da_Mushroom_25-05-08_0326-sound_stimulation2

May 14, 2025

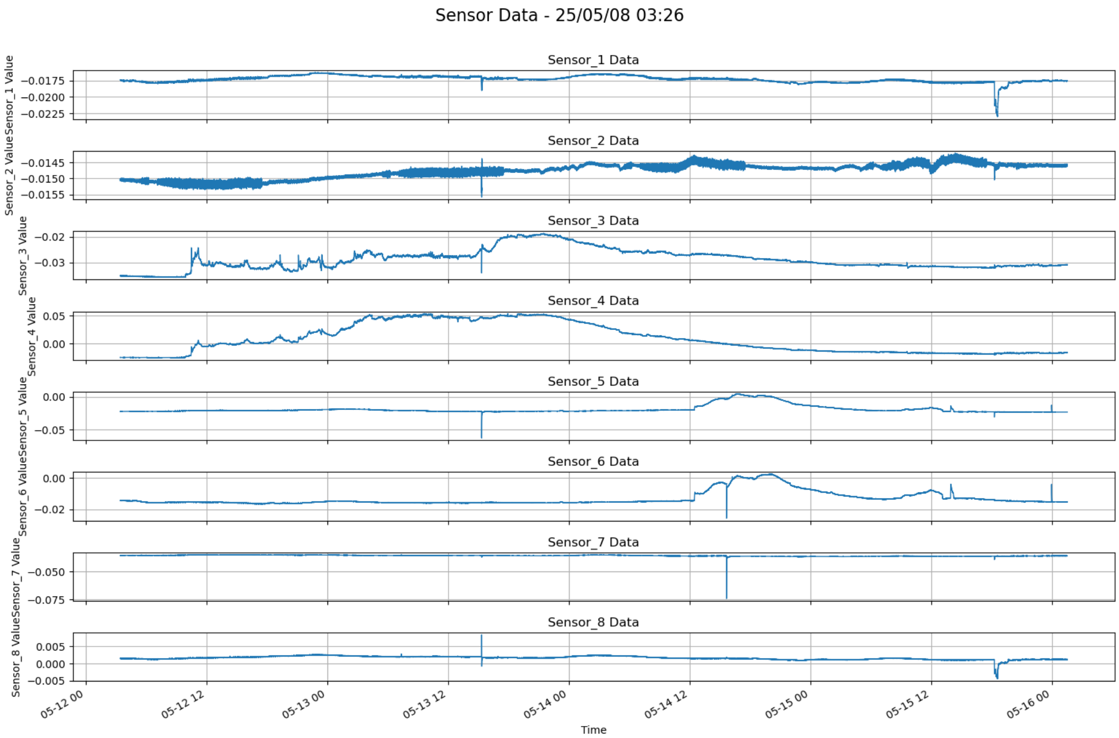
[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os

# Set file path
file_path = '../data/Mushroom_25-05-08_0326.lvm'

# Check if file exists
if not os.path.exists(file_path):
    print(f"Error: File {file_path} does not exist")
else:
    # Read LVM file
    # LVM files are tab-separated text files without header
    data = pd.read_csv(file_path, sep='\t', header=None)

    # Display basic information about the data
    print(f"Data shape: {data.shape}")
    print("\nFirst 5 rows of data:")
    print(data.head())

    # Based on file content, we need to name the columns
    # Assuming first column is timestamp, others are sensor data
    columns = ['Timestamp'] + [f'Sensor_{i}' for i in range(1, data.shape[1])]
    data.columns = columns

    print("\nData after renaming columns:")
    print(data.head())
```

```
Data shape: (1084420, 10)

First 5 rows of data:
               0         1         2         3         4         5         6  \
0  120386.537600 -0.017416 -0.015052 -0.035177 -0.024526 -0.022283 -0.014307
1  120386.714606 -0.017413 -0.015028 -0.035177 -0.024510 -0.022269 -0.014292
2  120386.889620 -0.017420 -0.015043 -0.035157 -0.024524 -0.022270 -0.014293
3  120387.088626 -0.017404 -0.015036 -0.035172 -0.024527 -0.022294 -0.014290
4  120387.273636 -0.017437 -0.015036 -0.035183 -0.024523 -0.022269 -0.014280
```

```
          7         8   9
0 -0.035494  0.001486 NaN
1 -0.035491  0.001480 NaN
2 -0.035494  0.001500 NaN
3 -0.035498  0.001483 NaN
4 -0.035490  0.001495 NaN

Data after renaming columns:
       Timestamp  Sensor_1  Sensor_2  Sensor_3  Sensor_4  Sensor_5  Sensor_6  \
0  120386.537600 -0.017416 -0.015052 -0.035177 -0.024526 -0.022283 -0.014307
1  120386.714606 -0.017413 -0.015028 -0.035177 -0.024510 -0.022269 -0.014292
2  120386.889620 -0.017420 -0.015043 -0.035157 -0.024524 -0.022270 -0.014293
3  120387.088626 -0.017404 -0.015036 -0.035172 -0.024527 -0.022294 -0.014290
4  120387.273636 -0.017437 -0.015036 -0.035183 -0.024523 -0.022269 -0.014280

   Sensor_7  Sensor_8  Sensor_9
0 -0.035494  0.001486       NaN
1 -0.035491  0.001480       NaN
2 -0.035494  0.001500       NaN
3 -0.035498  0.001483       NaN
4 -0.035490  0.001495       NaN
```

[2]:
```
# Extract date and time information from the filename
file_name = os.path.basename(file_path)  # Get the filename
date_time_str = file_name.split('_')[1:3]  # Extract date and time parts
date_str = date_time_str[0].replace('-', '/')  # Format date
time_str = date_time_str[1].replace('.lvm', '')  # Format time
# Parse time string, first two digits are hours, last two are minutes
hour = time_str[:2]
minute = time_str[2:]
formatted_time = f"{hour}:{minute}"

# Use actual timestamps and convert to specific times
actual_time = data['Timestamp']
# Calculate seconds relative to start time
start_time = actual_time.iloc[0]
relative_seconds = actual_time - start_time

# Create specific time labels
from datetime import datetime, timedelta
# Assume data recording started at the date and time specified in the filename
base_time = datetime(2025, 5, 12, int(hour), int(minute))  # Date and time␣
 ↪parsed from filename
time_labels = [base_time + timedelta(seconds=s) for s in relative_seconds]

# Determine the number of sensors in the dataset
```

```python
num_sensors = len([col for col in data.columns if 'Sensor_' in col]) - 1

# Create a figure with subplots for all sensors
plt.figure(figsize=(15, 10))

# Plot data for all sensors
for i in range(1, num_sensors + 1):
    sensor_name = f'Sensor_{i}'
    plt.subplot(num_sensors, 1, i)
    plt.plot(time_labels, data[sensor_name], linewidth=1)
    plt.title(f'{sensor_name} Data')
    plt.ylabel(f'{sensor_name} Value')
    plt.grid(True)

    # Only add x-label for the bottom subplot
    if i == num_sensors:
        plt.xlabel('Time')

    plt.gcf().autofmt_xdate()  # Automatically format x-axis date labels

# Add a main title for the entire figure
plt.suptitle(f'Sensor Data - {date_str} {formatted_time}', fontsize=16)

# Adjust layout
plt.tight_layout(rect=[0, 0, 1, 0.97])  # Make room for the suptitle

# Display the figure
plt.show()

# Print basic statistics for all sensors
print("Sensor Statistics:")
for i in range(1, num_sensors):
    sensor_name = f'Sensor_{i}'
    print(f"\n{sensor_name}:\n{data[sensor_name].describe()}")
```



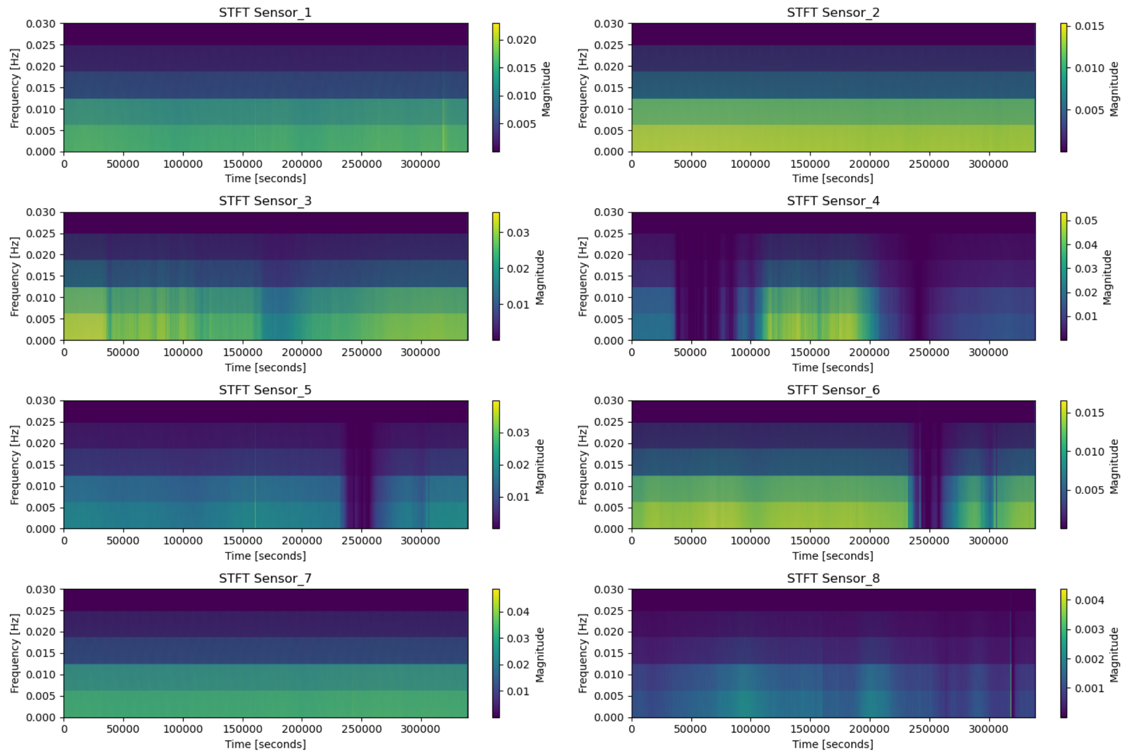

```
Sensor Statistics:

Sensor_1:
count    1.084420e+06
mean    -1.727884e-02
std      5.048720e-04
min     -2.300700e-02
25%     -1.762500e-02
50%     -1.728600e-02
75%     -1.690600e-02
max     -1.632500e-02
Name: Sensor_1, dtype: float64

Sensor_2:
count    1.084420e+06
mean    -1.481143e-02
std      2.283351e-04
min     -1.557400e-02
25%     -1.504800e-02
50%     -1.476700e-02
75%     -1.461900e-02
max     -1.421000e-02
Name: Sensor_2, dtype: float64
```

```
Sensor_3:
count    1.084420e+06
mean    -2.902471e-02
std      4.014688e-03
min     -3.576500e-02
25%     -3.148200e-02
50%     -2.978400e-02
75%     -2.700600e-02
max     -1.869200e-02
Name: Sensor_3, dtype: float64

Sensor_4:
count    1.084420e+06
mean     9.146397e-03
std      2.632990e-02
min     -2.506200e-02
25%     -1.520400e-02
50%      2.054000e-03
75%      3.857700e-02
max      5.387100e-02
Name: Sensor_4, dtype: float64

Sensor_5:
count    1.084420e+06
mean    -1.927404e-02
std      5.577440e-03
min     -6.273700e-02
25%     -2.202700e-02
50%     -2.094700e-02
75%     -1.956500e-02
max      4.554000e-03
Name: Sensor_5, dtype: float64

Sensor_6:
count    1.084420e+06
mean    -1.349133e-02
std      4.149826e-03
min     -2.560900e-02
25%     -1.566500e-02
50%     -1.521000e-02
75%     -1.375100e-02
max      2.503000e-03
Name: Sensor_6, dtype: float64

Sensor_7:
count    1.084420e+06
mean    -3.571238e-02
std      5.212150e-04
```

```
min     -7.406800e-02
25%     -3.605700e-02
50%     -3.561300e-02
75%     -3.531600e-02
max     -3.472400e-02
Name: Sensor_7, dtype: float64
```

[3]:

```python
# Perform Short-Time Fourier Transform (STFT) analysis
from scipy import signal
import matplotlib.pyplot as plt
import numpy as np

# Create a new figure for STFT analysis
plt.figure(figsize=(15, 10))

# Perform STFT on all sensor data
for i in range(1, 9):  # Assuming 8 sensors
    sensor_name = f'Sensor_{i}'

    # Get sensor data
    sensor_data = data[sensor_name].values

    # Calculate sampling rate (based on timestamp differences)
    sampling_rate = 1.0 / np.mean(np.diff(data['Timestamp']))

    # Perform STFT
    f, t, Zxx = signal.stft(sensor_data, fs=sampling_rate, nperseg=256)

    # Plot STFT results
    plt.subplot(4, 2, i)

    plt.pcolormesh(t, f, np.abs(Zxx), shading='gouraud')

    plt.title(f'STFT {sensor_name}')
    plt.ylabel('Frequency [Hz]')
    plt.xlabel('Time [seconds]')
    plt.colorbar(label='Magnitude')
    plt.ylim(0, 0.03)  # Limit y-axis to 0.03Hz

plt.tight_layout()
plt.show()

# Print basic information about the STFT analysis
print(f"STFT analysis completed")
print(f"Sampling rate: {sampling_rate:.2f} Hz")
print(f"Frequency resolution: {f[1]-f[0]:.4f} Hz")
print(f"Time resolution: {t[1]-t[0]:.4f} seconds")
```




```
STFT analysis completed
Sampling rate: 3.20 Hz
Frequency resolution: 0.0125 Hz
Time resolution: 39.9933 seconds
```

[4]:

```python
# Calculate the recording end time based on the timestamp
import datetime
# Extract start time from the filename (Mushroom_25-05-08_0326)
filename = file_path.split('/')[-1]
date_part = filename.split('_')[1]   # '25-05-08'
time_part = filename.split('_')[2]   # '0326'

# Handle potential file extension in time_part
if '.' in time_part:
    time_part = time_part.split('.')[0]  # Remove file extension if present

year = 2000 + int(date_part.split('-')[0])  # '25' -> 2025
month = int(date_part.split('-')[1])  # '05' -> 5
day = int(date_part.split('-')[2])  # '08' -> 8
hour = int(time_part[:2])  # '03' -> 3
minute = int(time_part[2:])  # '26' -> 26

start_time = datetime.datetime(year, month, day, hour, minute)
```

```python
# Get the first and last timestamp
first_timestamp = data['Timestamp'].iloc[0]
last_timestamp = data['Timestamp'].iloc[-1]

# Calculate the duration in seconds
duration_seconds = last_timestamp - first_timestamp

# Calculate the end time
end_time = start_time + datetime.timedelta(seconds=duration_seconds)

# Format and print the results
print(f"Recording start time: {start_time.strftime('%Y-%m-%d %H:%M:%S')}")
print(f"Recording end time: {end_time.strftime('%Y-%m-%d %H:%M:%S')}")
print(f"Total recording duration: {duration_seconds:.2f} seconds␣
↪({duration_seconds/60:.2f} minutes)")
```

```
Recording start time: 2025-05-08 03:26:00
Recording end time: 2025-05-12 01:33:04
Total recording duration: 338824.48 seconds (5647.07 minutes)
```

[5]:
```python
# Function to find the closest timestamp in the data to a given event time
import pytz
import datetime

# Parse the event time string
event_time_str = "2025-05-11T20:53:20.918Z"
event_time = datetime.datetime.strptime(event_time_str, "%Y-%m-%dT%H:%M:%S.%fZ")
event_time = event_time.replace(tzinfo=pytz.UTC)  # Make it timezone-aware

# Make start_time timezone-aware as well
start_time = start_time.replace(tzinfo=pytz.UTC)

# Calculate seconds elapsed since recording start
elapsed_seconds = (event_time - start_time).total_seconds()

print(f"Event time: {event_time_str}")
print(f"Recording start time: {start_time.strftime('%Y-%m-%d %H:%M:%S %Z')}")
print(f"Seconds elapsed since recording start: {elapsed_seconds:.2f} seconds")

# Get the first timestamp from the data
first_timestamp = data['Timestamp'].iloc[0]

# Calculate the target timestamp by adding elapsed seconds to the first␣
↪timestamp
target_timestamp = first_timestamp + elapsed_seconds
```

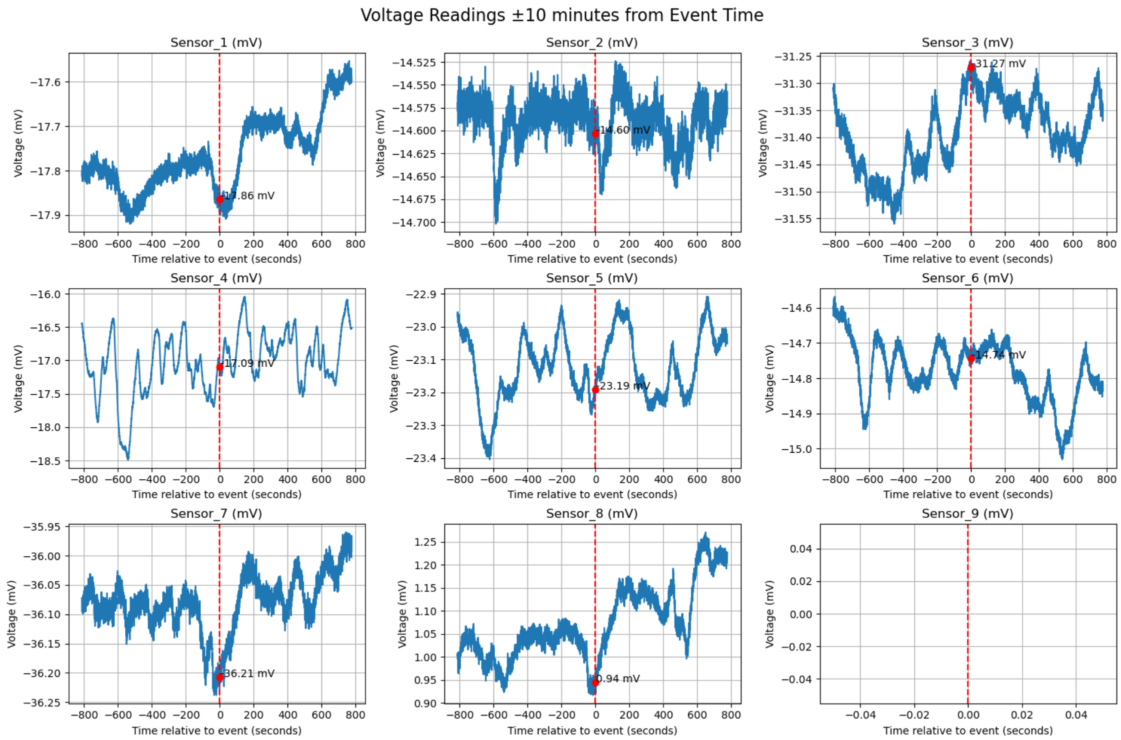
```python
# Find the closest timestamp in the data
closest_idx = (data['Timestamp'] - target_timestamp).abs().idxmin()
closest_timestamp = data['Timestamp'].iloc[closest_idx]
closest_time_diff = abs(closest_timestamp - target_timestamp)

print(f"First data timestamp: {first_timestamp:.2f} seconds")
print(f"Target timestamp: {target_timestamp:.2f} seconds")
print(f"Closest data timestamp: {closest_timestamp:.2f} seconds")
print(f"Difference from target: {closest_time_diff:.2f} seconds")

# Extract the data at the closest timestamp
event_data = data.iloc[closest_idx]
print("\nSensor readings at event time:")
for column in data.columns:
    if column != 'Timestamp':
        print(f"{column}: {event_data[column]}")
```

```
Event time: 2025-05-11T20:53:20.918Z
Recording start time: 2025-05-08 03:26:00 UTC
Seconds elapsed since recording start: 322040.92 seconds
First data timestamp: 120386.54 seconds
Target timestamp: 442427.46 seconds
Closest data timestamp: 442427.58 seconds
Difference from target: 0.13 seconds

Sensor readings at event time:
Sensor_1: -0.017864
Sensor_2: -0.014603
Sensor_3: -0.03127
Sensor_4: -0.017093
Sensor_5: -0.023191
Sensor_6: -0.014743
Sensor_7: -0.036207
Sensor_8: 0.000945
Sensor_9: nan
```

[6]:
```python
# Plot voltage data for 10 minutes before and after the event time
import matplotlib.pyplot as plt
import numpy as np

# Define the time window (10 minutes before and after the event)
window_minutes = 10
window_seconds = window_minutes * 60  # Convert minutes to seconds
event_idx = closest_idx
start_idx = max(0, event_idx - int(window_seconds * data['Timestamp'].diff().
 ↪median() ** -1))
```

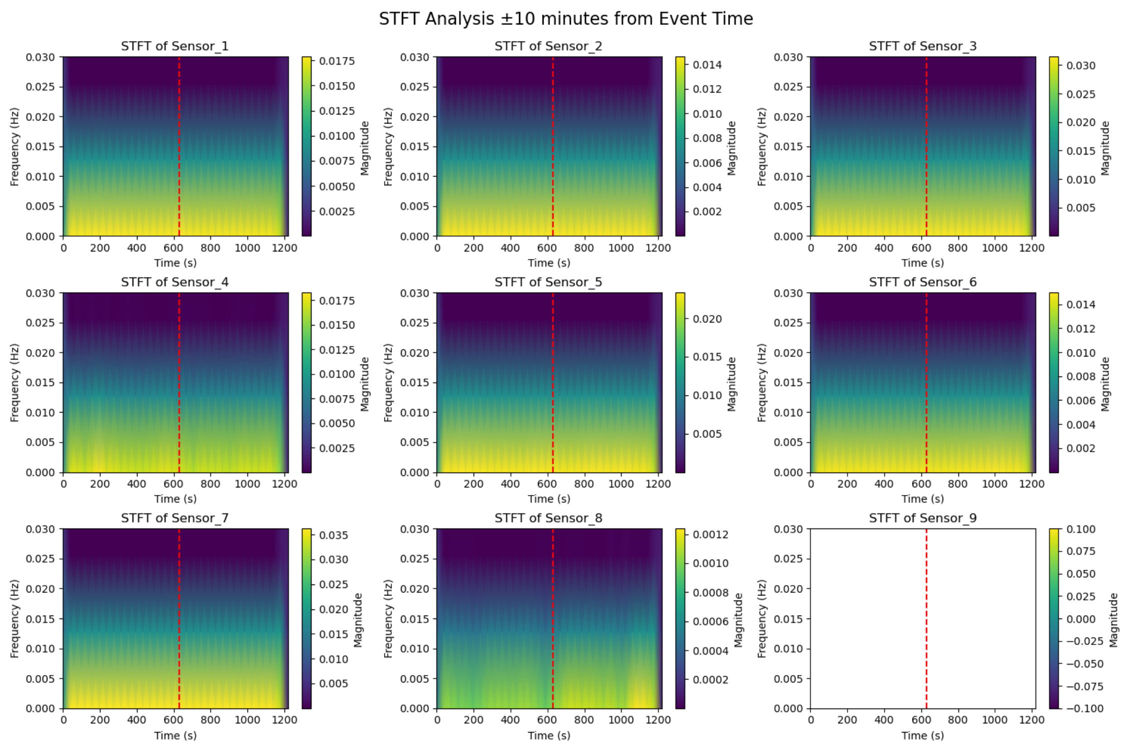
```python
end_idx = min(len(data) - 1, event_idx + int(window_seconds * data['Timestamp'].
    ↪diff().median() ** -1))

# Extract the data for the time window
window_data = data.iloc[start_idx:end_idx+1]

# Calculate time relative to the event (in seconds)
relative_time = window_data['Timestamp'] - closest_timestamp

# Create a figure with subplots for each voltage channel
plt.figure(figsize=(15, 10))
voltage_columns = [col for col in data.columns if col != 'Timestamp']

for i, column in enumerate(voltage_columns):
    plt.subplot(3, 3, i+1)

    # Convert voltage to millivolts
    voltage_mv = window_data[column] * 1000  # Convert to mV

    plt.plot(relative_time, voltage_mv)
    plt.axvline(x=0, color='r', linestyle='--', label='Event time')
    plt.title(f'{column} (mV)')
    plt.xlabel('Time relative to event (seconds)')
    plt.ylabel('Voltage (mV)')
    plt.grid(True)

    # Add a red dot at the event time point
    event_value_mv = event_data[column] * 1000  # Convert to mV
    plt.plot(0, event_value_mv, 'ro', markersize=6)  # Red dot at event time
    plt.text(1, event_value_mv, f'{event_value_mv:.2f} mV')  # Text label␣
    ↪without arrow

plt.tight_layout()
plt.suptitle('Voltage Readings ±10 minutes from Event Time', fontsize=16)
plt.subplots_adjust(top=0.92)
plt.show()
```

```
posx and posy should be finite values
posx and posy should be finite values
```




```
[7]: # Perform Short-Time Fourier Transform (STFT) analysis for each voltage channel
import matplotlib.pyplot as plt
from scipy import signal
import numpy as np

# Create a figure with subplots for STFT of each voltage channel
plt.figure(figsize=(15, 10))
voltage_columns = [col for col in data.columns if col != 'Timestamp']

# Calculate sampling frequency
sampling_freq = 1.0 / data['Timestamp'].diff().median()

for i, column in enumerate(voltage_columns):
    plt.subplot(3, 3, i+1)

    # Get voltage data for this channel
    voltage_data = window_data[column].values

    # Perform STFT
    f, t, Zxx = signal.stft(voltage_data, fs=sampling_freq, nperseg=256)

    # Plot the STFT magnitude (in dB)
    plt.pcolormesh(t, f, np.abs(Zxx), shading='gouraud')
```

```
    # Mark the event time
    plt.axvline(x=t[len(t)//2], color='r', linestyle='--', label='Event time')

    plt.title(f'STFT of {column}')
    plt.ylabel('Frequency (Hz)')
    plt.xlabel('Time (s)')
    plt.colorbar(label='Magnitude')
    plt.ylim(0, 0.03)

plt.tight_layout()
plt.suptitle('STFT Analysis ±10 minutes from Event Time', fontsize=16)
plt.subplots_adjust(top=0.92)
plt.show()
```



[8]:

```
# Analyze the 0.02Hz frequency band before and after event for each sensor
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import datetime

# Get dataset name from the notebook filename
```

```
notebook_name = os.path.basename(__file__) if '__file__' in globals() else␣
↪'Mushroom_25-05-08_0326'
if notebook_name.endswith('.ipynb'):
    notebook_name = notebook_name[:-6]  # Remove .ipynb extension
if notebook_name.startswith('da_'):
    notebook_name = notebook_name[3:]  # Remove da_ prefix

# Create a directory to save CSV files with dataset name
csv_dir = f"significant_changes_csv_{notebook_name}"
if not os.path.exists(csv_dir):
    os.makedirs(csv_dir)
    print(f"Created directory: {csv_dir}")

# Calculate sampling frequency
sampling_freq = 1.0 / data['Timestamp'].diff().median()

# Find the event time (assuming it's at the center of the filtered data)
event_time = window_data['Timestamp'].mean()

# Loop through each voltage channel
for channel_to_analyze in voltage_columns:
    print(f"\n=== Analysis for {channel_to_analyze} ===")
    voltage_data = window_data[channel_to_analyze].values

    # Perform STFT for the selected channel
    f, t, Zxx = signal.stft(voltage_data, fs=sampling_freq, nperseg=256)

    # Find the closest frequency to 0.02Hz in the STFT results
    target_freq = 0.02
    freq_idx = np.argmin(np.abs(f - target_freq))
    actual_freq = f[freq_idx]
    print(f"Analyzing frequency: {actual_freq:.4f} Hz (closest to 0.02 Hz)")

    # Extract the magnitude data for this frequency
    freq_magnitude = np.abs(Zxx[freq_idx, :])

    # Create a time axis in minutes for better visualization
    time_min = t / 60

    # Plot the magnitude of the 0.02Hz component over time
    plt.figure(figsize=(15, 6))

    # Plot the magnitude
    plt.plot(time_min, freq_magnitude, 'b-', linewidth=2, label=f'{actual_freq:.
↪4f} Hz Component')

    # Convert event time to minutes
```

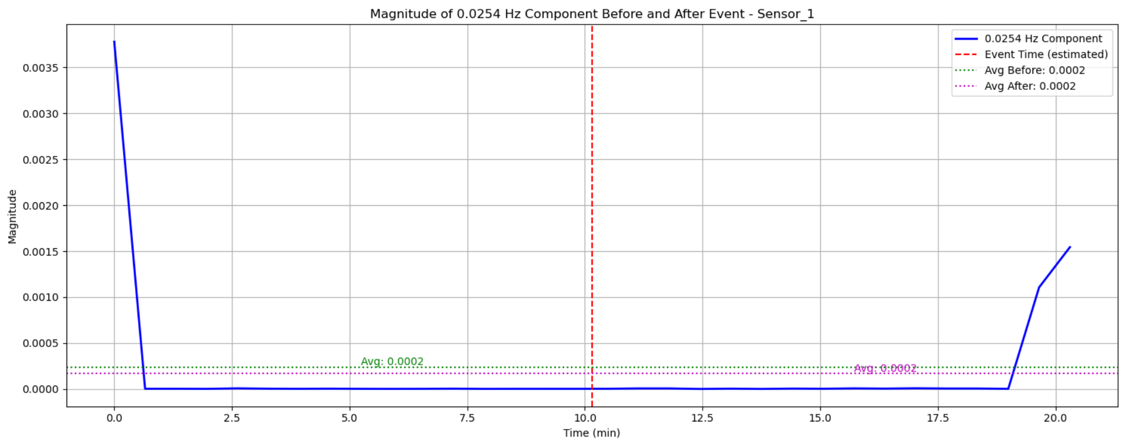
```
    event_time_min = t.mean() / 60
    plt.axvline(x=event_time_min, color='r', linestyle='--', label='Event Time␣
↪(estimated)')

    # Calculate average magnitude before and after event
    before_mask = t < t.mean()
    after_mask = t >= t.mean()

    avg_before = np.mean(freq_magnitude[before_mask])
    avg_after = np.mean(freq_magnitude[after_mask])

    print(f"Average magnitude before event: {avg_before:.4f}")
    print(f"Average magnitude after event: {avg_after:.4f}")
    print(f"Change: {(avg_after - avg_before):.4f} ({(avg_after - avg_before)/
↪avg_before*100:.2f}%)")

    # Add horizontal lines showing the average values
    plt.axhline(y=avg_before, color='g', linestyle=':', label=f'Avg Before:␣
↪{avg_before:.4f}')
    plt.axhline(y=avg_after, color='m', linestyle=':', label=f'Avg After:␣
↪{avg_after:.4f}')

    # Add annotations
    plt.annotate(f"Avg: {avg_before:.4f}", xy=(time_min[len(time_min)//4],␣
↪avg_before),
                 xytext=(time_min[len(time_min)//4], avg_before*1.1), color='g')
    plt.annotate(f"Avg: {avg_after:.4f}", xy=(time_min[3*len(time_min)//4],␣
↪avg_after),
                 xytext=(time_min[3*len(time_min)//4], avg_after*1.1),␣
↪color='m')

    # Set axis labels and title
    plt.xlabel('Time (min)')
    plt.ylabel('Magnitude')
    plt.title(f'Magnitude of {actual_freq:.4f} Hz Component Before and After␣
↪Event - {channel_to_analyze}')
    plt.grid(True)
    plt.legend()
    plt.tight_layout()
    plt.show()

    # Calculate energy (integral of magnitude squared) before and after event
    energy_before = np.sum(freq_magnitude[before_mask]**2)
    energy_after = np.sum(freq_magnitude[after_mask]**2)

    # Normalize by the number of samples to get average energy
```

```
    num_samples_before = np.sum(before_mask)
    num_samples_after = np.sum(after_mask)
    avg_energy_before = energy_before / num_samples_before
    avg_energy_after = energy_after / num_samples_after

    print("\nEnergy Analysis:")
    print(f"Total energy before event: {energy_before:.4f}")
    print(f"Total energy after event: {energy_after:.4f}")
    print(f"Average energy before event: {avg_energy_before:.4f}")
    print(f"Average energy after event: {avg_energy_after:.4f}")
    print(f"Energy change: {(avg_energy_after - avg_energy_before):.4f}␣
↪({(avg_energy_after - avg_energy_before)/avg_energy_before*100:.2f}%)")

    # Power Spectral Density (PSD) Analysis
    # Calculate power (magnitude squared)
    power_matrix = np.abs(Zxx) ** 2

    # Convert time to minutes for consistency with previous plots
    time_min = t / 60

    # Define the event time point (assuming same as before)
    event_time_min = time_min[len(time_min) // 2]  # Middle point as event time

    # Create masks for before and after event
    before_mask_time = time_min < event_time_min
    after_mask_time = time_min > event_time_min

    # Calculate average PSD before and after event
    avg_psd_before = np.mean(power_matrix[:, before_mask_time], axis=1)
    avg_psd_after = np.mean(power_matrix[:, after_mask_time], axis=1)

    # Plot the power spectral density comparison
    plt.figure(figsize=(15, 6))
    plt.plot(f, avg_psd_before, 'g-', label='Before Event')
    plt.plot(f, avg_psd_after, 'm-', label='After Event')

    # Calculate and display the difference
    psd_diff = avg_psd_after - avg_psd_before
    plt.plot(f, psd_diff, 'b--', label='Difference (After - Before)')

    # Set axis labels and title
    plt.xlabel('Frequency (Hz)')
    plt.xlim(0, 0.2)  # Limit x-axis to show only frequencies below 0.2 Hz
    plt.ylabel('Power Spectral Density')
    plt.title(f'Power Spectral Density Comparison Before and After Event -␣
↪{channel_to_analyze}')
    plt.grid(True)
```

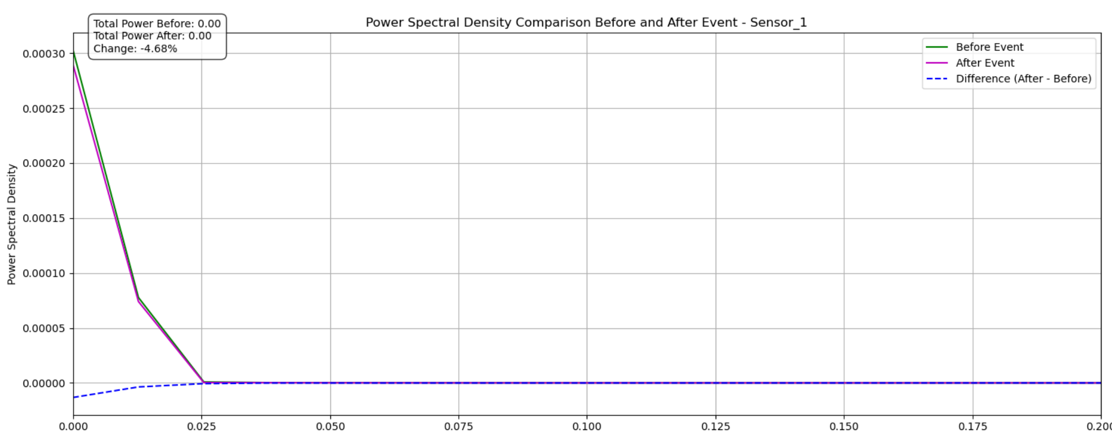
```
    plt.legend()

    # Add text box with summary statistics
    total_power_before = np.sum(avg_psd_before)
    total_power_after = np.sum(avg_psd_after)
    power_change = (total_power_after - total_power_before) /␣
↪total_power_before * 100

    stats_text = f"Total Power Before: {total_power_before:.2f}\n"
    stats_text += f"Total Power After: {total_power_after:.2f}\n"
    stats_text += f"Change: {power_change:.2f}%"

    plt.annotate(stats_text, xy=(0.02, 0.95), xycoords='axes fraction',
                 bbox=dict(boxstyle="round,pad=0.5", fc="white", alpha=0.8))

    plt.tight_layout()
    plt.show()

    # Print detailed statistics
    print("\nPower Spectral Density Analysis:")
    print(f"Total power before event: {total_power_before:.4f}")
    print(f"Total power after event: {total_power_after:.4f}")
    print(f"Absolute power change: {total_power_after - total_power_before:.
↪4f}")
    print(f"Relative power change: {power_change:.2f}%")

    # Find frequency bands with the most significant changes
    freq_change_percent = (avg_psd_after - avg_psd_before) / (avg_psd_before +␣
↪1e-10) * 100  # Avoid division by zero
    significant_changes = pd.DataFrame({
        'Frequency': f,
        'Before': avg_psd_before,
        'After': avg_psd_after,
        'Absolute_Change': avg_psd_after - avg_psd_before,
        'Percent_Change': freq_change_percent
    })

    # Save the significant_changes DataFrame to CSV
    csv_filename = os.path.join(csv_dir,␣
↪f"{channel_to_analyze}_significant_changes.csv")
    significant_changes.to_csv(csv_filename, index=False)
    print(f"Saved significant changes data to: {csv_filename}")

    # Display top 5 frequencies with largest increase and decrease
    print("\nTop 5 frequencies with largest power increase:")
    print(significant_changes.sort_values('Percent_Change', ascending=False).
↪head(5))
```

```python
    print("\nTop 5 frequencies with largest power decrease:")
    print(significant_changes.sort_values('Percent_Change', ascending=True).
    ↪head(5))
```

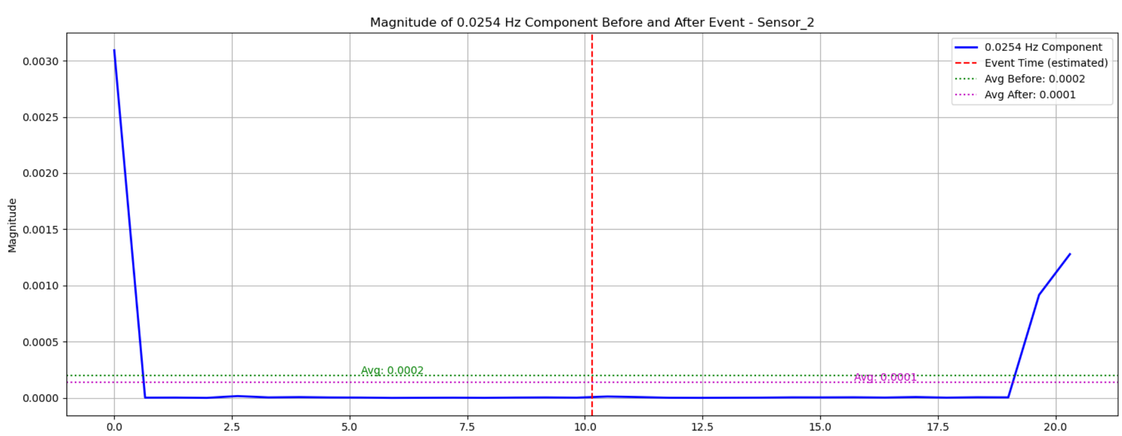
```
=== Analysis for Sensor_1 ===
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: 0.0002
Average magnitude after event: 0.0002
Change: -0.0001 (-28.99%)
```



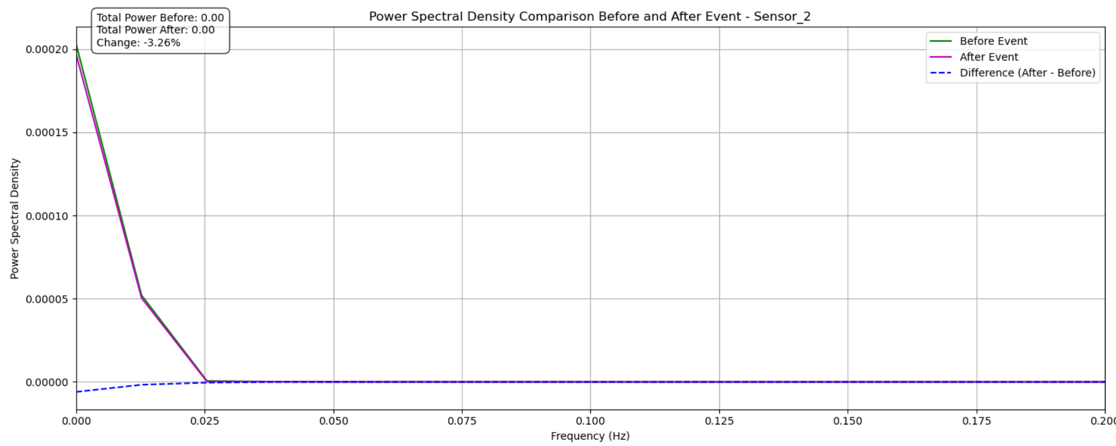

```
Energy Analysis:
Total energy before event: 0.0000
Total energy after event: 0.0000
Average energy before event: 0.0000
Average energy after event: 0.0000
Energy change: -0.0000 (-74.73%)
```



```
Power Spectral Density Analysis:
Total power before event: 0.0004
Total power after event: 0.0004
Absolute power change: -0.0000
Relative power change: -4.68%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_1_significant_changes.csv

Top 5 frequencies with largest power increase:
     Frequency        Before         After  Absolute_Change  Percent_Change
0     0.000000  3.027029e-04  2.894625e-04    -1.324038e-05       -4.374050
1     0.012722  7.770428e-05  7.404846e-05    -3.655814e-06       -4.704773
3     0.038165  2.230397e-07  1.473335e-07    -7.570617e-08      -33.927697
128   1.628394  2.872684e-10  1.555669e-10    -1.317015e-10      -34.007800
127   1.615672  2.928808e-10  1.586087e-10    -1.342720e-10      -34.176283

Top 5 frequencies with largest power decrease:
    Frequency        Before         After  Absolute_Change  Percent_Change
2    0.025444  8.919670e-07  2.404194e-07    -6.515476e-07      -73.037968
6    0.076331  5.911950e-08  2.902106e-08    -3.009844e-08      -50.825215
10   0.127218  2.055751e-08  1.065909e-08    -9.898418e-09      -47.916797
12   0.152662  1.422803e-08  7.487636e-09    -6.740392e-09      -47.043405
8    0.101775  3.244960e-08  1.715553e-08    -1.529408e-08      -46.986977

=== Analysis for Sensor_2 ===
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: 0.0002
Average magnitude after event: 0.0001
Change: -0.0001 (-28.13%)
```



Energy Analysis:
Total energy before event: 0.0000
Total energy after event: 0.0000
Average energy before event: 0.0000
Average energy after event: 0.0000
Energy change: -0.0000 (-74.09%)



Power Spectral Density Analysis:
Total power before event: 0.0003
Total power after event: 0.0002
Absolute power change: -0.0000
Relative power change: -3.26%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_2_significant_changes.csv

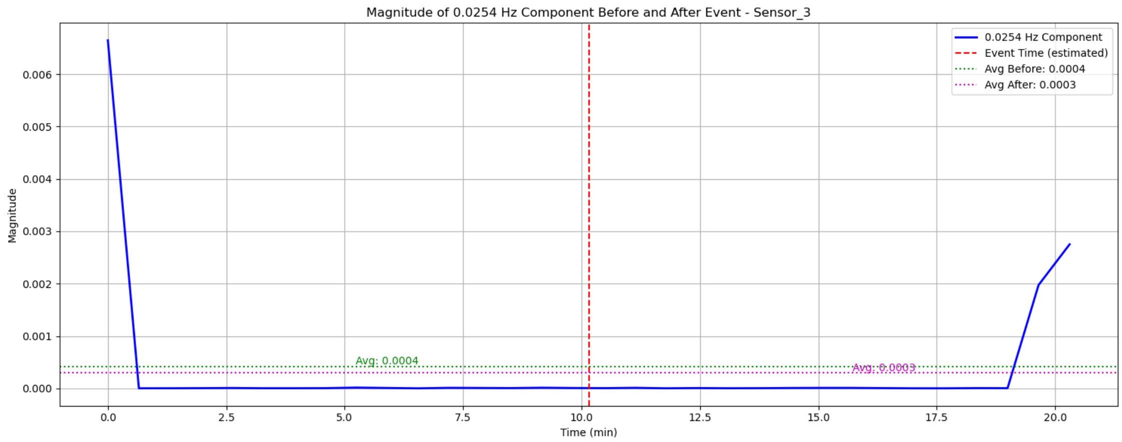
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
0	0.000000	2.028486e-04	1.968521e-04	-5.996497e-06	-2.956142
1	0.012722	5.205968e-05	5.036674e-05	-1.692937e-06	-3.251910
124	1.577507	1.998626e-10	1.128070e-10	-8.705563e-11	-29.031834
102	1.297626	2.201615e-10	1.268907e-10	-9.327083e-11	-29.132431
108	1.373957	2.087934e-10	1.185835e-10	-9.020996e-11	-29.213692

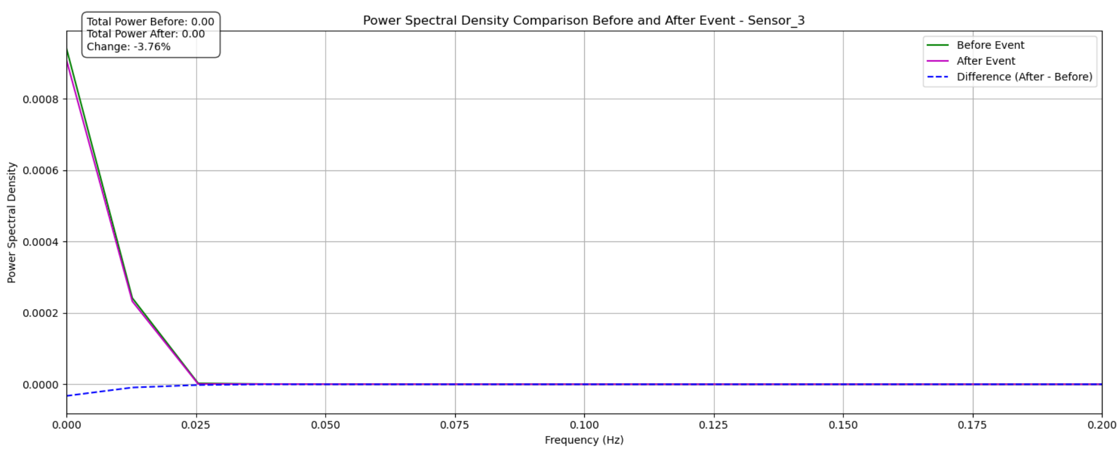
Top 5 frequencies with largest power decrease:

	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	5.976019e-07	1.651205e-07	-4.324814e-07	-72.357369
6	0.076331	3.962917e-08	1.986140e-08	-1.976777e-08	-49.756319
10	0.127218	1.381732e-08	7.295296e-09	-6.522023e-09	-46.862641
12	0.152662	9.562939e-09	5.140657e-09	-4.422282e-09	-45.765393

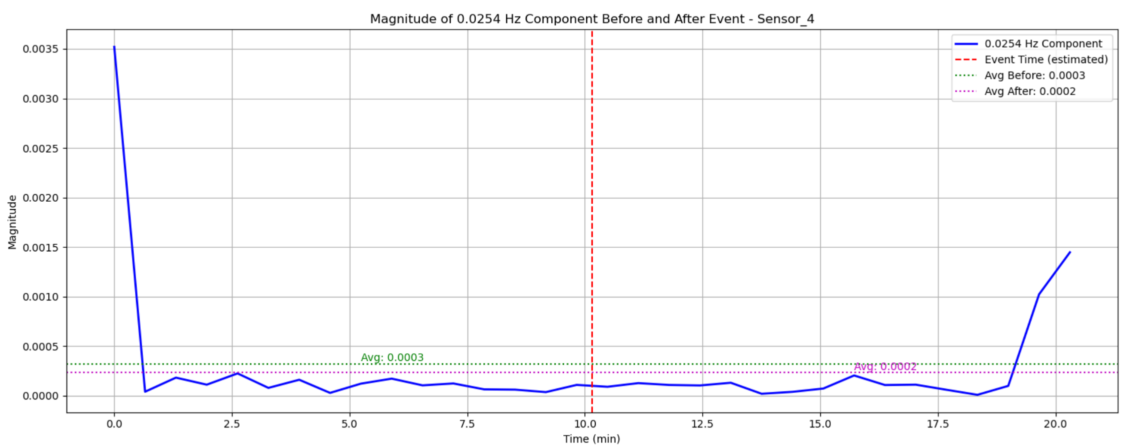
```
8    0.101775  2.181266e-08  1.179714e-08    -1.001552e-08      -45.706532

=== Analysis for Sensor_3 ===
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: 0.0004
Average magnitude after event: 0.0003
Change: -0.0001 (-28.79%)
```




```
Energy Analysis:
Total energy before event: 0.0000
Total energy after event: 0.0000
Average energy before event: 0.0000
Average energy after event: 0.0000
Energy change: -0.0000 (-74.04%)
```

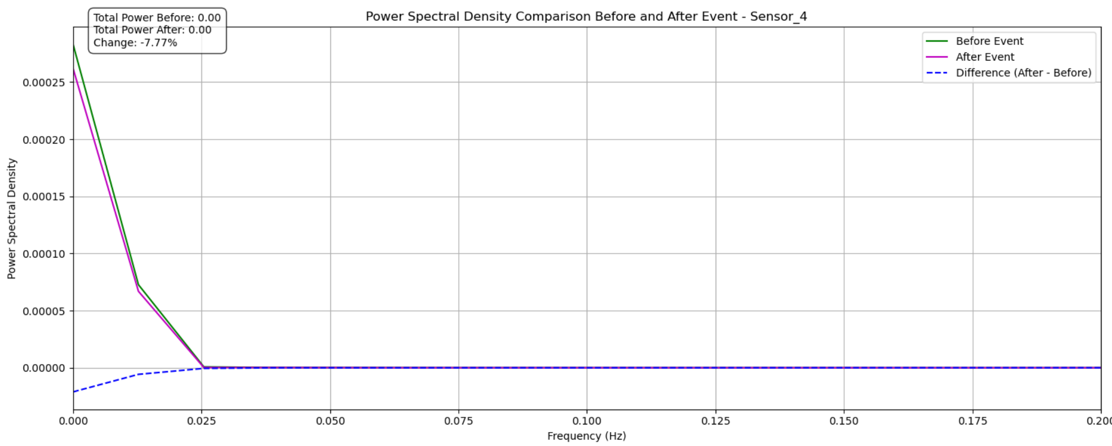


```
Power Spectral Density Analysis:
Total power before event: 0.0012
Total power after event: 0.0011
Absolute power change: -0.0000
Relative power change: -3.76%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_3_significant_changes.csv

Top 5 frequencies with largest power increase:
     Frequency        Before         After  Absolute_Change  Percent_Change
0     0.000000  9.417902e-04  9.092290e-04    -3.256121e-05       -3.457374
1     0.012722  2.417374e-04  2.326522e-04    -9.085204e-06       -3.758293
3     0.038165  6.895399e-07  4.688747e-07    -2.206653e-07      -31.997173
128   1.628394  9.211685e-10  5.138730e-10    -4.072954e-10      -39.885234
127   1.615672  9.208380e-10  5.100521e-10    -4.107860e-10      -40.240073

Top 5 frequencies with largest power decrease:
    Frequency        Before         After  Absolute_Change  Percent_Change
2    0.025444  2.761577e-06  7.646342e-07    -1.996943e-06      -72.309065
6    0.076331  1.827916e-07  9.220235e-08    -9.058929e-08      -49.531675
10   0.127218  6.365886e-08  3.382372e-08    -2.983514e-08      -46.793719
16   0.203549  2.479691e-08  1.331511e-08    -1.148180e-08      -46.117381
14   0.178106  3.232861e-08  1.738894e-08    -1.493967e-08      -46.069415

=== Analysis for Sensor_4 ===
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: 0.0003
Average magnitude after event: 0.0002
Change: -0.0001 (-26.98%)
```




```
Energy Analysis:
```

Total energy before event: 0.0000
Total energy after event: 0.0000
Average energy before event: 0.0000
Average energy after event: 0.0000
Energy change: -0.0000 (-73.90%)



Power Spectral Density Analysis:
Total power before event: 0.0004
Total power after event: 0.0003
Absolute power change: -0.0000
Relative power change: -7.77%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_4_significant_changes.csv

Top 5 frequencies with largest power increase:

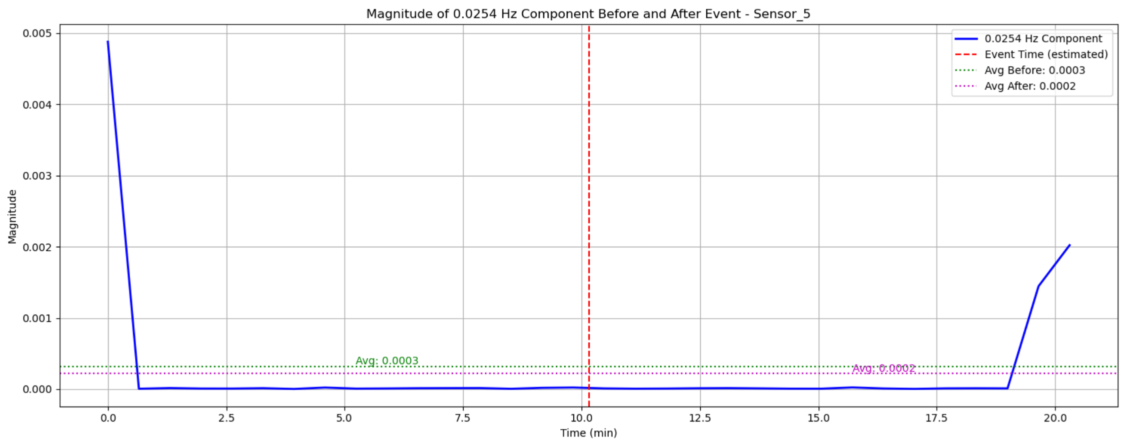
	Frequency	Before	After	Absolute_Change	Percent_Change
0	0.000000	2.830682e-04	2.619377e-04	-2.113046e-05	-7.464793
1	0.012722	7.266309e-05	6.689618e-05	-5.766906e-06	-7.936489
3	0.038165	1.908827e-07	1.354997e-07	-5.538306e-08	-28.998990
112	1.424845	2.660117e-10	1.510272e-10	-1.149844e-10	-31.415510
124	1.577507	2.549683e-10	1.428537e-10	-1.121145e-10	-31.584385

Top 5 frequencies with largest power decrease:

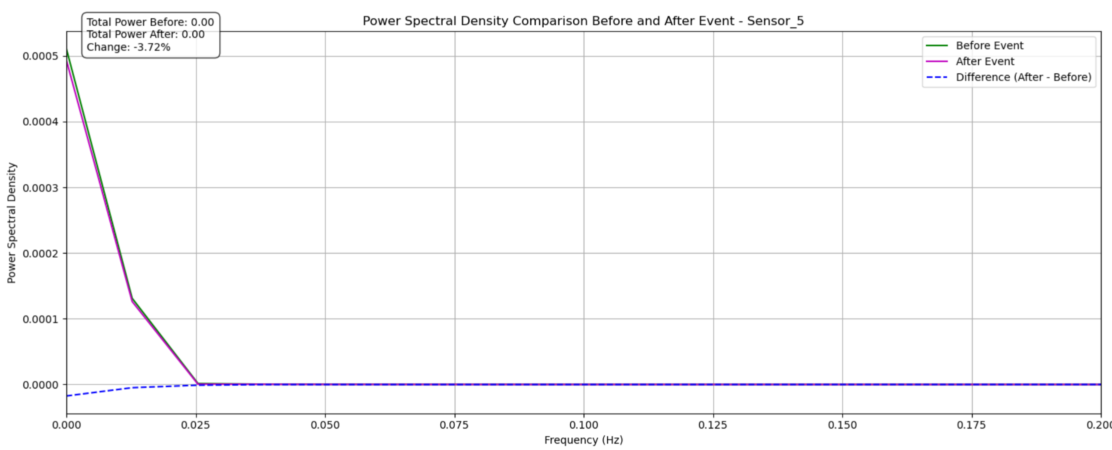
	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	7.883738e-07	2.189272e-07	-5.694466e-07	-72.221372
6	0.076331	5.070680e-08	2.607832e-08	-2.462848e-08	-48.474771
10	0.127218	1.758301e-08	9.400566e-09	-8.182441e-09	-46.272903
12	0.152662	1.218207e-08	6.589585e-09	-5.592480e-09	-45.533711
14	0.178106	8.915742e-09	4.813793e-09	-4.101949e-09	-45.497627

=== Analysis for Sensor_5 ===

```
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: 0.0003
Average magnitude after event: 0.0002
Change: -0.0001 (-28.55%)
```




```
Energy Analysis:
Total energy before event: 0.0000
Total energy after event: 0.0000
Average energy before event: 0.0000
Average energy after event: 0.0000
Energy change: -0.0000 (-74.03%)
```




```
Power Spectral Density Analysis:
Total power before event: 0.0006
Total power after event: 0.0006
```

Absolute power change: -0.0000
Relative power change: -3.72%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_5_significant_changes.csv

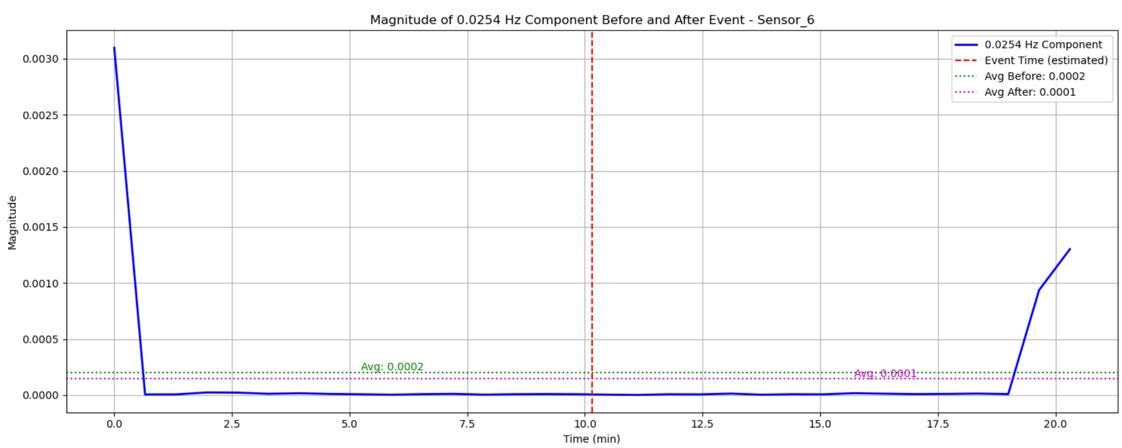
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
0	0.000000	5.107708e-04	4.933117e-04	-1.745911e-05	-3.418189
1	0.012722	1.310841e-04	1.262110e-04	-4.873110e-06	-3.717542
3	0.038165	3.712572e-07	2.527986e-07	-1.184586e-07	-31.898819
118	1.501176	5.087170e-10	2.838611e-10	-2.248560e-10	-36.939327
119	1.513898	5.085084e-10	2.825342e-10	-2.259743e-10	-37.135766

Top 5 frequencies with largest power decrease:

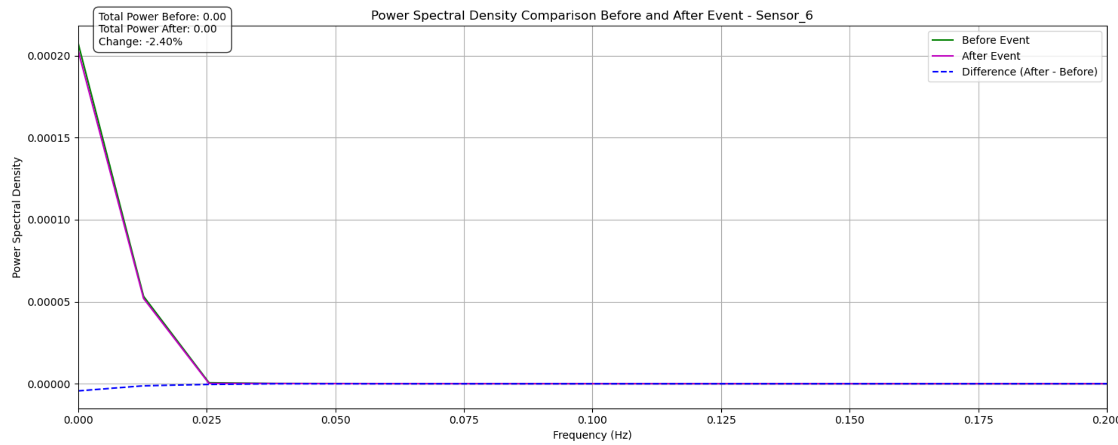
	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	1.487907e-06	4.121344e-07	-1.075773e-06	-72.296214
6	0.076331	9.835271e-08	4.986560e-08	-4.848711e-08	-49.249137
10	0.127218	3.429489e-08	1.825481e-08	-1.604008e-08	-46.635062
14	0.178106	1.740456e-08	9.407397e-09	-7.997159e-09	-45.686156
18	0.228993	1.057176e-08	5.704496e-09	-4.867261e-09	-45.608805

=== Analysis for Sensor_6 ===
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: 0.0002
Average magnitude after event: 0.0001
Change: -0.0001 (-27.49%)



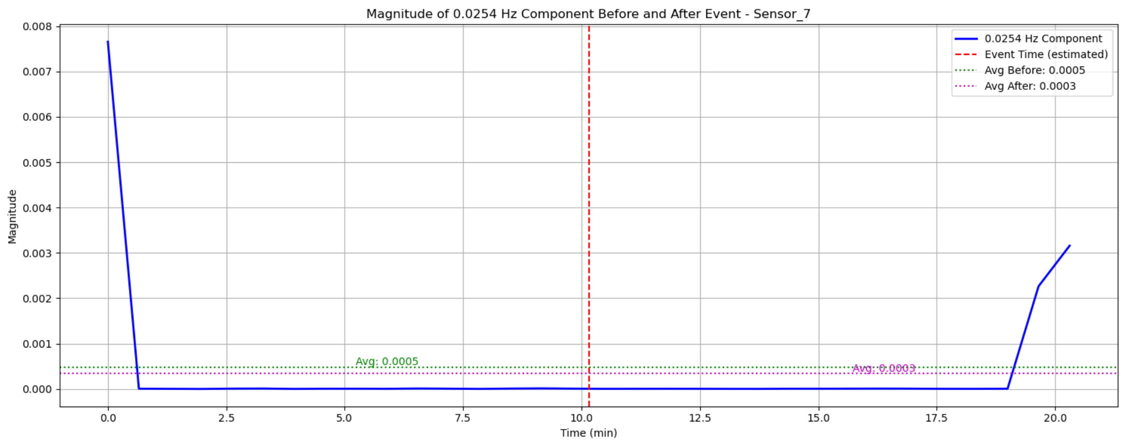
Energy Analysis:
Total energy before event: 0.0000
Total energy after event: 0.0000
Average energy before event: 0.0000

```
Average energy after event: 0.0000
Energy change: -0.0000 (-73.21%)
```

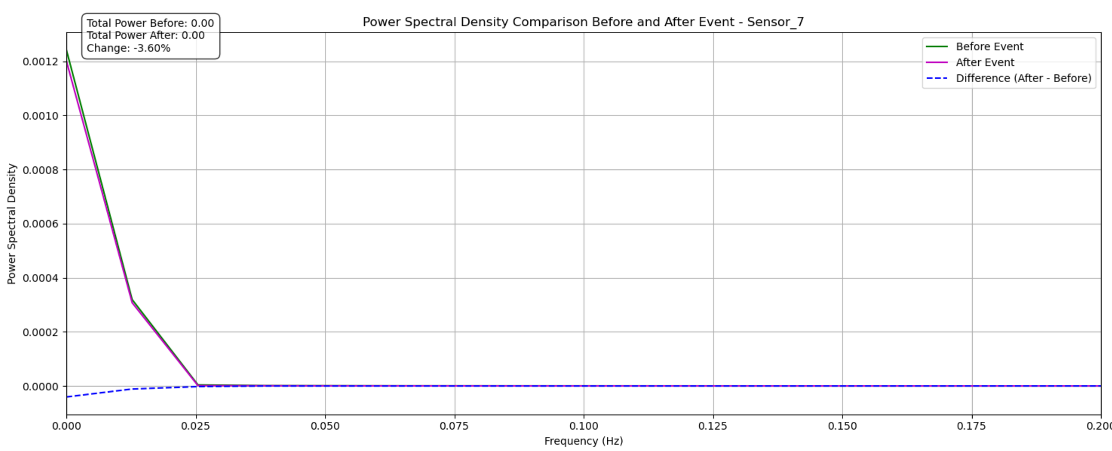



```
Power Spectral Density Analysis:
Total power before event: 0.0003
Total power after event: 0.0003
Absolute power change: -0.0000
Relative power change: -2.40%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_6_significant_changes.csv

Top 5 frequencies with largest power increase:
     Frequency        Before         After  Absolute_Change  Percent_Change
0     0.000000  2.074354e-04  2.030627e-04    -4.372709e-06       -2.107985
1     0.012722  5.322478e-05  5.196142e-05    -1.263358e-06       -2.373623
124   1.577507  2.005864e-10  1.159665e-10    -8.461988e-11      -28.151600
122   1.552063  2.056583e-10  1.178156e-10    -8.784274e-11      -28.738866
125   1.590228  2.029080e-10  1.156612e-10    -8.724685e-11      -28.803082

Top 5 frequencies with largest power decrease:
    Frequency        Before         After  Absolute_Change  Percent_Change
2    0.025444  5.998990e-07  1.714112e-07    -4.284878e-07      -71.414753
6    0.076331  3.970805e-08  2.062679e-08    -1.908127e-08      -47.933180
10   0.127218  1.385121e-08  7.580145e-09    -6.271069e-09      -44.949988
12   0.152662  9.578142e-09  5.285202e-09    -4.292940e-09      -44.357071
14   0.178106  7.043865e-09  3.881196e-09    -3.162669e-09      -44.271120

=== Analysis for Sensor_7 ===
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: 0.0005
Average magnitude after event: 0.0003
```

```
Change: -0.0001 (-29.12%)
```




```
Energy Analysis:
Total energy before event: 0.0001
Total energy after event: 0.0000
Average energy before event: 0.0000
Average energy after event: 0.0000
Energy change: -0.0000 (-74.22%)
```




```
Power Spectral Density Analysis:
Total power before event: 0.0016
Total power after event: 0.0015
Absolute power change: -0.0001
Relative power change: -3.60%
Saved significant changes data to:
```

significant_changes_csv_Mushroom_25-05-08_0326\Sensor_7_significant_changes.csv

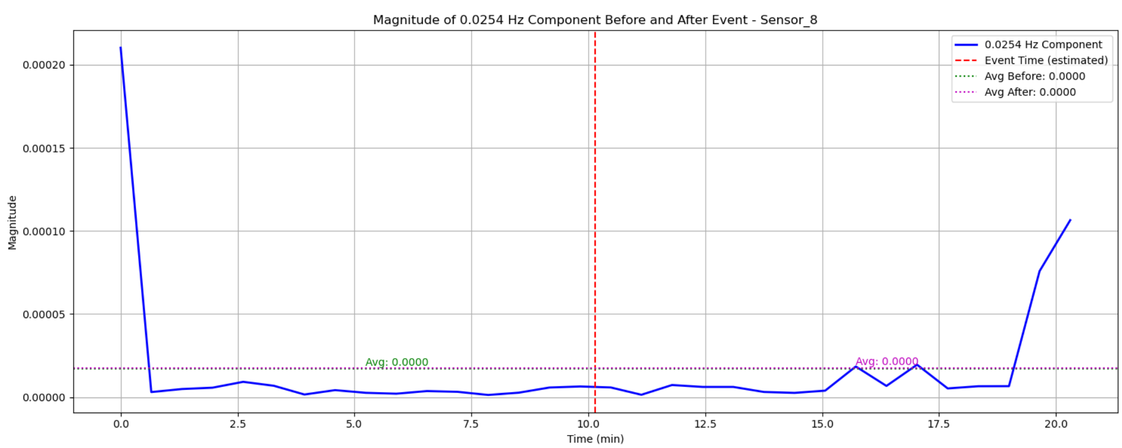
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
0	0.000000	1.242524e-03	1.201650e-03	-4.087410e-05	-3.289601
1	0.012722	3.189409e-04	3.074623e-04	-1.147866e-05	-3.598991
3	0.038165	9.165002e-07	6.164599e-07	-3.000404e-07	-32.734051
118	1.501176	1.255972e-09	6.853460e-10	-5.706263e-10	-42.082445
110	1.399401	1.304560e-09	7.126021e-10	-5.919575e-10	-42.145415

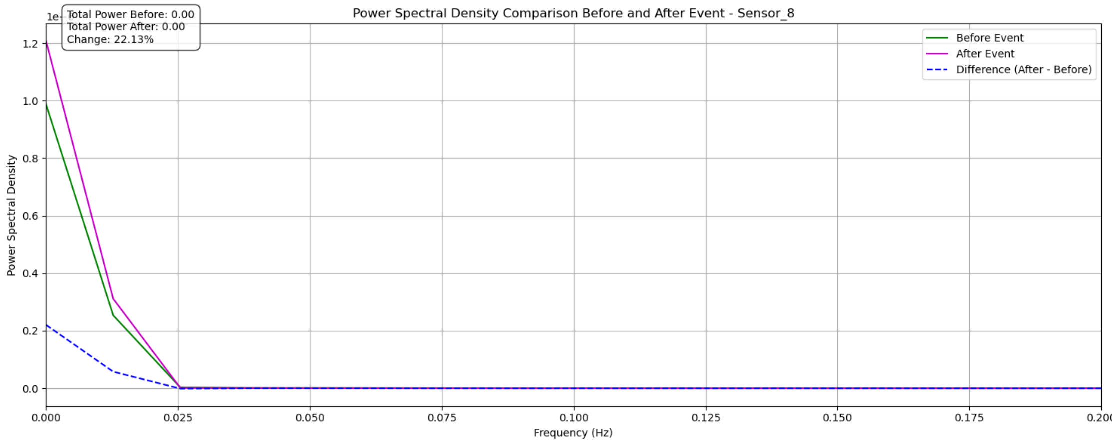
Top 5 frequencies with largest power decrease:

	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	3.664066e-06	1.007373e-06	-2.656693e-06	-72.504702
6	0.076331	2.428832e-07	1.213399e-07	-1.215433e-07	-50.021285
10	0.127218	8.442900e-08	4.453067e-08	-3.989834e-08	-47.200767
20	0.254437	2.112240e-08	1.124509e-08	-9.877312e-09	-46.541915
12	0.152662	5.845319e-08	3.123490e-08	-2.721829e-08	-46.484729

=== Analysis for Sensor_8 ===
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: 0.0000
Average magnitude after event: 0.0000
Change: 0.0000 (3.07%)



Energy Analysis:
Total energy before event: 0.0000
Total energy after event: 0.0000
Average energy before event: 0.0000
Average energy after event: 0.0000
Energy change: -0.0000 (-59.19%)



Power Spectral Density Analysis:
Total power before event: 0.0000
Total power after event: 0.0000
Absolute power change: 0.0000
Relative power change: 22.13%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_8_significant_changes.csv

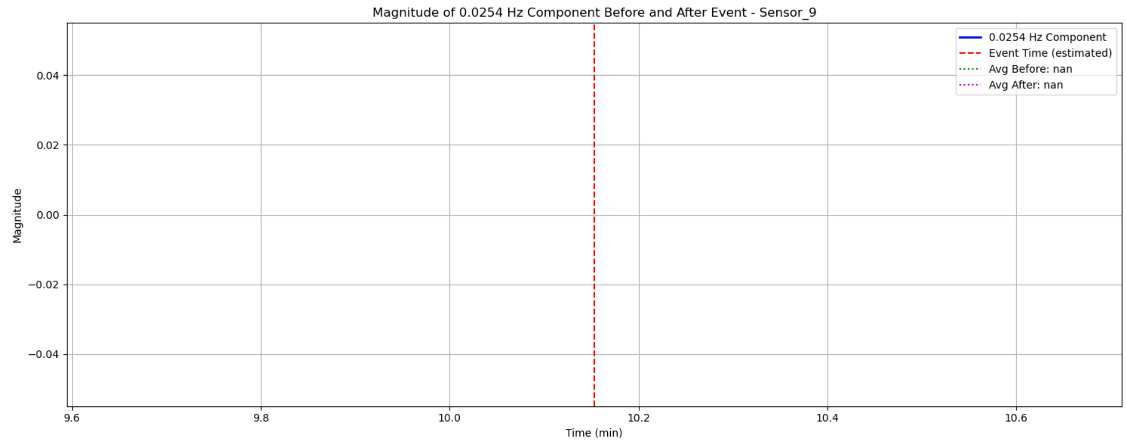
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
1	0.012722	2.536863e-07	3.112550e-07	5.756870e-08	22.683931
0	0.000000	9.870669e-07	1.207201e-06	2.201344e-07	22.299613
3	0.038165	6.620955e-10	7.074977e-10	4.540221e-11	5.957548
89	1.132243	1.354204e-12	1.897773e-12	5.435690e-13	0.536306
52	0.661535	2.593418e-12	3.067361e-12	4.739436e-13	0.461963

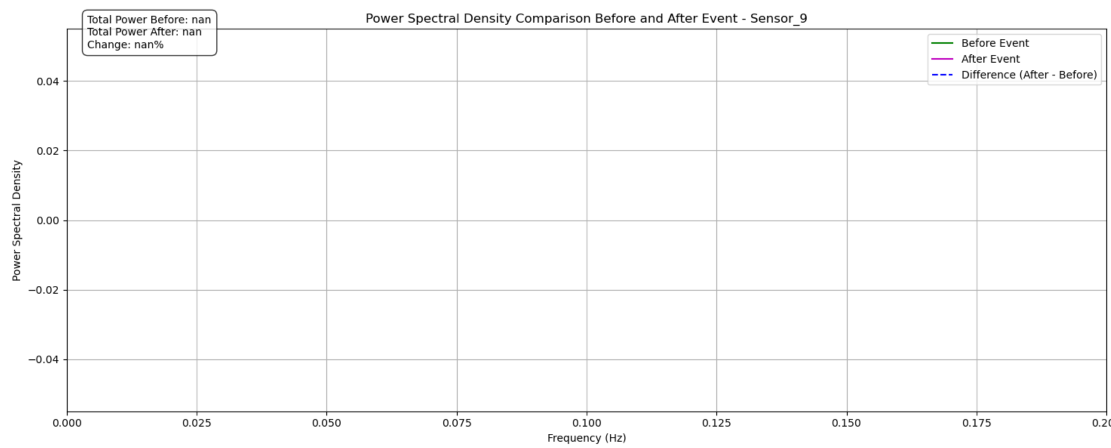
Top 5 frequencies with largest power decrease:

	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	2.784535e-09	1.209742e-09	-1.574794e-09	-54.594370
6	0.076331	1.853649e-10	1.382554e-10	-4.710952e-11	-16.508519
8	0.101775	1.054306e-10	8.114244e-11	-2.428813e-11	-11.823036
5	0.063609	2.465113e-10	2.076146e-10	-3.889679e-11	-11.225258
7	0.089053	1.308106e-10	1.049623e-10	-2.584831e-11	-11.198925

=== Analysis for Sensor_9 ===
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: nan
Average magnitude after event: nan
Change: nan (nan%)



Energy Analysis:
Total energy before event: nan
Total energy after event: nan
Average energy before event: nan
Average energy after event: nan
Energy change: nan (nan%)



Power Spectral Density Analysis:
Total power before event: nan
Total power after event: nan
Absolute power change: nan
Relative power change: nan%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_9_significant_changes.csv

```
Top 5 frequencies with largest power increase:
   Frequency  Before  After  Absolute_Change  Percent_Change
0   0.000000     NaN    NaN              NaN             NaN
1   0.012722     NaN    NaN              NaN             NaN
2   0.025444     NaN    NaN              NaN             NaN
3   0.038165     NaN    NaN              NaN             NaN
4   0.050887     NaN    NaN              NaN             NaN

Top 5 frequencies with largest power decrease:
   Frequency  Before  After  Absolute_Change  Percent_Change
0   0.000000     NaN    NaN              NaN             NaN
1   0.012722     NaN    NaN              NaN             NaN
2   0.025444     NaN    NaN              NaN             NaN
3   0.038165     NaN    NaN              NaN             NaN
4   0.050887     NaN    NaN              NaN             NaN
```

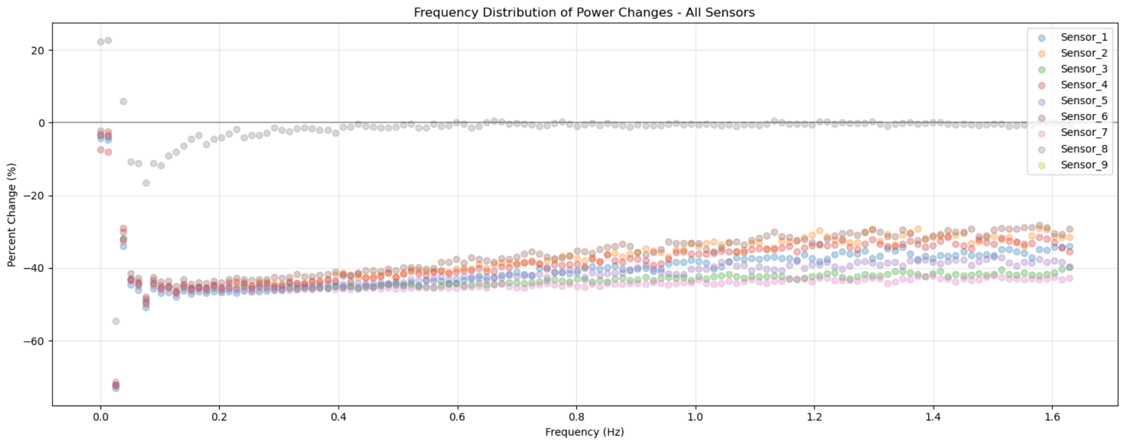
[9]:
```python
import seaborn as sns

# Analyze significant changes across all sensors
print("\nAnalyzing significant changes across all sensors...")

# Define the directory containing the CSV files
csv_dir_path = "significant_changes_csv_Mushroom_25-05-08_0326"

# Get all CSV files in the directory
csv_files = [f for f in os.listdir(csv_dir_path) if f.
 ↪endswith('_significant_changes.csv')]

# Initialize lists to store summary data
sensor_names = []
top_increase_freqs = []
top_decrease_freqs = []
all_sensor_data = {}

# Create a figure for comparing all sensors
plt.figure(figsize=(15, 6))

# Process each sensor's data
for csv_file in csv_files:
    # Extract sensor name from filename
    sensor_name = csv_file.split('_significant_changes.csv')[0]
    sensor_names.append(sensor_name)

    # Load the CSV data
    csv_path = os.path.join(csv_dir_path, csv_file)
    sensor_data = pd.read_csv(csv_path)
    all_sensor_data[sensor_name] = sensor_data
```

```
    # Sort by absolute percent change
    sensor_data['Abs_Percent_Change'] = np.abs(sensor_data['Percent_Change'])

    # Get top increases and decreases
    top_increases = sensor_data.sort_values('Percent_Change', ascending=False).
↪head(20)
    top_increase_freqs.append(top_increases['Frequency'].tolist())

    top_decreases = sensor_data.sort_values('Percent_Change', ascending=True).
↪head(20)
    top_decrease_freqs.append(top_decreases['Frequency'].tolist())

    # Plot frequency vs percent change for this sensor
    plt.scatter(sensor_data['Frequency'], sensor_data['Percent_Change'],
                alpha=0.3, label=sensor_name)

# Add plot details
plt.axhline(y=0, color='k', linestyle='-', alpha=0.3)
plt.xlabel('Frequency (Hz)')
plt.ylabel('Percent Change (%)')
plt.title('Frequency Distribution of Power Changes - All Sensors')
plt.legend()
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

# Analyze patterns in top increases and decreases
print("\nAnalyzing patterns in top increases and decreases...")

# Create figures for top increases and decreases
plt.figure(figsize=(15, 6))
plt.subplot(1, 2, 1)
for i, sensor_name in enumerate(sensor_names):
    sensor_data = all_sensor_data[sensor_name]
    top_increases = sensor_data.sort_values('Percent_Change', ascending=False).
↪head(10)
    plt.scatter(top_increases['Frequency'], top_increases['Percent_Change'],
                label=sensor_name, s=100, alpha=0.7)

    # Removed annotation of frequencies to avoid overlapping text

plt.title('Top 10 Frequencies with Largest Increases')
plt.xlabel('Frequency (Hz)')
plt.ylabel('Percent Change (%)')
plt.legend()
plt.grid(True, alpha=0.3)
```

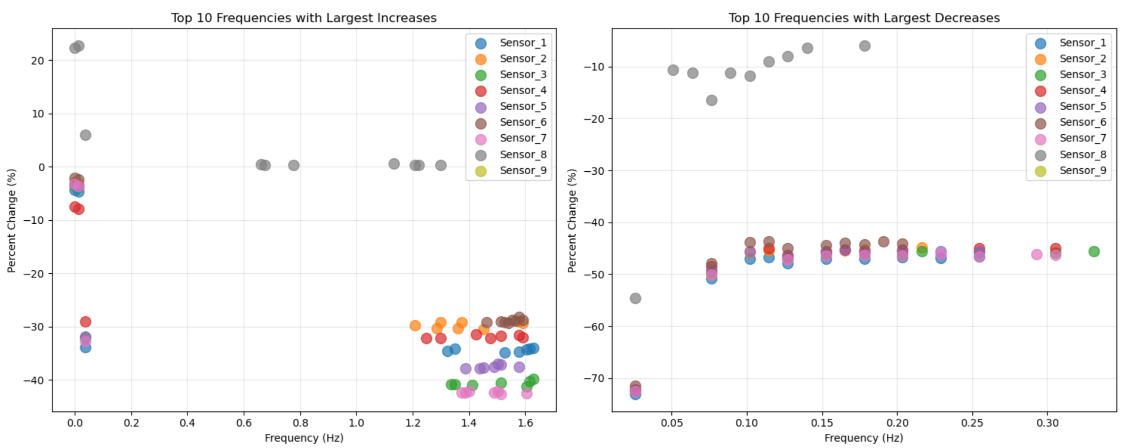
```
plt.subplot(1, 2, 2)
for i, sensor_name in enumerate(sensor_names):
    sensor_data = all_sensor_data[sensor_name]
    top_decreases = sensor_data.sort_values('Percent_Change', ascending=True).
 ↪head(10)
    plt.scatter(top_decreases['Frequency'], top_decreases['Percent_Change'],
                label=sensor_name, s=100, alpha=0.7)

    # Removed annotation of frequencies to avoid overlapping text

plt.title('Top 10 Frequencies with Largest Decreases')
plt.xlabel('Frequency (Hz)')
plt.ylabel('Percent Change (%)')
plt.legend()
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Analyze frequency overlap between sensors for top increases and decreases
print("\nAnalyzing frequency overlap between sensors...")

# For increases
increase_overlap = set(top_increase_freqs[0])
for freqs in top_increase_freqs[1:]:
    increase_overlap = increase_overlap.intersection(set(freqs))

# For decreases
decrease_overlap = set(top_decrease_freqs[0])
for freqs in top_decrease_freqs[1:]:
    decrease_overlap = decrease_overlap.intersection(set(freqs))

print(f"Common frequencies showing increases across all sensors:␣
 ↪{sorted(list(increase_overlap))}")
print(f"Common frequencies showing decreases across all sensors:␣
 ↪{sorted(list(decrease_overlap))}")

# Analyze the distribution of top changes by frequency range
for sensor_name in sensor_names:
    sensor_data = all_sensor_data[sensor_name]

    # Define frequency bands
    sensor_data['Frequency_Band'] = pd.cut(sensor_data['Frequency'],
                                           bins=[0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.
 ↪6, 0.7],
```

```
                                                labels=['0-0.1', '0.1-0.2', '0.2-0.
↪3', '0.3-0.4', '0.4-0.5', '0.5-0.6', '0.6-0.7'])

    # Count top increases and decreases by frequency band
    top_increases = sensor_data.sort_values('Percent_Change', ascending=False).
↪head(20)
    top_decreases = sensor_data.sort_values('Percent_Change', ascending=True).
↪head(20)

    increase_band_counts = top_increases['Frequency_Band'].value_counts().
↪sort_index()
    decrease_band_counts = top_decreases['Frequency_Band'].value_counts().
↪sort_index()

    # Plot distribution of top changes by frequency band
    plt.figure(figsize=(15, 6))
    plt.subplot(1, 2, 1)
    increase_band_counts.plot(kind='bar', color='green', alpha=0.7)
    plt.title(f'{sensor_name}: Distribution of Top 20 Increases by Frequency␣
↪Band')
    plt.xlabel('Frequency Band (Hz)')
    plt.ylabel('Count')
    plt.grid(True, alpha=0.3)

    plt.subplot(1, 2, 2)
    decrease_band_counts.plot(kind='bar', color='red', alpha=0.7)
    plt.title(f'{sensor_name}: Distribution of Top 20 Decreases by Frequency␣
↪Band')
    plt.xlabel('Frequency Band (Hz)')
    plt.ylabel('Count')
    plt.grid(True, alpha=0.3)

    plt.tight_layout()
    plt.show()
```

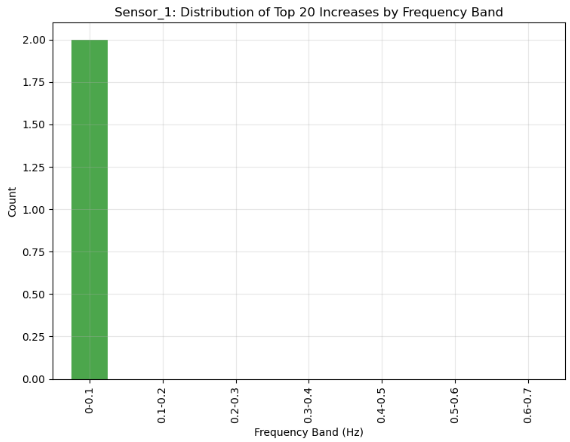
```
Analyzing significant changes across all sensors…
```

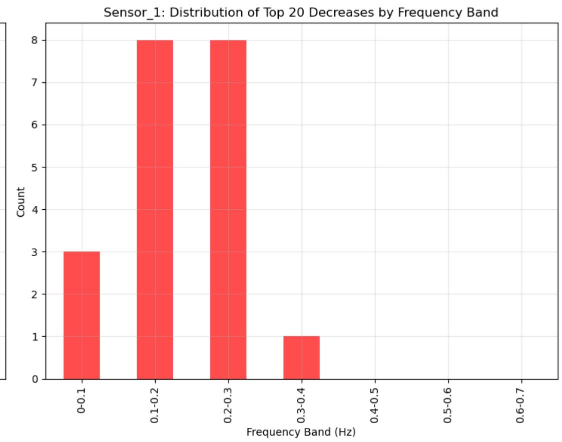


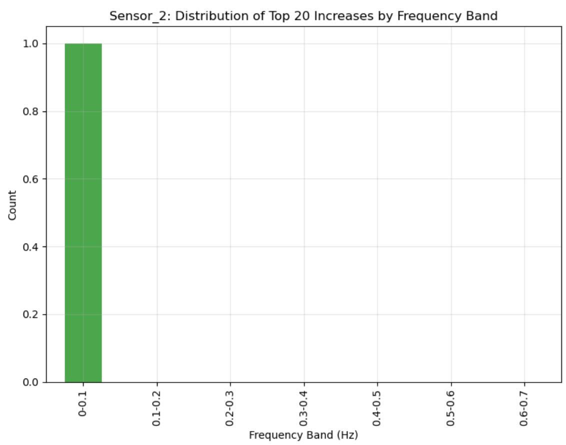
Analyzing patterns in top increases and decreases…

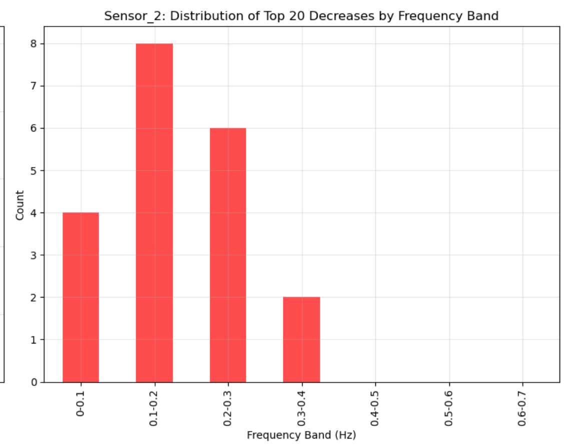


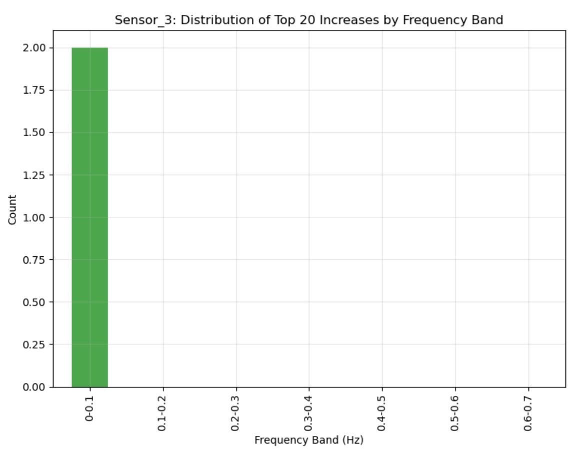
Analyzing frequency overlap between sensors…
Common frequencies showing increases across all sensors: [0.0, 0.0127218279707093]
Common frequencies showing decreases across all sensors: [0.0254436559414187, 0.0763309678242562, 0.101774623765675, 0.1272182797070937, 0.1526619356485125, 0.1653837636192219, 0.1781055915899312, 0.20354924753135]

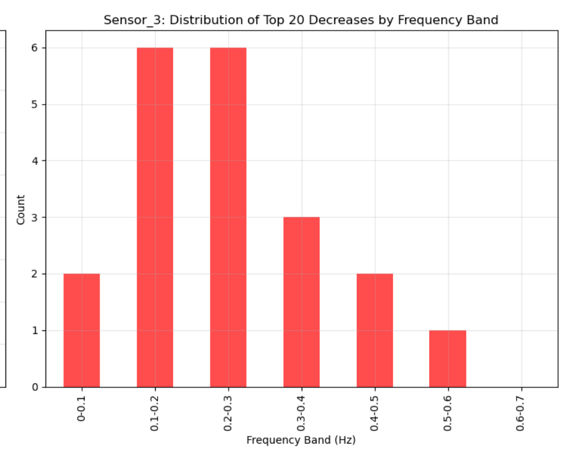

Sensor_1: Distribution of Top 20 Increases by Frequency Band
Count
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

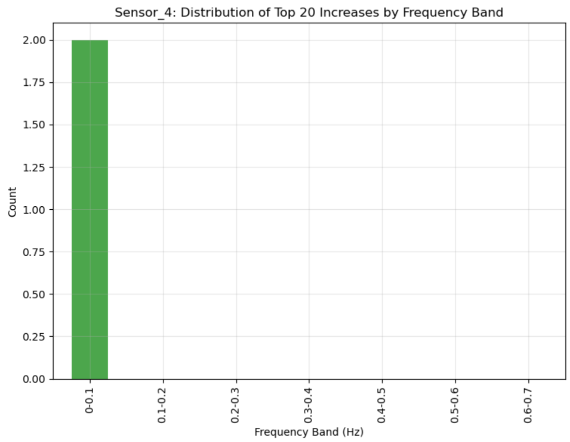

Sensor_1: Distribution of Top 20 Decreases by Frequency Band
Count
0
1
2
3
4
5
6
7
8
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

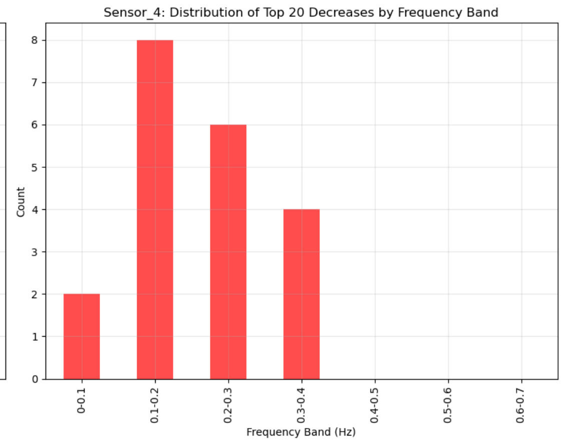

Sensor_2: Distribution of Top 20 Increases by Frequency Band
Count
0.0
0.2
0.4
0.6
0.8
1.0
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

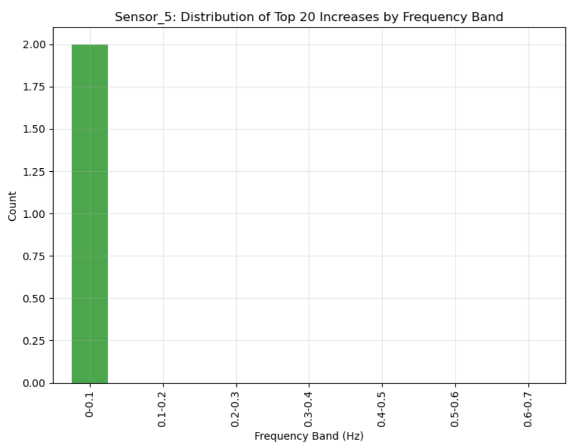

Sensor_2: Distribution of Top 20 Decreases by Frequency Band
Count
0
1
2
3
4
5
6
7
8
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

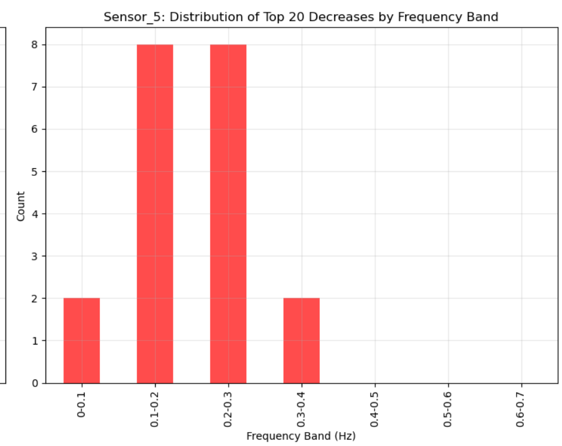

Sensor_3: Distribution of Top 20 Increases by Frequency Band
Count
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

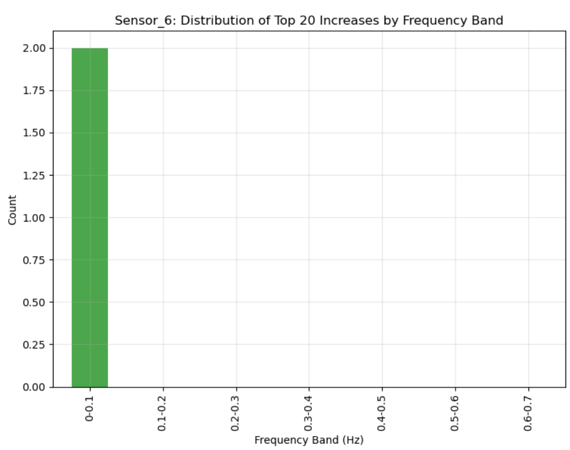

Sensor_3: Distribution of Top 20 Decreases by Frequency Band
Count
0
1
2
3
4
5
6
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

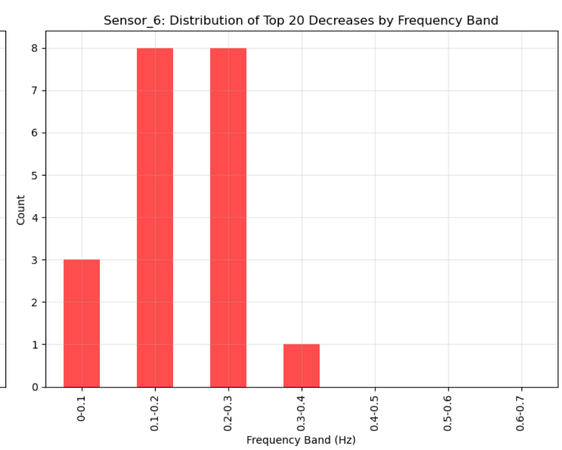

Sensor_4: Distribution of Top 20 Increases by Frequency Band
Count
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

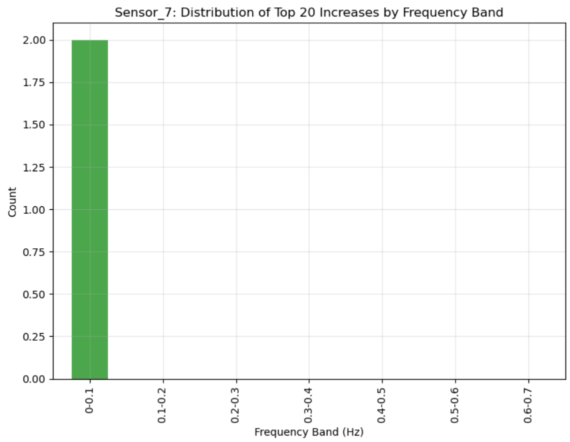

Sensor_4: Distribution of Top 20 Decreases by Frequency Band
Count
0
1
2
3
4
5
6
7
8
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

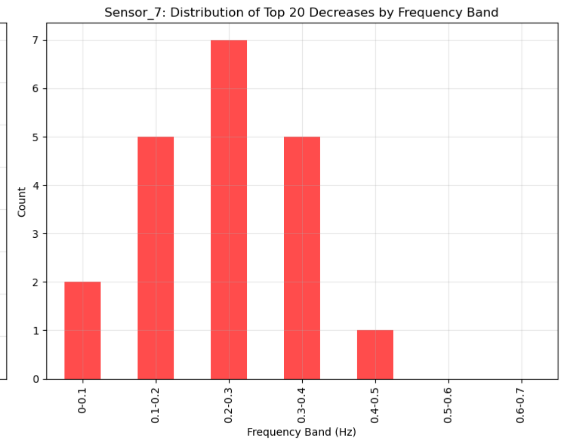

Sensor_5: Distribution of Top 20 Increases by Frequency Band
Count
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

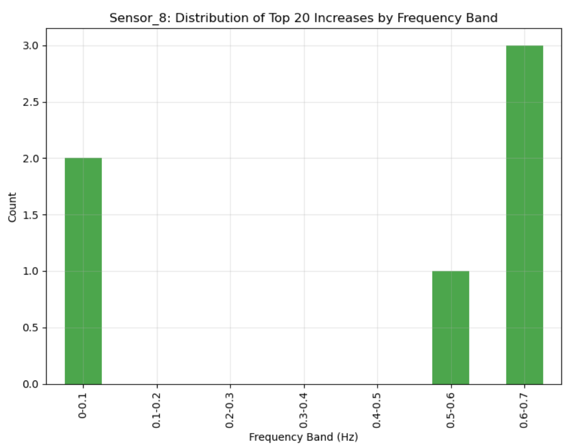

Sensor_5: Distribution of Top 20 Decreases by Frequency Band
Count
0
1
2
3
4
5
6
7
8
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

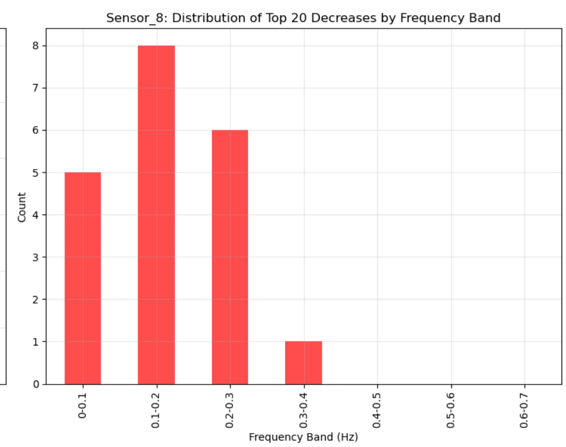

Sensor_6: Distribution of Top 20 Increases by Frequency Band
Count
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

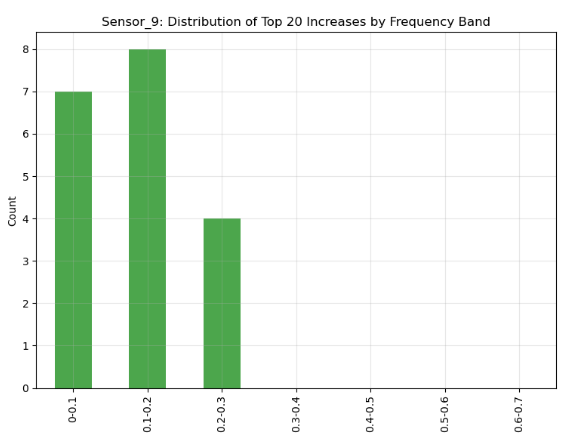

Sensor_6: Distribution of Top 20 Decreases by Frequency Band
Count
0
1
2
3
4
5
6
7
8
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

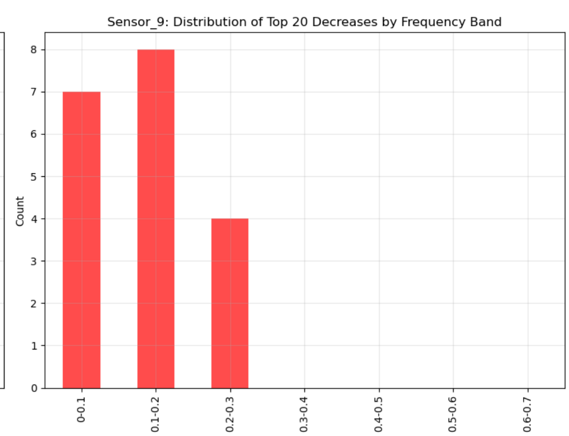

Sensor_7: Distribution of Top 20 Increases by Frequency Band
Count
Frequency Band (Hz)
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7


Sensor_7: Distribution of Top 20 Decreases by Frequency Band
Count
Frequency Band (Hz)
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7


Sensor_8: Distribution of Top 20 Increases by Frequency Band
Count
Frequency Band (Hz)
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7


Sensor_8: Distribution of Top 20 Decreases by Frequency Band
Count
Frequency Band (Hz)
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7


Sensor_9: Distribution of Top 20 Increases by Frequency Band
Count
Frequency Band (Hz)
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7


Sensor_9: Distribution of Top 20 Decreases by Frequency Band
Count
Frequency Band (Hz)
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7

[ ]: