Advancing Light Aircraft Health Monitoring with Flight Phase Clustering

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Abstract

This paper addresses the clustering of flight phases of a light aircraft for health monitoring using vibration data. The aim is to improve diagnostic and prognostic functions. Grouping condition monitoring data under similar operating conditions is significant for predictive maintenance. Clustering also supports advanced analytics for fault detection and estimation of remaining life. The proposed framework uses self-organizing maps for flight phase clustering. The findings show that the algorithm can recognize and classify flight phases in various operational domains. Additionally, visualization of cluster maps uncovers complex patterns and non-linear relationships in sensor data under different flight conditions. As a follow-up, analyzing the vibration properties within these estimated clusters (regimes) provides insights from condition monitoring data behavior during flight phases. The results confirm the effectiveness of the method, but also confirm that determining light aircraft regimes requires more focus due to their unique flight patterns that are absent in commercial airliners. In this context, this research has dealt with these unique patterns and provided the foundation for a new model for clustering with an attempt to contribute valuable insights into improving the reliability and efficiency of light aircrafts.

1. Introduction

Clustering aircraft condition monitoring data across multiple flight phases supports advanced analytics. Grouping data under similar operating conditions is key to transfer valuable data features to fault diagnosis and prognosis. Therefore, determining flight phases has the potential to improve the aircraft service life. In this regard, this study focuses on obtaining features from flight data by taking into account flight phases. Although the literature have paid attention to various aspects of aircraft health monitoring (Kordestani, Orchard, Khorasani, & Saif, 2023), little is known about the specific methods for flight phase identification when it comes to light aircraft. Much of the existing research focuses on general aviation or commercial airliners (Bektas, 2023; Lyu, Thapa, & Desell, 2024). This leaves a gap in the literature regarding light aircraft. Furthermore, the integration of advanced clustering techniques like self-organizing maps (SOM) with further predictive maintenance analytics remains under-explored. This gap is significant because the operating conditions and maintenance needs of light aircraft differ from those of larger aircraft. Addressing such a gap can improve reliability while reducing maintenance costs. This study combines SOM and vibration analysis to address this. This is a novel methodology specifically designed for light aircraft.

Flight data monitoring is a routine of data collection and analysis applied in commercial operations (Gavrilovski et al., 2016). Therefore, it deals with big data where it is not possible to manually review all the collected information by human experts (Oehling & Barry, 2019). Instead, the literature has witnessed various studies on the use of data mining and machine learning techniques to analyze flight data. In particular, transient flight phases can reveal more information, and clustering can help discover hidden insights from both frequent and infrequent flight phases. For this purpose, a previous study by (Bektas, 2023) grouped the phases of flight data according to the most important sensor readings. However, this study was for an airliner with regular flight regimes. However, the same tool introduced for self organizing maps (SOM) training by Wittek and Gao (Wittek & Gao, n.d.), called Somoclu, can also provide advanced visual inspection for light aircraft.

With such clustering mentioned above, flight phases can be identified and an additional data transformation analysis can be performed for a better feature engineering. Vibration analysis can play a critical role here, as it is a common condition monitoring scheme used in industry for machine systems and is considered an effective tool for fault diagnosis and prognosis (Amirat, Benbouzid, Al-Ahmar, Bensaker, & Turri, 2009; Yang, Tavner, & Wilkinson, 2009; Chen, Matthews, & Tavner, 2015; Saidi, Ali, Bechhoefer, & Benbouzid, 2017). Although these vibration-based methods have mostly found a place in literature to detect rotating equipment malfunctions with various techniques, (Yang et al., 2009; Ali, Fnaiech, Saidi, Chebel-Morello, & Fnaiech, 2015; Saidi et al., 2017; Ali, Saidi, Harrath, Bechhoefer, & Benbouzid, 2018), it has been shown in previous studies that they can be used to understand the health of smaller aerial vehicles such as drones (Bektash & la Cour-Harbo, 2020). This provides an application potential for light aircraft. Therefore, following the clustering phase, the study aims to gain a comprehensive understanding from the vibration analysis associated with flight characteristics that differ in each regime. This will be done by comparing the theoretical analysis of the Welch method for the application of the Fourier transform (Power spectrum estimation) (Welch, 1967) . The method is used as a slider of a window to create a status display of flight performance.

The remainder of this paper is structured as follows: it first presents the research procedures and data analysis in the methodology section. As the study is conducted in the context of light aircraft health monitoring, the methodology is validated using real flight data from a light aircraft operating under different conditions and environments. Therefore, the methodology section is followed by testing of the methods and findings of the research inquiry. The paper concludes with a discussion of implications and further work.

2. METHODOLOGY

2.1. Self Organizing Maps

SOM is an unsupervised-learning method that transforms complex and nonlinear relationships of an incoming signal pattern into simple geometric relationships on a low-dimensional map (Kohonen, 1990). This compresses data while preserving primary data relationships (Kohonen, 1998). The SOM configuration used for clustering features a finite two-dimensional grid of regular nodes. Each node is linked to a weight vector ($W = \{w_1(t), ..., w_k(t)\}$), representing a position in the input space. The nodes remain fixed in the map space ($M = \{m_1, ..., m_k\}$). Training involves moving the weight vectors towards the initial input data ($X = \{x(t) \mid t \in \{t_o, ..., t_f\}\}$) (Kohonen, 2013).

Data points are mapped to their best matching (BMU), the node whose weight vector is most similar to the input.

$$BMU(x(t)) = n_b \in M \tag{1}$$

where the unit's distance is lowest.

$$d(x(t), w_b(t)) \leq d(x(t), w_j(t)) \qquad \forall w_j(t) \in W, \tag{2}$$

Here, the nodes are organized on a 2D grid with two coordinates. BMU weights along with the nearby nodes are adjusted toward the input vector. The adjustment magnitude decreases over iterations and with the distance from the BMU as:

$$w_j(t+1) = w_j(t) + \alpha h_{b_j}(t)(x(t) - w_j(t)) \tag{3}$$

α (the learning factor) ranges between $0 < \alpha < 1$, and $h_{b_j}(t)$ (the neighborhood function) represents the distance between neurons across iterations. This function decreases for nodes farther from the BMU on the grid. A Gaussian function is commonly used to describe the function.

$$h_{b_j} = exp(\frac{-\|r_b - r_j\|}{\delta(t)}), \tag{4}$$

Training repeats each epoch on the same dataset to improve fit and stops when $h_{b_j}(t)$ decreases enough. A batch formulation is used in parallel implementations for updating the weights.

$$w_j(t_f) = \frac{\sum_{t'=t_0}^{t_f} h_{b_j}(t')x(t')}{\sum_{t'=t_0}^{t_f} h_{b_j}(t')} \tag{5}$$

2.2. Power Spectral Density Estimation by Welch's method

The next part of the framework uses the Welch method applying the Fourier transform to power spectrum estimation. The method uses a sliding window to form a condition indicator of flight performance.

The power spectral density (PSD, $P_{xx}(f)$) or power spectrum is the measure of a signal's power content falling within given frequency bins. A periodogram, for a finite time series $x_0, ..., x_{N-1}$, is defined as

$$P_{xx}(f) = \frac{1}{N}\left|X(f)\right|^2 \tag{6}$$

$X(f)$ is the Fourier transform of a sample sequence.

$$X(f) = \sum_{n=0}^{N-1} x(n)e^{-\frac{i2\pi}{N}fn}, \quad f = 0, ..., N-1 \tag{7}$$

The time series can then be transformed into a spectrum of

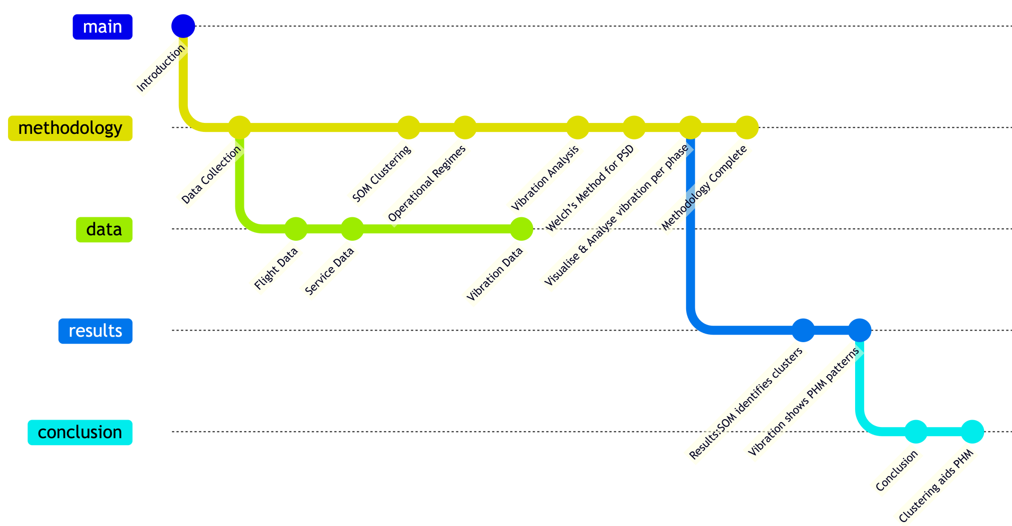


Figure 1. Representation of Proposed Aircraft Health Monitoring Methodology and Key stages

frequencies.

$$P_{xx}(f) = \frac{1}{N}\left|\sum_{n=0}^{N-1} x(n)e^{-\frac{i2\pi}{N}fn}\right|^2 \tag{8}$$

Welch's method, an adaptation of this conventional method (Welch, 1967; Barbé, Pintelon, & Schoukens, 2009), is carried out by splitting the time series into sequential segments. The periodogram formula is used for each segment, and the average is calculated (Smith III, 2011).

Here, the first and second segments can be given as

$$\begin{aligned} x_1(j) = x(j), \quad j \in \{0, 1, ..., L-1\} \\ x_2(j) = x(j+D), \quad j \in \{0, 1, ..., L-1\} \end{aligned} \tag{9}$$

The next modification involves weighting the segments with a window function. Applying these to the periodogram formula provides the "modified" periodogram.

$$\tilde{P}_{xx}^{(k)}(f) = \frac{1}{LU}\left|\sum_{j=0}^{L-1} x_k(j)w(j)e^{-\frac{i2\pi}{N}fn}\right|^2 \tag{10}$$

where N is the number of observed data, $k = 1, ..., K$ and K is the total number of segments. U, on the other hand, corresponds to a normalization factor for the power in the window function (Proakis, 2001).

$$U = \frac{1}{L}\sum_{j=0}^{L-1} w^2(j) \tag{11}$$

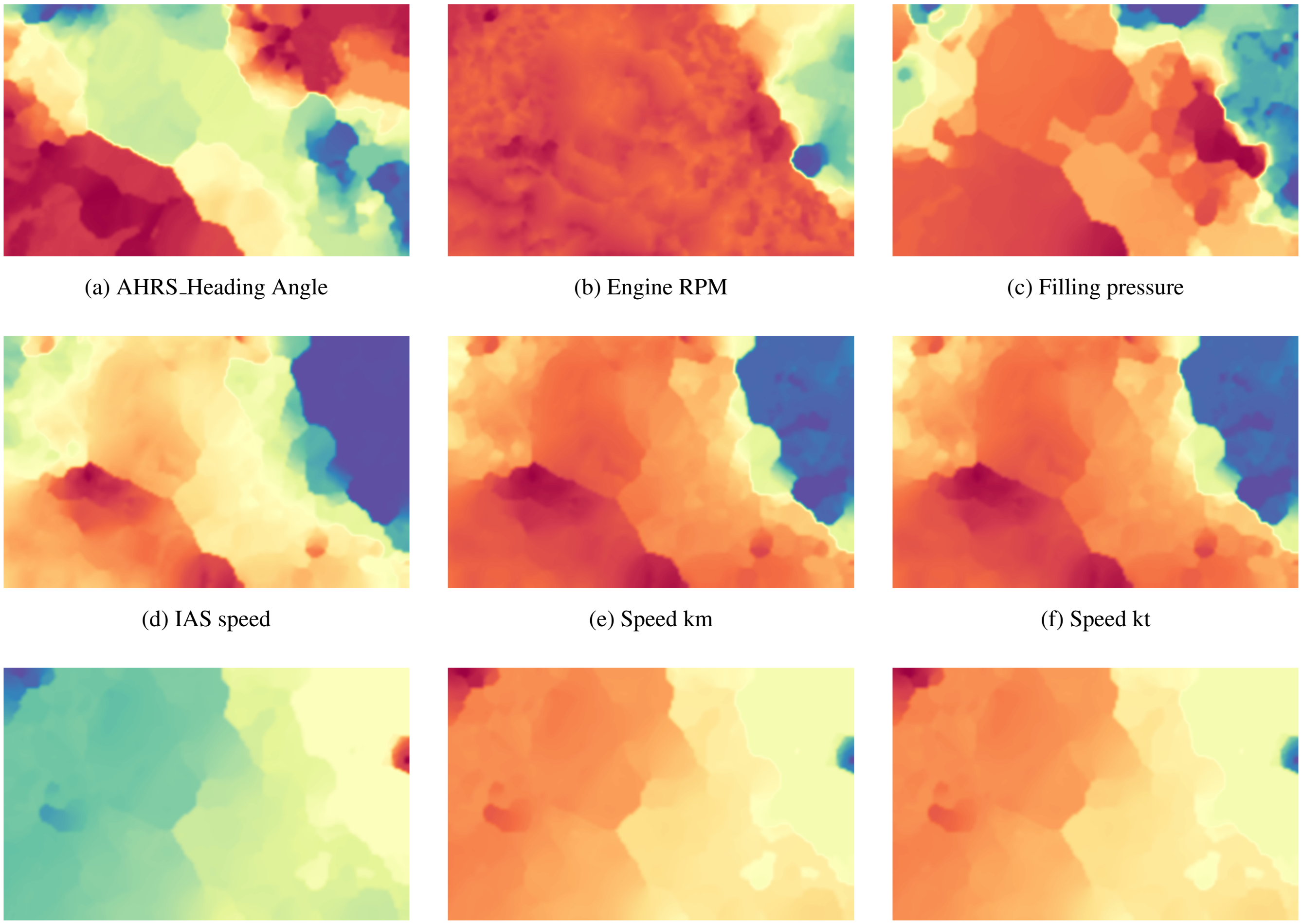
Eventually, $P_{xx}^{W}(f)$, takes the mean of these modified periodograms.

$$P_{xx}^{W}(f) = \frac{1}{K}\sum_{k=1}^{K} \tilde{P}_{xx}^{(k)}(f) \tag{12}$$

In Figure 1, the methodology is shown as a sequential workflow from data collection to clustering and vibration analysis. This process ultimately leads to aircraft health monitoring insights.

3. Testing and Results

The data record, which is processed in this paper, comes from a series of in-flight measurements on VUT-100 Cobra airplane manufactured by Evektor company. The campaign started as a prequel to measurements using newly developed sensing skin within the AVATAR project. In this preliminary phase, the aircraft was equipped with a network of 14 accelerometers distributed to various locations of the aircraft. This network generated acceleration signal on 18 channels, because some of the accelerometers were triaxial. The sampling frequency was set to 1000 Hz, taking into account the engine ignition frequency typically in flight in the range of 110-135 Hz. Apart from these acceleration signals, signals retrieved from AHRS (Attitude and Heading Reference System) were also recorded, this time with 10 Hz sampling frequency. These outputs concern some basic flight characteristics, as is the height of the flight, speed, GPS position, etc. Both types of input were recorded using the imc CRONOScompact 400-11 data acquisition unit. Although the data comes from one general service flight, it includes various flight phases, which makes it sufficient to test the relevance of the clustering method. The inclusion of multiple flight parameters across different phases ensures that clustering results are



(a) AHRS_Heading Angle

(b) Engine RPM

(c) Filling pressure

(d) IAS speed

(e) Speed km

(f) Speed kt

(g) Altitude (pressure)

(h) Altitude (ft)

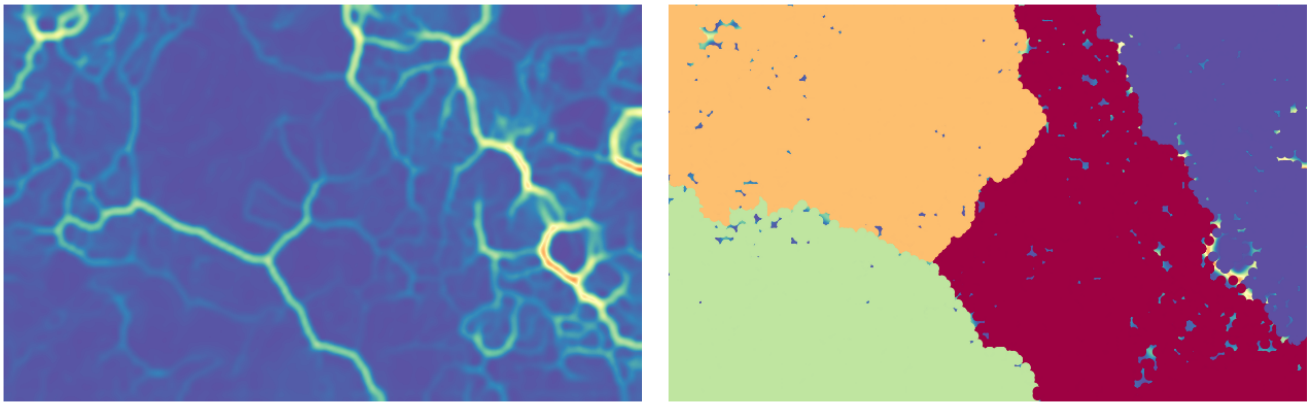
(i) Altitude (m)

Figure 2. Flight Data Used in the Clustering and Estimated Component Planes: x and y-axes represent the grid of SOM neurons where clustering estimated. Coloring of component planes indicates the value of the input variable for each neuron.

valid for similar operational conditions.

The flight data used in the clustering and estimated component planes are shown in Fig. 2 where the x and y-axes represent the grid of SOM neurons. Each subplot here has a structure representing a specific flight data parameter mapped into a component plane. Clusters here formed using the SOM and the Euclidean distance between neurons on a 2D grid. Each neuron represents a weight vector, and clustering occurs when nearby neurons exhibit similar weight vector patterns across input parameters. For better explanation of these patterns and/or thresholds, Fig. 3a provides the U-matrix is used to visualize the distance between neurons and the threshold between them. The regions with higher distances indicate cluster boundaries. The flight parameters used for clustering have a significant impact in identifying distinct flight regimes. AHRS Heading Angle (a) reflects characteristic patterns for different maneuvers and phases. Engine RPM helps identify phases like takeoff, cruise, and landing. Filling Pressure (c) shows changes in flight conditions. IAS (d) and Speed (e-f) indicate aircraft performance, while altitude readings (g-h-i) reflect vertical profiles and transitions. With these parameters as inputs, Fig. 2 represents component maps qualifying as an emergent self-organizing map for this input data. Here, the Somoclu library, an open-source tool for training self-organizing maps (SOMs) (Wittek & Gao, n.d.), is used to identify flight regimes based on the given data.

Based on these output component planes, some clusters with plain colors there are visually recognizable clusters. One of these is on the top-right of the maps, specifically in speed indicators (d-e-f). Additionally, the altitude indicators have plane map has a matching cluster in light yellow in the same region. On the other hand, AHRS and Filling pressure component maps hint another cluster in the bottom-right coloring with a match in Speed indicators. While the rest of the maps have certain indicators of divergence, some content splitting borders may still be observed. A boundary of colors in the



(a) U-Matrix without Labels

(b) SOM U-Matrix with Regime (Clustering) Labels

Figure 3. Regime clusters estimated by SOM

vertical center can be seen in the speed and altitude indicators,because the coloring assigned to these areas are nicely separated. Therefore, the overall component plane map results show that the two clusters of flight phases that remain in drift in the center have separated. However, specific color changes in each component planes might shed new light on the distinction between these relatively similar groupings. Clusters in these might be locally meaningful and can only be considered consistent at the neighborhood level. After all, some color groupings may represent a subset of a flight phase, mostly inactive content or an irregular flight behavior that can be commonly observed in light aircrafts. Overall, looking at the results in Fig. 2, it is clear that there is more or less turbulence in all maps , however, there are some lines or regions mentioned above that provides insights to form clusters.

It is also worth mentioning that SOM maps reward the stability of flight data at one stage, while others change over time. These can be observed in more detail from the combined distance matrix (U-matrix) in Fig. 3a which provides both with and without label coloring. The aim is to provides a better visualization of network topology by using the average Euclidean distance between neurons.

For neuron j with neighbors $N(j)$, the height value of U-matrix is:

$$U(j) = \frac{1}{\mid N(j) \mid} \sum_{i \in N(j)} d(w_i, w_j) \tag{13}$$

In the Fig. 3b, there are four regime labels presented. The main reason for this is that the majority (97%) of the flight phases recorded in a Sample Flight Data are in four regimes (Matthews, n.d.; Bektas, 2023). Additionally, focusing on these basic regimes in a typical airliner can enable a better understanding and monitoring of light aircraft operational conditions.

After the SOM model providing a near-optimal clustering of the flight phases, the Welch method was applied per regime to provide for spectral density estimation in each of these regimes. First, an acceleration signal is selected without any specific preference. Due to confidentiality, the data label and sensor location are not disclosed here. It is important to note that even though this signal is valuable to illustrate vibration signal regime changes related to health monitoring, this specific data may not be applicable for all diagnosis and prognosis scenarios. Then, the selected signal is segmented by dividing the recorded time series and grouping them sequentially into windows (also known as cycles). This allows the Welch framework to be applied these cycles individually. Here, the segments are continuous (per regime) and the overlapping technique ensures that temporal coherence is maintained throughout the calculation. However, some transitional regimes, occurring during both the early and late near-ground phases, are added up but remain continuous. So, each segment corresponds to the same flight condition and the results maintain this continuity to avoid any disruptions that could lead to inconsistencies in the power spectrum analysis. By using overlapping-continuous windows, the analysis preserves the integrity of the data across flight regimes and the accuracy of the aircraft's operational state representation.

In Fig. 4, there are four subplots (arranged in a 2x2 grid), each showings the power spectral density estimations across clustered flight phases. Each power spectrum is calculated by dividing the Welch-cycles (not to be confused with the windows above) into overlapping segments. A modified periodogram is then estimated for each segment. Then, these periodograms are averaged to produce the power spectrum density (PSD). The upper left subplot for clustered PH 0, shown in purple plot, is flat with minimal changes. This reflects stable conditions or minimal variation, which can be associated with regimes such as taxi and distribution. On the other hand, the bottom-right subplot (Clustered PH 3, orange graph) exhibits

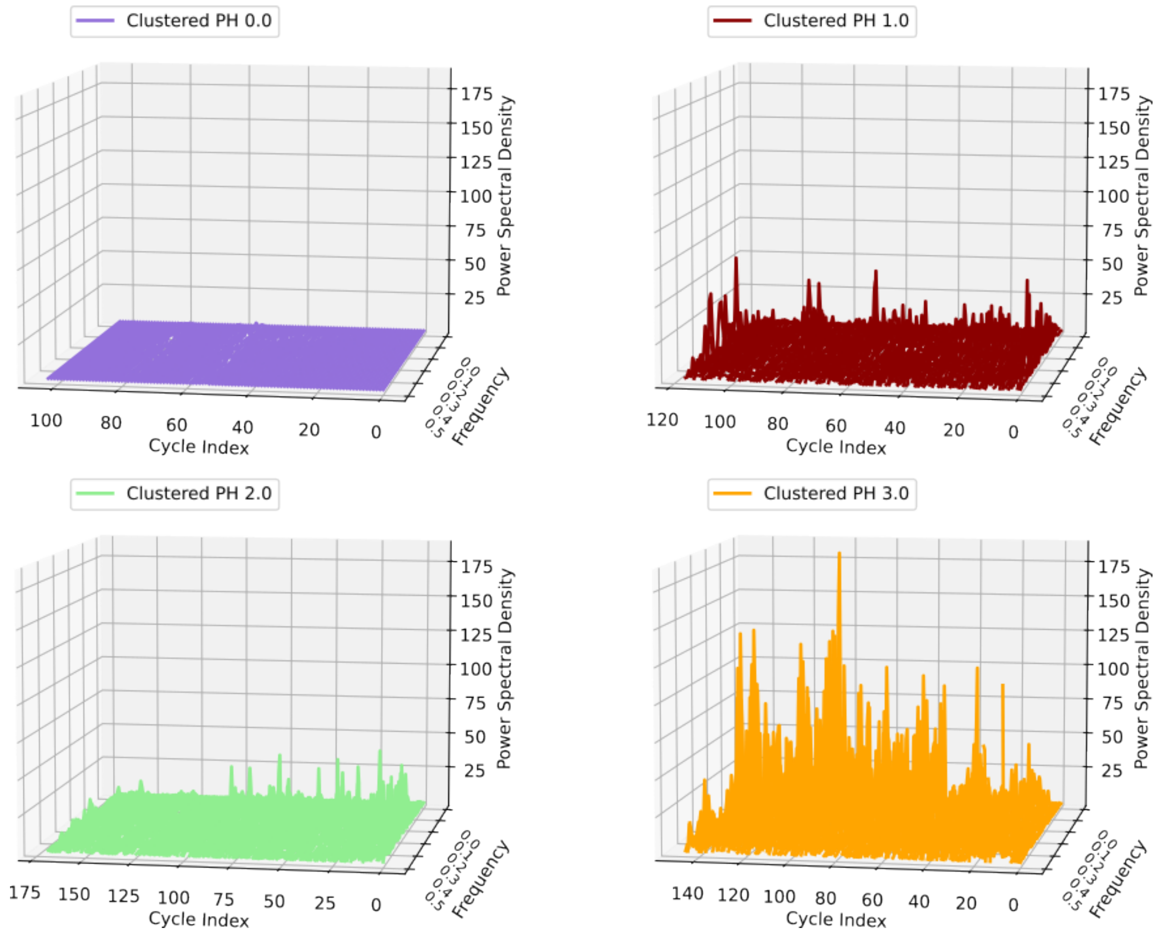


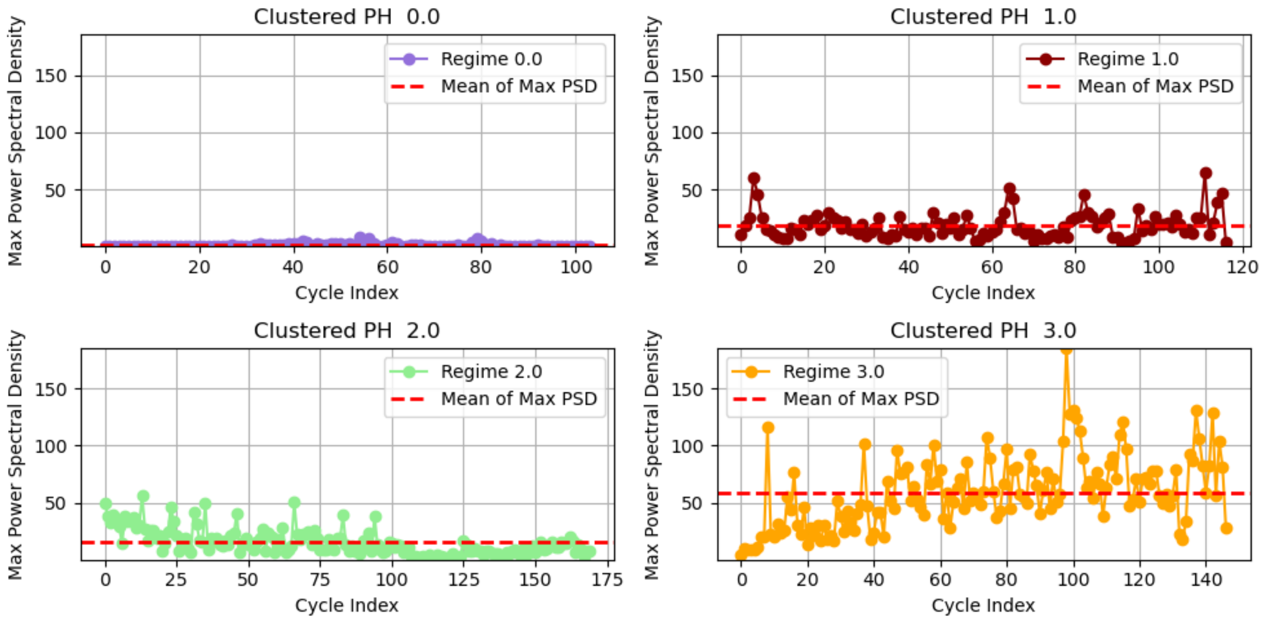
Figure 4. Power Spectral Density Estimations per Clustered Regimes - Flight Phases (PH)

the most significant variations, with peaks and higher values. Only the early and the late stages are relatively low here, and this might require further analysis. Since the signals used as input for clustering are not directly related to the signal here, an extended cluster analysis taking into account the vibrations might provide better grouping. However, these are also transitioning regimes, and the low PSD values can be considered normal. These speculations might be better tested in the context of the diagnosis and prognosis applications. Understanding the statistical properties of these periodograms is very important for studying aircraft health monitoring and flight anomalies. When considered on a regime basis, a very stable and normal health level can be seen in these graphs. On the other hand, if the regime factor is not included in the analysis, and for example regime 0 is considered normal, regime 3 has the potential to be associated with deterioration of overall system performance. Therefore, the flight phase clustering is a must in aircraft health monitoring.

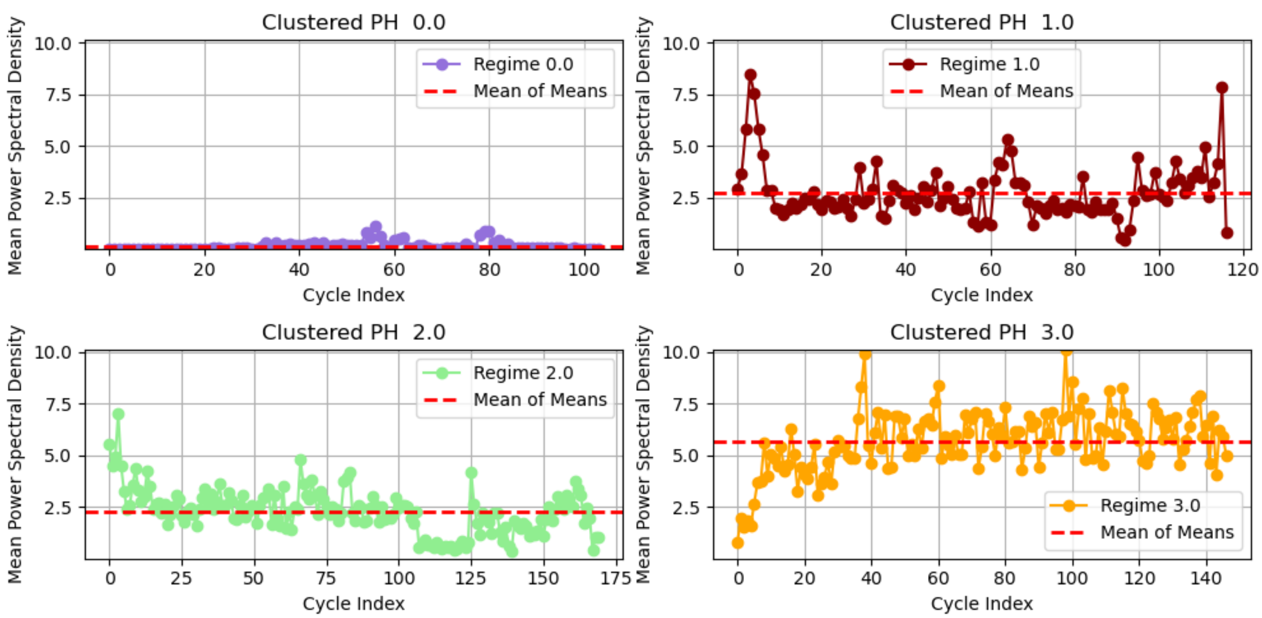
The remaining subplots (PH 2.0, green plot and PH 3.0, orange plot) in 4 shows similar trends. From a short review of these figures, it can be concluded that they have moderate variations with some noticeable peaks. This might indicate a moderate level of signal activity or anomalies. However some numerous peaks might be associated to the nature of light aircraft operations which do not follow regular flight phases. These peaks might require some extra clustering to be excluded in these regimes, or simply setting a threshold for algorithms to account for them. To that end, Fig. 5 provides maxima and mean progress for each cycle of power spectrum estimation. Both of these statistical measures could provide a comprehensive insights of the system's health level. They also highlight both extreme and average levels across different operating conditions.

4. Conclusions

This study introduced a framework for identifying flight regimes for light aircraft health monitoring systems. Through the use of Self-Organizing Maps, the framework could differentiate flight phases. This provided a structured approach for health monitoring. The Welch method was then applied to transform a flight vibration signal from the same flight. These transformed signals revealed patterns not visible in the



(a) Max PSD per Cycle



(b) Mean PSD per Cycle

Figure 5. The progress of max(spec) and mean(spec) from four different Flight Phases (PH)

raw data. Minimal differences were observed with two of the clustered regimes. However, more clustering might be necessary for additional regimes or anomalies due to the high magnitude of some cycles. This indicates that certain cycles may need further segmentation beyond the identified regimes.

The results highlight the value of Self-Organizing Maps as a useful tool for flight regime clustering. This provides a foundation for future methods for alternative unsupervised methods. Advanced data transformation techniques were also crucial in uncovering hidden patterns in the estimated clusters. This has the potential to improve flight data analysis and health management in regime level. Overall, the clustering approach with data transformation techniques provides a robust approach to analyze and segment flight data. This hold promise to improve the reliability of light aircraft operations.

The research provided insights into the unique flight patterns of light aircraft, which is different from typical commercial airliners.The findings highlight the need for tailored clustering methods to suit the specific operational conditions of light aircrafts. This presents opportunities for predictive maintenance and fault diagnosis capabilities. This method, while designed for light aircraft, can also be useful for larger commercial aircraft. SOM-based clustering has the potential to handle the complex data sets typical in commercial aviation. It can improve fault detection and predictive maintenance by grouping flight phases effectively. This can lead to more accurate health monitoring and life-cycle predictions, benefiting both safety and cost. Therefore, future research can build on this framework to further advance aircraft health monitoring.

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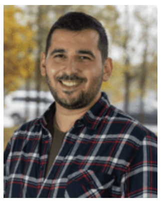
BIOGRAPHIES



Oguz BEKTAS is an academic researcher who has graduated from the University of Warwick with a PhD. He is currently affiliated with the University of Luxembourg (Interdisciplinary Centre for Security, Reliability, and Trust (SnT)) and has made contributions to research in areas such as prognostics, condition monitoring, and artificial intelligence. His work encompasses the development of neural network filtering approaches for remaining useful life estimation, computational prognostic methods for complex systems, and dimensionality reduction for failure prognostics. Additionally, Oguz has been involved in the development of models for gas turbine engine prognostics, automated emergency landing systems for drones, and anomaly detection in unmanned aircraft. Furthermore, his research includes the analysis of visual imagery for emergency drone landing, data-driven predictive maintenance models, and the definition of degradation curves for rotary mechanisms.

Jan Papuga is employed as a researcher in Evektor company as fatigue analyst and also at the Czech Technical University in Prague, Faculty of Mechanical Engineering . His work is focused above all on multiaxial fatigue, fatigue of notched components and general fatigue estimation procedures. More of his outputs can be found on www.pragtic.com

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