Solar Power Generation Prediction:

Nowadays, the amount of energy consumed has sharply increased. As a result, the human race has been increasingly investing in renewable energy due to concerns about the environment and global warming. Therefore, in parallel with the rise in consumption, it is also evident in some countries that photovoltaic energy and wind energy are gaining significance in the energy matrix. With this in mind, this project aims to analyze and predict the generation of solar power plants using a dataset downloaded from Kaggle.

Dictionary (Columns):

- WindSpeed
- Sunshine
- AirPressure
- Radiation
- AirTemperature
- RelativeAirHumidity
- SystemProduction (Target)

1) Importing Libraries and Data Loading

In [19]:

```
# Importing Libraries:

import pandas as pd
import numpy as np

from scipy.stats import shapiro, normaltest, kurtosis, skew
from statsmodels.stats.diagnostic import lilliefors
from statsmodels.api import qqplot
```

```
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, KFold, cross_validate
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
from sklearn.metrics import r2_score, mean_squared_error

from sklearn.linear_model import Lasso, Ridge
from sklearn.ensemble import RandomForestRegressor, ExtraTreesRegressor
from xgboost import XGBRegressor
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor

from sklearn.model_selection import GridSearchCV
from sklearn.base import clone
from sklearn.feature_selection import SelectKBest, f_regression, RFECV

import joblib
import os
```

In [20]:
```
# Importing data:

df_raw = pd.read_csv("Solar_Power_Plant_Data.csv")
```

In [21]:
```
# Copy of the dataset:

df = df_raw.copy()
```

In [22]:
```
# Looking at the first 5 rolls:

df.head()
```

Out[22]:

	Date-Hour(NMT)	WindSpeed	Sunshine	AirPressure	Radiation	AirTemperature	RelativeAirHumidity	SystemProduc
0	01.01.2017-00:00	0.6	0	1003.8	-7.4	0.1	97	
1	01.01.2017-01:00	1.7	0	1003.5	-7.4	-0.2	98	
2	01.01.2017-02:00	0.6	0	1003.4	-6.7	-1.2	99	
3	01.01.2017-03:00	2.4	0	1003.3	-7.2	-1.3	99	
4	01.01.2017-04:00	4.0	0	1003.1	-6.3	3.6	67	

2) Data Cleaning

In [23]:
```
# Information about the dataset:

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8760 entries, 0 to 8759
Data columns (total 8 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Date-Hour(NMT)      8760 non-null   object
```

```
 1   WindSpeed            8760 non-null   float64
 2   Sunshine             8760 non-null   int64
 3   AirPressure          8760 non-null   float64
 4   Radiation            8760 non-null   float64
 5   AirTemperature       8760 non-null   float64
 6   RelativeAirHumidity  8760 non-null   int64
 7   SystemProduction     8760 non-null   float64
dtypes: float64(5), int64(2), object(1)
memory usage: 547.6+ KB
```

In [24]:
```python
# Missing data:

df.isna().sum()
```

Out[24]:
```
Date-Hour(NMT)         0
WindSpeed              0
Sunshine               0
AirPressure            0
Radiation              0
AirTemperature         0
RelativeAirHumidity    0
SystemProduction       0
dtype: int64
```

In [25]:
```python
# Changing Date-Hour(NMT) column type:

df['Date-Hour(NMT)'] = pd.to_datetime(df['Date-Hour(NMT)'], format="%d.%m.%Y-%H:%M")

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8760 entries, 0 to 8759
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Date-Hour(NMT)       8760 non-null   datetime64[ns]
 1   WindSpeed            8760 non-null   float64
 2   Sunshine             8760 non-null   int64
 3   AirPressure          8760 non-null   float64
 4   Radiation            8760 non-null   float64
 5   AirTemperature       8760 non-null   float64
 6   RelativeAirHumidity  8760 non-null   int64
 7   SystemProduction     8760 non-null   float64
dtypes: datetime64[ns](1), float64(5), int64(2)
memory usage: 547.6 KB
```

In [26]:
```python
# Setting the Date-Hour(NUMT) as the index:

df.set_index("Date-Hour(NMT)", inplace=True)
```

In [27]:
```python
# Let's change the type of the numeric variables:

df['Sunshine'] = df['Sunshine'].astype("int16")
df['RelativeAirHumidity'] = df['RelativeAirHumidity'].astype("int16")
df['WindSpeed'] = df['WindSpeed'].astype("float32")
df['Radiation'] = df['Radiation'].astype("float32")
df['AirTemperature'] = df['AirTemperature'].astype("float32")
```

In [28]:
```python
# Information about the dataset:

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8760 entries, 2017-01-01 00:00:00 to 2017-12-31 23:00:00
Data columns (total 7 columns):
 #   Column               Non-Null Count  Dtype
```

```
---  ------               --------------  -----
 0   WindSpeed            8760 non-null   float32
 1   Sunshine             8760 non-null   int16
 2   AirPressure          8760 non-null   float64
 3   Radiation            8760 non-null   float32
 4   AirTemperature       8760 non-null   float32
 5   RelativeAirHumidity  8760 non-null   int16
 6   SystemProduction     8760 non-null   float64
dtypes: float32(3), float64(2), int16(2)
memory usage: 342.2 KB
```

Conclusions

- No missing data.
- Date-Hour(NMT) is now a datetime type.
- Memory usage of the dataset reduced from 547.6 to 342.2 KB.

3) Exploratory Data Analysis

3.1) Exploring the characteristics

In [29]:
```
# Descriptive Statistics:

df.describe()
```

Out[29]:

	WindSpeed	Sunshine	AirPressure	Radiation	AirTemperature	RelativeAirHumidity	SystemProductio
count	8760.000000	8760.000000	8760.000000	8760.000000	8760.000000	8760.000000	8760.00000
mean	2.639823	11.180479	1010.361781	97.538498	6.978892	76.719406	684.74607
std	1.628754	21.171295	12.793971	182.336029	7.604266	19.278996	1487.45466
min	0.000000	0.000000	965.900000	-9.300000	-12.400000	13.000000	0.00000
25%	1.400000	0.000000	1002.800000	-6.200000	0.500000	64.000000	0.00000
50%	2.300000	0.000000	1011.000000	-1.400000	6.400000	82.000000	0.00000
75%	3.600000	7.000000	1018.200000	115.599998	13.400000	93.000000	464.24995
max	10.900000	60.000000	1047.300000	899.700012	27.100000	100.000000	7701.00000

In [30]:
```
# Range of datetime column:

print(f"Range of Datetime column: ({df.index.min()}) to ({df.index.max()})")
```

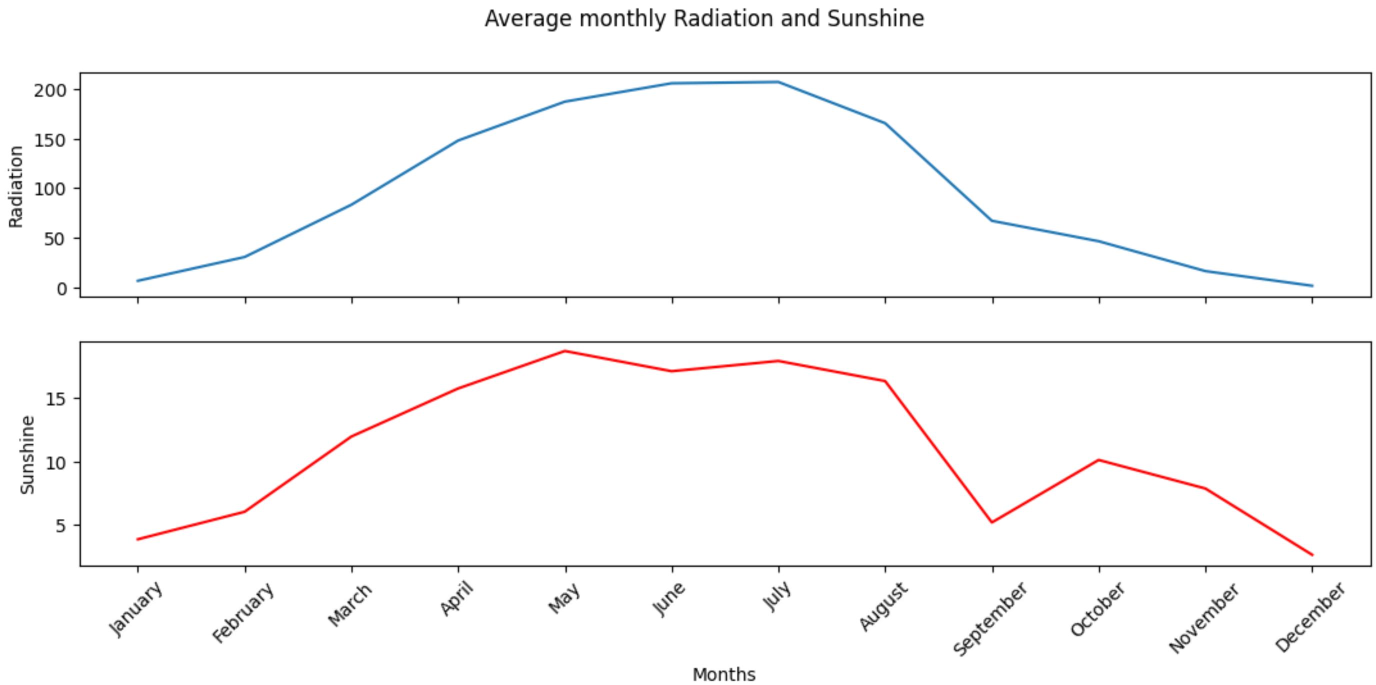
```
Range of Datetime column: (2017-01-01 00:00:00) to (2017-12-31 23:00:00)
```

In [31]:
```
# Let's see how many data points have negative Radiation:

df[df["Radiation"] < 0].shape
```

Out[31]:
```
(4464, 7)
```

In [32]:
```
# Analysing average monthly Radiation and Sunshine:

df["Months"] = df.index.month_name()
df["Month_number"] = df.index.month
monthly_rad_sun = df.groupby(["Month_number", "Months"]).agg({"Radiation":"mean", "Sunsh
    droplevel(level="Month_number")
```

In [33]:
```
# Line plot of the Average monthly Radiation and Sushine

fig, ax = plt.subplots(nrows=2, ncols=1, sharex=True, figsize=(13, 5))
fig.suptitle("Average monthly Radiation and Sunshine")
plt.xticks(rotation=45)

sns.lineplot(monthly_rad_sun["Radiation"], ax=ax[0])
sns.lineplot(monthly_rad_sun["Sunshine"], ax=ax[1], c="r");
```



In [34]:
```
# Dropping Months and Month_number columns:

df.drop(columns=["Months", "Month_number"], inplace=True)
```

Conclusions

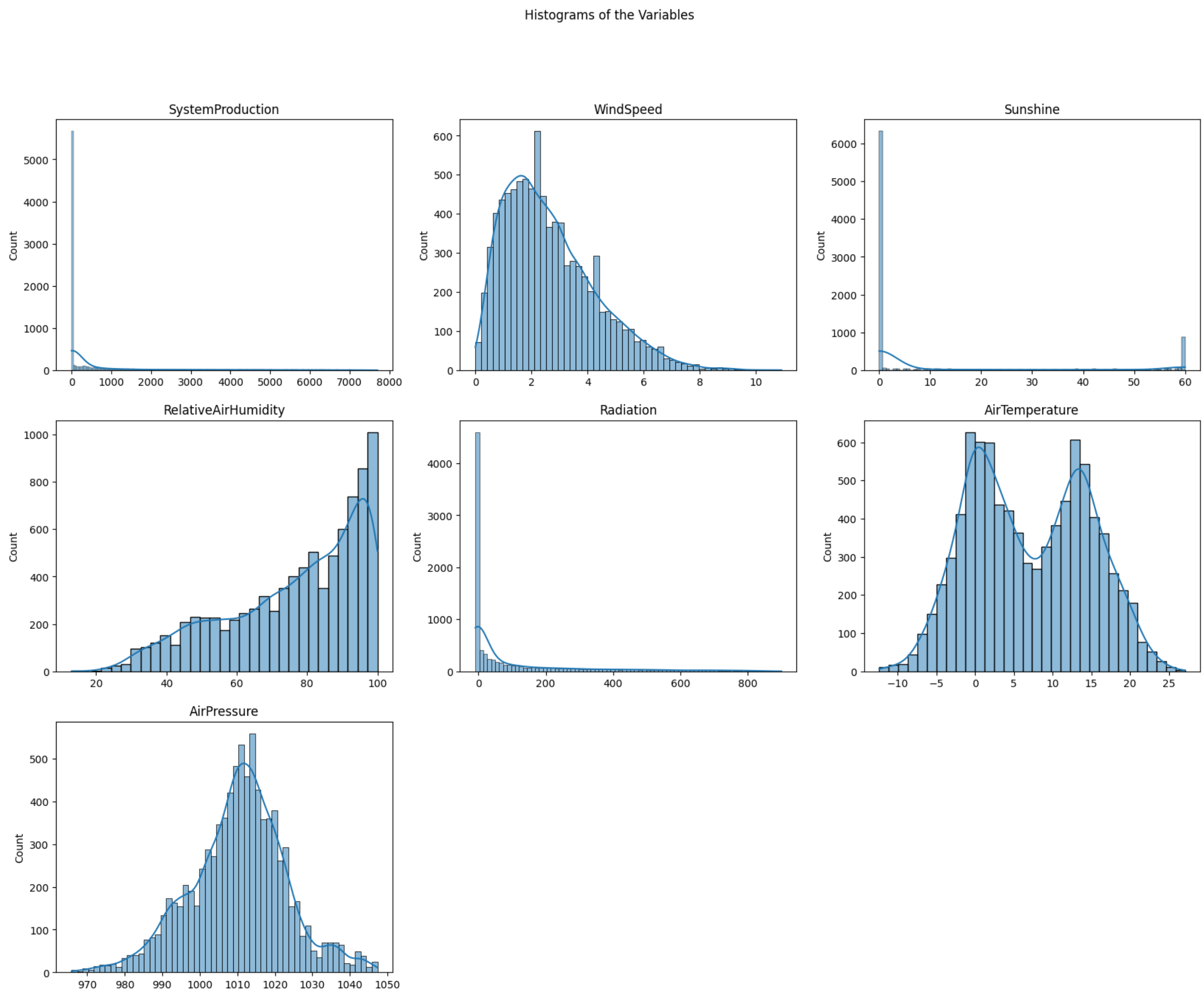
- One year of one-hour mesurements.
- As we can see from the statistic summary, there are some negative data points in Radiation column.
- Average Monthly Radiation is positive over the year.
- The increase of the Radiation and Sunshine between April and August may suggest that this location is situated in the Northern Hemisphere.
- Most data in SystemProduction and Sunshine columns may be zero.

3.2) Distribution

We will look at the histogram of all variables

In [35]:
```
# Histograms:

fig, axes = plt.subplots(nrows=3, ncols=3, sharey=False, figsize=(20, 15))
fig.suptitle("Histograms of the Variables")

sns.histplot(df["SystemProduction"].values, ax=axes[0, 0], kde=True)
axes[0, 0].set_title("SystemProduction")

sns.histplot(df["WindSpeed"].values, ax=axes[0, 1], kde=True)
axes[0, 1].set_title("WindSpeed")

sns.histplot(df["Sunshine"].values, ax=axes[0][2], kde=True)
axes[0][2].set_title("Sunshine")
```

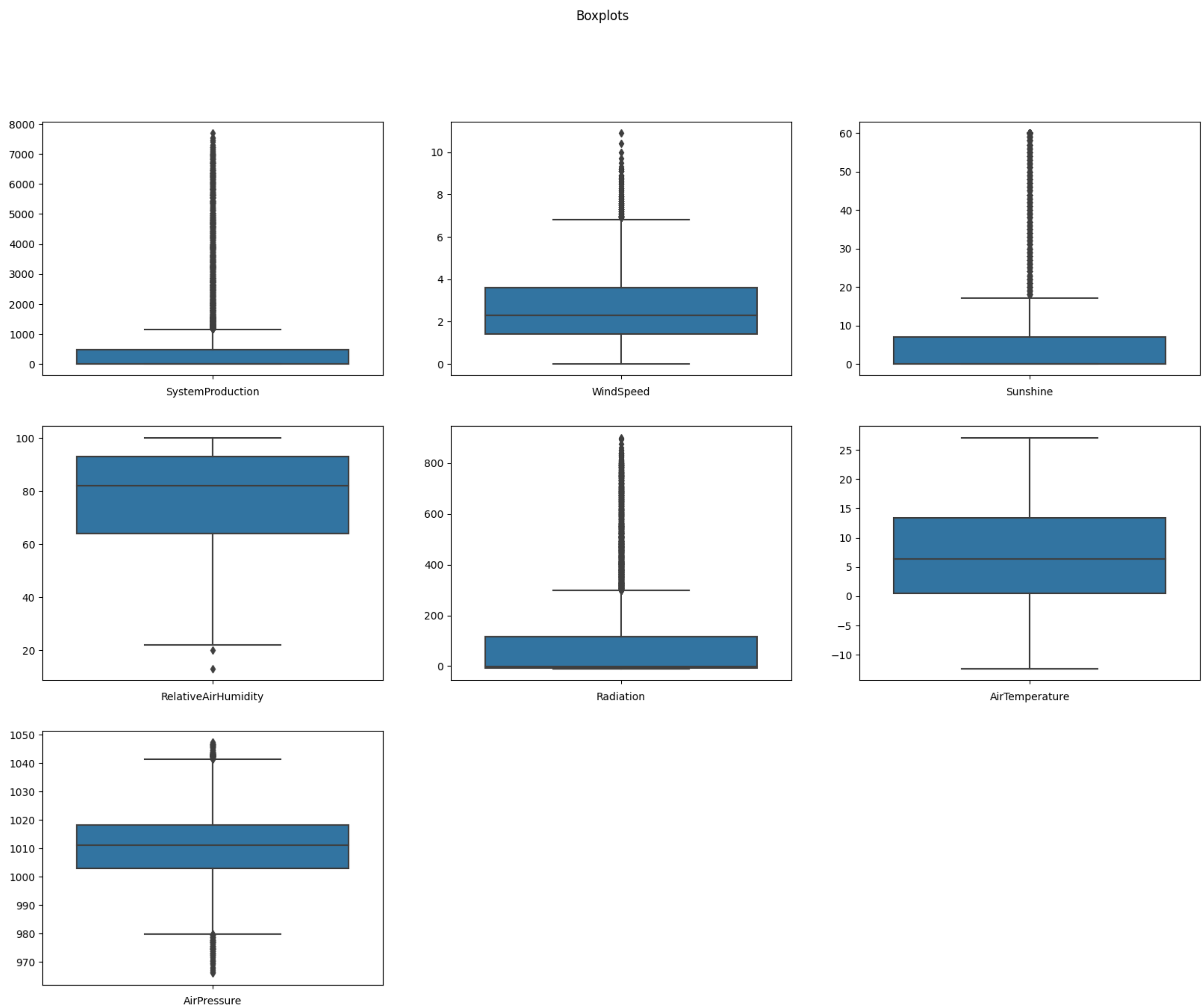
```
sns.histplot(df["RelativeAirHumidity"].values, ax=axes[1, 0], kde=True)
axes[1, 0].set_title("RelativeAirHumidity")

sns.histplot(df["Radiation"].values, ax=axes[1, 1], kde=True, legend=False)
axes[1, 1].set_title("Radiation")

sns.histplot(df["AirTemperature"].values, ax=axes[1, 2], kde=True)
axes[1, 2].set_title("AirTemperature")

sns.histplot(df["AirPressure"].values, ax=axes[2, 0], kde=True)
axes[2, 0].set_title("AirPressure");

axes[2, 1].set_visible(False)
axes[2, 2].set_visible(False)
```



Looking at the Histograms, we may think that AirPressure column was drew from a normal distribution. Let's look at the boxplots.

In [36]:
```
# BoxPlots:

fig, ax = plt.subplots(3, 3, figsize=(20, 15), sharey=False)
fig.suptitle("Boxplots")

sns.boxplot(y=df["SystemProduction"].values, ax=ax[0, 0])
ax[0, 0].set_xlabel("SystemProduction")

sns.boxplot(y=df["WindSpeed"].values, ax=ax[0, 1])
```

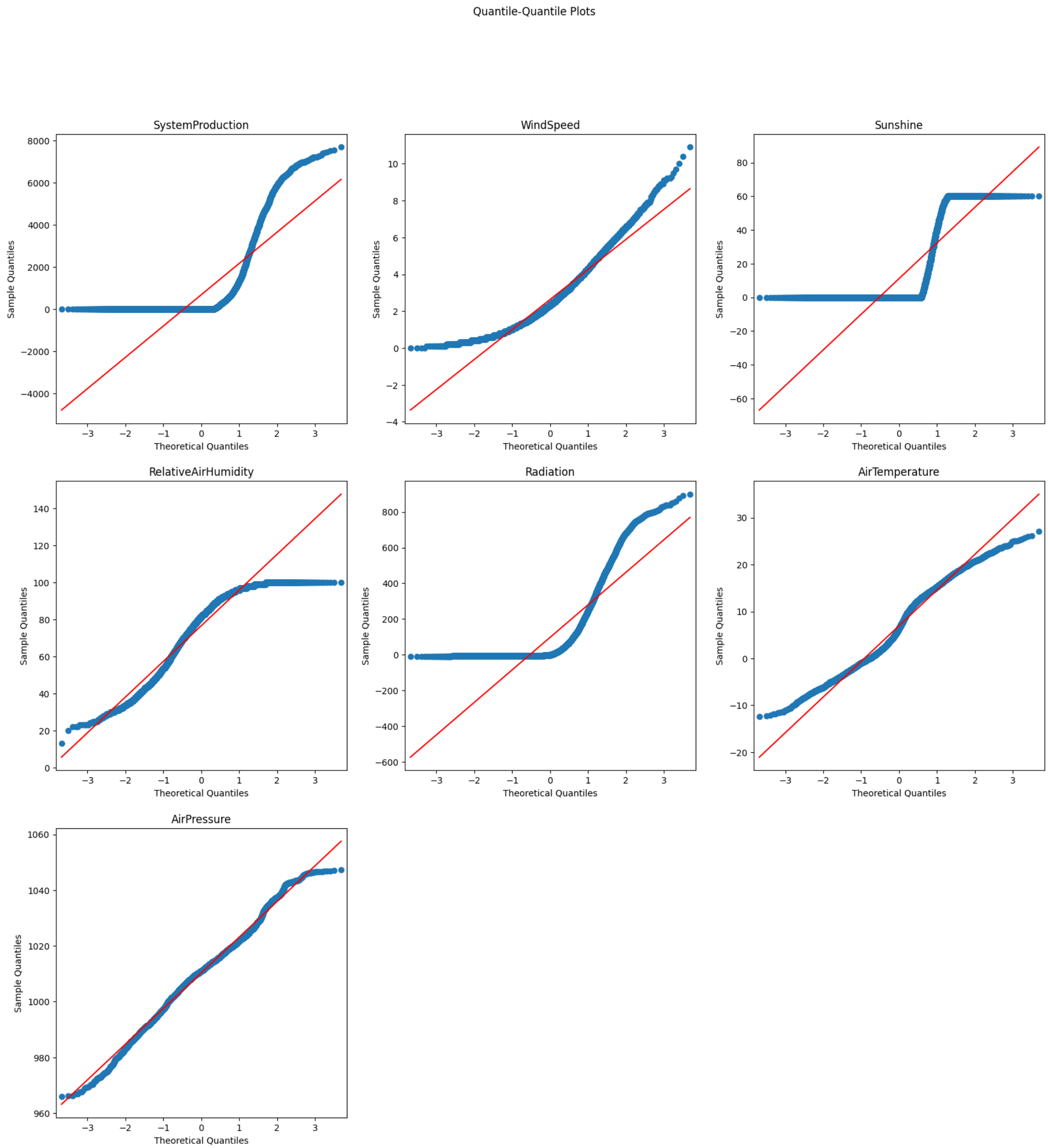
```
ax[0, 1].set_xlabel("WindSpeed")

sns.boxplot(y=df["Sunshine"].values, ax=ax[0, 2])
ax[0, 2].set_xlabel("Sunshine")

sns.boxplot(y=df["RelativeAirHumidity"].values, ax=ax[1, 0])
ax[1, 0].set_xlabel("RelativeAirHumidity")

sns.boxplot(y=df["Radiation"].values, ax=ax[1, 1])
ax[1, 1].set_xlabel("Radiation")

sns.boxplot(y=df["AirTemperature"].values, ax=ax[1, 2])
ax[1, 2].set_xlabel("AirTemperature")

sns.boxplot(y=df["AirPressure"].values, ax=ax[2, 0])
ax[2, 0].set_xlabel("AirPressure");

ax[2, 1].set_visible(False)
ax[2, 2].set_visible(False)
```



3.3) Normality tests

In [37]:
```
# QQ Plots:

# Defining subplots:
fig, axe = plt.subplots(3, 3, sharey=False, figsize=(20, 20))
fig.suptitle("Quantile-Quantile Plots")
```

```python
# Plotting SystemProduction data:
qqplot(df["SystemProduction"], ax=axe[0, 0], line="s");
axe[0, 0].set_title("SystemProduction")

# Plotting WindSpeed data:
qqplot(df["WindSpeed"], ax=axe[0, 1], line="s")
axe[0, 1].set_title("WindSpeed")

# Plotting Sunshine data:
qqplot(df["Sunshine"], ax=axe[0, 2], line="s")
axe[0, 2].set_title("Sunshine")

# Ploting RelativeAirHumidity:
qqplot(df["RelativeAirHumidity"], ax=axe[1, 0], line="s")
axe[1, 0].set_title("RelativeAirHumidity")

# Radiation:
qqplot(df["Radiation"], ax=axe[1, 1], line="s")
axe[1, 1].set_title("Radiation")

# AirTemperature:
qqplot(df["AirTemperature"], ax=axe[1, 2], line="s")
axe[1, 2].set_title("AirTemperature")

# AirPressure
qqplot(df["AirPressure"], ax=axe[2, 0], line="s")
axe[2, 0].set_title("AirPressure");

axe[2, 1].set_visible(False)
axe[2, 2].set_visible(False)
```



As we can see from the qqplot and the Histogram above, it seems tha AirPressure follows a normal distribution. Let's quantify this assumption using statistical tests for normality.

- H0: Data was drew from a normal distribution.
- H1: Data was not drew from a normal distribution.

OBS: Using level of significance of 5% (alpha).

OBS2: Shapiro wilk p value is an approximate value due to the size of the sample being more than 5000.

In [38]:
```
# Function that Calculates Shapiro-Wilk, Lilliefors and D'Agostino_K2 tests:

def normality_tests(df: any):
    tests_names = ["Shapiro-Wilk", "Lilliefors", "D'Agostino_K2"]
```

```python
    extern_index = np.array(sorted(tests_names*2))
    intern_index = np.array(["statistic", "p-value"]*len(tests_names))

    mult_index = [
        extern_index,
        intern_index
    ]

    results = pd.DataFrame(index=mult_index, columns=df.columns)

    for c in df.columns:

        # First D'Agostino's K-squared test:
        k2, k2_p = normaltest(df[c])

        # Secondly we will use the Lilliefors test:
        lilliefors_result = lilliefors(df[c])
        ksstat, lilliefours_p = lilliefors_result

        #  We will check the shapiro-Wilk test:
        shapiro_result = shapiro(df[c])
        shapiro_statistic, shapiro_p = shapiro_result.statistic, shapiro_result.pvalue

        results[c] = [k2, k2_p, ksstat, lilliefours_p, shapiro_statistic, shapiro_p]

    return results


# Function that calculates kurtosis and skewness of a dataset:

def kurtosis_skewness(dataset: any):
    index = ["Kurtosis", "Skewness"]
    results = pd.DataFrame(index=index, columns=dataset.columns)
    for c in dataset.columns:
        kurt = kurtosis(dataset[c])
        skewness = skew(dataset[c])
        results[c] = [kurt, skewness]

    return results
```

In [39]:
```python
# Normality test results:

normality_tests(df)
```

```
c:\Users\caios\AppData\Local\Programs\Python\Python311\Lib\site-packages\scipy\stats\_mo
restats.py:1816: UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

Out[39]:

		WindSpeed	Sunshine	AirPressure	Radiation	AirTemperature	RelativeAirHumid
D'Agostino_K2	statistic	9.806524e+02	2095.571343	6.722747e+01	3444.346422	2.245390e+03	7.997811e+
	p-value	1.132518e-213	0.000000	2.521971e-15	0.000000	0.000000e+00	2.136654e-1
Lilliefors	statistic	8.657087e-02	0.422402	4.527111e-02	0.278957	8.151557e-02	1.136078e-
	p-value	1.000000e-03	0.001000	1.000000e-03	0.001000	1.000000e-03	1.000000e-
Shapiro-Wilk	statistic	9.421549e-01	0.559635	9.922053e-01	0.640642	9.712175e-01	9.158114e-
	p-value	0.000000e+00	0.000000	1.640946e-21	0.000000	1.376139e-38	0.000000e+

In [40]:
```python
# Kurtosis and Skewness:

kurtosis_skewness(df)
```

Out[40]:

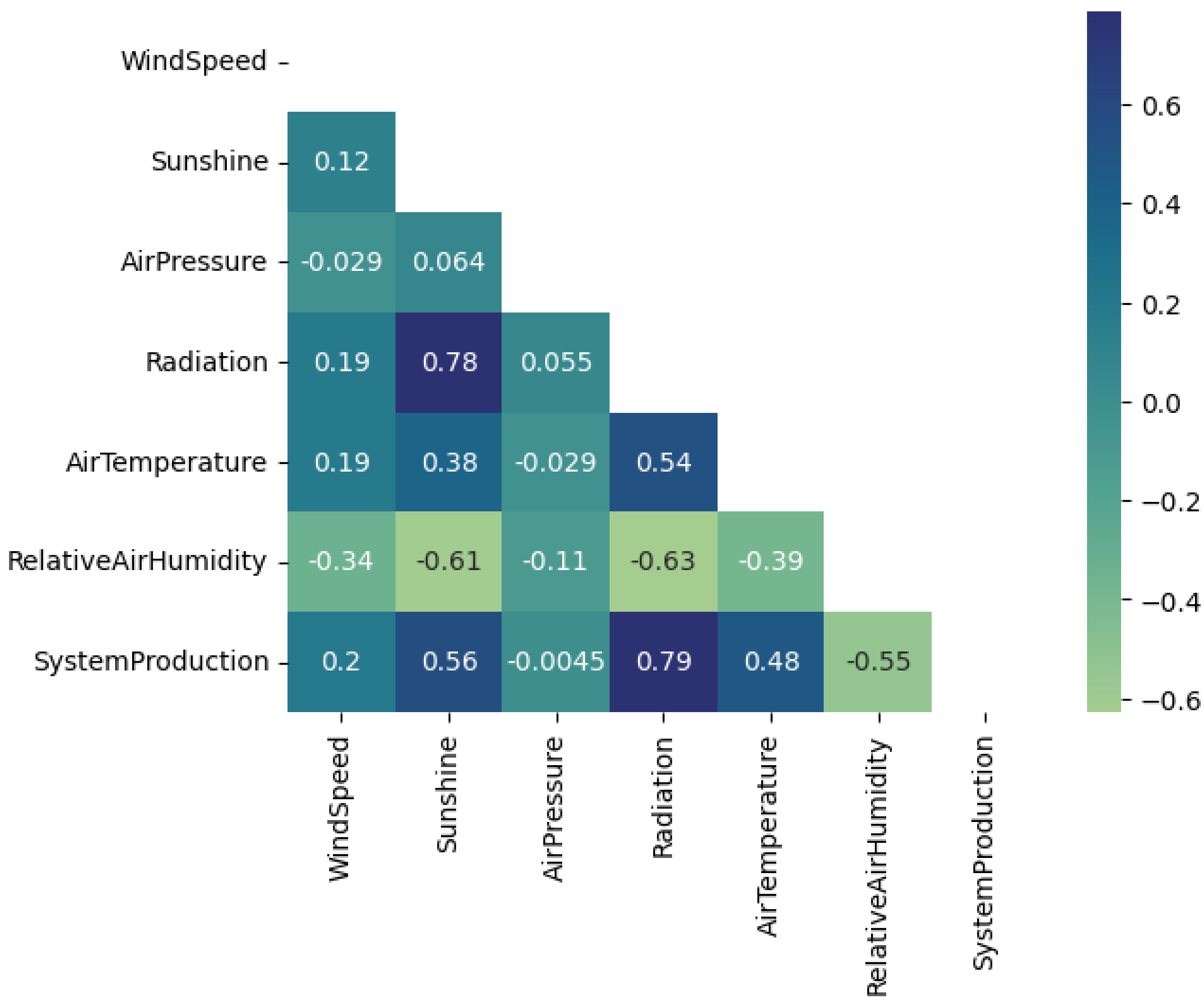
	WindSpeed	Sunshine	AirPressure	Radiation	AirTemperature	RelativeAirHumidity	SystemProduction
Kurtosis	0.645685	0.794225	0.413192	3.634802	-1.020777	-0.506118	5.930889
Skewness	0.904461	1.593429	-0.126781	2.078086	0.078606	-0.727069	2.568234

Distribution can be considered normal:

- Kurtosis between (-1, +1).
- Skewness between (-1, +1).
- Histogram and QQ Plot.

3.4) Correlation

In [41]:
```
# Correlation Matrix:

def heatmap_cor(df):
    cor = df.corr()
    mascara = np.zeros_like(cor)
    mascara[np.triu_indices_from(mascara)] = True
    sns.heatmap(cor, mask=mascara, cbar=True, annot=True, cmap="crest")


heatmap_cor(df)
```



Conclusions

- Most of the data in SystemProduction is 0 as we expected since median is zero and the variable can't be negative.
- Outliers exist in SystemProduction, AirPressure, RelativeHumidity, Radiation, WindSpeed and Sunshine.
- All statistical tests have shown that the AirPressure not follows a normal distribution. However, all these tests are very sensitive when the sample size is large. So we can't rely on them.
- Histogram, QQ Plot, Kurtosis and Skewness tell us that AirPressue follows a normal distribution. Therefore, we will assume that AirPressure is normally distributed.
- Radiation has the highest positive correlation coefficient associated with the SystemProdution (0.79). It is also hightly correlated with Sushine column.
- RelativeAirHumidity has the lowest correlation coefficient associated with the Target. (-0.55)

4) Preprocessing

4.1) Separating into training and testing sets

In [42]:
```
# Separating variables (features and target)

X = df.drop(columns="SystemProduction")
y = df["SystemProduction"]
```

In [43]:
```
# Dividing dataset in train and test:

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

4.2) Feature Selection

In [44]:
```
# Class that put together many feature selection techniques:

class feature_selector:
    seed = 42
    def __init__(self, X, y) -> None:
        self.X_train = X
        self.y_train = y

    def  randomforestR_imp(self) -> None:
        model = RandomForestRegressor(random_state=feature_selector.seed)
        model.fit(self.X_train, self.y_train)
        series = pd.Series(index=model.feature_names_in_, data=model.feature_importances

        # Plotting RandomForest Regression Importance:
        plt.title("RandomForest Importance")
        plt.xlabel("Importance")
        sns.barplot(x=series.values, y=series.index)


    def xgbR_imp(self) -> None:
        model = XGBRegressor(random_state=feature_selector.seed)
        model.fit(self.X_train, self.y_train)
        series = pd.Series(index=model.feature_names_in_, data=model.feature_importances

        # Plotting XGboost Regression Feature Importance:
        plt.title("XGBoost Feature Importance")
        plt.xlabel("Importance")
```

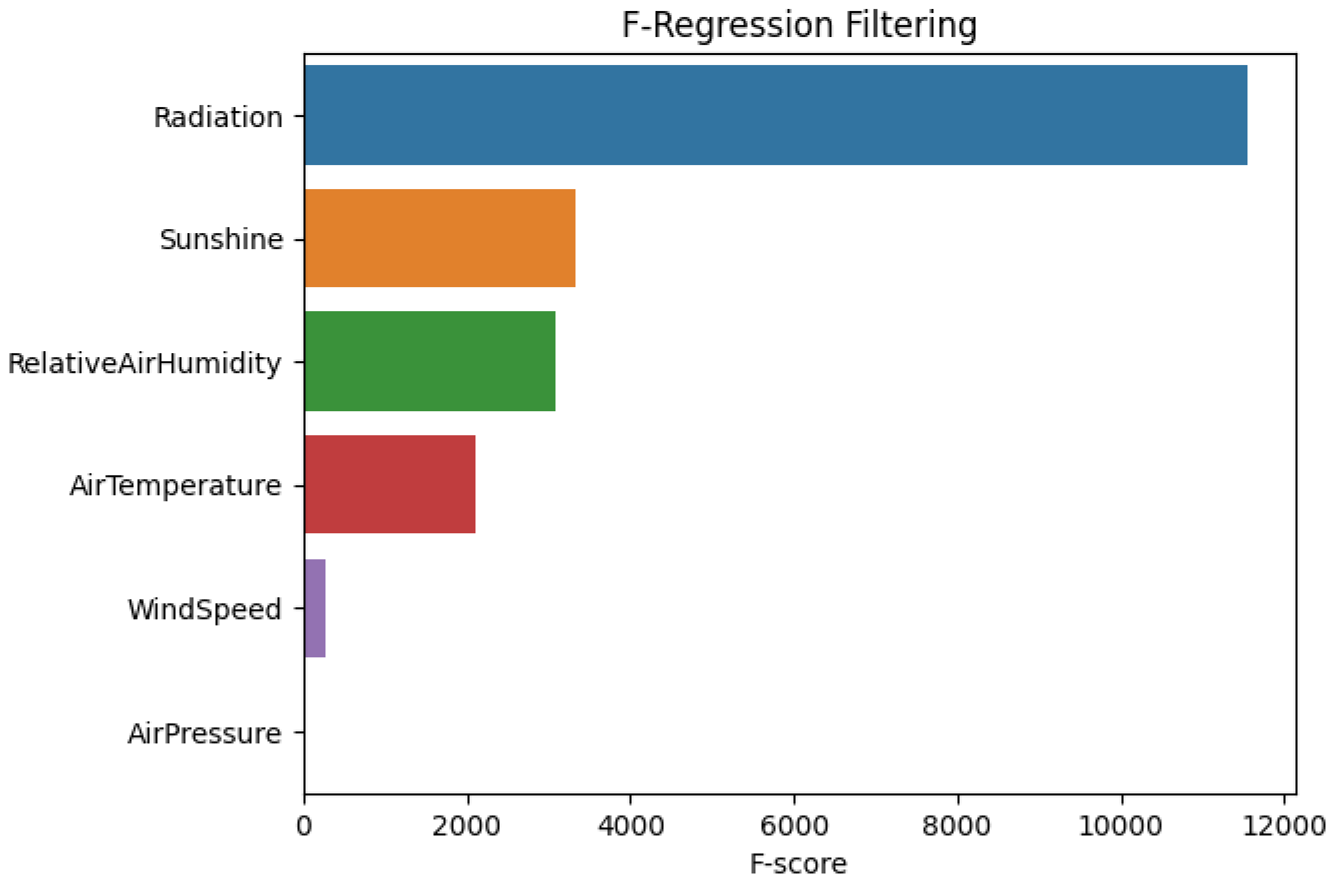
```
        sns.barplot(y=series.index, x=series.values)

    # Univariate feature selection:
    def univariate(self, statistic, n="all") -> None:
        selector = SelectKBest(score_func=statistic, k=n)
        selector.fit(self.X_train, self.y_train)

        series = pd.Series(index=selector.feature_names_in_, data=selector.scores_).\
            sort_values(ascending=False)
        plt.title("F-Regression Filtering")
        plt.xlabel("F-score")
        sns.barplot(y=series.index, x=series.values)

        return selector

    # Wrapper method for feature selection:
    def refcv(self):

        models = {
            "Lasso":Lasso(random_state=feature_selector.seed),
            "Ridge":Ridge(random_state=feature_selector.seed),
            "RandomForestR":RandomForestRegressor(random_state=feature_selector.seed),
            "ExtraTreeR":ExtraTreesRegressor(random_state=feature_selector.seed),
            "XGB":XGBRegressor(random_state=feature_selector.seed)
        }

        splits=10
        cross = KFold(n_splits=splits, random_state=feature_selector.seed, shuffle=True)
        ind = [f"Columns {i}" for i in range(1, len(self.X_train.columns) + 1)]
        df = pd.DataFrame(index=ind)

        minimo = np.inf
        name = ""
        for key, model in models.items():
            rfecv = RFECV(estimator=model, step=1, cv=cross, min_features_to_select=1, s
            rfecv.fit(self.X_train, self.y_train)
            root_mean = np.sqrt(-rfecv.cv_results_["mean_test_score"])
            df[key] = root_mean
            best_value = root_mean[np.argmin(root_mean)]

            if minimo > best_value:
                minimo = best_value
                best_features = rfecv.support_
                name = key

        df_features = pd.DataFrame(columns=self.X_train.columns, data=best_features.resh

        return df,  df_features
```

In [45]:
```
# Feature selector object:

feature = feature_selector(X_train, y_train)
```

4.2.1) Filtering selection

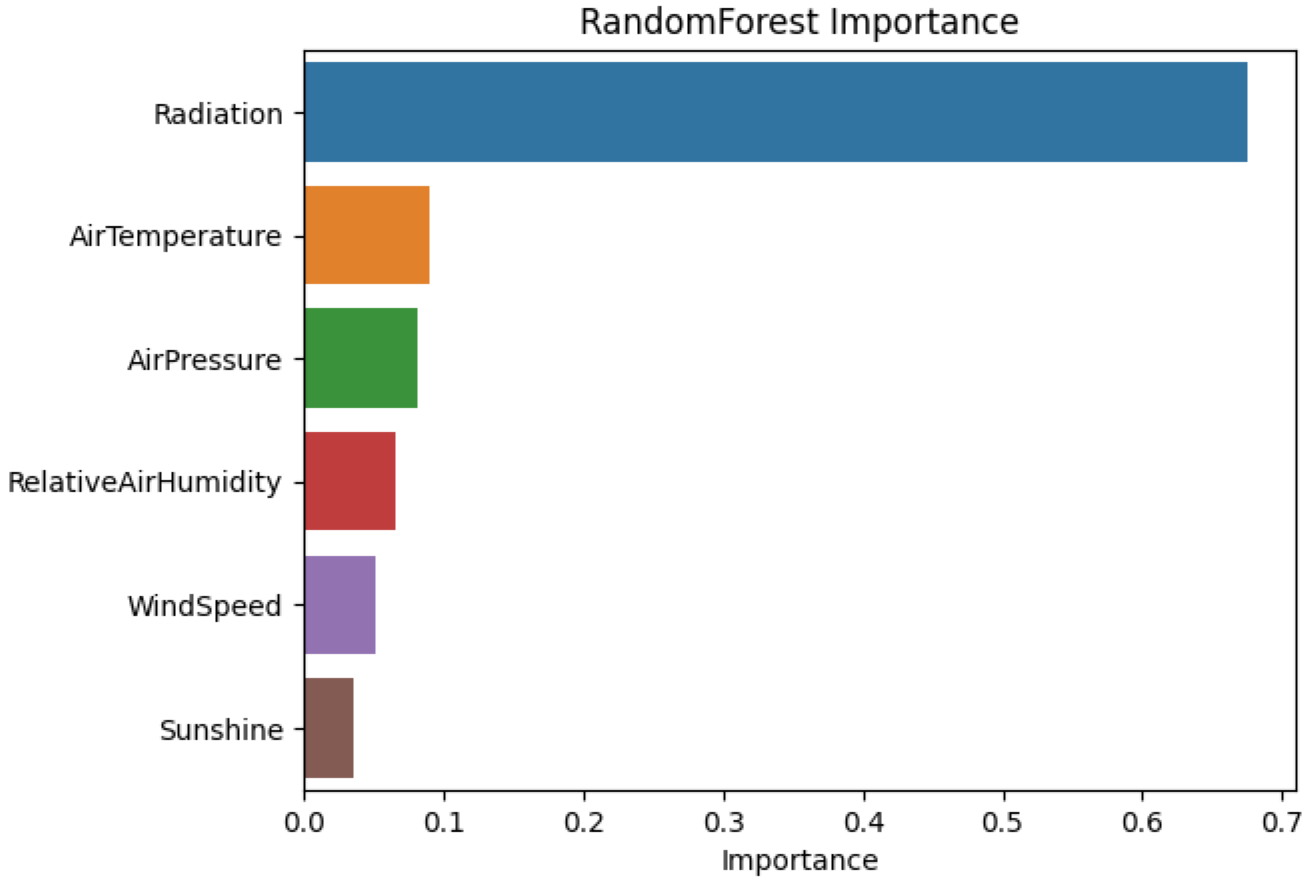
Filtering selection is a statistical feature selection technique that is based on the correlation score or dependence between the input variable and the target variable. So, after calculate this correlation or dependence based on a statistical approach, the variables can be filtered to choose the most relevant features. This problema has only continuous features and a continuous target so we will use a statistical measurement called f_regression that computes a univariate linear regression test called F-statistic and a p-value.

In [46]:
```
# Filtering feature selection using f_regression test:

selector_filtering = feature.univariate(statistic=f_regression)
```



4.2.2) Random Forest Importance

In [47]:
```
# Plotting Best features accordingly to the Random Forest Algorithm:

feature.randomforestR_imp()
```

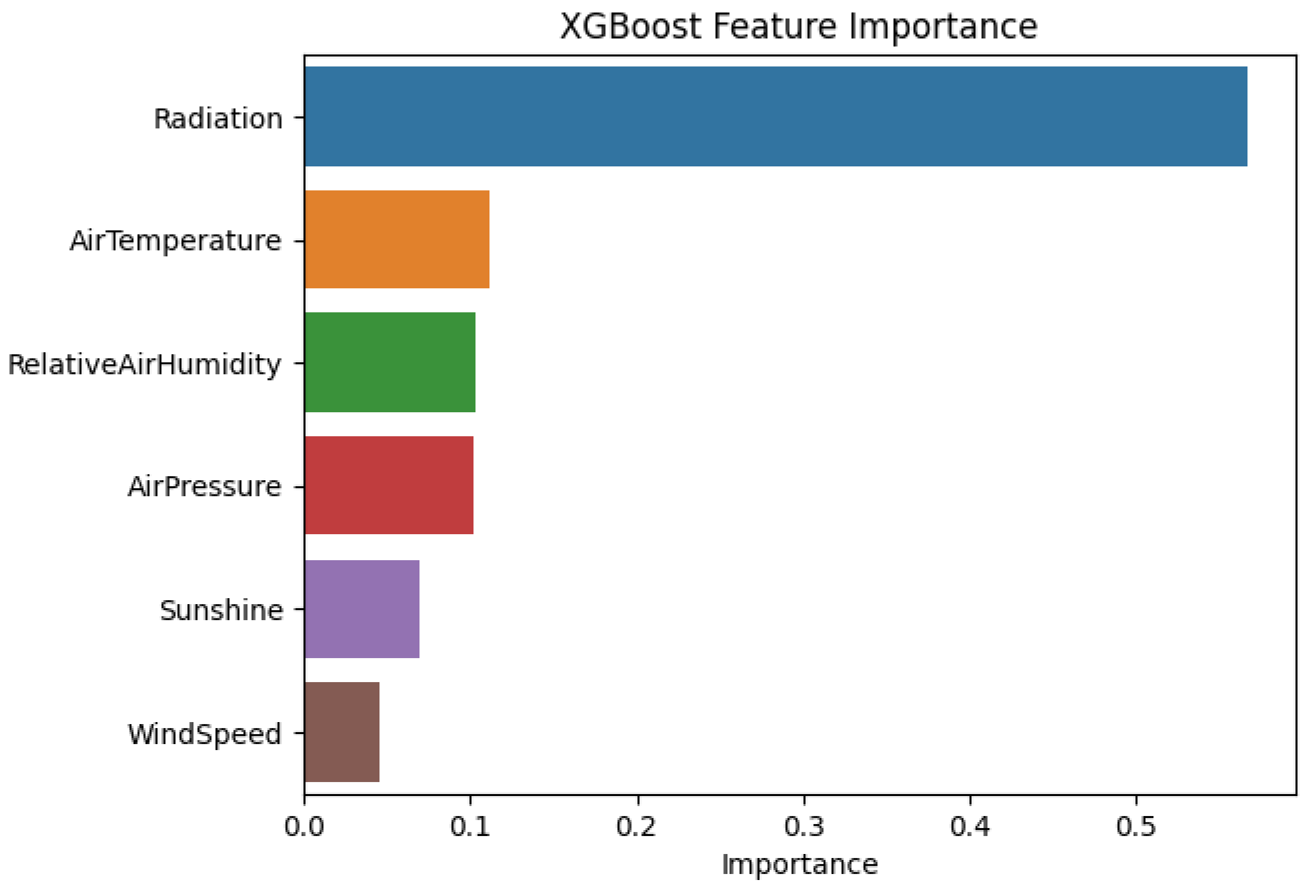


Conclusion

- Accordingly to the Random Forest algorithm, Radiation is the variable that most describes the output target.

4.2.3) XGBoost Importance

In [48]:
```
# Plotting the best features accordingly the XGBoost Algorithm:

feature.xgbR_imp()
```



Conclusion

- Accordingly to the XGboost algorithm, Radiation is the variable that most describes the output target.

4.2.4) Recursive Feature Elimination (RFE)

Recursive Feature Elimination (REF) is a feature selection technique that first fits an arbitrary estimator with all the features, and then uses an importance or coefficient attribute to identify the least important variable. It then drops this variable and fits another model without it until it reaches the minimal number of features.

In [49]:
```
# Mean test score for all of the Algorithms and for each number of columns:

df_results, df_features = feature.refcv()
```

In [50]:
```
# Recursive Feature Elimination results:

df_results
```

Out[50]:

	Lasso	Ridge	RandomForestR	ExtraTreeR	XGB
Columns 1	1467.860960	1477.986141	1133.246002	1207.972781	1045.061217
Columns 2	1301.266660	1312.583376	974.506010	1003.782575	973.252195
Columns 3	1155.614811	1158.127170	849.627134	934.740169	944.589000
Columns 4	1124.590002	1124.589720	819.966015	864.464221	848.063361
Columns 5	905.993187	905.993069	795.131463	785.949747	823.702505
Columns 6	903.620263	903.620225	772.033482	770.559293	788.551322

In [51]:
```
# Features selected using the best Algorithm (ExtraTreeRegression):
```

```
df_features
```

Out[51]:

	WindSpeed	Sunshine	AirPressure	Radiation	AirTemperature	RelativeAirHumidity
ExtraTreeR	True	True	True	True	True	True

Conclusions

Accordingly to the Recursive Feature Elimination:

- Best model to find important features is the ExtraTreeRegressor.
- Best number of features is 6, which means that we will use all of them for further analysis.

4.3) Transformations

4.3.1) MinMax Scaler

Definition:

- MinMax Scaler is also called as Normalization, which is a technique that rescale all the values, usually, within a range of 0 and 1.

Mathematical Definition:

$$X_{new_i} = \frac{X_i - X_{min_i}}{X_{max_i} - X_{min_i}}$$

In [52]:

```
# MinMax Scaler Transformation:

min_max = MinMaxScaler()
X_train_min_max = min_max.fit_transform(X_train)
X_test_min_max = min_max.transform(X_test)
```

4.3.2) Standard Scaler

Definition:

- The Standard Scaler is a technique that rescales the distribution of a variable so that the mean of the observed sample is 0 and the standard deviation is 1. It is particularly useful for algorithms that rely on distance measures, such as K-means and K-nearest neighbors (KNN). Additionally, it is a recommended choice for algorithms based on neural networks.

OBS: Standard Scaler can perform slightly worst than the other transformations because it assumes that the data is normally distributed. However you can still standarduze your data.

Matematical Definition:

$$X_{new_i} = \frac{X_i - \hat{\mu}_i}{\sigma_i}$$

- μ : Mean of the sample.
- σ : Standard Deviation of the sample.

In [53]:

```
# Standard Scaler Transformation:

std = StandardScaler()
```

```python
X_train_std = std.fit_transform(X_train)
X_test_std = std.transform(X_test)
```

4.3.3) Robust Scaler

Definition:

- Robust scaler is a technique which uses the median and the Interquartile range to transform the variables. This approach is very useful when the input variables have many outliers.

Mathematical Definition:

$$X_{new_i} = \frac{X_i - median_i}{IQR_i}$$

$$IQR_i = P_{75_i} - P_{25_i}$$

- IQR : Interquartile Range.
- P_{75} : 75th Percentile.
- P_{25} : 25th Percentile.

In [54]:
```python
# Robust Scaler Transformation:

rob = RobustScaler()
X_train_rb = rob.fit_transform(X_train)
X_test_rb = rob.fit_transform(X_test)
```

4.4) Selecting the best Algorithm and Transformation

In [55]:
```python
# Function used to evaluate the best algorithms:

def melhor_modelo(X_train, y_train):

    seed = 42
    cv = 5
    score = ['neg_root_mean_squared_error', 'r2']
    result_rmse = {}
    result_r2 = {}

    dicionario = {
                "Lasso":Lasso(random_state=seed),
                "Ridge":Ridge(random_state=seed),
                "SVR":SVR(),
                "RandomForestR":RandomForestRegressor(random_state=seed),
                "ExtraTreeR":ExtraTreesRegressor(random_state=seed),
                "XGB":XGBRegressor(random_state=seed),
                "MLP":MLPRegressor(random_state=seed, max_iter=2000)
                 }


    for name, model in dicionario.items():
        k_fold = KFold(n_splits=cv, random_state=seed, shuffle=True)
        result = cross_validate(model, X_train, y_train, cv=k_fold, scoring=score)

        result_rmse[name] = -result['test_neg_root_mean_squared_error']
        result_r2[name] = result['test_r2']


    result_pd_rmse = pd.DataFrame(data=result_rmse)
    result_pd_r2 = pd.DataFrame(data=result_r2)
```

```python
    return result_pd_rmse, result_pd_r2
```

4.4.1) Algorithms using MinMax Scaler

In [56]:
```python
# Best model:

resultado_rms, resultado_r2 = melhor_modelo(X_train_min_max, y_train)
```

In [57]:
```python
# Root mean squared error results:

resultado_rms.describe()
```

Out[57]:

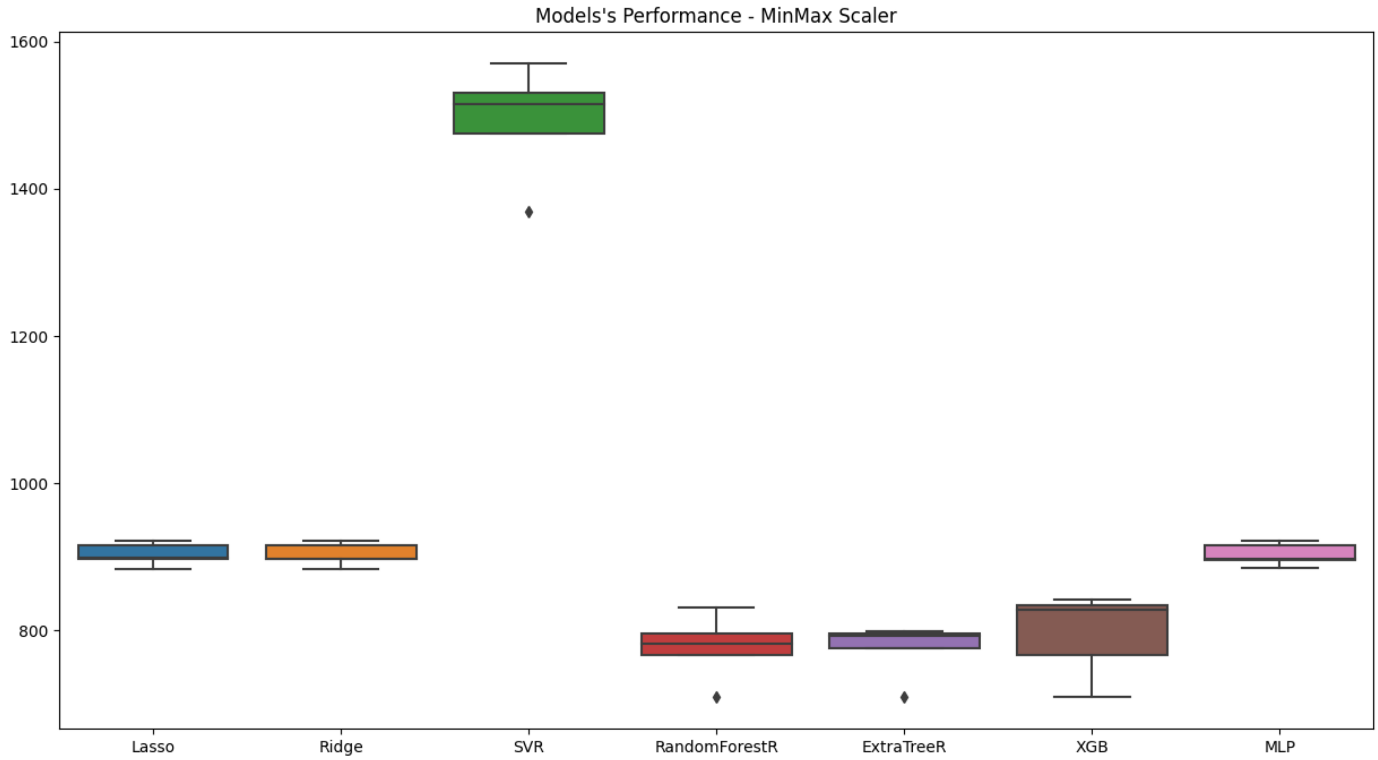
	Lasso	Ridge	SVR	RandomForestR	ExtraTreeR	XGB	MLP
count	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000
mean	903.485007	903.400786	1491.625424	777.359187	775.023285	796.631552	903.149462
std	15.562091	15.628135	76.724616	44.754904	37.517289	56.469978	15.249867
min	883.515021	883.085192	1368.718235	709.711976	709.776868	710.759720	884.950591
25%	897.526534	897.819708	1474.371484	767.563919	776.598713	767.368293	895.889170
50%	898.300154	898.192638	1515.347110	781.613578	793.488589	827.759964	897.119584
75%	915.613173	915.621307	1529.832640	796.014928	795.642869	834.921067	916.230928
max	922.470155	922.285084	1569.857651	831.891534	799.609385	842.348716	921.557038

In [58]:
```python
# R2 results:

resultado_r2.describe()
```

Out[58]:

	Lasso	Ridge	SVR	RandomForestR	ExtraTreeR	XGB	MLP
count	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000
mean	0.638294	0.638374	0.017998	0.732798	0.734620	0.719589	0.638508
std	0.026434	0.026218	0.015911	0.021213	0.012827	0.025073	0.027293
min	0.599661	0.600050	0.001504	0.704749	0.713481	0.687616	0.598359
25%	0.636953	0.637099	0.003063	0.716051	0.731379	0.707674	0.637671
50%	0.638390	0.638476	0.020332	0.741676	0.741629	0.712968	0.639340
75%	0.642333	0.642327	0.025882	0.748647	0.742695	0.740913	0.641850
max	0.674132	0.673919	0.039210	0.752867	0.743915	0.748775	0.675320

In [59]:
```python
# PLotting model's performance:

plt.figure(figsize=(15, 8))
plt.title("Models's Performance - MinMax Scaler")
sns.boxplot(resultado_rms);
```



4.4.2) Algorithms using Standard Scaler

In [60]:
```
# Best model:

resultado_rms, resultado_r2 = melhor_modelo(X_train_std, y_train)
```

In [61]:
```
# Root mean squared error results:

resultado_rms.describe()
```

Out[61]:

	Lasso	Ridge	SVR	RandomForestR	ExtraTreeR	XGB	MLP
count	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000
mean	903.358839	903.348724	1530.475777	777.358424	775.054472	796.703441	862.939395
std	15.613713	15.632424	77.459091	44.998844	37.425748	57.132829	22.959748
min	883.396953	883.376841	1407.559380	709.420058	709.974316	709.015132	830.902836
25%	897.503104	897.532799	1509.000499	766.761334	776.598713	768.916041	856.534749
50%	897.863026	897.762911	1557.105336	782.169400	793.488589	826.964465	863.601966
75%	915.705262	915.761676	1569.520962	796.460193	795.601359	834.373150	869.038325
max	922.325850	922.309391	1609.192706	831.981138	799.609385	844.248418	894.619098

In [62]:
```
# R2 results:

resultado_r2.describe()
```

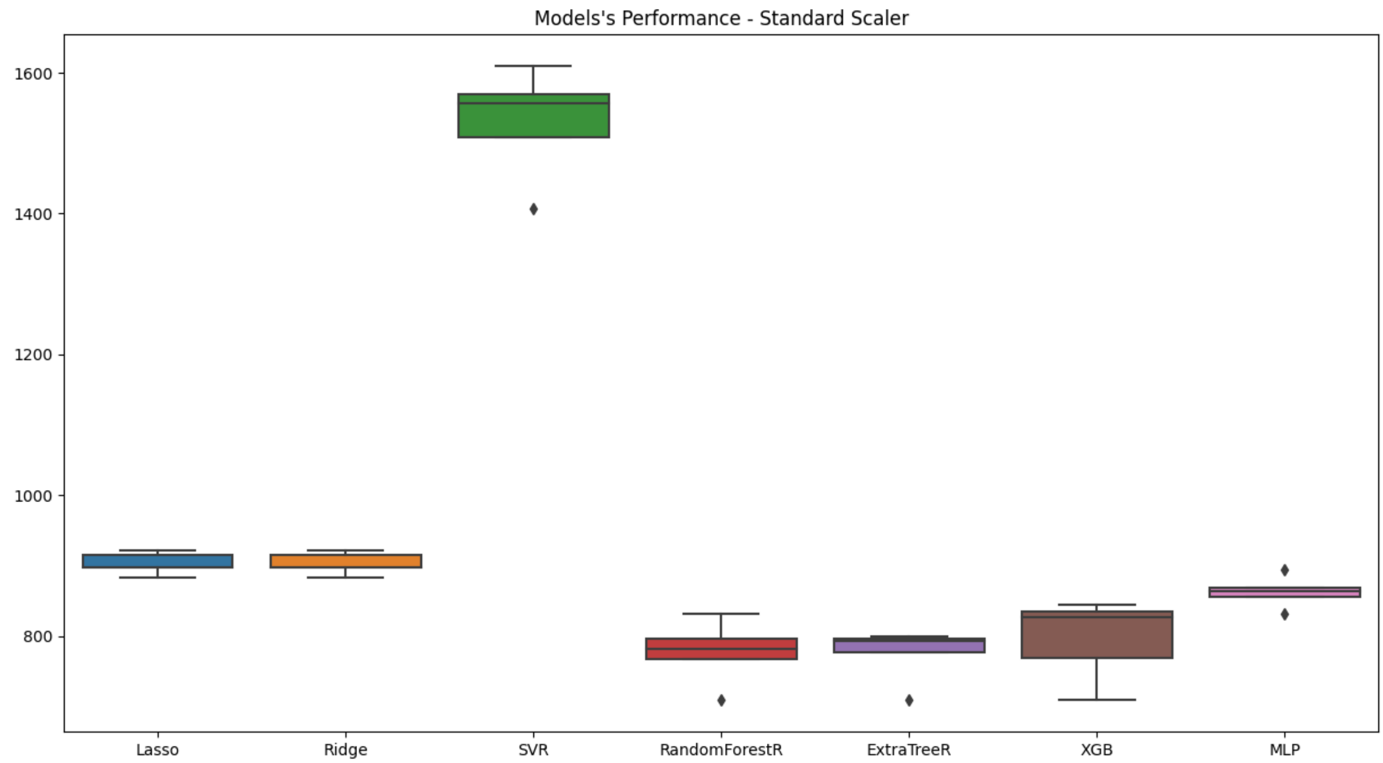
Out[62]:

	Lasso	Ridge	SVR	RandomForestR	ExtraTreeR	XGB	MLP
count	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000
mean	0.638397	0.638406	-0.033882	0.732799	0.734596	0.719575	0.670359
std	0.026397	0.026382	0.015623	0.021337	0.012812	0.024960	0.019834
min	0.599768	0.599786	-0.050976	0.704685	0.713481	0.688026	0.645921

25%	0.637066	0.637079	-0.047522	0.715733	0.731379	0.708236	0.658544
50%	0.638742	0.638822	-0.034406	0.741889	0.741485	0.711672	0.671233
75%	0.642261	0.642217	-0.020414	0.749172	0.742695	0.742183	0.677795
max	0.674149	0.674128	-0.016094	0.752515	0.743942	0.747761	0.698301

In [63]:

```
# PLotting model's performance:

plt.figure(figsize=(15, 8))
plt.title("Models's Performance - Standard Scaler")
sns.boxplot(resultado_rms);
```



4.4.3) Algorithms using Robust Scaler

In [64]:

```
# Best model:

resultado_rms, resultado_r2 = melhor_modelo(X_train_rb, y_train)
```

In [65]:

```
# Root mean squared error results:

resultado_rms.describe()
```

Out[65]:

	Lasso	Ridge	SVR	RandomForestR	ExtraTreeR	XGB	MLP
count	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000
mean	903.355648	903.348361	1482.596356	777.415145	775.018174	796.668225	876.956954
std	15.623197	15.632835	78.002979	44.754342	37.423964	57.775051	14.926458
min	883.412700	883.384740	1357.623438	709.669560	709.974316	706.881966	863.292220
25%	897.497262	897.526871	1464.431309	767.355707	776.417221	770.807039	867.246465
50%	897.797461	897.752247	1507.997183	781.161161	793.488589	826.768020	870.690222
75%	915.742087	915.767967	1521.297606	797.640675	795.601359	834.138524	883.666721
max	922.328731	922.309982	1561.632242	831.248623	799.609385	844.745576	899.889140

In [66]:

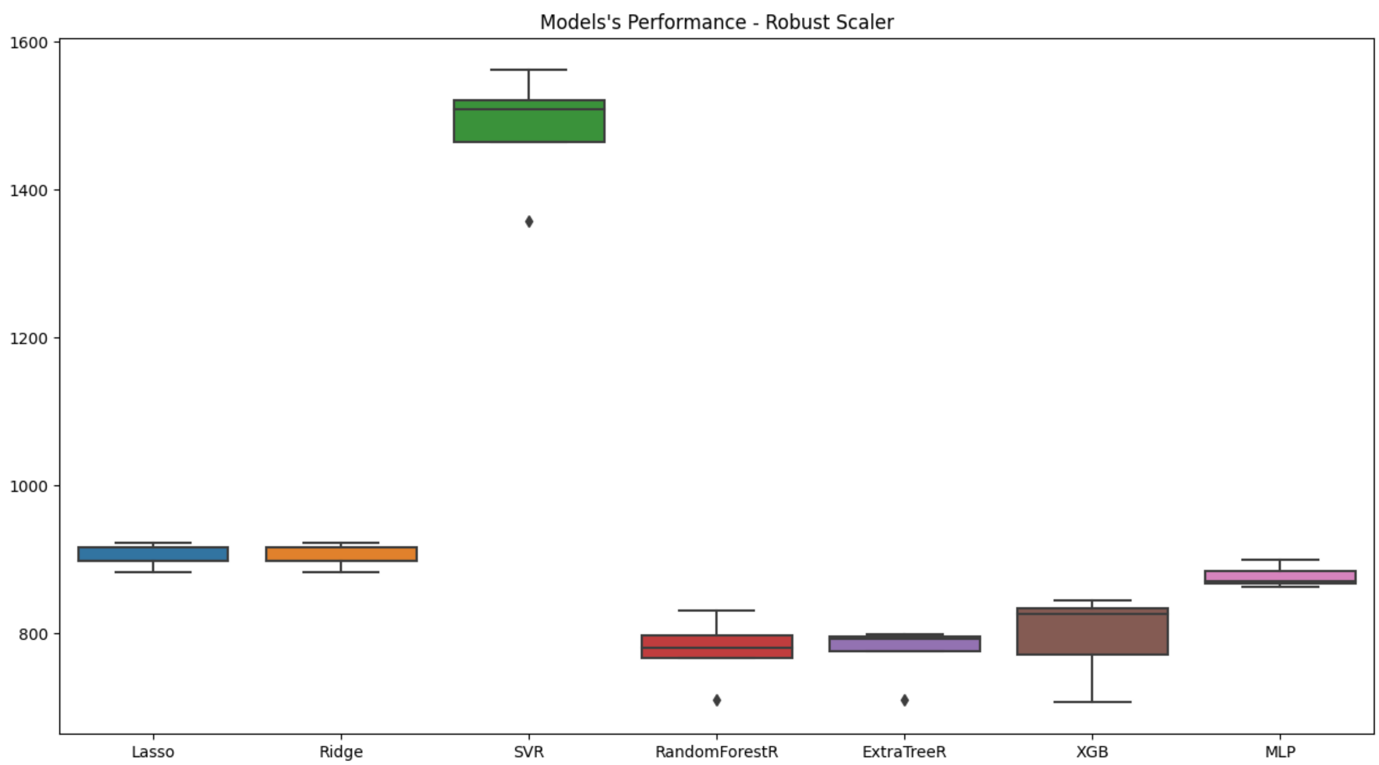
```
# R2 results:

resultado_r2.describe()
```

Out[66]:

	Lasso	Ridge	SVR	RandomForestR	ExtraTreeR	XGB	MLP
count	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000
mean	0.638400	0.638406	0.029921	0.732748	0.734621	0.719632	0.658997
std	0.026403	0.026386	0.017796	0.021397	0.012831	0.024936	0.028769
min	0.599753	0.599779	0.012615	0.705205	0.713481	0.688201	0.614268
25%	0.637064	0.637079	0.013483	0.714890	0.731379	0.708374	0.654509
50%	0.638794	0.638831	0.029812	0.741707	0.741485	0.711332	0.666025
75%	0.642232	0.642212	0.038972	0.748783	0.742815	0.743732	0.666856
max	0.674153	0.674132	0.054723	0.753153	0.743942	0.746519	0.693328

In [67]:

```
# PLotting model's performance:

plt.figure(figsize=(15, 8))
plt.title("Models's Performance - Robust Scaler")
sns.boxplot(resultado_rms);
```



Conclusions

- ExtraTres was the best Algorithm for all of the transformation algorithms.
- The Best Trasformation algorithm was Robust Scaler.

RMSE:

- Average: 775.018174
- Standard Deviation: 37.423964

R2

- Average: 0.734621
- Standard Deviation: 0.012831

5) Fine Tuning

In [68]:
```
# Function for fine tuning an arbitrary model:

def tuning(X_train, y_train, modelo, params):

    cv = 5
    score = "neg_root_mean_squared_error"
    grid  = GridSearchCV(modelo, cv=cv, param_grid=params,
                         scoring=score,
                         n_jobs=-1,
                         return_train_score=True,
                         )

    grid.fit(X_train, y_train)

    best_index = grid.best_index_
    result = grid.cv_results_

    train_score = -result['mean_train_score'][best_index]
    left_out = -result['mean_test_score'][best_index]



    print(f"Train score: {train_score}")
    print(f"Left out data score: {left_out}")

    return grid.best_estimator_
```

In [69]:
```
def save_model(model):
    try:
        joblib.dump(model, "modelo/extra_tree_model.joblib")
    except:
        os.makedirs("modelo")
        path = "modelo/extra_tree_model.joblib"
        joblib.dump(model, path)
```

In [73]:
```
# Hypeparameters grid:

params = {"n_estimators":[100, 110, 120],
          "max_depth":[4, 5, 6, 7],
          "max_features":[0.5, 0.6, 0.7],
          "min_samples_split":[3, 5, 6, 7, 10]}
```

In [74]:
```
# Fine Tuning an ExtraTreeRegressor:

extra_tree = ExtraTreesRegressor(random_state=42)
best_estimator = tuning(X_train_rb, y_train, extra_tree, params)
```

```
Train score: 765.3644951871554
Left out data score: 835.5946923397969
```

In [75]:
```
# Saving the best model:

save_model(best_estimator)
```

6) Predictions

In [53]:
```
# Training the best model using the whole training set:

best_model = clone(best_estimator)
best_model.fit(X_train_rb, y_train)
```

Out[53]:
```
ExtraTreesRegressor

ExtraTreesRegressor(max_depth=7, max_features=0.7, min_samples_split=3,
                    n_estimators=110, random_state=42)
```

In [54]:
```
# Computing Metrics for the training set:

y_pred = best_model.predict(X_train_rb)
rms_train = np.sqrt(mean_squared_error(y_pred, y_train))
r2_train = r2_score(y_pred, y_train)

print("Train set:")
print(f"RMSE: {rms_train}")
print(f"R2: {r2_train}")
```

```
Train set:
RMSE: 777.204892038056
R2: 0.5682232687504819
```

In [55]:
```
# Computing Metrics for the test set:

y_pred = best_model.predict(X_test_rb)
rmse_test = np.sqrt(mean_squared_error(y_pred, y_test))
r2_test = r2_score(y_pred, y_test)

print("Test set:")
print(f"RMSE: {rmse_test}")
print(f"R2: {r2_test}")
```

```
Test set:
RMSE: 819.7307706495565
R2: 0.5347937839096278
```

Conclusions

- RMSE improved from 835.595 to 819.731.
- R2 score is approximately 0.5349.
- Model does not seem to suffer from Overfitting.