da_Mushroom_25-05-08_0326-timeset2

May 14, 2025

[23]:
```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())
```

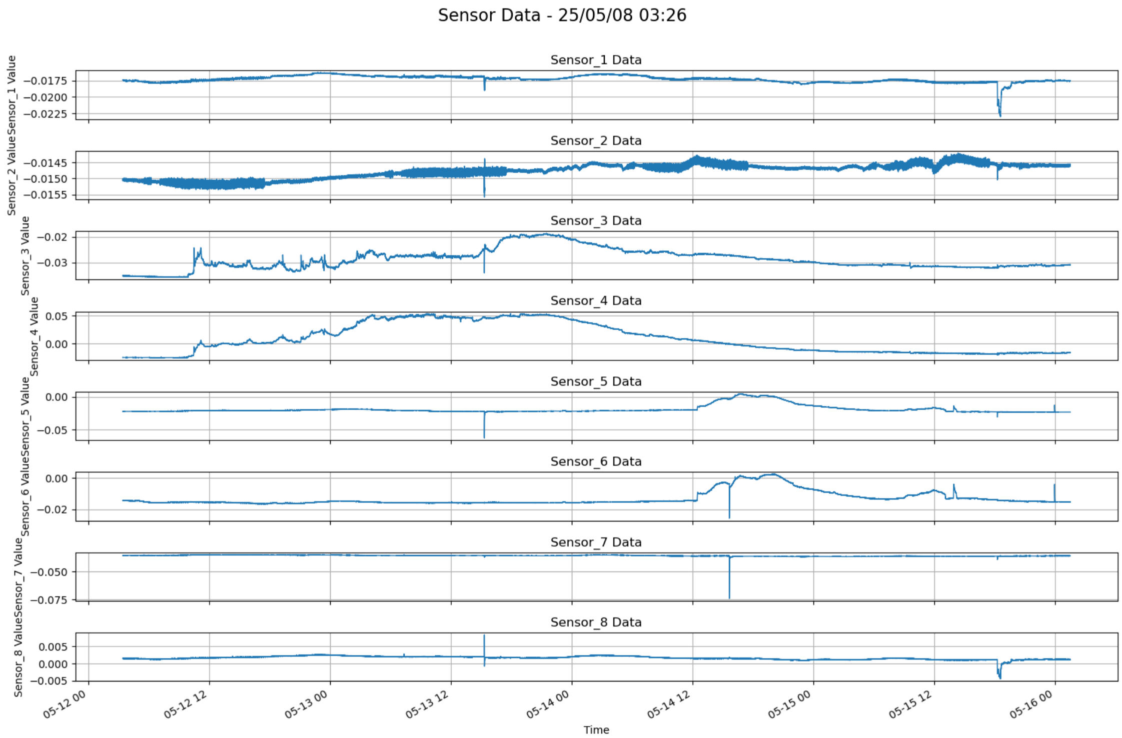
```
Data shape: (1084420, 10)

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
```

[24]:

```python
# 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()}")
```



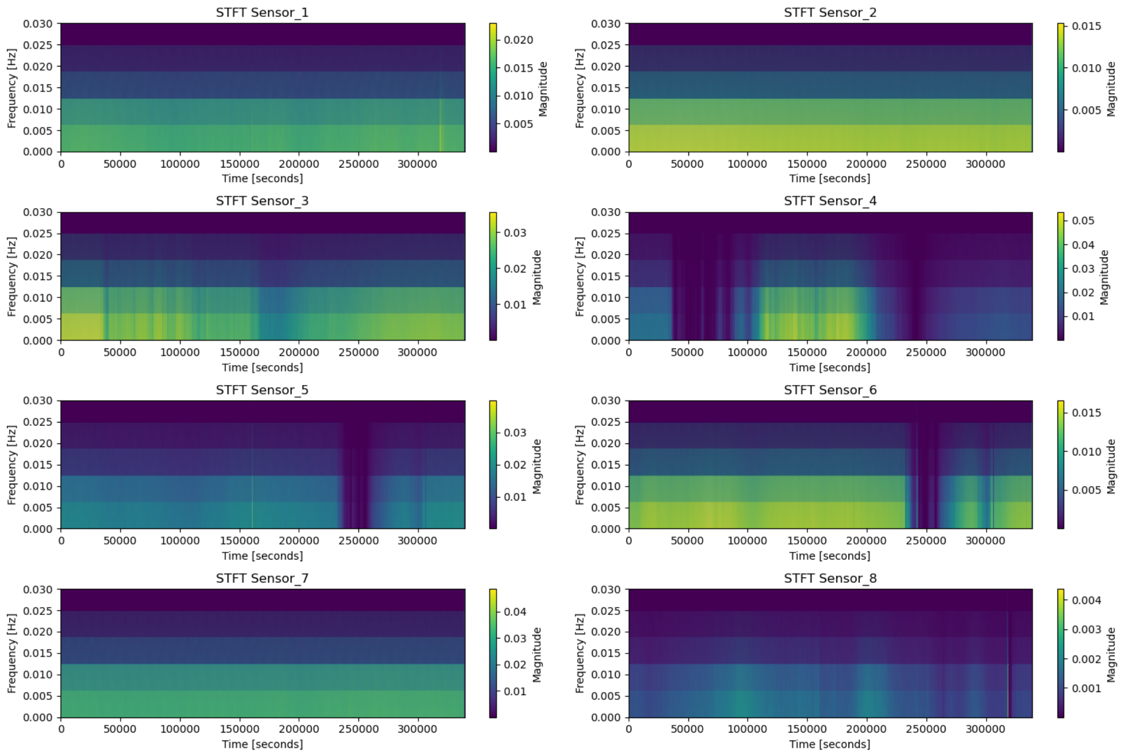

```
Sensor Statistics:

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
```

[25]:

```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
```

[26]:
```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)
```

```
# 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)
```

[27]:
```
# 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 = "2025-05-10T15:04:08.669Z"
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
```

```
# 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]}")
```

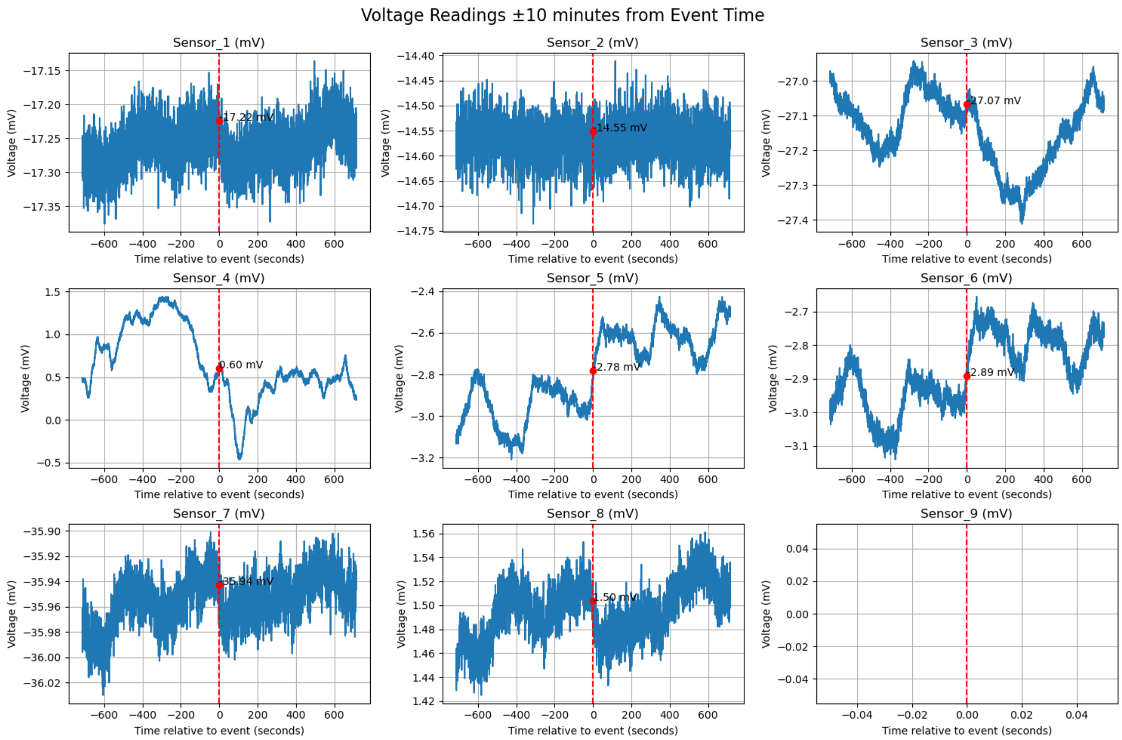
```
Event time: 2025-05-10T15:04:08.669Z
Recording start time: 2025-05-08 03:26:00 UTC
Seconds elapsed since recording start: 214688.67 seconds
First data timestamp: 120386.54 seconds
Target timestamp: 335075.21 seconds
Closest data timestamp: 335075.10 seconds
Difference from target: 0.11 seconds

Sensor readings at event time:
Sensor_1: -0.017224
Sensor_2: -0.014552
Sensor_3: -0.027067
Sensor_4: 0.000604
Sensor_5: -0.00278
Sensor_6: -0.002891
Sensor_7: -0.035943
Sensor_8: 0.001504
Sensor_9: nan
```

[28]:

```
# 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))
```

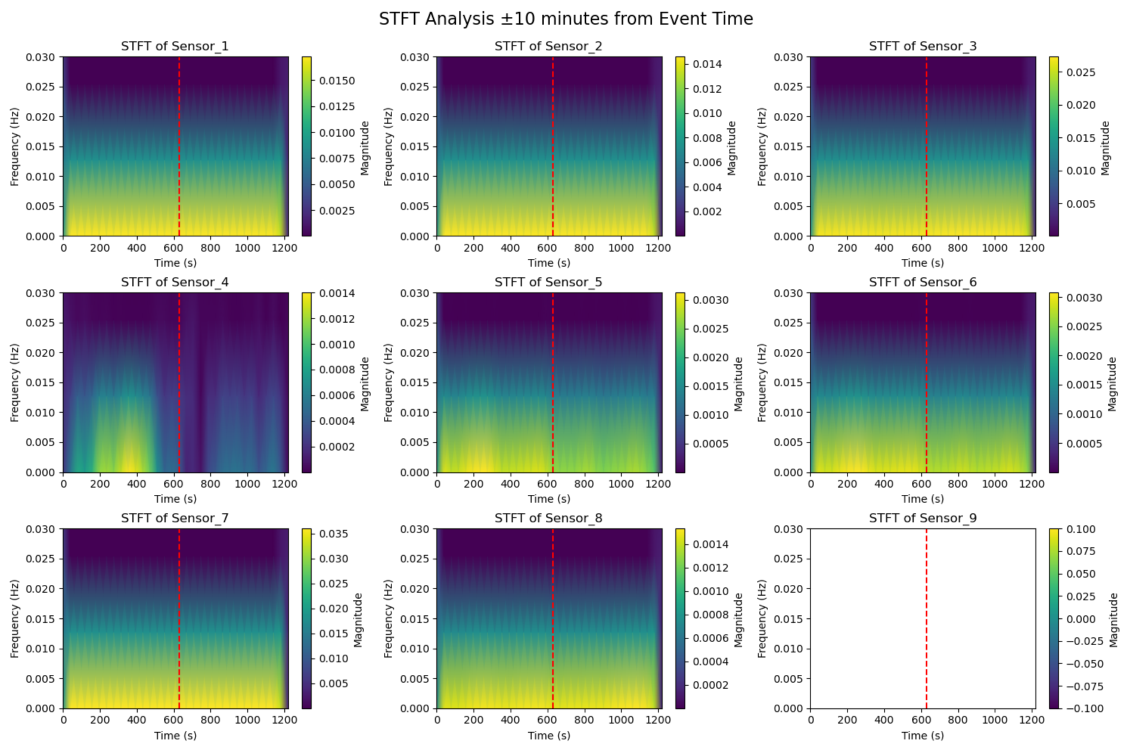
```
end_idx = min(len(data) - 1, event_idx + int(window_seconds * data['Timestamp'].
↪diff().median() ** -1))

# 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
```



[29]:
```python
# 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()
```



[30]:
```
# 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
```

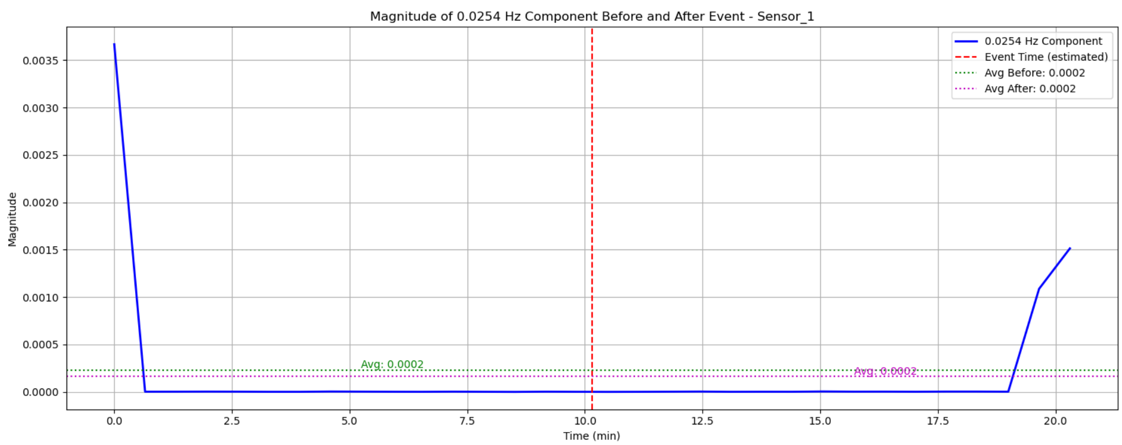
```python
    event_time_min = t.mean() / 60
    plt.axvline(x=event_time_min, color='r', linestyle='--', label='Event Time (estimated)')

    # 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
```

```python
    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)
```

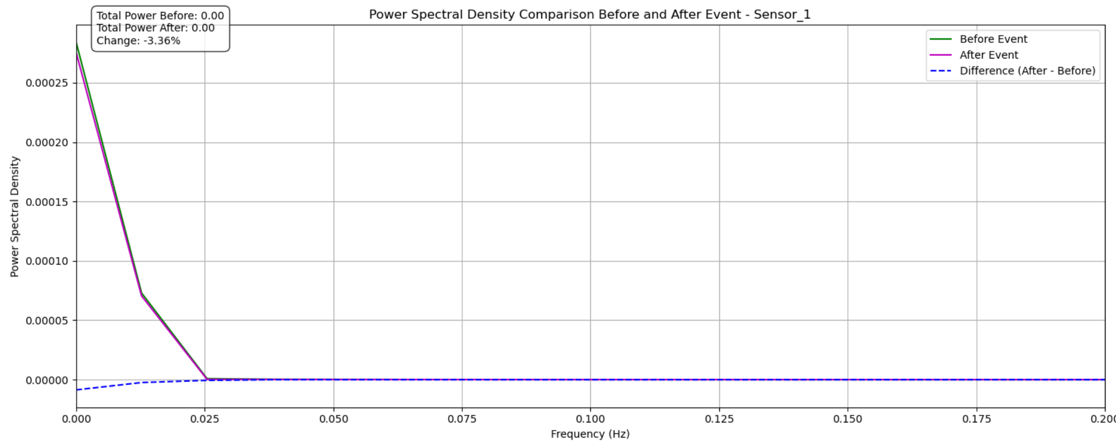
```python
    plt.legend()

    # 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))
```

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

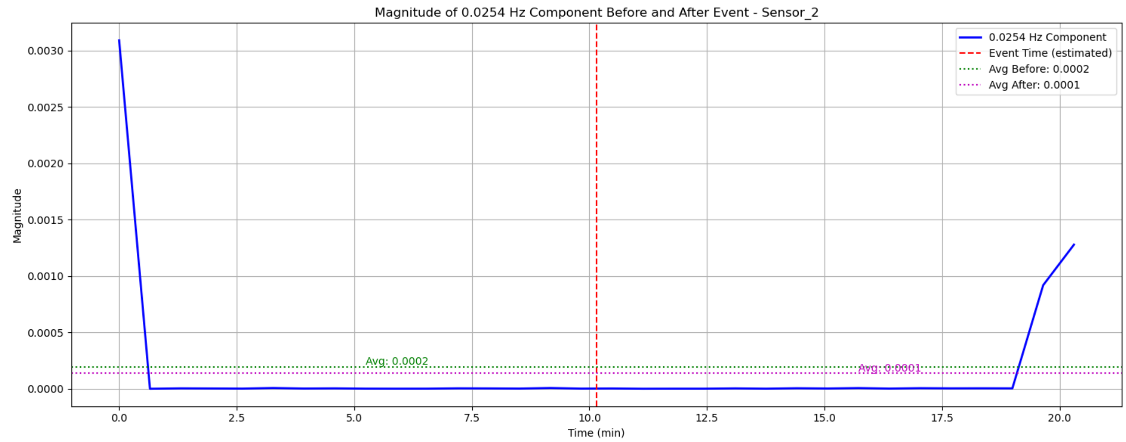
```
Created directory: significant_changes_csv_Mushroom_25-05-08_0326

=== 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 (-28.74%)
```



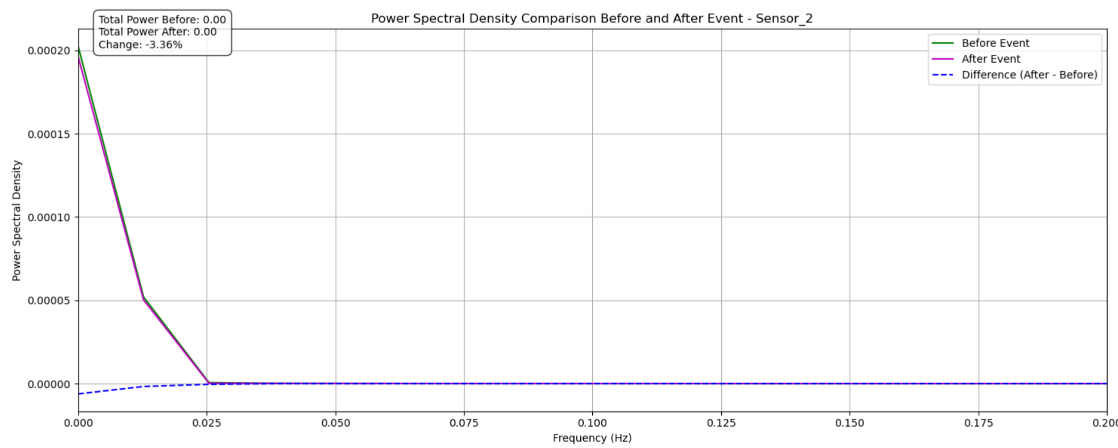

```
Energy Analysis:
Total energy before event: 0.0000
Total energy after event: 0.0000
Average energy before event: 0.0000
Average energy after event: 0.0000
Energy change: -0.0000 (-74.16%)
```




```
Power Spectral Density Analysis:
Total power before event: 0.0004
Total power after event: 0.0003
Absolute power change: -0.0000
Relative power change: -3.36%
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  2.840224e-04  2.753712e-04    -8.651119e-06       -3.045928
1     0.012722  7.291745e-05  7.046573e-05    -2.451723e-06       -3.362323
102   1.297626  3.088133e-10  1.848840e-10    -1.239293e-10      -30.314401
126   1.602950  2.824483e-10  1.661941e-10    -1.162541e-10      -30.397349
111   1.412123  2.937093e-10  1.724949e-10    -1.212144e-10      -30.787795

Top 5 frequencies with largest power decrease:
    Frequency        Before         After  Absolute_Change  Percent_Change
2    0.025444  8.409839e-07  2.318204e-07    -6.091635e-07      -72.426005
6    0.076331  5.578890e-08  2.794681e-08    -2.784209e-08      -49.816855
10   0.127218  1.939996e-08  1.024531e-08    -9.154652e-09      -46.947035
16   0.203549  7.588704e-09  4.014214e-09    -3.574490e-09      -46.490153
28   0.356211  2.569080e-09  1.335901e-09    -1.233179e-09      -46.202399

=== 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 (-28.43%)
```

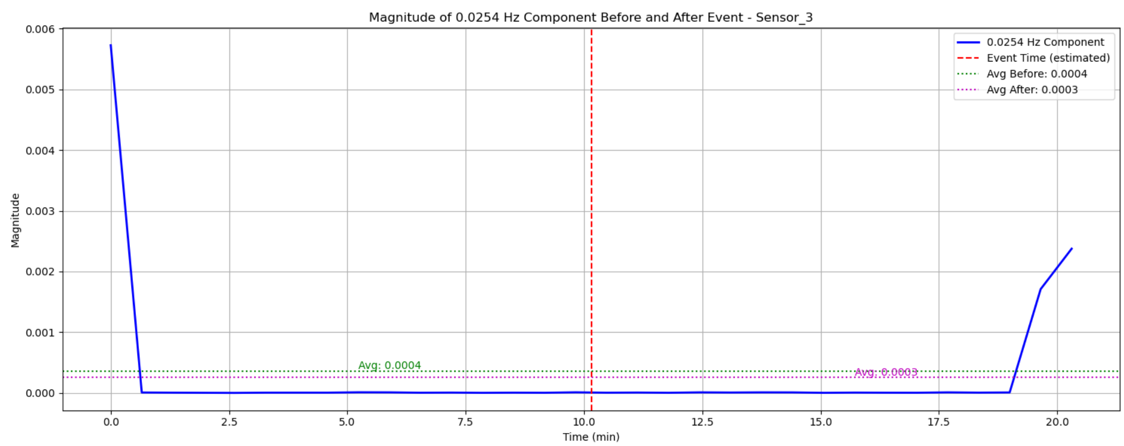


Energy Analysis:
Total energy before event: 0.0000
Total energy after event: 0.0000
Average energy before event: 0.0000
Average energy after event: 0.0000
Energy change: -0.0000 (-74.03%)

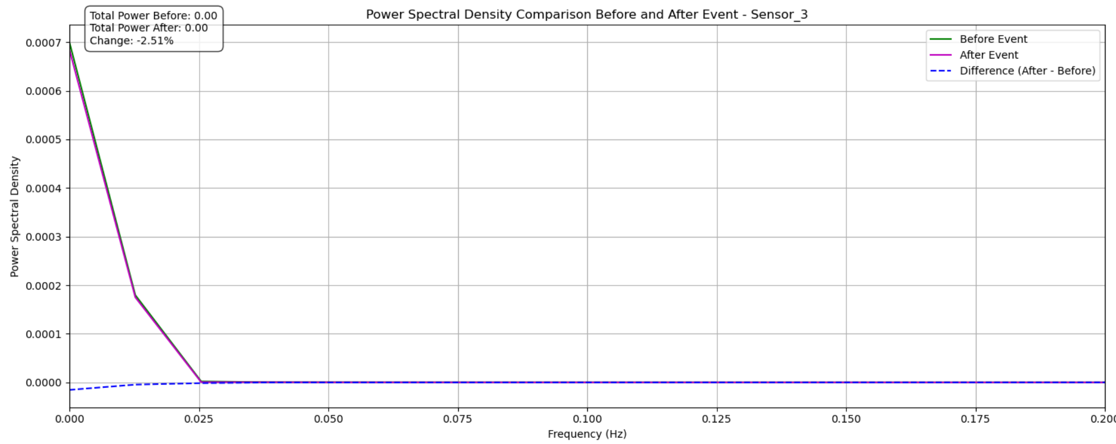


Power Spectral Density Analysis:
Total power before event: 0.0003
Total power after event: 0.0002
Absolute power change: -0.0000
Relative power change: -3.36%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_2_significant_changes.csv

```
Top 5 frequencies with largest power increase:
     Frequency         Before         After  Absolute_Change  Percent_Change
0     0.000000  2.024181e-04  1.962362e-04    -6.181930e-06       -3.054039
1     0.012722  5.195415e-05  5.021567e-05    -1.738478e-06       -3.346172
118   1.501176  2.072274e-10  1.389820e-10    -6.824537e-11      -22.213310
117   1.488454  2.140519e-10  1.419339e-10    -7.211797e-11      -22.963710
124   1.577507  1.986884e-10  1.300767e-10    -6.861166e-11      -22.970982

Top 5 frequencies with largest power decrease:
    Frequency         Before         After  Absolute_Change  Percent_Change
2    0.025444  5.969653e-07  1.653951e-07    -4.315702e-07      -72.281907
6    0.076331  3.976444e-08  1.976324e-08    -2.000119e-08      -50.173022
10   0.127218  1.391801e-08  7.357443e-09    -6.560563e-09      -46.800970
14   0.178106  7.030421e-09  3.695843e-09    -3.334579e-09      -46.765523
12   0.152662  9.601692e-09  5.087783e-09    -4.513909e-09      -46.527031

=== 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 (-28.14%)
```




```
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 (-73.87%)
```




```
Power Spectral Density Analysis:
Total power before event: 0.0009
Total power after event: 0.0009
Absolute power change: -0.0000
Relative power change: -2.51%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_3_significant_changes.csv
```

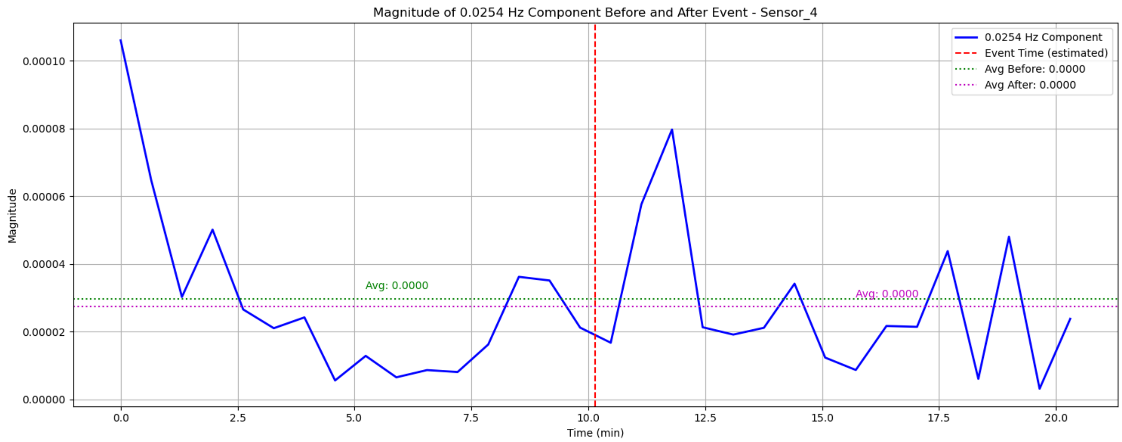
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
0	0.000000	6.996863e-04	6.842867e-04	-1.539968e-05	-2.200940
1	0.012722	1.795994e-04	1.750748e-04	-4.524577e-06	-2.519260
3	0.038165	5.126025e-07	3.487445e-07	-1.638580e-07	-31.959672
97	1.234017	7.998552e-10	4.508056e-10	-3.490496e-10	-38.789531
117	1.488454	7.044930e-10	3.920030e-10	-3.124900e-10	-38.843093

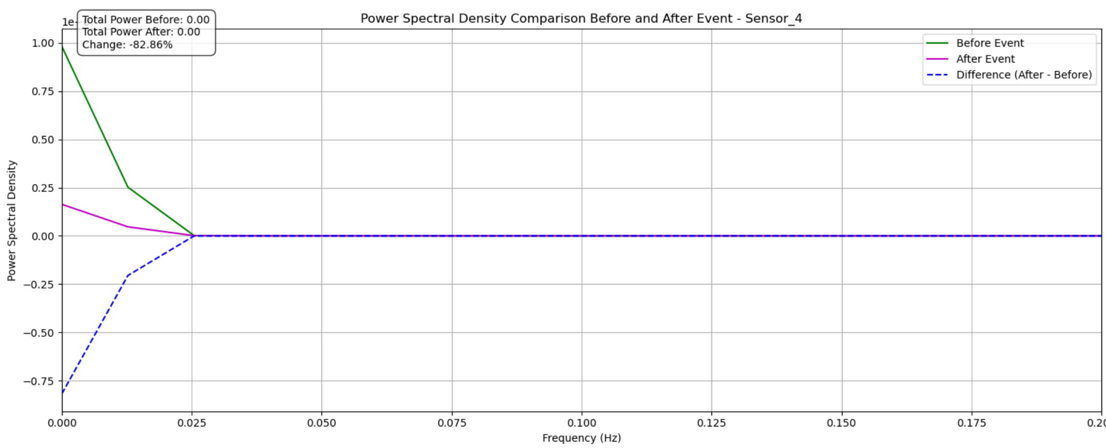
Top 5 frequencies with largest power decrease:

	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	2.049565e-06	5.712927e-07	-1.478272e-06	-72.122624
6	0.076331	1.356752e-07	6.873570e-08	-6.693948e-08	-49.301707
10	0.127218	4.724964e-08	2.517567e-08	-2.207398e-08	-46.619101
14	0.178106	2.405503e-08	1.296550e-08	-1.108954e-08	-45.909841
12	0.152662	3.270060e-08	1.767198e-08	-1.502862e-08	-45.818114

```
=== Analysis for Sensor_4 ===
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 (-7.28%)
```




```
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 (-24.07%)
```




```
Power Spectral Density Analysis:
Total power before event: 0.0000
Total power after event: 0.0000
Absolute power change: -0.0000
Relative power change: -82.86%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_4_significant_changes.csv
```

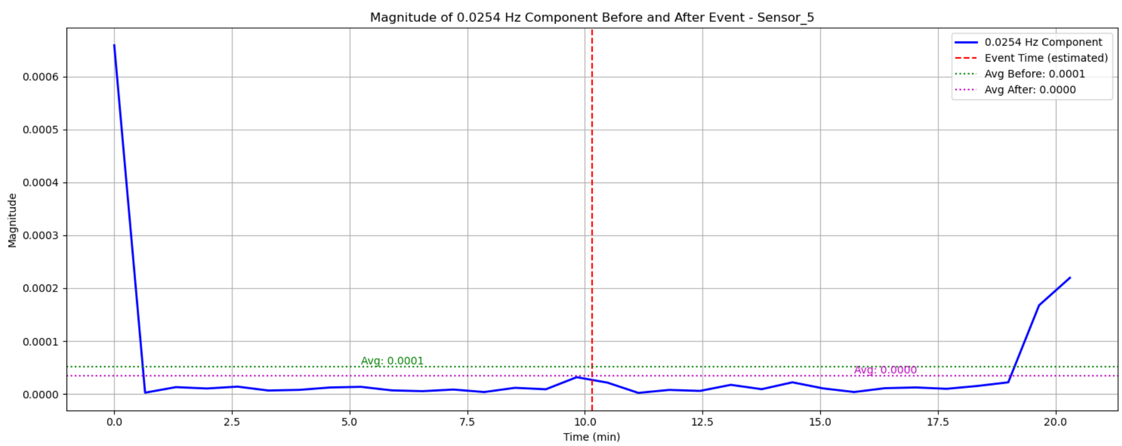
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
90	1.144965	7.380428e-13	2.123932e-12	1.385889e-12	1.375735
63	0.801475	1.068066e-12	2.031608e-12	9.635421e-13	0.953360
64	0.814197	1.117702e-12	1.956897e-12	8.391951e-13	0.829919
91	1.157686	9.541229e-13	1.700701e-12	7.465780e-13	0.739522
122	1.552063	8.793998e-13	1.580827e-12	7.014267e-13	0.695312

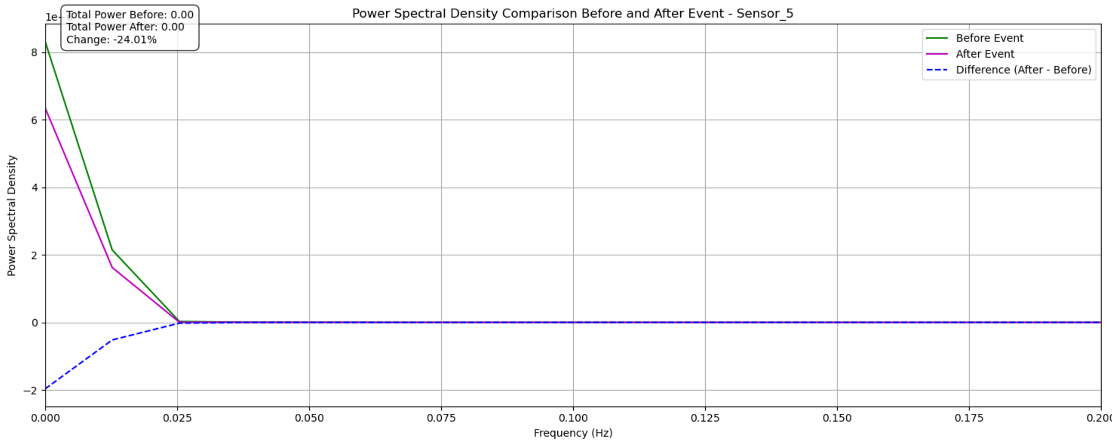
Top 5 frequencies with largest power decrease:

	Frequency	Before	After	Absolute_Change	Percent_Change
0	0.000000	9.819873e-07	1.634595e-07	-8.185278e-07	-83.345730
1	0.012722	2.520539e-07	4.680421e-08	-2.052496e-07	-81.398574
3	0.038165	3.720643e-10	1.679148e-10	-2.041495e-10	-43.246123
4	0.050887	1.440961e-10	8.977158e-11	-5.432448e-11	-22.255371
6	0.076331	5.783048e-11	2.350074e-11	-3.432974e-11	-21.751018

=== Analysis for Sensor_5 ===
Analyzing frequency: 0.0254 Hz (closest to 0.02 Hz)
Average magnitude before event: 0.0001
Average magnitude after event: 0.0000
Change: -0.0000 (-31.71%)



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 (-81.93%)



Power Spectral Density Analysis:
Total power before event: 0.0000
Total power after event: 0.0000
Absolute power change: -0.0000
Relative power change: -24.01%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_5_significant_changes.csv

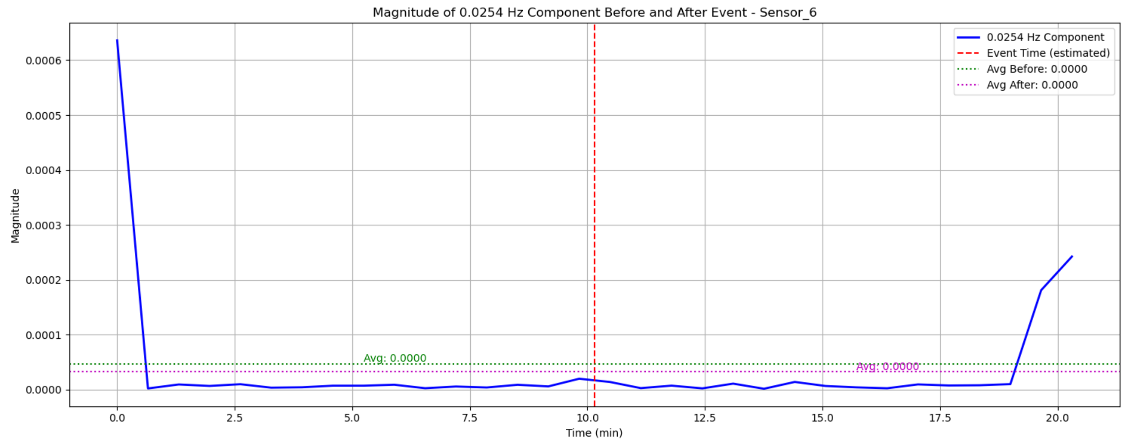
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
92	1.170408	1.061616e-11	5.946788e-12	-4.669371e-12	-4.221237
110	1.399401	1.011249e-11	5.406888e-12	-4.705601e-12	-4.273449
93	1.183130	1.060968e-11	5.845893e-12	-4.763783e-12	-4.306841
121	1.539341	9.813716e-12	4.795370e-12	-5.018346e-12	-4.569872
107	1.361236	1.023987e-11	5.184280e-12	-5.055592e-12	-4.585992

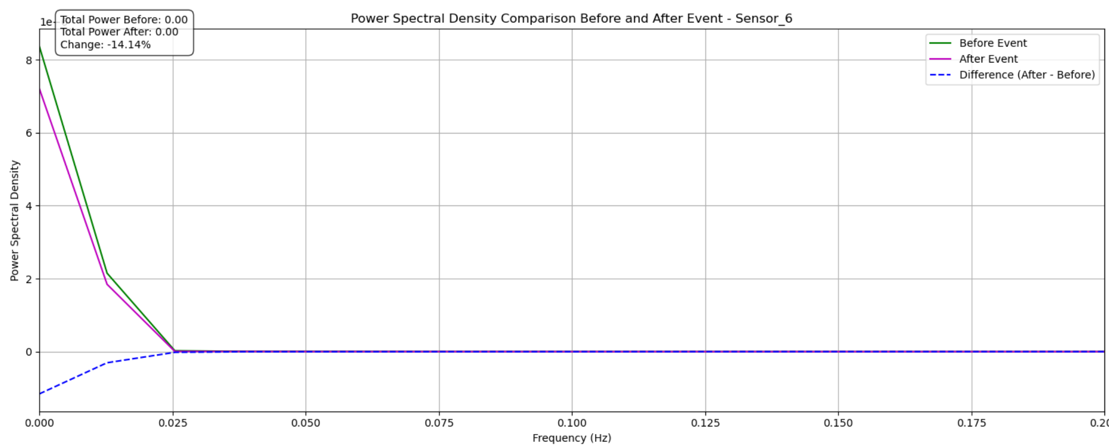
Top 5 frequencies with largest power decrease:

	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	2.726763e-08	5.224926e-09	-2.204270e-08	-80.542976
4	0.050887	4.384361e-09	1.537589e-09	-2.846772e-09	-63.482229
5	0.063609	2.489485e-09	8.608365e-10	-1.628649e-09	-62.894689
6	0.076331	1.792794e-09	6.037022e-10	-1.189092e-09	-62.822045
7	0.089053	1.218936e-09	4.446786e-10	-7.742573e-10	-58.703178

=== Analysis for Sensor_6 ===
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 (-29.45%)



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 (-77.23%)



Power Spectral Density Analysis:
Total power before event: 0.0000
Total power after event: 0.0000
Absolute power change: -0.0000
Relative power change: -14.14%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_6_significant_changes.csv

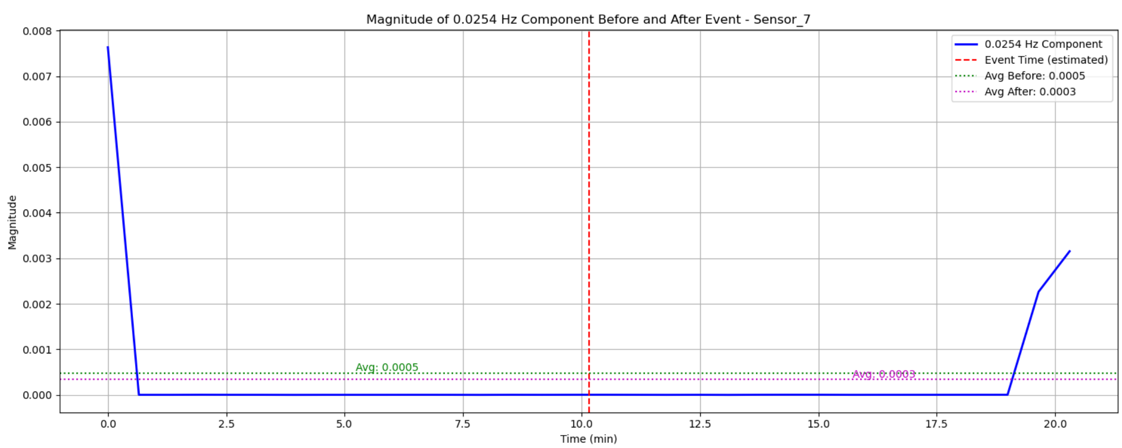
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
100	1.272183	8.703103e-12	7.931479e-12	-7.716231e-13	-0.709845
118	1.501176	9.004131e-12	7.797478e-12	-1.206653e-12	-1.106979
128	1.628394	8.508307e-12	6.359306e-12	-2.149001e-12	-1.980494
125	1.590228	8.945743e-12	6.095834e-12	-2.849910e-12	-2.615898
103	1.310348	9.924172e-12	6.898224e-12	-3.025947e-12	-2.752759

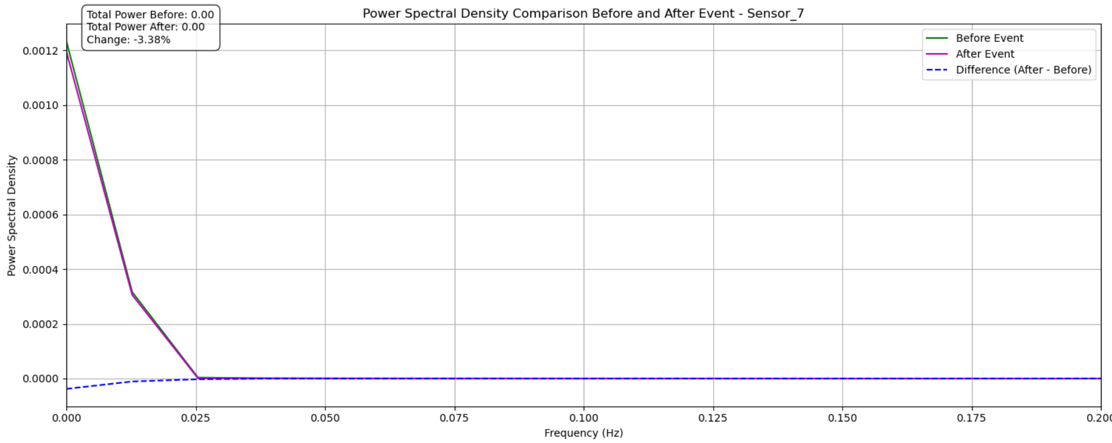
Top 5 frequencies with largest power decrease:

	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	2.534508e-08	6.144283e-09	-1.920080e-08	-75.459769
6	0.076331	1.682464e-09	7.227571e-10	-9.597068e-10	-53.841585
4	0.050887	4.090476e-09	1.882448e-09	-2.208028e-09	-52.691579
5	0.063609	2.314417e-09	1.046466e-09	-1.267951e-09	-52.515823
7	0.089053	1.162278e-09	5.419679e-10	-6.203100e-10	-49.142108

=== 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 (-28.81%)



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 (-74.11%)



Power Spectral Density Analysis:
Total power before event: 0.0016
Total power after event: 0.0015
Absolute power change: -0.0001
Relative power change: -3.38%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_7_significant_changes.csv

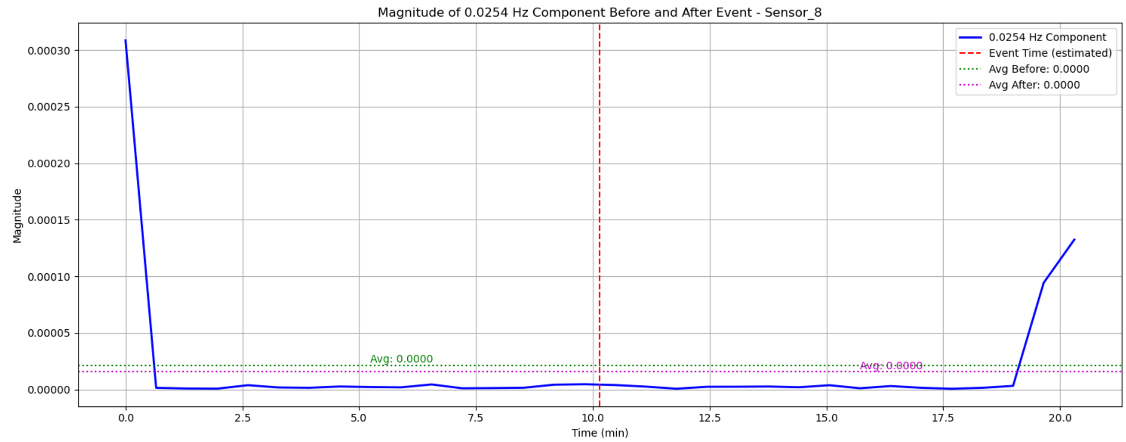
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
0	0.000000	1.232699e-03	1.194873e-03	-3.782522e-05	-3.068489
1	0.012722	3.164419e-04	3.057519e-04	-1.068998e-05	-3.378181
3	0.038165	9.108618e-07	6.141675e-07	-2.966944e-07	-32.569351
109	1.386679	1.281950e-09	7.101124e-10	-5.718380e-10	-41.379053
124	1.577507	1.228680e-09	6.758045e-10	-5.528756e-10	-41.610888

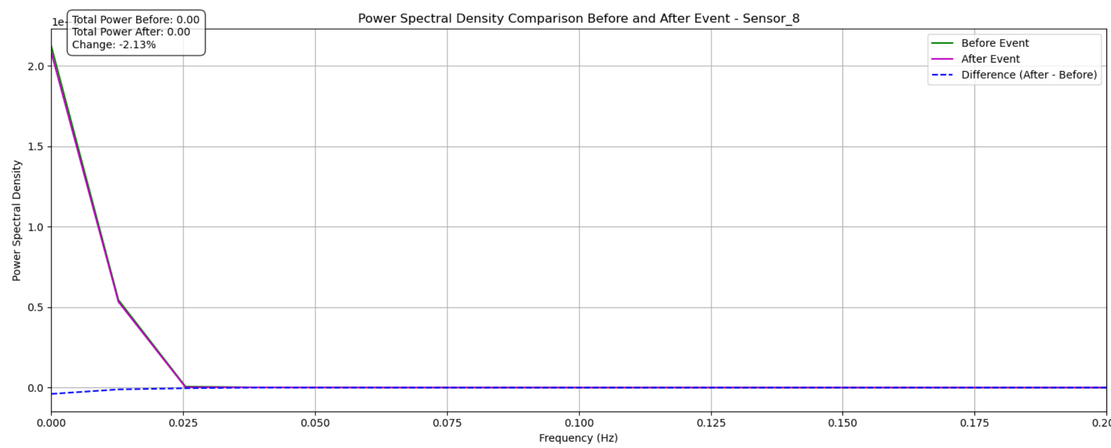
Top 5 frequencies with largest power decrease:

	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	3.641858e-06	1.005688e-06	-2.636170e-06	-72.383312
6	0.076331	2.410921e-07	1.209389e-07	-1.201533e-07	-49.816408
10	0.127218	8.407059e-08	4.440923e-08	-3.966136e-08	-47.120207
20	0.254437	2.100481e-08	1.121392e-08	-9.790893e-09	-46.391757
16	0.203549	3.275098e-08	1.751870e-08	-1.523228e-08	-46.367797

=== 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 (-24.78%)



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 (-72.22%)



Power Spectral Density Analysis:
Total power before event: 0.0000
Total power after event: 0.0000
Absolute power change: -0.0000
Relative power change: -2.13%
Saved significant changes data to:
significant_changes_csv_Mushroom_25-05-08_0326\Sensor_8_significant_changes.csv

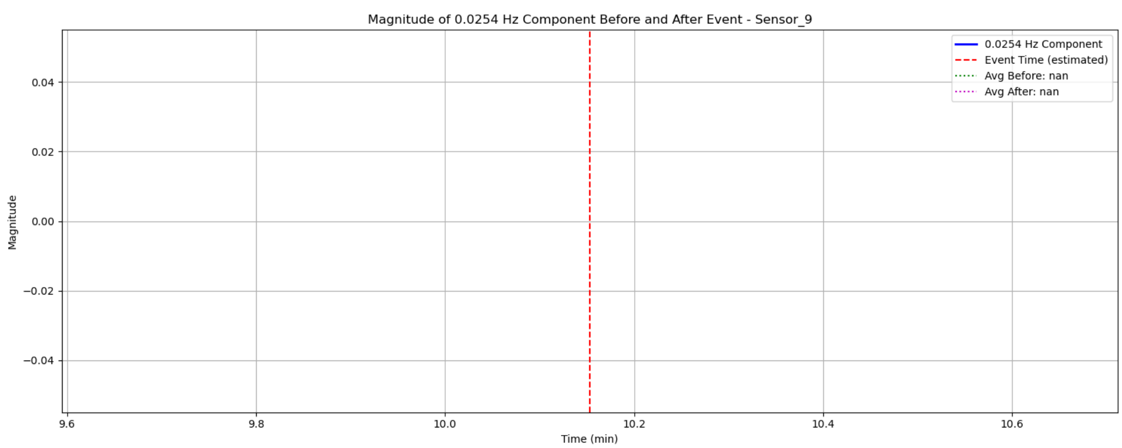
Top 5 frequencies with largest power increase:

	Frequency	Before	After	Absolute_Change	Percent_Change
125	1.590228	2.767397e-12	3.370623e-12	6.032261e-13	0.586982
109	1.386679	2.187443e-12	2.493848e-12	3.064052e-13	0.299846
123	1.564785	2.371650e-12	2.656441e-12	2.847909e-13	0.278193
110	1.399401	2.469557e-12	2.547168e-12	7.761063e-14	0.075740
124	1.577507	2.520601e-12	2.346248e-12	-1.743531e-13	-0.170066

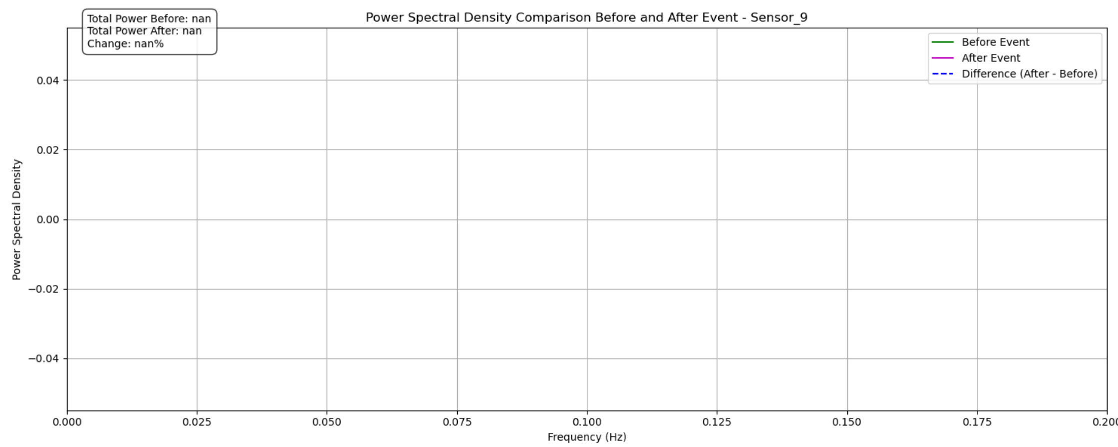
Top 5 frequencies with largest power decrease:

	Frequency	Before	After	Absolute_Change	Percent_Change
2	0.025444	5.955709e-09	1.763804e-09	-4.191906e-09	-69.222371
6	0.076331	3.978336e-10	2.152270e-10	-1.826066e-10	-36.680251
4	0.050887	9.427656e-10	5.773496e-10	-3.654160e-10	-35.042966
5	0.063609	5.403194e-10	3.211520e-10	-2.191674e-10	-34.227819
7	0.089053	2.685140e-10	1.668620e-10	-1.016520e-10	-27.584291

=== 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
```

[31]:

```python
# Delete data for the 9th sensor in the
↪significant_changes_csv_Mushroom_25-05-08_0326 directory

import os
import shutil

# 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')]

# Sort the files to ensure consistent ordering
csv_files.sort()

# Check if we have at least 9 sensors
if len(csv_files) >= 9:
    # Get the 9th sensor's filename (index 8 since zero-based)
    ninth_sensor_file = csv_files[8]
    ninth_sensor_path = os.path.join(csv_dir_path, ninth_sensor_file)

    # Print information about the file being deleted
    print(f"Deleting data for the 9th sensor: {ninth_sensor_file}")

    # Option 1: Delete the file
    os.remove(ninth_sensor_path)
    print(f"File {ninth_sensor_file} has been deleted.")

    # Alternative option (commented out): Create a backup instead of deleting
    # backup_path = ninth_sensor_path + ".backup"
    # shutil.copy2(ninth_sensor_path, backup_path)
    # os.remove(ninth_sensor_path)
    # print(f"File {ninth_sensor_file} has been deleted. Backup created at␣
↪{backup_path}")
else:
    print(f"There are only {len(csv_files)} sensor files in the directory,␣
↪cannot delete the 9th sensor.")
```

```
Deleting data for the 9th sensor: Sensor_9_significant_changes.csv
File Sensor_9_significant_changes.csv has been deleted.
```

[32]:

```
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')]
```

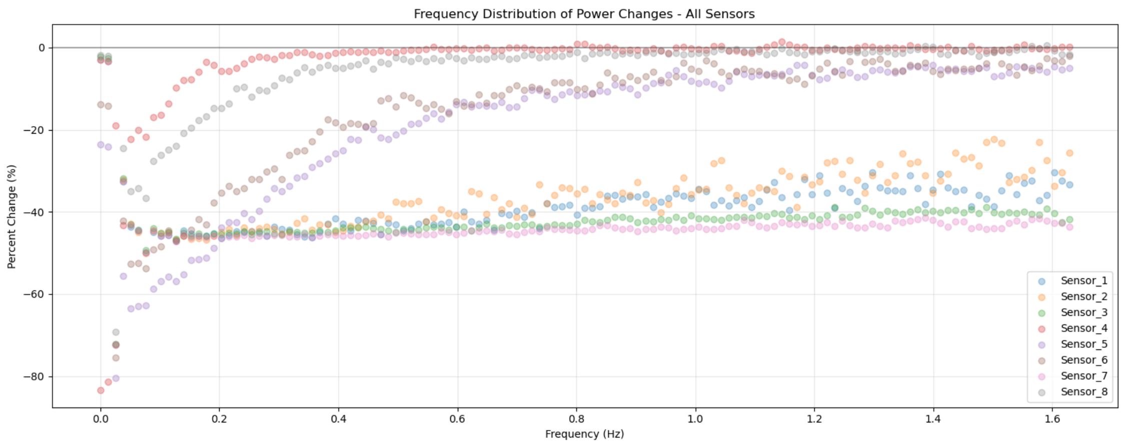
```
# Initialize lists to store summary data
sensor_names = []
top_increase_freqs = []
top_decrease_freqs = []
all_sensor_data = {}

# 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
```

```python
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))
```

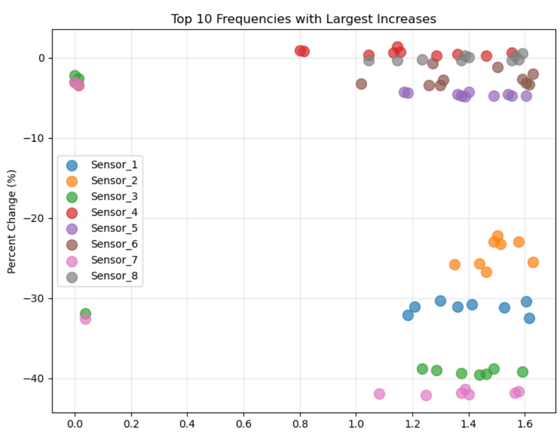
```
# For decreases
decrease_overlap = set(top_decrease_freqs[0])
for freqs in top_decrease_freqs[1:]:
    decrease_overlap = decrease_overlap.intersection(set(freqs))

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')
```

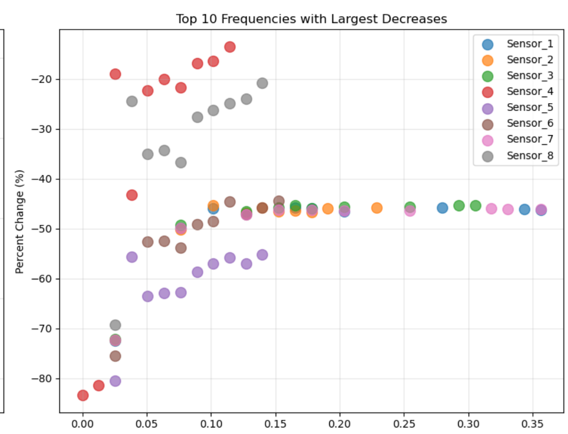
```
    plt.xlabel('Frequency Band (Hz)')
    plt.ylabel('Count')
    plt.grid(True, alpha=0.3)

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

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



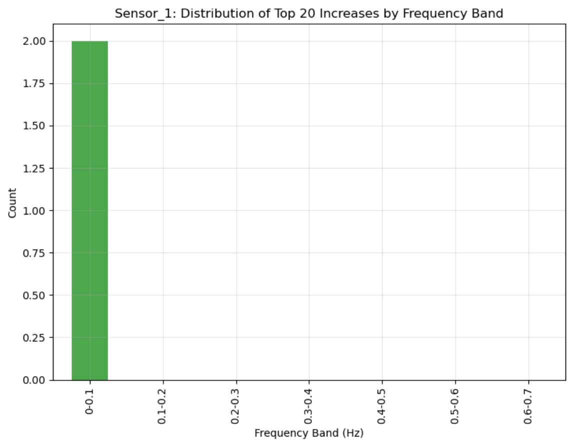

```
Analyzing patterns in top increases and decreases…
```

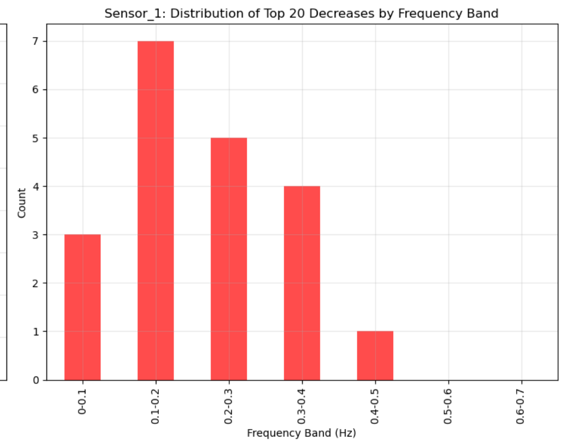


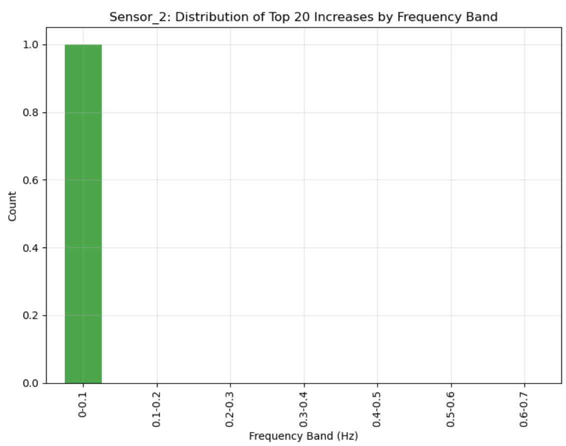


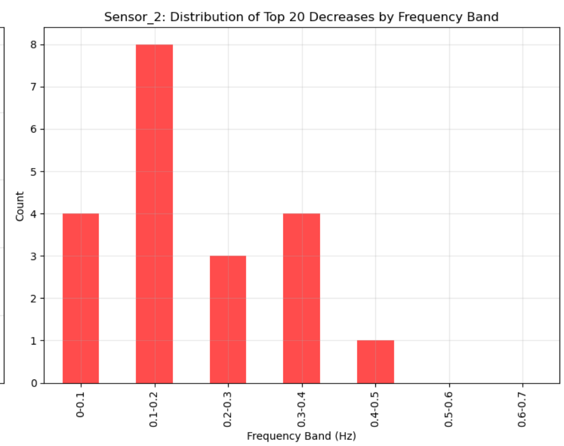

```
Analyzing frequency overlap between sensors…
Common frequencies showing increases across all sensors: [1.3612355928659037]
Common frequencies showing decreases across all sensors: [0.0254436559414187,
```

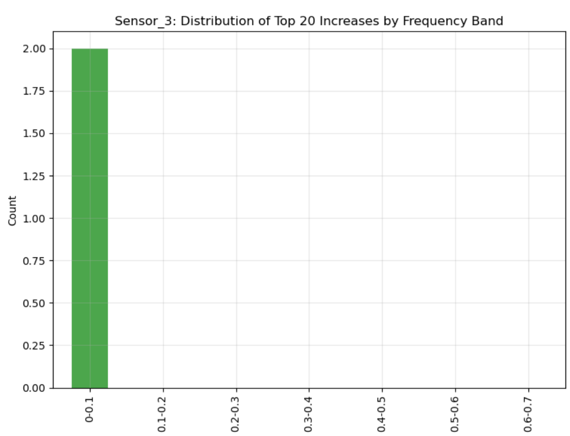
0.0763309678242562, 0.101774623765675, 0.1272182797070937, 0.1526619356485125, 0.1653837636192219, 0.1781055915899312, 0.1908274195606406, 0.20354924753135]

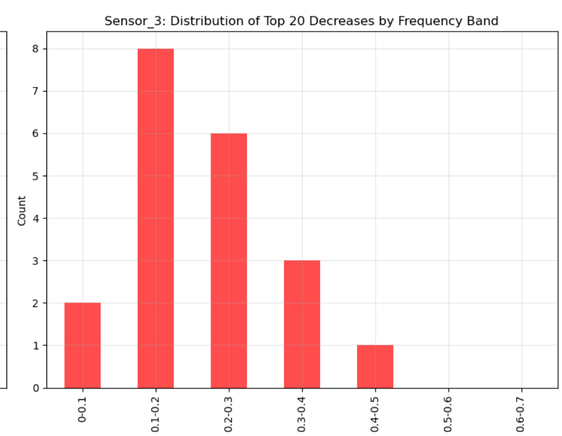


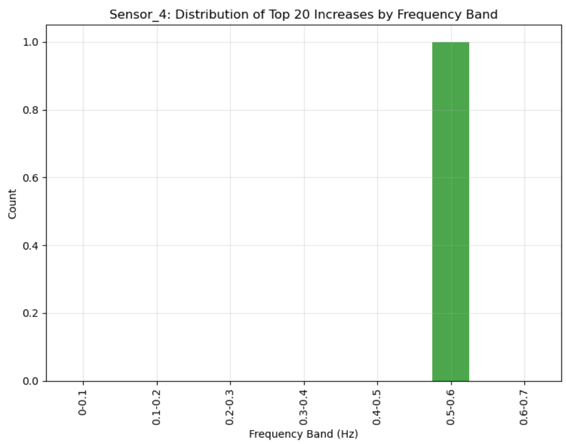


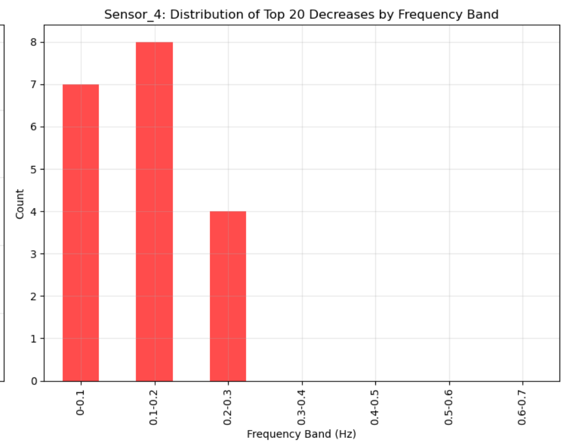


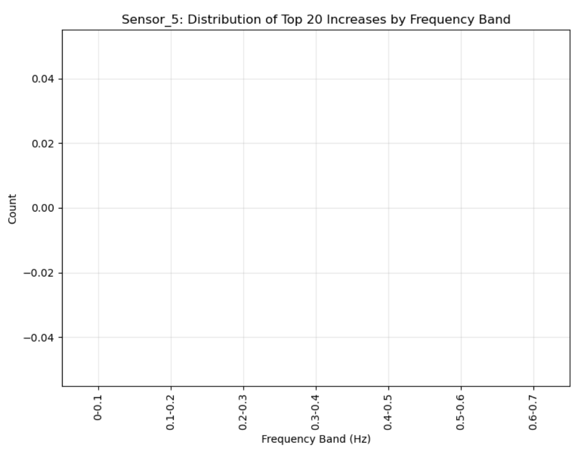


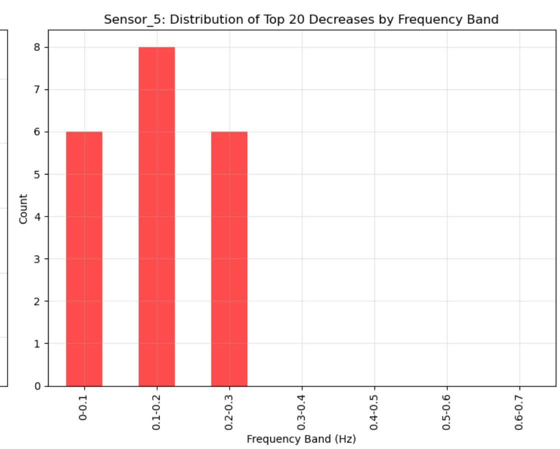


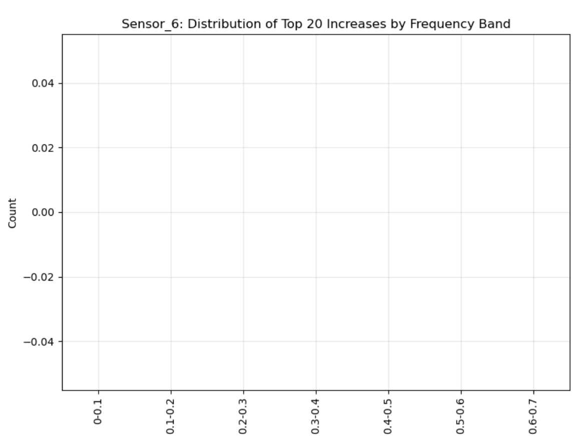


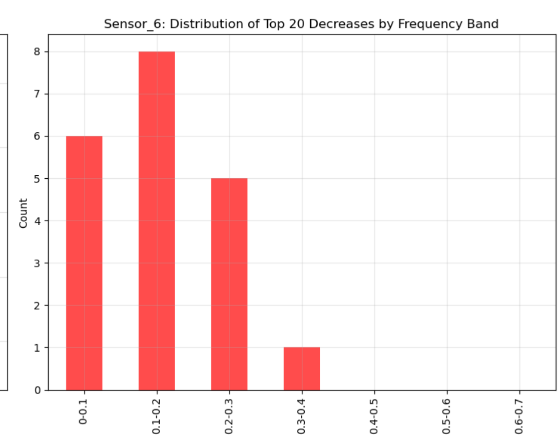

Sensor_4: Distribution of Top 20 Increases by Frequency Band
Count
0.0
0.2
0.4
0.6
0.8
1.0
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

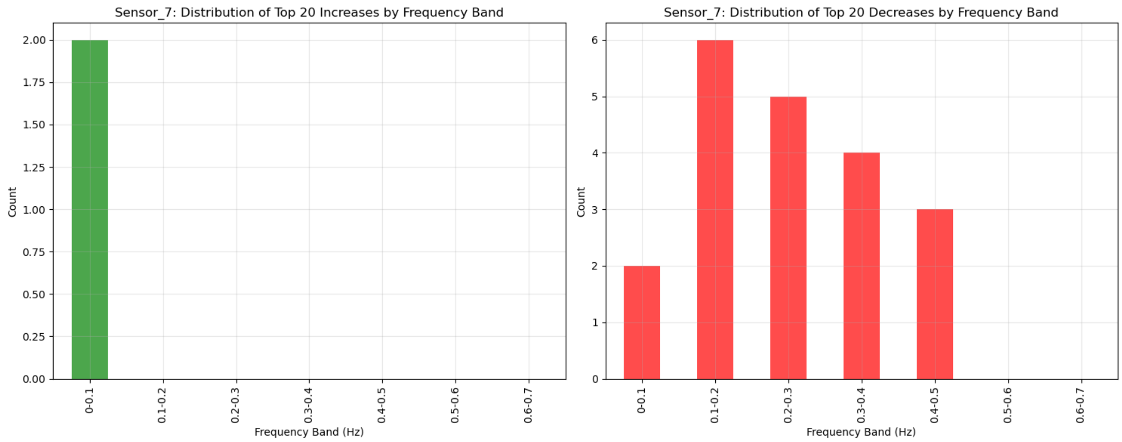

Sensor_4: Distribution of Top 20 Decreases by Frequency Band
Count
0
1
2
3
4
5
6
7
8
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)

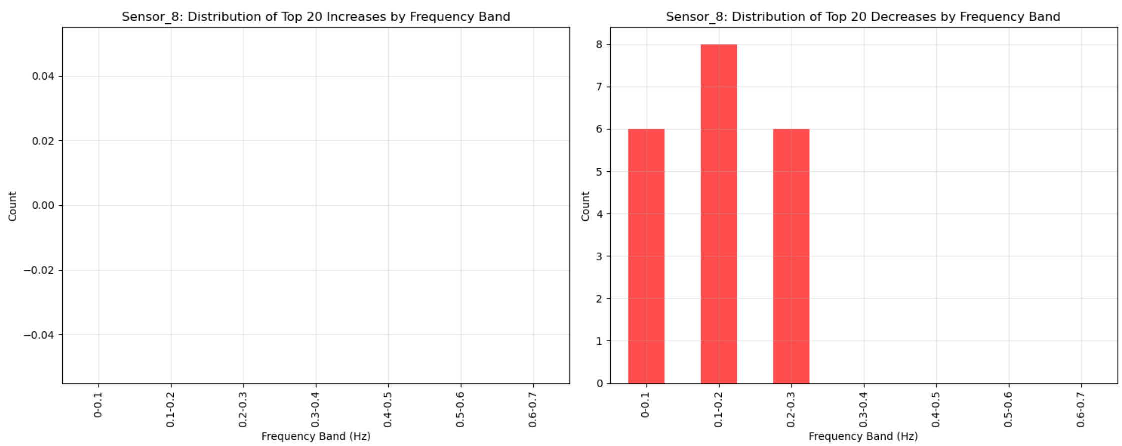

Sensor_5: Distribution of Top 20 Increases by Frequency Band
Count
−0.04
−0.02
0.00
0.02
0.04
0-0.1
0.1-0.2
0.2-0.3
0.3-0.4
0.4-0.5
0.5-0.6
0.6-0.7
Frequency Band (Hz)


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
−0.04
−0.02
0.00
0.02
0.04
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)


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)

[ ]: