Assignment 3: EDA and forecast model

In [1]:
```
import pandas as pd
#read the data
timeseries_data = pd.read_excel('.\data\Assignment 3 - timeseries_data.xlsx')
```

Check data types and missing values

In [2]:
```
print(timeseries_data.info())
null_counts = timeseries_data.isnull().sum()
print(null_counts)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14987 entries, 0 to 14986
Data columns (total 10 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   DATETIME                     14987 non-null  datetime64[ns]
 1   HB_NORTH (RTLMP)             14987 non-null  float64
 2   ERCOT (WIND_RTI)             14982 non-null  float64
 3   ERCOT (GENERATION_SOLAR_RT)  14983 non-null  float64
 4   ERCOT (RTLOAD)               14987 non-null  float64
 5   HOURENDING                   14987 non-null  int64
 6   MARKETDAY                    14987 non-null  datetime64[ns]
 7   PEAKTYPE                     14987 non-null  object
 8   MONTH                        14987 non-null  object
 9   YEAR                         14987 non-null  int64
dtypes: datetime64[ns](2), float64(4), int64(2), object(2)
memory usage: 1.1+ MB
None
DATETIME                       0
HB_NORTH (RTLMP)               0
ERCOT (WIND_RTI)               5
ERCOT (GENERATION_SOLAR_RT)    4
ERCOT (RTLOAD)                 0
HOURENDING                     0
MARKETDAY                      0
PEAKTYPE                       0
MONTH                          0
YEAR                           0
dtype: int64
```

In [3]:
```
means = timeseries_data.mean(numeric_only=True)

# Fill missing values with the mean of each column
timeseries_data.fillna(means, inplace=True)
```

Descriptive statistics

In [4]:
```
print(timeseries_data.describe())
```

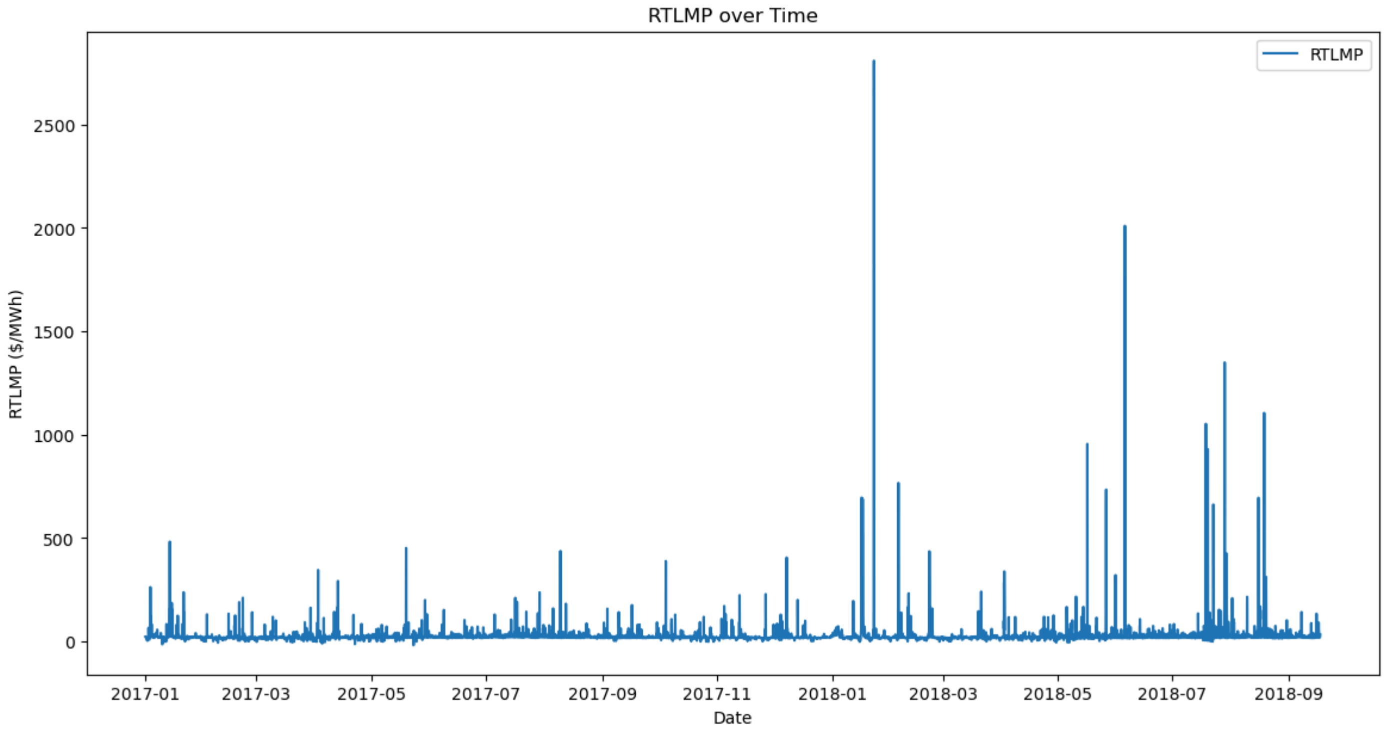
```
       HB_NORTH (RTLMP)  ERCOT (WIND_RTI)  ERCOT (GENERATION_SOLAR_RT)  \
count      14987.000000      14987.000000                 14987.000000
mean          25.766417       7532.436283                   291.989714
std           46.361945       3992.218676                   370.865092
min          -17.860000         54.440000                     0.000000
25%           18.041250       4138.390000                     0.000000
50%           20.057500       7283.460000                    22.200000
75%           25.030000      10851.280000                   608.580000
max         2809.357500      20350.400000                  1257.540000

       ERCOT (RTLOAD)    HOURENDING          YEAR
count    14987.000000  14987.000000  14987.000000
mean     42371.673703     12.495763   2017.415493
std       9874.339631      6.922309      0.492823
min      25566.511248      1.000000   2017.000000
25%      35431.636526      6.000000   2017.000000
50%      39934.007113     12.000000   2017.000000
75%      47873.100786     18.000000   2018.000000
max      73264.662123     24.000000   2018.000000
```

RTLMP has an extra maximum value, which could indicate an unusually high outlier or a data error. Locational marginal prices can sometimes be negative due to an oversupply of electricity or minimal demand. However, an unexpected maximum value might also suggest data errors or specific market conditions

Similarly, WIND_RTI has an extra minimum value. Like the previous example, this unusually low value could be an outlier or an error.

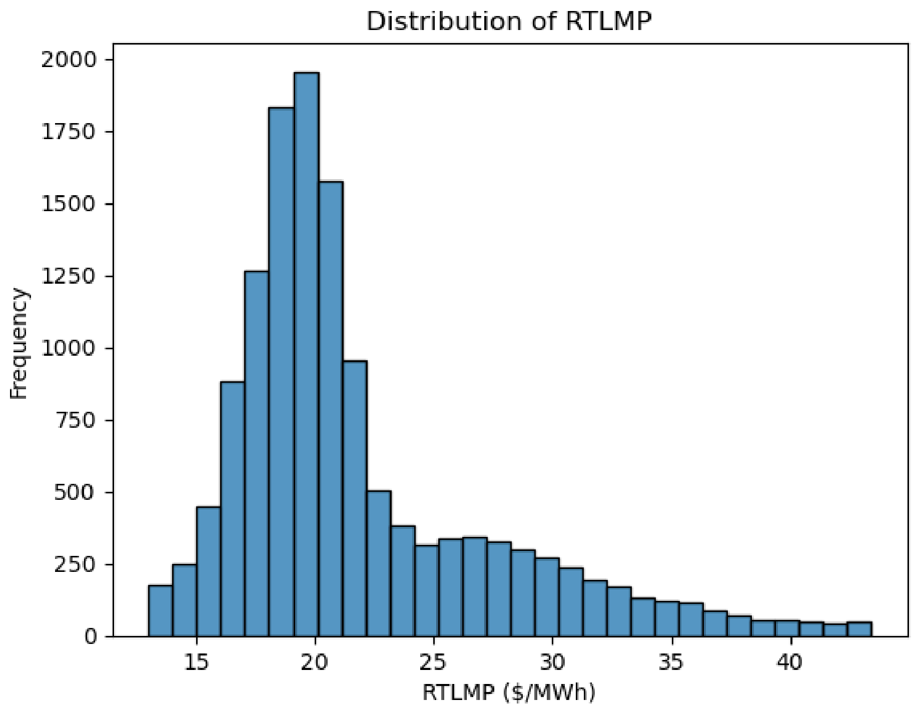
Visualization of RTLMP over time

In [5]:
```python
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt

# Visualization of RTLMP over time
plt.figure(figsize=(14, 7))
plt.plot(timeseries_data['DATETIME'], timeseries_data['HB_NORTH (RTLMP)'], label='RTLMP')
plt.title('RTLMP over Time')
plt.xlabel('Date')
plt.ylabel('RTLMP ($/MWh)')
plt.legend()
plt.show()
```



This graph depicts RTLMP over time. Most of the data points are below 500 USD/MWh. There are several noticeable spikes where the RTLMP reaches particularly high values. The most significant spike occurs around February 2018, where it exceeds 2500 USD/MWh. Other spike occurs around June 2018. These peaks suggest periods of high price volatility, which could be influenced by various factors such as demand decreases, supply shortages, or specific market events

In [6]:
```python
# Distribution of RTLMP

range_l = timeseries_data['HB_NORTH (RTLMP)'].quantile(0.05)
range_r = timeseries_data['HB_NORTH (RTLMP)'].quantile(0.95)

# Plot the histogram with range between 5% and 95%
sns.histplot(timeseries_data['HB_NORTH (RTLMP)'], bins=30,binrange=(range_l, range_r))
plt.title('Distribution of RTLMP')
plt.xlabel('RTLMP ($/MWh)')
plt.ylabel('Frequency')
plt.show()
```



The histogram displays the distribution of RTLMP values. The distribution shows a right skew. It means that there are a few instances of higher prices while most RTLMP values around the common price range.

Feature Engineering

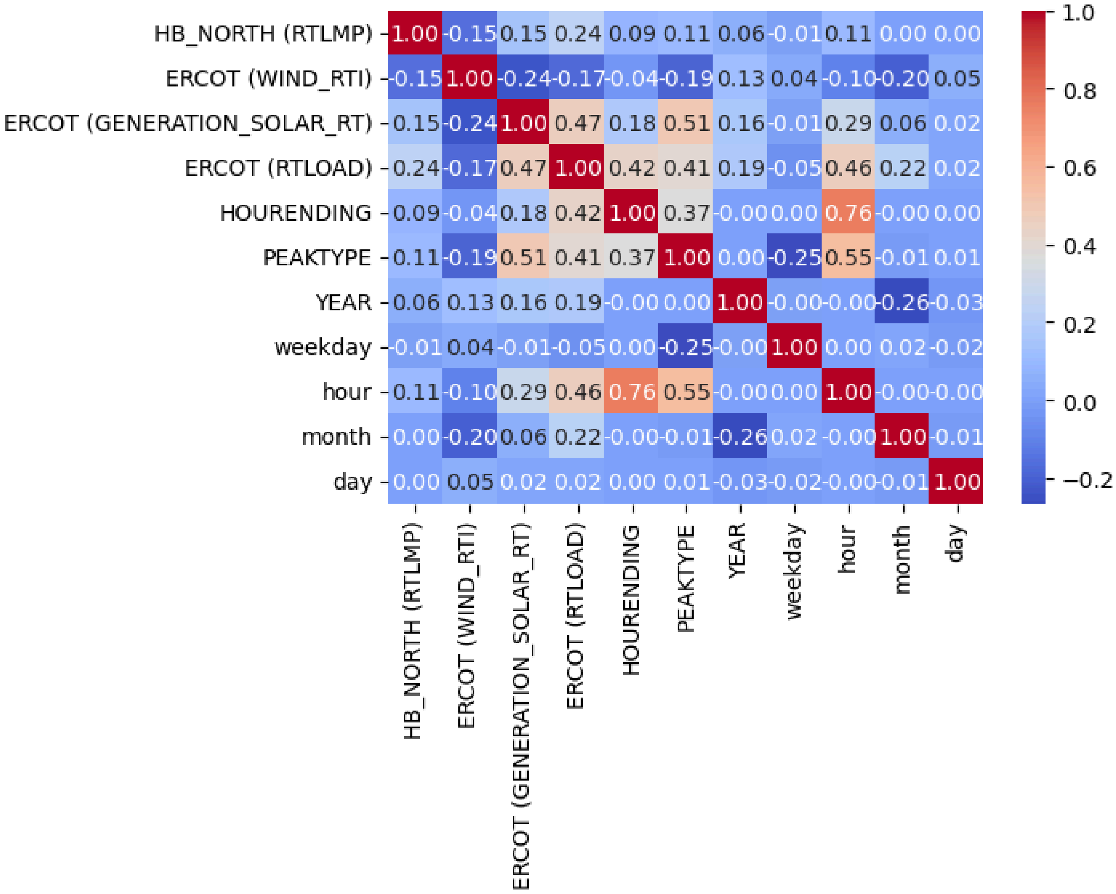
In [7]:
```
timeseries_data['weekday'] = timeseries_data['DATETIME'].dt.weekday
timeseries_data['hour'] = timeseries_data['DATETIME'].dt.hour
timeseries_data['month'] = timeseries_data['DATETIME'].dt.month
timeseries_data['day'] = timeseries_data['DATETIME'].dt.day
timeseries_data['PEAKTYPE'] = timeseries_data['PEAKTYPE'].map({'OFFPEAK': 0, 'WEPEAK': 1, 'WDPEAK': 2})
timeseries_data.head()


#Adding features like weekday, hour, and month helps capture daily, weekly, and seasonal patterns in RTLMP.
#PeakType is 1 if weekday peak, 0 if offpeak, 2 if weekend peak
```

Out[7]:

	DATETIME	HB_NORTH (RTLMP)	ERCOT (WIND_RTI)	ERCOT (GENERATION_SOLAR_RT)	ERCOT (RTLOAD)	HOURENDING	MARKETDAY	PEAKTYPE	MONTH	YEAR	wee
0	2017-01-01 01:00:00	23.3575	2155.31	0.0	29485.791355	1	2017-01-01	0	JANUARY	2017	
1	2017-01-01 02:00:00	21.4650	2313.81	0.0	28911.565913	2	2017-01-01	0	JANUARY	2017	
2	2017-01-01 03:00:00	20.7350	2587.68	0.0	28238.258175	3	2017-01-01	0	JANUARY	2017	
3	2017-01-01 04:00:00	20.2700	2748.65	0.0	27821.000513	4	2017-01-01	0	JANUARY	2017	
4	2017-01-01 05:00:00	20.1200	2757.49	0.0	27646.942413	5	2017-01-01	0	JANUARY	2017	

In [8]:
```
# Correlation matrix heatmap
plt.figure(figsize=(6, 4))
sns.heatmap(timeseries_data.corr(), annot=True, fmt=".2f", cmap='coolwarm')
plt.show()
```

```
C:\Users\02221\AppData\Local\Temp\ipykernel_23936\1983811340.py:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(timeseries_data.corr(), annot=True, fmt=".2f", cmap='coolwarm')
```



This correlation matrix provides insights into the relationships between the dependent variable (RTLMP) and other variables.

There is a moderate negative correlation (-0.15) between RTLMP and WIND_RTI. This suggests that higher wind energy production might lead to lower locational marginal prices, possibly due to increased supply lowering energy costs. RTLMP shows a positive correlation (0.15) with GENERATION_SOLAR_RT. This could indicate that increased solar power generation corresponds to higher marginal prices. A positive correlation (0.24) exists between RTLMP and RTLOAD, indicating that higher energy demand is associated with higher locational marginal prices; We can find a positive correlation (0.11) between RTLMP and the peak type. On weekday or weekend peak hour, the RTLMP tends to be higher;There is a positive correlation (0.11) between RTLMP and the hour of the day. This implies that RTLMP tends to be higher at certain times of the day. For example energy usage increases during peak demand that leads to higher prices.

Prediction

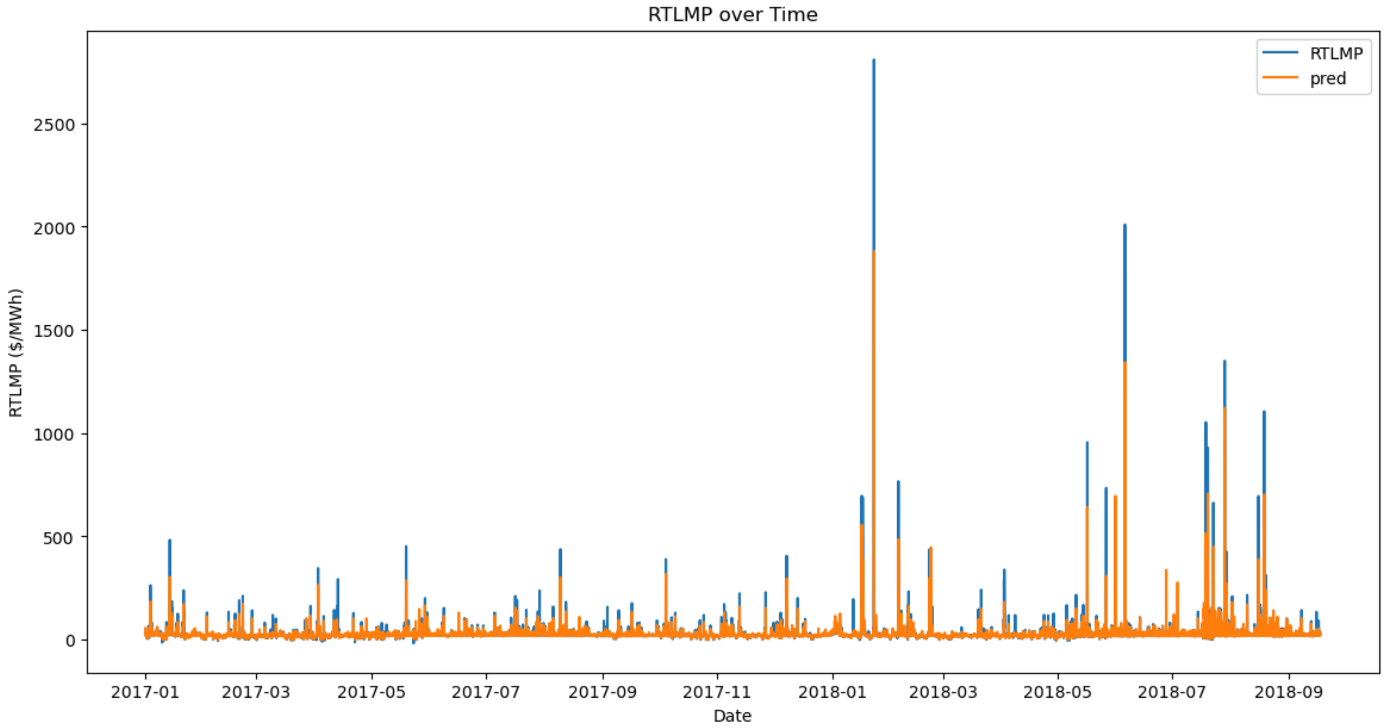
In [9]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import OneHotEncoder


X = timeseries_data.drop(['HB_NORTH (RTLMP)','PEAKTYPE', 'MONTH','DATETIME','MARKETDAY'], axis=1)  #independent var
y = timeseries_data['HB_NORTH (RTLMP)']  # dependent variable
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train model
model = RandomForestRegressor()
model.fit(X_train, y_train)

# Predict and evaluate
y_pred = model.predict(X_test)
print(f'RMSE: {mean_squared_error(y_test, y_pred, squared=False)}')  # RMSE
```

```
RMSE: 27.807612057627164
```

In [10]:

```
timeseries_data['pred'] = model.predict(X)

# Visualization of RTLMP over time
plt.figure(figsize=(14, 7))
plt.plot(timeseries_data['DATETIME'], timeseries_data['HB_NORTH (RTLMP)'], label='RTLMP')
plt.plot(timeseries_data['DATETIME'], timeseries_data['pred'], label='pred')
plt.title('RTLMP over Time')
plt.xlabel('Date')
plt.ylabel('RTLMP ($/MWh)')
plt.legend()
plt.show()
```



Note:for assignment3, I made an independent python file named forecast.py under the "code" folder

In [ ]:

In [ ]: