustic}$ [see Figure 4-22(d)]. Either of the LPC and MFCC features can be used to provide correlations $|\rho_{\dot{m}_{Bleed}}| > 0.8$, making them suitable for developing a regression model to translate the raw acoustic data into meaningful information about the mass flow through the bleed valve {Finding # 11}.

4.4.3.3 Effect of External Noise Sources on Near-field Acoustics

Having successfully demonstrated that the near-field acoustic features exhibit good correlations with APU operating states and performance parameters, this substantiates their potential to be implemented for APU condition monitoring purposes. In order to further strengthen their potential, the quantification of the effect of external noise sources on near-field acoustics needs to be addressed. To do this, the acoustics data corresponding to two microphones has been analyzed: one outside the APU compartment, mounted on the aircraft fuselage, labeled as Cooling Air Outlet (CAO), and the other one mounted inside of the APU shroud (GBL). Figure 4-23 shows the time domain signal and power spectrum for both microphones when the APU is not in operation. From the time domain signal [Figure 4-23(a)], it can be established that the (CAO) is more prone to external noise relative to the GBL. After listening to the audio files, the wind has been identified to be the major noise source for CAO, whereas for GBL it is

mostly silent with faint sound due to the chirping of birds at around 40-50 seconds.

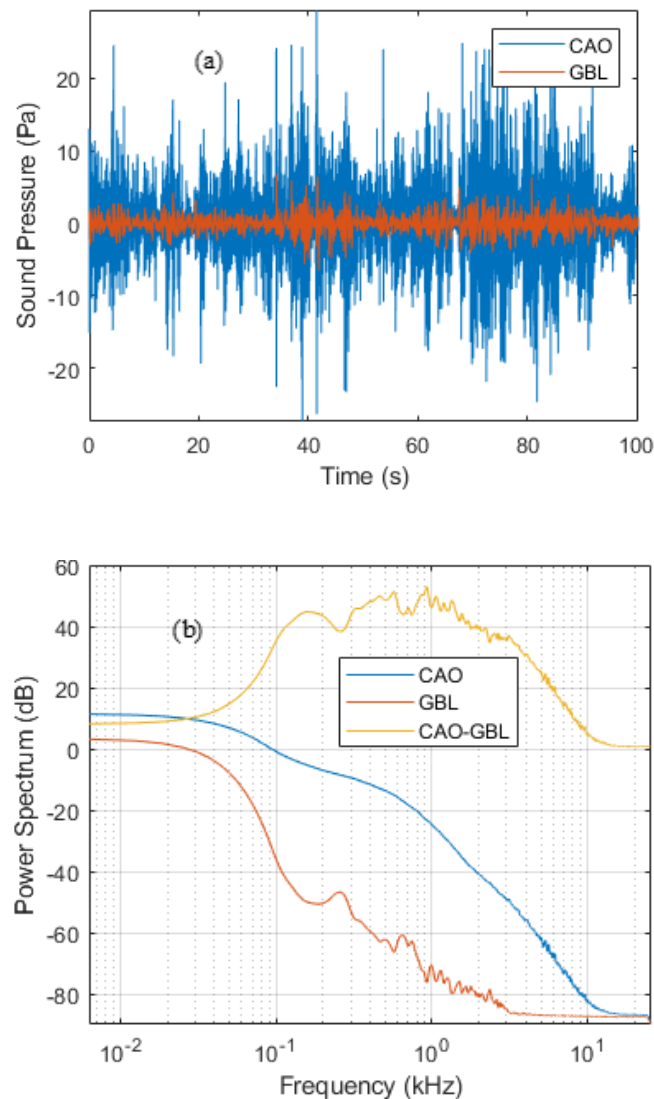


Figure 4-23 Analysis of external and internal microphone data (a) Time domain signal (b) Frequency Spectrum

To further elaborate on the results, the frequency spectrum of acoustics data at CAO and GBL and their difference has been analyzed, shown in Figure 4-23(b). Considering CAO first, it can be established that the external noise is present till 10 kHz with the noise dominating between 0-100 Hz region, after which the noise levels gradually decrease in the 100-10 kHz range. Such noise, while traversing through the aircraft's metallic structure, experiences a frequency-dependent reduction in the noise levels that can be observed at sensor location GBL. For

frequencies below 70 Hz, the noise is attenuated by 10dB-20dB, and for frequencies above 100 Hz, there is an average of 40dB reduction in the noise, which can reach a value of 53dB at 1 kHz. As there is no background noise present for frequencies above 3 kHz, the attenuation levels cannot be ascertained from this analysis. As reported in the literature, the sound attenuation increases for higher frequencies [40], therefore the acquired average attenuation level of 40dB can be extended for frequencies above 3 kHz.

The aircraft's metallic structure and the APU shroud are responsible for attenuating the sound originating from external sources. As per the design, the APU is covered by the shroud for decreasing the noise produced by the APU as well as for containing flames in case of fire. This noise is further reduced by the aircraft structure which is holding the APU, elevators, and rudder. Such a reduction is favorable for the acoustic data captured inside the APU during operation since it will attenuate the external noise.

4.5 Summary and Conclusion

A comprehensive evaluation of the APU near-field acoustic data has been conducted to determine its potential for online condition monitoring purposes. To support this study, experimental data has been acquired from an in-situ aircraft APU under various load conditions, to generate an elaborate set of near-field and far-field acoustic, vibration, and APU state data. The acquired data is then processed to support the underlying scientific understating associated with the APU state and performance parameters, as well as its potential utility for online condition monitoring. The major results of this research work, collected from the *{Findings}* in the text, can be summarised as:

(a) Microphones (and vibration sensors) installed inside the APU compartment are not useful for capturing the combustion process (or combustion noise) *{Findings # 1 and 4}*. The noise generated from the APU vibration and the pneumatic system flows is dominant, which swamps the combustion noise propagation, either through the APU structure or from the APU exhaust.

(b) Microphones external to the APU compartment can monitor APU shaft frequencies for potential faults *{Finding # 2}*.

(c) The near-field microphones only capture part of the tonal frequencies generated by the shaft, bearing, and gearbox under low-load operating conditions. Under the high load operating conditions, the capability of the near-field microphones is further limited and has been demonstrated to predominantly capture tones corresponding to the frequency of the shaft *{Finding # 3}*. The possible reasons for the limited ability of the microphone for capturing the tones can stem from RPM fluctuations, the Doppler effect, and the rise in overall noise levels due to the pneumatic flows through the load compressor, bleed duct, bleed valve, and the surge control valve.

(d) The Bicoherence analysis, which performs well on vibration data for condition monitoring, fails to respond in the same manner for the acoustic data regardless of the APU operating state due to low SNR *{Finding # 5}*.

(e) Vibration and acoustic sensors are equally good in segregating between the two primary states of APU operation (BL OFF and BL ON) using any of the feature extraction techniques *{Finding # 6}*. However, the vibration sensors are unable to sense the variations taking place when the APU starts delivering flow through the Bleed Valve, which otherwise can be done with acoustic sensors using MFCC features *{Findings # 7 and 8}*.

(f) The acoustic data outperforms vibration data by demonstrating high correlations with most of the APU parameters *{Findings # 9, 10, and 11}*.

The results acquired suggest that microphones have limited capability (as compared to the vibration sensors) to capture the tonal frequencies to enable condition monitoring of APU components (shaft, bearing, gears). However, the microphones prove to be an appropriate sensor for estimating the APU operating states and performance parameters to facilitate condition monitoring of lubrication oil cooling system and pneumatic system components (IGVs, SCV, and BV).

References

- [1] U. Ahmed, F. Ali, I. Jennions, "A review of aircraft auxiliary power unit faults, diagnostics and acoustic measurements," *Prog. Aerosp. Sci.* vol. 124, Jul. 2021, Art. no. 100721, doi: 10.1016/j.paerosci.2021.100721.
- [2] U. Ahmed, F. Ali, I.K. Jennions, "Development of a Far-Field Noise Estimation Model for an Aircraft Auxiliary Power Unit," *IEEE Access*. 9 (2021) 127703–127719. <https://doi.org/10.1109/ACCESS.2021.3112390.B>.
- [3] N. Shivashankara, "Gas turbine core noise source isolation by internal-to-far-field correlations," *J. Aircr.* 15 (1978) 597–600. <https://doi.org/10.2514/3.58412>.
- [4] J. Xu, C.K.W. Tam, S.A. Parrish, "On indirect combustion noise," in *50th AIAA Aerosp. Sci. Meet. Incl. New Horizons Forum Aerosp. Expo.* (2012) 1–16. <https://doi.org/10.2514/6.2012-543>.
- [5] M. Pott-Pollenske, W. Dobrzynski, H. Buchholz, D. Almonet, "Characteristics of noise from aircraft ground operations," in *13th AIAA/CEAS Aeroacoustics Conf. (28th AIAA Aeroacoustics Conf.)* (2007) 1–15. <https://doi.org/10.2514/6.2007-3560>.
- [6] R.L. Tubbs, "Case Studies Noise Exposure to Airline Ramp Employees," *Appl. Occup. Environ. Hyg.* 15 (2010).
- [7] K. Knobloch, A. Fischer, F. Bake, L. Enghardt, S. Busse-Gerstengarbe, "Full-scale tests on APU noise reduction," in *Proc. ASME Turbo Expo. 2A* (2014). <https://doi.org/10.1115/GT2014-26803>.
- [8] J. Wonho Jung, A. Bae, Y.-H. Park, "Acoustic Signal Based Non-Contact Ball Bearing Fault Diagnosis Using Adaptive Wavelet Denoising," *arXiv:2110.03348*, 2021.
- [9] S.V.V.S.N. Pichika, R. Yadav, S. Geetha Rajasekharan, H.M. Praveen, V. Inturi, "Optimal sensor placement for identifying multi-component failures in a wind turbine gearbox using integrated condition monitoring scheme," *Appl. Acoust.* 187 (2022) 108505. <https://doi.org/10.1016/j.apacoust.2021.108505>.

- [10] M.A. Khan, M.A. Shahid, S.A. Ahmed, S.Z. Khan, K.A. Khan, S.A. Ali, M. Tariq, "Gear misalignment diagnosis using statistical features of vibration and airborne sound spectrums," *Meas. J. Int. Meas. Confed.* 145 (2019) 419–435. <https://doi.org/10.1016/j.measurement.2019.05.088>.
- [11] R. Giri, S. V Tenneti, F. Cheng, K. Helwani, "Unsupervised Anomalous Sound Detection Using Self-Supervised Classification And Group Masked Autoencoder For Density Estimation," *Challenge on Detection and Classification of Acoustic Scenes and Events (DCASE 2020 Challenge) Tech. Rep*, 2020.
- [12] R.K. Mobley, "Signature Analysis," in: *Vibration. Fundamentals*, Elsevier, 1999: pp. 181–188. <https://doi.org/10.1016/B978-075067150-7/50053-7>.
- [13] P. Raharjo, S. Abdussalam, F. Gu, A.D. Ball, "Vibro-acoustic characteristic of a self aligning spherical journal bearing due to eccentric bore fault," in *9th Int. Conf. Cond. Monit. Mach. Fail. Prev. Technol.* 2012, C. 2012 MFPT 2012. 1 (2012) 124–140.
- [14] T. Vaimann, J. Sobra, A. Belahcen, A. Rassõlkin, M. Rolak, A. Kallaste, "Induction machine fault detection using smartphone recorded audible noise," *IET Sci. Meas. Technol.* 12 (2018) 554–560. <https://doi.org/10.1049/iet-smt.2017.0104>.
- [15] M. Holguín-Londoño, O. Cardona-Morales, E.F. Sierra-Alonso, J.D. Mejia-Henao, Á. Orozco-Gutiérrez, G. Castellanos-Dominguez, "Machine Fault Detection Based on Filter Bank Similarity Features Using Acoustic and Vibration Analysis," *Math. Probl. Eng.* 2016 (2016). <https://doi.org/10.1155/2016/7906834>.
- [16] K. Shibata, A. Takahashi, T. Shirai, "Fault diagnosis of rotating machinery through visualisation of sound signals," *Mech. Syst. Signal Process.* 14 (2000) 229–241. <https://doi.org/10.1006/mssp.1999.1255>.
- [17] C. Skliros, F. Ali, I. Jennions, "Fault simulations and diagnostics for a Boeing 747 Auxiliary Power Unit," *Expert Syst. Appl.* 184 (2021) 115504. <https://doi.org/10.1016/j.eswa.2021.115504>.

- [18] H. Gupta, D. Gupta, "LPC and LPCC method of feature extraction in Speech Recognition System," in *Proc. 6th Int. Conf. - Cloud Syst. Big Data Eng. Conflu.* (2016) 498–502. <https://doi.org/10.1109/CONFLUENCE.2016.7508171>.
- [19] O. Eltiraifi, E. Elbasheer, M. Nawari, "A Comparative Study of MFCC and LPCC Features for Speech Activity Detection Using Deep Belief Network," in *Int. Conf. Comput. Control. Electr. Electron. Eng. ICCCEEE*. (2018) 6–10. <https://doi.org/10.1109/ICCCEEE.2018.8515821>.
- [20] O. Chia Ai, M. Hariharan, S. Yaacob, L. Sin Chee, "Classification of speech dysfluencies with MFCC and LPCC features," *Expert Syst. Appl.* 39 (2012) 2157–2165. <https://doi.org/10.1016/j.eswa.2011.07.065>.
- [21] M. Rana, S. Miglani, "Performance Analysis of MFCC and LPCC Techniques in Automatic Speech Recognition," *Int. J. Eng. Comput. Sci.* 3 (2014) 7727–7732.
- [22] S. Oue, R. Marxer, F. Rudzicz, "Automatic dysfluency detection in dysarthric speech using deep belief networks," in *SLPAT - 6th Work. Speech Lang. Process. Assist. Technol. Proc.* (2015) 60–64. <https://doi.org/10.18653/v1/w15-5111>.
- [23] U. Bhattacharjee, "A Comparative Study Of LPCC And MFCC Features For The Recognition Of Assamese Phonemes," *Int. J. Eng. Res. Technol.* (2013).
- [24] E. Raimy, C.E. Cairns, "The Segment in Phonetics and Phonology," *Segm. Phonetics Phonol.* (2014) 1–345. <https://doi.org/10.1002/9781118555491>.
- [25] Y. Petetin, C. Laroche, A. Mayoue, Y. Petetin, C. Laroche, A. Mayoue, "Deep neural networks for audio scene recognition" *Proc. Eur. Signal Process. Conf.*, pp. 125-129, 2015.
- [26] B. Lehner, G. Widmer, R. Sonnleitner, "On the reduction of false positives in singing voice detection," *Proc. IEEE Int. Conf. Acoustics Speech and Signal Processing*, pp. 7480-7484, 2014. <https://doi.org/10.1109/ICASSP.2014.6855054>.

- [27] S. Zhang, Y. Guo, Q. Zhang, "Robust voice activity detection feature design based on spectral kurtosis," in: *Proc. of ETCS'09, 2009*, pp. 269-272. <https://doi.org/10.1109/ETCS.2009.587>.
- [28] B. Schuster, L. Lieber, "Narrowband model for gas turbine engine combustion noise prediction," In *12th AIAA/CEAS aeroacoustics conference*, AIAA 2006-2677, Cambridge, MA, May 2006. <https://doi.org/10.2514/6.2006-2677>.
- [29] *Gas Turbine Jet Exhaust Prediction*, document ARP876F, SAE 2013.
- [30] J.W. Rawls, J.C. Yeager, "High Speed Research Noise Prediction Code (HSRNOISE) User's and Theoretical Manual," NASA, Richmond, VA, USA, Tech. Rep. Nasa/Cr-2004-213014, Nov. 2004.
- [31] G. R. Ibrahim and A. Albarbar, "Gearbox fault features extraction using vibration measurements and novel adaptive filtering scheme," *Adv. Acoust. Vibrat.*, vol. 2012, pp. 1–7, Jul. 2012, doi: 10.1155/2012/283535.
- [32] L. T. Ikelle and L. Amundsen, *Introduction to Petroleum Seismology*. Houston, TX, USA: Society of Exploration Geophysicists, 2018, doi: 10.1190/1.9781560803447.ch6.
- [33] O. M. Eidous and S. A. D. A. AL-Talafha, "Kernel method for overlapping coefficients estimation," *Commun. Statist. Simul. Comput.*, vol. 51, no. 9, pp. 5139–5156, Sep. 2022, doi: 10.1080/03610918.2020.1757711.
- [34] A. Swami, J. M. Mendel, and C. L. Nikias, *Higher-Order Spectral Analysis Toolbox for Use With MATLAB*. Natick, MA, USA: The Mathworks Inc., 1995.
- [35] W. Bolton, "Alternating current," in *Engineering Science*, 6th ed. Abingdon, U.K.: Routledge, 2021, pp. 177–188, doi: 10.4324/9781315737973-19.
- [36] R. Wunenburger, N. Mujica, and S. Fauve, "Experimental study of the Doppler shift generated by a vibrating scatterer," *J. Acoust. Soc. Amer.*, vol. 115, no. 2, pp. 507–514, Feb. 2004, doi: 10.1121/1.1635414.

- [37] C. J. Li, J. Ma, and B. Hwang, "Bearing condition monitoring by pattern recognition based on bicoherence analysis of vibrations," *Proc. Inst. Mech. Eng., C, J. Mech. Eng. Sci.*, vol. 210, no. 3, pp. 277–285, May 1996.
- [38] I.M. Howard, "Higher-order spectral techniques for machine vibration condition monitoring," *Proc. Inst. Mech. Eng. Part G J. Aerosp. Eng.* 211 (1997) 211–218. <https://doi.org/10.1243/0954410971532622>.
- [39] G. Tacchino, S. Coelli, P. Reali, M. Galli, A.M. Bianchi, "Bicoherence Interpretation in EEG Requires Signal to Noise Ratio Quantification: An Application to Sensorimotor Rhythms," *IEEE Trans. Biomed. Eng.* 67 (2020) 2696–2704. <https://doi.org/10.1109/TBME.2020.2969278>.
- [40] C. Soares, *Gas Turbines: A Handbook of Air, Land and Sea Application*. Oxford, U.K.: Butterworth-Heinemann, 2015.

5 Acoustic Monitoring of an Aircraft Auxiliary Power Unit

In this thesis, 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.

5.1 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 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 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 thesis, 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 chapter is organized as shown in Figure 5-1. Section 5.2 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 5.3. 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 5.4.

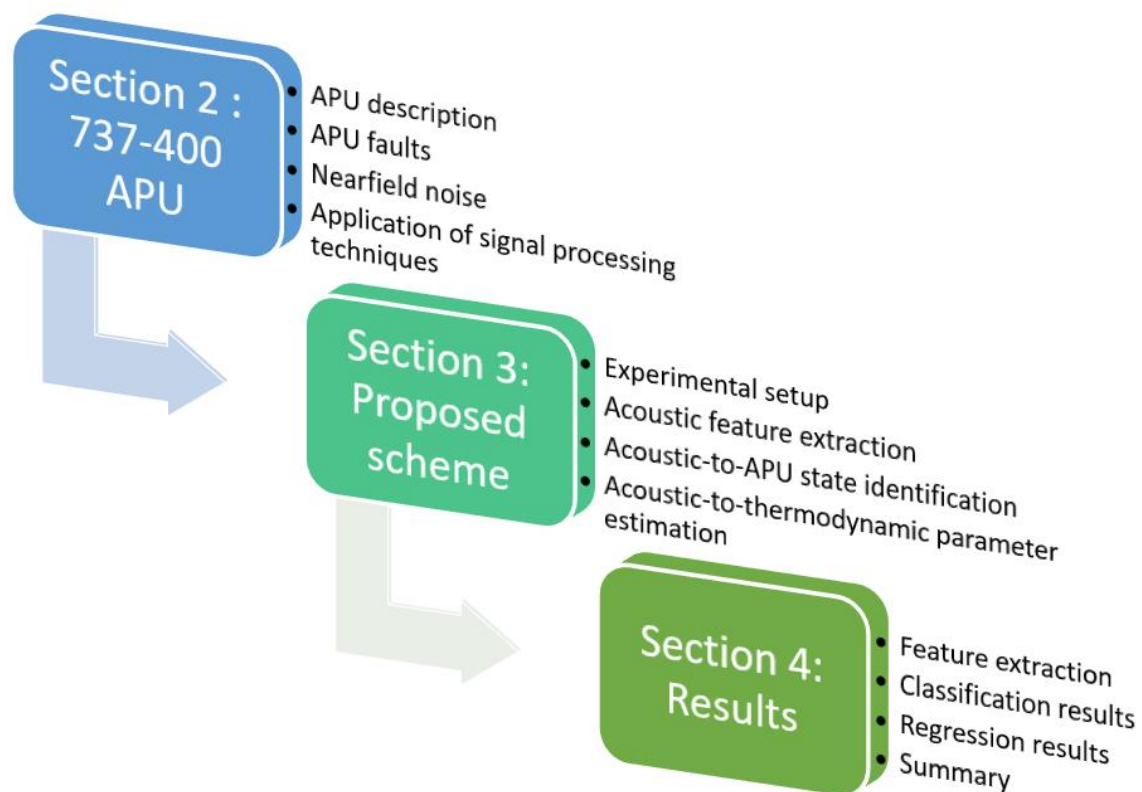


Figure 5-1 Overview of the chapter

5.2 Problem Description and Background

5.2.1 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 Figure 5-2. 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.

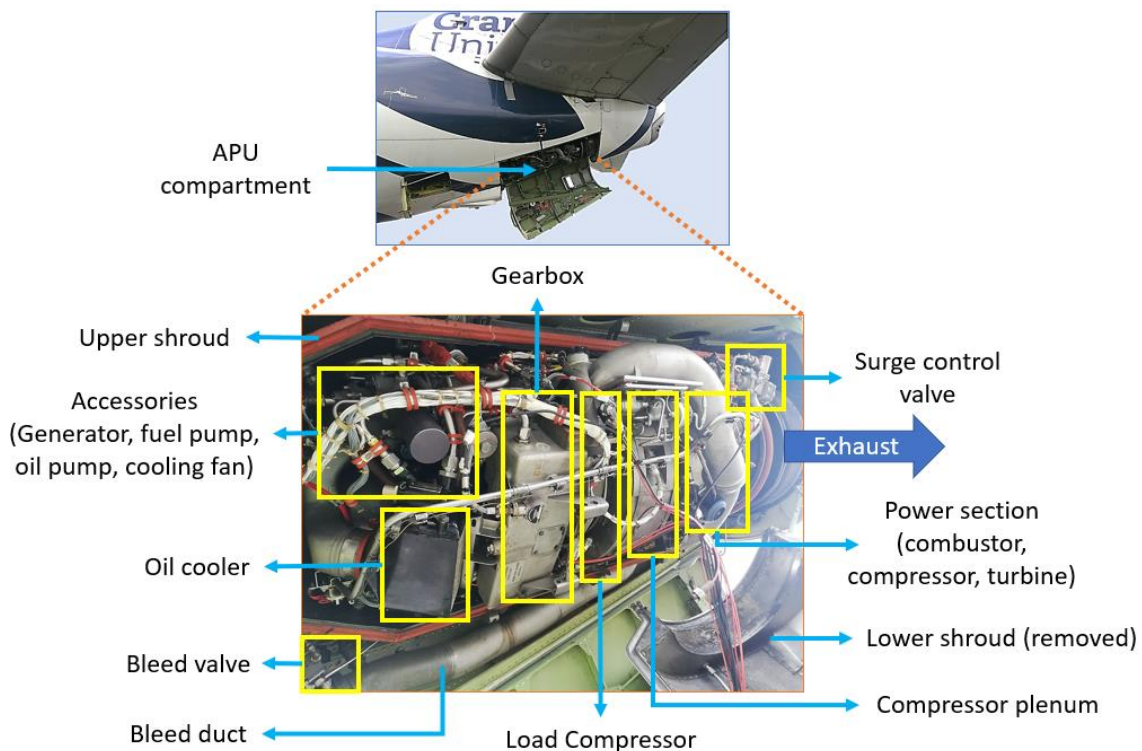


Figure 5-2 Schematics of the adopted APU

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 the onboard intrusive sensors can be visualized using the FADEC display, the details of which are presented in Section 5.3.2.

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].

5.2.2 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 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].

5.2.3 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 5-1 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.

Table 5-1 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 $BL\ ON\ LD$ state	
6	Surge Valve Malfunction		
7	Gearbox tooth wear / tooth crack	Variation in Gear Mesh Frequencies and Side Bands	Not Considered
8	Bearing Inner / Outer Race Defect	Appearance of Bearing frequencies	
9	Generator wiring fault	Mechanical power demanded by the generator increases	
10	Compressor / Turbine degradation	Variation in thermodynamic parameters of the core	

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 Figure 5-3(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 Figure 5-3(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 Figure 5-3(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 ($\dot{m}_{Bleed}$).

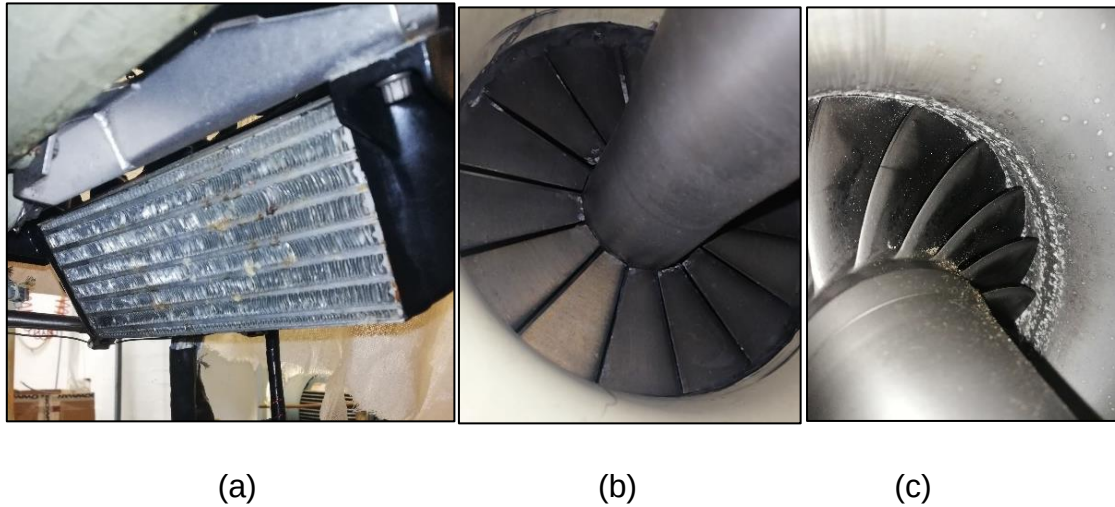


Figure 5-3 Degradation of APU components (a) Oil cooler fouling (b) IGVs closed (c) Wearing effects around the load compressor

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

5.2.4 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 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 40dB [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 aluminium 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.

5.3 Proposed Scheme for Fault Detection

5.3.1 Overview

In this thesis a novel system for monitoring an aircraft APU is presented; it is shown schematically in Figure 5-4. 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, 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.

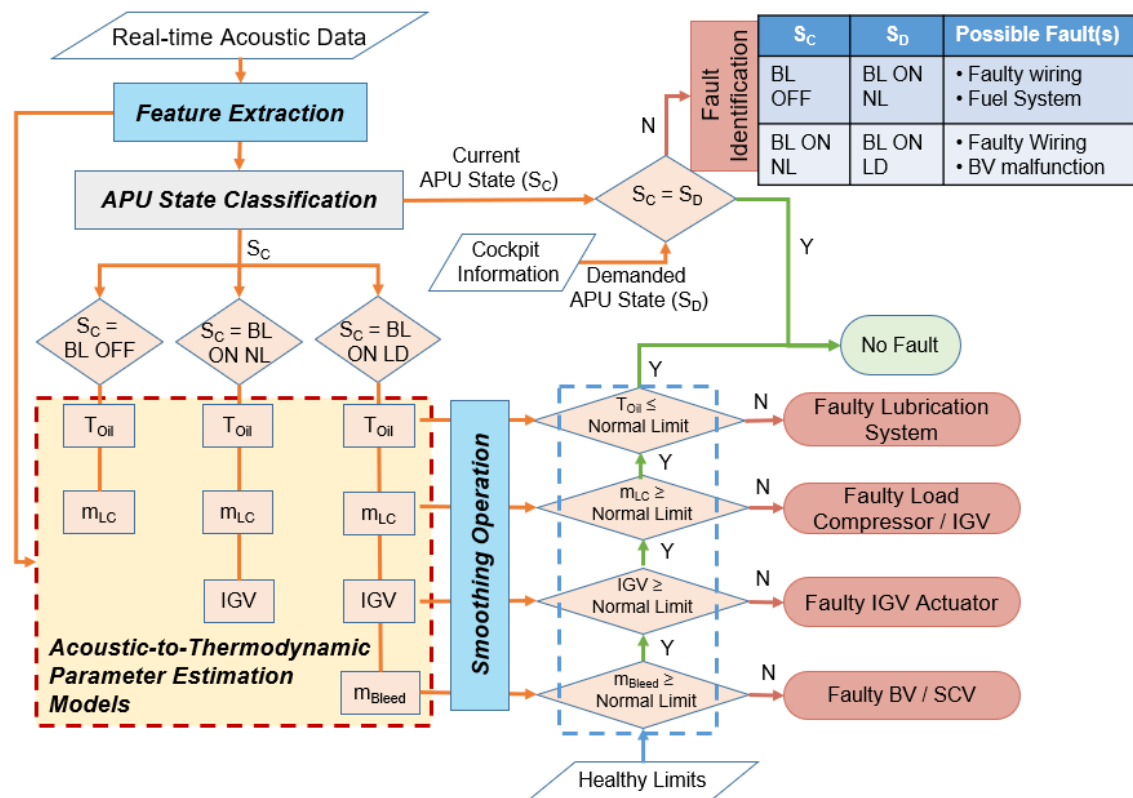


Figure 5-4 Proposed novel system for APU fault detection and isolation using acoustics

To evaluate the effectiveness of the proposed system, a detailed study has been undertaken to develop the desired classification and regression models and to

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.

5.3.2 Experimental Data Collection

This study focuses on near-field acoustic data collected from an in-situ aircraft APU. The data is collected by instrumenting Cranfield University's Boeing 737-400 aircraft (see Figure 5-6). 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 ¼" 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 Figure 5-7. 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.

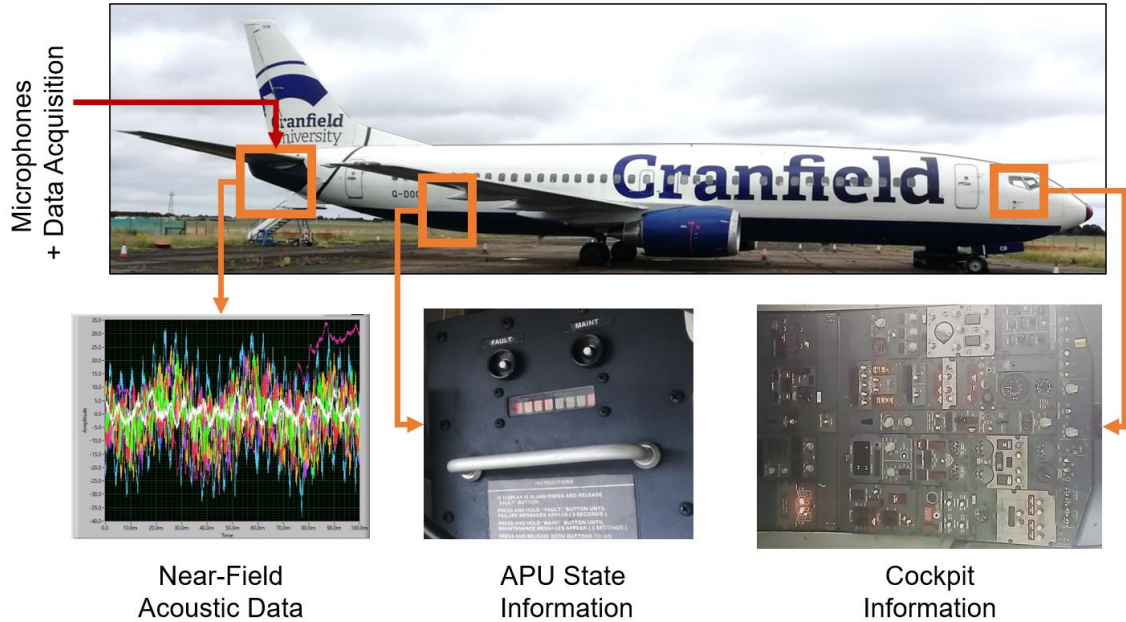


Figure 5-6 Experimental setup for APU state and acoustic data collection.

In addition to the microphones, a camera is installed in the aircraft's cargo compartment, Figure 5-8. This camera records the thermodynamic parameters shown in the FADEC display: T_{oil} , IGV angle, output pressure from the Load Compressor, and SVTM 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 5-2 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 minutes 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.

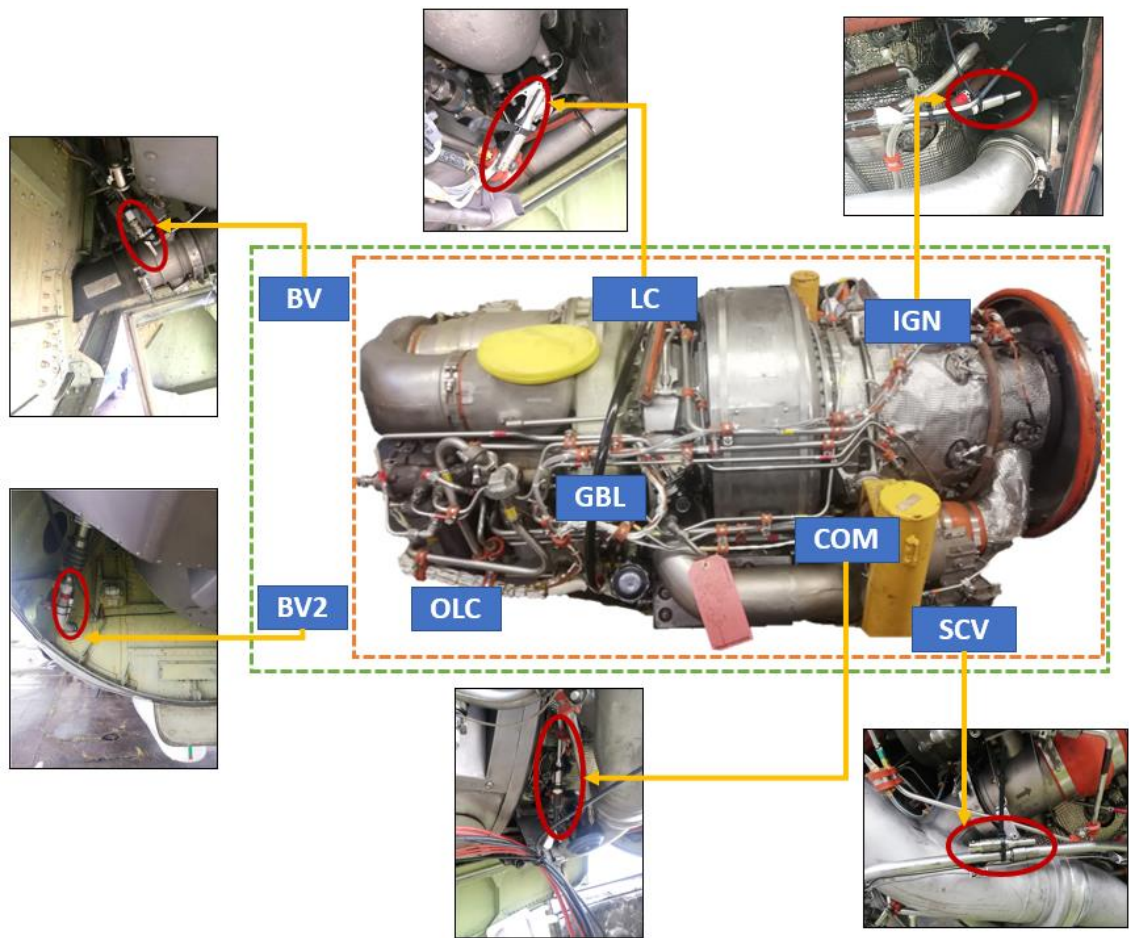


Figure 5-7 Microphone placement in the APU compartment



Figure 5-8 Recording of FADEC Display

Table 5-2 Data collection duration during experimentation.

Day #	Duration (sec)			
	Bleed Sys OFF	Bleed Sys ON without Load	Bleed Sys ON with Load	Total
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	1,263	824	704	2,791

5.3.3 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 5.3.4, 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 5-3. 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 5-3 Data allocation for modeling and testing of models

	Classification	Regression		
		<i>BL OFF</i>	<i>BL ON NL</i>	<i>BL ON LD</i>
Training Data	11722 (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

5.3.4 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 thesis 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 minimize the error between the linearly predicted signal $\hat{s}(n)$ and the actual signal $s(n)$, where

$$\hat{s}(n) = \sum_{k=1}^p a_k s(n - k) \quad (5-1)$$

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 weightage scheme in the lower frequency band [Figure 5-9(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 equally capture noise variations between 0 and 25.6 kHz [Figure 5-9(b)], where the upper limit is defined 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 category of features. The power for each sub-band can be computed as follows:

$$P_{1,2} = \int_{f_1}^{f_2} P_{yy}(f) df \approx \sum_{i_1}^{i_2} P_{yy}[i] \quad (5-2)$$

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. This approach is adopted because it is computationally efficient than using the 'bandpower' function mentioned in Section 4.3.5.1.

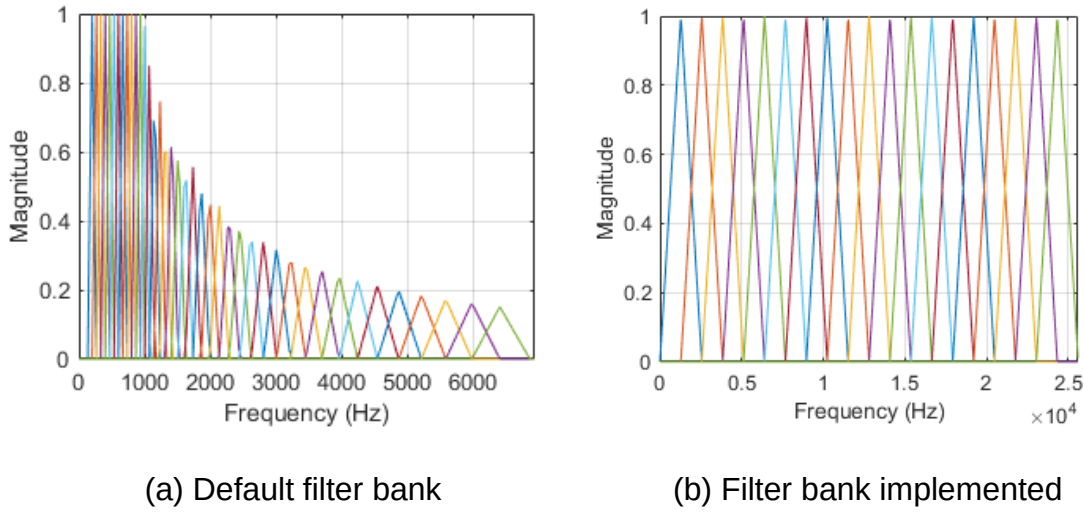


Figure 5-9 MFCC filter bank

(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:

$$RMS = \sqrt{\frac{1}{N} \sum x_t^2}, \quad (5-3)$$

$$Kurtosis = \frac{1}{n} \sum \frac{(x-\mu)^4}{\sigma^4}, \quad (5-4)$$

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

$$ZCR = \frac{1}{N} \sum |sgn[x(n)] - sgn[x(n-1)]|, \quad (5-6)$$

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

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

$$\text{Negentropy} = 33.67 \left(\frac{1}{N} \sum e^{-\frac{x_t^2}{2}} - 0.707 \right)^2, \quad (5-7)$$

$$\text{Shape Factor} = \text{RMS} / \frac{1}{N} \sum |x|, \quad (5-8)$$

$$\text{Impulse Factor} = x_{\text{peak}} / \frac{1}{N} \sum |x|, \quad (5-9)$$

$$\text{Shape Factor} = x_{\text{peak}} / \text{RMS}, \quad (5-10)$$

(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:

$$\text{Sp. Centroid} = \frac{\sum_{k=b_1}^{b_2} f_k s_k}{\sum_{k=b_1}^{b_2} s_k}, \quad (5-11)$$

$$\text{Sp. Spread} = \sqrt{\frac{\sum_{k=b_1}^{b_2} (f_k - \text{Sp. Centroid})^2 s_k}{\sum_{k=b_1}^{b_2} s_k}}, \quad (5-12)$$

$$\text{Sp. Skewness} = \frac{\sum_{k=b_1}^{b_2} (f_k - \text{Sp. Centroid})^3 s_k}{(\text{Sp. Spread})^3 \sum_{k=b_1}^{b_2} s_k}, \quad (5-13)$$

$$\text{Sp. AM} = \frac{1}{b_2 - b_1} \sum_{b_1}^{b_2} s_k, \quad (5-14)$$

$$\text{Sp. GM} = \left(\prod_{b_1}^{b_2} s_k \right)^{\frac{1}{b_2 - b_1}}, \quad (5-15)$$

$$\text{Sp. Flatness} = \text{Sp. GM} / \text{Sp. AM} \quad (5-16)$$

$$\text{Sp. Peak} = \max(s_k) \quad (5-17)$$

$$\text{Sp. Crest} = \text{Sp. Peak} / \text{Sp. AM} \quad (5-18)$$

$$Sp. Flux = \sqrt{\sum_{k=b_1}^{b_2} |s_k(t) - s_k(t-1)|^2}, \quad (5-19)$$

$$Sp. Slope = \frac{\sum_{k=b_1}^{b_2} (f_k - \mu_f)(s_k - \mu_s)}{\sum_{k=b_1}^{b_2} (f_k - \mu_f)^2}, \quad (5-20)$$

$$Sp. Decrease = \frac{\sum_{k=b_1+1}^{b_2} \frac{s_k - s_{b_1}}{k-1}}{\sum_{k=b_1+1}^{b_2} s_k}, \quad (5-21)$$

$$Sp. Roll off = \{i \mid \sum_{k=b_1}^i s_k = 0.5 \sum_{k=b_1}^{b_2} s_k\}, \quad (5-22)$$

5.3.5 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 5.3.1, 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:

$$Accuracy (\%) = \frac{TP + TN}{TP + FP + FN + TN} \times 100 \quad (5-23)$$

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 thesis, PCA has only been used for data visualization.

5.3.6 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*):

$$MAPE(\%) = \frac{100}{n} \sum_{i=1}^n \left| \frac{A_i - E_i}{A_i} \right| \quad (5-24)$$

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 over-fitting 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 5.4.3.3.

Table 5-4 Parameters of 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

The regression techniques evaluated in this study are described in Table 5-4. 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:

$$\min_{\beta_0, \beta} \left(\frac{1}{2N} \sum_{i=1}^N (y_i - \beta_0 - x_i^T \beta)^2 + \lambda \sum_{j=1}^p |\beta_j| \right) \quad (5-25)$$

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 5-4.

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 Figure 5-4):

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

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.

5.4 Results and Discussion

This section presents the results acquired based on the successful implementation of the proposed methodology presented in Figure 5-5. 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.

5.4.1 Features Extraction

A significant amount of near-field acoustic and FADEC data has been acquired for this study. Several features (mentioned in section 5.3.4) 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 second of acoustic data. The time required to compute the LPC, MFCC, and Time domain features for each 1 second 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. Figure 5-10 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 (Figure 5-7) from BV through COM and back to BV2. Several inferences can be drawn from Figure 5-10. The sensor BV2 picks up the least noise as compared to the rest of the sensors, probably because this location is the farthest from the main sources of noise. On the contrary, at the COM sensor, high noise levels are registered (SPL $\approx$ 125dB corresponding to RMS of 37 Pa). For the rest of the sensors, the noise levels go down with respect to their distance away from the combustor.

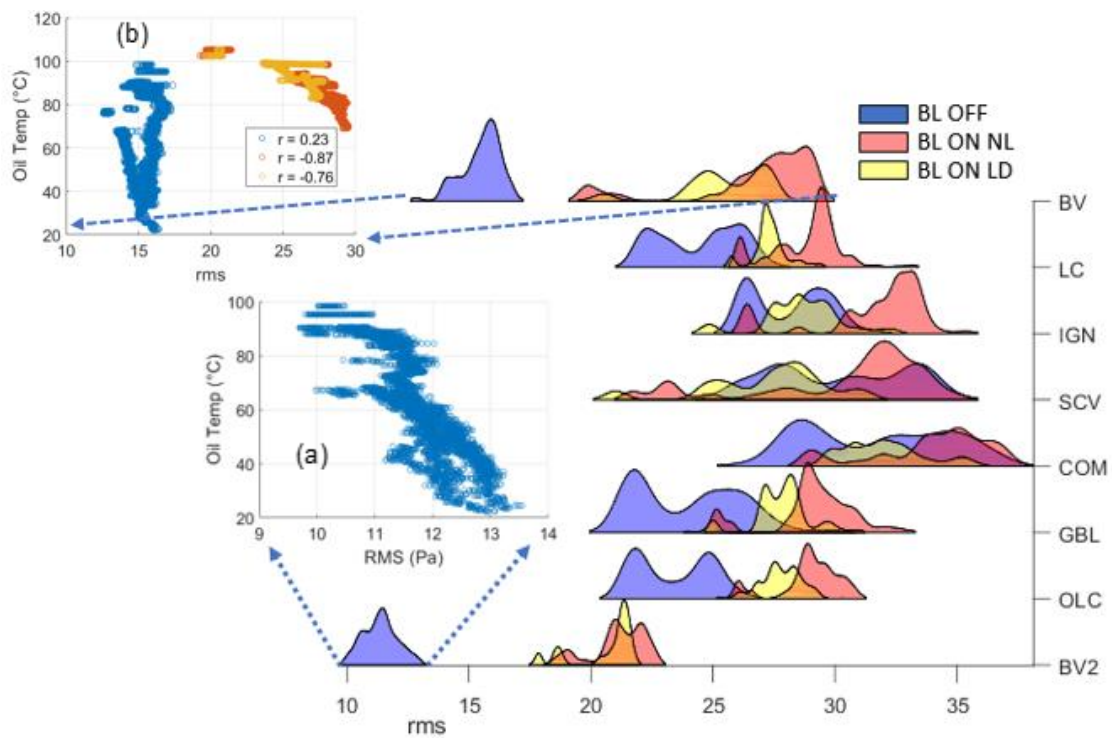


Figure 5-10 Histogram of the RMS Time Domain Feature at different sensor locations.

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 [Figure 5-10(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 behaviour, see Figure 5-10(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 Figure 5-11. 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 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 Figure 5-11. Although noisy, there exists a negative correlation ($\rho = -0.74$) between the two values, making this feature compatible with regression.

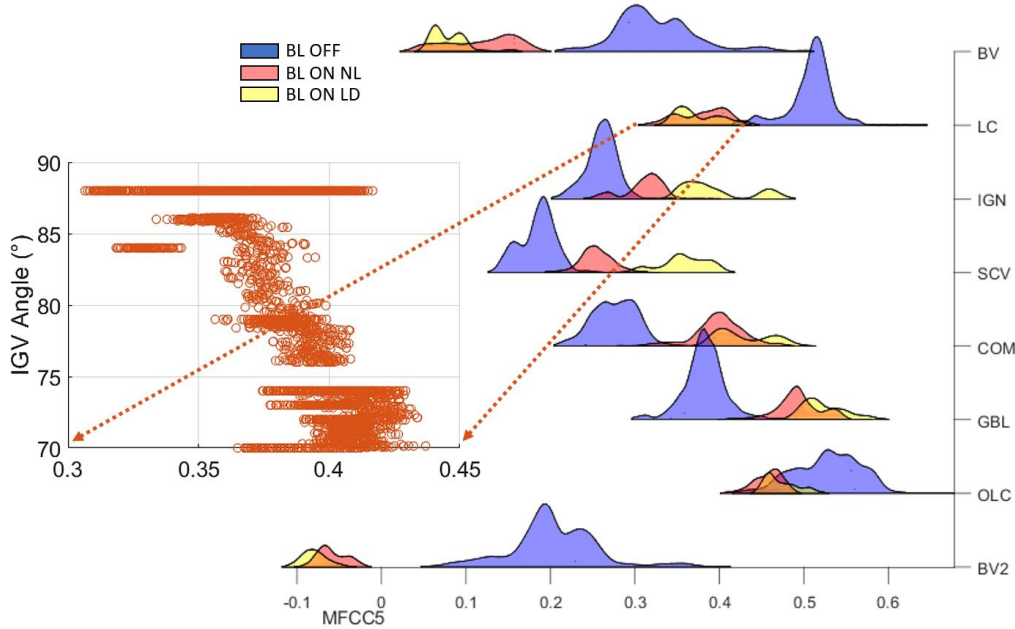


Figure 5-11 Histogram of an MFCC Feature (F5) at different sensor locations

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.

5.4.2 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 5-5. 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%.

Table 5-5 Classification Results

		Colour Code							
Accuracy (%)		100				95			25
		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

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 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 Figure 5-12. 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 Figure 5-7). 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 states, PCA is employed for visualization, Figure 5-13. 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.

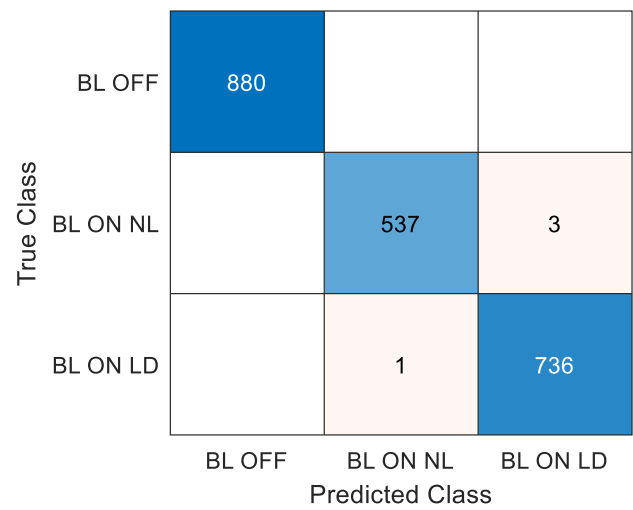


Figure 5-12 Confusion Matrix for APU State classification using Spectral-Pow features

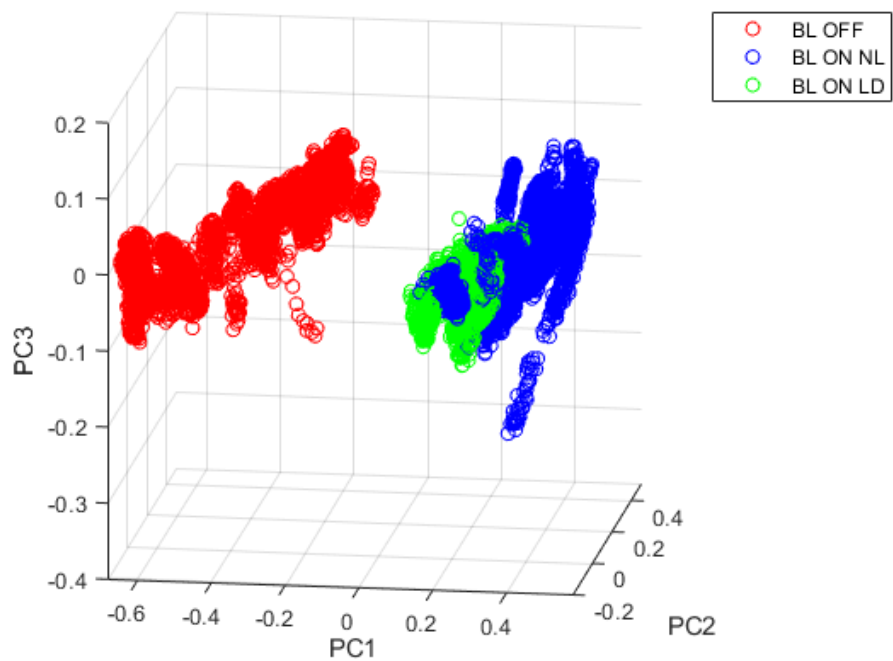


Figure 5-13 MFCC Features visualization using PCA

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 modelling.

5.4.3 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 5.3.6 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 respectively. 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.

5.4.3.1 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 Figure 5-14. 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.

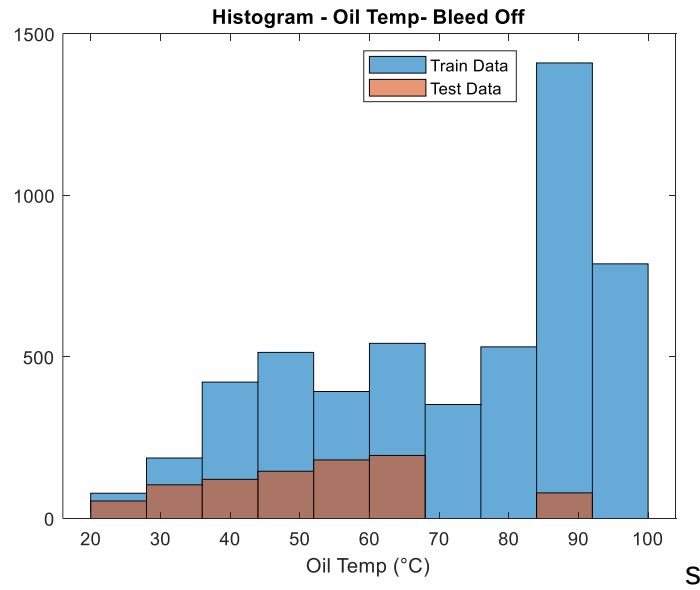


Figure 5-14 Histogram of training and test data (T_{oil} at *BL OFF* state)

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 Figure 5-15. 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:

$$T_{oil} = 0.014 \text{ Sp. Centroid} - 229.7 \text{ Sp. ArithmeticMean} + 8.3 \quad (5-26)$$

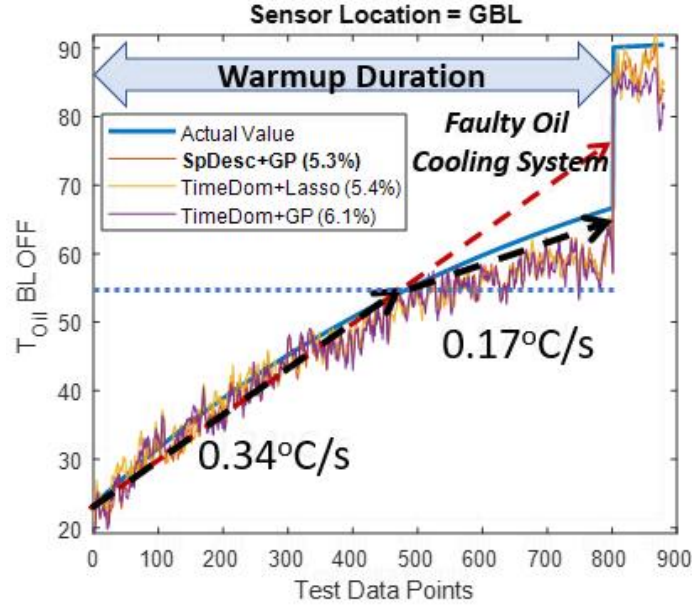


Figure 5-15 Predicted vs actual T_{oil} values at location GBL

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

$$T_{oil} = 238 - 0.12 \frac{RMS^2}{ZCR} \quad (5-27)$$

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 Figure 5-16). 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, Figure 5-17. The oil temperature affects the characteristics of the airflow (and thus the nearby

acoustics) in the vicinity of the oil heat 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 behaviour 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.

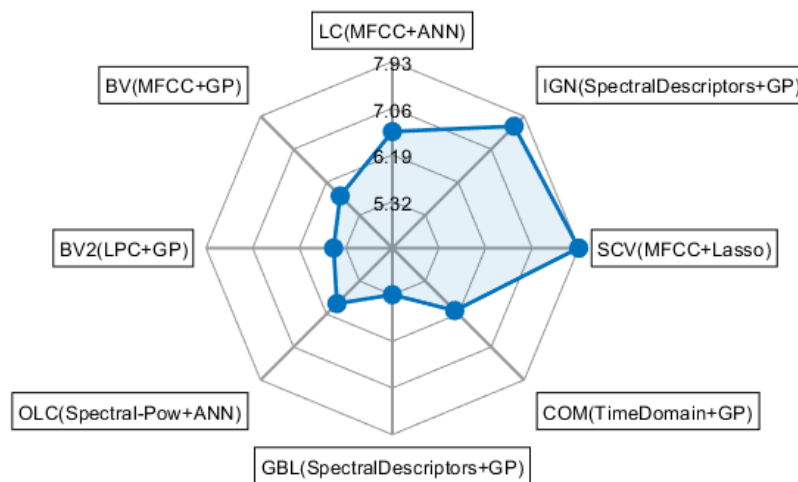


Figure 5-16 Test data MAPE (%) and best models for estimating T_{oil} at various locations



Figure 5-17 Location of GBL and OLC sensors with respect to oil cooler

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 Figure 5-18. The x and y axes correspond to the axial and lateral coordinates of the APU, as in the diagram on the left of Figure 5-18. The x and y axes correspond to the axial and lateral directions of the APU, as in the diagram on the left of Figure 5-18. The labels indicate the position of the sensors in 2-D space and the height/colour indicates the error. The colours 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.

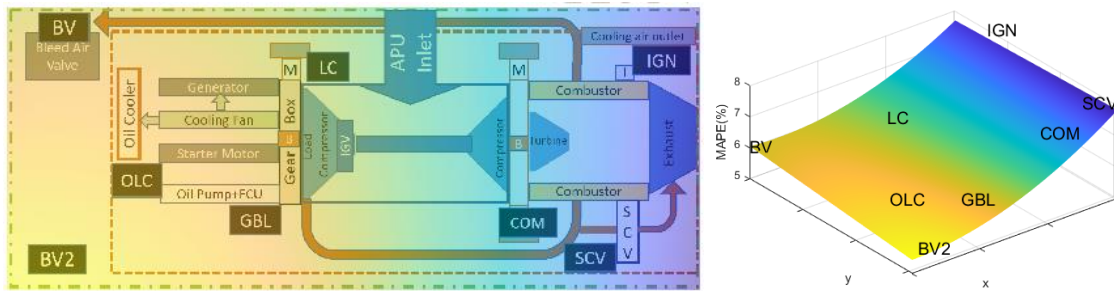


Figure 5-18 Variation of oil temperature model accuracy across the APU

5.4.3.2 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 Figure 5-19). 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 minutes of operation (data not acquired during the transition time). This is not a degraded condition and is not discussed in detail.

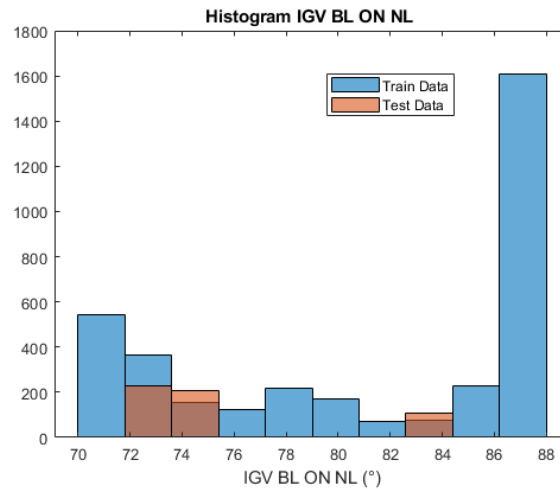


Figure 5-19 Histogram of training and test data (IGV Angles at BL ON NL State)

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 Figure 5-20). 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 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, Figure 5-21(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 a suitable smoothing operation (moving average applied with a span of 30 samples), with the results shown in Figure 5-21(a).

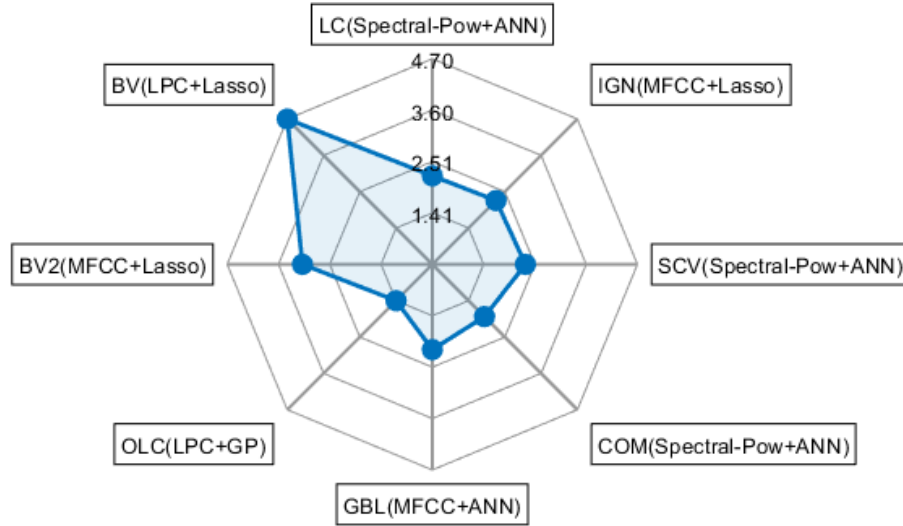


Figure 5-20 Test data MAPE (%) and Best Models for estimating IGV angles at various locations

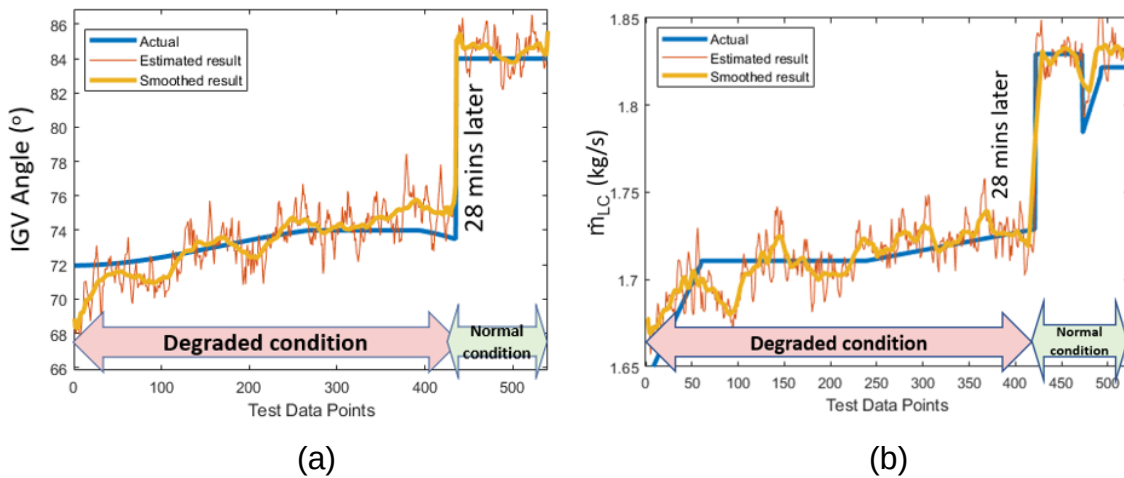


Figure 5-21 Actual, estimated and smoothed values for IGV angles and $\dot{m}_{LC}$ at location OLC

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, Figure 5-21(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.

5.4.3.3 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 Figure 5-22. The models are trained with data present at two separate ranges ($72^\circ - 76^\circ$ and $86^\circ - 88^\circ$), whereas the test data exists at 84° . The model trained at the location COM produced the best result on test data with *MAPE* of 1.25%; Figure 5-23 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 (corresponds to 6 s) has been applied, which reduced the error from 1.29% to 0.77%.

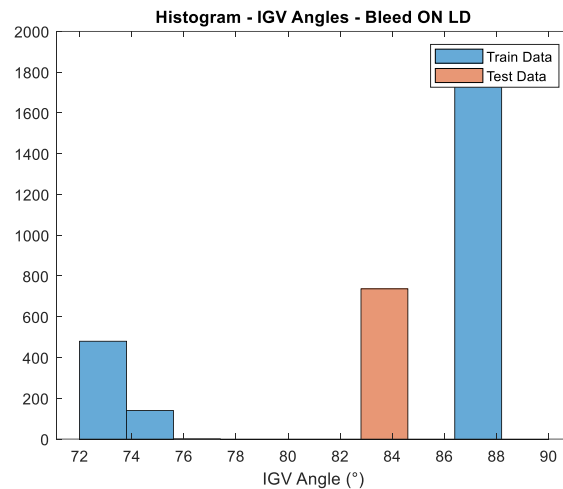


Figure 5-22 Histogram of training and test data (IGV Angles at BL ON LD state)

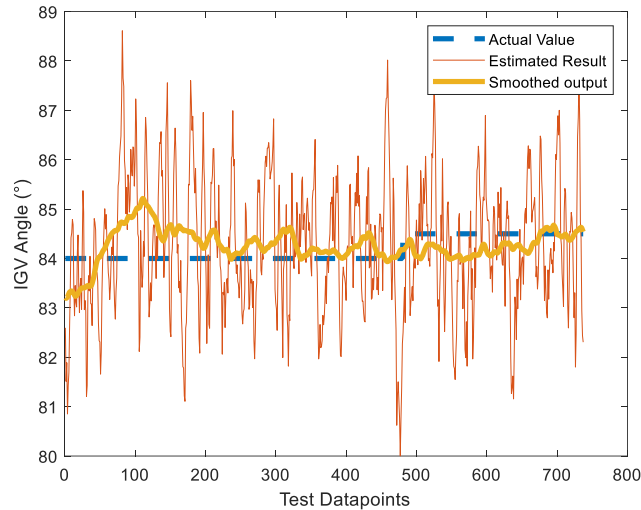


Figure 5-23 Actual, estimated and smoothed values for IGv angles

5.4.3.4 Detailed Analysis ($\dot{m}_{Bleed}$ *Bleed 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 Figure 5-24. 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.

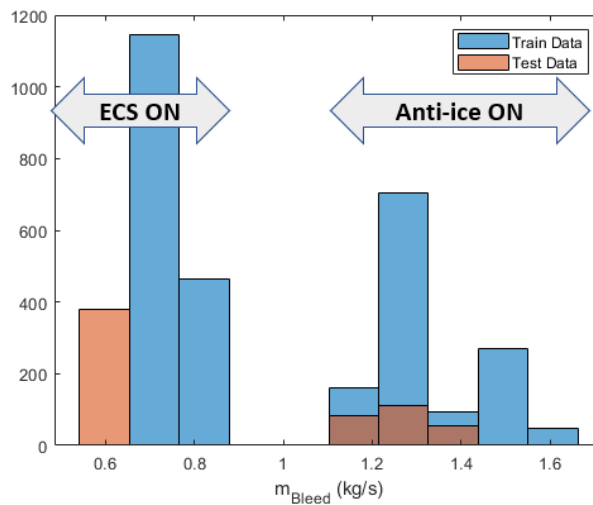


Figure 5-24 Histogram of training and test Data ($\dot{m}_{Bleed}$ at *BL ON LD* state)

Using the acoustic-to-thermodynamic model, the decrease in $\dot{m}_{Bleed}$ can be detected (Figure 5-25), 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. Figure 5-26 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 (Figure 5-27). 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).

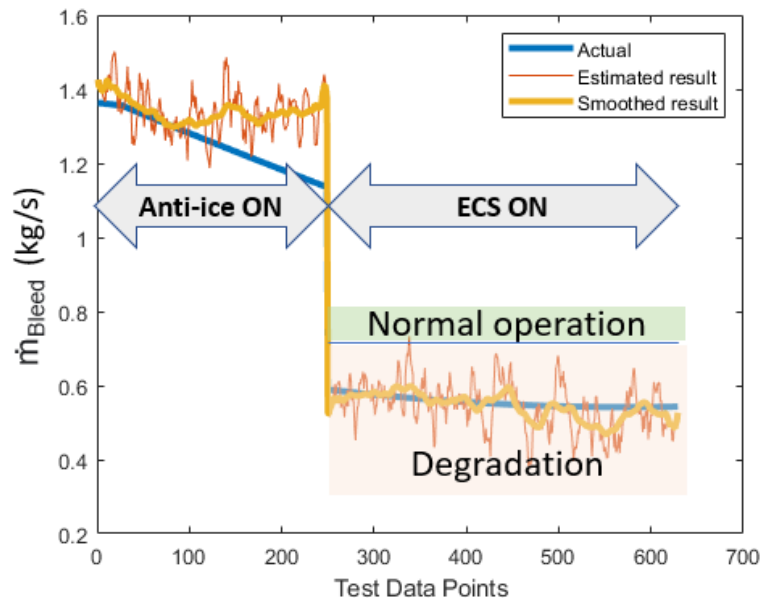


Figure 5-25 Actual, estimated and smoothed values for $\dot{m}_{Bleed}$

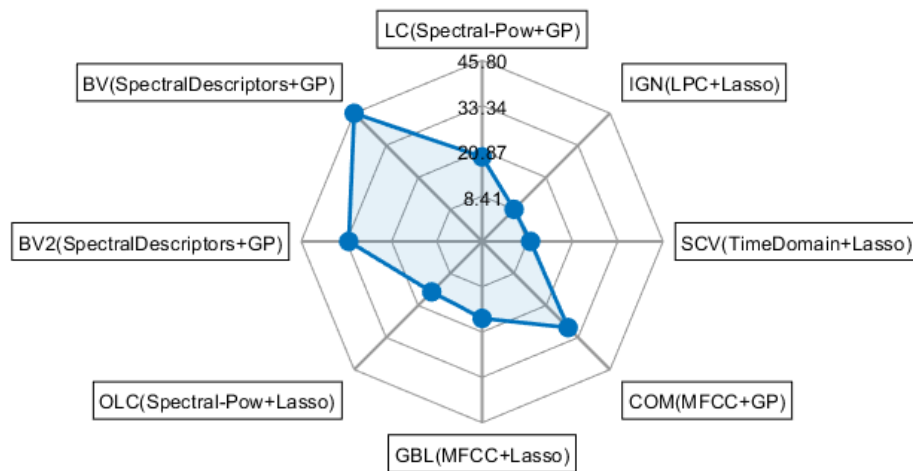


Figure 5-26 Estimating $\dot{m}_{Bleed}$ - MAPE (%) for best models at each location

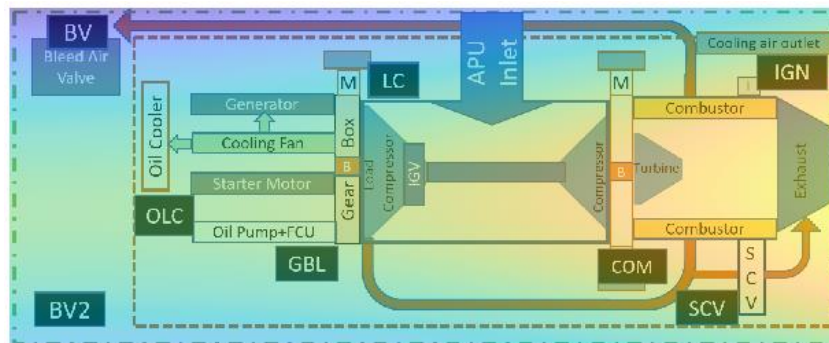


Figure 5-27 Variation of $\dot{m}_{Bleed}$ model accuracy across the APU

5.4.3.5 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 5-6. 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 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 cannot be 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%.

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

(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 favourable 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.

Table 5-6 The Minimum MAPE value for each parameter at each different sensor locations

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

5.5 Conclusion and future directions

In this thesis, 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 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:

- (a) 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.
- (b) Evaluating the proposed methodology on other aircraft systems, e.g., ECS, engines, and hydraulics.
- (c) Analyzing the acoustic data from the microphones for stability and reliability.
- (d) 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.

References

- [1] U. Ahmed, F. Ali, I. Jennions, A review of aircraft auxiliary power unit faults, diagnostics and acoustic measurements, *Prog. Aerosp. Sci.* 124 (2021) 100721. <https://doi.org/10.1016/j.paerosci.2021.100721>.

- [2] P. Hollinger, Smarter aircraft create a wealth of data but it remains underexploited, *Financ. Times*. (n.d.). www.ft.com/content/3f956a92-0943-11e5-b643-00144feabdc0 (accessed February 25, 2022).
- [3] D. Costanza, B. Prentice, *Recover and Rebuild - Toward a Leaner, More Agile MRO Industry*, Oliver Wyman. (2021). <https://www.oliverwyman.com/our-expertise/insights/2021/apr/mro-maintenance-repair-overhaul-survey-2021.html> (accessed February 25, 2022).
- [4] M. Esperon-Miguez, P. John, I.K. Jennions, A review of Integrated Vehicle Health Management tools for legacy platforms: Challenges and opportunities, *Prog. Aerosp. Sci.* 56 (2013) 19–34. <https://doi.org/10.1016/j.paerosci.2012.04.003>.
- [5] Y. Lei, B. Yang, X. Jiang, F. Jia, N. Li, A.K. Nandi, Applications of machine learning to machine fault diagnosis: A review and roadmap, *Mech. Syst. Signal Process.* 138 (2020) 106587. <https://doi.org/10.1016/j.ymssp.2019.106587>.
- [6] C. Skliros, F. Ali, I. Jennions, Fault simulations and diagnostics for a Boeing 747 Auxiliary Power Unit, *Expert Syst. Appl.* 184 (2021) 115504. <https://doi.org/10.1016/j.eswa.2021.115504>.
- [7] V.E. Atasoy, A.E. Suzer, S. Ekici, A Comparative Analysis of Exhaust Gas Temperature Based on Machine Learning Models for Aviation Applications, *J. Energy Resour. Technol. Trans. ASME.* 144 (2022) 1–13. <https://doi.org/10.1115/1.4052771>.
- [8] K.N. Amrutha, Y.K. Bharath, J. Jayanthi, Aircraft Engine Fuel Flow Parameter Prediction and Health Monitoring System, 2019 4th IEEE Int. Conf. Recent Trends Electron. Information, Commun. Technol. RTEICT 2019 - Proc. (2019) 39–44. <https://doi.org/10.1109/RTEICT46194.2019.9016703>.
- [9] R.M. Pascoal, W.O.L. Vianna, J.P.P. Gomes, R.K.H. Galvão, Estimation of APU failure parameters employing linear regression and neural networks, *PHM 2013 - Proc. Annu. Conf. Progn. Heal. Manag. Soc.* 2013. (2013) 664–670.

- [10] N. Balakrishnan, A.I. Devasigamani, K.R. Anupama, N. Sharma, Aero-Engine Health Monitoring with Real Flight Data Using Whale Optimization Algorithm Based Artificial Neural Network Technique, *Opt. Mem. Neural Networks* (Information Opt. 30 (2021) 80–96. <https://doi.org/10.3103/S1060992X21010094>.
- [11] K. Knobloch, L. Enghardt, F. Bake, APU-noise reduction by novel muffler concepts, *Proc. ASME Turbo Expo.* 2B-2018 (2018) 1–11. <https://doi.org/10.1115/GT2018-76762>.
- [12] R.L. Tubbs, Case Studies Noise Exposure to Airline Ramp Employees, *Appl. Occup. Environ. Hyg.* 15 (2010).
- [13] T. Siebel, J. Zanger, A. Huber, M. Aigner, K. Knobloch, F. Bake, Experimental investigation of cycle properties, noise, and air pollutant emissions of an APS3200 auxiliary power unit, *J. Eng. Gas Turbines Power.* 140 (2018) 1–9. <https://doi.org/10.1115/1.4038159>.
- [14] U. Ahmed, F. Ali, I.K. Jennions, Development of a Far-Field Noise Estimation Model for an Aircraft Auxiliary Power Unit, *IEEE Access.* 9 (2021) 127703–127719. <https://doi.org/10.1109/ACCESS.2021.3112390>.
- [15] U. Ahmed, F. Ali, I. Jennions, Signal Processing of Acoustic Data for Condition Monitoring of an Aircraft Ignition System, *Machines.* 10 (2022) 822. <https://doi.org/10.3390/machines10090822>.
- [16] M.A. Khan, M.A. Shahid, S.A. Ahmed, S.Z. Khan, K.A. Khan, S.A. Ali, M. Tariq, Gear misalignment diagnosis using statistical features of vibration and airborne sound spectrums, *Meas. J. Int. Meas. Confed.* 145 (2019) 419–435. <https://doi.org/10.1016/j.measurement.2019.05.088>.
- [17] S.V.V.S.N. Pichika, R. Yadav, S. Geetha Rajasekharan, H.M. Praveen, V. Inturi, Optimal sensor placement for identifying multi-component failures in a wind turbine gearbox using integrated condition monitoring scheme, *Appl. Acoust.* 187 (2022) 108505. <https://doi.org/10.1016/j.apacoust.2021.108505>.

- [18] W. Jung, J. Bae, Y.-H. Park, Acoustic Signal based Non-Contact Ball Bearing Fault Diagnosis Using Adaptive Wavelet Denoising, (2021). <http://arxiv.org/abs/2110.03348>.
- [19] H.R. Al Bugarbee, A.S. Al-Bunduqee, F.O. Hamdoon, A new audio signal-based methodology for fault detection in gears, *J. Mech. Eng. Res. Dev.* 43 (2020) 12–21.
- [20] A. Daraz, S. Alabied, F. Gu, A.D. Ball, A Comparative Study of Acoustic and Vibration Signals for Bearing Fault Detection and Diagnosis Based on MSB Analysis, Springer International Publishing, 2021. https://doi.org/10.1007/978-3-030-75793-9_80.
- [21] K. Lu, J.X. Gu, H. Fan, X. Sun, B. Li, F. Gu, Acoustics Based Monitoring and Diagnostics for the Progressive Deterioration of Helical Gearboxes, *Chinese J. Mech. Eng.* 34 (2021) 1–12. <https://doi.org/10.1186/s10033-021-00603-1>.
- [22] L. Yu, X. Yao, J. Yang, C. Li, Gear fault diagnosis through vibration and acoustic signal combination based on convolutional neural network, *Inf.* 11 (2020). <https://doi.org/10.3390/INFO11050266>.
- [23] G. Ciaburro, G. Iannace, V. Puyana-Romero, A. Trematerra, Machine learning-based tools for wind turbine acoustic monitoring, *Appl. Sci.* 11 (2021). <https://doi.org/10.3390/app11146488>.
- [24] T.S. Mohammed, M. Rasheed, M. Al-Ani, Q. Al-Shayea, F. Alnaimi, Fault Diagnosis of Rotating Machine Based on Audio Signal Recognition System: An Efficient Approach, *Int. J. Simul. Syst. Sci. Technol.* (2020). <https://doi.org/10.5013/ijssst.a.21.01.08>.
- [25] S.K. Mathew, Y. Zhang, Acoustic-based engine fault diagnosis using WPT, PCA and bayesian optimization, *Appl. Sci.* 10 (2020) 1–18. <https://doi.org/10.3390/app10196890>.
- [26] J. Da Wu, C.Q. Chuang, Fault diagnosis of internal combustion engines using visual dot patterns of acoustic and vibration signals, *NDT E Int.* 38 (2005) 605–614. <https://doi.org/10.1016/j.ndteint.2005.02.007>.

- [27] C.-S.A. Gong, C.-H.S. Su, Y.-E. Liu, D.-Y. Guu, Y.-H. Chen, Deep Learning with LPC and Wavelet Algorithms for Driving Fault Diagnosis, *Sensors*. 22 (2022) 7072. <https://doi.org/10.3390/s22187072>.
- [28] J.W.A. Fackrell, S. McLaughlin, Quadratic phase coupling detection using higher order statistics, *IEE Colloq.* (1995). <https://doi.org/10.1049/ic:19950736>.
- [29] Boeing 737-300/400/500 Aircraft Maintenance Manual, 2015.
- [30] FAA, Aircraft Metal Structural Repair, *Aviat. Maint. Tech. Handbook—Airframe Vol. 1.* (2012).
- [31] C. Soares, *Gas Turbines: A Handbook of Air, Land and Sea Application*, Butterworth-Heinemann, 2015.
- [32] U. Ahmed, F. Ali, I. Jennions, Evaluation of Aircraft Auxiliary Power Unit Near-Field Acoustics for Condition Monitoring, *IEEE Access*. (2022) 1–1. <https://doi.org/10.1109/ACCESS.2022.3213698>.
- [33] T.C. Lieuwen, V. Yang, Implementation Of Instability Prediction In Design: Alstom Approaches, *Combust. Instab. Gas Turbine Engines*. (2006) 445–480. <https://doi.org/10.2514/5.9781600866807.0445.0480>.
- [34] S. Vouros, I. Goulos, V. Pachidis, Integrated methodology for the prediction of helicopter rotor noise at mission level, *Aerosp. Sci. Technol.* 89 (2019) 136–149. <https://doi.org/10.1016/j.ast.2019.03.061>.
- [35] A. Seppanen, *Utilizing acoustic measurements in equipment condition monitoring*, Aalto University, 2016.
- [36] S. Vizzini, M. Knutsson, M. Dybeck, M. Abom, Flow Noise Generation in a Pipe Bend, *SAE Tech. Pap.* 2018-June (2018) 20180831. <https://doi.org/10.4271/2018-01-1525>.
- [37] P. Raharjo, S. Abdussalam, F. Gu, A.D. Ball, Vibro-acoustic characteristic of a self aligning spherical journal bearing due to eccentric bore fault, *9th Int. Conf. Cond. Monit. Mach. Fail. Prev. Technol.* 2012, C. 2012 MFPT 2012. 1 (2012) 124–140.

- [38] X. Zhong, Y. Huang, G. Bin, A. Chen, Effect of the inlet oil temperature on vibration characteristics of the high-speed turbocharger rotor system, *Proc. Inst. Mech. Eng. Part J J. Eng. Tribol.* 235 (2021) 2086–2098. <https://doi.org/10.1177/1350650120987033>.
- [39] P. Liptai, M. Badida, K. Lukáčová, *Influence of Atmospheric Conditions on Sound Propagation-Mathematical Modeling*, 2015.
- [40] Y.T. Cho, M.J. Roan, Adaptive near-field beamforming techniques for sound source imaging, *J. Acoust. Soc. Am.* 125 (2009) 944–957. <https://doi.org/10.1121/1.3050248>.
- [41] T. Suzuki, Identification of multipole noise sources in low Mach number jets near the peak frequency, *J. Acoust. Soc. Am.* 119 (2006) 3649–3659. <https://doi.org/10.1121/1.2200070>.
- [42] G.G. Podboy, C. Horvath, Phased array noise source localization measurements made on a Williams International FJ44 engine, 15th AIAA/CEAS Aeroacoustics Conf. (30th AIAA Aeroacoustics Conf. (2009) 11–13. <https://doi.org/10.2514/6.2009-3183>.
- [43] C. Noël, V. Planeau, D. Habault, A new temporal method for the identification of source directions in a reverberant hall, *J. Sound Vib.* 296 (2006) 518–538. <https://doi.org/10.1016/j.jsv.2005.12.056>.
- [44] D. Levin, E.A.P. Habets, S. Gannot, Maximum likelihood estimation of direction of arrival using an acoustic vector-sensor, *J. Acoust. Soc. Am.* 131 (2012) 1240–1248. <https://doi.org/10.1121/1.3676699>.
- [45] Brüel & Kjær, *Sound Intensity: Introduction to Intensity Measurements What is Sound Intensity?*, (n.d.) 1–14. <https://www.bksv.com/en/knowledge/blog/sound/sound-intensity>.
- [46] M.R. Bai, C. Wang, S.-W. Juan, Optimal two-layer directive microphone array with application in near-field acoustical holography, *J. Acoust. Soc. Am.* 132 (2012) 862–871. <https://doi.org/10.1121/1.4734238>.

- [47] G. Moschioni, B. Saggin, M. Tarabini, F. Scamoni, Use of intensimetric techniques for measurements of airport noise, in: INTER-NOISE, 2007.
- [48] L. Kumar, R.M. Hegde, Near-Field Acoustic Source Localization and Beamforming in Spherical Harmonics Domain, *IEEE Trans. Signal Process.* 64 (2016) 3351–3361. <https://doi.org/10.1109/TSP.2016.2543201>.
- [49] E. Fisher, B. Rafaely, Near-field spherical microphone array processing with radial filtering, *IEEE Trans. Audio, Speech Lang. Process.* 19 (2011) 256–265. <https://doi.org/10.1109/TASL.2010.2047421>.
- [50] Y. Yang, Z. Li, X. Wang, D. Zhang, Noise source separation based on the blind source separation, *Proc. 2011 Chinese Control Decis. Conf. CCDC 2011.* (2011) 2236–2240. <https://doi.org/10.1109/CCDC.2011.5968579>.
- [51] J.B. Khan, T. Jan, R.A. Khalil, N. Saeed, M. Almutiry, An efficient multistage approach for blind source separation of noisy convolutive speech mixture, *Appl. Sci.* 11 (2021). <https://doi.org/10.3390/app11135968>.
- [52] W. Zhou, D. Chelidze, Blind source separation based vibration mode identification, *Mech. Syst. Signal Process.* 21 (2007) 3072–3087. <https://doi.org/10.1016/j.ymssp.2007.05.007>.
- [53] G. Gelle, M. Colas, Blind source separation applied to rotating machine monitoring and fault detection, *Noise Vib. Worldw.* 1 (2001) 11–16.
- [54] J. Yao, Y. Xiang, S. Qian, S. Wang, Noise Source Separation of an Internal Combustion Engine Based on a Single-Channel Algorithm, *Shock Vib.* 2019 (2019). <https://doi.org/10.1155/2019/1283263>.
- [55] X. Yang, F. Bi, L. Zhang, X. Bi, T. Ma, D. Tang, Noise Source Identification of a Gasoline Engine Based on Parameters Optimized Variational Mode Decomposition and Robust Independent Component Analysis, *SAE Tech. Pap.* 2020-April (2020) 1–9. <https://doi.org/10.4271/2020-01-0425>.

- [56] K.F.C. Yiu, S.Y. Low, On a Real-Time Blind Signal Separation Noise Reduction System, *Int. J. Reconfigurable Comput.* 2018 (2018). <https://doi.org/10.1155/2018/3721756>.
- [57] G. Martínez-Arellano, R. Cant, L. Nolle, Prediction of jet engine parameters for control design using genetic programming, *Proc. - UKSim-AMSS 16th Int. Conf. Comput. Model. Simulation, UKSim 2014.* (2014) 45–50. <https://doi.org/10.1109/UKSim.2014.64>.
- [58] D.F. Yela, F. Thalmann, V. Nicosia, D. Stowell, M. Sandler, Efficient On-line Computation of Visibility Graphs, (2019) 1–9. <https://doi.org/10.1103/PhysRevResearch.2.023069>.
- [59] L.T. Ikelle, L. Amundsen, *Introduction to Petroleum Seismology*, Society of Exploration Geophysicists, 2018. <https://doi.org/10.1190/1.9781560803447.ch6>.
- [60] L. Delchambre, Weighted principal component analysis: A weighted covariance eigen decomposition approach, *Mon. Not. R. Astron. Soc.* 446 (2015) 3545–3555. <https://doi.org/10.1093/mnras/stu2219>.
- [61] J. Abonyi, *Genetic Programming MATLAB Toolbox*, (2014). <https://uk.mathworks.com/matlabcentral/fileexchange/47197-genetic-programming-matlab-toolbox>.

6 Signal processing of Acoustics Data for Aircraft APU Ignition System

Degradation of the ignition system can result in startup failure in an aircraft's auxiliary power unit. In this thesis, a novel acoustics-based solution that can enable condition monitoring of an APU ignition system was proposed. In order to support the implementation of this research study, the experimental data set from Cranfield University's Boeing 737-400 aircraft was utilized. The overall execution of the approach comprised background noise suppression, estimation of the spark repetition frequency and its fluctuation, spark event segmentation, and feature extraction, in order to monitor the state of the ignition system. The methodology successfully demonstrated the usefulness of the approach in terms of detecting inconsistencies in the behavior of the ignition exciter, as well as detecting trends in the degradation of spark acoustic characteristics. The identified features proved to be robust against non-stationary background noise, and were also found to be independent of the acoustic path between the igniter and microphone locations, qualifying an acoustics-based approach to be practically viable.

6.1 Introduction

The auxiliary power unit (APU) is one of the key systems in aircraft. Its function is to supply electrical and pneumatic power during ground operation, and in the event of in-flight emergencies. An APU is a gas-turbine engine that is composed of multiple integrated sub-systems that are prone to degradation during operation. The APU has been reported to be one of the major drivers of aircraft maintenance [1], with an associated \$4 billion worth of maintenance, repair, and overhaul costs reported within a single year (2018). These costs and activities increase further when operations are disrupted as a result of unscheduled maintenance. Around 10% of the time, startup failure has been reported to be the cause of such disruptions [2]. Some possible causes of startup failure can result from degradation of the starter motor [3], or anomalies in the fuel or ignition system [4].

An APU's ignition system is responsible for generating a series of sparks to initiate the combustion process. The ignition system comprises an exciter that provides high-voltage signals to an igniter, and is activated by the APU controller during predefined ranges of rotational speeds. Any degradation/failure in the ignition system leads to weak and/or inconsistent sparks, which can delay the combustion process to such an extent that the APU does not reach the desired level of acceleration required for a successful startup. Therefore, monitoring of the ignition system is desirable so that any deviation from the designed characteristics can be detected in the early stages of component degradation; thus, monitoring can support proactive maintenance and prevent APU failures. The industry is proactively working towards the development of innovative strategies that can enable reductions in maintenance costs [5]. For legacy systems, developing a means for ignition system monitoring is challenging due to the lack of technical data [6] from the APU built-in test equipment (BITE). Furthermore, retrofitting any additional intrusive sensors will require hardware modifications, and may also impose additional testing and certification requirements.

A novel approach to support condition monitoring can be implemented by incorporating microphones that are installed in the near periphery of APU key sub-systems. This is a convenient, non-intrusive, readily deployable approach. The microphones do not interfere with the safety and performance of the machines, and therefore should not require extensive efforts for certification. For an APU ignition system, continuous analysis of the acoustics that are associated with spark discharge may provide useful information about the health of the system. During a spark discharge, an ionization process takes place that creates a channel of ionized gas between the electrodes; this gas expands as a result of intense Joule heating. The process radiates an intense shock wave that transforms into an acoustic pressure pulse that propagates into the surrounding medium at the local speed of sound [7,8]. This research aims to conduct a feasibility study on the implementation of spark acoustic characteristics to support an APU ignition system diagnostics solution.

6.1.1 Boeing 737-400 APU

In order to support successful implementation of the research addressed in this thesis, experimental testing was conducted on an APU in situ. Cranfield University's ground demonstrator Boeing 737 (B737) aircraft was utilized to support the experimentation. As illustrated in Figure 6-1(a), the reference APU is shielded by a fire enclosure and is installed inside the tail section of the aircraft. As per the specifications provided in the aircraft maintenance manual (AMM), the APU is a single shaft gas-turbine engine that provides auxiliary power (electrical and pneumatic) to the aircraft using an electrical generator and pneumatic flow from the load compressor (LC) [see Figure 6-1(b)]. The power section consists of a centrifugal compressor, reverse annular flow combustor, and a radial turbine. The compressor and turbine are mounted on the same shaft, and rotate at a constant (63,830) rpm throughout the APU operating modes. The APU pneumatic system consists of a load compressor, inlet guide vanes (IGV), surge control valve (SCV), and bleed valve (BV). The APU draws air from the atmosphere through an inlet door at the side of the fuselage, which remains open only during operation. The overall operation of the APU is controlled by a full authority digital engine controller (FADEC), which is installed in the cargo compartment. One of our previous studies [9] reported further on the details of the reference APU's operation and parameters. Herein, our focus is on the startup operation of the APU.

The APU's startup system consists of a starter motor assembly and ignition system (ignition exciter, igniter, and igniter lead). Aircraft DC power is required to start the APU, which can either be provided externally or by using onboard batteries. This power is utilized by the starter motor to spool up the APU so that the fuel and air mixture reaches the combustor. As per the AMM, from 7–95% of the rated rpm (7,768–60,638 rpm), the ignition system is energized using the same DC power to produce a series of sparks that initiates combustion. In the case of a fault or degradation in any of the components of the ignition system, the combustion process will not initiate. Under such conditions, the FADEC terminates the startup sequence, and a 'No Flame' error is displayed.

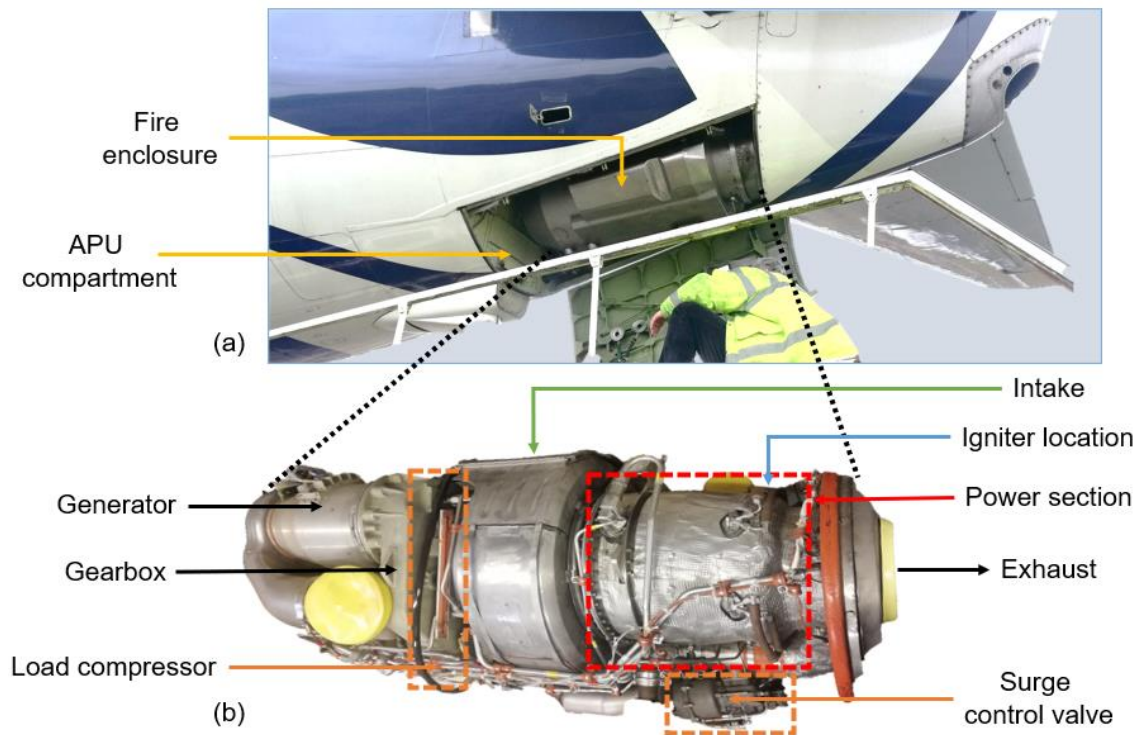


Figure 6-1: The APU of a Boeing 737-400 (a) aircraft tail section and APU compartment (b) components of the APU.

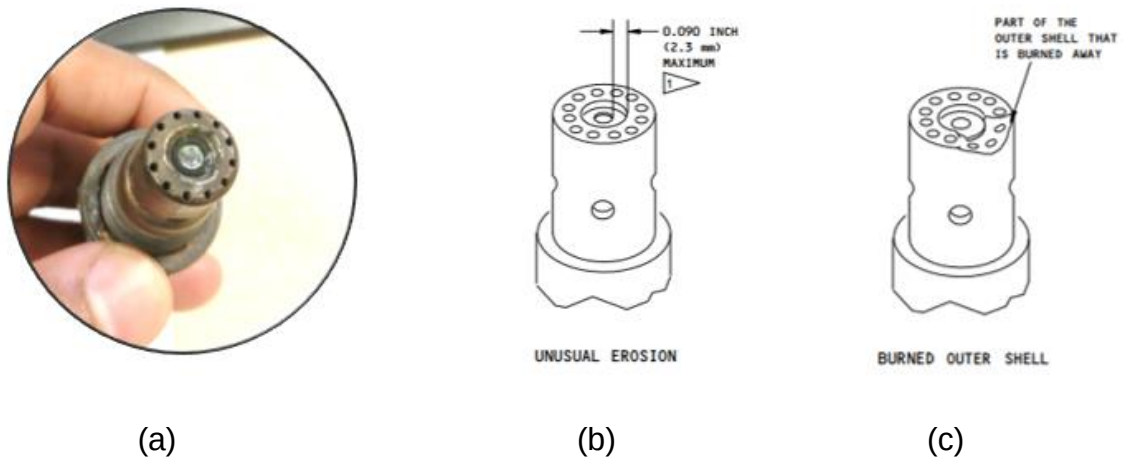


Figure 6-2 APU igniter and faults (a) Actual igniter with eroded tip (b) Nominal limit of erosion (c) Burnt outer shell fault, adapted from [10]

The most common type of degradation that is associated with the igniters stems from their tips being exposed to water or ice, as well as due to their intrinsic wear and tear. As per the AMM, as illustrated in Figure 6-2, the wear can appear as erosion or damage to the outer surface. This can increase the gap between the

electrodes to such an extent that the supplied voltage is unable to produce a spark, consequently leading to the loss of sparks during the startup sequence. On the other hand, a faulty ignition exciter will not produce a series of sparks at the desired frequency or may not generate the desired voltage to produce a spark. Furthermore, a degraded igniter cable can also lead to a reduction in the amount of electrical energy that is supplied to the igniter, which can result in similar effects.

6.1.2 Literature Review

Condition monitoring of the ignition system can be performed by monitoring the high-energy voltage pulses at the output of the exciter [11]. However, the proposed analog circuitry needs to be electrically coupled with the ignition exciter, and should incorporate a safety mechanism while handling the high voltages. A similar solution was also reported [12] which determines the time period required for the current in a capacitive discharge ignition system to decay to a zero-ampere level, as an indicator of system health. In [13], it was suggested to use the accumulated number of spark counts as an indication of the wear on an igniter. However, this approach makes use of the commanded number of sparks from the engine controller, and does not utilize the actual number of sparks that may be taking place for more accurate results. A different methodology was presented in [14], which proposed the utilization of a spark detector and a pressure transducer to detect faults in the igniter. For a degraded igniter, the spark gap increases to such an extent that sparks do not take place at high ambient pressures. Such a solution requires intrusive sensors with associated hardware complexities that can withstand the harsh environment of the combustor. The safety measures recommended by [15] can ensure the reliability of the spark plugs in a gas turbine, but they require human involvement, and the procedures cannot be automated. From the perspective of signal processing, the impulsive nature of the spark signal makes it comparable to the signals that are generated by faulty gears [16] and bearings [17–21]. However, during such studies, vibration sensors are used, and the foremost aim is to detect such signals without further characterization of the detected time domain signal; this could be used as a

potential metric for monitoring the state of degradation. The reported acoustics-based condition monitoring applications are limited, and the experimentation is generally conducted in controlled environments. The research reported in [22] on bearings is among such examples. The applications where microphones have been used for impulsive sound detection are dissimilar to the scope of this thesis (for example, for gunshot sound detection [23], detection of partial discharges on electrical transmission lines [24], and direction-finding applications [25]), but the underlying methodologies can be modified for the current application. The study conducted by [26] offers useful insight into spark characteristics, but the methodology used an elaborate set of sensing mechanisms that make it unsuitable for online condition monitoring. The electrical and acoustic characteristics of spark discharge have been greatly studied by the research community. A study conducted by [27] extensively analyzed the time domain and frequency domain characteristics of acoustic radiation from electrical spark discharge, and related the time domain signal with N-wave acoustic pressure waves. A study by [28] investigated the directional characteristics of sparks, and found that the angular position of the microphone affects the widths and peak sound pressures of the received pulses. The authors in [29] observed the acoustic characteristics of lightning current discharge as a function of peak values of discharge currents. Spark characteristics have also been studied for enabling their utilization in studying acoustic phenomena on scale models [7]. The research by [30] focused on the electrical characteristics of sparks, and correlated them to variations in the capacitance, voltage, and spark gap. The above experiments were conducted in controlled environments using high sampling rates so that each acoustic pulse was clearly visible without corruption from background noise, multi-path reflections, and distortions due to low temporal resolutions. For an aircraft APU, such conditions cannot be achieved because of the presence of background noise from APU operation, as well as from multi-path effects caused by the acoustically reflecting aircraft surfaces around it. The requirement of a very high sampling rate for acoustic data acquisition cannot be satisfied, as it demands more complex hardware which is incompatible for onboard applications.

6.1.3 Scope of Research

In light of the aforementioned literature, there exists a gap in knowledge regarding the investigation of spark acoustic characteristics for online condition monitoring. The research addressed in this thesis is dedicated to the evaluation of ignition system spark acoustic characteristics that can be implemented to support an ignition system diagnostics solution. The overall strategy involves the collection of data from microphones installed in the periphery of the APU sub-systems, and the exploration of features that can enable the conversion of noise into meaningful information for condition monitoring. The outcome of this research suggests that a well-placed microphone can capture certain characteristics of the sparking sound, which can potentially be employed to support an ignition system fault diagnostics solution. This chapter of the thesis is organized as follows: Section 6.2 describes the experimental setup utilized for this study, Section 6.3 explains the analysis that were carried out on the acquired data and Section 6.4 presents the results.

6.2 Experimental Data Collection

For this study, experimental data were acquired from Cranfield University's Boeing 737-400 aircraft APU. Multiple PCB Piezotronics 130F20 $\frac{1}{4}$ inch IEPE microphones were installed around the APU, as shown in Figure 6-3(a). The microphones had a sensitivity of 45 mV/Pa, and a flat frequency response in the 20 Hz–20 kHz range. They were integrated with NI-DAQ using NI-9234 modules which sampled the acoustic data at 51.2 kHz for each channel. The sensitivity of the selected microphones and voltage limit of ± 5 V of the NI-9234 modules allowed noise data acquisition with peak noise levels up to 111 Pa or 134 dB. Six of the nine microphones were placed inside the fire enclosure, two were installed outside but inside the APU compartment, while one microphone (shown as FF in Figure 6-3) was placed 10 m away in the far-field of the APU exhaust. Initially, vibration sensors were also considered for this study, but it was found that they were unable to detect any sparks, and were therefore excluded from the detailed study. The low energy produced by sparks is unlikely to induce considerable

vibrations in the APU structure, and thus cannot be picked up by vibration sensors.

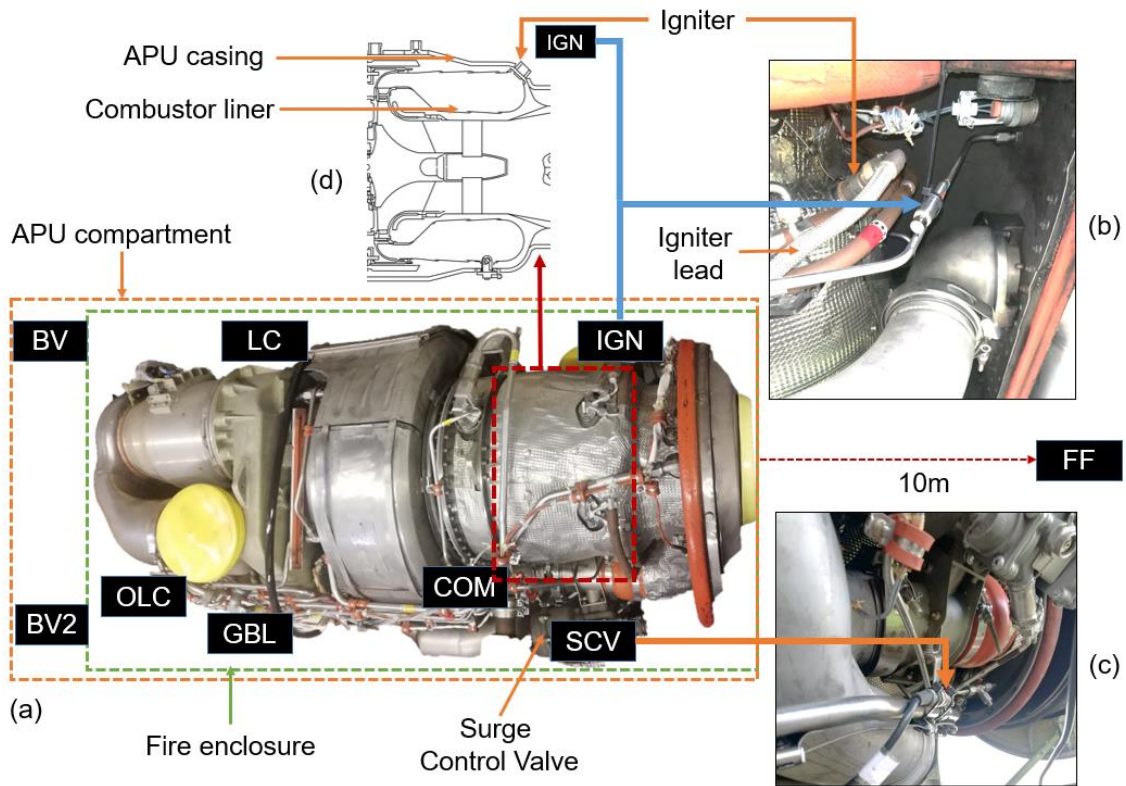


Figure 6-3 Experimental setup (a) APU and sensor locations (b) IGN microphone location (c) SCV microphone location (d) Cross-sectional view of the APU combustor, adapted from [10]

6.2.1 Initial Analysis and Data Preparation

The acoustic data were acquired for APU startups on eight different occasions (represented as a day for the purposes of analysis demonstration), out of which six startups utilized the internal aircraft battery, while the remaining startups used external ground power. On six of these occasions, the aircraft was parked on a taxiway, while the other two experiments were conducted inside a partially enclosed hangar near the runway. Initially, the acoustic data were manually analyzed in order to identify the microphone locations where the spark noise was clear and remained audible for longer durations as the APU spooled up and the background noise increased. In the far-field of the APU, the spark signal was found to degrade sharply as soon as the combustion process initialized, making

it impossible to detect the presence of a spark for a longer duration of time. This observation remained the same for all microphone locations where the background noise was high compared to the spark-generated noise. On the other hand, microphones that were placed closest to the igniter [the locations denoted by IGN and SCV in Figure 6-3(b,c)] were found to be the most suitable locations to capture spark characteristics, and therefore remained the primary focus of discussion in this thesis. The IGN sensor location indicates that the microphone is near the igniter, while SCV specifies the sensor's proximity to the surge control valve. These two sensor locations are the closest to the igniter, with the SCV being on the opposite side compared to the IGN's location. Between the igniter and the microphones, there are multiple layers that may incur a shielding effect on the acoustics. These layers can be identified as, amongst others, combustor liner and APU casing [see zoomed-in cross-sectional view of the combustor in Figure 6-3(d)].

The acquired data were able to capture most of the events taking place throughout the APU startup sequence, which included: inlet door actuation, starter motor engagement, activation of ignition system from 7–95% rpm, combustion build up, IGVs opening at 45%, starter motor disengagement at 50%, and the APU settling at 100% rpm. Note that to support the spark characteristics evaluation in this thesis, only the data segment that represented the spark was implemented. For this purpose, the time duration where the APU rpm was between 7–20% (4468–12,766 rpm) was found to contain information about the spark events; hence, a detailed analysis for this duration is presented.

6.3 Employed Methodology

The employed approach to investigate the spark characteristics from the aircraft's APU startup is presented in Figure 6-4. There are two steps involved: Step 1 deals with the estimation of spark repetition frequency (SRF), while Step 2 is related to the evaluation of various feature extraction techniques on the acquired spark signals. The initial application of a high-pass filter (Step 0) to suppress background noise was a precursor for each step. For SRF, the envelope

spectrum was analyzed to enable visualization of the degree of fluctuations for a given day of operation.

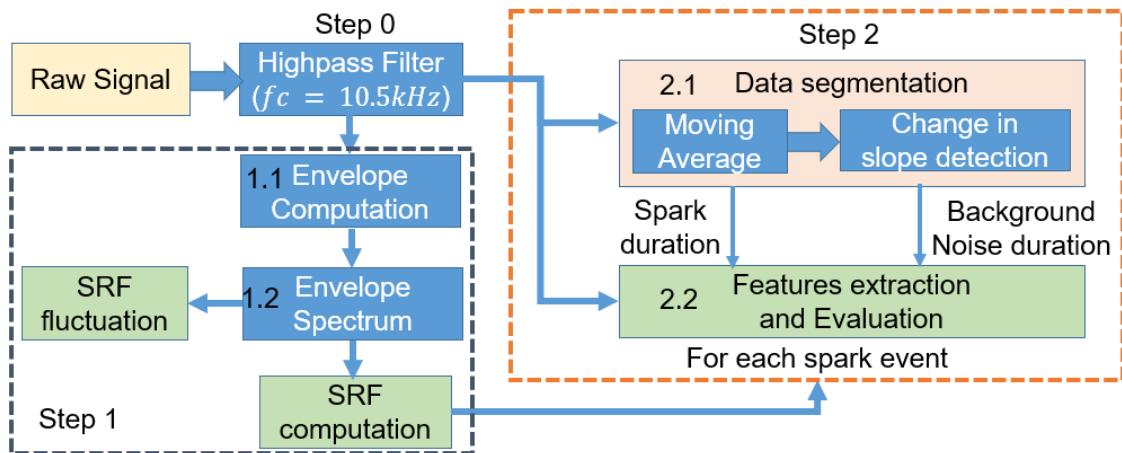


Figure 6-4 Flow chart of the employed methodology

With regards to the second step of the overall approach, each spark signal was separately processed once the average time difference between spark events was known (equal to $1/\text{SRF}$). Within each spark event, the signal was further segregated into background noise, and the region between the onset of the spark and the peak acoustic pressure. The onset time for each spark was estimated by analyzing the slope of the acoustic signal, once a moving average filter was applied. The segregated segments were then analyzed using various feature extraction techniques, and their performance was evaluated using various metrics and visual inspection.

6.4 Results and Discussion

This section presents the results acquired through the successful implementation of the developed methodology elaborated in the preceding section. First, the acquired spark acoustics data were analyzed to devise and implement a high-pass filter to address background noise suppression. The filtered data were subsequently evaluated to determine the SRF, their fluctuations, and the acoustic features for each spark throughout the complete data set. Finally, the acquired overall results were assessed to substantiate the potential of employing spark

acoustics characteristics to support an online condition monitoring solution for the ignition system.

6.4.1 Implementation of High-Pass Filter

The noise generated during the spark event can be masked by the background noise. For an APU operating in situ, the background noise is a complex phenomenon. In general, a major part of the background noise stems from the superposition of tonal noise generated by the shaft, compressor blades, cooling fan blades, gears, the broadband noise produced by the combustion process, and acoustical reflections taking place within the APU compartment. The resultant overall background noise during APU startup is non-stationary, which is due to variations in the APU rpm and gradual build-up of the combustion process. The tonal noise dominates the lower frequencies because the rpm is low (e.g., APU shaft frequency is in the range of 75–210 Hz for 7–20% rpm). The combustion noise is also present at low frequencies [9]. Figure 6-5(a) shows a portion of one cycle of the sparking sequence; initially, a spark occurs and then gradually fades away into the background noise. In Figure 6-5(b), the power spectrum of these two signals demonstrates that the noise generated by the spark is present for frequencies greater than 5 kHz. This observation is in agreement with the analysis reported in [31].

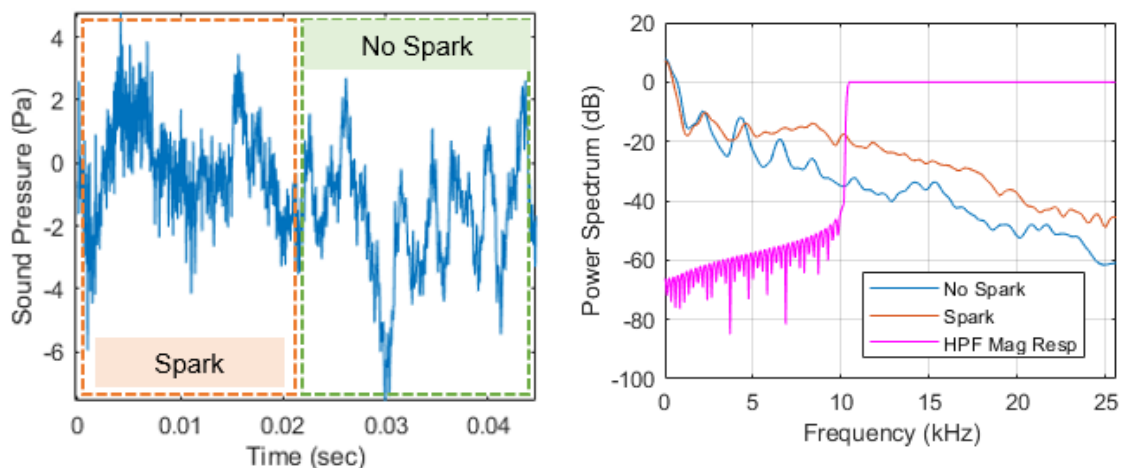


Figure 6-5 Comparison between spark and no spark signal (a) Time domain representation (b) Frequency domain analysis and magnitude response of the high-pass filter

The application of a high-pass filter with a cut-off frequency of 5 kHz can be a good choice to suppress the no spark characteristics. However, the figure only shows the spark taking place at a very early stage of the startup sequence where the tones generated by the shaft, compressor blades, cooling fan blades, and gears are at lower frequencies. As the APU spools up, these frequencies also increase and begin to overlap with the spark noise frequencies. The impulse noise generated by a spark discharge is almost broadband in nature and peaks at around 10.5 kHz, with a 6 dB/octave drop on either side of the peak [27]. A high-pass filter with an f_c at around 10.5 kHz represents an appropriate filter for suppressing the background noise at the lower frequencies. Therefore, a high-pass filter was applied to the raw acoustic data using MATLAB's 'highpass' function with an $f_c = 10.5$ kHz transition band steepness and stop-band attenuation of 0.98 and 80 dB, respectively. The filter produced by this function is a FIR filter with 829 coefficients and a stop-band frequency of 10.19 kHz [magnitude response of the filter is shown in Figure 6-5(b)].

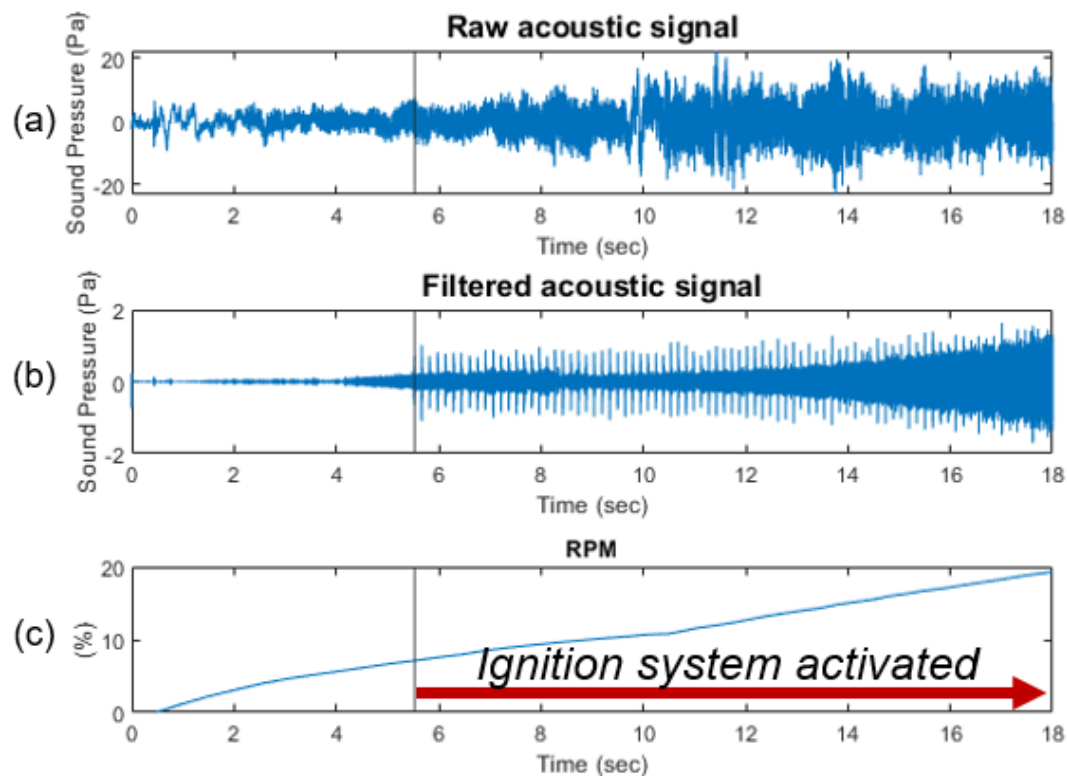


Figure 6-6 Results of application of high pass filtering on acquired data (a) Raw acoustic data (b) Filtered acoustic data (c) APU RPM

The acquired results are shown in Figure 6-6; part (a) of the figure shows the raw signal for the selected duration, as well as how the noise levels progressively increase as the APU spools up. The weak spark signals are not observable in the graph; however, with the application of the high-pass filter, a series of impulse signals emerge after 7% RPM as illustrated in Figure 6-6(b). The instances where the sparking sound was generated are noticeable, and the gradual increase in the background noise level in between these instances is also visible. After 20% of the rated RPM [at 18 sec—see Figure 6-6(c)], the background was found to significantly increase, which resulted in it completely masking the sparking sound.

6.4.2 SRF estimation

Envelope analysis was performed on the filtered acoustic signal to estimate the average *SRF*. MATLAB's '*envspectrum*' function was used for this purpose. It initially computes the envelope of the input signal by taking the absolute of the analytic signal, and then takes the FFT of the envelope. For Day#1 of the operation, the results are shown in Figure 6-7(a) for the acquired acoustic data corresponding to location IGN (for location SCV, the results are identical and are not presented to avoid repetition). It can be seen that multiple peaks occurred in the envelope spectrum. The first peak is at 76 μ Hz, and does not correspond to the time period of the peaks occurring in the envelope signal. The next peak, which occurs at 6.6 Hz, is in line with the periodic spikes in the time series data, and can therefore be regarded as the repetition frequency (*SRF*) of the high-energy impulse signals.

The same analysis was repeated for the complete data set, and the results are presented in Figure 6-7(b). The variation in the source of aircraft power modifies the *SRF*; 6.6 Hz on battery, and 8 Hz with external power. A similar variation in the *SRF* can also occur if there is degradation in the components (resistances and capacitances) that control the repetition frequency; hence, the *SRF* can be regarded as an appropriate metric to monitor the health of the ignition system. Moreover, the approximate number of sparks (N_{sparks}) can be estimated for a given startup, even if all of the sparks have not been detected by knowing the

SRF and the time required to transition from 7–95% rpm ($t_{7-95\% rpm}$); that is, the estimate can be obtained as follows:

$$N_{sparks} = t_{7\%-95\% rpm} \times SRF \quad (6-1)$$

The time $t_{7-95\% rpm}$ is already known through the FADEC as it monitors the APU rpm. Eventually, the N_{sparks} can be accumulated after each startup for estimating the RUL of the igniter. Furthermore, inconsistencies in the sparks that are caused by a fault in the ignition system will broaden the width of the SRF peak, which can also be used as a potential condition monitoring indicator. These widths have been estimated using MATLAB's 'findpeaks' function, and have been placed as bars on top of the SRF values in Figure 6-7(b). During experimentation, the fluctuations in SRF are mostly marginal, with a slight exception on Day#2 (lowest SRF and highest fluctuations). On this day, the APU was powered by the aircraft battery which may not have been sufficiently charged, leading to the low-frequency inconsistent sparks.

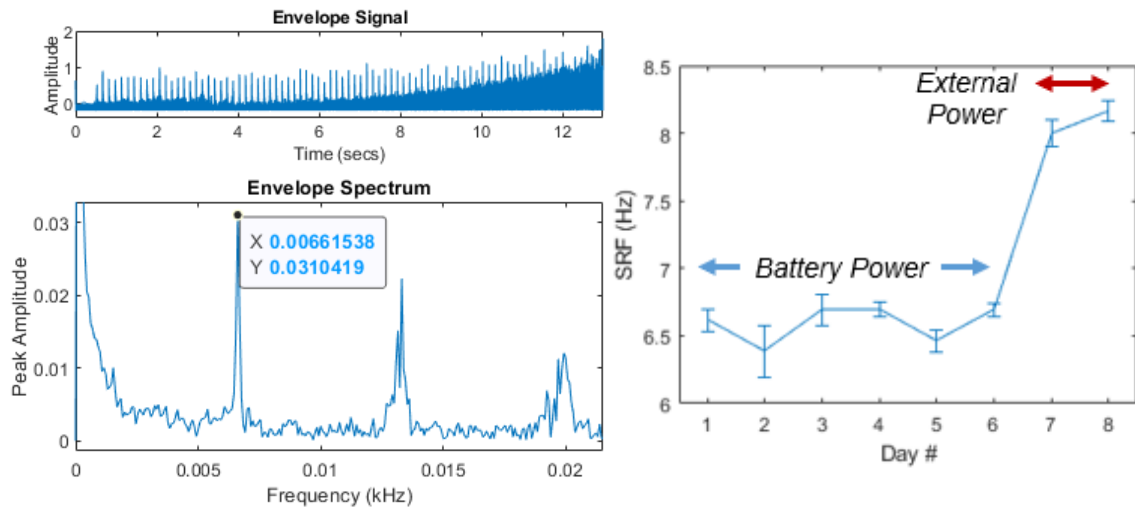


Figure 6-7 SRF computation (a) Envelope signal and envelope spectrum for acoustic data from Day#1 (b) Computed SRF and their fluctuations across all days of experimentation.

6.4.3 Spark event segmentation

Having successfully estimated the SRF , each corresponding impulse signal could be individually analyzed to extract the acoustic features from the region where

the spark characteristics were dominant. Each spark signal is composed of background noise, the onset of spark, peak acoustic pressure, and the gradual decay in energy which eventually diminishes due to the presence of the background noise, as shown in Figure 6-8. The region of significant interest occurs between the onset of the spark (t_{onset}), and the time (t_{peak}) where peak pressure is observed. Within this region, spark characteristics are found to be dominant, and less affected by background noise.

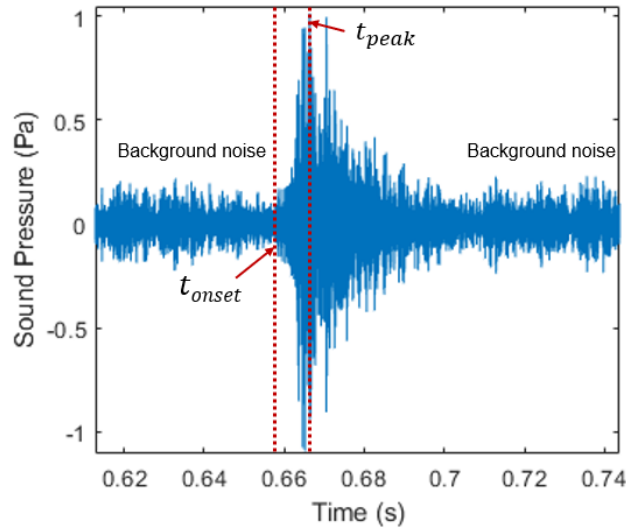


Figure 6-8 Time series data around a spark event

In order to estimate t_{onset} , a change detection strategy based on slope values was applied to the moving averaged version of the filtered acoustic signal. In order to do this, an averaging filter with window size = 256 was applied after taking the absolute of the filtered signal; this allowed for the reduction in the background noise while preserving the spark event locations, as shown in Figure 6-9(a). MATLAB's 'ischange' function was then utilized to provide the time location (t_{onset}) for each spark event where the highest positive change occurred in the slope of the averaged version of the signal. Figure 6-9(b) shows the time (t_{onset}) where the rise in acoustic pressure is taking place, which was identified by the function. Using t_{onset} and t_{peak} , the high-pass filtered acoustic data was segmented around each of the spark events, as follows:

$$\text{Background noise: } t_{onset} - 0.08 \leq t < t_{onset}$$

$$\text{Spark signal : } t_{onset} \leq t \leq t_{peak}$$

The initial 8 ms of the time was deemed appropriate to represent the background noise. In conjunction with this assumption, using the aforementioned approach, estimates were determined for the rise times that corresponded to each detected spark ($t_{rise} = t_{peak} - t_{onset}$). Figure 6-10 presents the acquired values of t_{rise} for all 8 test days at sensor locations IGN and SCV; the overall variation is captured in the form of boxplots. Each plot shows the range, median (red solid line), and mean (labeled as a black unfilled diamond symbol) values of the rise times on each day at a given sensor location. The median and mean values of t_{rise} remained stable (4–5 ms) for location IGN throughout the data set. For location SCV, large deviations (5–9 ms) were observed. The t_{rise} values also varied, due to the change in surroundings (see plots for SCV for Day#7 and Day#8, where the aircraft was parked inside a semi-enclosed hangar that led to high values of t_{rise}). Based on the analysis, t_{rise} values were found to be an inappropriate feature to be observed for condition monitoring due to their inconsistent behavior. However, the samples existing between t_{onset} and t_{peak} were useful for characterizing the spark using various features.

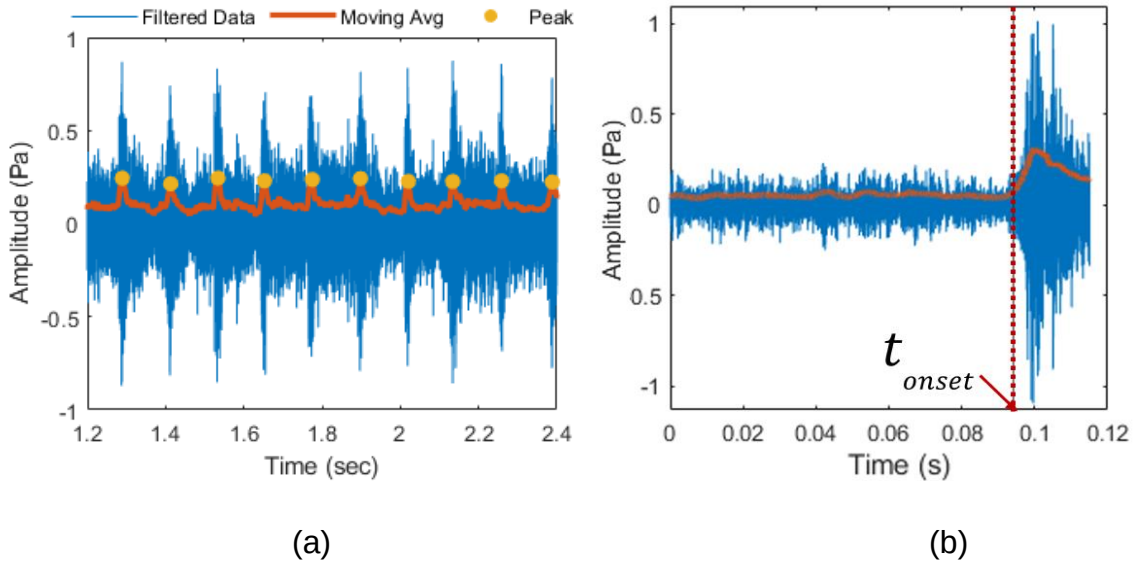


Figure 6-9 Moving average filter results (a) series of sparks (b) single spark with identified location of t_{onset}

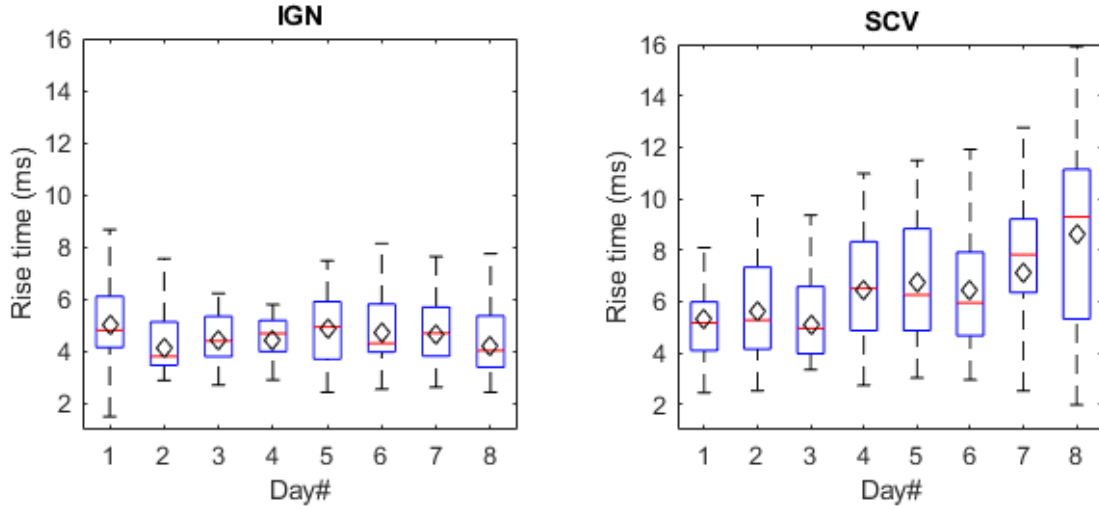


Figure 6-10 Rise times computed for the complete dataset at two sensor locations

6.4.4 Performance Metric for Feature Evaluation

Several features were computed for the background noise and the spark signal around each spark event. The aim was to identify those features that exhibited stable values across all the sparks for a given day of operation, regardless of the sensor location, while maintaining distinct behavior against the background noise. A performance metric was needed to compare the performance of each feature in terms of similarity between the results at the two sensor locations, and if applicable, its similarity with background noise features. For this purpose, the average values of the coefficients of overlap [32] were selected, and are defined as follows:

1. Mean value of the coefficient of overlap between the distribution of feature values computed at the two sensor locations:

$$\Delta_{IGN}^{SCV} = 1/n \sum_i \Delta_i^{SCV:IGN} \quad (6-2)$$

Here, ' n ' is the number of days of data collection, and

$$\Delta_i^{SCV:IGN} = \int \min \{f_i^{SCV}(x), f_i^{IGN}(x)\} dx \quad (6-3)$$

In the above equation, f_i^{SCV} and f_i^{IGN} are the probability density functions of a feature at locations SCV and IGN, respectively, for a day ' i '.

MATLAB's '*ksdensity*' function was used to estimate the probability density function of a feature, and the '*trapz*' function was employed to perform the required numerical integration after the '*min*' operation.

2. Mean value of the coefficient of overlap between the distribution of feature values computed at a sensor location, and for the corresponding background noise:

$$\Delta_{Noise}^S = 1/n \sum_i \Delta_i^{S:Noise} \quad (6-4)$$

Here,

$$\Delta_i^{S:Noise} = \int \min \{f_i^S(x), f_i^{Noise}(x)\} dx \quad (6-5)$$

where S can either be IGN or SCV depending on the selected sensor, and f_i^{Noise} corresponds to the probability density function of the features computed for the background noise, using that sensor on day ' i '.

The values of the above coefficients of overlap (Δ_{IGN}^{SCV} , Δ_{Noise}^{IGN} and Δ_{Noise}^{SCV}) for a particular feature can range between [0,1]. A stable feature will exhibit very high values for Δ_{IGN}^{SCV} , which means that the feature is insensitive to the change in sensor location. Moreover, it is desirable to have a feature that is dissimilar to the noise characteristics; this corresponds to low values for Δ_{Noise}^{IGN} and Δ_{Noise}^{SCV} . Such a feature will be sensitive to the igniter (or ignition system) degradations, and can therefore be utilized for ignition system condition monitoring.

6.4.5 Selected Features for Evaluation

Several categories (statistical, spectral descriptors impulsive metrics, and features from visibility graphs) of features were considered in this thesis. An initial assessment of the features was done using the defined performance metrics, and the worst performing features were excluded from the detailed analysis. The least performing features were identified using the following criteria:

$$\Delta_{IGN}^{SCV} < 0.6 \text{ or } \Delta_{Noise}^{IGN} > 0.2 \text{ or } \Delta_{Noise}^{SCV} > 0.2$$

The low-performing features included, among others, ZCR, kurtosis, skewness, impulse factor, and spectral skewness. As an example, consider the zero-cross rate (ZCR) feature that gives the average number of sign-changes in the signal [33]:

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

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

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

The ZCR values for the sparks and the background noise were found to be similar (very high values for Δ_{Noise}^{IGN} and Δ_{Noise}^{SCV}), which shows that the feature is sensitive to the noise present within the spark duration, and is unable to capture any unique characteristics of the spark. Similarly, the kurtosis value was found to be highly sensitive to sensor location, and also indicated the level of Gaussian behavior in the data. Figure 6-11 shows the box plots for kurtosis values that were computed for the spark and background noise duration for the two sensor locations. The background noise can be seen to have a Gaussian response (kurtosis ≈ 3 [34]). For IGN, the mean kurtosis value is around 5–6, while for SCV it is less than 5, and falls as low as 4 for Day#7 and Day#8 (leading to a high value of Δ_{Noise}^{SCV}). This behavior indicates that the background noise corrupted the acoustic data, even during the sparking event. The low value of 0.62 for Δ_{IGN}^{SCV} is also an indicator of the high level of dissimilarity that existed between the feature values at the two sensor locations.

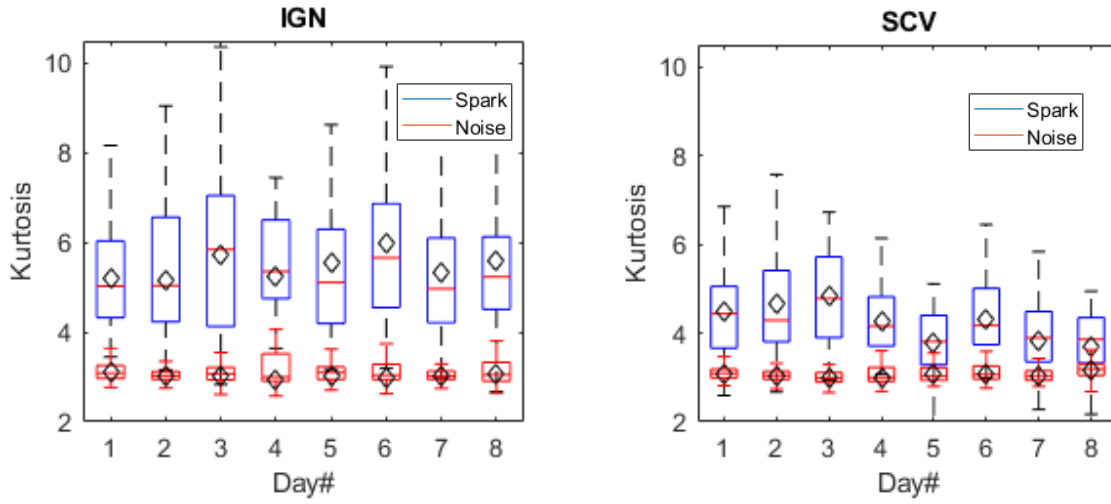


Figure 6-11 Kurtosis values computed for spark and noise data at two sensor locations

After carrying out the initial assessment, the following appropriate features were identified for a detailed comparison:

1. Peak value after application of moving average filter on the high-pass filtered signal (*Peak*),

$$Peak = ||x||_{\infty}$$

2. *RMS*:

$$RMS_{Spark} = \sqrt{\frac{1}{N} \sum x_t^2} \text{ for } t_{onset} \leq t \leq t_{peak}$$

$$RMS_{Noise} = \sqrt{\frac{1}{N} \sum x_t^2} \text{ for } t_{onset} - 0.08 \leq t < t_{onset}$$

where x_t is the high-pass filtered signal around each spark signal, and 'N' is the number of samples within the time duration.

3. Difference between RMS of spark signal and background noise (δ_{RMS})

$$\delta_{RMS} = RMS_{Spark} - RMS_{Noise}$$

4. Mean (μ)
5. Shape factor (*SF*),

$$SF = \frac{RMS}{\frac{1}{N} \sum |x_t|}$$

6. The average number of connected nodes found using a visibility graph (μ_{HVG}). The horizontal visibility graph was chosen for evaluation, in which two nodes (x_i and x_j) are said to be connected only if a horizontal line can be drawn between them that does not intersect any of the intermediate data points [35]:

$$x_i, x_j > x_n, \forall n \mid i < n < j$$

7. Spectral arithmetic mean (*Sp.AM*)

$$Sp.AM = \frac{1}{b_2 - b_1} \sum_{b_1}^{b_2} s_k$$

8. Spectral geometric mean (*Sp.GM*)

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

9. Spectral flatness (*Sp.Flatness*)

$$Sp.Flatness = Sp.GM / Sp.AM$$

10. Spectral crest (*Sp.Crest*)

$$Sp.Crest = \frac{\max(s_k)}{Sp.AM}$$

where s_k is the spectral value at bin k , and b_1 and b_2 are the band edges, in bins, over which to calculate the spectral spread.

6.4.6 Feature Extraction Results

In this section, the results acquired for the selected feature extraction techniques are presented. The goal of this analysis was to identify features that have the

potential to be employed for ignition system condition monitoring purposes. The values of Δ_{IGN}^{SCV} , Δ_{Noise}^{IGN} , and Δ_{Noise}^{SCV} were used as a performance metric to systematically identify the most effective features. Table 6-1 presents the acquired results for all the selected features against the defined performance metrics. The features were sorted in decreasing order of Δ_{IGN}^{SCV} values.

In terms of similarity with the background noise, the *SF* and *RMS* features were the worst performing. The values of Δ_{Noise}^{IGN} and Δ_{Noise}^{SCV} are 0.07 and 0.13 for *SF* and 0.10 and 0.19 for *RMS*. These numbers indicate the degree to which the feature values for spark and noise resemble one another, thus making them prone to noise. Similarly, the *Sp.Crest* feature is also susceptible to background noise. Lastly, the *Peak* feature is also slightly affected by background noise if the sensor is far from the igniter ($\Delta_{Noise}^{SCV} = 0.1$). However, for this feature, the value of Δ_{IGN}^{SCV} is 0.81, which indicates that it does not significantly vary with a change in the acoustic path, and can therefore be a direct consequence of the variations in spark discharge characteristics. Figure 6-12 shows how the peak values vary for spark and noise duration for the two sensor locations under different days of operation. Several useful observations can be made through the figure: the peak values are higher than the background noise if the sensor is close to the igniter; the mean values are similar (~ 0.25) across the two sensors; and there is a gradual decrease in the peak values as the time progresses from Day#1 to Day#8. The gradual decrease in these values may be an indicator of the level of degradation in the ignition system. It is to be noted that there was a five-month delay between the first day and the last day of operation, during which it is probable that atmospheric effects may have degraded the igniter. A similar trend was also observed for the δ_{RMS} feature (see Figure 6-13), which surpassed all of the other features in displaying a very high value for Δ_{SCV}^{IGN} (0.84). The δ_{RMS} appears to gradually decrease after each day of operation. This feature corresponded to the energy that was added into the acoustic channel by the spark discharge, and can be an appropriate parameter to ascertain the health of the system.

Table 6-1 Performance analysis of selected features

Feature Name	Δ_{IGN}^{SCV}	Δ_{Noise}^{IGN}	Δ_{Noise}^{SCV}
δ_{RMS}	0.83	-	-
<i>Peak</i>	0.81	0.02	0.10
<i>RMS</i>	0.80	0.10	0.19
<i>Sp. Crest</i>	0.76	0.09	0.07
<i>Sp. Flatness</i>	0.72	0.02	0.05
μ	0.70	0.01	0.02
<i>SF</i>	0.65	0.07	0.13
<i>Sp. AM</i>	0.63	0.00	0.00
<i>Sp. GM</i>	0.62	0.00	0.00
μ_{HVG}	0.61	0.00	0.01

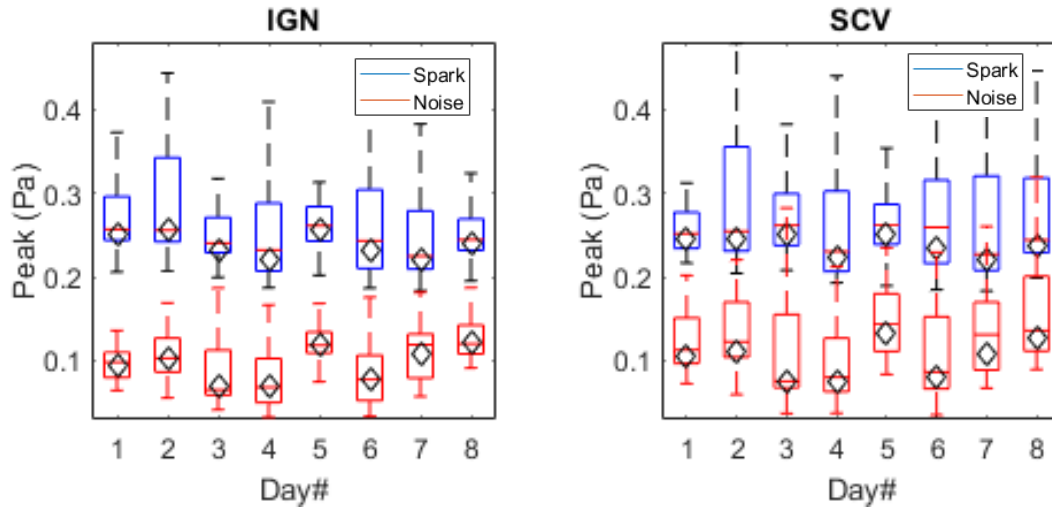


Figure 6-12 Peak values computed for spark and noise data at two sensor locations

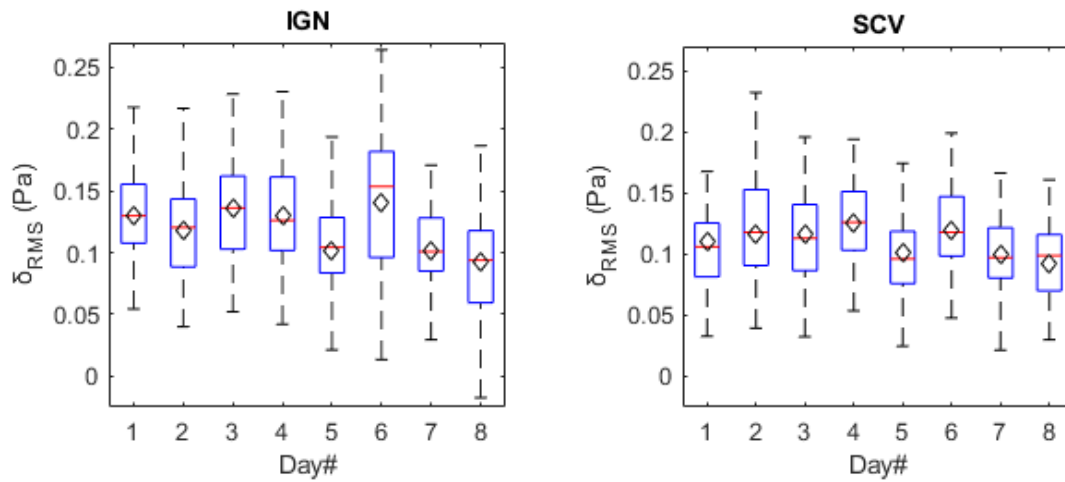


Figure 6-13 δ_{RMS} values computed for spark signals at two sensor locations

The μ_{HVG} feature performed well in terms of its resistance against background noise (see Figure 6-14). This value refers to the mean number of samples which are horizontally visible in a time series data set. For the background noise, the mean value for the feature was 3.99, while for spark, the values ranged between 3.8 and 0.94. Although μ_{HVG} had very low values for Δ_{Noise}^{IGN} and Δ_{Noise}^{SCV} ; however, it was sensitive to the sensor location ($\Delta_{SCV}^{IGN} = 0.73$). For SCV, the values reduced for Day#8, which may have been attributed to the increase in the rise times at location SCV (see Figure 6-10), when more samples of background noise were captured and analyzed within the spark duration.

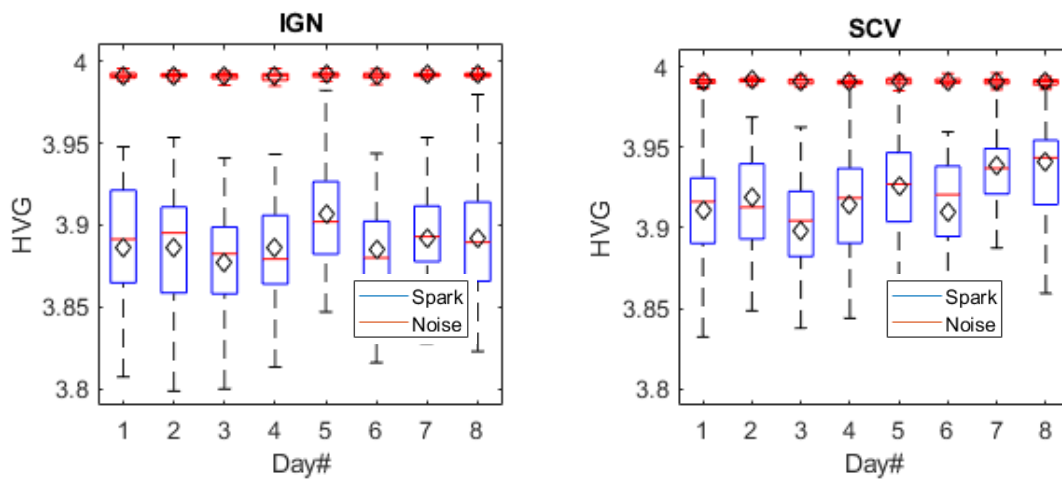


Figure 6-14 HVG values computed for spark and noise data at two sensor locations

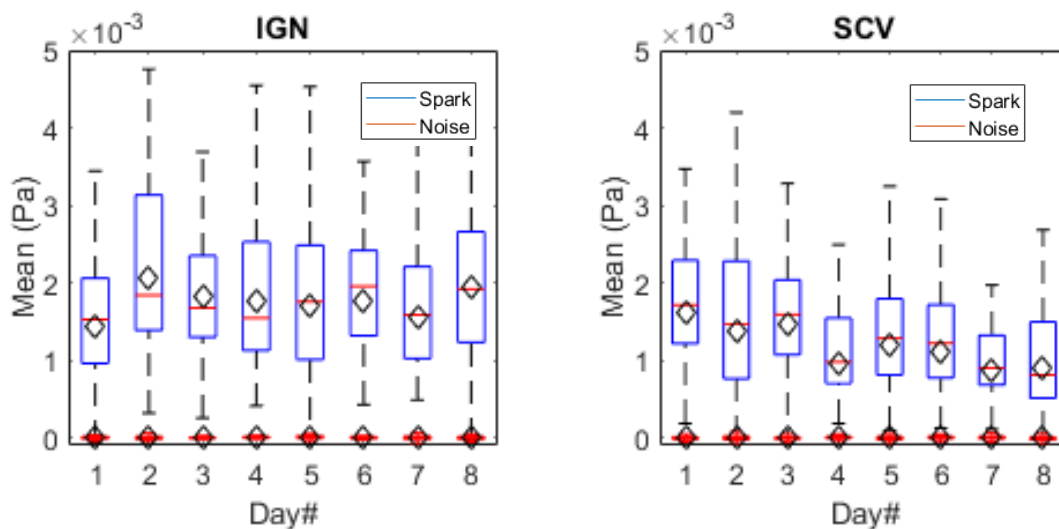


Figure 6-15 Mean values computed for spark and noise data at two sensor locations

The results for feature μ are also interesting (see Figure 6-15). The value of μ for noise is zero, while for the spark it is positive for the majority of the data set. The wave that originated from the spark discharge took the shape of an N-wave, which has more energy towards the positive side [7], making the mean > 0 . During the propagation of such a wave through a multi-path channel, it is likely that the outcome will also have a positive mean. Variations in the spark discharge characteristics due to ignition system degradation will lead to changes in the shape of the N-wave, which can be manifested in the change in the mean value of the samples taken during the spark duration. The remaining features (*Sp. AM*, *Sp. GM*, and *Sp. Flatness*) were also found to be highly robust against background noise, regardless of the sensor location ($\Delta_{Noise}^{IGN} \sim 0$ and $\Delta_{Noise}^{SCV} \sim 0$). These features, therefore, present strong potential for capturing the characteristics desired to support the development of an online condition monitoring solution. It is noted that, in order to fully comprehend the sensitivities of the acquired features, experimentation should be conducted under an actual degraded/faulty ignition system.

6.5 Conclusion

An ignition system plays a critical role in the startup of an APU. Failures during APU startup can have safety implications, and lead to disruptions in aircraft operation. The principal function of an ignition system is to generate sparks to initiate combustion. A faulty/degraded ignition system can lead to startup failure(s), compromising aircraft availability and safety. In order to monitor the health of the ignition system, an onboard condition monitoring strategy is needed; it must be universally applicable on any aircraft, with minimum hardware modifications. Existing methodologies require an electrical interface with the ignition system. Moreover, no consideration used thus far was dedicated to exploit the spark acoustic characteristics for formulating an ignition system monitoring solution.

The incorporation of microphones to support the condition monitoring of an APU ignition system have strong application potential due to their inherent non-intrusive and non-interfering nature. However, for an APU, the observation of

spark acoustic characteristics can be convoluted, as they are subject to multi-path reflections as well as background noise produced by the turbomachinery components. In this thesis, a feasibility study was conducted to determine the potential of using a microphone for monitoring an APU ignition system. The overall study was carried out based on the actual startup acoustic data set that corresponded to a Boeing 737-400 aircraft APU. The devised methodology enabled the translation of the acquired raw acoustic data into ignition system state-indicating parameters. The derived parameters can be compared against healthy limits to detect a fault or degradation in the system. The successful implementation of the reported methodology leads to the following conclusions:

- (1) Signal processing of the raw acoustic data acquired from a well-placed microphone (preferably close to the igniter) can produce condition indicators that are representative of the health of an ignition system.
- (2) A high pass filter with $f_c = 10.5 \text{ kHz}$ is suitable to suppress the background noise while retaining the spark acoustic characteristics till 20% RPM of the APU.
- (3) Envelope spectrum technique can compute the spark repetition frequency (and the degree of its fluctuations), which can be compared against nominal limits in order to detect inconsistencies in the ignition exciter electrical characteristics (such as input voltage).
- (4) The onset time (t_{onset}) can be reliably estimated by detecting the slope of the signal, once a moving average filter has been applied.
- (5) Samples taken between t_{onset} and t_{peak} of each spark pulse are appropriate for computing features that can be used as indicators of the ignition system's health.
- (6) The results show that there are certain features that are robust against time-varying background noise, and are insensitive to a change in sensor location; thus, these features can be employed as condition indicators. For example, the features μ and δ_{RMS} have been found to show a particular

trend that is associated with igniter wear taking place over a period of five months.

References

- [1] Skliros, C.; Ali, F.; Jennions, I.K.; Fakhre, A. Experimental Investigation and Simulation of a Boeing 747 Auxiliary Power Unit. *J. Eng. Gas Turbines Power* 2020, 142, 081005.
- [2] Ahmed, U.; Ali, F.; Jennions, I. A review of aircraft auxiliary power unit faults, diagnostics and acoustic measurements. *Prog. Aerosp. Sci.* 2021, 124, 100721.
- [3] Zhang, Y.; Hanachi, H.; Liu, J.; Yang, C. Model-based degradation inference for auxiliary power unit start system. *Eng. Fail. Anal.* 2020, 118, 104895.
- [4] Kim, K.; Uluyol, O.; Parthasarathy, G.; Mylaraswamy, D. Fault diagnosis of gas turbine engine LRUs using the startup characteristics. *Proc. Annu. Conf. Progn. Health Manag. Soc.* 2012, 2012, 93–102.
- [5] Jennions, I.K. *Integrated Vehicle Health Management-Business Case Theory and Practice*; SAE International: Warrendale, PA, USA, 2012.
- [6] Esperon-Miguez, M.; John, P.; Jennions, I. A review of Integrated Vehicle Health Management tools for legacy platforms: Challenges and opportunities. *Prog. Aerosp. Sci.* 2012, 56, 19–34.
- [7] Ayrault, C.; Béquin, P.; Baudin, S.; Ayrault, C.; Béquin, P.; Baudin, S. Characteristics of a spark discharge as an adjustable acoustic source for scale model measurements. *Proc. Acoust.* 2012, 2012, 5. Available online: <https://hal.archives-ouvertes.fr/hal-00810828/document> (accessed on 17 August 2022).
- [8] Zel'Dovich, Y.; Raizer, Y. *Physics of Shock Waves and High-Temperature Hydrodynamic Phenomena*; Academic Press: Cambridge, MA, USA, 1967.

- [9] Ahmed, U.; Ali, F.; Jennions, I.K. Development of a Far-Field Noise Estimation Model for an Aircraft Auxiliary Power Unit. *IEEE Access* 2021, 9, 127703–127719.
- [10] Boeing. 737-300/400/500: Aircraft Maintenance Manual; Boeing: Seattle, DC, USA, 2015.
- [11] Frus, J.R. Diagnostic Device for Gas Turbine Ignition System. US Patent 5,155,437, 13 October 1992.
- [12] Gary, R. Hoeflich, Ignition Performance Monitor and Monitoring Method for Capacitive Discharge Ignition Systems. US Patent 5,208,540, 4 May 1993.
- [13] Youssef, M. Health Monitoring of Igniters. US Patent 2015/0036781 A1, 5 February 2015.
- [14] Ponziani, R.L. Method and Apparatus for Gas Turbine Engines. US Patent 2006/0241886 A1, 26 October 2006.
- [15] Pond, C.; Lucier, D. Caring for Spark Plugs. *Turbomach. Int.* 2006, 47, 36–37.
- [16] Staszewski, W.; Tomlinson, G. Local Tooth Fault Detection In Gearboxes Using A Moving Window Procedure. *Mech. Syst. Signal Process.* 1997, 11, 331–350. <https://doi.org/10.1006/mssp.1996.0087>.
- [17] Bastami, A.R.; Bashari, A. Rolling element bearing diagnosis using spectral kurtosis based on optimized impulse response wavelet. *J. Vib. Control* 2020, 26, 175–185. <https://doi.org/10.1177/1077546319877702>.
- [18] Liang, L.; Shan, L.; Liu, F.; Li, M.; Niu, B.; Xu, G. Impulse Feature Extraction of Bearing Faults Based on Convolutional Nonnegative Matrix Factorization. *IEEE Access* 2020, 8, 88617–88632. <https://doi.org/10.1109/ACCESS.2020.2993226>.
- [19] Yang, W.-X.; Ren, X.-M. Detecting Impulses in Mechanical Signals by Wavelets. *EURASIP J. Adv. Signal Process.* 2004, 2004, 946162. <https://doi.org/10.1155/S1110865704311091>.

- [20] Liu, Y.; Chai, Y.; Liu, B.; Wang, Y. Impulse Signal Detection for Bearing Fault Diagnosis via Residual-Variational Mode Decomposition. *Appl. Sci.* 2021, 11, 3053. <https://doi.org/10.3390/app11073053>.
- [21] Zhuang, Z.; Ding, J.; Tan, A.C.; Shi, Y.; Lin, J. Fault Detection of High-Speed Train Wheelset Bearing Based on Impulse-Envelope Manifold. *Shock Vib.* 2017, 2017, 2104720. <https://doi.org/10.1155/2017/2104720>.
- [22] Wang, Y.; Chi, Y.; Wu, X.; Liu, C. Extracting acoustical impulse signal of faulty bearing using blind deconvolution method. In *Proceedings of the 2009 Second International Conference on Intelligent Computation Technology and Automation*, Changsha, China, 10–11 October 2009; Volume 1, pp. 590–594. <https://doi.org/10.1109/ICICTA.2009.149>.
- [23] Arslan, Y. A new approach to real time impulsive sound detection for surveillance applications. *arXiv* 2019, arXiv:1906.06586.
- [24] Dos Reis, C.F.; Altafim, R.A.P.; Gutnik, Y.; Altafim, R.A.C.; Cavalcanti, C.A. Comparative analysis between impulsive detection methods applied on partial discharge acoustic signals. In *Proceedings of the 2014 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) Proceedings*, Montevideo, Uruguay, 12–15 May 2014; pp. 418–421. <https://doi.org/10.1109/I2MTC.2014.6860779>.
- [25] Peck, C.H.; Moore, P. A direction-finding technique for wide-band impulsive noise source. *IEEE Trans. Electromagn. Compat.* 2001, 43, 149–154. <https://doi.org/10.1109/15.925534>.
- [26] Tilz, A.; Meyer, G.; Kiesling, C.; Pirker, G.; Salbrechter, S.; Wimmer, A. Design of a test rig for fundamental investigations of spark characteristics. *Int. J. Engine Res.* 2020, 21, 1412–1425. <https://doi.org/10.1177/1468087419828943>.
- [27] Edward, R. A Study of Acoustic Radiation from an Electrical Spark Discharge in Air. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, 1974.

- [28] Shibayama, H.; Fukunaga, K.; Kido, K. Directional characteristics of pulse sound source with spark discharge. *J. Acoust. Soc. Jpn.* 1985, 6, 73–77.
- [29] Wang, J.; Cao, J.; Cai, L.; Fan, Y.; Zhou, M.; Li, Q. Characteristics of acoustic response from simulated impulsive lightning current discharge. *High Volt.* 2019, 4, 221–227. <https://doi.org/10.1049/hve.2019.0030>.
- [30] Liu, J.; Bi, M.; Jiang, H.; Gao, W. Evaluation of spark discharge. *J. Electrostat.* 2020, 107, 103500. <https://doi.org/10.1016/j.elstat.2020.103500>.
- [31] Wyber, R. The design of a spark discharge acoustic impulse generator. *IEEE Trans. Acoust. Speech Signal Process.* 1975, 23, 157–162. <https://doi.org/10.1109/TASSP.1975.1162666>.
- [32] Eidous, O.M.; Al-Talafha, S.A.-D.A. Kernel method for overlapping coefficients estimation. *Commun. Stat.-Simul. Comput.* 2020, 1–18. <https://doi.org/10.1080/03610918.2020.1757711>.
- [33] Giannakopoulos, T.; Pikrakis, A. *Introduction to Audio Analysis*; Academic Press: Cambridge, MA, USA, 2014.
- [34] Najim, K.; Ikonen, E.; Daoud, A.K. Kaddour Najim, *Stochastic Processes: Estimation, Optimization and Analysis*; Kogan Page: London, UK, 2004.
- [35] Miguez, M.E.; Uriondo, A.; Rodriguez, J.; Luque, B. A Feasibility Study on the Implementation of Visibility Algorithms for Fault Diagnosis in Aircraft Fuel Systems. *Int. J. Progn. Health Manag.* 2019, 10, 1. <https://doi.org/10.36001/ijphm.2019.v10i1.2745>.

7 Summary and Future Work

This chapter highlights the contributions made during the PhD and the potential impact of the key findings. It concludes with a discussion on the areas where acoustics can be further exploited for condition monitoring of an aircraft system in a real environment and how the proposed solutions / analysis can be further strengthened.

7.1 Addressing the Research Aim and Objectives

The overall aim of this research is to ascertain the possibility of utilizing microphones for condition monitoring of an aircraft APU. This research achieves this aim by fulfilling various objectives as described below:

Objective 1: Literature review covering aircraft auxiliary power units, their faults, acoustic measurements, and the available condition monitoring techniques.

Evidence: In chapter 2 and in the literature review sections of the technical chapters (3 to 6), a review of the existing techniques for APU condition monitoring and the experimentation carried out on their noise characteristics is presented. The review of the open literature suggests that these two areas do not overlap and there exists a research gap in identifying the potential of utilizing microphones for condition monitoring / fault detection. The available acoustics-based condition monitoring solutions found in the literature have been devised for a sub-set of turbomachinery, that too in a controlled environment.

The APUs, being an important part of aircraft, should be free from failure in order to ensure the smooth execution of an airline's operations. The existing techniques require a set of non-intrusive sensors for monitoring, fault detection, and identification. The legacy aircraft lack an all-encompassing set of sensors to enable simultaneous monitoring of multiple APU components. Using microphones to achieve the desired purposes may prove to be a convenient approach for such a category of aircraft since they are readily deployable and may not require extensive certification requirements. In the literature, such an

approach has not been evaluated, and the possible faults that can be detected / identified using microphones are not known.

Objective 2: Data acquisition from Boeing 737-400 aircraft.

Evidence: As per the literature survey, a data repository containing APU noise data does not exist. Therefore, in order to support this research, Cranfield University's Boeing 737-400 aircraft has been extensively instrumented to acquire near-field and far-field acoustic, vibration, cockpit, FADEC, and muffler exit temperature data on multiple occasions. The complete experimentation spans over a period of five months and contains the data during startup, shutdown, and various other steady-state conditions. A detailed explanation of the experimental setup is presented in chapters 3, 4, 5, and 6.

Objective 3: Development and validation of far-field noise estimation model for the APU and quantifying the effect of components' degradation on the noise characteristics.

Evidence: In chapter 3, the far-field noise model for the reference APU has been developed using the semi-empirical relationships for combustion and jet noise. The NASA, ESDU, and SAE noise models have been evaluated during this process, and the unknown parameters (required by the models) have been estimated by developing the APU thermodynamic model using T-MATS libraries. The effect of spectral distortions due to multi-path propagation on the model's output has also been incorporated. The resultant noise model has been validated against the experimentally acquired noise data, and the appropriate semi-empirical relationships have also been identified. The validated model has been further exploited by incorporating component degradations and quantifying their effect on the far-field noise levels.

Objective 4: Analyse the behaviour of the acquired near-field noise data under various load conditions in order to evaluate it for condition monitoring.

Evidence: In chapter 4, a detailed analysis of the acquired near-field acoustic data has been carried out and presented. The aim of the analysis has been: (1) to ascertain the possibility of detecting the combustion noise inside the APU

compartment, (2) to determine the consistency of acoustically acquired tonal frequencies, and (3) to establish relationships (if any) between the features extracted from the noisy data and the APU states and parameters.

Objective 5: Propose a methodology for APU monitoring using microphones installed within the APU compartment.

Evidence: Based on the results of chapter 4, acoustic-to-APU state identification and acoustic-to-thermodynamic parameter estimation models have been proposed in chapter 5. The former model can detect a faulty condition if the APU is unable to transition between the different states as per the demand. The latter category of models can potentially detect a fault in the lubrication oil cooling system and pneumatic system components (IGVs, SCV, and BV) by acoustically estimating the underlying parameters that can get affected under a faulty condition. Various feature extraction, classification, and regression techniques have been employed and evaluated at multiple sensor locations and the models have been tested using unseen data acquired from a different day of operation. The appropriate sensor locations have also been identified that can provide a holistic picture of the APU operation and enable monitoring of the APU for potential faults.

Objective 6: Identify the prospects of utilizing a microphone for monitoring the APU ignition system.

Evidence: In chapter 6, the acoustic data acquired during multiple startup sequences have been analyzed and an appropriate methodology has been devised to translate the raw data into useful information about the APU ignition system using a microphone. The various stages of the methodology include high-pass filtering, computation of the envelope of the time series data and its spectrum, data segmentation, and feature extraction. This results in the estimation of the spark repetition frequency and its fluctuations that can be used to monitor the ignition exciter and support the accumulation of the number of sparks for condition monitoring of the igniter. Another aspect of the methodology is to identify those acoustic features that are robust against the background noise and are also invariant to the sensor location. Such features are believed to be an

intrinsic characteristic of the igniter's spark signal and can therefore be used to monitor the ignition system.

7.2 Contribution to knowledge

During this research, several contributions have been made and are listed as follows:

1. The literature review provides a consolidated view of the APU faults, the existing condition monitoring techniques, and the experimentation that has been done on the APU noise. The review identifies the opportunities as well as the challenges involved with using microphones for condition monitoring in a real environment. Several research gaps have also been highlighted at the culmination of the review, most of which have been addressed during this PhD.
2. Identification of dominant sources of noise in the far-field of an actual aircraft APU.
3. Estimation of unknown thermodynamic parameters by developing the APU model using T-MATS libraries in MATLAB Simulink.
4. Identification of the appropriate semi-empirical noise estimation models for the reference APU.
5. Development and validation of a far-field noise model for estimation of noise from the aircraft APU.
6. Development of analytical relationship for quantifying the effect of multi-path propagation due to ground reflections on the received acoustic levels.
7. Quantification of the effect of the APU component degradation on the far-field noise components and thermodynamic parameters.
8. Detailed analysis of the tonal frequencies in the nearfield noise for condition monitoring of tones-generating components. Fluctuation in the APU RPM, doppler effect, and high level of background noise have been identified as the possible causes for the loss in the consistency of the tones, which inhibits acoustic monitoring of the APU gearbox and bearings.

9. Proved the non-existence of the combustor noise within the APU compartment by carrying out coherence analysis between the far-field noise (which has a dominant contribution from combustion) and the near-field acoustic data.
10. Proposed utilization of microphones for identifying APU states and estimating the key APU parameters for fault detection. During the process of evaluating this approach, a combination of various feature extraction, classification and regression techniques have been carried out and the most appropriate microphone locations have been identified.
11. Analyzed the acoustic signal during APU startup and proposed a methodology for estimating parameters / features that can enable condition monitoring of the APU ignition system.

7.3 Potential impacts of the findings

During this PhD, the acoustic characteristics originating from the reference APU have been extensively studied using appropriate techniques with an aim to identify the potential of using microphones for condition monitoring. Apart from the academic impact (coming through the publications), this research can be crucial to the industry in the following ways:

This research has provided a solution to estimate the far-field noise from an aircraft APU. This can be utilized by noise experts who would want to quantify the APU noise under a wide range of operating conditions. The solution inherently includes source separation, and multi-path propagation effects that may affect the experimental results. The overall methodology produces a noise model which is accurate to within 1.5dB. The model also allows for ascertaining the important thermodynamic and geometrical parameters on which the far-field noise is dependent. The study shows that it is possible to build a noise model using limited knowledge about the thermodynamic parameters available through APU electronic controller (or FADEC).

The research has also quantified the variations in the far-field noise which can arise due to the reduction in components efficiencies. As per the results, a reduction in the turbine efficiency by 10% can change the combustion noise level

by 1% as compared to a healthy condition. Similarly, a 10% reduction in the load compressor mass flow leads to a 1.5% drop in the jet noise that can be picked by a far-field microphone using the proposed source separation technique. The far-field microphone can therefore be useful to detect significant degradation in the system. However, since the far-field microphone is prone to be corrupted by external noise-generating sources, it is advisable to concentrate on utilizing the near-field noise for condition monitoring purposes.

The research also suggests that, although the microphones are convenient to install and offer fewer hardware complexities during integration, they are not capable of monitoring the tonal frequencies and hence the tone-generating components. So, the prospects of utilizing microphones for condition monitoring of the bearing and gears of a small gas turbine (which has a high RPM) enclosed in a metal casing are quite low and undertaking research in this domain may prove to be unsuccessful and hence not recommended. The shaft frequencies are however found to be stable in the nearfield and far-field and a microphone at a suitable location can be employed to monitor the shaft for an impending fault.

The variations in the broadband acoustic characteristics are not random and are correlated well with the APU states and parameters. A well-placed microphone with an appropriate feature extraction technique may be able to cover a wide range of thermodynamic parameters which can then be used to identify faults/degradation in the system. The novel approach can be applied to similar systems (ECS, engines, hydraulics) for the desired purposes.

Lastly, this research will pave the way for a more extensive analysis of the spark signals generated by the APU ignition system for its condition monitoring using only a single microphone that too outside the combustor where it can be conveniently installed.

7.4 Future recommendations

Due to time constraints, safety concerns, and operational limitations, certain research activities have not been carried out during this PhD and are recommended to be undertaken as future work. These include:

1) Experimental data collection from the aircraft APU in faulty conditions. Several faulty conditions may be implemented on the APU in situ to further expand the research. Such experimentations will require careful planning, hardware modifications, risk assessments, and execution in a safe environment to contain any untoward accident. This set of activities will aim to acquire vibroacoustic data in faulty conditions to ascertain the possibility of detecting such faults using the trained models developed in Chapter 5. The following conditions may be induced in the APU for the desired analysis:

- a. Degradation in the oil cooling system. This can be achieved by installing an oil cooler suffering from fouling. A similar degradation can also be achieved by introducing a gap between the cooling air fan and the cooling air duct or by blocking the inlet screen for the cooling fan. Installation of a faulty oil temperature sensor may also produce similar behavior. Such modifications may not require the removal of the APU, however, they might trigger an automatic shutdown. The objective is to create a scenario where the oil temperature rises much faster than it should such that the ability of the developed acoustic-to-oil temperature estimation model to detect such a condition is validated.
- b. A more elaborate form of experimentation will be required to validate the findings of section 3.4, where the internal components (compressors, turbine, and IGVs) of the APU have to be replaced with the ones in degraded states. The objective of this activity will be to empirically study the variations in the far-field noise due to components' degradations and relate the findings with the sensitivity analysis performed in section 3.4. Such activity may have inherent challenges including the inability of the APU to start normally and accelerate to 100% RPM.
- c. Introducing leakage in the ducts of the APU bleed system can prove to be very useful research for evaluating the usefulness of utilizing microphones and the developed models to detect such leakages.
- d. Partial inlet blockage can also be among the potential faults that can be introduced on the aircraft. This can be achieved by deliberately misadjusting the inlet door actuator and the door switches, or by installing

a faulty actuator. The adjustments should be done carefully so that the inlet door is not closed to an extent that leads to compressor surges and ultimately damages the APU. It is possible that the FADEC may detect an abnormal increase in the EGT and inhibit a successful startup.

e. Installation of igniter plugs and ignition exciter units with varying degradation levels can be encouraging and safe research to further validate the findings of chapter 6.

2) Simultaneous utilization of multiple feature extraction techniques for classification and regression models can be considered for increasing the accuracies of the models. This approach might affect the computation times and thus the online capability, which can be offset by utilizing hardware with the desired computational resources.

3) Acquisition of FADEC data using ARINC-429 databus. The FADEC of the APU studied during this PhD has an ARINC-429 interface that might enable high-speed data acquisition of the APU thermodynamic parameters. During the initial stages of research, it was found that the interface is not connected to any other system on the aircraft and the connecting pins were also missing. Moreover, due to intellectual property (IP) constraints, the exact information (if any) being relayed onto that interface is not known. Also, the word format employed during the data transfer is proprietary and may not be known a-priori. If the OEM agrees to share such information, the databus can be exploited using any of the available ARINC-429 decoders (for example PicoScope 4000 oscilloscope offers such a feature) to provide high-resolution data at a higher update rate. With the current experimental setup, each of the parameters is recorded after every 2 seconds. This setup is appropriate for analysing steady-state conditions, however, for transient conditions, a better approach (like utilization of ARINC-429) needs to be followed. High-speed data acquisition can further expand the research to study the relationship between acoustics and IGV / SCV / BV / fuel flow / RPM fluctuations during all the transient stages (including startup and shutdown).

4) Another useful research will be the evaluation of utilizing microphone(s) for RPM estimation. During the APU startup, once the starter motor is engaged, several events take place at pre-defined RPM values. In the case of RPM sensor

fault / degradation, such events will not take place at the right RPM, and an acoustics-to-RPM estimation model will be able to detect such a fault. This approach can also allow uninterrupted APU operation in case of RPM sensor failure.

5) Analysis of acoustic signals during startup sequence to provide automated information about the timings of various events that take place. This information can be compared against the predefined ranges described in the maintenance manual, such that the deviations can be regarded as anomalous behaviour. The events include inlet door operation, started motor engage and disengage, ignition system operation, etc.

6) The effect of variations in the elevation on microphone performance needs to be experimentally determined. Aircraft operate around airports with varying elevations, and since the microphones are sensitive to pressure, their performance might vary. For an acoustic-based solution, it is important to first determine the degree to which the microphone response varies with the elevation change. If the variation is found to be significant, then those acoustic features should be identified that show robustness even if the ambient pressure is varying.

7) Microphones have been shown to be sensitive to temperature variations and the mass flows around them. This phenomenon, in conjunction with other non-intrusive sensors (like external temperature sensors), can be exploited to form a non-intrusive solution for similar aircraft systems like ECS, engine, hydraulics and fuel system.

8) The complete methodology adopted for this research may be validated on another APU.