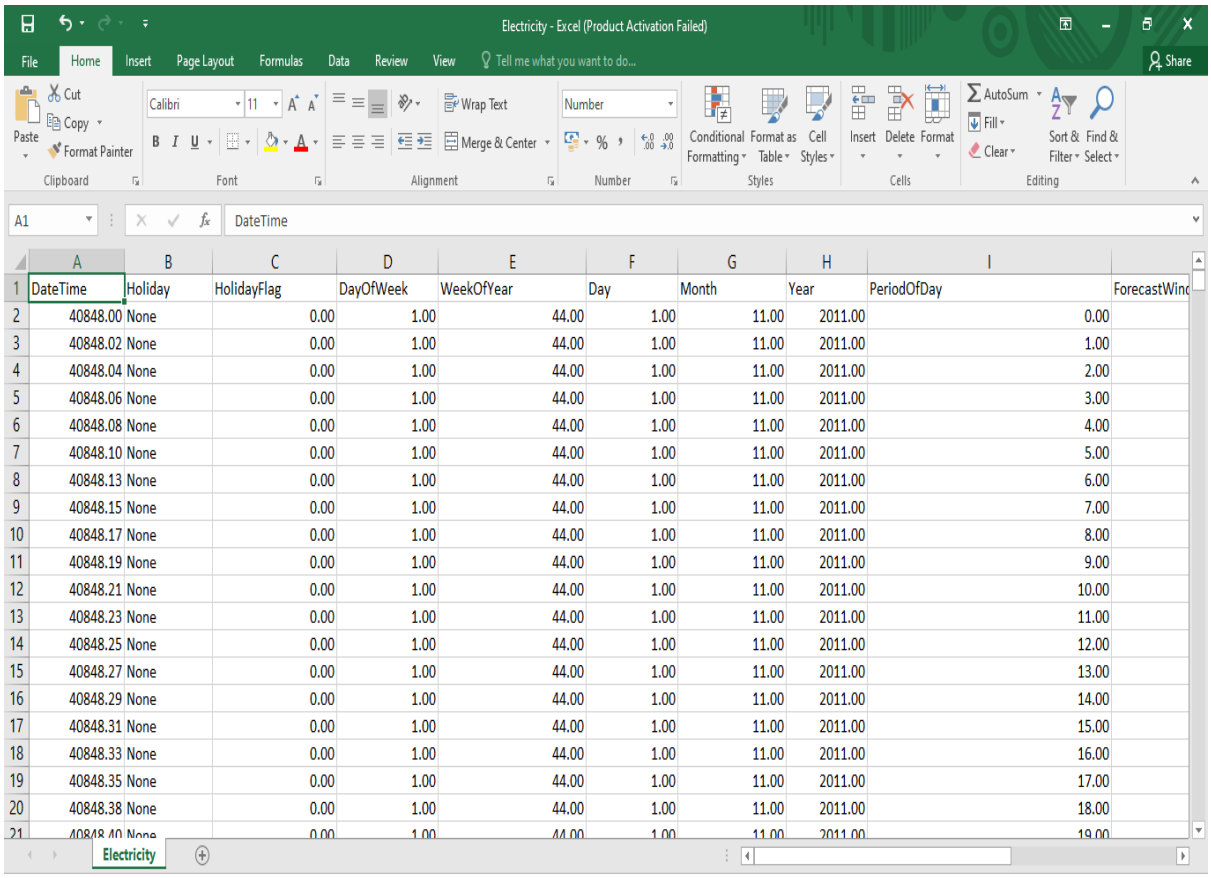
TITLE: ELECTRICITY PRICE PREDICTION

INTRODUCTION:

In this part of the project, the main goal is to build a prediction model for electricity prices. This report outlines the steps involved in loading and preprocessing the dataset to prepare it for analysis.

DATASET DESCRIPTION:

The dataset used for this project contains historical electricity prices. It includes various features such as date, time, and the corresponding electricity price for each observation.



	A	B	C	D	E	F	G	H	I	
1	DateTime	Holiday	HolidayFlag	DayOfWeek	WeekOfYear	Day	Month	Year	PeriodOfDay	ForecastWind
2	40848.00	None	0.00	1.00	44.00	1.00	11.00	2011.00	0.00	
3	40848.02	None	0.00	1.00	44.00	1.00	11.00	2011.00	1.00	
4	40848.04	None	0.00	1.00	44.00	1.00	11.00	2011.00	2.00	
5	40848.06	None	0.00	1.00	44.00	1.00	11.00	2011.00	3.00	
6	40848.08	None	0.00	1.00	44.00	1.00	11.00	2011.00	4.00	
7	40848.10	None	0.00	1.00	44.00	1.00	11.00	2011.00	5.00	
8	40848.13	None	0.00	1.00	44.00	1.00	11.00	2011.00	6.00	
9	40848.15	None	0.00	1.00	44.00	1.00	11.00	2011.00	7.00	
10	40848.17	None	0.00	1.00	44.00	1.00	11.00	2011.00	8.00	
11	40848.19	None	0.00	1.00	44.00	1.00	11.00	2011.00	9.00	
12	40848.21	None	0.00	1.00	44.00	1.00	11.00	2011.00	10.00	
13	40848.23	None	0.00	1.00	44.00	1.00	11.00	2011.00	11.00	
14	40848.25	None	0.00	1.00	44.00	1.00	11.00	2011.00	12.00	
15	40848.27	None	0.00	1.00	44.00	1.00	11.00	2011.00	13.00	
16	40848.29	None	0.00	1.00	44.00	1.00	11.00	2011.00	14.00	
17	40848.31	None	0.00	1.00	44.00	1.00	11.00	2011.00	15.00	
18	40848.33	None	0.00	1.00	44.00	1.00	11.00	2011.00	16.00	
19	40848.35	None	0.00	1.00	44.00	1.00	11.00	2011.00	17.00	
20	40848.38	None	0.00	1.00	44.00	1.00	11.00	2011.00	18.00	
21	40848.40	None	0.00	1.00	44.00	1.00	11.00	2011.00	19.00	

ALGORITHM:

1) Loading the Dataset:

The first step in the development process is to load the historical electricity prices dataset. This can be done using a variety of tools and programming languages, such as Python and its data manipulation libraries like Pandas.

2) Handling Missing Values:

Missing values can be filled in or removed depending on the nature and significance of the missing data. This can be done using techniques such as mean imputation or interpolation.

3) Converting Data Types:

Sometimes, the dataset may contain columns with incorrect data types. For example, a column that represents dates may be stored as strings instead of datetime objects. In such cases, it is important to convert the data types to the appropriate format.

4) Removing Outliers:

Outliers are data points that deviate significantly from the rest of the dataset. These outliers can distort the analysis and prediction models. Removing outliers can be done by using statistical techniques such as z-score or interquartile range.

5) Scaling and Normalization:

Scaling and normalization are important preprocessing steps to ensure that all features are on a similar scale. This helps in preventing certain features from dominating the analysis or prediction models.

PROGRAM:

```
import pandas as pd
# Load the dataset
dataset = pd.read_csv('/Electricity.csv')

# Handle missing values

dataset = dataset.fillna(method='ffill')  # Forward fill missing values
print(dataset)
```

OUTPUT:

```
                    DateTime        Holiday  HolidayFlag  DayOfWeek  \
0     1970-01-01 00:00:00.000040848          None          0.0        1.0
1     1970-01-01 00:00:00.000040848          None          0.0        1.0
2     1970-01-01 00:00:00.000040848          None          0.0        1.0
3     1970-01-01 00:00:00.000040848          None          0.0        1.0
4     1970-01-01 00:00:00.000040848          None          0.0        1.0
...                             ...           ...          ...        ...
38009 1970-01-01 00:00:00.000041639  New Year's Eve          1.0        1.0
38010 1970-01-01 00:00:00.000041639  New Year's Eve          1.0        1.0
38011 1970-01-01 00:00:00.000041639  New Year's Eve          1.0        1.0
38012 1970-01-01 00:00:00.000041639  New Year's Eve          1.0        1.0
38013 1970-01-01 00:00:00.000041639  New Year's Eve          1.0        1.0

      WeekOfYear   Day  Month    Year  PeriodOfDay ForecastWindProduction  \
0           44.0   1.0   11.0  2011.0    -1.696450                315.31
1           44.0   1.0   11.0  2011.0    -1.624264                321.80
2           44.0   1.0   11.0  2011.0    -1.552078                328.57
3           44.0   1.0   11.0  2011.0    -1.479892                335.60
4           44.0   1.0   11.0  2011.0    -1.407706                342.90
...          ...   ...    ...     ...          ...                   ...
38009        1.0  31.0   12.0  2013.0     1.407547                1179.14
38010        1.0  31.0   12.0  2013.0     1.479733                1152.01
38011        1.0  31.0   12.0  2013.0     1.551919                1123.67
38012        1.0  31.0   12.0  2013.0     1.624105                1094.24
38013        1.0  31.0   12.0  2013.0     1.696290                 1064.0

      SystemLoadEA  SMPEA ORKTemperature ORKWindspeed CO2Intensity  \
0          3388.77  49.26           6.00         9.30       600.71
```

```
1         3196.66  49.26         6.00        11.10       605.42
2         3060.71  49.10         5.00        11.10       589.97
3         2945.56  48.04         6.00         9.30       585.94
4         2849.34  33.75         6.00        11.10       571.52
...           ...    ...          ...         ...         ...
38009     3932.22  34.51         6.00        22.20       285.31
38010     3821.44  33.83         5.00        24.10       278.31
38011     3724.21  31.75         4.00        20.40       280.91
38012     3638.16  33.83         5.00        14.80       302.46
38013     3624.25  33.83         5.00        16.70       308.01

      ActualWindProduction SystemLoadEP2 SMPEP2
0                   356.00       3159.60  54.32
1                   317.00       2973.01  54.23
2                   311.00       2834.00  54.23
3                   313.00       2725.99  53.47
4                   346.00       2655.64  39.87
...                    ...          ...    ...
38009                812.0       3692.95  42.45
38010                852.0        3571.0  33.83
38011                962.0       3460.29  31.75
38012                950.0       3563.99   50.6
38013               1020.0        3517.08   34.9

[38014 rows x 18 columns]
```

 # Convert data types

```
dataset['DateTime'] = pd.to_datetime(dataset['DateTime'])
print(dataset['DateTime'])
```

OUTPUT:

```
0       1970-01-01 00:00:00.000040848
1       1970-01-01 00:00:00.000040848
2       1970-01-01 00:00:00.000040848
3       1970-01-01 00:00:00.000040848
4       1970-01-01 00:00:00.000040848
                    ...
38009   1970-01-01 00:00:00.000041639
38010   1970-01-01 00:00:00.000041639
38011   1970-01-01 00:00:00.000041639
```

38012 1970-01-01 00:00:00.000041639
38013 1970-01-01 00:00:00.000041639
Name: DateTime, Length: 38014, dtype: datetime64[ns]

#REMOVE OUTLIERS

```
outliers = dataset['PeriodOfDay'].between(0, 47)  # Define a range for valid prices
dataset = dataset[outliers]
print(outliers)
```

OUTPUT:

```
24      True
25      True
26      True
27      True
28      True
       ...
38009   True
38010   True
38011   True
38012   True
38013   True
Name: PeriodOfDay, Length: 19008, dtype: bool
```

#Scale and normalize feature

```
dataset['PeriodOfDay'] = (dataset['PeriodOfDay'] - dataset['PeriodOfDay'].mean()) /
dataset['PeriodOfDay'].std()
print(dataset['PeriodOfDay'])
```

OUTPUT:

```
24     -1.661281
25     -1.516822
26     -1.372363
27     -1.227903
28     -1.083444
         ...
38009   1.083444
38010   1.227903
38011   1.372363
38012   1.516822
```

38013 1.661281
Name: PeriodOfDay, Length: 19008, dtype: float64

CONCLUSION:

In this part of the project, we have successfully loaded and preprocessed the historical electricity prices dataset. The dataset is now ready for further analysis and the development of a prediction model for electricity prices.