assignment_3

November 7, 2025

1 IND320 - Data to Decision

Student: Sofie Lauvås

Project: Building an interactive Streamlit application for Elhub energy and climate data analysis

GitHub Repository: https://github.com/sofielauvaas/IND320_sofielauvaas_project

Streamlit App: https://ind320sofielauvaasproject.streamlit.app/

1.0.1 1. Project Setup and Library Imports

[ ]:
```python
import pandas as pd
import numpy as np
import requests
import datetime as dt
import json
from pymongo.mongo_client import MongoClient
import tomllib
from scipy.fft import dct, idct
from scipy.signal import spectrogram
from statsmodels.tsa.seasonal import STL
from sklearn.neighbors import LocalOutlierFactor
import matplotlib.pyplot as plt
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# had to add this because the plots werent showing up when converting to pdf
import plotly.io as pio
pio.renderers.default = "notebook+pdf"
```

1.0.2 2. Data Acquisition: Open-Meteo Weather API

2.1 Geographic Definition for Price Areas

[ ]:
```python
# Coordinates for the five Norwegian electricity price area representatives.
geo_data = {
    'Price_Area': ['NO1', 'NO2', 'NO3', 'NO4', 'NO5'],
    'City': ['Oslo', 'Kristiansand', 'Trondheim', 'Tromsø', 'Bergen'],
    'Latitude': [59.9122, 58.1599, 63.4305, 69.6498, 60.3913],
```

```
    'Longitude': [10.7313, 8.0182, 10.3951, 18.9841, 5.3221]
}
df_geo = pd.DataFrame(geo_data)
print("Geographical Data:")
print(df_geo)
```

```
Geographical Data:
  Price_Area         City  Latitude  Longitude
0        NO1         Oslo   59.9122    10.7313
1        NO2  Kristiansand  58.1599     8.0182
2        NO3    Trondheim   63.4305    10.3951
3        NO4       Tromsø   69.6498    18.9841
4        NO5       Bergen   60.3913     5.3221
```

2.2 API Download Function and Test

[ ]:
```
def download_weather_data(latitude, longitude, year):
    """
    Downloads hourly historical ERA5 Reanalysis weather data from Open-Meteo.
    """
    start_date = f"{year}-01-01"
    end_date = f"{year}-12-31"

    BASE_URL = "https://archive-api.open-meteo.com/v1/archive?"

    # Required weather properties
    hourly_variables = [
        "temperature_2m",
        "precipitation",
        "wind_speed_10m",
        "wind_gusts_10m",
        "wind_direction_10m"
    ]

    params = {
        "latitude": latitude,
        "longitude": longitude,
        "start_date": start_date,
        "end_date": end_date,
        "hourly": hourly_variables,
        "timezone": "auto",
    }

    response = requests.get(BASE_URL, params=params)
    response.raise_for_status() # Check for HTTP errors
    data = response.json()

    # Convert the hourly data into a Pandas DataFrame
```

```
    hourly_data = data['hourly']
    df = pd.DataFrame(hourly_data)
    df['time'] = pd.to_datetime(df['time'])
    df = df.set_index('time')

    print(f"\nDownloaded data for Lat: {latitude}, Lon: {longitude} for {year}.
↪")
    return df

# Test the API Function (Bergen, 2019)
bergen_coords = df_geo[df_geo['City'] == 'Bergen'].iloc[0]
bergen_lat = bergen_coords['Latitude']
bergen_lon = bergen_coords['Longitude']

df_bergen_2019 = download_weather_data(bergen_lat, bergen_lon, 2019)
print("\nBergen 2019 Data Head:")
print(df_bergen_2019.head())
print(f"Shape: {df_bergen_2019.shape}")
```

```
Downloaded data for Lat: 60.3913, Lon: 5.3221 for 2019.

Bergen 2019 Data Head:
                     temperature_2m  precipitation  wind_speed_10m  \
time
2019-01-01 00:00:00             5.7            0.7            37.0
2019-01-01 01:00:00             5.8            0.2            41.0
2019-01-01 02:00:00             6.1            0.7            42.0
2019-01-01 03:00:00             6.3            0.5            40.9
2019-01-01 04:00:00             5.8            1.1            41.2

                     wind_gusts_10m  wind_direction_10m
time
2019-01-01 00:00:00            99.7                 263
2019-01-01 01:00:00           107.3                 278
2019-01-01 02:00:00           112.0                 286
2019-01-01 03:00:00           105.8                 298
2019-01-01 04:00:00           110.2                 315
Shape: (8760, 5)
```

1.0.3 3. Data Sourcing: Elhub Production Data via MongoDB

[ ]:
```
# Read secrets from the TOML file
with open("../.streamlit/secrets.toml", "rb") as f:
    cfg = tomllib.load(f)

# Access connection details
```

```
uri = cfg["mongodb"]["uri"]
db_name = cfg["mongodb"]["database"]
col_name = cfg["mongodb"]["collection"]

# Connect and fetch data
client = MongoClient(uri)
db = client[db_name]
collection = db[col_name]

# Retrieve all documents into a list (excluding the MongoDB '_id')
data = list(collection.find({}, {"_id": 0}))
df = pd.DataFrame(data)

# Standardize column names and types
if 'starttime' in df.columns:
    df["starttime"] = pd.to_datetime(df["starttime"])
df.columns = [c.lower() for c in df.columns]

print(f"Elhub data loaded. Shape: {df.shape}")
print(df.head())
```

```
Elhub data loaded. Shape: (215353, 4)
  pricearea productiongroup           starttime  quantitykwh
0       NO3           other 2021-01-01 00:00:00          0.0
1       NO3           other 2021-01-01 01:00:00          0.0
2       NO3           other 2021-01-01 02:00:00          0.0
3       NO3           other 2021-01-01 03:00:00          0.0
4       NO3           other 2021-01-01 04:00:00          0.0
```

1.0.4 4. Outliers and Anomalies Detection

4.1 Temperature SPC Function Definition (DCT Helper & SPC)

[ ]:
```
# Helper Function for DCT Filtering
def dct_highpass_filter(signal, keep_index):
    """ High-pass filter using DCT to separate trend from SATV. """
    x = np.asarray(signal, dtype=float)
    X = dct(x, norm="ortho")
    n = len(X)
    k_low = max(1, min(n, int(keep_index)))

    # Trend (Low-Pass Component)
    X_lp = np.zeros_like(X)
    X_lp[:k_low] = X[:k_low]
    trend = idct(X_lp, norm="ortho")

    # SATV (High-Pass Component)
    satv = x - trend
    return satv, trend
```

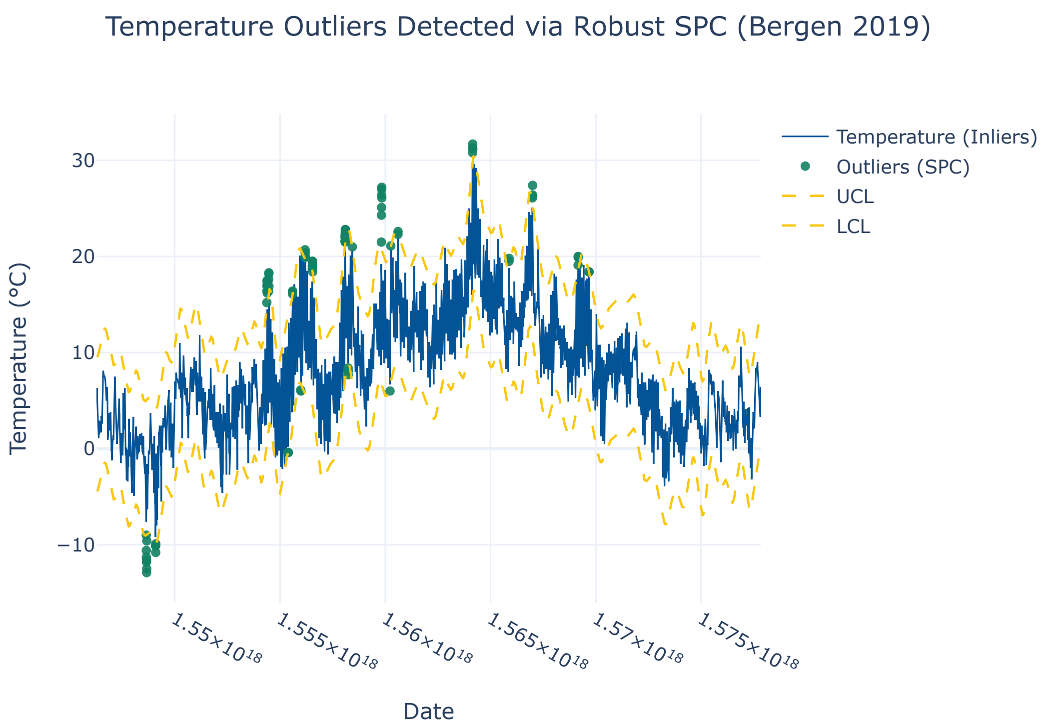
```
[ ]: def temperature_spc_from_satv(
         time, temperature,
         keep_low_index=100, k=3.0):
         """
         Detects temperature outliers using robust SPC boundaries derived from SATV␣
      ↪(DCT Adjusted).

         Returns the Plotly figure and a summary dictionary of outlier statistics.
         """
         t = np.asarray(time)
         x = np.asarray(temperature, dtype=float)
         n = len(x)

         # Separate SATV and Trend
         satv, trend = dct_highpass_filter(x, keep_low_index)

         # Robust statistics on SATV
         center = np.median(satv)
         mad = np.median(np.abs(satv - center))
         spread = (1.4826 * mad)

         upper_satv = center + k * spread
         lower_satv = center - k * spread

         # Dynamic control curves
         upper_curve = trend + upper_satv
         lower_curve = trend + lower_satv

         # Outliers determined in SATV space
         is_outlier = (satv > upper_satv) | (satv < lower_satv)

         # Build Plotly figure
         fig = go.Figure()

         UCL_name = f"UCL"
         LCL_name = f"LCL"

         fig.add_trace(go.Scatter(
             x=t[~is_outlier], y=x[~is_outlier],
             mode="lines", name="Temperature (Inliers)",
             line=dict(color='#035397', width=1.0)
         ))
         fig.add_trace(go.Scatter(
             x=t[is_outlier], y=x[is_outlier],
             mode="markers", name="Outliers (SPC)",
             marker=dict(color='#128264', size=6, opacity=0.9)
         ))
```

```
    fig.add_trace(go.Scatter(
        x=t, y=upper_curve, mode="lines", name=UCL_name,
        line=dict(color='#f9c80e', dash="dash", width=1.5)
    ))
    fig.add_trace(go.Scatter(
        x=t, y=lower_curve, mode="lines", name=LCL_name,
        line=dict(color='#f9c80e', dash="dash", width=1.5)
    ))

    fig.update_layout(
        template="plotly_white",
        title=f"Temperature Outliers Detected via Robust SPC (Bergen 2019)",
        xaxis_title="Date", yaxis_title="Temperature (°C)", title_x=0.5
    )

    summary = {"n_outliers": int(is_outlier.sum()), "n_total": int(n),␣
 ↪"percent_outliers": round(100 * is_outlier.mean(), 2)}
    return fig, summary
```

4.2 SPC Test and Plot

[ ]:
```
# Prepare data for plotting
bergen_2019 = df_bergen_2019.reset_index().rename(columns={'time': 'time'})

# Test Temperature SPC
print("Temperature SPC Summary")
fig_spc, summary_spc = temperature_spc_from_satv(
    time=bergen_2019["time"].to_numpy(),
    temperature=bergen_2019["temperature_2m"].to_numpy(),
)
print(summary_spc)
fig_spc.show()
```

```
Temperature SPC Summary
{'n_outliers': 81, 'n_total': 8760, 'percent_outliers': np.float64(0.92)}
```



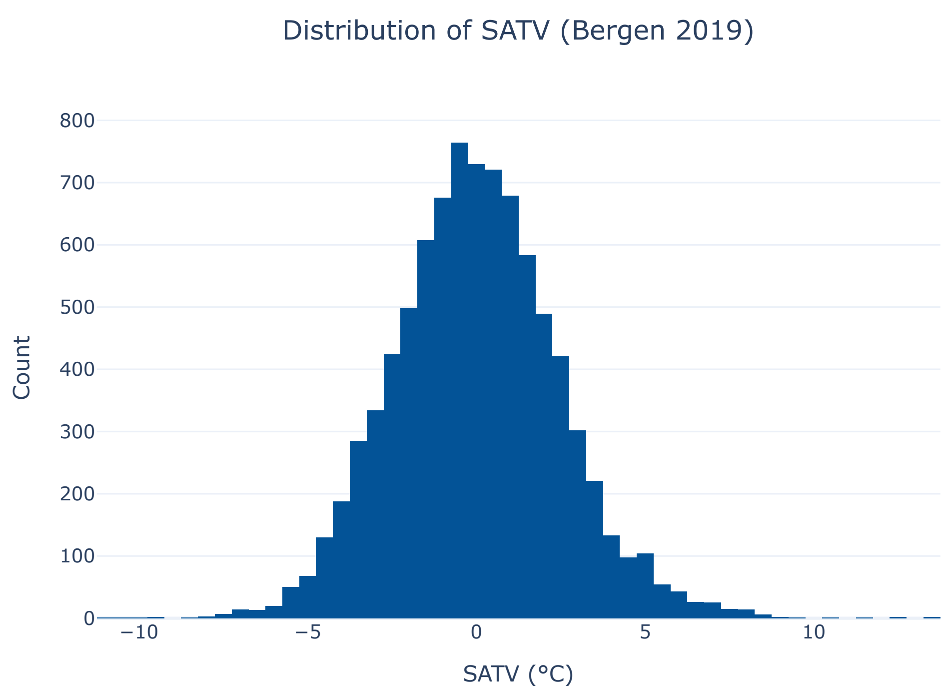
The SPC plot shows temperature with dynamic control limits based on the Seasonally Adjusted Temperature Variation (SATV). The detected outliers (red markers) represent short, extreme cold and heat spells that are unusual for their respective seasons.

4.3 SATV Distribution Check (Histogram)

[ ]:
```
# Apply the DCT high-pass filter
satv_values, _ = dct_highpass_filter(
    bergen_2019["temperature_2m"].to_numpy(),
    keep_index=100
)
bergen_2019["SATV"] = satv_values


# Plot histogram of SATV values to confirm normal distribution
SATV_COLOR = '#035397'

fig_hist = go.Figure(data=[go.Histogram(
    x=bergen_2019["SATV"],
    nbinsx=50,
    marker_color=SATV_COLOR
)])
```

```
fig_hist.update_layout(
    template="plotly_white",
    title="Distribution of SATV (Bergen 2019)",
    xaxis_title="SATV (°C)",
    yaxis_title="Count",
    title_x=0.5
)
fig_hist.show()
```

```
WARNING Thread(Thread-7 (run)) Task(Task-40)
choreographer.browser_async:browser_async.py:_close()- Resorting to unclean kill
browser.
```



The histogram of SATV shows a symmetric, bell-shaped distribution centered near zero. This confirms that the DCT filtering successfully removed the slow seasonal trend, leaving short-term variations that are approximately normally distributed, which validates the use of robust SPC methods for anomaly detection on this feature.

4.4 Precipitation LOF Function Definition

```
[ ]: # LOF Function
def precipitation_lof_plot(time, precipitation, contamination=0.01,␣
 ↪n_neighbors=30):
```

```
    """
    Detects and plots precipitation anomalies using the Local Outlier Factor␣
↪(LOF).

    Returns the Plotly figure and a summary dictionary of anomaly statistics.
    """
    X = np.array(precipitation.fillna(0)).reshape(-1, 1)

    # Fit Local Outlier Factor
    lof = LocalOutlierFactor(n_neighbors=n_neighbors,␣
↪contamination=contamination)
    labels = lof.fit_predict(X)
    is_outlier = labels == -1
    n_outliers = int(is_outlier.sum())
    n_total = len(X)

    # Plotting
    fig = go.Figure()

    fig.add_trace(go.Scatter(
        x=np.array(time)[~is_outlier], y=X[~is_outlier, 0],
        mode="lines", name="Precipitation (Inliers)",
        line=dict(color='#035397', width=1.0)
    ))

    fig.add_trace(go.Scatter(
        x=np.array(time)[is_outlier], y=X[is_outlier, 0],
        mode="markers", name="Anomalies (LOF)",
        marker=dict(color="#128264", size=6, opacity=0.8)
    ))

    fig.update_layout(
        template="plotly_white",
        title=f"Precipitation Anomalies via LOF (Contamination:␣
↪{contamination*100:.1f}%)",
        xaxis_title="Date", yaxis_title="Precipitation (mm/h)", title_x=0.5
    )

    summary = {"n_total": n_total, "n_outliers": n_outliers, "percent_outliers":
↪ round(100 * n_outliers / n_total, 2)}
    return fig, summary
```

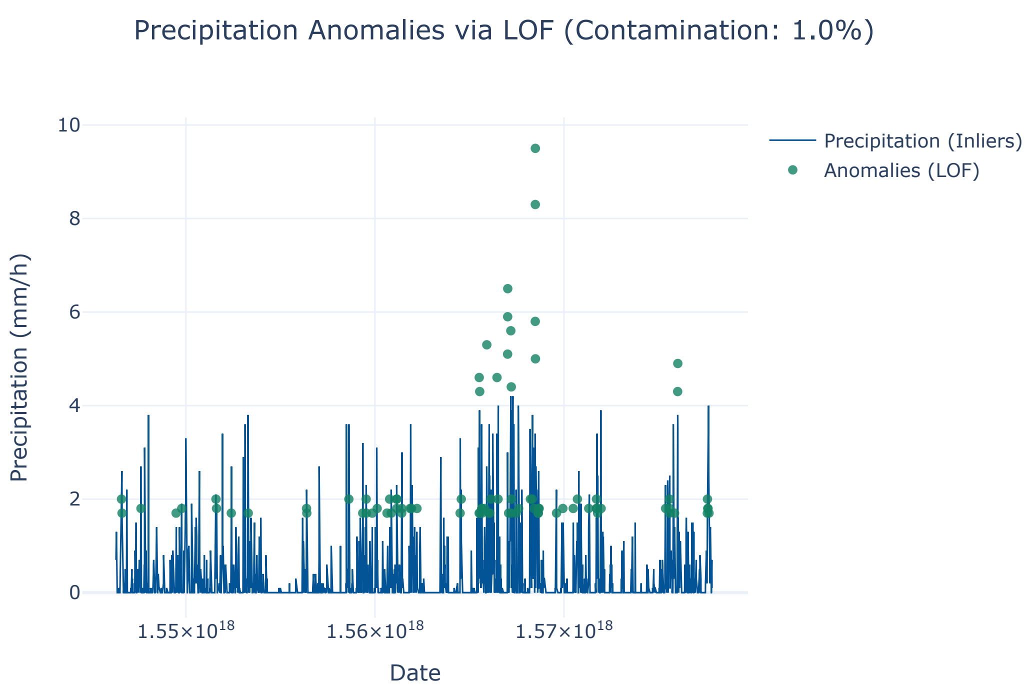
4.5 LOF Test and Plot

[ ]:

```
# Test Precipitation LOF
print("\nPrecipitation LOF Summary:")
fig_lof, summary_lof = precipitation_lof_plot(
    time=bergen_2019["time"],
```

```
    precipitation=bergen_2019["precipitation"],
)
print(summary_lof)
fig_lof.show()
```

```
Precipitation LOF Summary:

/opt/miniconda3/envs/D2D_env/lib/python3.12/site-
packages/sklearn/neighbors/_lof.py:322: UserWarning:

Duplicate values are leading to incorrect results. Increase the number of
neighbors for more accurate results.

{'n_total': 8760, 'n_outliers': 87, 'percent_outliers': 0.99}

WARNING Thread(Thread-9 (run)) Task(Task-77)
choreographer.browser_async:browser_async.py:_close()- Resorting to unclean kill
browser.
```



The LOF plot identifies the least dense points as anomalies. Due to the high frequency of zero precipitation, LOF flags both the extreme high-magnitude rain spikes and some intermediate non-zero values (around 2 mm/h) which are locally sparse relative to the dense cluster at zero.

Note: The scikit-learn LOF algorithm issues a `UserWarning` regarding "duplicate values" because of this massive cluster of identical zero-precipitation entries.

1.0.5 5. Seasonal-Trend Decomposition (STL)

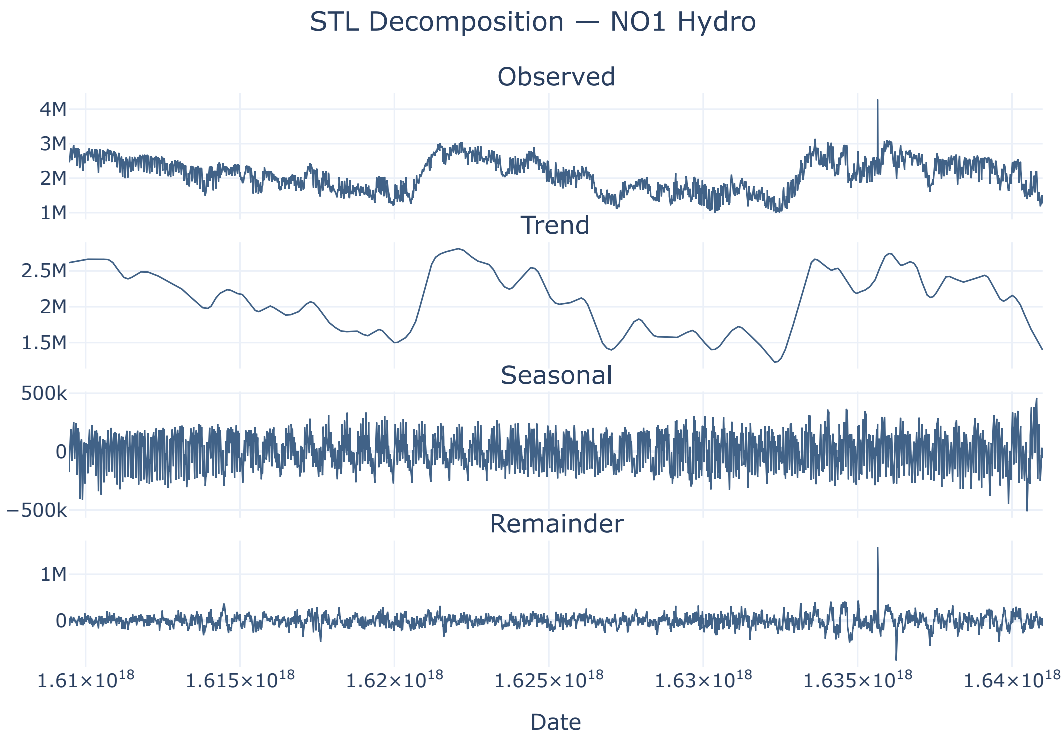
5.1 STL Function Definition

[ ]:
```
# STL Decomposition Function
def stl_decomposition_elhub(df, pricearea="NO5", productiongroup="hydro",␣
↪period=168, seasonal=9, trend=241, robust=False):
    """
    Performs STL decomposition on Elhub production data and returns a Plotly␣
↪figure
    of the Observed, Trend, Seasonal, and Remainder components.
    """
    line_color = '#416287'
    subset = df[(df["pricearea"].str.upper() == pricearea.upper()) &␣
↪(df["productiongroup"].str.lower() == productiongroup.lower())].copy()

    # Prepare time series: ensure hourly frequency and fill any missing values
    subset = subset.set_index(pd.to_datetime(subset["starttime"]))
    ts = subset.groupby(level=0)['quantitykwh'].sum().asfreq('h').ffill().
↪sort_index()

    # STL fitting
    result = STL(ts, period=period, seasonal=seasonal, trend=trend,␣
↪robust=robust).fit()
    components_map = {"Observed": ts, "Trend": result.trend, "Seasonal": result.
↪seasonal, "Remainder": result.resid}

    # Plotly subplot creation
    fig = make_subplots(rows=4, cols=1, shared_xaxes=True,␣
↪subplot_titles=("Observed", "Trend", "Seasonal", "Remainder"),␣
↪vertical_spacing=0.04)
    for i, (name, component_series) in enumerate(components_map.items()):
        fig.add_trace(go.Scatter(x=component_series.index, y=component_series.
↪values, mode="lines", line=dict(color=line_color, width=1), name=name),␣
↪row=i + 1, col=1)

    fig.update_layout(height=950, template="plotly_white", title=f"STL␣
↪Decomposition - {pricearea.upper()} {productiongroup.capitalize()}",␣
↪title_x=0.5, showlegend=False, margin=dict(t=80, b=50, l=50, r=20))
    fig.update_xaxes(title_text="Date", row=4, col=1)
    return fig
```

5.2 STL Test and Plot

[ ]:
```
# Test STL Function
```

```
fig_stl = stl_decomposition_elhub(df=df, pricearea="NO1",␣
 ↪productiongroup="hydro")
fig_stl.show()
```



The STL decomposition for NO1 Hydro production clearly separates the seasonal patterns from the long-term trend and the residual noise. The seasonal component shows strong recurring cycles, while the remainder now distinctly highlights two major anomalies in late October and early November, which are production events not captured by the normal trend or seasonality.

1.0.6 6. Frequency Analysis (Spectrogram)

6.1 Spectrogram Function Definition

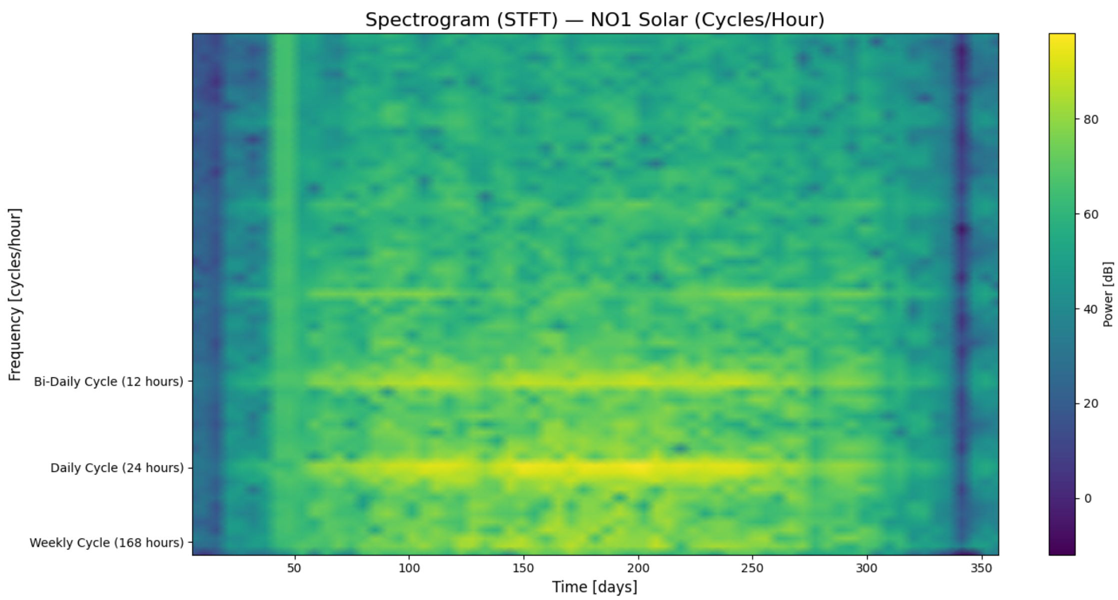
[ ]:
```
# Spectrogram
def create_spectrogram(
    df_prod,
    price_area='NO5',
    production_group='hydro',
    window_length=256, # 256 hours for good frequency resolution
    overlap=128          # 50% overlap for smooth transitions
):
    """ Creates a power spectrogram (using Short-Time Fourier Transform - STFT)
```

```
    to visualize the strength of different frequency cycles (e.g., daily,␣
↪weekly)
    over the entire year. """

    subset = df_prod[
        (df_prod['pricearea'].str.upper() == price_area.upper()) &
        (df_prod['productiongroup'].str.lower() == production_group.lower())
    ].sort_values("starttime")

    # Prepare time series: ensure hourly frequency and fill any missing values
    subset = subset.set_index(pd.to_datetime(subset["starttime"]))
    ts = subset.groupby(level=0)['quantitykwh'].sum().asfreq('h').ffill().values

    if ts.min() <= 0:
        ts = ts + 1e-9 # Ensure positivity for logarithmic scaling

    fs = 1.0 # 1 sample per hour
    f, t_hours, Sxx = spectrogram(ts, fs=fs, nperseg=window_length,␣
↪noverlap=overlap, detrend='constant')

    power_db = 10 * np.log10(Sxx)

    # Matplotlib plotting
    fig, ax = plt.subplots(figsize=(14, 7))
    im = ax.pcolormesh(
        t_hours / 24,
        f,
        power_db,
        shading='gouraud',
        cmap='viridis'
    )

    ax.set_title(f"Spectrogram (STFT) - {price_area.upper()} {production_group.
↪capitalize()} (Cycles/Hour)", fontsize=16)
    ax.set_xlabel("Time [days]", fontsize=12)
    ax.set_ylabel("Frequency [cycles/hour]", fontsize=12)

    # Set Y-axis to focus on the key cycles
    ax.set_ylim(0, 0.25)
    ax.set_yticks([1/24, 2/24, 1/168])
    ax.set_yticklabels([
        'Daily Cycle (24 hours)',
        'Bi-Daily Cycle (12 hours)',
        'Weekly Cycle (168 hours)'
    ])
    fig.colorbar(im, ax=ax, label="Power [dB]")
    plt.tight_layout()
```

```
    return fig
```

6.2 Spectrogram Test and Plot

[ ]:
```
# Test Spectrogram
plot_spectrogram = create_spectrogram(df, price_area='NO1',␣
  ↪production_group='solar')
plt.show()
```



The resulting Spectrogram for NO1 Solar production confirms the signal is driven by strong, predictable, and clean cycles. The plot's power is concentrated in the low-frequency area, with the brightest band being the Daily Cycle (24 hours), showing the sun's rhythm is the main source of power. The Bi-Daily Cycle (12 hours) is also strong. You can see several fainter bands above the 12-hour cycle (the harmonics), which represent other mathematical components needed to model the sharp shape of the solar signal. The areas outside these bands are mostly darker, confirming the signal is generally very smooth with only low, random background noise.

1.1 Log

This project was quite difficult, demanding many full days of concentrated work. I used a lot of time on this project because I was really determined to create a good application and understand the code. While I still have some uncertainty about a few advanced implementations, I put forth my best effort to understand the concepts and ensure the final product was stable.

The journey began with building the core analysis functions in the notebook, using guidance from lectures, my own research, and AI. This phase was immediately frustrating because getting the complex, interconnected functions—such as the Seasonal-Trend Decomposition (STL) and the Spectrogram—to work together proved extremely difficult. I quickly found that when I made a change, other parts could break and require fixing.

Moving the finished analysis into the multi-page Streamlit app was the next significant hurdle, as code that worked fine in the notebook sometimes failed in the new web environment. My most frustrating technical battle was stabilizing the network request libraries. This involved a lot of troubleshooting, forcing me into a difficult cycle of uninstalling, reinstalling, and eventually pinning specific versions of packages in the requirements file. This huge amount of trial and error was required just to get the API client to stop failing during deployment.

Performance was another major issue: the plot page was incredibly slow and almost unusable. After significant troubleshooting, I identified the solution wad to cache the data download locally using the @st.cache_data function. This fix dramatically improved the plot page's speed, and I applied this optimization to all the other weather-dependent pages. I also used AI to help me restructure all my files with clear headers to make the entire project easier to follow.

Finally, after the core project was functional, I went back to add polish and improve the user experience. I adopted an option with my own adjustments suggested by my peer, Terese Ivesdal, which was to use the sidebar for global data control, a good structural addition that greatly improved the app's intuition. I also replaced the basic wind visualization with a more sophisticated plot showing wind direction over time, using logic inspired by Terese. Despite the many technical struggles, I am very proud of the final, working application that resulted from all this hard work.

1.2 AI Usage

I found this project very difficult, but my main focus when using AI was always to understand the code it provided. I used both Gemini and Copilot constantly for help with coding, fixing tough errors (especially the network and stability problems during deployment), restructuring my files, and getting explanations for complex analysis topics like STL and DCT. When the AI suggested advanced code, I always spent extra time checking and simplifying it. I combined AI assistance with lectures, videos, and help from my peers.