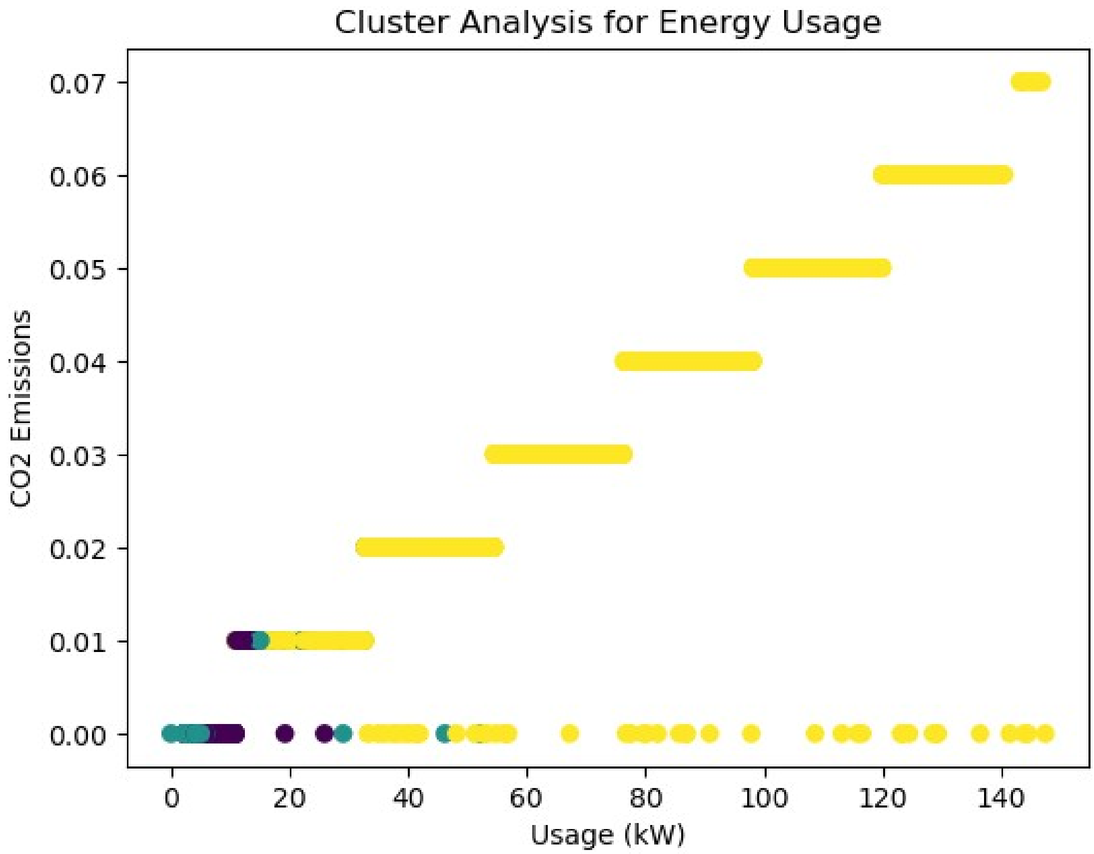
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# Load dataset (replace 'your_dataset.csv' with your file path)
data = pd.read_csv('Steel_industry_data.csv')

# Preprocessing: Handle missing or incorrect data
data['date'] = pd.to_datetime(data['date'], errors='coerce')  # Fix date formatting
data = data.dropna()  # Drop rows with missing values

# Feature Engineering: Convert categorical variables to numerical
data['WeekStatus'] = data['WeekStatus'].apply(lambda x: 1 if x == 'Weekday' else 0)
data['Load_Type'] = data['Load_Type'].apply(lambda x: 1 if x == 'Light_Load' else 0)

# Standardize numerical features for clustering
features = ['Usage_kWh', 'CO2(tCO2)', 'Lagging_Current_Power_Factor', 'Leading_Current_Power_Factor', 'NSM']
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data[features])

# Step 1: Clustering to identify inefficiencies
kmeans = KMeans(n_clusters=3, random_state=42)
data['Cluster'] = kmeans.fit_predict(data_scaled)

# Visualize clusters
plt.scatter(data['Usage_kWh'], data['CO2(tCO2)'], c=data['Cluster'], cmap='viridis')
plt.xlabel('Usage (kW)')
plt.ylabel('CO2 Emissions')
plt.title('Cluster Analysis for Energy Usage')
plt.show()

# Step 2: Train Regression Models to Predict and Optimize Energy Consumption
X = data[['CO2(tCO2)', 'Lagging_Current_Power_Factor', 'Leading_Current_Power_Factor', 'NSM', 'WeekStatus', 'Load_Type']]
y = data['Usage_kWh']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```python
# Use Random Forest Regressor
model = RandomForestRegressor(random_state=42)
model.fit(X_train, y_train)

# Predictions
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")

# Feature Importance
importance = model.feature_importances_
for i, col in enumerate(X.columns):
    print(f"{col}: {importance[i]}")

# Step 3: Optimization
# Find inefficient clusters and suggest improvements
inefficient_cluster = data[data['Cluster'] == data['Cluster'].max()]
# Assuming the highest cluster is least efficient
avg_usage = inefficient_cluster['Usage_kWh'].mean()
optimized_usage = avg_usage * 0.5  # Target a 50% reduction

print(f"Current Avg Usage in Inefficient Cluster: {avg_usage} kW")
print(f"Optimized Target Usage: {optimized_usage} kW")

# Recommendations:
# - Focus on Load_Type values with the highest inefficiency.
# - Adjust operational hours to non-peak NSM values.
# - Improve power factor by balancing Lagging_C and Leading_C.
# - Replace equipment with high CO2 emissions in the identified
cluster.

# Save insights
data.to_csv('optimized_resource_usage.csv', index=False)
print(data)
```




```
Mean Squared Error: 15.004346602870838
CO2(tCO2): 0.9661572485113403
Lagging_Current_Power_Factor: 0.015518690462007753
Leading_Current_Power_Factor: 0.008576547946170836
NSM: 0.008151923177905312
WeekStatus: 0.000694101754533372
Load_Type: 0.0009014881480425325
Current Avg Usage in Inefficient Cluster: 66.2193660765277 kW
Optimized Target Usage: 33.10968303826385 kW
                     date  Usage_kWh
Lagging_Current_Reactive.Power_kVarh  \
0     2018-01-01 00:15:00       3.17
2.95
1     2018-01-01 00:30:00       4.00
4.46
2     2018-01-01 00:45:00       3.24
3.28
3     2018-01-01 01:00:00       3.31
3.56
4     2018-01-01 01:15:00       3.82
4.50
...                   ...        ...
...
```

```
33211 2018-12-12 23:00:00       4.21
3.31
33212 2018-12-12 23:15:00       4.14
2.88
33213 2018-12-12 23:30:00       4.10
2.45
33214 2018-12-12 23:45:00       4.10
2.66
33215 2018-12-12 00:00:00       4.21
2.84

       Leading_Current_Reactive_Power_kVarh  CO2(tCO2)  \
0                                      0.00        0.0
1                                      0.00        0.0
2                                      0.00        0.0
3                                      0.00        0.0
4                                      0.00        0.0
...                                     ...        ...
33211                                  0.18        0.0
33212                                  0.32        0.0
33213                                  0.50        0.0
33214                                  0.43        0.0
33215                                  0.40        0.0

       Lagging_Current_Power_Factor  Leading_Current_Power_Factor
NSM  \
0                             73.21                        100.00
900
1                             66.77                        100.00
1800
2                             70.28                        100.00
2700
3                             68.09                        100.00
3600
4                             64.72                        100.00
4500
...                             ...                           ...     .
..
33211                         78.61                         99.91
82800
33212                         82.09                         99.70
83700
33213                         85.84                         99.26
84600
33214                         83.89                         99.45
85500
33215                         82.90                         99.55
0

       WeekStatus Day_of_week  Load_Type  Cluster
```

```
0                1      Monday          1        1
1                1      Monday          1        1
2                1      Monday          1        1
3                1      Monday          1        1
4                1      Monday          1        1
...            ...         ...        ...      ...
33211            1   Wednesday          0        1
33212            1   Wednesday          1        1
33213            1   Wednesday          1        0
33214            1   Wednesday          1        1
33215            1   Wednesday          1        1

[13824 rows x 12 columns]
```

```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Load dataset (replace 'your_dataset.csv' with your file path)
data = pd.read_csv('Steel_industry_data.csv')

# Ensure the date column is parsed correctly
data['date'] = pd.to_datetime(data['date'], errors='coerce')
data = data.dropna()  # Remove rows with missing values

# Measures of Central Tendency
print("Measures of Central Tendency:")
print("Mean of Usage (kWh):", data['Usage_kWh'].mean())
print("Median of Usage (kWh):", data['Usage_kWh'].median())
print("Mode of Usage (kWh):", data['Usage_kWh'].mode()[0])

# Step 1: Correlation Analysis
correlation = data.corr()
print("\nCorrelation Matrix:")
print(correlation)

# Visualize the Correlation Matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation, annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Matrix")
plt.show()

# Step 2: Pairwise Relationship with Energy Consumption
sns.pairplot(data, vars=['Usage_kWh', 'CO2(tCO2)', '',
'Leading_Current_Power_Factor', 'NSM'], kind='scatter')
plt.suptitle("Pairwise Relationships with Energy Consumption", y=1.02)
plt.show()
```

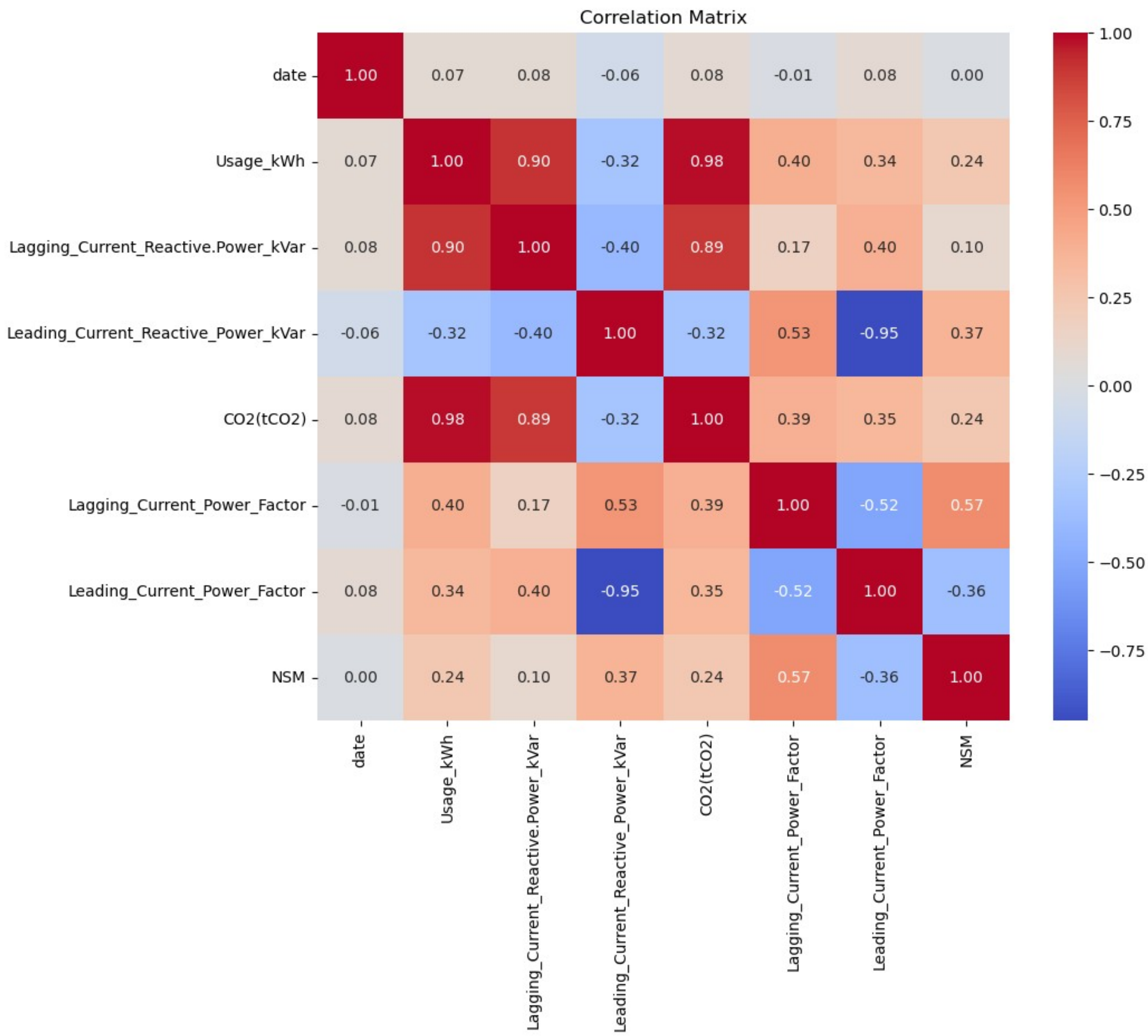
```
# Step 3: Reduce Energy Consumption by 50%
data['Optimized_Usage_kWh'] = data['Usage_kWh'] * 0.5

# Recalculate correlations for reduced energy consumption
correlation_reduced = data.corr()
print("\nCorrelation Matrix (After 50% Reduction in Energy
Consumption):")
print(correlation_reduced)

# Visualize the Updated Correlation Matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_reduced, annot=True, cmap='coolwarm',
fmt='.2f')
plt.title("Correlation Matrix (Reduced Energy Consumption)")
plt.show()

# Step 4: Clustering Analysis
features = ['Usage_kWh', 'CO2(tCO2)', 'Lagging_Current_Power_Factor',
'Leading_Current_Power_Factor', 'NSM']
scaler = StandardScaler()
scaled_data = scaler.fit_transform(data[features])

# Apply KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42)
data['Cluster'] = kmeans.fit_predict(scaled_data)

# Visualize Clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x=data['Usage_kWh'], y=data['CO2(tCO2)'],
hue=data['Cluster'], palette='viridis')
plt.title("Clusters Based on Energy Consumption and CO2 Emissions")
plt.xlabel("Usage (kWh)")
plt.ylabel("CO2 Emissions")
plt.show()

# Visualize Clusters for Optimized Usage
plt.figure(figsize=(10, 6))
sns.scatterplot(x=data['Optimized_Usage_kWh'], y=data['CO2(tCO2)'],
hue=data['Cluster'], palette='cool')
plt.title("Clusters (After Reducing Energy Consumption by 50%)")
plt.xlabel("Optimized Usage (kW)")
plt.ylabel("CO2 Emissions")
plt.show()

# Step 5: Graphical Representation of Measures of Central Tendency
plt.figure(figsize=(8, 6))
sns.histplot(data['Usage_kWh'], kde=True, color='blue', bins=20,
label='Original Usage')
sns.histplot(data['Optimized_Usage_kW'], kde=True, color='orange',
```

```
bins=20, label='Optimized Usage')
plt.axvline(data['Usage_kWh'].mean(), color='blue', linestyle='--',
label='Mean (Original)')
plt.axvline(data['Optimized_Usage_kW'].mean(), color='orange',
linestyle='--', label='Mean (Optimized)')
plt.title("Energy Usage Distribution (Original vs Optimized)")
plt.xlabel("Usage (kW)")
plt.ylabel("Frequency")
plt.legend()
plt.show()
```

```
Measures of Central Tendency:
Mean of Usage (kWh): 27.74799479166667
Median of Usage (kWh): 4.57
Mode of Usage (kWh): 3.06

Correlation Matrix:
                                          date  Usage_kWh  \
date                                  1.000000   0.074347
Usage_kWh                             0.074347   1.000000
Lagging_Current_Reactive.Power_kVar   0.077267   0.901565
Leading_Current_Reactive_Power_kVar  -0.061768  -0.317518
CO2(tCO2)                             0.082968   0.982978
Lagging_Current_Power_Factor         -0.007434   0.402954
Leading_Current_Power_Factor          0.082834   0.341754
NSM                                   0.002747   0.243597


Lagging_Current_Reactive.Power_kVar  \
date
0.077267
Usage_kWh
0.901565
Lagging_Current_Reactive.Power_kVar
1.000000
Leading_Current_Reactive_Power_kVar                             -
0.400027
CO2(tCO2)
0.888691
Lagging_Current_Power_Factor
0.168781
Leading_Current_Power_Factor
0.398593
NSM
0.099845


Leading_Current_Reactive_Power_kVar  \
date                                                            -
0.061768
```

```
Usage_kWh                                                          -
0.317518
Lagging_Current_Reactive.Power_kVar                                -
0.400027
Leading_Current_Reactive_Power_kVar
1.000000
CO2(tCO2)                                                          -
0.322852
Lagging_Current_Power_Factor
0.531925
Leading_Current_Power_Factor                                       -
0.948378
NSM
0.369622

                                       CO2(tCO2)
Lagging_Current_Power_Factor  \
date                                    0.082968                       -
0.007434
Usage_kWh                               0.982978
0.402954
Lagging_Current_Reactive.Power_kVar     0.888691
0.168781
Leading_Current_Reactive_Power_kVar    -0.322852
0.531925
CO2(tCO2)                               1.000000
0.393785
Lagging_Current_Power_Factor            0.393785
1.000000
Leading_Current_Power_Factor            0.345539                       -
0.518988
NSM                                     0.240084
0.572313

                                       Leading_Current_Power_Factor
NSM
date                                                       0.082834
0.002747
Usage_kWh                                                  0.341754
0.243597
Lagging_Current_Reactive.Power_kVar                        0.398593
0.099845
Leading_Current_Reactive_Power_kVar                       -0.948378
0.369622
CO2(tCO2)                                                  0.345539
0.240084
Lagging_Current_Power_Factor                              -0.518988
0.572313
Leading_Current_Power_Factor                               1.000000 -
```

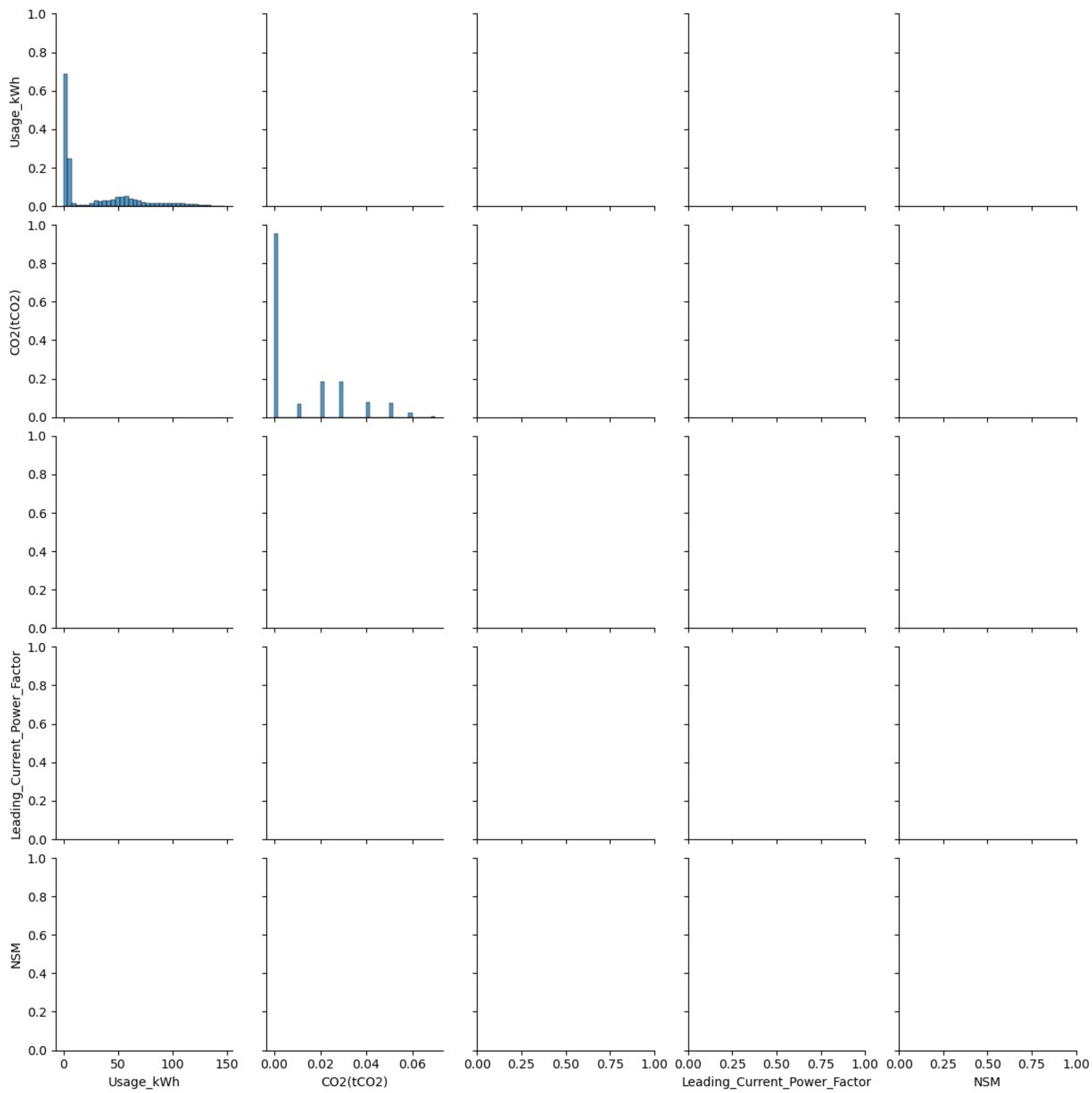
```
0.360049
NSM                                                                        -0.360049
1.000000
```




```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:3805, in Index.get_loc(self, key)
   3804 try:
-> 3805     return self._engine.get_loc(casted_key)
   3806 except KeyError as err:

File index.pyx:167, in pandas._libs.index.IndexEngine.get_loc()
```

```
File index.pyx:196, in pandas._libs.index.IndexEngine.get_loc()

File pandas\\_libs\\hashtable_class_helper.pxi:7081, in
pandas._libs.hashtable.PyObjectHashTable.get_item()

File pandas\\_libs\\hashtable_class_helper.pxi:7089, in
pandas._libs.hashtable.PyObjectHashTable.get_item()

KeyError: ''

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call
last)
Cell In[35], line 33
     30 plt.show()
     32 # Step 2: Pairwise Relationship with Energy Consumption
---> 33 sns.pairplot(data, vars=['Usage_kWh', 'CO2(tCO2)', '',
'Leading_Current_Power_Factor', 'NSM'], kind='scatter')
     34 plt.suptitle("Pairwise Relationships with Energy Consumption",
y=1.02)
     35 plt.show()

File ~\anaconda3\Lib\site-packages\seaborn\axisgrid.py:2149, in
pairplot(data, hue, hue_order, palette, vars, x_vars, y_vars, kind,
diag_kind, markers, height, aspect, corner, dropna, plot_kws,
diag_kws, grid_kws, size)
   2147 diag_kws.setdefault("legend", False)
   2148 if diag_kind == "hist":
-> 2149     grid.map_diag(histplot, **diag_kws)
   2150 elif diag_kind == "kde":
   2151     diag_kws.setdefault("fill", True)

File ~\anaconda3\Lib\site-packages\seaborn\axisgrid.py:1496, in
PairGrid.map_diag(self, func, **kwargs)
   1493 else:
   1494     plt.sca(ax)
-> 1496 vector = self.data[var]
   1497 if self._hue_var is not None:
   1498     hue = self.data[self._hue_var]

File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:4102, in
DataFrame.__getitem__(self, key)
   4100 if self.columns.nlevels > 1:
   4101     return self._getitem_multilevel(key)
-> 4102 indexer = self.columns.get_loc(key)
   4103 if is_integer(indexer):
   4104     indexer = [indexer]
```

```
File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:3812,
in Index.get_loc(self, key)
   3807     if isinstance(casted_key, slice) or (
   3808         isinstance(casted_key, abc.Iterable)
   3809         and any(isinstance(x, slice) for x in casted_key)
   3810     ):
   3811         raise InvalidIndexError(key)
-> 3812     raise KeyError(key) from err
   3813 except TypeError:
   3814     # If we have a listlike key, _check_indexing_error will
raise
   3815     #  InvalidIndexError. Otherwise we fall through and re-
raise
   3816     #  the TypeError.
   3817     self._check_indexing_error(key)

KeyError: ''
```



Usage_kWh
CO2(tCO2)
Leading_Current_Power_Factor
NSM