Technical University of Denmark

42186 - Model-based machine learning

Project Outline

Group 16

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1 Research Question

Whenever you turn on the light, start your dishwasher, or turn on the TV, you consume electricity and therefore must pay for it. Depending on the supply and demand for the given hour, a price per kWh is determined. This price is established on the spot-market, also referred to as the day-ahead market, because the price is set at 12:00 noon the day before for the 24 hours of the following day. This means that after 12:00, the prices for the next hour are known. These day-ahead prices (DA-prices) are set for each bidding zone. In Denmark, there are two bidding zones (DK1 and DK2), whereas Norway, for instance, has five bidding zones (NO1, NO2, NO3, NO4, and NO5). The bidding zones are connected by transmission lines, as shown in Figure 1, which allows for trade between the bidding zones, limited by their capacity.

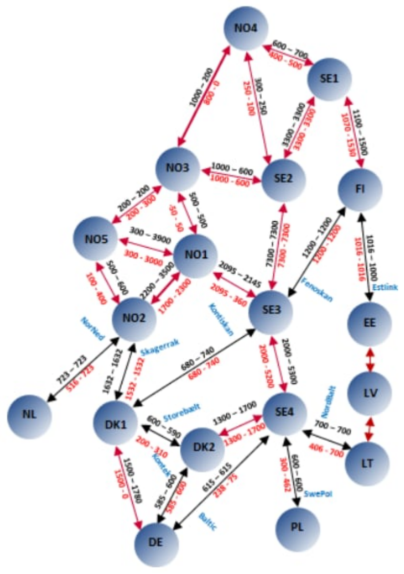


Figure 1: Diagram of the north European bidding zones and their connections.

This dynamic results in the bidding zones having equal DA-prices as long as the transmission is not congested since the marginal producer in the most expensive bidding zone also becomes the marginal producer in the region to which power is exported, as long as there is sufficient transmission capacity.

The DA-price for each bidding zone is influenced by the demand for electricity at the given hour for the bidding zone, the supply of renewable power generation (wind and solar) and conventional power generation, but also by the dynamics in the neighboring bidding zones due to the trade between bidding zones and even the neighboring bidding zones' neighbors.

Our goal is to model all of these dynamics in order to provide the best prediction of the DA-prices in the Nordic bidding zones, leading to the following research question:

- **What factors influence the day-ahead prices in the Nordic bidding zones, and how can these dynamics be accurately modeled to predict the DA-prices using model-based machine learning techniques?**

2 Dataset

In order to model this problem, data has been obtained from ENTSO-E (european network of transmission system operators for electricity), which has a publicly available API. A variety of datasets have been queried from the API and after a thorough data pro-processing part, a complete data set for the Nordic Region has been created with the following variables:

- Timestamp: Date with hourly granularity
- Country code: 12 different bidding zones in Northern Europe
- Day Ahead Price: Actual electricity price for the Day Ahead market [€ / MWh]
- Wind Offshore: Forecast of offshore wind generation [MWh]
- Wind Onshore: Forecast of onshore wind generation [MWh]
- Solar: Forecast of solar generation [MWh]
- Total Generation: Forecast of total power generation [MWh]
- Forecasted Load: Forecast of power demand [MWh]
- Actual Load: Actual power demand [MWh]

- Export to: Power exported to neighbouring bidding zones [MWh]
- Import from: Power imported from neighbouring bidding zones [MWh]
- Capacity to: Power capacity in transmission lines to neighbouring bidding zones [MWh]

For the bidding zone DK1, a variety of the data is visualized for a single month in the appendix. We can see the fluctuations in the DA-price, which is the one we are interested in predicting, how it varies from specific days and hours and how it to some extend also looks to follow the trends of the load and generation of renewable energy.

3 First draft of model

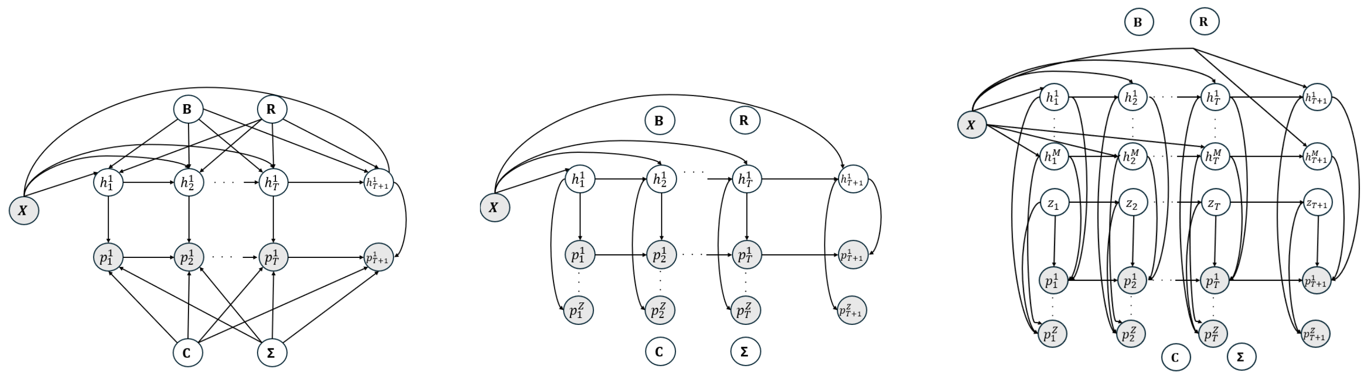
The goal is to model DA-prices in the Nordic countries, namely Denmark, Sweden, Norway, and Finland. The Nordic electricity market is divided into 12 bidding zones, each of which produces electricity and sets a price in its respective zone.

The simplest version of the problem considers all 12 Nordic bidding zones as independent zones. In each bidding zone, renewable power forecasts are provided by ENTSOE, and the expected load in the bidding zone is obtained from ENTSOE. These features are represented by X in Figure 2a.

This process is depicted as a probabilistic graphical model in Figure 2a, which is of the type linear dynamic system (LDS) with inputs. This model will be the first to be explored.

However, the bidding zones are not independent entities but rather connected, as shown in the diagram in Figure 1. This results in possible power exchanges between the connected bidding zones, which in turn influence the DA-prices. If there is no congestion on a transmission line, electricity can flow, and the prices will be similar.

These connections lead us to consider a more complex graphical model where the output is multivariate since the DA-price predictions are made for all of the bidding zones in the same model, as illustrated in Figure 2b.



(a) The simple probabilistic graphical model.

(b) The probabilistic graphical model (multivariate).

(c) The probabilistic graphical model (advanced temporal model).

Figure 2: Probabilistic graphical models taking the interaction between bidding zones into account.

Finally, the more advanced model to consider will include the incorporation of regimes, as depicted in Figure 2c. Since the price is heavily influenced by whether there is congestion in the transmission lines connecting the bidding zones with the neighboring bidding zones, we consider it valuable to implement at least two regimes. These regimes define whether there is congestion or not in the transmission lines.
This results in an LDS model with:

1. External input
2. Extended Kalman filter
3. Forecast
4. Switching between different regimes

In [ ]:
```
from entsoe import EntsoePandasClient
from tqdm import tqdm
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
```

Scrape data from ENTSOE API

- https://github.com/EnergieID/entsoe-py
- Day ahead prices
- Load
- Load Forecast
- Load and forecast
- Generation Forecast
- Wind and Solar Forecast
- Scheduled Exchanges
- Net Transfer Capacity

In [ ]:
```
# Define the EntsoePandasClient object with the API key
client = EntsoePandasClient(api_key='a6160036-4d49-4c39-960f-99c3c690b6da

# Define the time period and the country codes
# start = pd.Timestamp('20220601', tz='Europe/Copenhagen')
# end = pd.Timestamp('20220630', tz='Europe/Copenhagen')
start_date = pd.Timestamp('20220601 00:00:00', tz='Europe/Brussels').tz_c
end_date = pd.Timestamp('20220630 23:00:00', tz='Europe/Brussels').tz_con
country_codes = ['DK_1', 'DK_2', 'SE_1', 'SE_2', 'SE_3', 'SE_4', 'NO_1',
```

In [ ]:
```
# Create empty dataframes for storing the data
day_ahead_prices = pd.DataFrame()
scheduled_exchanges = pd.DataFrame()
net_transfer_capacity = pd.DataFrame()
load = pd.DataFrame()
load_forecast = pd.DataFrame()
load_and_forecast = pd.DataFrame()
generation_forecast = pd.DataFrame()
wind_and_solar_forecast = pd.DataFrame()
```

In [ ]:
```
# Loop over the country codes and query the data
for country_code in country_codes:
    # day ahead prices
    day_ahead = pd.DataFrame(client.query_day_ahead_prices(country_code,
    day_ahead['country_code'] = country_code
    day_ahead_prices = pd.concat([day_ahead_prices, day_ahead])
    # load
    ld = pd.DataFrame(client.query_load(country_code, start=start_date, e
    ld['country_code'] = country_code
    load = pd.concat([load, ld])
    # load forecast
    ld_fc = pd.DataFrame(client.query_load_forecast(country_code, start=s
    ld_fc['country_code'] = country_code
    load_forecast = pd.concat([load_forecast, ld_fc])
    # load and forecast
    ld_fc = pd.DataFrame(client.query_load_and_forecast(country_code, sta
    ld_fc['country_code'] = country_code
    load_and_forecast = pd.concat([load_and_forecast, ld_fc])
    # generation forecast
    gen_fc = pd.DataFrame(client.query_generation_forecast(country_code,
    gen_fc['country_code'] = country_code
    generation_forecast = pd.concat([generation_forecast, gen_fc])
    # wind and solar forecast
    ws_fc = pd.DataFrame(client.query_wind_and_solar_forecast(country_cod
    ws_fc['country_code'] = country_code
    wind_and_solar_forecast = pd.concat([wind_and_solar_forecast, ws_fc])
```

```
Connection Error, retrying in 10 seconds
Connection Error, retrying in 10 seconds
```

In [ ]:
```
data_frame_lists = ['day_ahead_prices', 'load', 'load_forecast', 'load_an
# save dataframes to csv
for data_frame_list in data_frame_lists:
    data = eval(data_frame_list)
    # adjust hour for finnish data as it is in UTC+2
    data_finnish = data[data['country_code'] == 'FI']
    data = data[data['country_code'] != 'FI']
    # subtract 1 hour from the index
    data_finnish.index = data_finnish.index - pd.DateOffset(hours=1)
    # Concat to the original dataframe
    data = pd.concat([data, data_finnish])
    # change the index to be a column
    # data['Timestamp'] = data.index
    # data.index = range(len(data))
    # data['Timestamp'] = pd.to_datetime(data['Timestamp'])
    data.to_csv(f'data/{data_frame_list}.csv')
```

In [ ]:
```
da = pd.read_csv('data/day_ahead_prices.csv')
# rename Unnamed: 0 to Timestamp
da.rename(columns={'Unnamed: 0': 'Timestamp'}, inplace=True)
# convert Timestamp to datetime
da_finnish = da[da['country_code'] == 'FI']
da = da[da['country_code'] != 'FI']
da['Timestamp'] = pd.to_datetime(da['Timestamp'])
da['Timestamp'] = da['Timestamp'].dt.tz_localize(None)
da_finnish['Timestamp'] = pd.to_datetime(da_finnish['Timestamp'])
da_finnish['Timestamp'] = da_finnish['Timestamp'].dt.tz_localize(None)
da = pd.concat([da, da_finnish])
da[da['country_code'] == 'FI'].head()
```

Out[ ]:

	Timestamp	0	country_code
7920	2022-06-01 00:00:00	10.00	FI
7921	2022-06-01 01:00:00	9.50	FI
7922	2022-06-01 02:00:00	9.00	FI
7923	2022-06-01 03:00:00	9.99	FI
7924	2022-06-01 04:00:00	11.59	FI

Download of cross border data

In [ ]:
```
# Function to query cross-border flows
def queryWeekAheadCapacities(mapping_table, start_date, end_date):

    """
    Query cross-border flows from the ENTSO-E API based on a mapping tabl

    Parameters:
    - mapping_table (dict): A mapping table with key-value pairs represen
    - start_date (str): Start date for the query.
    - end_date (str): End date for the query.

    Returns:
    pd.DataFrame: DataFrame containing cross-border flow data with column

    """

    df_list = []
    for key, values in tqdm(mapping_table.items(), desc='Processing NTCs'
        for value in tqdm(values, desc=f'Processing NTC from {key}'):
            try:
                data_temp = client.query_net_transfer_capacity_weekahead(
                data_temp = data_temp.reset_index()
                data_temp['From'] = key
                data_temp['To'] = value
                df_list.append(data_temp)
            except:
                tqdm.write(f'No data for {key} -> {value}')

    print('Done')
    df_queried = pd.concat(df_list, ignore_index=True)
    df_queried = df_queried.rename(columns={0:'WeekAhead_NTC', 'index':'M

    return df_queried
```

In [ ]:
```
# Function to convert daily granularity to hourly granularity for cross-b
def fromDailyToHourlyGranularity(NTCs, start_date, end_date):

    # Assuming 'index' is the index of your DataFrame
    # Convert 'index' to datetime if it's not already
    NTCs['MTU'] = pd.to_datetime(NTCs['MTU'])

    # Set 'index' as the index of your DataFrame
    NTCs.set_index('MTU', inplace=True)

    # Create a secondary index by combining 'From' and 'To'
    NTCs['secondary_index'] = NTCs['From'] + '_' + NTCs['To']

    NTCs_hourly = pd.DataFrame()
    for secondary in NTCs['secondary_index'].unique():
        selection = NTCs.loc[NTCs['secondary_index'] == secondary]

        new_index = pd.date_range(start=start_date, end=end_date, freq='h
        selection = selection.reindex(new_index)

        # Reset the index to get 'dateTimeUtc' back as a column
        #selection.reset_index(inplace=True)

        # Forward fill to propagate values for new timestamps
        selection = selection.ffill()

        # concat the result to new_table
        NTCs_hourly = pd.concat([NTCs_hourly, selection])

    # drop the secondary index
    NTCs_hourly.drop('secondary_index', axis=1, inplace=True)

    # rename From and To to biddingZoneFrom and biddingZoneTo
    NTCs_hourly.rename(columns={'From':'biddingZoneFrom', 'To':'biddingZo
    NTCs_hourly.index.rename('MTU', inplace=True)

    return NTCs_hourly
```

In [ ]:

```
# Function to query scheduled exchanges
def query_scheduled_exchanges_ENTSOE(mapping_table, start_date, end_date)

    """
    Query cross-border flows from the ENTSO-E API based on a mapping tabl

    Parameters:
    - mapping_table (dict): A mapping table with key-value pairs represen
    - start_date (str): Start date for the query.
    - end_date (str): End date for the query.

    Returns:
    pd.DataFrame: DataFrame containing cross-border flow data with column

    """

    df_list = []
    for key, values in tqdm(mapping_table.items(), desc='Processing sched
        for value in tqdm(values, desc=f'Processing scheduled exchanges f
            try:
                data_temp = client.query_scheduled_exchanges(key, value,
                data_temp = data_temp.reset_index()
                data_temp['From'] = key
                data_temp['To'] = value
                df_list.append(data_temp)
            except:
                tqdm.write(f'No data for {key} -> {value}')

    print('Done')
    df_queried = pd.concat(df_list, ignore_index=True)
    df_queried = df_queried.rename(columns={0:'Sch_Exchange', 'index':'MT

    return df_queried
```

In [ ]:

```
# Function to achieve hourly granularity of scheduled exchanges
def achieve_hourly_granularity(df):

    """
    Process a DataFrame to achieve hourly granularity of flow data.

    Parameters:
    - df (pd.DataFrame): Input DataFrame containing flow data with column
                         Here, some MTU may be of 15 minutes granularity,

    Returns:
    pd.DataFrame: Processed DataFrame with hourly granularity, where the
                  for each hour between 'From' and 'To'.

    Notes:
    - The 'MTU' column is converted to UTC datetime.
    - New columns 'Hour' and 'Date' are created to store the hour and dat
    - The DataFrame is then grouped by 'Date', 'Hour', 'From', and 'To' t
    - The 'Date' column is adjusted to represent the midpoint of each hou
    - The 'Hour' column is dropped from the final result.

    """

    # Convert 'MTU' column to UTC datetime
    df['MTU'] = pd.to_datetime(df['MTU'], utc=True)

    # Create a new column 'Hour' to store the hour information
    df['Hour'] = df['MTU'].dt.hour

    # Create a new column 'Date' to store the date information
    df['Date'] = df['MTU'].dt.date

    # Group by 'Date', 'Hour', 'From', and 'To' and calculate the average
    df = df.groupby(['Date', 'Hour', 'From', 'To'])['Sch_Exchange'].mean(

    # Convert 'index' column to datetime
    df['Date'] = pd.to_datetime(df['Date'])

    df['Date'] = df['Date'] + pd.to_timedelta(df['Hour'].astype(str) + ':
```

```
    df.drop(columns=['Hour'], inplace=True)

    df.rename(columns={'Date': 'MTU'}, inplace=True)

    return df
```

In [ ]:
```
# Function to define cross border connections and run the queries
def main_border_queries(start_date, end_date):

    #####################
    ### MAPPING TABLE ###
    #####################

    NEIGHBOURS_Real_System = {
        'NL': ['NO_2', 'DK_1'],
        'DE_AT_LU': ['DK_1', 'DK_2', 'SE_4'],
        'GB': ['NO_2','DK_1'],
        'NO_2': ['DE_LU', 'DK_1', 'NL', 'NO_1', 'NO_5', 'GB'],
        'PL': ['SE_4'],
        'DK_1': ['DE_AT_LU', 'DE_LU', 'DK_2', 'NO_2', 'SE_3', 'NL','GB'],
        'LT': ['SE_4'],
        'SE_3': ['DK_1', 'FI', 'NO_1', 'SE_2', 'SE_4'],
        'NO_1': ['NO_2', 'NO_3', 'NO_5', 'SE_3'],
        'SE_4': ['DE_AT_LU', 'DE_LU', 'DK_2', 'LT', 'PL', 'SE_3'],
        'NO_5': ['NO_1', 'NO_2', 'NO_3'],
        'EE': ['FI'],
        'DK_2': ['DE_AT_LU', 'DE_LU', 'DK_1', 'SE_4'],
        'FI': ['EE', 'NO_4', 'RU', 'SE_1', 'SE_3'],
        'NO_4': ['SE_2', 'FI', 'NO_3', 'SE_1'],
        'SE_1': ['FI', 'NO_4', 'SE_2'],
        'SE_2': ['NO_3', 'NO_4', 'SE_1', 'SE_3'],
        'DE_LU': ['DK_1', 'DK_2', 'NO_2', 'SE_4'],
        'NO_3': ['NO_1', 'NO_4', 'NO_5', 'SE_2']
    }

    NTCs = queryWeekAheadCapacities(NEIGHBOURS_Real_System, start_date, e
    NTCs = fromDailyToHourlyGranularity(NTCs, start_date, end_date)

    # Query cross-border scheduled exchanges from ENTSO-E
    SchExch = query_scheduled_exchanges_ENTSOE(NEIGHBOURS_Real_System, st
    SchExch_H = achieve_hourly_granularity(SchExch)

    return NTCs, SchExch, SchExch_H
```

In [ ]:
```
NTCs, SchExch, SchExch_H = main_border_queries(start_date, end_date)

# Putting the cross border exchange data in the right format
NTCs_pivot = NTCs.copy(deep=True).reset_index()
NTCs_pivot = NTCs_pivot.pivot_table(index=['MTU', 'biddingZoneFrom'], col
NTCs_pivot = NTCs_pivot.rename(columns={col: f'Cap_to_{col}' if col != 'M
NTCs_pivot = NTCs_pivot.fillna(0)
NTCs_pivot.rename(columns={'biddingZoneFrom': 'From'}, inplace=True)
```

```
# Scheduled Hourly Export
SchExch_H_Ex = SchExch_H.copy(deep=True)
SchExch_H_Ex = SchExch_H_Ex.pivot_table(index=['MTU', 'From'], columns='T
SchExch_H_Ex = SchExch_H_Ex.rename(columns={col: f'Ex_to_{col}' if col !=
SchExch_H_Ex = SchExch_H_Ex.fillna(0)

# Scheduled Hourly Import
SchExch_H_Imp = SchExch_H.copy(deep=True)
SchExch_H_Imp['From'], SchExch_H_Imp['To'] = SchExch_H_Imp['To'], SchExch
SchExch_H_Imp = SchExch_H_Imp.pivot_table(index=['MTU', 'From'], columns=
SchExch_H_Imp = SchExch_H_Imp.rename(columns={col: f'Imp_from_{col}' if c
SchExch_H_Imp = SchExch_H_Imp.fillna(0)

# Scheduled exchanges merge
Border_data = SchExch_H_Ex.merge(SchExch_H_Imp, on=['MTU', 'From'], how='
Border_data['MTU'] = pd.to_datetime(Border_data['MTU']).dt.tz_localize('U
Border_data = Border_data.merge(NTCs_pivot, on=['MTU', 'From'], how='left
```

```
Processing NTC from NL: 100%|██████████| 2/2 [00:04<00:00,  2.28s/it]
Processing NTCs:   5%|▌          | 1/19 [00:04<01:22,  4.61s/it]
Processing NTCs:   5%|▌          | 1/19 [00:05<01:22,  4.61s/it]
No data for DE_AT_LU -> DK_1
Processing NTCs:   5%|▌          | 1/19 [00:08<01:22,  4.61s/it]
Processing NTC from DE_AT_LU: 100%|██████████| 3/3 [00:04<00:00,  1.49s/i
t]
Processing NTCs:  11%|█          | 2/19 [00:09<01:17,  4.54s/it]
No data for DE_AT_LU -> DK_2
No data for DE_AT_LU -> SE_4
Processing NTC from GB: 100%|██████████| 2/2 [00:00<00:00,  2.49it/s]
Processing NTCs:  16%|█▌         | 3/19 [00:09<00:45,  2.84s/it]
No data for GB -> DK_1
Connection Error, retrying in 10 seconds
Connection Error, retrying in 10 seconds
Processing NTC from NO_2: 100%|██████████| 6/6 [01:53<00:00, 18.93s/it]
Processing NTCs:  21%|██         | 4/19 [02:03<11:38, 46.55s/it]Connection
Error, retrying in 10 seconds
Processing NTC from PL: 100%|██████████| 1/1 [00:11<00:00, 11.18s/it]
Processing NTCs:  26%|██▋        | 5/19 [02:14<07:53, 33.80s/it]
Processing NTCs:  26%|██▋        | 5/19 [02:15<07:53, 33.80s/it]
No data for DK_1 -> DE_AT_LU
Processing NTC from DK_1: 100%|██████████| 7/7 [00:07<00:00,  1.01s/it]
Processing NTCs:  32%|███▏       | 6/19 [02:21<05:21, 24.71s/it]
No data for DK_1 -> GB
Processing NTC from LT: 100%|██████████| 1/1 [00:00<00:00,  1.43it/s]
Processing NTC from SE_3: 100%|██████████| 5/5 [00:05<00:00,  1.06s/it]
Processing NTC from NO_1: 100%|██████████| 4/4 [00:04<00:00,  1.01s/it]
Processing NTCs:  47%|████▋      | 9/19 [02:31<01:43, 10.32s/it]
Processing NTCs:  47%|████▋      | 9/19 [02:32<01:43, 10.32s/it]
No data for SE_4 -> DE_AT_LU
```

```
Processing NTC from SE_4: 100%|██████████| 6/6 [00:12<00:00,  2.02s/it]
Processing NTC from NO_5: 100%|██████████| 3/3 [00:03<00:00,  1.29s/it]
Processing NTC from EE: 100%|██████████| 1/1 [00:02<00:00,  2.35s/it]
Processing NTCs:  63%|██████    | 12/19 [02:50<00:47,  6.79s/it]
Processing NTCs:  63%|██████    | 12/19 [02:51<00:47,  6.79s/it]
No data for DK_2 -> DE_AT_LU
Processing NTC from DK_2: 100%|██████████| 4/4 [00:06<00:00,  1.59s/it]
Processing NTCs:  68%|██████▊   | 13/19 [02:56<00:39,  6.66s/it]
Processing NTCs:  68%|██████▊   | 13/19 [02:59<00:39,  6.66s/it]
No data for FI -> NO_4
Processing NTC from FI: 100%|██████████| 5/5 [00:17<00:00,  3.44s/it]
Processing NTCs:  74%|███████▎  | 14/19 [03:13<00:49,  9.84s/it]
Processing NTCs:  74%|███████▎  | 14/19 [03:17<00:49,  9.84s/it]
No data for NO_4 -> FI
Processing NTC from NO_4: 100%|██████████| 4/4 [00:06<00:00,  1.56s/it]
Processing NTC from SE_1: 100%|██████████| 3/3 [00:07<00:00,  2.66s/it]
Processing NTC from SE_2: 100%|██████████| 4/4 [00:10<00:00,  2.61s/it]
Processing NTC from DE_LU: 100%|██████████| 4/4 [00:07<00:00,  1.81s/it]
Processing NTC from NO_3: 100%|██████████| 4/4 [00:06<00:00,  1.74s/it]
Processing NTCs: 100%|██████████| 19/19 [03:52<00:00, 12.24s/it]
Done
Processing scheduled exchanges from NL: 100%|██████████| 2/2 [00:04<00:00,
2.01s/it]
Processing scheduled exchanges:   5%|▌         | 1/19 [00:04<01:12,  4.03
s/it]
Processing scheduled exchanges:   5%|▌         | 1/19 [00:05<01:12,  4.03
s/it]
No data for DE_AT_LU -> DK_1
Processing scheduled exchanges:   5%|▌         | 1/19 [00:06<01:12,  4.03
s/it]
No data for DE_AT_LU -> DK_2
Processing scheduled exchanges from DE_AT_LU: 100%|██████████| 3/3 [00:02<
00:00,  1.04it/s]
Processing scheduled exchanges:  11%|█         | 2/19 [00:06<00:57,  3.37
s/it]
No data for DE_AT_LU -> SE_4
Processing scheduled exchanges from GB: 100%|██████████| 2/2 [00:09<00:00,
4.79s/it]
Processing scheduled exchanges:  16%|█▌        | 3/19 [00:16<01:39,  6.22
s/it]
No data for GB -> DK_1
Processing scheduled exchanges from NO_2: 100%|██████████| 6/6 [00:20<00:0
0,  3.38s/it]
Processing scheduled exchanges from PL: 100%|██████████| 1/1 [00:02<00:00,
2.08s/it]
Processing scheduled exchanges:  26%|██▋       | 5/19 [00:38<01:56,  8.29
s/it]
Processing scheduled exchanges:  26%|██▋       | 5/19 [00:41<01:56,  8.29
s/it]
No data for DK_1 -> DE_AT_LU
```

```
Processing scheduled exchanges from DK_1: 100%|██████████| 7/7 [00:13<00:0
0,  1.98s/it]
Processing scheduled exchanges:  32%|███▏      | 6/19 [00:52<02:12, 10.18
s/it]
```

```
No data for DK_1 -> GB
```

```
Processing scheduled exchanges from LT: 100%|██████████| 1/1 [00:02<00:00,
2.37s/it]
Processing scheduled exchanges from SE_3: 100%|██████████| 5/5 [00:09<00:0
0,  1.85s/it]
Processing scheduled exchanges from NO_1: 100%|██████████| 4/4 [00:09<00:0
0,  2.47s/it]
Processing scheduled exchanges:  47%|████▋     | 9/19 [01:14<01:26,  8.68
s/it]
Processing scheduled exchanges:  47%|████▋     | 9/19 [01:14<01:26,  8.68
s/it]
```

```
No data for SE_4 -> DE_AT_LU
```

```
Processing scheduled exchanges from SE_4: 100%|██████████| 6/6 [00:14<00:0
0,  2.40s/it]
Processing scheduled exchanges from NO_5: 100%|██████████| 3/3 [00:14<00:0
0,  4.70s/it]
Processing scheduled exchanges from EE: 100%|██████████| 1/1 [00:04<00:00,
4.61s/it]
Processing scheduled exchanges:  63%|██████▎   | 12/19 [01:47<01:06,  9.45
s/it]
Processing scheduled exchanges:  63%|██████▎   | 12/19 [01:48<01:06,  9.45
s/it]
```

```
No data for DK_2 -> DE_AT_LU
```

```
Processing scheduled exchanges from DK_2: 100%|██████████| 4/4 [00:09<00:0
0,  2.34s/it]
Processing scheduled exchanges:  68%|██████▊   | 13/19 [01:56<00:56,  9.43
s/it]
Processing scheduled exchanges:  68%|██████▊   | 13/19 [02:02<00:56,  9.43
s/it]
```

```
No data for FI -> RU
```

```
Processing scheduled exchanges from FI: 100%|██████████| 5/5 [00:16<00:00,
3.31s/it]
Processing scheduled exchanges from NO_4: 100%|██████████| 4/4 [00:08<00:0
0,  2.19s/it]
Processing scheduled exchanges from SE_1: 100%|██████████| 3/3 [00:13<00:0
0,  4.51s/it]
Processing scheduled exchanges:  84%|████████▍ | 16/19 [02:35<00:34, 11.57
s/it]Connection Error, retrying in 10 seconds
Processing scheduled exchanges from SE_2: 100%|██████████| 4/4 [00:28<00:0
0,  7.01s/it]
Processing scheduled exchanges:  89%|████████▉ | 17/19 [03:03<00:33, 16.53
s/it]Connection Error, retrying in 10 seconds
Processing scheduled exchanges from DE_LU: 100%|██████████| 4/4 [00:18<00:
00,  4.69s/it]
Processing scheduled exchanges from NO_3: 100%|██████████| 4/4 [00:18<00:0
0,  4.63s/it]
Processing scheduled exchanges: 100%|██████████| 19/19 [03:40<00:00, 11.63
s/it]
```

```
Done
```

In [ ]:
```
# convert MTU to timezone "Europe/Brussels" for all From, besides From =
Border_data['MTU'] = pd.to_datetime(Border_data['MTU']).dt.tz_convert('Eu
# save as csv
Border_data.to_csv('data/Border_data.csv')
```

In [ ]:
```
da = pd.read_csv('data/day_ahead_prices.csv')
```

Out[ ]:

	Unnamed: 0	0	country_code	Timestamp
0	0	220.00	DK_1	2022-06-01 00:00:00+02:00
1	1	207.45	DK_1	2022-06-01 01:00:00+02:00
2	2	199.09	DK_1	2022-06-01 02:00:00+02:00
3	3	182.53	DK_1	2022-06-01 03:00:00+02:00
4	4	182.28	DK_1	2022-06-01 04:00:00+02:00

Merge datasets to a complete final dataframe

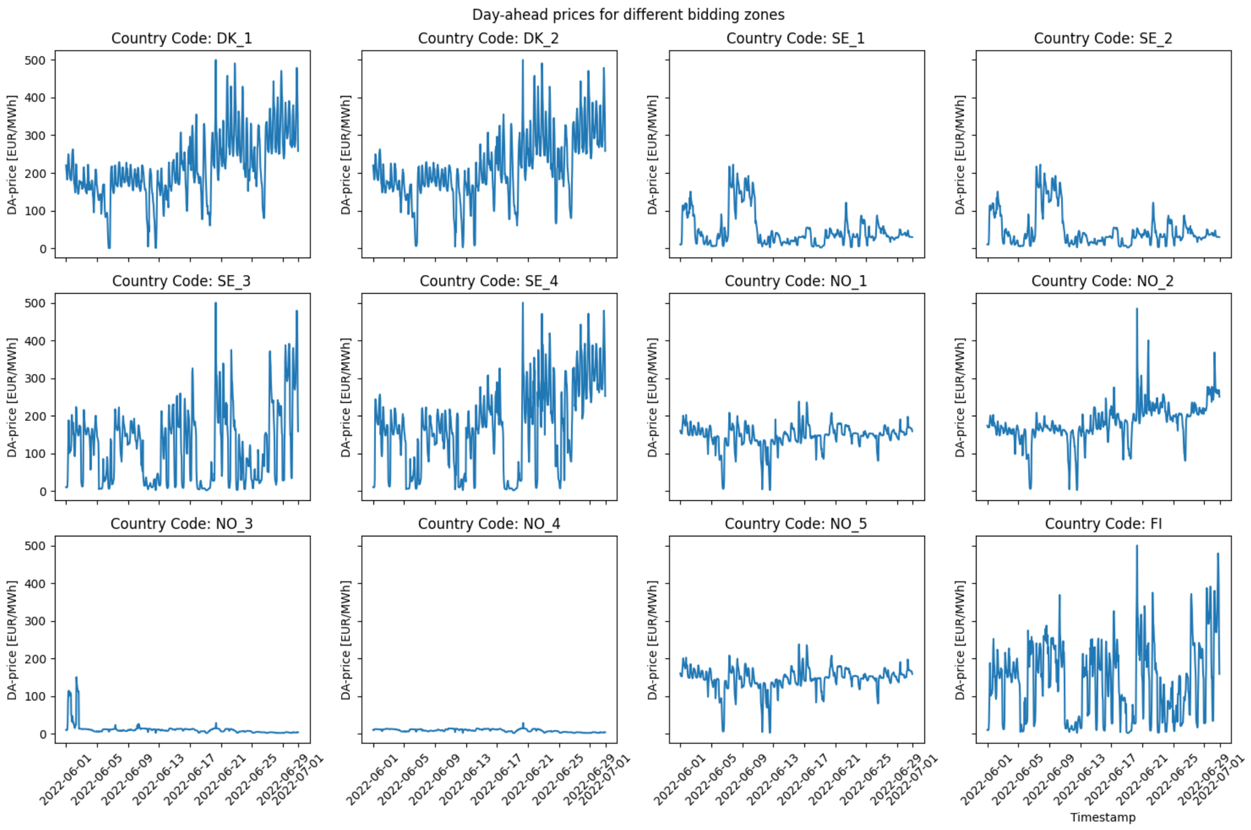
In [ ]:
```
# add Border_data to data_frame_lists
data_frame_lists = ['day_ahead_prices', 'load_and_forecast', 'generation_
work_dir = os.getcwd()

# import data using os library
data = {}
for data_frame in data_frame_lists:
    data[data_frame] = pd.read_csv(os.path.join(work_dir + '/data', data_

# make dataframe data_df from the dict for each data_frame
day_ahead_prices = data['day_ahead_prices']
day_ahead_prices.rename(columns={'0': 'DA-price [EUR/MWh]'}, inplace=True

load_and_forecast = data['load_and_forecast']

generation_forecast = data['generation_forecast']
generation_forecast.rename(columns={'Actual Aggregated': 'Forecasted Gene

wind_and_solar_forecast = data['wind_and_solar_forecast']

cross_border_data = data['Border_data']
cross_border_data.rename(columns={'MTU': 'Timestamp', 'From': 'country_co
cross_border_data = cross_border_data.drop(columns=['Unnamed: 0'])
cross_border_data['Timestamp'] = pd.to_datetime(cross_border_data['Timest
cross_border_data['Timestamp'] = cross_border_data['Timestamp'].dt.tz_loc

#merge dataframes based on the Unnamed: 0 column and country_code column
data_df = pd.merge(day_ahead_prices, load_and_forecast, on=['Unnamed: 0',
data_df = pd.merge(data_df, generation_forecast, on=['Unnamed: 0', 'count
data_df = pd.merge(data_df, wind_and_solar_forecast, on=['Unnamed: 0', 'c

# Separate the finnish data and adjust the timezone
data_df.rename(columns={'Unnamed: 0': 'Timestamp'}, inplace=True)
data_finnish = data_df[data_df['country_code'] == 'FI']
data_df = data_df[data_df['country_code'] != 'FI']
data_df['Timestamp'] = pd.to_datetime(data_df['Timestamp'])
data_df['Timestamp'] = data_df['Timestamp'].dt.tz_localize(None)
data_finnish['Timestamp'] = pd.to_datetime(data_finnish['Timestamp'])
data_finnish['Timestamp'] = data_finnish['Timestamp'].dt.tz_localize(None
data_df = pd.concat([data_df, data_finnish])

# merge the cross border data
data_df = pd.merge(data_df, cross_border_data, on=['Timestamp', 'country_

#save the data to csv
data_df.to_csv('data/nordic_energy_data.csv')
```

```
(8640, 64)
```

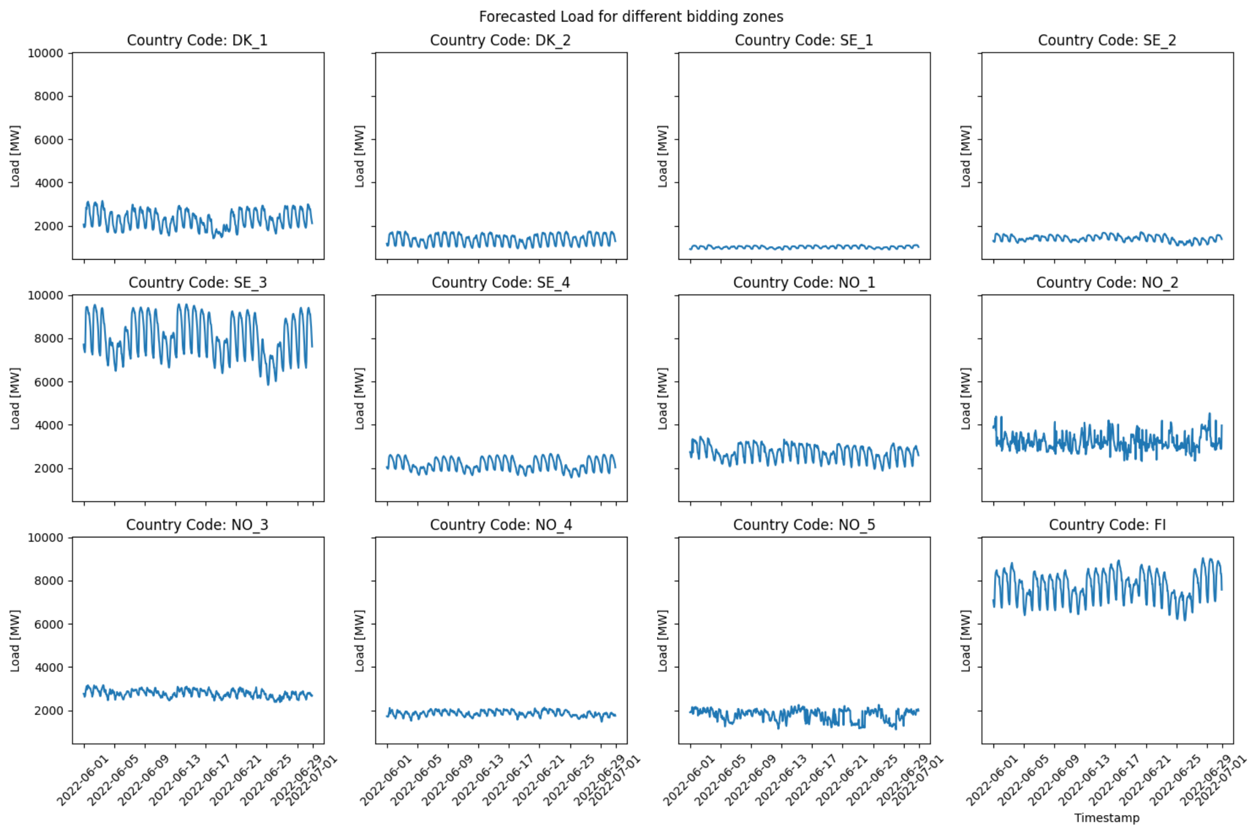
Exploratory Data analysis

In [ ]:

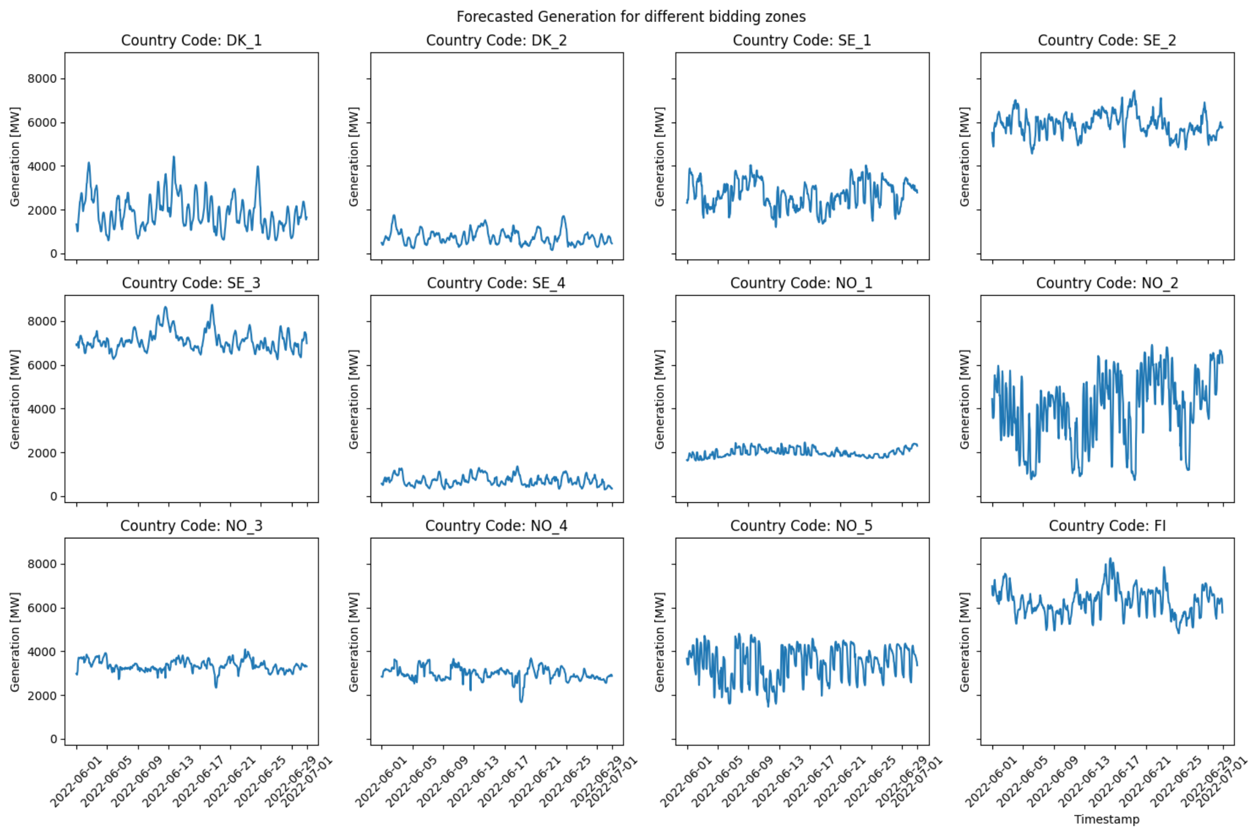
```
# Get unique country codes
unique_country_codes = data_df['country_code'].unique()

# Create subplots for each country code in a 3x4 grid
fig, axs = plt.subplots(3, 4, figsize=(15, 10), sharex=True, sharey=True)

# Flatten axs array for easier iteration
axs = axs.flatten()

# Plot DA-prices with the country_code as labels
for i, country_code in enumerate(unique_country_codes):
    data_df_country = data_df[data_df['country_code'] == country_code]
    axs[i].plot(data_df_country['Timestamp'], data_df_country['DA-price [
    axs[i].set_ylabel('DA-price [EUR/MWh]')
    axs[i].set_title(f'Country Code: {country_code}')
    axs[i].tick_params(axis='x', rotation=45)


# Set common x-label
plt.xlabel('Timestamp')
# make overall title
plt.suptitle('Day-ahead prices for different bidding zones')
#rotate x-labels for all subplots

# Adjust layout
plt.tight_layout()

# Show plot
plt.savefig('plots/DA-prices.png')
plt.show()
```



In [ ]:
```
#%%
#make similar plots for the other dataframes
#load
fig, axs = plt.subplots(3, 4, figsize=(15, 10), sharex=True, sharey=True)
axs = axs.flatten()
for i, country_code in enumerate(unique_country_codes):
    data_df_country = data_df[data_df['country_code'] == country_code]
    axs[i].plot(data_df_country['Timestamp'], data_df_country['Forecasted
    axs[i].set_ylabel('Load [MW]')
    axs[i].set_title(f'Country Code: {country_code}')
    axs[i].tick_params(axis='x', rotation=45)

plt.xlabel('Timestamp')
plt.suptitle('Forecasted Load for different bidding zones')

plt.tight_layout()
plt.savefig('plots/Forecasted_Load.png')
plt.show()
```

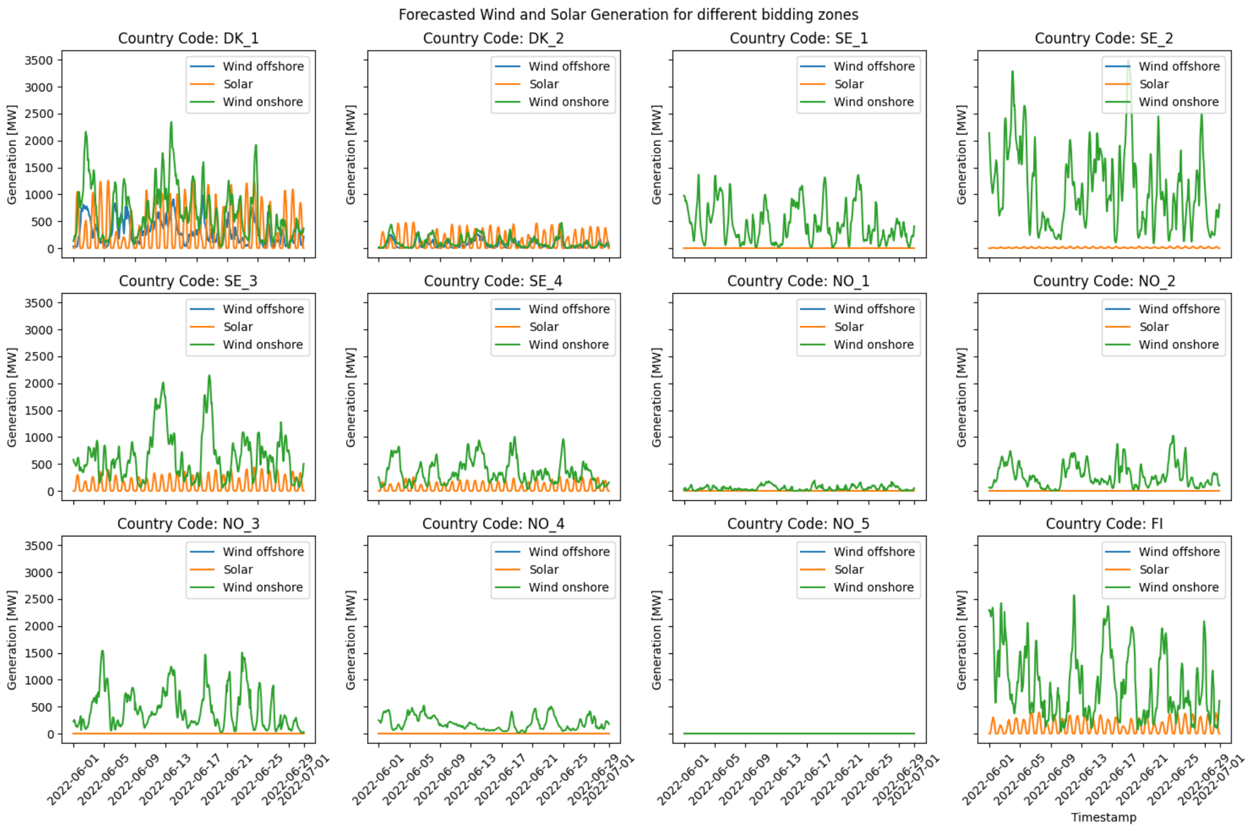


```
In [ ]: #%%
        #generation forecast
        fig, axs = plt.subplots(3, 4, figsize=(15, 10), sharex=True, sharey=True)
        axs = axs.flatten()
        for i, country_code in enumerate(unique_country_codes):
            data_df_country = data_df[data_df['country_code'] == country_code]
            axs[i].plot(data_df_country['Timestamp'], data_df_country['Forecasted
            axs[i].set_ylabel('Generation [MW]')
            axs[i].set_title(f'Country Code: {country_code}')
            axs[i].tick_params(axis='x', rotation=45)

        plt.xlabel('Timestamp')
        plt.suptitle('Forecasted Generation for different bidding zones')

        plt.tight_layout()
        plt.savefig('plots/Forecasted_Generation.png')
        plt.show()
```



In [ ]:

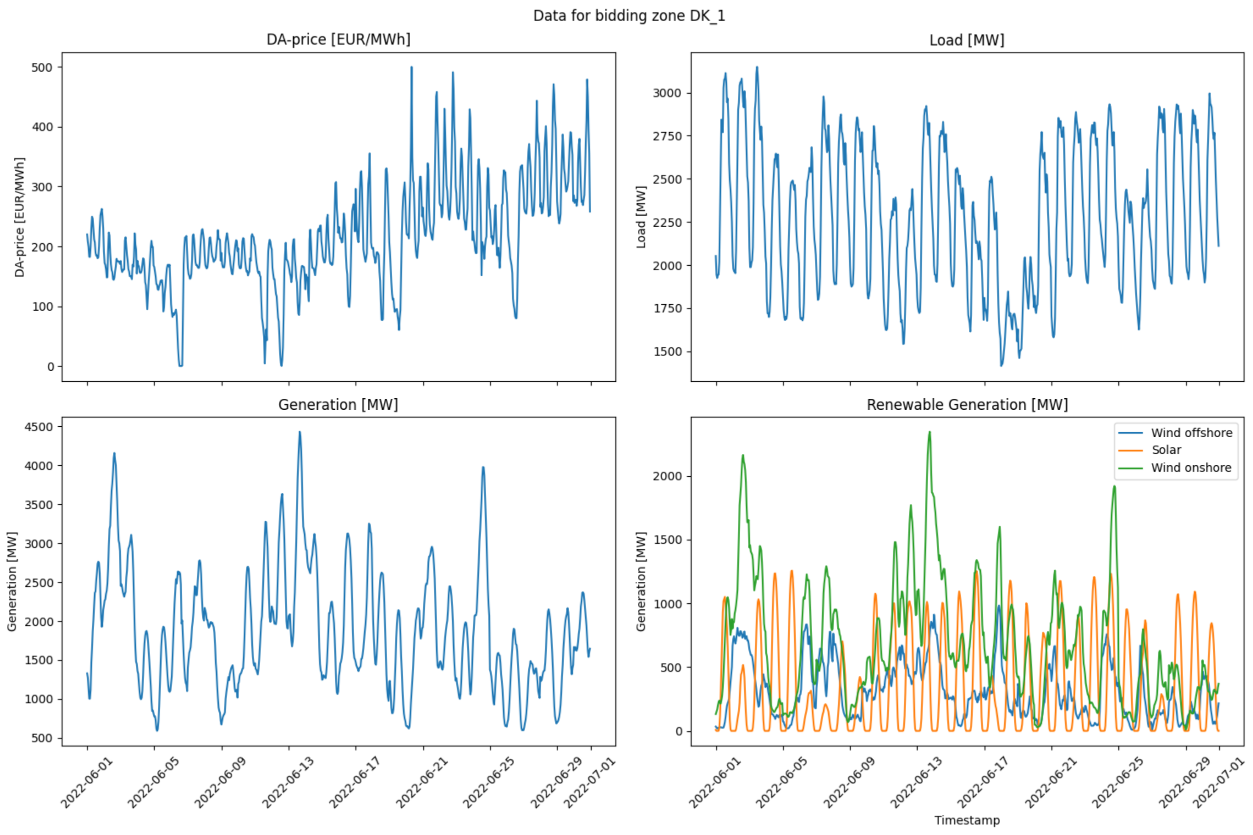
```
#%%
#wind and solar forecast
fig, axs = plt.subplots(3, 4, figsize=(15, 10), sharex=True, sharey=True)
axs = axs.flatten()
for i, country_code in enumerate(unique_country_codes):
    data_df_country = data_df[data_df['country_code'] == country_code]
    axs[i].plot(data_df_country['Timestamp'], data_df_country['Wind Offsh
    axs[i].plot(data_df_country['Timestamp'], data_df_country['Solar'], l
    axs[i].plot(data_df_country['Timestamp'], data_df_country['Wind Onsho
    axs[i].set_ylabel('Generation [MW]')
    axs[i].set_title(f'Country Code: {country_code}')
    axs[i].tick_params(axis='x', rotation=45)
    axs[i].legend()

plt.xlabel('Timestamp')
plt.suptitle('Forecasted Wind and Solar Generation for different bidding

plt.tight_layout()
plt.savefig('plots/Forecasted_Wind_Solar.png')
plt.show()
```



In [ ]:

```python
#%%
# for DK_1, plot day-ahead prices, load, forecasted generation, wind and
fig, axs = plt.subplots(2, 2, figsize=(15, 10), sharex=True, sharey=False
axs = axs.flatten()
country_code = 'DK_1'
data_df_country = data_df[data_df['country_code'] == country_code]
axs[0].plot(data_df_country['Timestamp'], data_df_country['DA-price [EUR/
axs[0].set_ylabel('DA-price [EUR/MWh]')
axs[0].set_title('DA-price [EUR/MWh]')
axs[0].tick_params(axis='x', rotation=45)

axs[1].plot(data_df_country['Timestamp'], data_df_country['Forecasted Loa
axs[1].set_ylabel('Load [MW]')
axs[1].set_title('Load [MW]')
axs[1].tick_params(axis='x', rotation=45)

axs[2].plot(data_df_country['Timestamp'], data_df_country['Forecasted Gen
axs[2].set_ylabel('Generation [MW]')
axs[2].set_title('Generation [MW]')
axs[2].tick_params(axis='x', rotation=45)

axs[3].plot(data_df_country['Timestamp'], data_df_country['Wind Offshore'
axs[3].plot(data_df_country['Timestamp'], data_df_country['Solar'], label
axs[3].plot(data_df_country['Timestamp'], data_df_country['Wind Onshore']
axs[3].set_ylabel('Generation [MW]')
axs[3].set_title('Renewable Generation [MW]')
axs[3].tick_params(axis='x', rotation=45)
axs[3].legend()
```

```
plt.xlabel('Timestamp')
plt.suptitle('Data for bidding zone DK_1')

plt.tight_layout()
plt.savefig('plots/DK_1_data.png')
plt.show()
```



```
In [ ]:
```