Project work, part 3

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Links

GitHub repo link: https://github.com/sarahorte/ind320project.git

Streamlit app link: https://ind320project.streamlit.app/

Log

I began by familiarizing myself with the Open-Meteo API (https://open-meteo.com/en/docs) to determine how to fetch the weather data I needed. I also identified the latitude and longitude coordinates for the cities representing each Norwegian price area. Using this information, I implemented a function to retrieve hourly weather data and tested it successfully on Bergen for 2019. This provided a foundation for integrating live weather data into the application instead of relying on static CSV files.

Next, I developed functions for detecting outliers and anomalies in the weather data. I implemented both SPC-based outlier detection for temperature series and Local Outlier Factor (LOF) for precipitation. While testing these functions on Bergen, I found selecting appropriate parameters challenging, as their optimal values depend on the data characteristics. Nevertheless, the functions worked as intended, providing both visualizations and summary statistics, and I designed them to allow easy parameter adjustments as I gain more experience.

Following this, I focused on time series analysis techniques. I implemented Seasonal-Trend decomposition using LOESS (STL) and a spectrogram analysis to explore patterns in Elhub electricity production data. To do this efficiently, I reused and adapted code from a previous assignment, ensuring it could handle the Elhub data structure. Choosing parameters for STL and the spectrogram proved difficult, and I realized that interpreting the spectrogram plots meaningfully requires a deeper understanding of frequency-domain patterns in production data.

Once the analysis functions were in place, I turned to integrating them into the Streamlit application. I reorganized the app structure and created skeletons for the new pages. I updated existing pages to fetch weather data directly from the API rather than static files, ensuring that the data tables and interactive plots dynamically reflected the selected price area. I then developed the new “Outlier & Anomaly” page (page B), reusing the functions from the notebook. To maintain clarity and functionality, I included the entire functions at the start of the script.

Finally, I created the “STL & Spectrogram” page (page A). Here, users can select a production group and adjust analysis parameters interactively. I ensured the data preparation accounted for duplicates by summing production values when multiple entries existed for the same timestamp. This allowed the STL and spectrogram functions to work reliably on hourly production data. Overall, the development process involved iterative testing, parameter tuning, and careful data preparation to ensure that the application provides meaningful insights into both weather and energy production patterns.

For convenience, I reused the selected price area from the Energy page across all subsequent pages, though in the future I think it might be more user-friendly to allow the user to choose a price area individually on each page.

AI usage

AI was used extensively throughout this project, primarily through ChatGPT and GitHub Copilot in VS Code. I leveraged AI to generate code suggestions, adapt examples from lectures, and refine solutions for specific tasks. For instance, when implementing the Local Outlier Factor method, I combined code snippets from lectures with AI-generated suggestions, then iteratively adjusted and tested the code until it functioned correctly.

I also used AI to interpret error messages and propose potential fixes. By testing different solutions suggested by ChatGPT, I was able to identify the most effective approach. Additionally, AI assisted in generating initial visualizations, which I later fine-tuned to achieve the desired appearance. For parameter selection in the various analysis functions, ChatGPT provided guidance, which was helpful as a starting point, though understanding the underlying concepts is essential for making meaningful choices.

The interactive nature of the Streamlit app made it easy to experiment with different parameters, and AI guidance accelerated this process. Beyond coding, I also used ChatGPT to refine and improve the wording of both the project log and the AI usage section itself, ensuring clarity and readability.

Overall, AI proved to be a valuable tool for both code development and documentation, complementing my own understanding and enabling more efficient problem-solving.

In [1]:
```python
# To make sure plotly plots are included correctly in nbconvert exports
import plotly.io as pio

# Temporarily set renderer for nbconvert
if "JPY_PARENT_PID" in globals():
    # Running inside Jupyter Notebook
    pio.renderers.default = "notebook_connected"  # keeps interactive plots
else:
    # For nbconvert / webpdf
    pio.renderers.default = "png"  # renders as image in PDF
```

Weather data

In [2]:
```
# Use Oslo, Kristiansand, Trondheim, Tromsø and Bergen as representatives fo
import pandas as pd

# Define representative cities for each price area
price_area_data = [
    {"price_area": "NO1", "city": "Oslo", "latitude": 59.9127, "longitude":
    {"price_area": "NO2", "city": "Kristiansand", "latitude": 58.1467, "long
    {"price_area": "NO3", "city": "Trondheim", "latitude": 63.4305, "longitu
    {"price_area": "NO4", "city": "Tromsø", "latitude": 69.6489, "longitude"
    {"price_area": "NO5", "city": "Bergen", "latitude": 60.393, "longitude":
]

# Create DataFrame
df_price_areas = pd.DataFrame(price_area_data)

# Display
print(df_price_areas)
```

```
  price_area          city  latitude  longitude
0        NO1          Oslo   59.9127    10.7461
1        NO2  Kristiansand   58.1467     7.9956
2        NO3     Trondheim   63.4305    10.3951
3        NO4        Tromsø   69.6489    18.9551
4        NO5        Bergen   60.3930     5.3242
```

In [3]:
```
# --- Cell: ERA5 API fetch function ---
import openmeteo_requests
import pandas as pd
import requests_cache
from retry_requests import retry

# Setup cached session (so you don't overload the API)
cache_session = requests_cache.CachedSession(".cache", expire_after=-1)
retry_session = retry(cache_session, retries=5, backoff_factor=0.2)
openmeteo = openmeteo_requests.Client(session=retry_session)


def fetch_era5_data(lat, lon, year):
    """
    Downloads hourly ERA5 reanalysis data for a given location and year
    using Open-Meteo's historical archive API.
    """
    url = "https://archive-api.open-meteo.com/v1/archive"
    params = {
        "latitude": lat,
        "longitude": lon,
        "start_date": f"{year}-01-01",
        "end_date": f"{year}-12-31",
        "hourly": [
            "temperature_2m",
            "precipitation",
            "wind_speed_10m",
            "wind_gusts_10m",
```

```
            "wind_direction_10m"
        ],
        "timezone": "Europe/Oslo",
        "wind_speed_unit": "ms",
        "models": "era5"   # explicitly request ERA5 reanalysis data
    }

    responses = openmeteo.weather_api(url, params=params)
    response = responses[0]

    hourly = response.Hourly()
    data = {
        "time": pd.date_range(
            start=pd.to_datetime(hourly.Time(), unit="s", utc=True),
            end=pd.to_datetime(hourly.TimeEnd(), unit="s", utc=True),
            freq=pd.Timedelta(seconds=hourly.Interval()),
            inclusive="left"
        ),
        "temperature_2m": hourly.Variables(0).ValuesAsNumpy(),
        "precipitation": hourly.Variables(1).ValuesAsNumpy(),
        "wind_speed_10m": hourly.Variables(2).ValuesAsNumpy(),
        "wind_gusts_10m": hourly.Variables(3).ValuesAsNumpy(),
        "wind_direction_10m": hourly.Variables(4).ValuesAsNumpy(),
    }

    df = pd.DataFrame(data)
    df["time"] = pd.to_datetime(df["time"]).dt.tz_convert("Europe/Oslo")
    df.set_index("time", inplace=True)
    return df
```

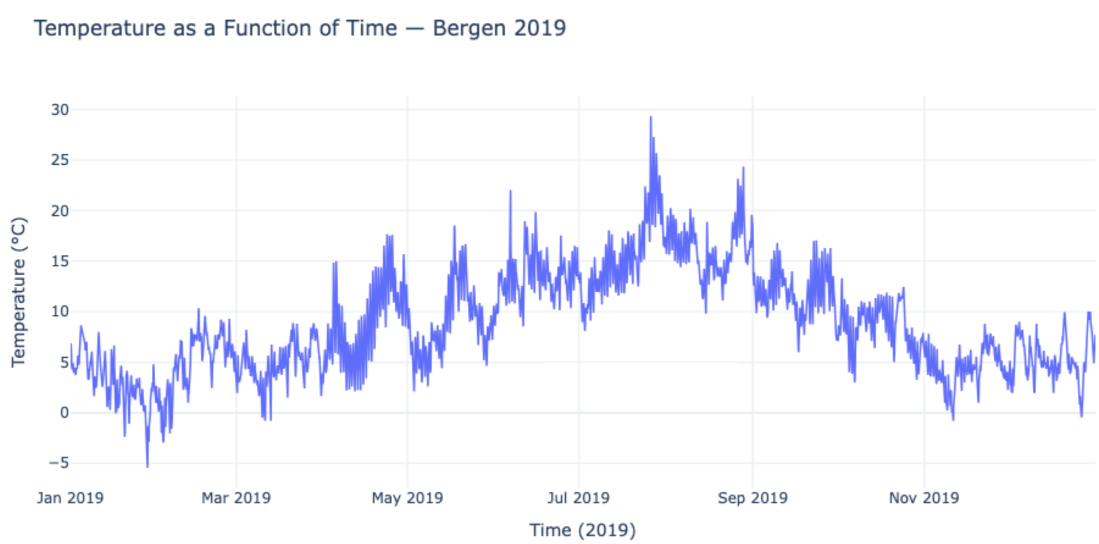
In [4]:
```
# Bergen coordinates
bergen_lat, bergen_lon = 60.393, 5.3242
bergen_2019 = fetch_era5_data(bergen_lat, bergen_lon, 2019)

print(bergen_2019.head())
```

```
                           temperature_2m  precipitation  wind_speed_10m  \
time
2019-01-01 00:00:00+01:00            6.70            0.4       11.853270
2019-01-01 01:00:00+01:00            6.55            0.5       13.322162
2019-01-01 02:00:00+01:00            6.80            0.9       13.505925
2019-01-01 03:00:00+01:00            6.85            0.7       14.621901
2019-01-01 04:00:00+01:00            6.55            0.6       15.487092

                           wind_gusts_10m  wind_direction_10m
time
2019-01-01 00:00:00+01:00       22.700001          260.776154
2019-01-01 01:00:00+01:00       24.400000          277.765076
2019-01-01 02:00:00+01:00       22.299999          296.375275
2019-01-01 03:00:00+01:00       23.700001          310.006195
2019-01-01 04:00:00+01:00       27.400000          314.215271
```

Outliers and anomalies

Plotting temperature

In [5]:
```
import plotly.graph_objects as go

# Extract temperature data
temp_series = bergen_2019["temperature_2m"]

# Create interactive line plot
fig = go.Figure()

fig.add_trace(go.Scatter(
    x=temp_series.index,
    y=temp_series.values,
    mode='lines',
    name='Temperature (°C)',
    line=dict(width=1.5)
))

fig.update_layout(
    title='Temperature as a Function of Time — Bergen 2019',
    xaxis_title='Time (2019)',
    yaxis_title='Temperature (°C)',
    hovermode='x unified',
    template='plotly_white',
    height=500,
    width=1000
)

fig.show()
```

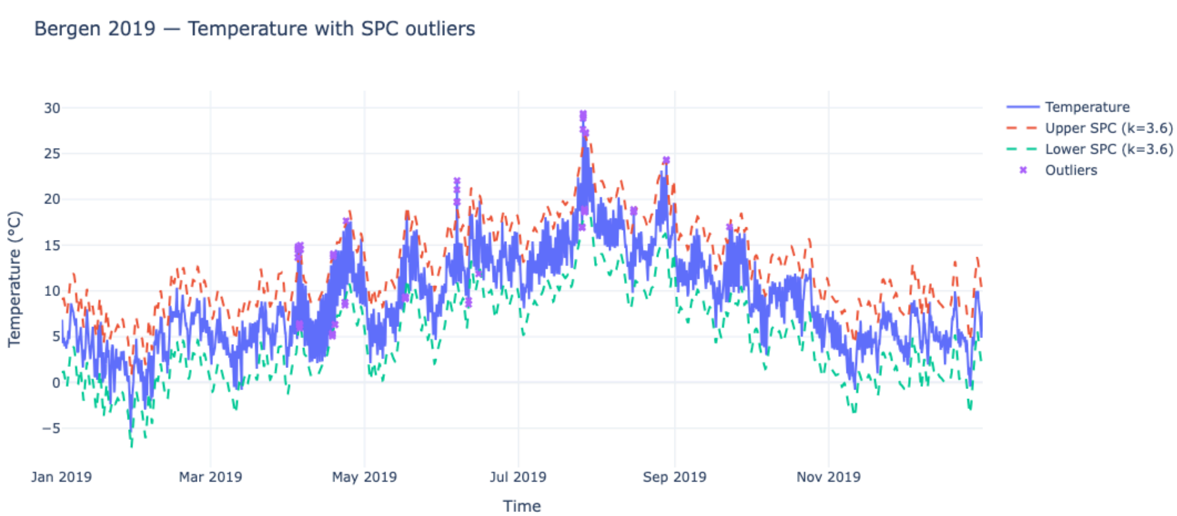


In [6]:
```
# --- Cell: SPC outlier detection (DCT SATV) + Plotly plotting ---
import numpy as np
import pandas as pd
from scipy.fftpack import dct, idct
import plotly.graph_objects as go
```

```python
# DCT-based seasonal decomposition and SATV calculation
def dct_seasonal_and_satv(series: pd.Series, cutoff_frac: float = 0.05):
    """Return seasonal component (low-frequency DCT reconstruction) and SATV
    x = series.values.astype(float)
    n = len(x)
    X = dct(x, norm='ortho')
    keep = int(np.floor(cutoff_frac * n))
    if keep < 1:
        keep = 1
    seasonal_coeffs = np.zeros_like(X)
    seasonal_coeffs[:keep] = X[:keep]
    seasonal = idct(seasonal_coeffs, norm='ortho')
    satv = x - seasonal
    return pd.Series(seasonal, index=series.index), pd.Series(satv, index=se

# Median Absolute Deviation
def mad(arr):
    med = np.median(arr)
    return np.median(np.abs(arr - med))

# SPC outlier detection and Plotly plotting function
def spc_outlier_plotly(temp_series: pd.Series, cutoff_frac: float = 0.05, k:
    """
    temp_series: pandas Series with datetime index and temperature values (°
    cutoff_frac: fraction of lowest DCT frequencies to KEEP as seasonal (def
    k: number of robust standard deviations to use for SPC boundaries (defau
    Returns: (plotly_fig, summary_dict)
    """
    if not isinstance(temp_series.index, pd.DatetimeIndex):
        temp_series = temp_series.copy()
        temp_series.index = pd.to_datetime(temp_series.index)

    temp_series = temp_series.sort_index()
    seasonal, satv = dct_seasonal_and_satv(temp_series, cutoff_frac=cutoff_f

    # robust stats on SATV
    med = float(np.median(satv.values))
    mad_val = float(mad(satv.values))
    sigma = float(1.4826 * mad_val) if mad_val > 0 else float(np.std(satv.va

    # SATV thresholds (constant values) and convert to original scale by add
    lower_satv = med - k * sigma
    upper_satv = med + k * sigma
    lower_curve = seasonal + lower_satv
    upper_curve = seasonal + upper_satv

    outlier_mask = (satv < lower_satv) | (satv > upper_satv)
    n_points = len(temp_series)
    n_outliers = int(outlier_mask.sum())
    outlier_fraction = n_outliers / n_points if n_points > 0 else 0.0

    # Build Plotly figure
    fig = go.Figure()
    fig.add_trace(go.Scatter(x=temp_series.index, y=temp_series.values, mode
    fig.add_trace(go.Scatter(x=temp_series.index, y=upper_curve.values, mode
    fig.add_trace(go.Scatter(x=temp_series.index, y=lower_curve.values, mode
```

```
    if n_outliers > 0:
        fig.add_trace(go.Scatter(x=temp_series.index[outlier_mask], y=temp_s
                                 mode='markers', name='Outliers', marker=dic

    fig.update_layout(
        title=title or 'Temperature and SPC outliers (DCT-based SATV)',
        xaxis_title='Time',
        yaxis_title='Temperature (°C)',
        hovermode='x unified',
        template='plotly_white',
        height=520,
        width=1100
    )

    summary = {
        'n_points': n_points, # total number of data points
        'n_outliers': n_outliers, # number of detected outliers
        'outlier_fraction': outlier_fraction, # fraction of outliers
        'median_satv': med, # median of SATV
        'mad_satv': mad_val, # MAD of SATV
        'sigma_est': sigma, # robust std dev estimate of SATV
        'cutoff_frac': float(cutoff_frac), # DCT cutoff fraction
        'k': float(k), # SPC k parameter
        'example_outlier_times': list(map(str, temp_series.index[outlier_mas
    }

    return fig, summary
```

In [7]:
```
# For Bergen 2019  temperature data. Testing the function with different par
temp_series = bergen_2019['temperature_2m']
fig, summary = spc_outlier_plotly(temp_series, cutoff_frac=0.04, k=3.6, titl
fig.show()
print(summary)
```



{'n_points': 8760, 'n_outliers': 57, 'outlier_fraction': 0.006506849315068493, 'median_satv': -0.04621085265696934, 'mad_satv': 0.7490424516043817, 'sigma_est': 1.1105303387486563, 'cutoff_frac': 0.04, 'k': 3.6, 'example_outlier_times': ['2019-04-04 13:00:00+02:00', '2019-04-04 14:00:00+02:00', '2019-04-04 15:00:00+02:00', '2019-04-04 16:00:00+02:00', '2019-04-04 17:00:00+02:00', '2019-04-04 18:00:00+02:00', '2019-04-05 04:00:00+02:00', '2019-04-05 05:00:00+02:00', '2019-04-05 06:00:00+02:00', '2019-04-05 07:00:00+02:00', '2019-04-05 08:00:00+02:00', '2019-04-05 13:00:00+02:00', '2019-04-05 14:00:00+02:00', '2019-04-05 15:00:00+02:00', '2019-04-18 05:00:00+02:00', '2019-04-18 06:00:00+02:00', '2019-04-18 07:00:00+02:00', '2019-04-18 14:00:00+02:00', '2019-04-18 15:00:00+02:00', '2019-04-18 16:00:00+02:00']}

In [8]:
```
# --- Experiment 1: vary k ---
cutoff_frac = 0.04
k_values = [2.5, 3.0, 3.5, 4.0]
results_k = []

for k in k_values:
    _, summary = spc_outlier_plotly(bergen_2019['temperature_2m'], cutoff_fr
    results_k.append({'k': k, 'outlier_fraction': summary['outlier_fraction'

df_k = pd.DataFrame(results_k)
df_k
```

Out[8]:

	k	outlier_fraction
0	2.5	0.047489
1	3.0	0.021804
2	3.5	0.007991
3	4.0	0.002740

In [9]:
```
# --- Experiment 2: vary cutoff_frac ---
k = 3.0
cutoff_values = [0.02, 0.03, 0.04, 0.05, 0.06]
results_cutoff = []

for cf in cutoff_values:
    _, summary = spc_outlier_plotly(bergen_2019['temperature_2m'], cutoff_fr
    results_cutoff.append({'cutoff_frac': cf, 'outlier_fraction': summary['c

df_cutoff = pd.DataFrame(results_cutoff)
df_cutoff
```

Out[9]:

	cutoff_frac	outlier_fraction
0	0.02	0.011986
1	0.03	0.014840
2	0.04	0.021804
3	0.05	0.027283
4	0.06	0.031164

Plotting percipitation

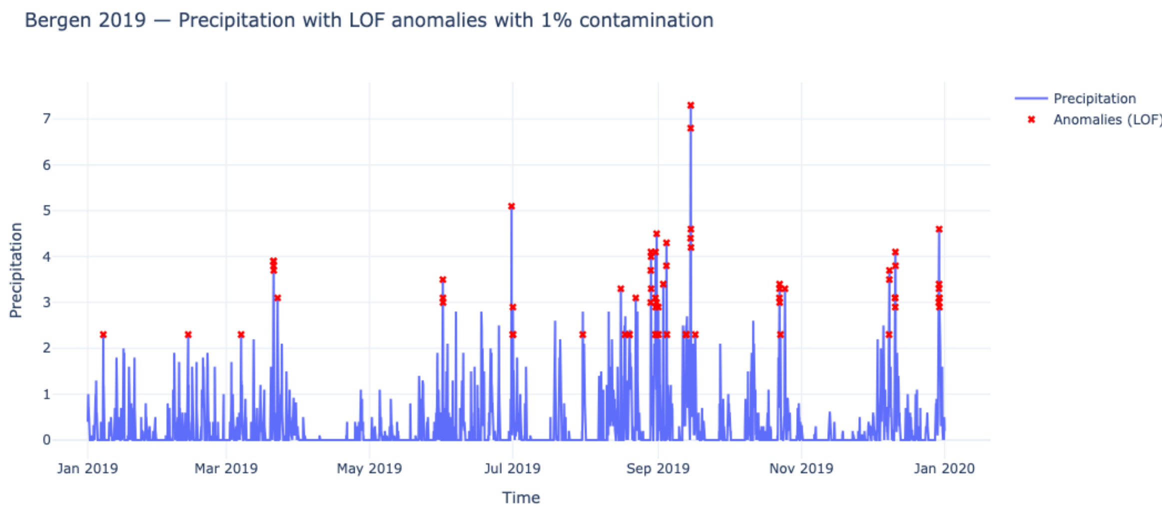
In [10]:

```
import numpy as np
import pandas as pd
import plotly.graph_objects as go
from sklearn.neighbors import LocalOutlierFactor

def lof_precipitation_plotly(precip_series: pd.Series, contamination: float
    """
    Detect precipitation anomalies using the Local Outlier Factor (LOF) meth

    Parameters
    ----------
    precip_series : pandas.Series
        Time series of precipitation (mm/hour or mm/day) with datetime index
    contamination : float, optional
        Proportion of outliers (default 0.01 = 1%).
    n_neighbors : int, optional
        Number of neighbors to use for LOF (default 20).
    title : str, optional
        Custom plot title.

    Returns
    -------
    fig : plotly.graph_objects.Figure
        Interactive Plotly figure of precipitation with anomalies marked.
    summary : dict
        Summary with counts, proportions, and example outlier timestamps.
    """

    # Ensure datetime index
    if not isinstance(precip_series.index, pd.DatetimeIndex):
        precip_series = precip_series.copy()
        precip_series.index = pd.to_datetime(precip_series.index)
    precip_series = precip_series.sort_index()

    # Prepare data for LOF (2D input required)
    X = precip_series.values.reshape(-1, 1)

    # Fit LOF model
    lof = LocalOutlierFactor(n_neighbors=n_neighbors, contamination=contamir
    preds = lof.fit_predict(X)
    lof_scores = -lof.negative_outlier_factor_
```

```python
    # Identify outliers
    outlier_mask = preds == -1
    n_points = len(precip_series)
    n_outliers = int(outlier_mask.sum())
    outlier_fraction = n_outliers / n_points if n_points > 0 else 0.0

    # Build Plotly figure
    fig = go.Figure()
    fig.add_trace(go.Scatter(
        x=precip_series.index, y=precip_series.values,
        mode='lines', name='Precipitation'
    ))

    if n_outliers > 0:
        fig.add_trace(go.Scatter(
            x=precip_series.index[outlier_mask],
            y=precip_series.values[outlier_mask],
            mode='markers',
            name='Anomalies (LOF)',
            marker=dict(color='red', size=6, symbol='x')
        ))

    fig.update_layout(
        title=title or f'Precipitation anomalies (LOF, contamination={contam
        xaxis_title='Time',
        yaxis_title='Precipitation',
        hovermode='x unified',
        template='plotly_white',
        height=520,
        width=1100
    )

    summary = {
        'n_points': n_points,
        'n_outliers': n_outliers,
        'outlier_fraction': outlier_fraction,
        'contamination_param': contamination,
        'n_neighbors': n_neighbors,
        'lof_score_min': float(lof_scores.min()),
        'lof_score_max': float(lof_scores.max()) # max LOF score. LOF scores
        }

    return fig, summary
```

In [11]:
```python
# Example test for Bergen 2019 precipitation data
fig_lof, summary_lof = lof_precipitation_plotly(bergen_2019["precipitation"]
fig_lof.show()
summary_lof
```

```
/opt/anaconda3/envs/D2D_env/lib/python3.11/site-packages/sklearn/neighbors/_
lof.py:322: UserWarning:

Duplicate values are leading to incorrect results. Increase the number of ne
ighbors for more accurate results.
```



Out[11]:
```
{'n_points': 8760,
 'n_outliers': 68,
 'outlier_fraction': 0.007762557077625571,
 'contamination_param': 0.01,
 'n_neighbors': 20,
 'lof_score_min': 0.9841943979263306,
 'lof_score_max': 149999856.0}
```

Seasonal-Trend decomposition using LOESS (STL)

In [12]:
```
# Copying code from part 2 of the project to fetch Elhub data

# ==============================
# 1️⃣ FETCH DATA FROM ELHUB API
# ==============================
import requests
import pandas as pd
from datetime import datetime, timedelta
import time

# --- API SETTINGS ---
BASE_URL = "https://api.elhub.no/energy-data/v0/price-areas"
DATASET = "PRODUCTION_PER_GROUP_MBA_HOUR"

# --- FUNCTION TO FORMAT DATES ---
def format_date(dt_obj):
    """Formats datetime with timezone offset for Elhub (%2B02:00)."""
    return dt_obj.strftime("%Y-%m-%dT%H:%M:%S%%2B02:00")  # +02:00 is used f

all_records = []

# --- FETCH MONTHLY DATA FOR 2021 ---
for month in range(1, 13):
    start = datetime(2021, month, 1)
    next_month = (start + timedelta(days=32)).replace(day=1)
    end = next_month - timedelta(seconds=1)

    start_str = format_date(start)
```

```
    end_str = format_date(end)

    url = f"{BASE_URL}?dataset={DATASET}&startDate={start_str}&endDate={end_
    print(f"=== Fetching {start.date()} → {end.date()} ===")

    response = requests.get(url)
    if response.status_code != 200:
        print(f"❌ Error {response.status_code}")
        continue

    data = response.json()
    month_records = []

    for entry in data.get("data", []):
        attrs = entry.get("attributes", {})
        recs = attrs.get("productionPerGroupMbaHour", [])
        # Filter out placeholders
        recs = [r for r in recs if r.get("productionGroup") != "*"]
        month_records.extend(recs)

    all_records.extend(month_records)
    print(f"✅ {len(month_records)} records added")

    # Be kind to API
    time.sleep(1)

print(f"\nTotal records collected: {len(all_records)}")

# --- CONVERT TO DATAFRAME ---
df = pd.DataFrame(all_records)
df['startTime'] = pd.to_datetime(df['startTime'], utc=True)
df['endTime'] = pd.to_datetime(df['endTime'], utc=True)
df['quantityKwh'] = pd.to_numeric(df['quantityKwh'], errors='coerce')
df = df[['priceArea', 'productionGroup', 'startTime', 'quantityKwh']]
df.sort_values('startTime', inplace=True)
df.set_index('startTime', inplace=True)

print(df.info())
print(df.head(50))
print(f"DataFrame shape: {df.shape}")
```

```
=== Fetching 2021-01-01 → 2021-01-31 ===
✅ 17856 records added
=== Fetching 2021-02-01 → 2021-02-28 ===
✅ 16128 records added
=== Fetching 2021-03-01 → 2021-03-31 ===
✅ 17832 records added
=== Fetching 2021-04-01 → 2021-04-30 ===
✅ 17280 records added
=== Fetching 2021-05-01 → 2021-05-31 ===
✅ 17856 records added
=== Fetching 2021-06-01 → 2021-06-30 ===
✅ 17976 records added
=== Fetching 2021-07-01 → 2021-07-31 ===
✅ 18600 records added
=== Fetching 2021-08-01 → 2021-08-31 ===
✅ 18600 records added
=== Fetching 2021-09-01 → 2021-09-30 ===
✅ 18000 records added
=== Fetching 2021-10-01 → 2021-10-31 ===
✅ 18625 records added
=== Fetching 2021-11-01 → 2021-11-30 ===
✅ 18000 records added
=== Fetching 2021-12-01 → 2021-12-31 ===
✅ 18600 records added

Total records collected: 215353
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 215353 entries, 2020-12-31 23:00:00+00:00 to 2021-12-31 22:0
0:00+00:00
Data columns (total 3 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   priceArea        215353 non-null  object 
 1   productionGroup  215353 non-null  object 
 2   quantityKwh      215353 non-null  float64
dtypes: float64(1), object(2)
memory usage: 6.6+ MB
None
                          priceArea productionGroup  quantityKwh
startTime                                                       
2020-12-31 23:00:00+00:00       NO1           hydro  2507716.800
2020-12-31 23:00:00+00:00       NO2           other        4.346
2020-12-31 23:00:00+00:00       NO5           solar        3.720
2020-12-31 23:00:00+00:00       NO2            wind      706.206
2020-12-31 23:00:00+00:00       NO3           hydro  2836774.000
2020-12-31 23:00:00+00:00       NO4            wind   381065.000
2020-12-31 23:00:00+00:00       NO2           hydro  7245923.500
2020-12-31 23:00:00+00:00       NO3           other        0.000
2020-12-31 23:00:00+00:00       NO5         thermal    77742.000
2020-12-31 23:00:00+00:00       NO4         thermal    21349.000
2020-12-31 23:00:00+00:00       NO2         thermal    24171.203
2020-12-31 23:00:00+00:00       NO3           solar       19.722
2020-12-31 23:00:00+00:00       NO1            wind      937.072
2020-12-31 23:00:00+00:00       NO5           other        0.000
2020-12-31 23:00:00+00:00       NO3         thermal        0.000
2020-12-31 23:00:00+00:00       NO3            wind   259312.200
```

```
2020-12-31 23:00:00+00:00       NO4          solar        0.000
2020-12-31 23:00:00+00:00       NO5          hydro  4068096.500
2020-12-31 23:00:00+00:00       NO1        thermal    51369.035
2020-12-31 23:00:00+00:00       NO4          hydro  3740830.000
2020-12-31 23:00:00+00:00       NO4          other        0.161
2020-12-31 23:00:00+00:00       NO1          other        0.000
2020-12-31 23:00:00+00:00       NO2          solar      876.556
2020-12-31 23:00:00+00:00       NO1          solar        6.106
2021-01-01 00:00:00+00:00       NO1        thermal    51673.934
2021-01-01 00:00:00+00:00       NO3           wind   225762.900
2021-01-01 00:00:00+00:00       NO3          solar       25.433
2021-01-01 00:00:00+00:00       NO5          other        0.000
2021-01-01 00:00:00+00:00       NO3        thermal        0.000
2021-01-01 00:00:00+00:00       NO3          other        0.000
2021-01-01 00:00:00+00:00       NO4           wind   369910.000
2021-01-01 00:00:00+00:00       NO1          solar        4.030
2021-01-01 00:00:00+00:00       NO5          solar        3.600
2021-01-01 00:00:00+00:00       NO2           wind     3431.889
2021-01-01 00:00:00+00:00       NO2        thermal    24195.646
2021-01-01 00:00:00+00:00       NO1          other        0.000
2021-01-01 00:00:00+00:00       NO2          other        3.642
2021-01-01 00:00:00+00:00       NO5        thermal    77575.000
2021-01-01 00:00:00+00:00       NO4          hydro  3746663.500
2021-01-01 00:00:00+00:00       NO4          solar        0.000
2021-01-01 00:00:00+00:00       NO1           wind      649.068
2021-01-01 00:00:00+00:00       NO5          hydro  4104306.000
2021-01-01 00:00:00+00:00       NO4          other        0.161
2021-01-01 00:00:00+00:00       NO3          hydro  2836189.800
2021-01-01 00:00:00+00:00       NO4        thermal    22554.000
2021-01-01 00:00:00+00:00       NO2          solar      876.398
2021-01-01 00:00:00+00:00       NO1          hydro  2494728.000
2021-01-01 00:00:00+00:00       NO2          hydro  6750958.000
2021-01-01 01:00:00+00:00       NO2          other        3.562
2021-01-01 01:00:00+00:00       NO2        thermal    23558.420
DataFrame shape: (215353, 3)
```

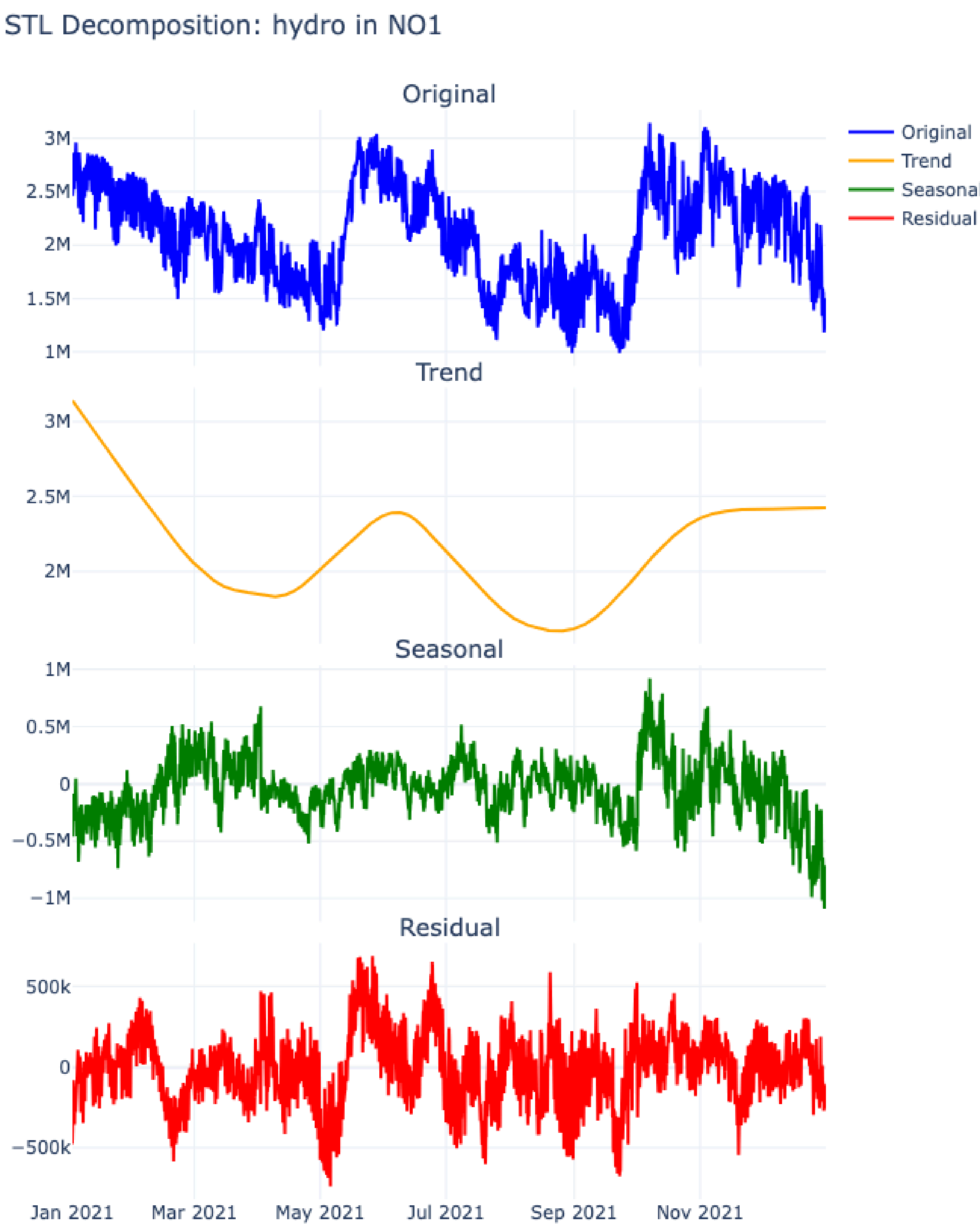
In [13]:

```
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from statsmodels.tsa.seasonal import STL

def stl_decomposition_plotly_subplots(
    df,
    price_area='NO1',
    production_group='hydro',
    period=24,
    seasonal=13,
    trend=25,
    robust=True
):
    """
    STL decomposition with four stacked subplots (Original, Trend, Seasonal,

    Returns the figure and STL results object.
    """
    # Case-insensitive filtering
    ts = df[(df['priceArea'].str.lower() == price_area.lower()) &
```

```python
            (df['productionGroup'].str.lower() == production_group.lower())]

    if ts.empty:
        raise ValueError(f"No data found for price area '{price_area}' and p

    # Fill missing values
    ts = ts.asfreq('h').ffill()

    # Fit STL
    stl = STL(ts, period=period, seasonal=seasonal, trend=trend, robust=robu
    res = stl.fit()

    # Create subplots
    fig = make_subplots(
        rows=4, cols=1, shared_xaxes=True,
        vertical_spacing=0.02,
        subplot_titles=['Original', 'Trend', 'Seasonal', 'Residual']
    )

    # Original
    fig.add_trace(go.Scatter(x=ts.index, y=ts, mode='lines', name='Original'
    # Trend
    fig.add_trace(go.Scatter(x=ts.index, y=res.trend, mode='lines', name='Tr
    # Seasonal
    fig.add_trace(go.Scatter(x=ts.index, y=res.seasonal, mode='lines', name=
    # Residual
    fig.add_trace(go.Scatter(x=ts.index, y=res.resid, mode='lines', name='Re

    fig.update_layout(
        height=900,
        title_text=f"STL Decomposition: {production_group} in {price_area}",
        template='plotly_white'
    )

    fig.show()

    return fig, res
```

In [14]:

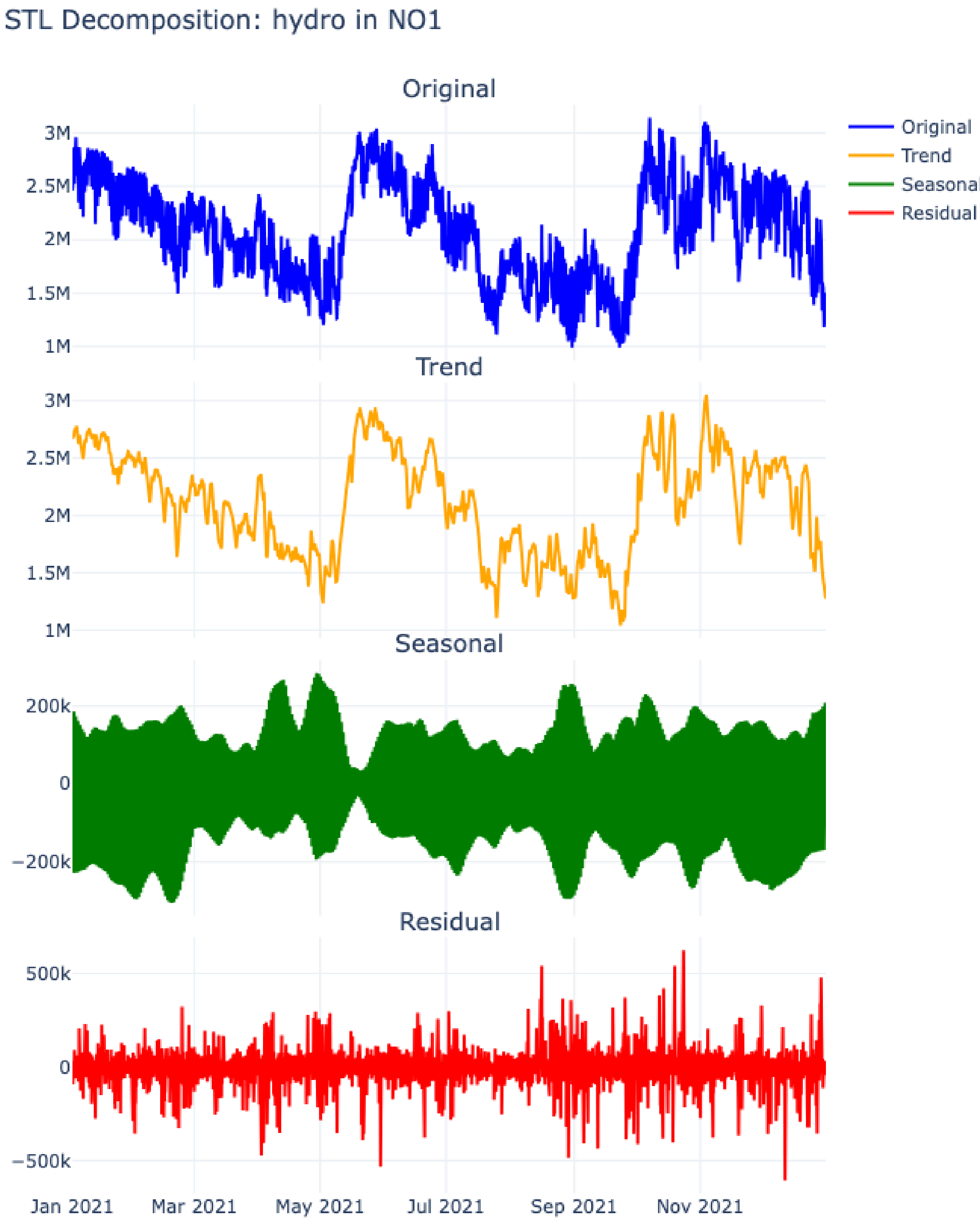
```python
# Using large parameters tp se the long-term seasonality in hydro productio
fig, res = stl_decomposition_plotly_subplots(
    df,
    price_area='NO1',
    production_group='hydro',
    period= 2190,
    seasonal=2191,
    trend=2191,
    robust=False
)
```



In [15]:

```
# Using other parameters. Suggestion from chatGPT
fig, res = stl_decomposition_plotly_subplots(
    df,
    price_area='NO1',
    production_group='hydro',
    period=24,      # daily seasonality
    seasonal=13,    # smooth daily pattern
    trend=25,       # slow trend over the year
```

```
    robust=True
)
```



Spectrogram

In [16]:
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.signal import stft
```

```
def matplotlib_spectrogram(
    df,
    price_area='NO1',
    production_group='hydro',
    window_length=168,   # nperseg in STFT
    window_overlap=84,   # noverlap in STFT
    fs=1                 # sampling frequency (1 per hour)
):
    """
    Compute and plot a spectrogram for electricity production data using Mat

    Parameters
    ----------
    df : pd.DataFrame
        DataFrame with ['priceArea','productionGroup','quantityKwh'] indexed
    price_area : str
        Electricity price area to filter.
    production_group : str
        Production group to filter.
    window_length : int
        Number of samples per STFT window (nperseg).
    window_overlap : int
        Overlap between windows (noverlap).
    fs : float
        Sampling frequency. For hourly data, fs=1.

    Returns
    -------
    f : np.ndarray
        Frequency bins.
    t : np.ndarray
        Time bins.
    Zxx : np.ndarray
        STFT complex values.
    """
    # Filter data
    ts = df[(df['priceArea'].str.lower() == price_area.lower()) &
            (df['productionGroup'].str.lower() == production_group.lower())]

    if ts.empty:
        raise ValueError(f"No data for price area '{price_area}' and product

    ts = ts.asfreq('h').ffill()

    # Compute STFT
    f, t, Zxx = stft(ts.values, fs=fs, nperseg=window_length, noverlap=windo

    # Plot with Matplotlib
    plt.figure(figsize=(12, 5))
    plt.pcolormesh(t, f, np.abs(Zxx), shading='gouraud', cmap='viridis', vmi
    plt.title(f'Spectrogram: {production_group} in {price_area}')
    plt.ylabel('Frequency [1/hour]')
    plt.xlabel('Time [hours]')
    plt.colorbar(label='Amplitude')
    plt.tight_layout()
```

```
    plt.show()

    return f, t, Zxx
```

In [17]:
```
# Testing the spectrogram function with solar production data
f, t, Zxx = matplotlib_spectrogram(
    df,
    price_area='NO1',
    production_group='solar',
    window_length=24,    # 1 day of hourly data
    window_overlap=12,    # 50% overlap
    fs=1
)
```