Using Spectral Flatness to Detect and Label Power System Oscillations in the Presence of Intermittent Broadband Noise

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***Abstract*—With the ubiquitous deployment of phasor measurement units, the ability to automatically parse large-scale historical data sets to detect and label unwanted system dynamics is becoming increasingly important as it can lead to better informed decision making by power system operators. Most oscillation detection algorithms rely on pre-defined energy thresholds for discrete frequency bands to estimate the presence of oscillations, however, such techniques may not perform satisfactorily in systems with intermittent, high energy forced inputs from industrial equipment such as an electric arc furnace that increases the system's energy across the entire frequency spectrum. In this paper, we propose a method for detecting oscillations based on the flatness of the spectrum as opposed to the magnitude of its energy. It is shown that the proposed method is effective at detecting oscillations irrespective of a changing magnitude of input broadband noise.**

***Index Terms*—Oscillation detection, spectral analysis, synchrophasor measurement, phasor measurement unit, clustering**

I. Introduction

Oscillatory responses in power systems have always been of concern as they can indicate system-wide or localized problems such as equipment malfunction, system disturbances, and poor operating conditions [1]. As unstable oscillations can result in partial or total system collapse [2], the ability to detect and address the appearance of such modes is critical in ensuring the reliable operation of the bulk power system.

Traditionally, the detection of oscillations has required extensive baselining studies [3] to set appropriate energy thresholds for discrete frequency bands, as analytical expressions are not available [4]. In real-time applications, when the energy in a certain frequency band exceeds the specified threshold, the system operator is alerted to take appropriate action [1].

One such approach that is widely accepted by industry uses the root mean square (RMS) value of a signal's energy to detect oscillations in multiple frequency bands selected according to the range of certain dynamics of interest [1], [4]–[6]. Several of these RMS methods attempt to circumvent the time-consuming task of examining large-scale data sets for every possible input signal to derive appropriate thresholds for detecting oscillations. A simplified process for setting thresholds is proposed in [4] where the statistical distribution of a signal's power spectral density (PSD) and its cumulative distribution function are utilized to establish thresholds for the frequency bins of an RMS-energy detector. A fast, automated method for determining appropriate energy thresholds that utilizes a k-means clustering algorithm is proposed in [7]. This method clusters the measured RMS energy of a signal into a user-defined number of clusters to capture large variations. The centroids of each cluster can provide insight into the frequencies that may be of interest in detecting oscillations.

Another prevalent detection method utilizes the coherence spectrum of two measured signals to detect forced oscillations in the presence of significant noise [8], [9]. This method estimates the power spectral density and cross spectral density of signals using time-series measurements and fast Fourier transforms to estimate a coherence spectrum. If this coherence spectrum exceeds a predetermined threshold value, an oscillation is likely at the frequency of the coherence spectrum where there is a peak.

In some situations, however, these existing detection methods may be ineffective. For example, high energy density devices, such as electric arc furnaces [10], inject intermittent broadband noise into the system, as measured by phasor measurement units (PMU). When in operation, this noise drastically raises the level of energy across the spectrum. This effect can be observed in the spectrogram shown in Fig. 1 created from PMU data near an arc furnace in Dominion Energy's service territory. The horizontal striations in Fig. 1 represent persistent oscillations while the vertical striations represent the intermittent operation of the arc furnace. In these cases, an energy threshold established for when the arc furnace is in operation could be too high to detect oscillations when the arc furnace is not in operation.

This paper presents an algorithm to detect the appearance and estimate the frequency of power system oscillations from historical PMU data streams in the presence of intermittent, high-energy broadband noise.

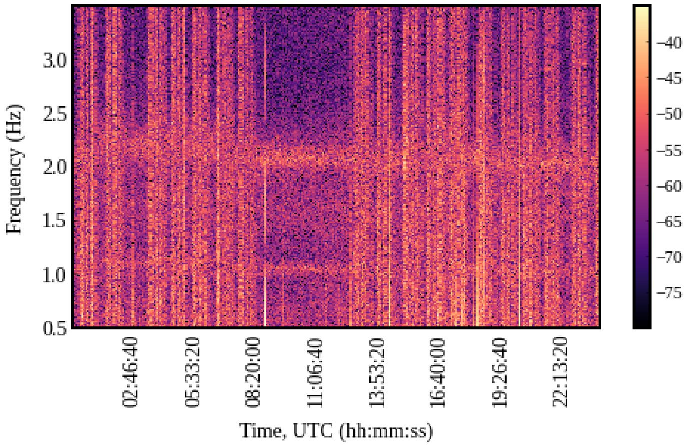

Fig. 1. Spectrogram illustrating the effects of intermittent arc furnace operation on the overall energy of the measured signal.

II. Spectral Flatness

As existing oscillation detection methods are ineffective in the presence of intermittent high-energy broadband noise, it is necessary to determine when a measurement's frequency spectrum displays clearly defined dynamics and when it is flat or noise-like. This can be characterized by the measurement's spectral flatness, a measure that quantifies the relative magnitude of any peaks present in the power spectrum of a signal, as opposed to how similar to white noise it is. The spectral flatness measurement (SFM) of a signal is defined as a ratio of the geometric mean to the arithmetic mean of its power spectrum,

$$SFM = \frac{\sqrt[N]{\prod_{n=0}^{N-1} x(n)}}{\frac{\sum_{N-1}^{n=0} x(n)}{N}} = \frac{\exp(\frac{1}{N}\sum_{n=0}^{N-1}\ln x(n))}{\frac{1}{N}\sum_{n=0}^{N-1} x(n)}, \quad (1)$$

where $x(n)$ is the magnitude of frequency bin n of the power spectrum. The power spectrum for a pure white noise signal is completely flat or constant. The geometric and arithmetic means of such a spectrum are therefore equal, and as a ratio of the two means, the SFM is equal to one. The geometric mean of a power spectrum is always less than or equal to its arithmetic mean, so the SFM will never exceed a value of one. Conversely, the spectrum of a pure sinusoidal function is expressed as two delta functions separated by zeros. From the above expression, it can be observed that a spectrum with samples of magnitude zero will have a geometric mean of zero with a nonzero arithmetic mean. The SFM for a pure sinusoid will therefore be equal to zero. It can therefore be inferred that a SFM closer to one indicates a flat or white noise-like spectrum while a SFM closer to zero indicates the presence of oscillatory behavior.

To illustrate the function of SFM in labeling oscillations, a synthetic data set was generated with its corresponding spectrogram shown in Fig. 2. This signal was designed to evaluate the behavior of SFM under three distinct conditions,

a) A pure oscillation with no broadband noise,
b) An oscillation in the presence of broadband noise, and
c) Broadband noise without an oscillatory component.

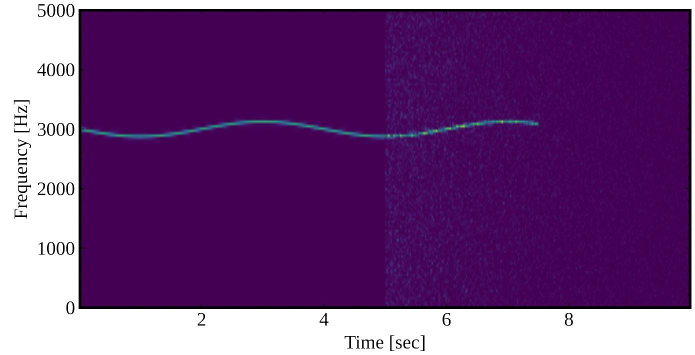

Fig. 2. Spectrogram for the simulated data set. The content of the simulated data includes a pure oscillation with no broadband noise from 0 to 5 seconds, an oscillation in the presence of broadband noise from 5 to 7.5 seconds, and broadband noise without an oscillatory component from 7.5 to 10 seconds.

The PSDs of the signal calculated over the time periods corresponding with each of the three conditions are shown in Fig.3.

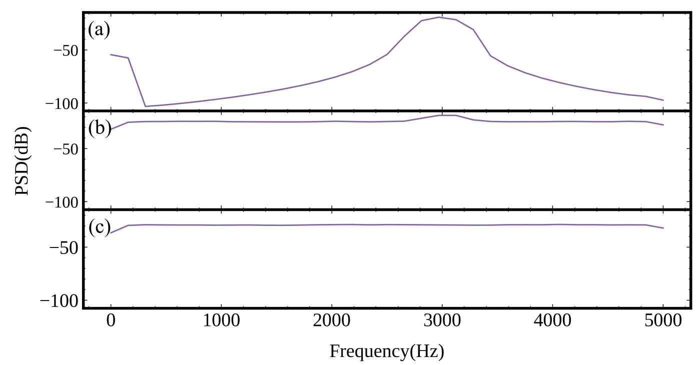

Fig. 3. PSDs for the simulated data set from (a) 0 to 5 seconds (pure oscillation with no broadband noise), (b) 5 to 7.5 seconds (oscillation in the presence of broadband noise), and (c) 7.5 to 10 seconds (broadband noise with no oscillatory component).

For the spectrogram in Fig. 2, the corresponding SFM values for each time window are shown in Fig. 4. The three clusters represent periods where an oscillation is clearly present (SFM $\approx$ 0), likely present (SFM is relatively low), and not present (SFM is relatively high). In comparing the two figures, it can be observed that SFM can be used to correctly label time periods containing oscillatory activity.

III. Oscillation Detection Algorithm

The proposed oscillation detection algorithm is illustratedas a flowchart in Fig. 5 and elaborated upon in the following.

(a) Connect to a database to access historical time-stream data. For synchrophasor data injection, storage, visualization, and analysis, Dominion Energy, uses a cloud-based platform, PredictiveGrid. The platform currently holds over 100 TB of data from hundreds of PMUs and over one hundred thousand 30 Hz data streams [7].

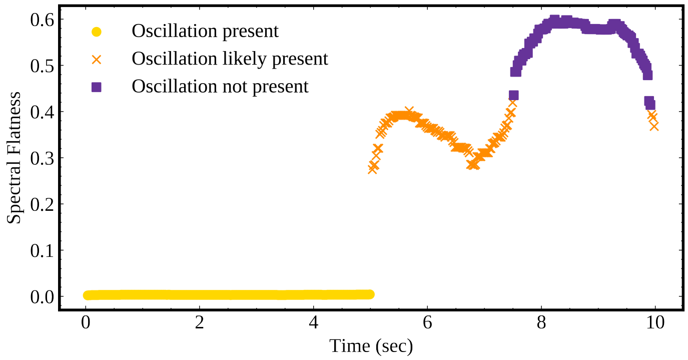

Fig. 4. Clustered spectral flatness plot for the simulated data set.

(b) Declare all variables necessary to access the desired data streams[1], sample the data streams for the desired duration, pre-process the data for the frequency range of interest, and establish the appropriate parameters for clustering.
(c) Iteratively estimate oscillation frequencies by determining the frequency bins where the magnitude of the PSD calculated in 10-minute windows is sufficiently large.
(d) Establish the frequency bands of interest. The data set of PSD magnitude peaks collected in the previous step is grouped in a user-defined number of clusters using a k-means clustering algorithm to determine the frequency centers of interest. From these center frequencies, frequency bands are established with a user-defined tolerance.
(e) Calculate the spectral flatness of the spectrogram within each frequency band established in the previous step.
(f) Estimate the duration of any oscillations detected within each frequency band by finding the duration of clusters corresponding to low spectral flatness calculated in the previous step.
(g) Print the estimated duration of any oscillations detected and plot spectrograms of their approximate frequency bands to confirm their presence.

IV. Case Studies

PMU data from multiple substations impacted by an electric arc furnace in Dominion Energy's system are used to illustrate the effectiveness of the proposed algorithm.

1) High Energy Oscillations: In this scenario, the data being analyzed is the current magnitude from the low voltage side of a 115/34.5 kV distribution transformer. The ambient oscillation to be detected, which can be observed around 1.3 Hz as a brightly colored horizontal line in the spectrogram shown in Fig. 6.

First, the PSD of the current magnitude is evaluated in 10-minute windows over a 24-hour period. The PSD for one of these windows with a peak indicating an oscillation around 1.3 Hz is shown in Fig. 7. As the transformer acts as a filter, the effect of arc furnace on the distribution side can

[1]For further information on accessing the Berkeley Tree Database in Python, please reference the `btrdb-python` documentation [12].

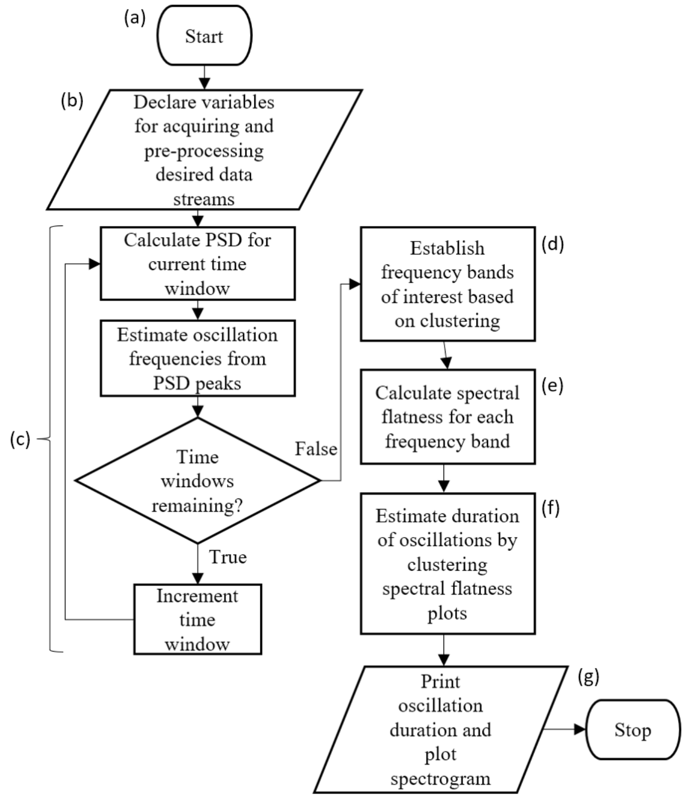

Fig. 5. Flowchart representing the proposed algorithm for oscillation detection in the presence of intermittent broadband noise.

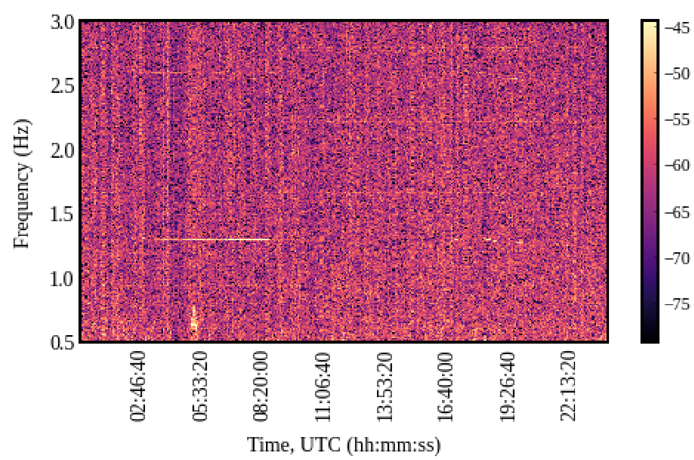

Fig. 6. Spectrogram of a 34.5 kV current magnitude data stream with an oscillation clearly visible against intermittent noise from the arc furnace.

be considered negligible, therefore a significant portion of the signal power comes from the oscillation of interest, allowing for easier detection.

Next, a possible oscillatory frequency is identified at approximately 1.295 Hz by clustering the peak PSD values calculated over a 24-hour period and determining the frequency of the centroid of the cluster. Using a user defined tolerance of ± 0.1 Hz, a frequency band of [1.195 Hz, 1.395 Hz] is established to compute the SFM for. The SFM of this frequency band calculated in 10-minute windows over a 24-

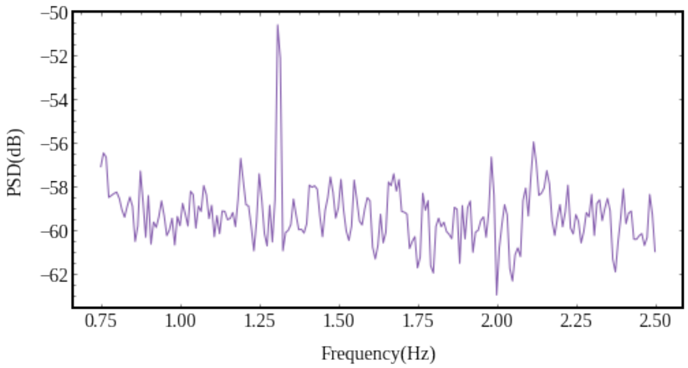

Fig. 7. PSD of the current magnitude within [0.5 Hz, 3.5 Hz] for a single 10-minute window.

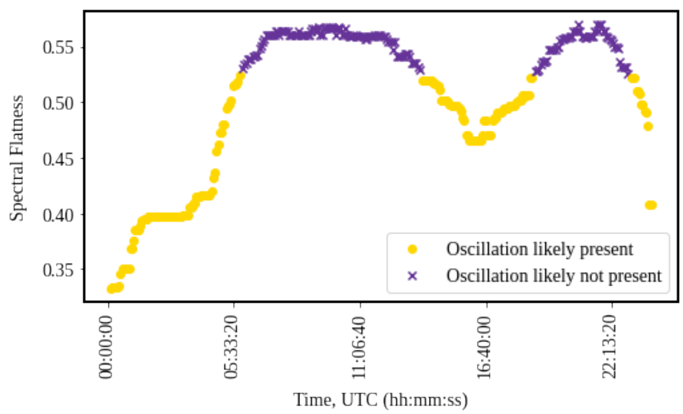

Fig. 8. SFM of a data stream within [1.195 Hz, 1.395 Hz] clustered to indicate the duration of groups of low spectral flatness.

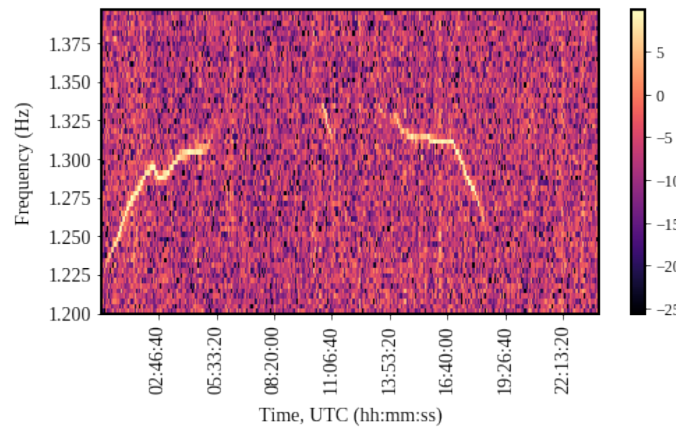

Fig. 9. Spectrogram of a data stream within [1.195 Hz, 1.395 Hz] to confirm the presence of oscillations at the frequencies and times indicated by the algorithm.

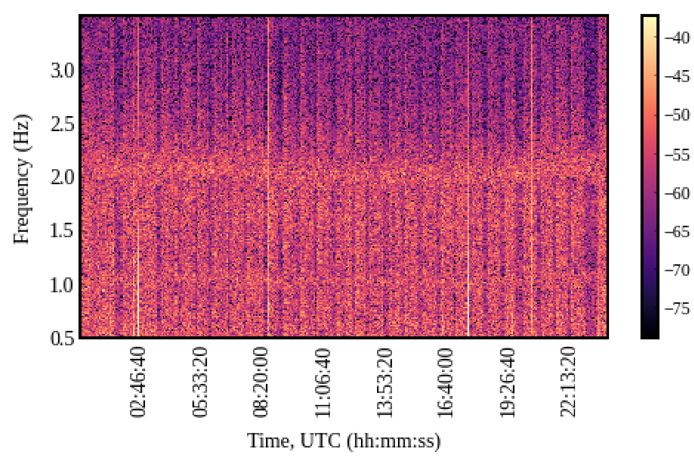

Fig. 10. Spectrogram of a current magnitude data stream where the oscillation has lower observability against intermittent noise from the arc furnace.

hour period is plotted in Fig. 8.

Comparing the SFM plot in Fig. 8 with the spectrogram for that day as shown in Fig. 9, it can be observed that the algorithm correctly predicts the presence of oscillations from 0:00:00 to 5:45:46 UTC and 13:47:14 to 18:40:29 UTC.

2) Lower Energy Oscillations: In this scenario, current magnitude data is collected from a 230 kV STATCOM that is actively responding to an electric arc furnace in order to regulate the voltage at its terminals. Naturally, the observability of the local controller dynamics is heavily impacted, making it a challenging detection problem compared to the previous case.

The impact of arc furnace is clearly visible in the corresponding spectrogram shown in Fig. 10. As before, the intermittent broadband noise injected by the arc furnace can be observed as the vertical striations in the spectrogram.

In the spectrogram in Fig. 10, the modes to be detected can be seen at approximately 1 Hz and 2 Hz respectively, likely as a harmonic pair. First, the PSD of the current magnitude is calculated in 10-minute windows over a 24-hour period. Fig. 11 shows the PSD for a ten-minute window during which the arc furnace was not operating, where the peaks of interest can be observed around 1.2 Hz and 2.1 Hz. Meanwhile, Fig. 12 shows the PSD for a window during which the arc furnace was in operation. In comparing the plots, it can be inferred that the observability of the oscillations of interest is masked in Fig. 12 due to the arc furnace's distortion of the spectrum.

Next, the centroids of the clusters of PSD peaks collected over a 24-hour period are determined as shown in Fig. 13. From these clusters, oscillations are estimated to be present around 0.8 Hz, 1 Hz, and 2 Hz.

While oscillations centered around these frequencies can be observed persistently for the 24-hour period analyzed, the clustered spectral flatness plots falsely indicate that the modes are not present between 0.943 Hz and 1.143 Hz from 12:45:47 UTC to 18:27:09 UTC and 20:42:02 UTC to 23:44:14 UTC (Fig. 14) and between 1.919 Hz and 2.119 Hz from 17:45:06 UTC to 21:53:52 UTC. These time periods correspond with high arc furnace activity similar to the conditions under which the PSD shown in Fig.12 was plotted. In comparing the PSD plots shown in Fig. 11 and Fig. 12 with the SFM plot shown in Fig. 14, however, it can be observed that while arc furnace activity induced an approximately +4 dB change in PSD at frequencies without oscillatory behavior across the spectrum, the equivalent variance in SFM was only around 0.02. This could indicate that SFM varies less than PSD in the presence of intermittent broadband noise, making it a more attractive metric for oscillation detection under such conditions.

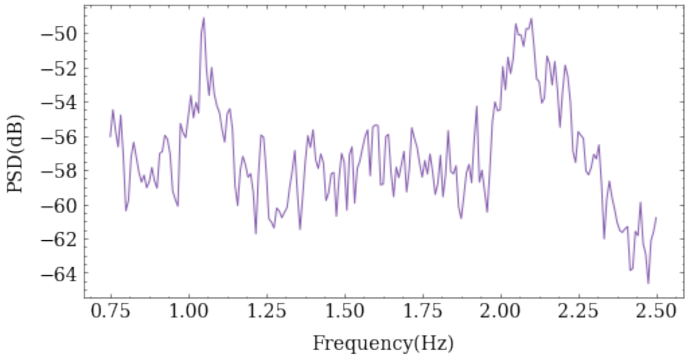

Fig. 11. PSD of the current magnitude within [0.75 Hz, 2.5 Hz] for a single 10-minute window where the arc furnace is not operating.

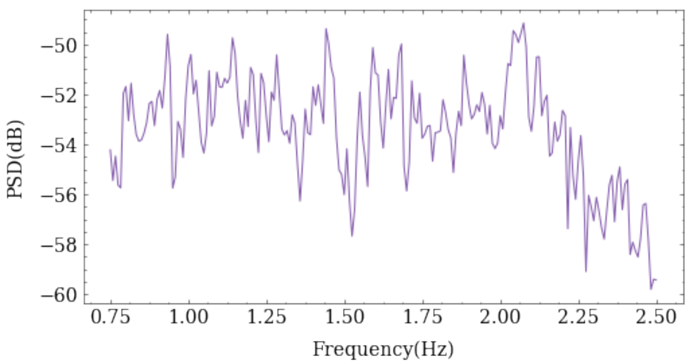

Fig. 12. PSD of the current magnitude within [0.75 Hz, 2.5 Hz] for a single 10-minute window where the arc furnace is operating.

V. Conclusions and Future Work

The spectral flatness of historical PMU data and k-means clustering methods can be exploited to detect and label oscillations irrespective of the presence of intermittent, high energy broadband noise. As shown in this work, this can be a useful complement to coherence spectrum-based detection algorithms when analyzing data from PMUs located near high energy density devices such as electric arc furnaces. As oscillations become damped and decrease in energy, however, the method can be less reliable, which is only of concern when attempting to automate the analysis of large-scale historical data archives. Future work includes the further automation of this algorithm to improve its detection capabilities and reduce the amount of user input required in selecting data streams and frequencies of interest. Additionally, a generic framework can be established to apply the detection algorithm to any form of database and analysis platform.

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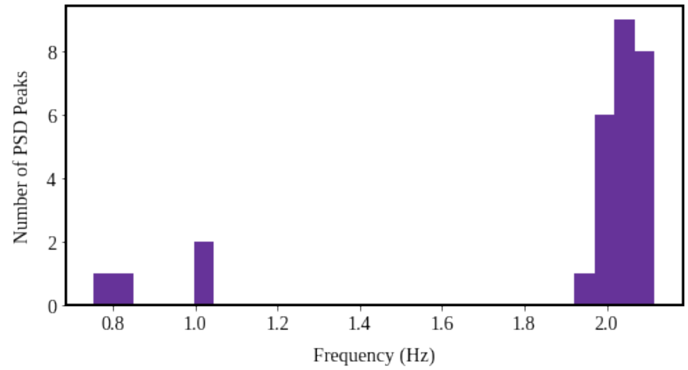

Fig. 13. Histogram showing the frequency of the detected PSD peaks indicating the center frequency of possible oscillations.

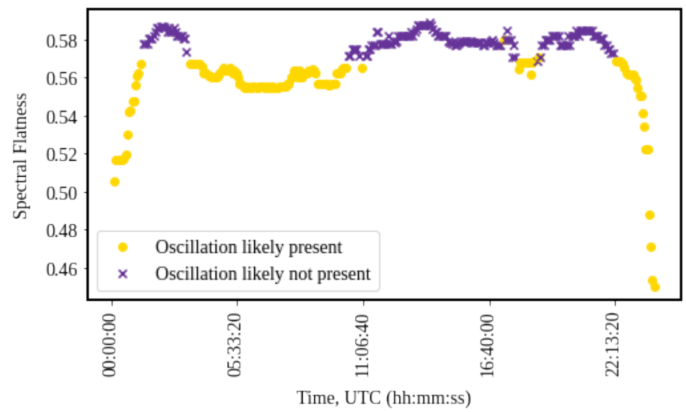

Fig. 14. SFM of a data stream within [0.943 Hz, 1.143 Hz] clustered to indicate the duration of groups of low spectral flatness with some false negative results.

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