eda-univariate

January 29, 2026

1 Wind and Solar Energy Production

Wind & Solar Energy Production Dataset contains hourly wind and solar generation data from France spanning January 2020 to November 2025, featuring 51,864 complete records with 9 key columns.

It includes temporal features (date, hours, day-of-year, day name, month, season) and source classification (Wind, Solar, Mixed), with total production ranging from 58 to 23,446 MWh per hour and wind dominating at 81.9% of records.

This comprehensive dataset supports advanced renewable energy forecasting through regression and time series models, detailed pattern analysis of diurnal/seasonal/weekly trends, machine learning applications like classification and clustering, anomaly detection for production outliers, and statistical trend evaluation.

The dataset is available at the link.

1.1 Business Objective

To understand the key drivers of energy production variability and identify long-term trends to optimize grid planning.

1.1.1 Key Business Questions:

1. **Seasonal & Source Dynamics:** How does production efficiency shift across seasons for each energy source? Specifically, does the inverse relationship between Solar (summer-peak) and Wind (often winter-peak) provide grid stability?
2. **Long-Term Trends:** Is there an observable year-over-year growth in total production capacity from 2020 to 2024? (Excluding the incomplete 2025 data to ensure fair comparison).
3. **Monthly Consistency:** Are production patterns consistent across the same month in different years, or do we observe significant anomalies driven by external factors (e.g., extreme weather events)?

2 1. Loading the dataset

[1]:
```
import kagglehub
from kagglehub import KaggleDatasetAdapter
from IPython.display import clear_output
```

```python
# Filepath to the dataset
file_path = "Energy Production Dataset.csv"

# Load the latest version
data = kagglehub.dataset_load(
  KaggleDatasetAdapter.PANDAS,
  "ahmeduzaki/wind-and-solar-energy-production-dataset",
  file_path,
)

clear_output()
print("Dataset loaded successfully!")
```

```
Dataset loaded successfully!
```

3 2. Data Exploration

In the data exploration phase the goal is to understand the structure of the data. We verify: * Are there missing or extreme values? * Are there any invalid data? * Variable types * Distribution and dispersion (statistical analysis and visualization) * Frequency * Discretization if applicable * Impact of X on Y

[2]:
```python
df = data.copy()
df.columns
```

[2]:
```
Index(['Date', 'Start_Hour', 'End_Hour', 'Source', 'Day_of_Year', 'Day_Name',
       'Month_Name', 'Season', 'Production'],
      dtype='str')
```

[3]:
```python
df.head()
```

[3]:
```
         Date  Start_Hour  End_Hour Source  Day_of_Year Day_Name Month_Name  \
0  11/30/2025          21        22   Wind          334   Sunday   November
1  11/30/2025          18        19   Wind          334   Sunday   November
2  11/30/2025          16        17   Wind          334   Sunday   November
3  11/30/2025          23         0   Wind          334   Sunday   November
4  11/30/2025           6         7   Wind          334   Sunday   November

  Season  Production
0   Fall        5281
1   Fall        3824
2   Fall        3824
3   Fall        6120
4   Fall        4387
```

[4]:
```python
df.describe()
```

[4]:

	Start_Hour	End_Hour	Day_of_Year	Production
count	51864.000000	51864.000000	51864.000000	51864.000000
mean	11.500000	11.500000	180.798415	6215.069933
std	6.922253	6.922253	104.291387	3978.364965
min	0.000000	0.000000	1.000000	58.000000
25%	5.750000	5.750000	91.000000	3111.000000
50%	11.500000	11.500000	181.000000	5372.000000
75%	17.250000	17.250000	271.000000	8501.000000
max	23.000000	23.000000	366.000000	23446.000000

[5]:

```
df.duplicated().any()
```

[5]: np.False_

[6]:

```
if (df.duplicated()).any():
    print("Found duplicated values!")
else:
    print("Did not find any duplicated values!")
```

```
Did not find any duplicated values!
```

[7]:

```
df.info()
```

```
<class 'pandas.DataFrame'>
RangeIndex: 51864 entries, 0 to 51863
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Date         51864 non-null  str
 1   Start_Hour   51864 non-null  int64
 2   End_Hour     51864 non-null  int64
 3   Source       51864 non-null  str
 4   Day_of_Year  51864 non-null  int64
 5   Day_Name     51864 non-null  str
 6   Month_Name   51864 non-null  str
 7   Season       51864 non-null  str
 8   Production   51864 non-null  int64
dtypes: int64(4), str(5)
memory usage: 3.6 MB
```

There are no null values in the dataset.

3.1 Analysis of Numerical data

3.1.1 Analysis of "Date"

[8]:

```
df.Date # mm-dd-yyyy
print("The current format is mm-dd-yyyy")
```

```
The current format is mm-dd-yyyy
```

[9]:
```python
# Convert string to Datetime
import pandas as pd
df.Date = pd.to_datetime(df.Date)
df.info()
```

```
<class 'pandas.DataFrame'>
RangeIndex: 51864 entries, 0 to 51863
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Date         51864 non-null  datetime64[us]
 1   Start_Hour   51864 non-null  int64
 2   End_Hour     51864 non-null  int64
 3   Source       51864 non-null  str
 4   Day_of_Year  51864 non-null  int64
 5   Day_Name     51864 non-null  str
 6   Month_Name   51864 non-null  str
 7   Season       51864 non-null  str
 8   Production   51864 non-null  int64
dtypes: datetime64[us](1), int64(4), str(4)
memory usage: 3.6 MB
```

[10]:
```python
year = df.Date.apply(lambda x: x.year)
print(year.min())
print(year.max())

df["year"] = year
```

```
2020
2025
```

The dataset contains information of the production for the years 2020 to 2025.

[11]:
```python
import numpy as np
month = df.Date.apply(lambda x: x.month)
print(np.sort(month.unique()))

df["month"] = month
```

```
[ 1  2  3  4  5  6  7  8  9 10 11 12]
```

[12]:
```python
df.groupby(["year"])["month"].unique()
```

[12]:
```
year
2020    [12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1]
2021    [12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1]
2022    [12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1]
2023    [12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1]
2024    [12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1]
```

```
2025          [11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1]
Name: month, dtype: object
```

From 2020 to 2024 we have measures of the production on all months of the year. The year 2025 we have measures from January to November, that is, no measurement in December. The impact of that, is that we cannot perform an analysis of december's production from 2020 to 2025, only from 2020 to 2024.

(i.e. Missing value for december)

[13]:
```python
day = df.Date.apply(lambda x: x.day)
df["day"] = day
```

[14]:
```python
unique_days = df.groupby(["year", "month"])["day"].unique().reset_index()
```

[15]:
```python
unique_days.loc[2, "day"]
```

[15]:
```
array([31, 30, 29, 28, 27, 26, 25, 24, 23, 22, 21, 20, 19, 18, 17, 16, 15,
       14, 13, 12, 11, 10,  9,  8,  7,  6,  5,  4,  3,  2,  1])
```

[16]:
```python
unique_days[unique_days["month"] == 2].iloc[0]
```

[16]:
```
year                                                      2020
month                                                        2
day      [29, 28, 27, 26, 25, 24, 23, 22, 21, 20, 19, 1…
Name: 1, dtype: object
```

[17]:
```python
# check missing days in the dataset:
def check_missing_day(unique_days):
    all_months = list(range(1,13))
    n_days = [31,28,31,30,31,30,31,31,30,31,30,31]

    dict_days_by_month = dict(zip(all_months, n_days))
    leap_years = [2020, 2024]

    for month, days in dict_days_by_month.items():

        temp = unique_days[unique_days["month"] == month]
        if month == 2:
            leap = temp[unique_days["year"].isin(leap_years)]
            is_complete = leap["day"].map(lambda x: x.shape[0])==(days+1)
            if not is_complete.all():
                print(is_complete[is_complete==False].index())

        else:
            is_complete = temp["day"].map(lambda x: x.shape[0])==(days)
            if not is_complete.all():
                print(is_complete[is_complete==False].index())
```

[18]:
```
check_missing_day(unique_days)
```

```
/var/folders/xm/3ksp3z452z1fgpzrq_nfylnm0000gp/T/ipykernel_86926/3970797402.py:1
3: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
  leap = temp[unique_days["year"].isin(leap_years)]
```

3.1.2 Verifying hours of the day

No missing values were found considering the days.

[19]:
```
#Verifying if all days have 24 hours of measurements
measurements= df.groupby("Date")["Start_Hour"].unique()
```

[20]:
```
# Hours without 24 hours of measurements
measurements = measurements.reset_index()
non_standard_measurements = measurements[measurements["Start_Hour"].map(lambda␣
↪x: x.shape[0]!=24)]
non_standard_measurements
```

[20]:

	Date	Start_Hour
88	2020-03-29	[15, 18, 11, 4, 21, 22, 0, 12, 9, 13, 3, 1, 20…
452	2021-03-28	[15, 23, 18, 1, 3, 14, 12, 8, 9, 20, 17, 4, 5,…
816	2022-03-27	[19, 20, 17, 18, 16, 10, 4, 15, 11, 22, 5, 12,…
1180	2023-03-26	[9, 22, 17, 5, 14, 0, 20, 10, 6, 13, 16, 1, 11…
1551	2024-03-31	[21, 14, 15, 10, 1, 18, 0, 16, 4, 12, 5, 19, 2…
1915	2025-03-30	[9, 14, 3, 1, 17, 15, 11, 5, 4, 0, 13, 23, 21,…

[21]:
```
# How many hours of measurement in the day
non_standard_measurements["Start_Hour"].map(lambda x: x.shape[0])
```

[21]:
```
88      23
452     23
816     23
1180    23
1551    23
1915    23
Name: Start_Hour, dtype: int64
```

3.1.3 Repeated hours in the day

[22]:
```
# example of repeated hours
measurements= df.groupby("Date")["Date"].value_counts()
non_standard_measurements = measurements[measurements >24]
```

[23]:
```
day = non_standard_measurements.reset_index().iloc[0].Date
one_day = df[df.Date == day]
one_day.sort_values("Start_Hour")
```

[23]:

	Date	Start_Hour	End_Hour	Source	Day_of_Year	Day_Name	\
44694	2020-10-25	0	1	Wind	299	Sunday	
44693	2020-10-25	1	2	Wind	299	Sunday	
44707	2020-10-25	2	3	Wind	299	Sunday	
44698	2020-10-25	2	3	Wind	299	Sunday	
44703	2020-10-25	3	4	Wind	299	Sunday	
44705	2020-10-25	4	5	Wind	299	Sunday	
44699	2020-10-25	5	6	Wind	299	Sunday	
44691	2020-10-25	6	7	Wind	299	Sunday	
44708	2020-10-25	7	8	Wind	299	Sunday	
44702	2020-10-25	8	9	Wind	299	Sunday	
44711	2020-10-25	9	10	Wind	299	Sunday	
44710	2020-10-25	10	11	Wind	299	Sunday	
44712	2020-10-25	11	12	Wind	299	Sunday	
44697	2020-10-25	12	13	Wind	299	Sunday	
44692	2020-10-25	13	14	Wind	299	Sunday	
44700	2020-10-25	14	15	Wind	299	Sunday	
44696	2020-10-25	15	16	Wind	299	Sunday	
44704	2020-10-25	16	17	Wind	299	Sunday	
44690	2020-10-25	17	18	Wind	299	Sunday	
44701	2020-10-25	18	19	Wind	299	Sunday	
44688	2020-10-25	19	20	Wind	299	Sunday	
44689	2020-10-25	20	21	Wind	299	Sunday	
44709	2020-10-25	21	22	Wind	299	Sunday	
44695	2020-10-25	22	23	Wind	299	Sunday	
44706	2020-10-25	23	0	Wind	299	Sunday	

	Month_Name	Season	Production	year	month	day
44694	October	Fall	11467	2020	10	25
44693	October	Fall	11525	2020	10	25
44707	October	Fall	10696	2020	10	25
44698	October	Fall	11001	2020	10	25
44703	October	Fall	8774	2020	10	25
44705	October	Fall	8234	2020	10	25
44699	October	Fall	7800	2020	10	25
44691	October	Fall	8401	2020	10	25
44708	October	Fall	8284	2020	10	25
44702	October	Fall	8012	2020	10	25
44711	October	Fall	8318	2020	10	25
44710	October	Fall	8575	2020	10	25
44712	October	Fall	8207	2020	10	25
44697	October	Fall	8191	2020	10	25
44692	October	Fall	7456	2020	10	25
44700	October	Fall	7236	2020	10	25
44696	October	Fall	7515	2020	10	25
44704	October	Fall	6359	2020	10	25
44690	October	Fall	5228	2020	10	25

```
44701     October   Fall        4988  2020      10   25
44688     October   Fall        4809  2020      10   25
44689     October   Fall        5286  2020      10   25
44709     October   Fall        5910  2020      10   25
44695     October   Fall        6154  2020      10   25
44706     October   Fall        5979  2020      10   25
```

[24]:
```
from IPython.display import Markdown

report = f"""
### Analysis: Date & Time Anomalies

**1. Irregular Measurement Counts**
We observed that certain dates contain more than the standard 24 hourly␣
↪measurements. An initial duplicate check confirms these are **not exact␣
↪duplicates**; rows with identical timestamps record diverging *Production*␣
↪values.
This likely stems from data aggregation issues where inputs from multiple␣
↪generation units (e.g., separate power plants or regional substations) were␣
↪merged without preserving a unique identifier for each source.
Conversely, a small subset of the data contains incomplete days with missing␣
↪hourly slots.

**2. Mitigation Strategy**
Since we lack the metadata (e.g., Power Plant ID) to distinguish the sources of␣
↪overlapping entries, dropping them risks significant information loss.
We will aggregate to the monthly level to analyse seasonal trends for now and␣
↪reserve the daily analysis for a future
more in depth analysis.

### Conclusion: Date Column

*   **Temporal Coverage:** The dataset spans from **January 2020** to␣
↪**November 2025**.
*   **Completeness:** There are no gaps *within* the observed range; however,␣
↪the dataset is **truncated**, meaning data for **December 2025** is absent␣
↪because the collection period ended in November.
*   **Data Quality:** Aside from the hourly aggregation inconsistencies, all␣
↪date formats are valid.
*   **Preprocessing:** The column should be converted from string to `datetime`␣
↪objects for efficient manipulation.

**Implications for Analysis:**
```

```
The absence of December 2025 restricts year-over-year comparisons for December␣
↪to the 2020-2024 period. Additionally, the inconsistent hourly granularity␣
↪(overlapping timestamps and missing hours) makes strict hourly analysis␣
↪unreliable, validating the decision to aggregate data by month.
"""
display(Markdown(report))
```

3.1.4 Analysis: Date & Time Anomalies

1. Irregular Measurement Counts We observed that certain dates contain more than the standard 24 hourly measurements. An initial duplicate check confirms these are **not exact duplicates**; rows with identical timestamps record diverging *Production* values. This likely stems from data aggregation issues where inputs from multiple generation units (e.g., separate power plants or regional substations) were merged without preserving a unique identifier for each source. Conversely, a small subset of the data contains incomplete days with missing hourly slots.

2. Mitigation Strategy Since we lack the metadata (e.g., Power Plant ID) to distinguish the sources of overlapping entries, dropping them risks significant information loss. We will aggregate to the monthly level to analyse seasonal trends for now and reserve the daily analysis for a future more in depth analysis.

3.1.5 Conclusion: Date Column

- **Temporal Coverage:** The dataset spans from **January 2020** to **November 2025**.
- **Completeness:** There are no gaps *within* the observed range; however, the dataset is **truncated**, meaning data for **December 2025** is absent because the collection period ended in November.
- **Data Quality:** Aside from the hourly aggregation inconsistencies, all date formats are valid.
- **Preprocessing:** The column should be converted from string to `datetime` objects for efficient manipulation.

Implications for Analysis: The absence of December 2025 restricts year-over-year comparisons for December to the 2020–2024 period. Additionally, the inconsistent hourly granularity (overlapping timestamps and missing hours) makes strict hourly analysis unreliable, validating the decision to aggregate data by month.

3.2 Production

[25]:
```
summary = df.Production.describe()
summary["IQR"] = summary['75%'] - summary['25%']
summary["median"] = df.Production.median()
summary["skew"] = df.Production.skew()
summary["kurtosis"] = df.Production.kurtosis()

display(summary)
```

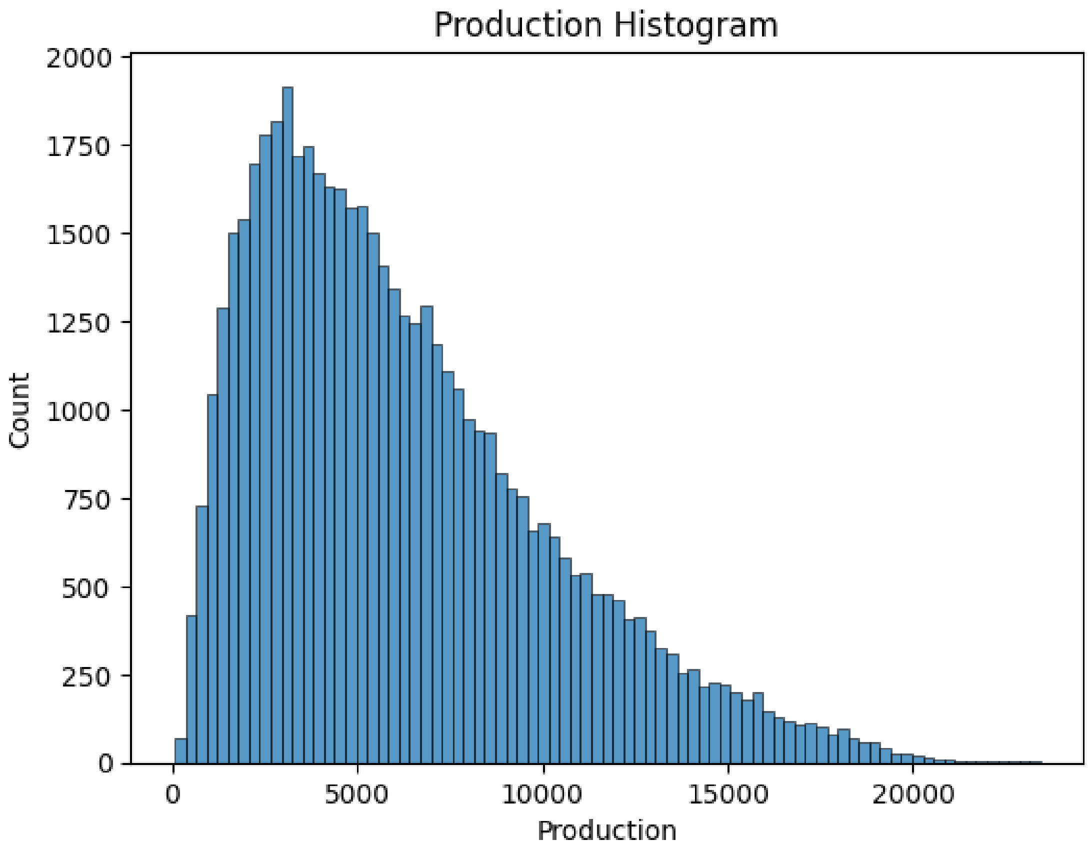
```
count       51864.000000
mean         6215.069933
std          3978.364965
```

```
min            58.000000
25%          3111.000000
50%          5372.000000
75%          8501.000000
max         23446.000000
IQR          5390.000000
median       5372.000000
skew            0.928561
kurtosis        0.469162
Name: Production, dtype: float64
```

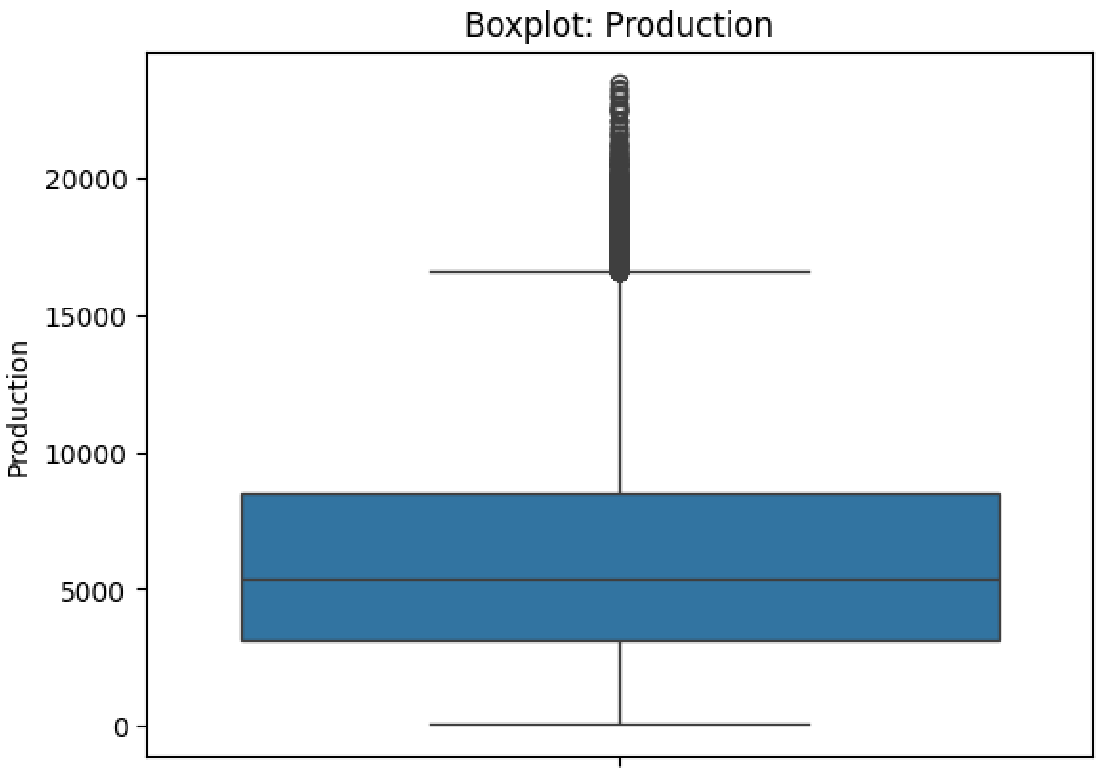
[26]:
```
# Skew
skew = summary["skew"]

if skew == 0:
    print("The distribution is perfectly symmetrical, resembling a normal␣
 ↪distribution.")
elif skew>0:
    print("The distribution is positively skewed")
else:
    print("The distribution is negatively skewed")

# Kurtosis
kurtosis = summary["kurtosis"]

if kurtosis > 0:
    print("The distribution has a sharp peak and heavy tails (lots of␣
 ↪outliers)")

elif kurtosis <0:
    print("The distribution is flat with thin tails.")
else:
    print("The distribution is a standard Normal Distribution (the classic bell␣
 ↪curve)")
```

```
The distribution is positively skewed
The distribution has a sharp peak and heavy tails (lots of outliers)
```

[27]:
```
import seaborn as sns
import matplotlib.pyplot as plt


ax = sns.histplot(df.Production, bins="auto")
ax.set_title("Production Histogram")
plt.show()
```



[28]:
```
sns.boxplot(df.Production)
plt.title(f"Boxplot: Production")
plt.show()
```




```
[29]: from IPython.display import Markdown

report = f"""

## Conclusion: Production

The Production variable contains {df.shape} complete observations (no missing␣
↪values).
The average hourly production is approximately {round(summary["mean"],2)}␣
↪units, with a standard deviation of {round(summary["std"],2)} units,␣
↪indicating substantial variability in production levels (coefficient of␣
↪variation  {round(summary["std"]/summary["mean"],2)}).
The median production is {round(summary["median"],2)} units, which is lower␣
↪than the mean, suggesting a right-skewed distribution influenced by high␣
↪production peaks.

The interquartile range (IQR) is {round(summary["IQR"],2)} units (from␣
↪{round(summary["25%"],2)} to {round(summary["75%"],2)}),
```

```
meaning the middle 50% of observations fall within this range. The maximum␣
 ↪observed production is {round(summary["max"],2)} units, which is␣
 ↪considerably higher than the 75th percentile, indicating the presence of␣
 ↪extreme but potentially plausible peak production events.
The skewness of the Production variable is {round(skew,2)}, confirming a␣
 ↪moderate positive (right) skew. The kurtosis is {round(kurtosis,2)},␣
 ↪suggesting mildly heavier tails than a normal distribution and therefore a␣
 ↪higher likelihood of extreme values.

A possible explanation for the skewness of the production distribution is a a␣
 ↪potential multimodality.
This suggests that analyzing the production globally instead of considering its␣
 ↪source, is masking specific behaviors,
which will be explored in the bivariate analysis.

The histogram supports by showing a concentration of observations consistent␣
 ↪with a right-skewed distribution. The boxplot also shows many high-end␣
 ↪outliers.
If these high values are operationally plausible, it is best to retain them and␣
 ↪investigate potential drivers (e.g., seasonality, production spikes, etc.)␣
 ↪rather than removing them by default.
"""
display(Markdown(report))
```

3.3 Conclusion: Production

The Production variable contains (51864, 12) complete observations (no missing values). The average hourly production is approximately 6215.07 units, with a standard deviation of 3978.36 units, indicating substantial variability in production levels (coefficient of variation 0.64). The median production is 5372.0 units, which is lower than the mean, suggesting a right-skewed distribution influenced by high production peaks.

The interquartile range (IQR) is 5390.0 units (from 3111.0 to 8501.0), meaning the middle 50% of observations fall within this range. The maximum observed production is 23446.0 units, which is considerably higher than the 75th percentile, indicating the presence of extreme but potentially plausible peak production events. The skewness of the Production variable is 0.93, confirming a moderate positive (right) skew. The kurtosis is 0.47, suggesting mildly heavier tails than a normal distribution and therefore a higher likelihood of extreme values.

A possible explanation for the skewness of the production distribution is a a potential multimodality. This suggests that analyzing the production globally instead of considering its source, is masking specific behaviors, which will be explored in the bivariate analysis.

The histogram supports by showing a concentration of observations consistent with a right-skewed distribution. The boxplot also shows many high-end outliers. If these high values are operationally plausible, it is best to retain them and investigate potential drivers (e.g., seasonality, production spikes, etc.) rather than removing them by default.

4 Analysis of the Categorical Data

[30]:
```
categorical_data = df.select_dtypes(exclude="number")
```

[31]:
```
print("Unique values:")
display(categorical_data.nunique())
```

```
Unique values:

Date          2161
Source           3
Day_Name         7
Month_Name      12
Season           4
dtype: int64
```

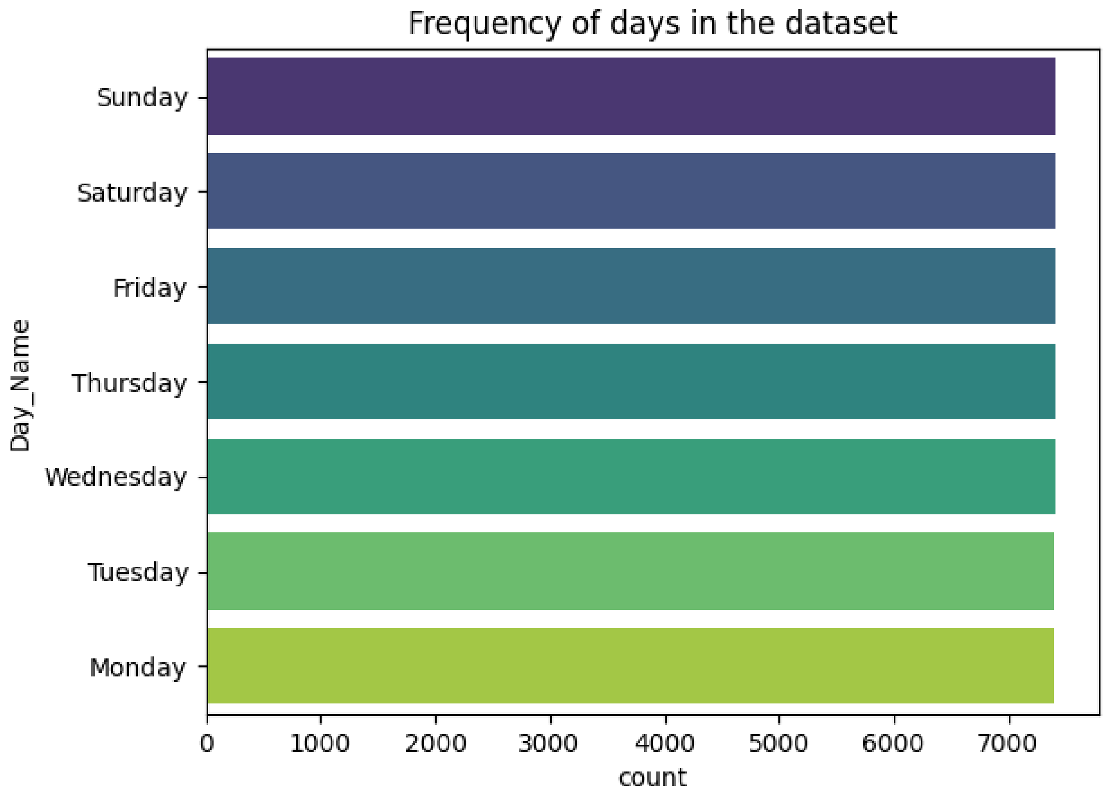
[32]:
```
print("Data types:")
display(categorical_data.info())
```

```
Data types:
<class 'pandas.DataFrame'>
RangeIndex: 51864 entries, 0 to 51863
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Date        51864 non-null  datetime64[us]
 1   Source      51864 non-null  str
 2   Day_Name    51864 non-null  str
 3   Month_Name  51864 non-null  str
 4   Season      51864 non-null  str
dtypes: datetime64[us](1), str(4)
memory usage: 2.0 MB

None
```

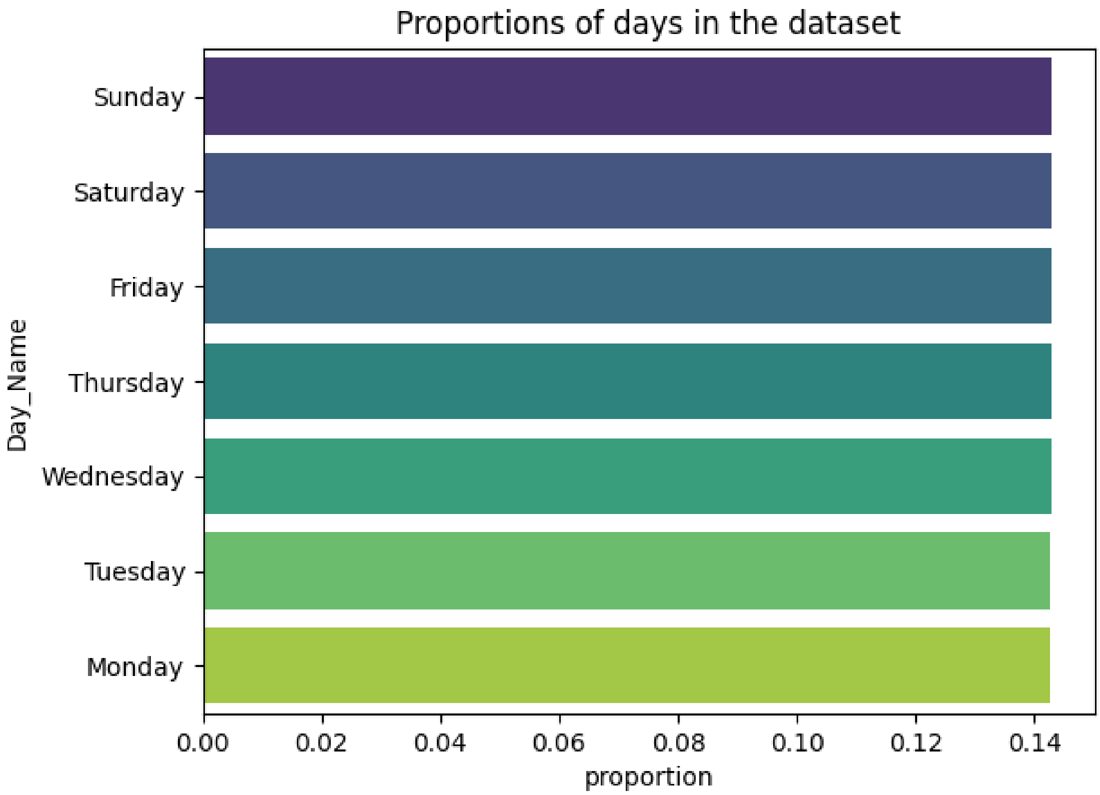
4.0.1 Days of the Week distribution (Day_Name)

[33]:
```
frequency_table = categorical_data.Day_Name.value_counts().reset_index()
proportions_table = categorical_data.Day_Name.value_counts(normalize=True).
 ↪reset_index()
```

[34]:
```
import seaborn as sns
import matplotlib.pyplot as plt


ax = sns.barplot(y="Day_Name", x = "count",␣
 ↪data=frequency_table,palette='viridis', hue="Day_Name")
ax.set_title("Frequency of days in the dataset")
plt.show()
```



[35]:
```
import seaborn as sns
import matplotlib.pyplot as plt


ax = sns.barplot(y="Day_Name", x = "proportion",␣
 ↪data=proportions_table,palette='viridis', hue="Day_Name")
ax.set_title("Proportions of days in the dataset")
plt.show()
```

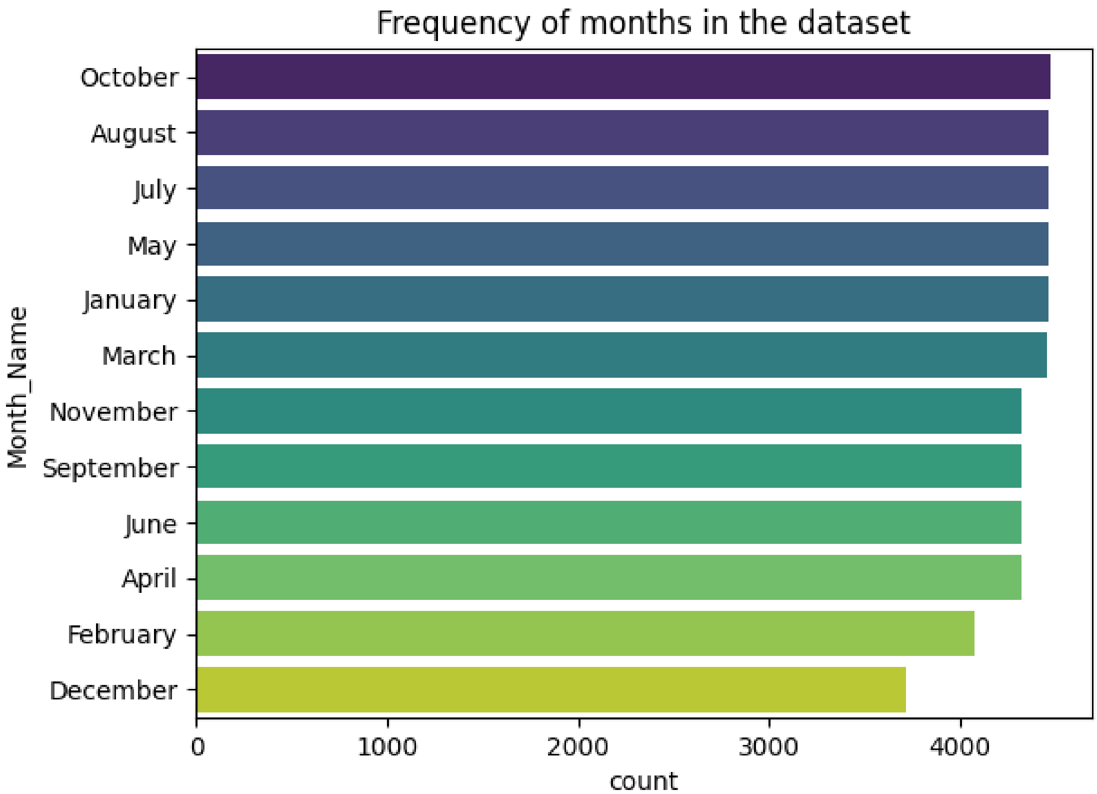


The distribution of datapoints by week days is balanced in the dataset.

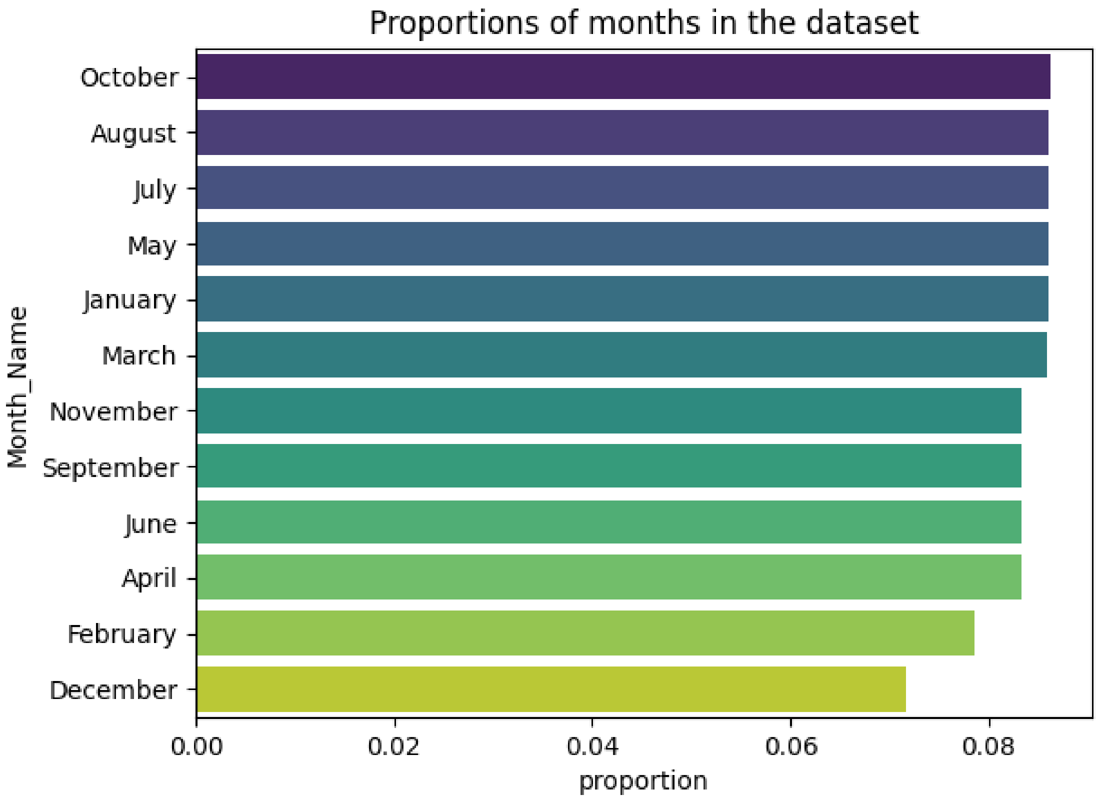
4.1 Months distribution (Month_Name)

[36]:
```
frequency_table = categorical_data.Month_Name.value_counts().reset_index()
proportions_table = categorical_data.Month_Name.value_counts(normalize=True).
  ↪reset_index()
```

[37]:
```
import seaborn as sns
import matplotlib.pyplot as plt


ax = sns.barplot(y="Month_Name", x = "count",␣
  ↪data=frequency_table,palette='viridis', hue="Month_Name")
ax.set_title("Frequency of months in the dataset")
plt.show()
```



[38]:
```python
import seaborn as sns
import matplotlib.pyplot as plt


ax = sns.barplot(y="Month_Name", x = "proportion", data=proportions_table,␣
    ↪palette='viridis', hue="Month_Name")
ax.set_title("Proportions of months in the dataset")
plt.show()
```



[39]:
```python
from IPython.display import Markdown


report = f"""
### Conclusion: Monthly Distribution

The dataset exhibits slight imbalances across months, primarily driven by␣
↪**calendar variations** and temporal coverage gaps.

**December** and **February** are the most notable underrepresented months:␣
↪December due to the missing data for **2025**, and February due to its␣
↪naturally shorter length. Similarly, months with **30 days** (e.g., April,␣
↪June, September, November) show slightly lower proportions than 31-day␣
↪months, reflecting the same impact of differing calendar lengths.
"""
display(Markdown(report))
```

4.1.1 Conclusion: Monthly Distribution

The dataset exhibits slight imbalances across months, primarily driven by **calendar variations** and temporal coverage gaps.

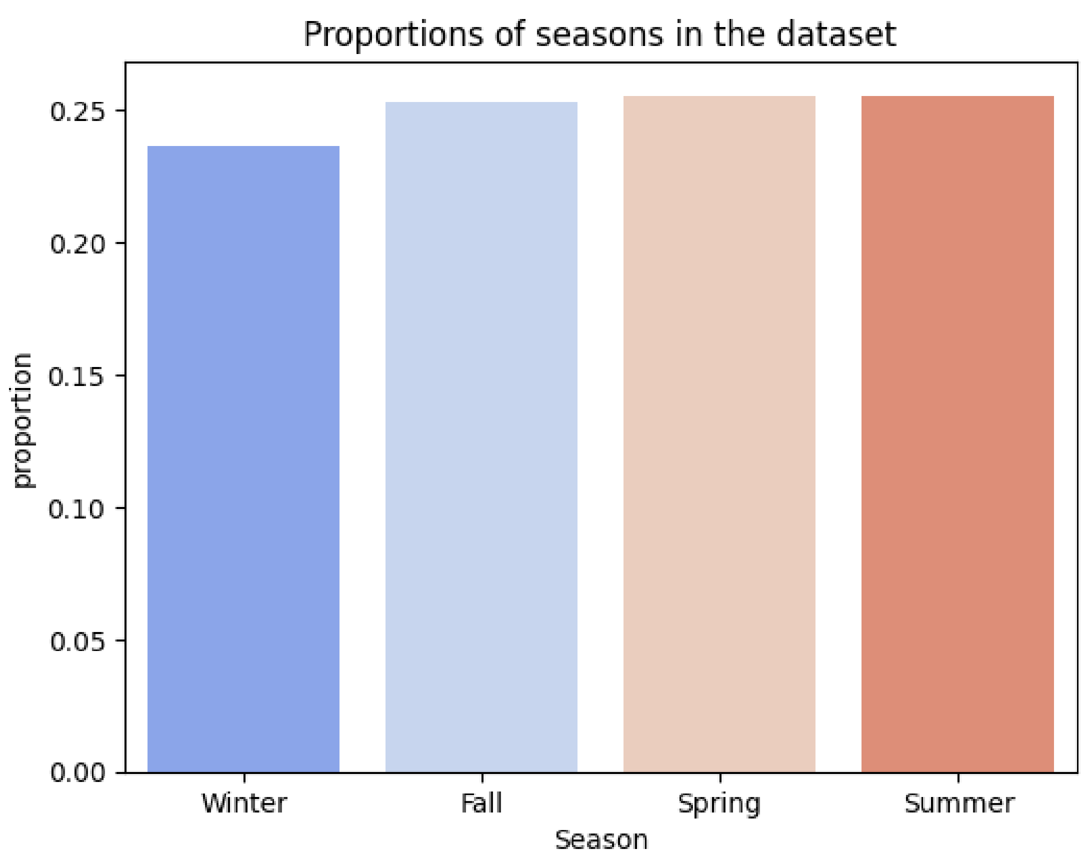
December and **February** are the most notable underrepresented months: December due to the missing data for **2025**, and February due to its naturally shorter length. Similarly, months with **30 days** (e.g., April, June, September, November) show slightly lower proportions than 31-day months, reflecting the same impact of differing calendar lengths.

The datapoints by months varies according to two factors: the length of the month, and the one month worth of missing data we already discovered when analyzing the Date column. Even so, the dataset is fairly balanced.

4.2 Season

[40]:
```
proportions_table = categorical_data.Season.value_counts(normalize=True).
  ↪sort_values(ascending=True).reset_index()
```

[41]:
```
import seaborn as sns
import matplotlib.pyplot as plt


ax = sns.barplot(x="Season", y = "proportion", data=proportions_table,␣
  ↪palette='coolwarm', hue="Season")
ax.set_title("Proportions of seasons in the dataset")
plt.show()
```



[42]:
```
from IPython.display import Markdown


report = f"""
### Conclusion: Seasons

The dataset exhibits a slight imbalance across seasons, with **Winter** being␣
 ↪underrepresented.
This discrepancy is likely due to temporal coverage gaps, specifically the␣
 ↪absence of data for
**December 2025**, combined with the naturally shorter duration of **February**.
"""
display(Markdown(report))
```

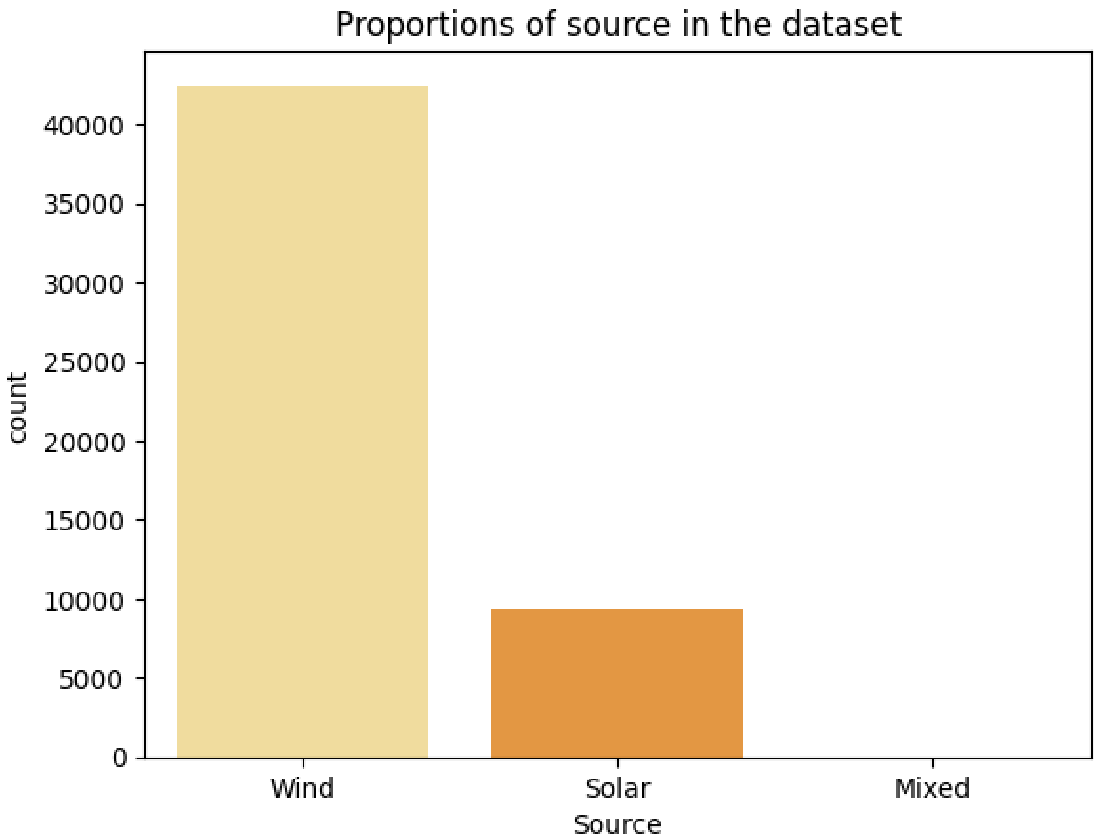
4.2.1 Conclusion: Seasons

The dataset exhibits a slight imbalance across seasons, with **Winter** being underrepresented. This discrepancy is likely due to temporal coverage gaps, specifically the absence of data for **December 2025**, combined with the naturally shorter duration of **February**.

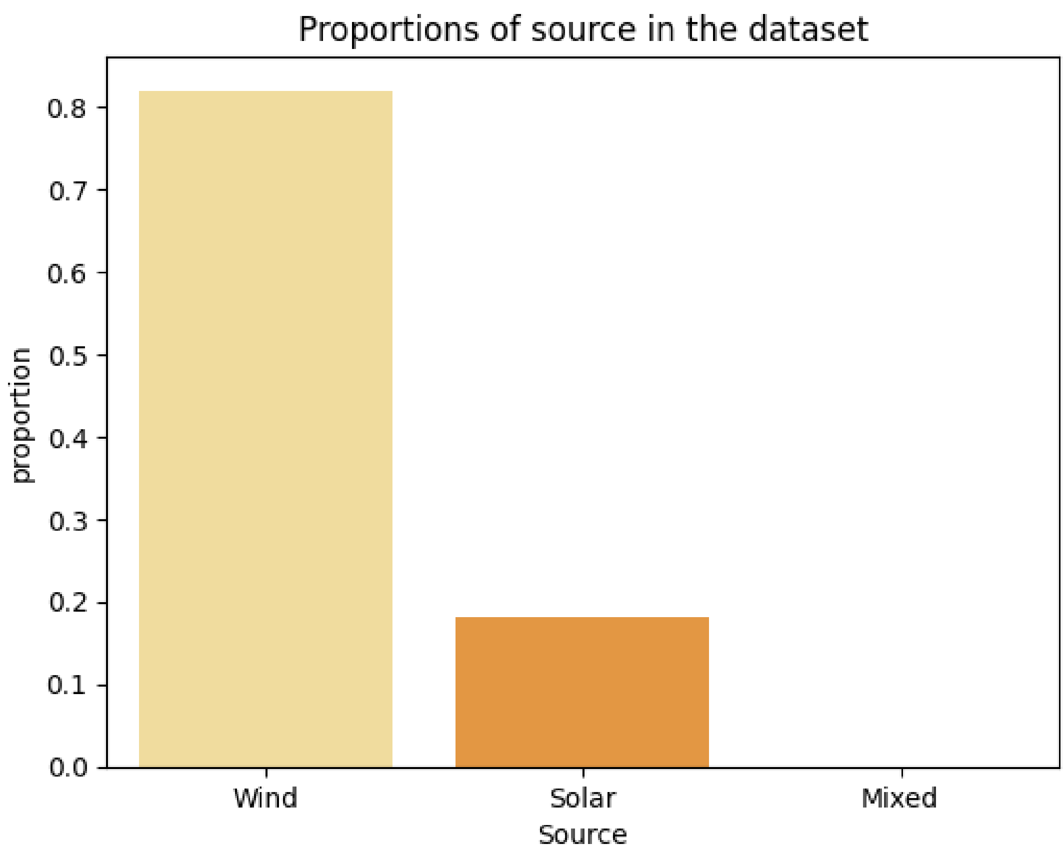
4.3 Type of energy source (Source)

[43]:
```
frequency_table = categorical_data.Source.value_counts()
proportions_table = categorical_data.Source.value_counts(normalize=True)
```

[44]:
```
import seaborn as sns
import matplotlib.pyplot as plt


ax = sns.barplot(x="Source", y = "count", data=frequency_table.reset_index(),␣
 ↪palette='YlOrBr', hue="Source")
ax.set_title("Proportions of source in the dataset")
plt.show()
```



[45]:
```
import seaborn as sns
import matplotlib.pyplot as plt


ax = sns.barplot(x="Source", y = "proportion", data=proportions_table.
 ↪reset_index(), palette='YlOrBr', hue="Source")
ax.set_title("Proportions of source in the dataset")
plt.show()
```



[46]:
```
proportions_table
```

[46]:
```
Source
Wind     0.819142
Solar    0.180819
Mixed    0.000039
Name: proportion, dtype: float64
```

[47]:
```
from IPython.display import Markdown


report = f"""
### Conclusion: Sources

The dataset exhibits a significant imbalance in energy sources.
**Wind** is the predominant source, accounting for **{proportions_table.Wind:.
 ↪1%}** of the data,
while **Solar** comprises **{proportions_table.Solar:.1%}**. The **Mixed**␣
 ↪category is statistically
```

```
negligible, represented by only 2 observations, representing less than 1% of␣
↪the data.
To ensure clear separation between Wind and Solar behaviours, and since the␣
↪**Mixed** category
has no statistical significance, this data will be droped from the analysis."""
display(Markdown(report))
```

4.3.1 Conclusion: Sources

The dataset exhibits a significant imbalance in energy sources. **Wind** is the predominant source, accounting for **81.9%** of the data, while **Solar** comprises **18.1%**. The **Mixed** category is statistically negligible, represented by only 2 observations, representing less than 1% of the data. To ensure clear separation between Wind and Solar behaviours, and since the **Mixed** category has no statistical significance, this data will be droped from the analysis.

[ ]:

```

```