Towards a condition monitoring scheme for thermoacoustic instability detection and fuel blend performance classification using machine learning

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Abstract

The investigation and improvement in fuel performance and combustion is necessary in order to minimize emissions and operation costs in various engineering applications e.g. aerospace. Among these factors, nevertheless, ensuring safe operation is a priority: undesired phenomena, such as thermoacoustic instabilities, can have detrimental effects on jet engines, gas turbines and combustors, in general, due to excessive vibrations. It is for this reason that monitoring and design schemes should be able to identify the potential of occurrence of such events. This is a difficult task due to the complexity of the nature of these events. This paper is a preliminary investigation into the performance and characterization of various fuel blends and the examination of the vibration levels expected for different combustion states of a gas turbine engine. We tackle the issue from the perspective of modifying the input to the system (i.e. the fuel composition) in order to investigate nonlinear behavior of the gas turbine engine through the development of a multi-class classification algorithm. Features from a vibration channel for each of the fuel blends were extracted for both classification modelling and cluster analysis.

Keywords: Machine learning and pattern recognition, Feature extraction, Engine vibration, Thermoacoustic instability, Cluster analysis, Support vector machine, Gas turbine engines.

1. INTRODUCTION

The paper follows a machine learning approach for the condition monitoring of gas turbine engines. Issues that should potentially be detected are related to phenomena described in the literature as thermoacoustic instabilities [1]. Given that combustors are highly resonant systems, acoustic waves reflecting from the walls will add energy to the flame, when the relative phase of fluctuation is between 0 and 90 degrees (Rayleigh criteria). As a result, self-sustained pressure oscillations take place inside the combustor, initiating high structural vibration levels and heat transfer to the walls [1]. Many attempts were made to solve the problem, for instance in [2], several analytical techniques that are based on active feedback control are described. These methods can be used to stabilise the system by decoupling sound pressure and unsteady heat release. Research in carrying out numerical analysis using physics-based models, as an attempt to predict the instabilities, also exists in the literature. For instance, in [3] a finite element model employs the three-dimensional acoustic wave energy equation, while in [4] a very sophisticated computational fluid dynamics model is used. Equations that govern physics-based models are solved using several assumptions, such as small perturbations around stable equilibriums. In reality, complex interactions coupled by strong nonlinearities do exist between the numerous processes involved during instability [5]. For over twenty years,
bifurcation theory has been used in an effort to explain the existence of limit-cycle oscillations experimentally [6, 7]. Recently, the investigation is extended to study nonlinear complex interactions between flame, heat release and acoustic waves [8].

In this paper, the authors attempt to overcome certain limitations of physics-based models (accuracy, complexity and high uncertainty) by examining the potential use of data-driven strategies, alongside purpose-built experiments, for the detection and prediction of thermoacoustic instabilities. The framework for developing such a condition monitoring scheme involves the following consecutive steps, as described in greater detail in [9]: (a) operational evaluation, (b) data acquisition, normalisation and cleansing, (c) feature selection and information condensation, and, (d) statistical model development for classification. In a recent study [10], the authors designed a novelty detection scheme with features extracted from the energy of wavelet detail coefficients and mean values from light intensity and combustion dynamic pressure measurements. A support vector machine algorithm was trained, stretching the importance of assigning conditional probabilities in this one-class classification problem.

In [11], the authors designed an algorithm to classify different operating conditions of an experimental burner using features extracted from the geometric structure of the two-dimensional phase space of heat release. Another study [12] concerned with the early detection of thermoacoustic instabilities in a gas turbine engine by training an artificial neural network to classify known health conditions using exhaust gas temperature profiles. Another novelty detection study [13] utilizes vibration sensor signals from a jet engine in a healthy state to train a NeuroScale model [14]. Selected features from a number of tracked-orders were used and appropriate novelty thresholds were set. Depending on the characteristics of the signals, e.g. weakly stationary or not, features can be selected from different domains, as explained in [15].

In this paper we present a preliminary investigation into fuel blend performance by means of support vector machines and is able to classify a range of combustion conditions by running the engine with different fuel blends. In addition, cluster analysis reveals similarities between the fuel blends. The paper is organised as follows: in chapter 2 a description of the data and the experimental engine test rig is provided, in chapter 3 the methods used are described briefly, followed by the discussion and presentation of the results in chapter 4, while in chapter 5 we draw the conclusions of this paper and future work.

2. GAS TURBINE ENGINE TEST RIG AND DATA DESCRIPTION

The engine test rig houses a Honeywell GTCP85 gas turbine, with a maximum output shaft power of 149.2 kW, providing a constant rotational speed of approximately 40,000 revolutions per minute. The power section of the engine comprises of a two-stage centrifugal compression, a single-stage expansion (turbine section) and a combustion chamber. A gearbox assembly driving accessories is also placed on the front of the engine. Air is drawn from the first compression stage and guided out of the engine, through a controllable butterfly-type valve, after passing the second compression stage. By increasing valve position opening, the ratio of air-to-fuel mass (AFM) flow rate that passes into the combustion chamber drops. To maintain constant speed, the electronic control system of the engine pumps more fuel into the combustion chamber to recover the lost energy. Therefore, by controlling the position of the valve, allowed us to repeat each test on three operating conditions $c_k=1,\ldots,3$ with a different AFM, where $c_1$ is fully closed, $c_2$ is partially open and $c_3$ is fully open. The average value of AFM flow rate for each $c_k = \{135.9, 84.4, 62.2\} \ g/s$.

Vibration data were collected from the engine running with fourteen different fuel compositions $f_j=1,\ldots,14$ of fuel Jet-A1, a biofuel and natural gas under each $c_k$ (a vibration data
matrix $x_{jk}(t)$ is constructed). The maximum sampling time for each test was set at 110 seconds. One piezoelectric acceleration sensor (Dytran 3225F1) with a sensitivity of 10 mV/g was attached to the engine test rig support structure sampling at a rate of 2 kHz. Examples of vibration data for $f_2, f_4, f_5$ and $f_8$ recorded during two operating conditions $c_{k=1,2}$ are shown in Figure 1. The engine was given sufficient time to reach steady-state condition, by observing exhaust gas temperature and speed, prior to recording vibration data. Nevertheless, nonstationary behaviour is still observed under such conditions when no external input of excitation is applied. Such behaviour is characteristic of an intrinsically unstable system. Peaks of acceleration amplitude of low frequency content, e.g. at around 80 seconds for $f_2$ and 10 seconds for $f_5$, are clearly distinguishable from the rest of the signal. Fuel blend composition strongly influences the vibration amplitude level over time, and can therefore be used as a measure of engine performance. Between each operating condition, the difference in vibration amplitude level is also noticeable, however, for the purposes of this paper each $c_k$ is treated separately and no attempt is made to find relations between them. It should be noted here that the first eleven fuel blends $f_{j=1,...,11}$ correspond to an increasing percentage of biofuel, from $f_1$ having 98 % Jet A-1 and 2 % biofuel composition up to 100 % biofuel composition ($f_{1,1}$). Fuel blends $f_{j=12,...,14}$ correspond to an increasing percentage of natural gas, from 50 % up to 100 %.

![Figure 1: Vibration response data of the engine operating with fuel blends $f_2, f_4, f_5$ and $f_8$ recorded on three operating conditions $c_{1-3}$.](image1)

A look at the histograms of the fuel blends (Figure 2), including $f_3$ and $f_{13}$, reveal two distinct groups of data. The first are the fuel blends that follow a normal distribution closely, $f_2, f_4, f_5, f_8$, while the second group are the ones that have strong sinusoidal structure, $f_3, f_{13}$. Hence, it is possible to use descriptive statistics, e.g. kurtosis in this case, to discriminate the two groups of data. However, that would be inadequate for discriminating among fuel blends within each group as the distributions are very similar. Another feature shown in Figure 2, is the histogram of $f_8$, which is very distinguishable from both the rest of the fuel blends and its normal distribution fit (higher kurtosis and skewness value).

![Figure 2: Histograms of the vibration data of the fuel blends $f_{j=2,...,8}, f_{j=9}, f_{j=13}$ on $c_2$ with their normal distribution fits.](image2)
Histogram plots give some insight into the characteristics of the data examined and can be helpful in order to make more informed and appropriate choices of the data analysis methods chosen later on. Examining the frequency-domain representation of the datasets gives even more insight, especially on the vibration frequency components. Here, the classical method developed by Welch [16], is used to estimate the one-sided power spectrum of each vibration time-series \( P_{j,k}(f) \). This is done by averaging 500 overlapping modified periodograms of 1100 samples each, over the positive Nyquist frequency range \( 0 \leq f \leq 1 \) kHz with a Hamming window function (chosen due to its good trade-off between side roll-off attenuation and mainlobe width at \(-3dB\)). By averaging segments, the variability in the frequency domain is reduced, and main components of the signal are more distinguishable.

The power spectral densities of six fuels \( f_{j=1,\ldots,4}, f_8 \) and \( f_{13} \) at operating condition \( c_2 \) are shown in Figure 3. The overall power amplitude level across the whole spectrum for \( f_1 \) is around 15 dB greater than the one from \( f_{j=2,4,5} \) and 25 dB greater than the spectrum of \( f_8 \) and \( f_{13} \). This might result from one or a combination of the following factors: the engine wasn’t running under the same operating conditions than the rest of the fuels, or the particular fuel composition resulted in a very irregular engine operation. It can also be said that the relationship between increasing biofuel percentage and engine vibration level is not a linear one. Also, specific regions, e.g. between 400 and 600 Hz, show high variability of power between the fuel blends. The same can be observed at 100 Hz, in which two of the fuel blends show high peak power. The dynamic range over the whole spectrum of the signals recorded with \( f_3 \) and \( f_{13} \) is in the range of 45 decibels (higher than the rest), owing to their strong periodicity (see Figure 2).

![Figure 3: Power spectral density of acceleration for the engine operating on six different fuels \( f_{j=1,\ldots,4,8,13,k=2} \).](image)

3. DATA ANALYSIS APPROACHES

What is of major importance at this preliminary stage of our study, is to examine the vibration levels expected for each fuel blend. The first step is to extract a series of features that can classify the different scenarios examined. Here we refer to feature extraction as the transformation of the raw high-dimensional time-series into a set of discriminatory quantities, which can provide better separation between the classes, i.e. fuel blends \( f_{j=1,\ldots,14} \). This enables the algorithm to classify each class more accurately. Usually extracted features are of lower dimension than the original dataset. Which means that this process also protects against overfitting, since the algorithm learns general characteristics, from the lower dimensional feature space [17].

3.1 Time-series modelling

Firstly, each time-series \( x_{j=1,\ldots,14,k=1,\ldots,3}(t) \) has been shifted to have a mean value of zero, and then divided into a number of non-overlapping segments of equal number of points \( N_{seg} \) (clipping the last segment).
A different autoregressive model of order $p$ is constructed for each segment on each $j,k$ combination according to [16],

$$\hat{x}_n = \sum_{i=1}^{p} \phi_i x_{n-i} + \varepsilon_n$$  \hspace{1cm} (1)

Where, the error term at time $n$, $\varepsilon_n \sim iid(0, \sigma^2)$. The autoregressive parameters $\phi_i$ of the lag polynomial model, used to predict the current value of $x_{j,k}$ – denoted as $\hat{x}_n$ in (1) for simplicity – are calculated as follows: (a) determine the maximum upper bound for the lags, as suggested by [18], such that $p_{\text{max}} = \left\lfloor 0.12\frac{\bar{\delta}}{\bar{\sigma}_n} \right\rfloor$, (b) find the value of the optimised log-likelihood objective function $\hat{\mathcal{L}}$ by using maximum likelihood estimation for fitting an autoregressive model with lags in the range $\phi_j = [0, p_{\text{max}}]$, from 3 segments on 10 different fuel blends, chosen arbitrarily, (c) from the $\hat{\mathcal{L}}$ of each $\phi_j$ calculate the Bayesian Information Criterion (considers model parsimony with goodness-of-fit [17]): $-2\log\hat{\mathcal{L}} + \phi_j\log l$ and choose the $\phi_j$ that minimizes it, (d) use this $\phi_j$ value as the order number (or number of lags) to calculate the autoregressive terms $\phi_j$ using Burg method. Burg’s method is regarded to be a reliable technique for parameter estimation, especially when time-series has an almost periodic structure [19].

The $D$ autoregressive terms calculated for the segments on each time-series are used to construct the features matrix for each $c_k$, separately, i.e. $\Phi_{k=1,...,3} = [\phi_1, ..., \phi_D]$. Each $\phi_{i=1,...,D}$ is of length $N = \left\lfloor \text{length}\left(x_{j,k}(t)\right) \cdot N_{\text{seg}}^{-1} \right\rfloor \cdot j$.

3.2 Principal components analysis for feature visualization

In order to investigate how well the various $f_{j=1,...,14}$ are separated in this $D$-dimensional feature space (data space, $\mathbb{R}^D$), the data were projected into two dimensions (latent space, $\mathbb{R}^q$) using the method of principal component analysis (PCA) [17]. PCA uses eigenvalue decomposition to obtain eigenvectors $V$ and eigenvalues $\Lambda$ of the covariance matrix $\Sigma$ of the matrix $\Phi_k$.

$$\Sigma_k = V_k \Lambda_k V_k^T$$  \hspace{1cm} (2)

Each data point in $\Phi_k$ is converted into a score $y_i$ by projection onto the eigenvectors of $\Sigma$.

$$y_i = V_k^T(\phi_i - \bar{\phi}_k)$$  \hspace{1cm} (3)

The scores representing the projected points onto the first two eigenvectors, which correspond to the largest eigenvalues, explain the highest variance on those two orthogonal axes.

3.3 Cluster analysis using K-means

Cluster analysis is used to identify groups of data in the feature space of $\Phi_k$ for different segment lengths. In an ideal scenario, cluster analysis will be expected to find as many clusters as the number of labels, $f_{j=1,...,14}$. The classifier will be, therefore, expected to assign data to the right classes within the feature space $D$, very accurately. To determine $K$ groups of data within the feature space, the $K$-means algorithm is used. The algorithm works iteratively, so as to minimise the Euclidean distances of all $\Phi_{n=1,...,N}$ to the $K$ centres of the clusters $\mu_d$. The algorithm initialises by randomly assigning the locations of $\mu_d$ using the $k$-means ++ algorithm [20]. The first computation step is to allocate each data point to the cluster that gives the minimum Euclidean distance. Then the location of the $K^{th}$ cluster centre $\mu_K$ is recomputed by calculating the mean value of all the data points that fell into that cluster. The process repeats until no further assignments of data points to the clusters can be made. This corresponds to
finding the minimum of \( f \) by varying \( r_{nd} \) and \( \mu_d \) in each iteration [17]:

\[
f = \sum_{n=1}^{N} \sum_{d=1}^{K} r_{nd} ||\phi_n - \mu_d||^2
\]

(4)

Where, \( r_{nd} = 1 \) when \( \phi_n = 1, \ldots, N \) has been assigned to the \( d \)th cluster and \( r_{nd} = 0 \) otherwise.

### 3.4 Artificial observations generation

Forty nine additional observations for each of the time-series \( x_{j=1,\ldots,14}(t) \) were generated by contaminating them with broadband Gaussian white noise \( w(t) \sim N(0, \sigma^2) \). Firstly, a ninth-order Butterworth low-pass filter was applied to the noise signal \( w_{raw}(t) \) with a cut-off frequency of 800 Hz, since there was almost no energy in frequencies above that in the original signal. A signal-to-noise ratio \( \psi \) of 7 dB was considered, thus, the low-pass filtered and scaled Gaussian white noise signal \( w(t) \), that can be added to the original time-series, is calculated as: \( w(t) = \sqrt{\psi \frac{\sigma(x)}{\sigma(w_{raw})}} w_{raw}(t) \), where \( \sigma(x) \) is the standard deviation of a given time-series \( x \).

Following the artificial data generation, a new feature matrix \( \Phi_k \) with length \( N = 49 \) \( N \) is formed, by repeating the time-series modelling procedure. The method of augmenting the original matrix with artificial data features is a common practise in machine learning [14], especially, when a limited number of observations is available for the process of training-validation-testing. To restrict our focus and for the purposes of this paper, only the analysis from operating condition \( c_1 \) will be demonstrated in the subsequent parts of the paper.

### 3.5 Classification using support vector machines

Using 40\% of the labelled observations in \( \Phi \), we build a multi-class support vector machine (SVM) [17] with linear kernel, that can assign each observation from every fuel blend \( f_{j=1,\ldots,14} \) to its class. Assuming linearly separable training data \( (\phi_n, t_n) \) in their feature space, a general linear classifier of the form \( f(\phi_n) = w^T \phi_n + b \), where \( w \) is a normal vector of the hyperplane \( f(\phi_n) \) and \( b \) the bias parameter, is trained such that it separates the two classes \( t_n \in \{-1, +1\} \). SVM does that by calculating the maximum distance between the decision boundary \( f(\phi_n) = 0 \) and the closest training data point \( \phi_n \) from both classes. This distance is defined as \( \frac{|f(\phi_n)|}{||w||} \) and the task is the following optimization problem,

\[
arg \min_{w,b} \frac{1}{2} ||w||^2 \\
subject to \ t_n f(\phi_n) \geq 1 \text{ for all } n
\]

(5)

In practise, training data cannot be assumed to be linearly separable in the whole space of \( \phi_n \). This motivates the need to introduce a variable \( \xi_n \) for each training data point such that the optimisation constraint is relaxed, allowing misclassifications. The optimisation argument is still to maximize the same distance, but, with a relaxed constraint. In standard form,

\[
arg \min_{w,b} \frac{1}{2} ||w||^2 + C \sum_{n=1}^{N} \xi_n \\
subject to \ t_n f(\phi_n) \geq (1 - \xi_n) \text{ for all } n
\]

(6)

The parameter \( C \) is always greater than zero, and can be thought of as the weight for misclassifications. A trade-off needs to be made between large distance (good generalisation)
and misclassifications. The value of $C$ chosen in this paper is 1. For the validation and training stage, the rest of the observations were used. Note that the one-against-one method is implemented, which resulted in 91 different SVM classification models. Validations and testing can be done using a voting scheme [17].

4. RESULTS AND DISCUSSION

As mentioned previously, in order to visualise how the labelled observations are distributed in the feature space, they are projected into two orthogonal axes. This two-dimensional latent space, explains the highest variance of the data points. The first two PCA scores for three different segment sizes (having different number of sample data points $N_{seg}$) used to construct different feature matrices $\Phi$, are shown in Figure 4. Note that the dimension of $\Phi$ varies for each of the three according to the procedure in section 3.1. For segment size of 1 second $\Phi$ is constructed using 10 AR coefficients for each of the 109 equal segments for each of the $x_j=1,...,14(t)$ time-series (Figure 4 (a)), while for 2.5 seconds of segment size there are 12 AR coefficients for each of the 43 equal segments (Figure 4 (b)), and for the 4 seconds of segment size there are 20 AR coefficients for each of the 27 equal segments (Figure 4 (c)). As depicted by all plots (a)-(c), two main clusters can be identified. These two groups of data were shown previously by examining the histograms. However, the selected features offer the additional ability to discriminate observations of different fuel blends within each group. As an example, the histograms from $f_{j=7,k=1}$ and $f_{j=10,k=1}$ (not shown here) are almost identical. However, by fitting a suitable autoregressive model to each segment of the two time-series, a better separation is achieved as seen in Figure 4 (a)-(c). Figure 4 also shows that increasing segment size the spread of each fuel blend $f_j$ decreases significantly. As a consequence, less number of points from different $f_j$ are overlaid, which is expected to improve the classification predictive accuracy on unseen observations. Such separation can be seen, for instance, by looking at the observations from $f_{j=3}$, which are overlaid with both observations in $f_{j=2}$ and $f_{j=4}$ in (a). By increasing the segment size to 2.5 seconds (b) $f_{j=3}$ separates from the group. This is expected, since by increasing segment size implies that nonstationary characteristics and transients in the scale of a few hundred milliseconds are smoothed out. Smoothing effects are undesirable for monitoring, and, therefore, a compromise needs to be made between classification performance and monitoring short time-scale phenomena. Although an AR process assumes a stationary time-series, it is still expected to capture localised dynamic characteristics.

![Figure 4: Principal component analysis of feature matrix $\Phi$, on three different variants corresponding to segment lengths. From left to right, the segment time durations are 1 second, 2.5 seconds and 4 seconds.](image-url)
Since PCA explains the highest variance on its two orthogonal axes, it has shown important characteristics that occur in the higher dimensional feature space, including the ability to observe separation of different class labels with an increase in segment size. A more quantifiable approach is needed to find the number of natural groupings that exist within this feature space, and this is done using cluster analysis. For a range of segment sizes $Dt \in \{0.1, 1, 2, 3, 4, 5\}$ seconds the $k$-means algorithm assigns the features into different $K$ clusters. The number of clusters $K$ used as an input to the algorithm, as a requirement, range from 2 up to 14. For each of the $K$ cluster analyses on every segment $Dt$, silhouette values [21] are computed from the clustered data. Silhouette measures the quality of the clustering by the following metric: 

$$ S = \frac{(b_{i,j} - a_{i,i})}{\max(a_{i,i}, b_{i,j})}, $$

where $a_{i,i}$ is the average cluster Euclidean distance from the $i^{th}$ data point to the rest of the data in cluster $i$, and $b_{i,j}$ is the average nearest-cluster Euclidean distance from the $i^{th}$ data point to the rest of the data in the nearest cluster $j$. The maximum of all the average silhouette values $\hat{S}_{\text{max}} = \max(\frac{1}{13}\sum_{k=1}^{13} S_k)$ calculated for each $Dt$ is used to measure the quality of separation (a value close to +1 indicates dense and well separated clusters). The variation of the mean silhouette value $S_{\text{avg}}$ calculated for each of the number of clusters specified to the $k$-means algorithm is shown in Figure 5 (b). The graph shows that the number of clusters increases with the segment size, i.e. $\hat{S}_{\text{max}}$ is shifted to a higher number of clusters. In particular, for $Dt = 0.1$ s, only two main clusters exist in the feature space, whereas when $Dt \leq 2$ s, four clusters can be identified. As the segment size increases, $\hat{S}_{\text{max}}$ occurs at higher cluster number, e.g. for $Dt = 4$ s the highest mean silhouette value occurs when $K = 7$ clusters. Figure 5 (a) shows the 7 clusters calculated by the $k$-means algorithm in the feature space of the first two AR coefficients with $Dt = 4$ s, while (c) is the scatter plot of the fourteen fuel blends in the same feature space. The members assignments to the 7 clusters are as follows: Cluster 1 includes $f_{j=7, 9, 10, 11, 12}$, Cluster 2 includes $f_{j=8}$, Cluster 3 includes $f_{j=14}$, Cluster 4 includes $f_{j=3, 13}$, Cluster 5 includes $f_{j=1}$, Cluster 6 includes $f_{j=2, 4, 5}$ and Cluster 7 includes $f_{j=6}$.

![Figure 5](image-url)

Figure 5: Clustering using $k$-means algorithm for segment size of $Dt = 4$ s, specifying 7 clusters (a), variation of the mean silhouette value $S_{\text{avg}}$ for clusters ranging from 2 to 14 (b), scatter plot using the first two AR coefficients (two features out of the 20) of fuel blends $f_{j=1,…,14}$ with segment size $Dt = 4$ s.

Interestingly, $f_{j=1}$, $f_{j=8}$ and $f_{j=14}$ each form three separate clusters, while Cluster 1 contains the fuel blends that looked very similar in the previous stages of the analysis, excluding $f_{j=13}$.
and \( f_{j=14} \), which are now separated. As mentioned in section 2, fuel blends \( f_{j=1,...,11} \) are the ones with an increasing percentage of biofuel, whereas \( f_{j=12,...,14} \) contain an increasing percentage of natural gas. Hence, it is also important to see that fuel blends with different chemical compositions can be clustered together, e.g. fuel blends in Cluster 4.

A threshold of 90% in validation accuracy for classification was considered suitable for the purposes of this analysis. This means that the matrix \( \Phi \) had to be constructed with AR coefficients of segment size of no less than 15 seconds. Given the segment size, an autoregressive model of order \( p = 30 \) was determined and its coefficients calculated, according to the procedure described in section 3.1. Forty percent of the overall observations of \( \Phi \) were used to train an SVM with a linear kernel, while 25% of those were used for validation and the rest for testing. Ninety-one percent of the observations used for the validation were classified correctly, while the classification accuracy calculated for the observations used for testing was 93%. The confusion matrix in Figure 6 explains the predictive performance of the classifier on the test data. The class representing the fuel blend \( f_{j=9} \), has been misclassified by 1.3% as \( f_{j=12} \), while \( f_{j=7} \) was thought to be \( f_{j=9} \) with a rate of 0.76% and \( f_{j=12} \) to be \( f_{j=7} \) 0.82% of the times. This confirms the above finding that those three fuel blends are not separable (Cluster 1) at least, in a linear sense. Generally, almost half of the classes in the training set are classified with 100% of accuracy, which will aid a valid further investigation into the combustion dynamics by including a range of new fuel blends.

5. CONCLUSIONS

This paper presented a preliminary investigation into the condition monitoring of gas turbine engines with a focus on characterizing the vibrations of a variety of fuel blends. This is an important step for further investigation on phenomena such as thermoacoustic instabilities. According to the vibration data recorded with each fuel blend, different groups were identified. Fuel blends with different chemical compositions showed similar performance. This is something that is needed to be considered since it is clear that the processes taking place are not linear; especially the processes that describe our system's combustion dynamics.

The current work has established an initial understanding of the expected vibration levels of the fuel blends and different engine operational conditions examined. This can significantly help to carry on further investigation on the thermoacoustic instability issue. Monitoring the dynamic pressure within the combustion chamber might be a useful next step towards that. Experiments that monitor variables like pressure and temperature have been carried out. It is expected that the analysis of the new data will provide more insight, in terms of combustion dynamics, through the design of a nonlinear regression model using Gaussian Processes.

![Figure 6: Confusion matrix for predictions made by the trained SVM with classes representing the fuel blends.](image-url)
REFERENCES