Understanding the local electricity market

💾 The data You have access to over five years of energy price and demand data (source):

- "date" - from January 1, 2015, to October 6, 2020.
- "demand" - daily electricity demand in MWh.
- "price" - recommended retail price in AUD/MWh.
- "demand_pos_price" - total daily demand at a positive price in MWh.
- "price_positive" - average positive price, weighted by the corresponding intraday demand in AUD/MWh.
- "demand_neg_price" - total daily demand at a negative price in MWh.
- "price_negative" - average negative price, weighted by the corresponding intraday demand in AUD/MWh.
- "frac_neg_price" - the fraction of the day when the demand traded at a negative price.
- "min_temperature" - minimum temperature during the day in Celsius.
- "max_temperature" - maximum temperature during the day in Celsius.
- "solar_exposure" - total daily sunlight energy in MJ/m^2.
- "rainfall" - daily rainfall in mm.
- "school_day" - "Y" if that day was a school day, "N" otherwise.
- "holiday" - "Y" if the day was a state or national holiday, "N" otherwise.

Note: The price was negative during some intraday intervals, so energy producers were paying buyers rather than vice-versa.

```
## 💪 Competition challenge

Create a report that covers the following:

1. How do energy prices change throughout the year? Are there any patterns by season or month of the year?
2. Build a forecast of daily energy prices the company can use as the basis of its financial planning.
```

In [1]:
```
#conda install -c anaconda py-xgboost
```

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from datetime import datetime
import dateutil.parser
from sklearn import linear_model
from pandas.tseries.offsets import MonthEnd
import warnings
warnings.filterwarnings("ignore")

pd.set_option("expand_frame_repr", True)
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.preprocessing import MinMaxScaler
import xgboost as xgb

col_pal = sns.color_palette()
plt.style.use("fivethirtyeight")
```

In [3]:

```
df =  pd.read_csv('energy_demand.csv', parse_dates = True)
df.head()
```

Out[3]:

	date	demand	price	demand_pos_price	price_positive	demand_neg_price	price_negati
0	2015-01-01	99635.030	25.633696	97319.240	26.415953	2315.790	-7.2400
1	2015-01-02	129606.010	33.138988	121082.015	38.837661	8523.995	-47.8097
2	2015-01-03	142300.540	34.564855	142300.540	34.564855	0.000	0.0000
3	2015-01-04	104330.715	25.005560	104330.715	25.005560	0.000	0.0000
4	2015-01-05	118132.200	26.724176	118132.200	26.724176	0.000	0.0000

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2106 entries, 0 to 2105
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   date             2106 non-null   object 
 1   demand           2106 non-null   float64
 2   price            2106 non-null   float64
 3   demand_pos_price 2106 non-null   float64
 4   price_positive   2106 non-null   float64
 5   demand_neg_price 2106 non-null   float64
 6   price_negative   2106 non-null   float64
 7   frac_neg_price   2106 non-null   float64
 8   min_temperature  2106 non-null   float64
 9   max_temperature  2106 non-null   float64
 10  solar_exposure   2105 non-null   float64
 11  rainfall         2103 non-null   float64
 12  school_day       2106 non-null   object 
 13  holiday          2106 non-null   object 
dtypes: float64(11), object(3)
memory usage: 230.5+ KB
```

In [5]:
```
# A copy of the data to be used for creating a model for making the predicti
df1 = df.copy()
```

In [6]:
```
df['date'] = pd.to_datetime(df['date'])
```

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2106 entries, 0 to 2105
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype         
---  ------           --------------  -----         
 0   date             2106 non-null   datetime64[ns]
 1   demand           2106 non-null   float64       
 2   price            2106 non-null   float64       
 3   demand_pos_price 2106 non-null   float64       
 4   price_positive   2106 non-null   float64       
 5   demand_neg_price 2106 non-null   float64       
 6   price_negative   2106 non-null   float64       
 7   frac_neg_price   2106 non-null   float64       
 8   min_temperature  2106 non-null   float64       
 9   max_temperature  2106 non-null   float64       
 10  solar_exposure   2105 non-null   float64       
 11  rainfall         2103 non-null   float64       
 12  school_day       2106 non-null   object        
 13  holiday          2106 non-null   object        
dtypes: datetime64[ns](1), float64(11), object(2)
memory usage: 230.5+ KB
```

In [8]:
```
df.describe()
```

Out[8]:

	demand	price	demand_pos_price	price_positive	demand_neg_price	price_ne
count	2106.000000	2106.000000	2106.000000	2106.000000	2106.000000	2106.0
mean	120035.476503	76.079554	119252.305055	76.553847	783.171448	-2.6
std	13747.993761	130.246805	14818.631319	130.114184	3578.920686	19.4
min	85094.375000	-6.076028	41988.240000	13.568986	0.000000	-342.2
25%	109963.650000	38.707040	109246.250000	39.117361	0.000000	0.0
50%	119585.912500	66.596738	119148.082500	66.869058	0.000000	0.0
75%	130436.006250	95.075012	130119.477500	95.130181	0.000000	0.0
max	170653.840000	4549.645105	170653.840000	4549.645105	57597.595000	0.0

In [9]:
```
#checking for missing values

df.isnull().sum()
```

Out[9]:
```
date                0
demand              0
price               0
demand_pos_price    0
price_positive      0
demand_neg_price    0
price_negative      0
frac_neg_price      0
min_temperature     0
max_temperature     0
solar_exposure      1
rainfall            3
school_day          0
holiday             0
dtype: int64
```

In [10]:
```
#filling the missing data using mode
df['solar_exposure'] = df['solar_exposure'].fillna(df['solar_exposure'].mode
df['rainfall'] = df['rainfall'].fillna(df['rainfall'].mode()[0])
```

In [11]:
```python
# Checking for duplicates
df.isnull().sum()
```

Out[11]:
```
date                0
demand              0
price               0
demand_pos_price    0
price_positive      0
demand_neg_price    0
price_negative      0
frac_neg_price      0
min_temperature     0
max_temperature     0
solar_exposure      0
rainfall            0
school_day          0
holiday             0
dtype: int64
```

In [12]:
```python
df.duplicated().sum()
```

Out[12]:
```
0
```

In [13]:
```python
# Splitting the date time for plotting purposes

df['date'] = pd.to_datetime(df['date'])
df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.month
df['day'] = df['date'].dt.day
```

In [14]:
```python
df.columns
```

Out[14]:
```
Index(['date', 'demand', 'price', 'demand_pos_price', 'price_positive',
       'demand_neg_price', 'price_negative', 'frac_neg_price',
       'min_temperature', 'max_temperature', 'solar_exposure', 'rainfall',
       'school_day', 'holiday', 'year', 'month', 'day'],
      dtype='object')
```

In [15]:
```python
# Drop date column
df.drop('date', axis = 1, inplace = True)
```

In [16]:
```python
df.sample(3)
```

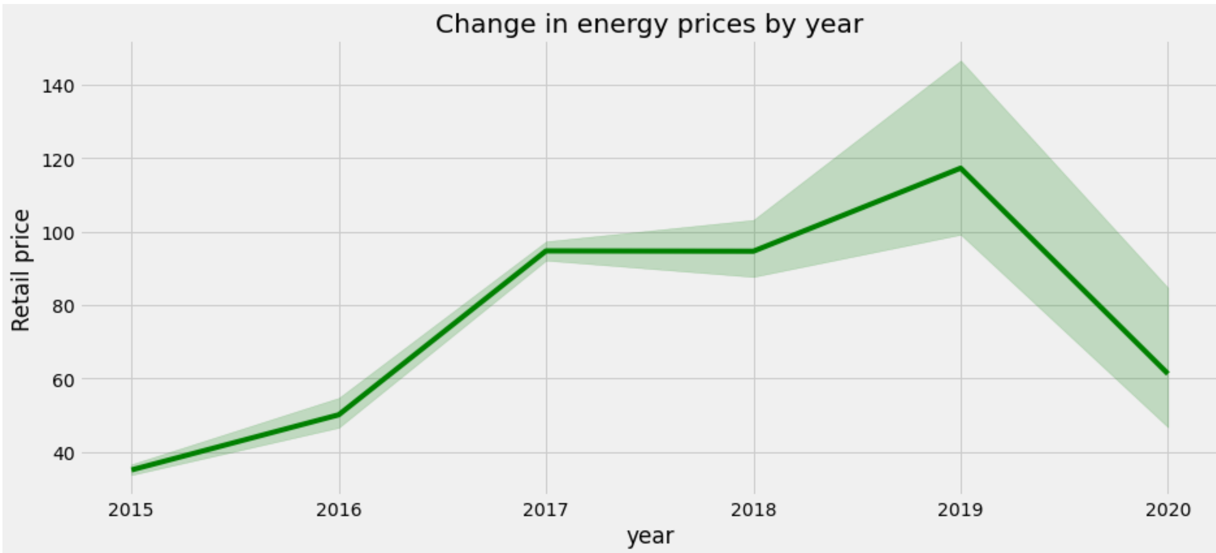
Out[16]:

	demand	price	demand_pos_price	price_positive	demand_neg_price	price_negative
1850	102445.880	50.132823	102445.88	50.132823	0.000	0.00000
1921	105098.025	23.780908	79509.45	36.334744	25588.575	-15.22668
1385	112592.260	122.200670	112592.26	122.200670	0.000	0.00000

In [17]:
```
# Checking the cardinality of the year column
len(df.year.unique())
```

Out[17]: 6

In [18]:
```
# Y axis is price closing
plt.figure(figsize=(14,6))
sns.lineplot(y='price', x ='year', data = df, color = "green")
plt.title("Change in energy prices by year")
plt.ylabel("Retail price")
plt.show()
```



In [19]:
```
my = df.groupby(['year', 'month', 'day'], as_index =False)['price'].mean()
my.sample(3)
```

Out[19]:

	year	month	day	price
1226	2018	5	11	63.673070
1877	2020	2	21	48.658203
458	2016	4	3	15.804000

In [20]:
```
my2 = df.groupby(['year', 'month'], as_index =False)['price'].mean()
my2.sample(3)
```

Out[20]:

	year	month	price
15	2016	4	47.962939
33	2017	10	74.471315
21	2016	10	34.440483

In [21]:
```
my3 = df.groupby('month')[['price']].mean()
my3.sample(3)
```

Out[21]:

month	price
12	66.229981
9	68.578842
6	81.245597

In [22]:
```
my4 = df.groupby('year')[['price']].mean()
my4.sample(3)
```

Out[22]:

year	price
2019	117.281370
2017	94.740161
2016	50.094252

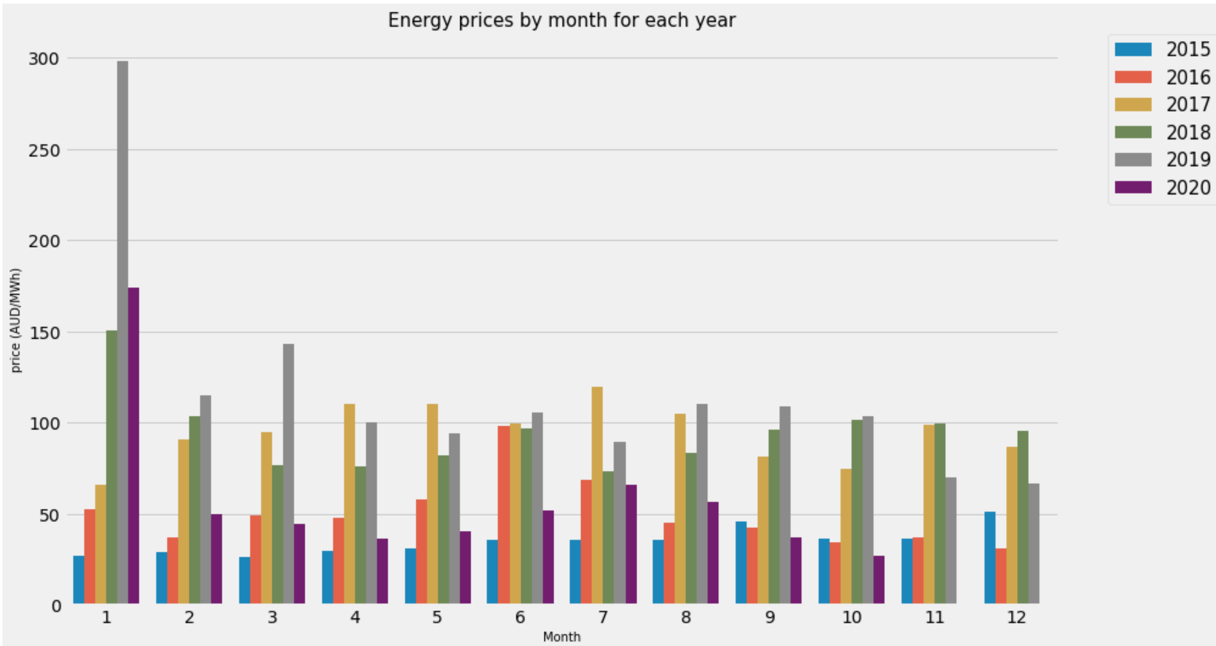
In [23]:
```
#add a new date time column to my2 dataframe with the date as the end of the
my2['datetime'] = pd.to_datetime(my2.year.astype(str) + my2.month.astype(str
my2.sample(3)
```

Out[23]:

	year	month	price	datetime
56	2019	9	109.025825	2019-09-30
15	2016	4	47.962939	2016-04-30
48	2019	1	298.171896	2019-01-31

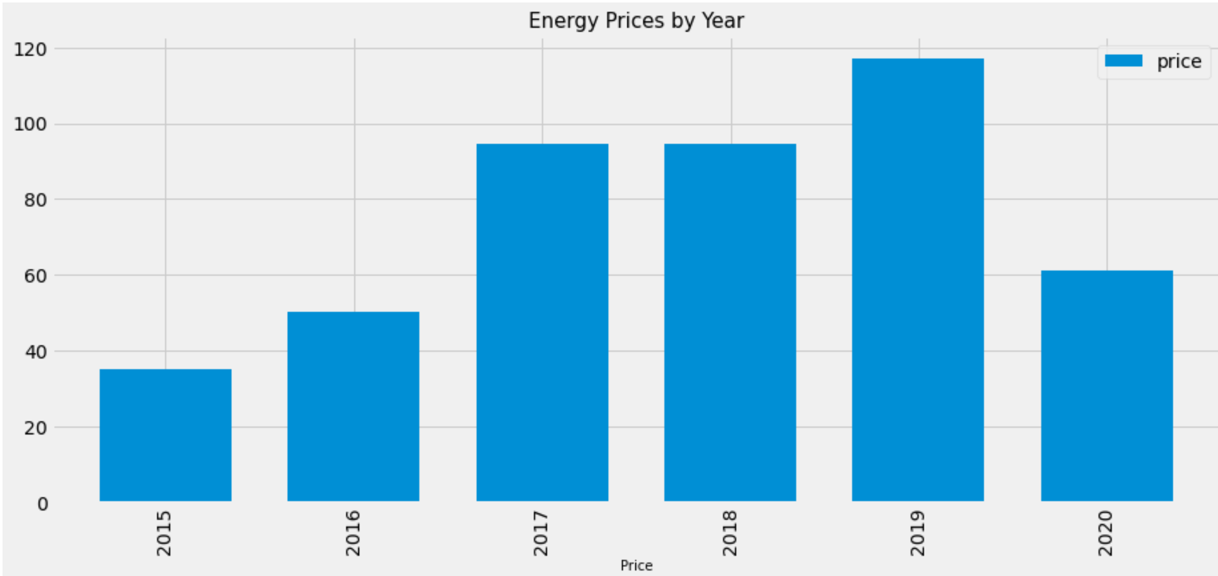
In [24]:

```
# Prices by month and year
plt.figure(figsize = (13, 8))
sns.barplot(data = my2, x = 'month', y = 'price', hue = 'year')
plt.legend(bbox_to_anchor = (1.05, 1), borderaxespad = 0,fontsize = 15)
plt.title('Energy prices by month for each year',fontsize = 15)
plt.ylabel('price (AUD/MWh)',fontsize = 10)
plt.xlabel("Month",fontsize = 10)
plt.show()
```

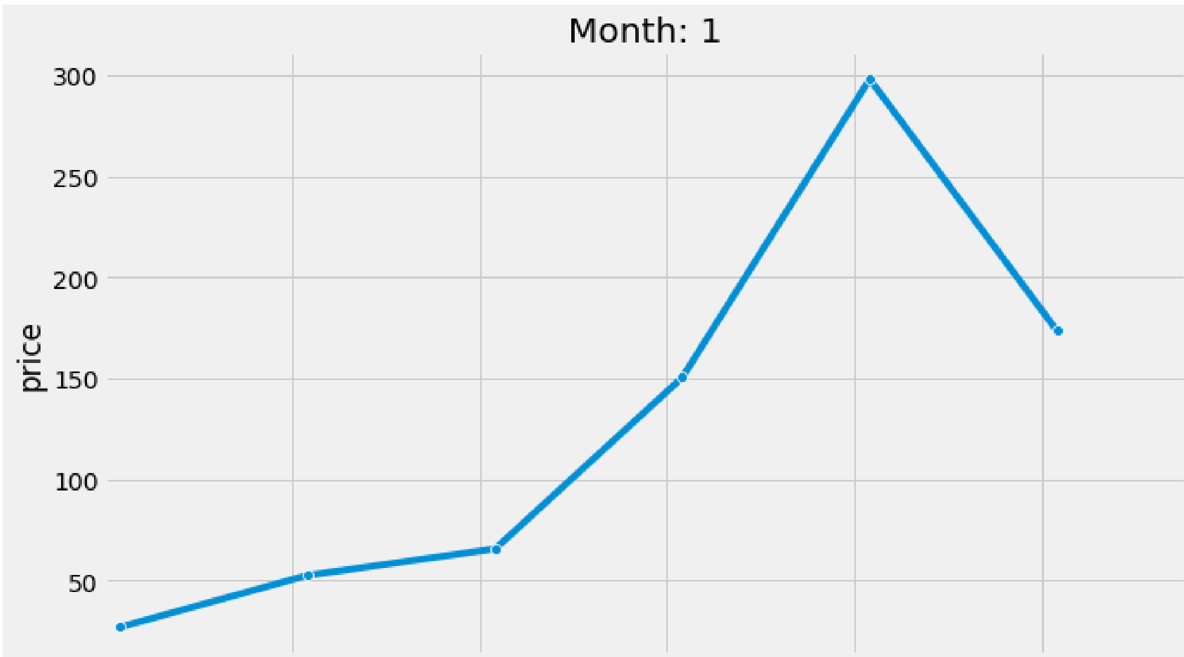


In [25]:

```
#Prices by year
my4.plot(kind = 'bar', width = 0.7, figsize = (14,6))
plt.title("Energy Prices by Year", fontsize = 15)
plt.xlabel("Year",fontsize = 10)
plt.xlabel("Price",fontsize = 10)
plt.show()
```



In [26]:
```
for month in my2.month.unique():
    data = my2[my2.month == month]
    plt.figure(figsize=(10,6))
    sns.lineplot(data.datetime, data.price, marker = 'o')
    plt.xlim(datetime(2015, 1, 1), datetime(2020, 10, 6))
    plt.title(f'Month: {month}')
    plt.ylabel('price')
    plt.xlabel('Year')
```



seasons in australia

- #Summer - three hottest month which falls in December to February
- #Autumn - the transition month which falls in March to May
- #Winter - the three coldest months falls in June to August
- #spring - the three transition months which is September to November

Lets represent the months in numbers

- 1 = Summer (months id 12th - 2nd)
- 2 = Autumn (months id 3th - 5th)
- 3 = Winter (months id 6th - 8th)
- 4 = Spring (months id 9th - 11th)

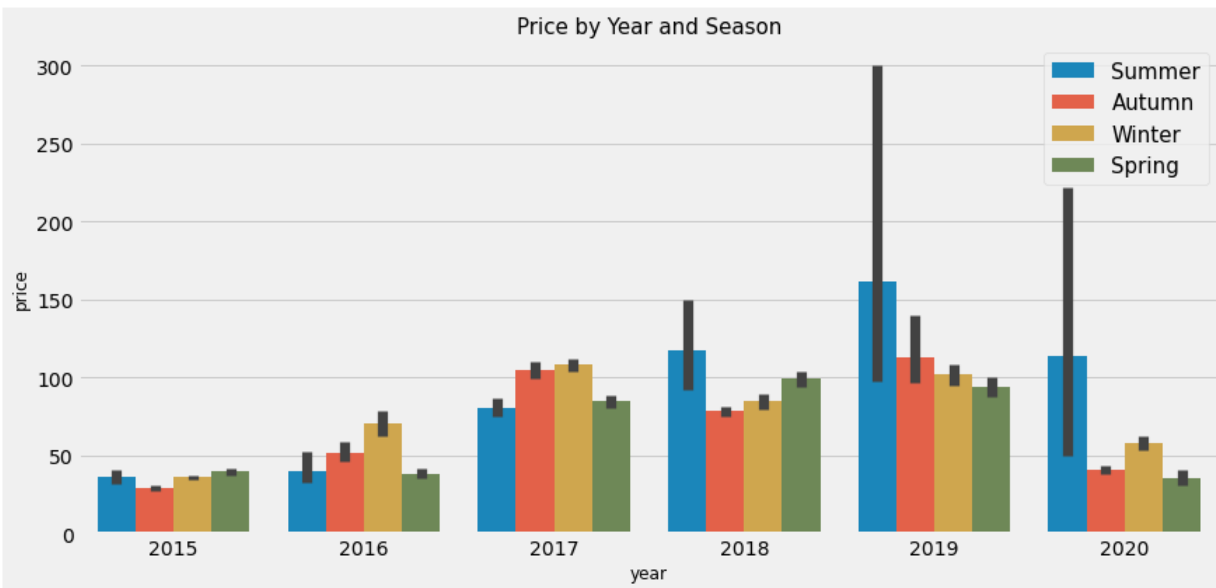
In [27]:
```
seasons = [1, 1, 2, 2, 2, 3, 3, 3, 4, 4, 4, 1]
month_to_season= dict(zip(range(1, 13), seasons))
df['season_id'] = df.month.map(month_to_season)
df['season'] = df['season_id'].map({1:'Summer', 2:'Autumn', 3:'Winter', 4:'S
df['rain'] = df['rainfall'] > 1
```

In [28]:
```
# Patterns by seasons
price_by_season = df.groupby(['season'], as_index = False)['price'].mean()
price_by_season
```

Out[28]:

	season	price
0	Autumn	69.517789
1	Spring	68.451242
2	Summer	90.115702
3	Winter	76.433038

In [29]:
```
# comparing price by season..
plt.figure(figsize=(13,6))
sns.barplot(data = df, x = 'year', y = 'price', hue = 'season')
plt.legend(bbox_to_anchor = (1,1), fontsize = 15)
plt.xlabel('year', fontsize = 12)
plt.ylabel('price', fontsize = 12)
plt.title('Price by Year and Season', fontsize = 15)
plt.show()
```



Forecast of daily energy prices the company can use as the basis of its financial planning.

In [30]:
```
df1.head()
```

Out[30]:

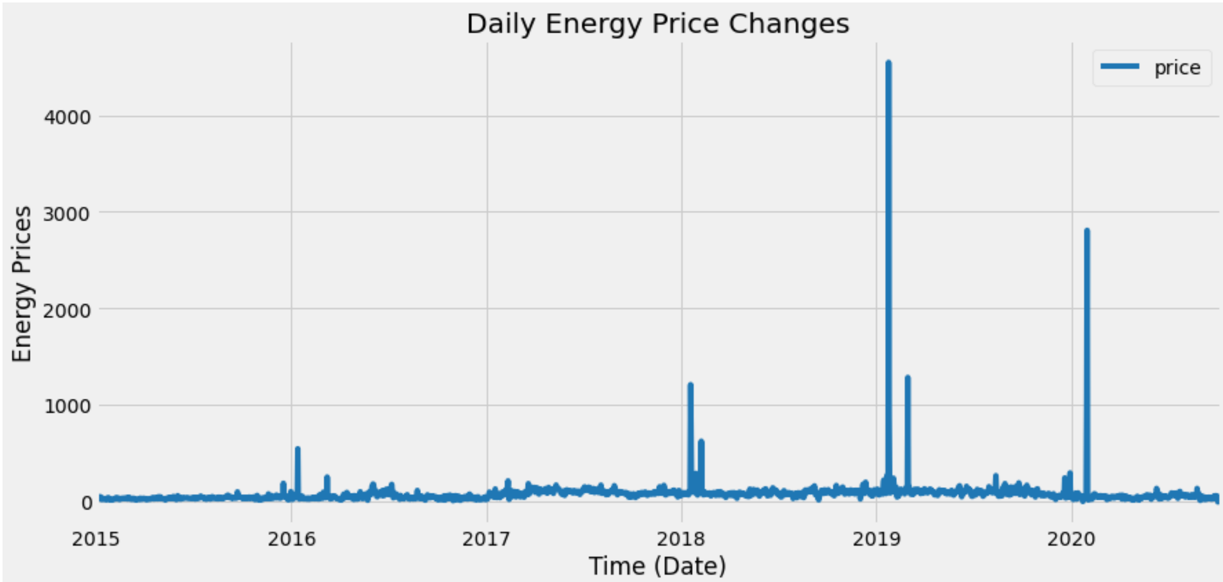
	date	demand	price	demand_pos_price	price_positive	demand_neg_price	price_negati
0	2015-01-01	99635.030	25.633696	97319.240	26.415953	2315.790	-7.2400
1	2015-01-02	129606.010	33.138988	121082.015	38.837661	8523.995	-47.8097
2	2015-01-03	142300.540	34.564855	142300.540	34.564855	0.000	0.0000
3	2015-01-04	104330.715	25.005560	104330.715	25.005560	0.000	0.0000
4	2015-01-05	118132.200	26.724176	118132.200	26.724176	0.000	0.0000

In [31]:
```
df1.index = pd.to_datetime(df1['date'])
df1.drop("date",axis = 1, inplace = True)
df1.sample(3)
```

Out[31]:

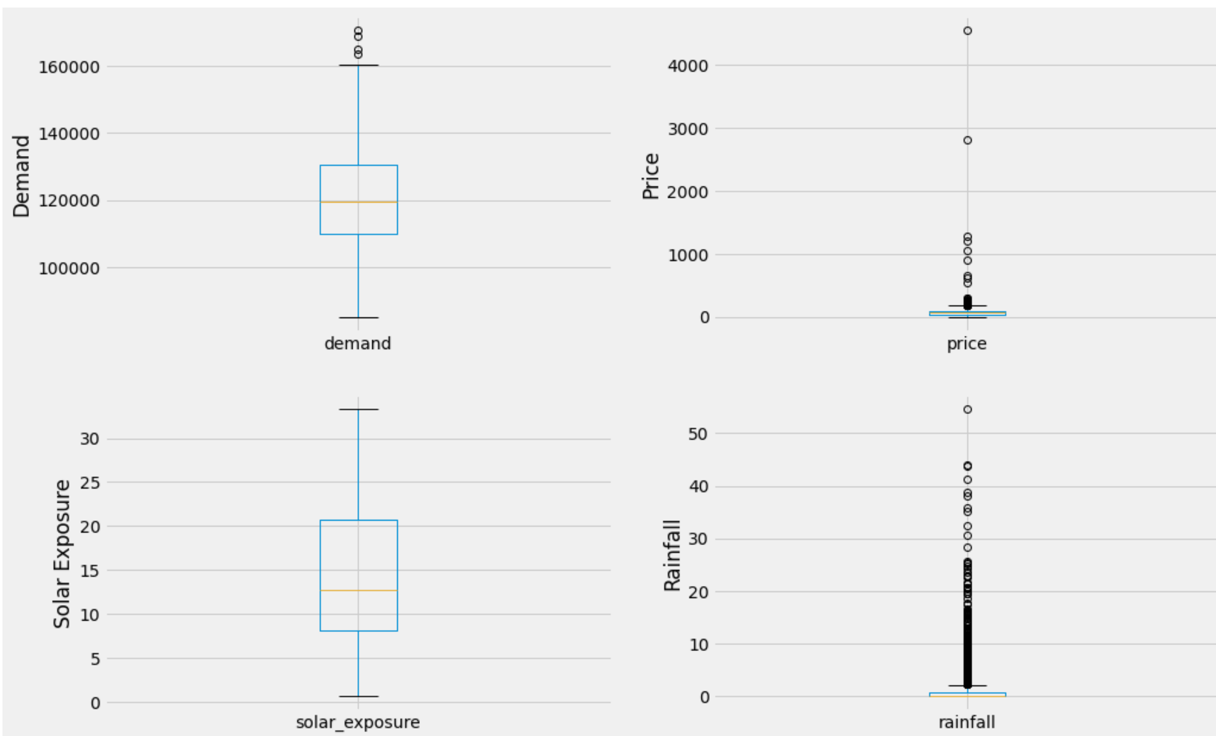
	demand	price	demand_pos_price	price_positive	demand_neg_price	price_negative
date						
2016-02-19	122991.660	43.694897	122991.660	43.694897	0.0	0.0
2015-11-20	123412.685	38.026498	123412.685	38.026498	0.0	0.0
2017-11-10	115156.445	92.615537	115156.445	92.615537	0.0	0.0

In [32]:
```
# Daily energy price chnages
df1.plot(y = 'price', color= col_pal[0],figsize = (13,6))
plt.title("Daily Energy Price Changes")
plt.ylabel("Energy Prices")
plt.xlabel("Time (Date)")
plt.show()
```



In [33]:
```
#Check for outliers
plt.figure(figsize=(15,10))

plt.subplot(2,2,1)
fig = df1.boxplot(column='demand')
fig.set_ylabel('Demand')

plt.subplot(2,2,2)
fig = df1.boxplot(column='price')
fig.set_ylabel('Price')

plt.subplot(2,2,3)
fig = df1.boxplot(column='solar_exposure')
fig.set_ylabel('Solar Exposure')

plt.subplot(2,2,4)
fig = df1.boxplot(column='rainfall')
fig.set_ylabel('Rainfall')
```

Out[33]: Text(0, 0.5, 'Rainfall')



Train and Test Split

In [34]:
```
len(df1.index)
```

Out[34]: 2106

In [35]:
```
# An estimate of around where the 70% of the data lies below(train set)
df1.iloc[1475]
```

Out[35]:
```
demand              152496.245
price               222.438419
demand_pos_price    152496.245
price_positive      222.438419
demand_neg_price           0.0
price_negative             0.0
frac_neg_price             0.0
min_temperature           19.4
max_temperature           30.4
solar_exposure            22.3
rainfall                   0.0
school_day                   N
holiday                      N
Name: 2019-01-15 00:00:00, dtype: object
```

In [36]:
```
# splitting the date
df1['year'] = df1.index.year
df1['month'] = df1.index.month
df1['day'] = df1.index.day
df1['day of week'] = df1.index.dayofweek
```

In [37]:
```
# Splitting the date into test and train data
split_date = '2019-01-01'
train = df1[df1.index < pd.to_datetime(split_date)]
test = df1[df1.index >= pd.to_datetime(split_date)]
```

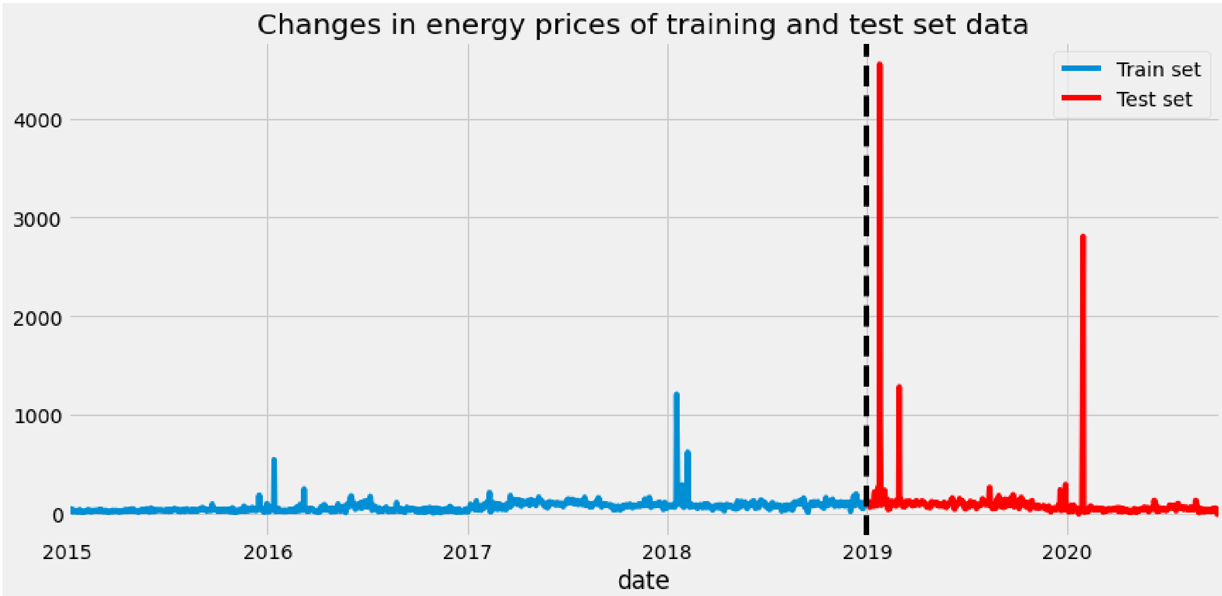
In [38]:
```
train.shape
```

Out[38]:
```
(1461, 17)
```

In [39]:
```
test.shape
```

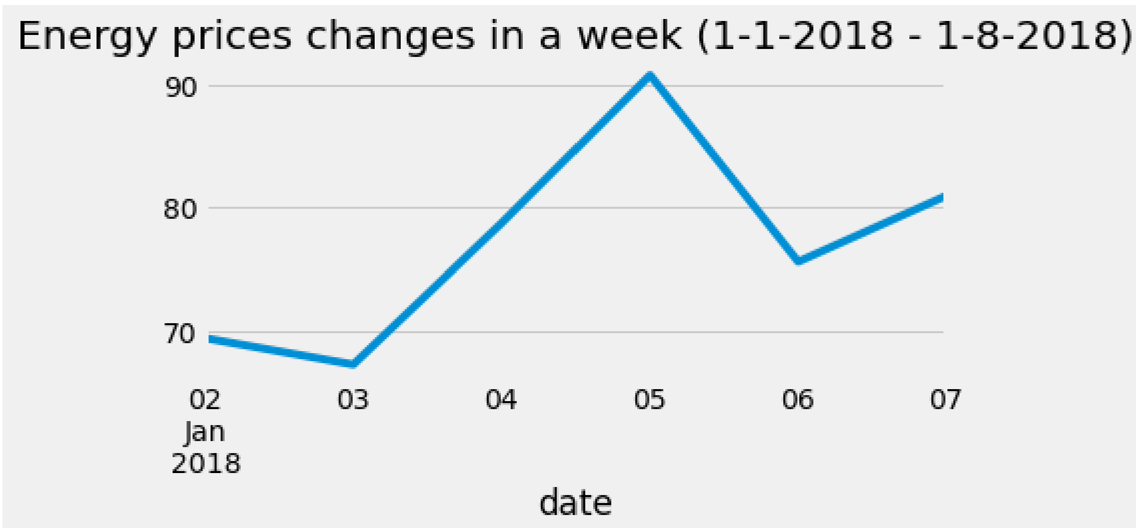
Out[39]:
```
(645, 17)
```

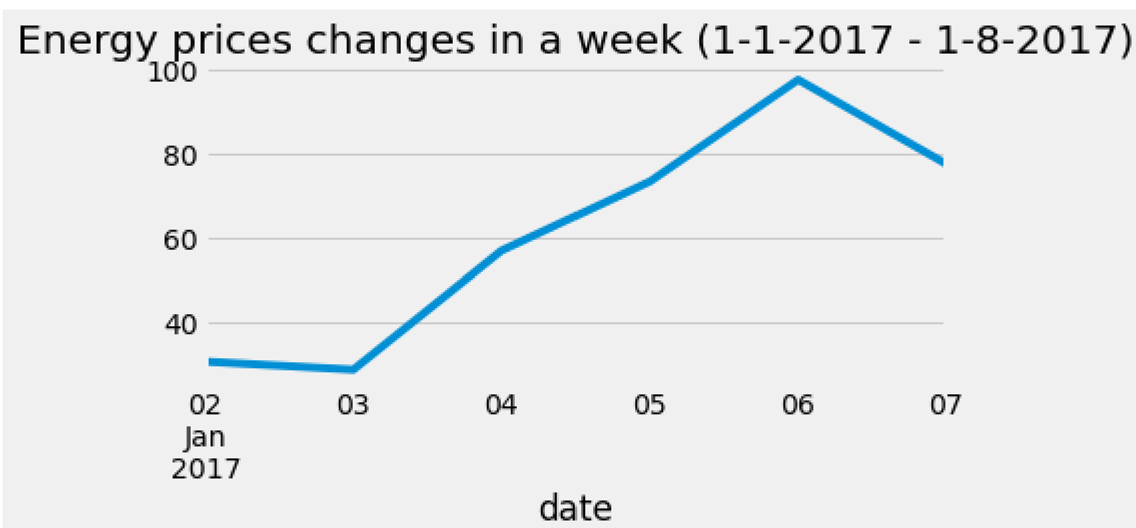
In [40]:
```
fig, ax = plt.subplots(figsize=(13,6))
train.price.plot()
test.price.plot(color = "r")
plt.title("Changes in energy prices of training and test set data")
ax.axvline('2019-1-1', color = "black", ls ="--")
ax.legend(["Train set", "Test set"])
plt.show()
```

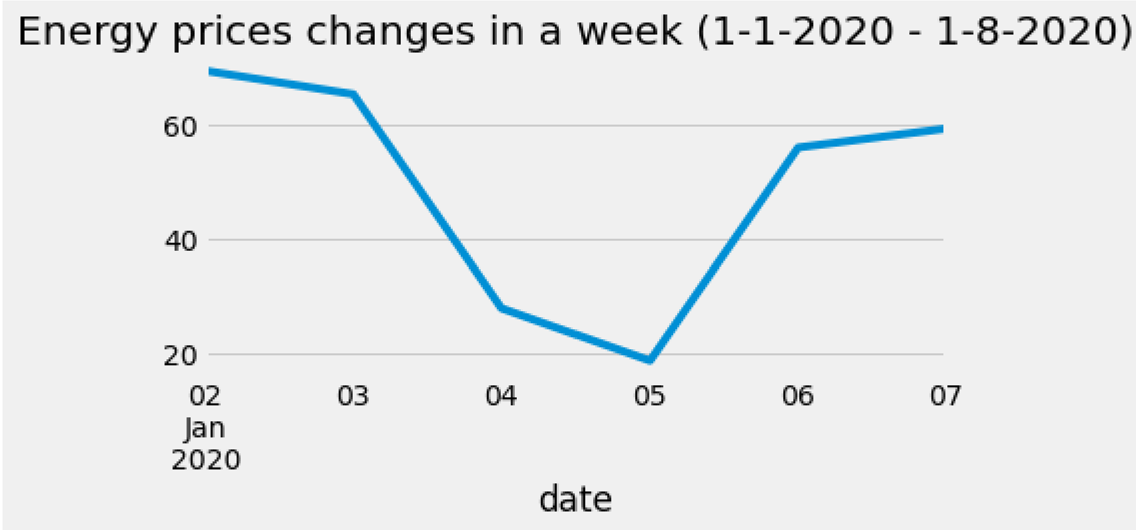


In [41]:

```
# Energy price changes in a random week
plt.figure(figsize=(10,6))

plt.subplot(2,2,1)
df1.loc[(df1.index > "1-1-2018") & (df1.index < "1-8-2018")].price.plot(figs
plt.title("Energy prices changes in a week (1-1-2018 - 1-8-2018)")
plt.show()

plt.subplot(2,2,2)
df1.loc[(df1.index > "1-1-2017") & (df1.index < "1-8-2017")].price.plot(figs
plt.title("Energy prices changes in a week (1-1-2017 - 1-8-2017)")
plt.show()

plt.subplot(2,2,3)
df1.loc[(df1.index > "1-1-2020") & (df1.index < "1-8-2020")].price.plot(figs
plt.title("Energy prices changes in a week (1-1-2020 - 1-8-2020)");
```

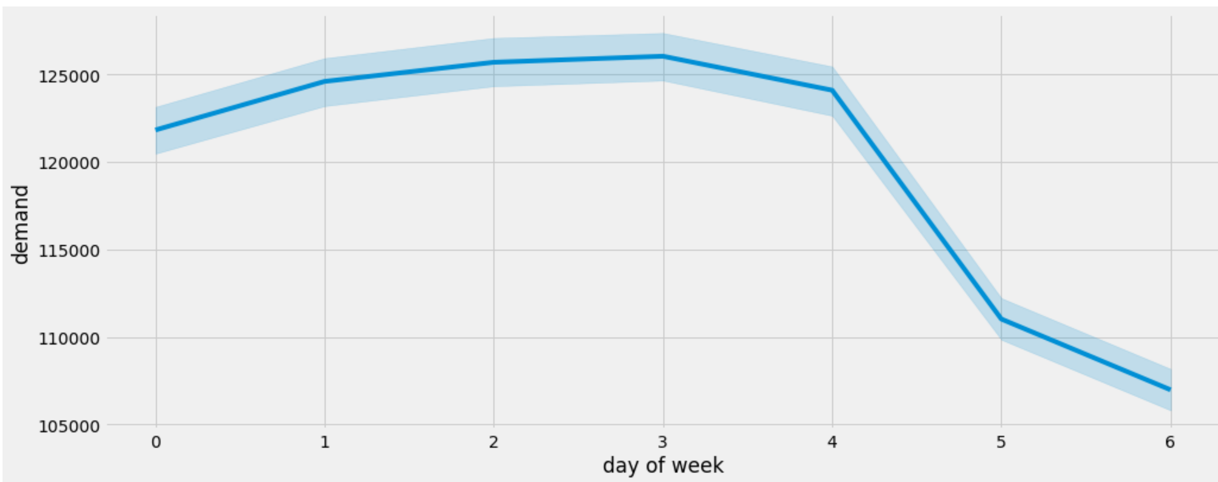






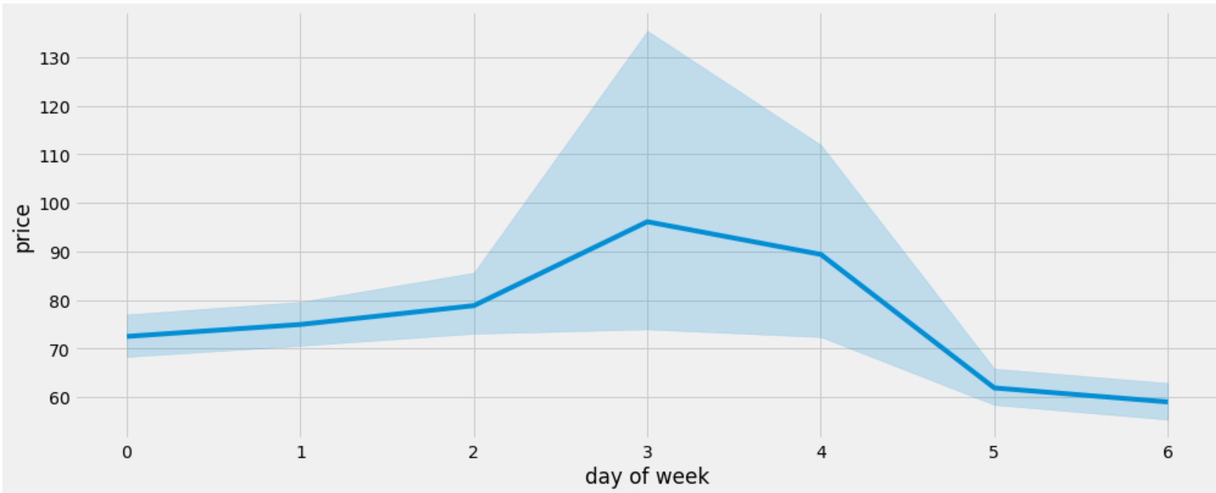
In [42]:
```
# Energy demand in a week
plt.subplots(figsize=(15,6))
sns.lineplot(data = df1, x = "day of week", y ="demand")
```

Out[42]: <AxesSubplot:xlabel='day of week', ylabel='demand'>



In [43]:
```
# Energy demand in a week
plt.subplots(figsize=(15,6))
sns.lineplot(data = df1, x = "day of week", y ="price")
```

Out[43]:
```
<AxesSubplot:xlabel='day of week', ylabel='price'>
```



In [44]:
```
features = df1.drop("price", axis = 1).columns
print("Features: ", features)
target = 'price'
print("Target: ",target)
```

```
Features:  Index(['demand', 'demand_pos_price', 'price_positive', 'demand_neg_p
rice',
       'price_negative', 'frac_neg_price', 'min_temperature',
       'max_temperature', 'solar_exposure', 'rainfall', 'school_day',
       'holiday', 'year', 'month', 'day', 'day of week'],
      dtype='object')
Target:  price
```

In [45]:
```
X_train = train[features]
y_train = train[target]

X_test = test[features]
y_test = test[target]
```

In [46]:
```
#check the shape of our split data

print(X_train.shape, X_test.shape)
print(y_train.shape, y_test.shape)
```

```
(1461, 16) (645, 16)
(1461,) (645,)
```

In [47]:
```
X_train.columns
```

Out[47]:
```
Index(['demand', 'demand_pos_price', 'price_positive', 'demand_neg_price',
       'price_negative', 'frac_neg_price', 'min_temperature',
       'max_temperature', 'solar_exposure', 'rainfall', 'school_day',
       'holiday', 'year', 'month', 'day', 'day of week'],
      dtype='object')
```

In [48]:
```
y_train = pd.DataFrame(y_train)
y_test = pd.DataFrame(y_test)
```

In [49]:
```
def missing_values(x):
    return (sum(x.isna()))
print("Missing values for each split: \n")

print("y_train: \n",y_train.apply(missing_values).where(lambda x:x!=0).dropn
print("y_test: \n",y_test.apply(missing_values).where(lambda x:x!=0).dropna(
print("X_train: \n",X_train.apply(missing_values).where(lambda x:x!=0).dropn
print("X_test: \n",X_test.apply(missing_values).where(lambda x:x!=0).dropna(
```

```
Missing values for each split: 

y_train: 
 Series([], dtype: float64)

y_test: 
 Series([], dtype: float64)

X_train: 
 solar_exposure    1.0
rainfall          3.0
dtype: float64

X_test: 
 Series([], dtype: float64)
```

In [50]:
```
# filling missing values with mode.
X_train['solar_exposure'] = X_train['solar_exposure'].fillna(X_train['solar_
X_train['rainfall'] = X_train['rainfall'].fillna(X_train['rainfall'].mode()[
```

In [51]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1461 entries, 2015-01-01 to 2018-12-31
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   demand            1461 non-null   float64
 1   demand_pos_price  1461 non-null   float64
 2   price_positive    1461 non-null   float64
 3   demand_neg_price  1461 non-null   float64
 4   price_negative    1461 non-null   float64
 5   frac_neg_price    1461 non-null   float64
 6   min_temperature   1461 non-null   float64
 7   max_temperature   1461 non-null   float64
 8   solar_exposure    1461 non-null   float64
 9   rainfall          1461 non-null   float64
 10  school_day        1461 non-null   object 
 11  holiday           1461 non-null   object 
 12  year              1461 non-null   int64  
 13  month             1461 non-null   int64  
 14  day               1461 non-null   int64  
 15  day of week       1461 non-null   int64  
dtypes: float64(10), int64(4), object(2)
memory usage: 194.0+ KB
```

In [52]:
```
#extraxt the categorical features
categorical = [var for var in X_train.columns if X_train[var].dtype=='O']

print('There are {} categorical variables \n'.format(len(categorical)))

print('They are: ', categorical)
```

```
There are 2 categorical variables 

They are:  ['school_day', 'holiday']
```

In [53]:
```
numerical = [var for var in X_train.columns if X_train[var].dtype!='O']

print('There are {} numerical variables. \n'.format(len(numerical)))

print('They are: \n', numerical)
```

```
There are 14 numerical variables. 

They are: 
 ['demand', 'demand_pos_price', 'price_positive', 'demand_neg_price', 'price_ne
gative', 'frac_neg_price', 'min_temperature', 'max_temperature', 'solar_exposur
e', 'rainfall', 'year', 'month', 'day', 'day of week']
```

In [54]:
```
print("Unique values in school day:", X_train.school_day.unique())
print("Unique values in holiday:", X_train.holiday.unique())
```

```
Unique values in school day: ['N' 'Y']
Unique values in holiday: ['Y' 'N']
```

In [55]:
```
#encoding categorocal data
import category_encoders as ce

encoder =ce.BinaryEncoder(cols=['school_day', 'holiday'])
X_train= encoder.fit_transform(X_train)
X_test= encoder.fit_transform(X_test)
```

In [56]:
```
X_train.columns
```

Out[56]:
```
Index(['demand', 'demand_pos_price', 'price_positive', 'demand_neg_price',
       'price_negative', 'frac_neg_price', 'min_temperature',
       'max_temperature', 'solar_exposure', 'rainfall', 'school_day_0',
       'school_day_1', 'holiday_0', 'holiday_1', 'year', 'month', 'day',
       'day of week'],
      dtype='object')
```

In [57]:
```
X_train.sample(3)
```

Out[57]:

	demand	demand_pos_price	price_positive	demand_neg_price	price_negative	frac_neg_p
date						
2016-06-29	136071.965	136071.965	80.125243	0.0	0.0	
2018-06-13	131574.605	131574.605	84.579533	0.0	0.0	
2018-11-22	107278.830	107278.830	77.208903	0.0	0.0	

In [58]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1461 entries, 2015-01-01 to 2018-12-31
Data columns (total 18 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   demand             1461 non-null   float64
 1   demand_pos_price   1461 non-null   float64
 2   price_positive     1461 non-null   float64
 3   demand_neg_price   1461 non-null   float64
 4   price_negative     1461 non-null   float64
 5   frac_neg_price     1461 non-null   float64
 6   min_temperature    1461 non-null   float64
 7   max_temperature    1461 non-null   float64
 8   solar_exposure     1461 non-null   float64
 9   rainfall           1461 non-null   float64
 10  school_day_0       1461 non-null   int64  
 11  school_day_1       1461 non-null   int64  
 12  holiday_0          1461 non-null   int64  
 13  holiday_1          1461 non-null   int64  
 14  year               1461 non-null   int64  
 15  month              1461 non-null   int64  
 16  day                1461 non-null   int64  
 17  day of week        1461 non-null   int64  
dtypes: float64(10), int64(8)
memory usage: 216.9 KB
```

In [59]:
```
X_test.head()
```

Out[59]:

	demand	demand_pos_price	price_positive	demand_neg_price	price_negative	frac_neg_p
date						
2019-01-01	98933.060	98933.060	78.560979	0.0	0.0	
2019-01-02	106470.675	106470.675	92.202011	0.0	0.0	
2019-01-03	118789.605	118789.605	127.380303	0.0	0.0	
2019-01-04	133288.460	133288.460	121.020997	0.0	0.0	
2019-01-05	97262.790	97262.790	83.493520	0.0	0.0	

In [60]:
```
X_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 645 entries, 2019-01-01 to 2020-10-06
Data columns (total 18 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   demand            645 non-null    float64
 1   demand_pos_price  645 non-null    float64
 2   price_positive    645 non-null    float64
 3   demand_neg_price  645 non-null    float64
 4   price_negative    645 non-null    float64
 5   frac_neg_price    645 non-null    float64
 6   min_temperature   645 non-null    float64
 7   max_temperature   645 non-null    float64
 8   solar_exposure    645 non-null    float64
 9   rainfall          645 non-null    float64
 10  school_day_0      645 non-null    int64  
 11  school_day_1      645 non-null    int64  
 12  holiday_0         645 non-null    int64  
 13  holiday_1         645 non-null    int64  
 14  year              645 non-null    int64  
 15  month             645 non-null    int64  
 16  day               645 non-null    int64  
 17  day of week       645 non-null    int64  
dtypes: float64(10), int64(8)
memory usage: 95.7 KB
```

In [61]:
```
#feature scaling`
scaler= MinMaxScaler()

X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)
```

In [62]:
```
# Model
# an estimation of 1000 trees to be created
model = xgb.XGBRegressor(n_estimator = 1000, early_stopping_rounds = 50, lea
model.fit(X_train, y_train,eval_set= [(X_train, y_train),( X_test, y_test)],
```

```
[17:58:38] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling
-group-i-03de431ba26204c4d-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "n_estimator" } are not used.

[0]	validation_0-rmse:78.11403	validation_1-rmse:234.96259
[10]	validation_0-rmse:31.85523	validation_1-rmse:206.09387
[20]	validation_0-rmse:14.84897	validation_1-rmse:192.16578
[30]	validation_0-rmse:7.77317	validation_1-rmse:184.57245
[40]	validation_0-rmse:4.39702	validation_1-rmse:180.38736
[50]	validation_0-rmse:2.58362	validation_1-rmse:178.04991
[60]	validation_0-rmse:1.54986	validation_1-rmse:176.66196
[70]	validation_0-rmse:0.94759	validation_1-rmse:175.86546
[80]	validation_0-rmse:0.59968	validation_1-rmse:175.39540
[90]	validation_0-rmse:0.40597	validation_1-rmse:175.11223
[99]	validation_0-rmse:0.31197	validation_1-rmse:174.95185
```

Out[62]:
```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=50, enable_categorical=False,
             eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
             grow_policy='depthwise', importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_bin=256,
             max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
             max_depth=6, max_leaves=0, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimator=1000, n_estimators=100,
             n_jobs=0, num_parallel_tree=1, predictor='auto', ...)
```

Forecast on the test data

In [63]:
```
y_pred = model.predict(X_test)
```

In [64]:
```
y_pred = pd.DataFrame(y_pred, columns = ['Predicted energy prices'])
y_pred.head(3)
```

Out[64]:

	Predicted energy prices
0	30.785151
1	34.032856
2	43.501045

In [65]:
```
y_test.head(3)
```

Out[65]:

	price
date	
2019-01-01	78.560979
2019-01-02	92.202011
2019-01-03	127.380303

In [66]:
```
mse = mean_squared_error(y_test,y_pred)
rmse = np.sqrt(mse)
rmse
```

Out[66]:
```
174.9518464452088
```

In [67]:
```
mae = mean_absolute_error(y_test,y_pred)
mae
```

Out[67]:
```
59.073529425444185
```

In [68]:
```
df1.index.max()
```

Out[68]:
```
Timestamp('2020-10-06 00:00:00')
```

forecasting prices for the next one year

In [69]:
```
df1.index.max()
```

Out[69]:
```
Timestamp('2020-10-06 00:00:00')
```

In [70]:
```
# Creating a future data frame of one year for each of the days
dates = pd.date_range('2020-10-7','2021-10-6', freq = '1d')
dates
```

Out[70]:
```
DatetimeIndex(['2020-10-07', '2020-10-08', '2020-10-09', '2020-10-10',
               '2020-10-11', '2020-10-12', '2020-10-13', '2020-10-14',
               '2020-10-15', '2020-10-16',
               ...
               '2021-09-27', '2021-09-28', '2021-09-29', '2021-09-30',
               '2021-10-01', '2021-10-02', '2021-10-03', '2021-10-04',
               '2021-10-05', '2021-10-06'],
              dtype='datetime64[ns]', length=365, freq='D')
```

In [71]:
```
dates_df = pd.DataFrame(index =dates)
dates_df.head()
```

Out[71]:

2020-10-07
2020-10-08
2020-10-09
2020-10-10
2020-10-11

In [ ]:
```

```