Exercise 3 - Internal Energy Benchmarking

November 8, 2024

Gestione Energetica ed Automazione negli Edifici (GEAE) A.A. 2024/2025

1 Internal Energy Benchmarking

1.1 Introduction and pre-processing

1.1.1 Importing necessary libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# For linear regression and metrics
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_percentage_error, mean_squared_error,␣
  ↪r2_score
from math import sqrt
```

[2]:
```
df = pd.read_csv('../data/pre_retrofit.csv')
```

[3]:
```
df['DATA_misura'] = pd.to_datetime(df['DATA_misura'], format="%Y-%m-%d")
df['DATA_inizio'] = pd.to_datetime(df['DATA_inizio'], format="%Y-%m-%d")
```

1.1.2 Extract days and hours of operations of the system

[4]:
```
# Calculate the number of days between measurement dates
df['giorni_letture'] = (df['DATA_misura'] - df['DATA_inizio']).dt.days

# Calculate total hours in the metering period
df['ore_tot'] = df['giorni_letture'] * 24

# Calculate the hours when the heat generator is ON
```

```
df['ore_ON'] = df['ore_tot'] - df['giorni_off'] * 24
```

1.1.3 Calculate the average thermal power of the system

[5]:
```
# Define the conversion factor
cf = 10.94

# Calculate the average thermal power
df['potenza'] = (df['consumo_gasm_smc'] * cf) / df['ore_ON']

# Replace infinite or NaN values with 0
df['potenza'] = df['potenza'].replace([np.inf, -np.inf], np.nan)
df = df.dropna(subset=['potenza'])

# Filter out records where 'tipo_misura' is 'OFF'
df1 = df[df['tipo_misura'] != 'OFF']
```

1.2 Fitting linear regression model for each season

1.2.1 Define a function to fit a linear model within a loop

[6]:
```
def fit_linear_model(data, season):
    """
    Fits a linear model of 'potenza' vs 'T_media' for a given season using␣
 ↪scikit-learn.
    """
    # Filter data for the specific season
    season_data = data[data['Stagione'] == season]

    # Define independent and dependent variables
    X = season_data[['T_media']].values # 2D array for scikit-learn
    y = season_data['potenza'].values # 1D array

    # Fit the linear regression model
    model = LinearRegression().fit(X, y)

    return model
```

1. **`season_data = data[data['Stagione'] == season]`**
   - This line filters the input DataFrame (`data`) to create a new DataFrame (`season_data`) containing only the rows where the value in the `'Stagione'` column matches the given `season`.
   - This allows us to focus the analysis on a specific season (e.g., winter, summer).
2. **`X = season_data[['T_media']].values.reshape(-1, 1)`**
   - This line defines the independent variable (`X`) for the linear regression model.
   - **`season_data[['T_media']]`** selects the column `'T_media'` from `season_data`, which represents the average temperature.
3. **`y = season_data['potenza'].values`**

- This line defines the dependent variable (y) for the linear regression model.
- `season_data['potenza']` selects the column `'potenza'` from `season_data`, representing the power values.
- `.values` converts the selected column into a NumPy array.

4. `model = LinearRegression().fit(X, y)`
   - This line creates an instance of the `LinearRegression` model from scikit-learn and fits it to the independent (X) and dependent (y) variables.
   - `LinearRegression().fit(X, y)` estimates the coefficients of the linear model that best fits the data provided.

[7]:
```
# List of seasons
seasons = ['2012-2013', '2013-2014', '2014-2015', '2015-2016']
```

1.2.2 Call the function to fit the model for each season in a loop

[8]:
```
# Dictionary to store models
models = {}

# Fit models for each season
for season in seasons:
    models[season] = fit_linear_model(df1, season)
    X = df1[df1['Stagione'] == season][['T_media']].values
    y = df1[df1['Stagione'] == season]['potenza'].values
    r2 = models[season].score(X, y)
    intercept = models[season].intercept_
    coef = models[season].coef_[0]
    print(f"Summary for season {season}: R² = {r2:.2f} / Intercept = {intercept:
↪.2f} / Coefficient = {coef:.2f}")
```

```
Summary for season 2012-2013: R² = 0.98 / Intercept = 76.42 / Coefficient =
-4.35
Summary for season 2013-2014: R² = 0.97 / Intercept = 76.89 / Coefficient =
-4.46
Summary for season 2014-2015: R² = 0.98 / Intercept = 75.55 / Coefficient =
-4.68
Summary for season 2015-2016: R² = 0.98 / Intercept = 69.58 / Coefficient =
-3.90
```

1.2.3 Define a function to plot the regression line and data points for each season

[9]:
```
def plot_regression(data, model, season):
    """
    Plots the regression line and data points for a given season.
    """
    # Filter data for the season
    season_data = data[data['Stagione'] == season]

    # Create scatter plot of the data points
```

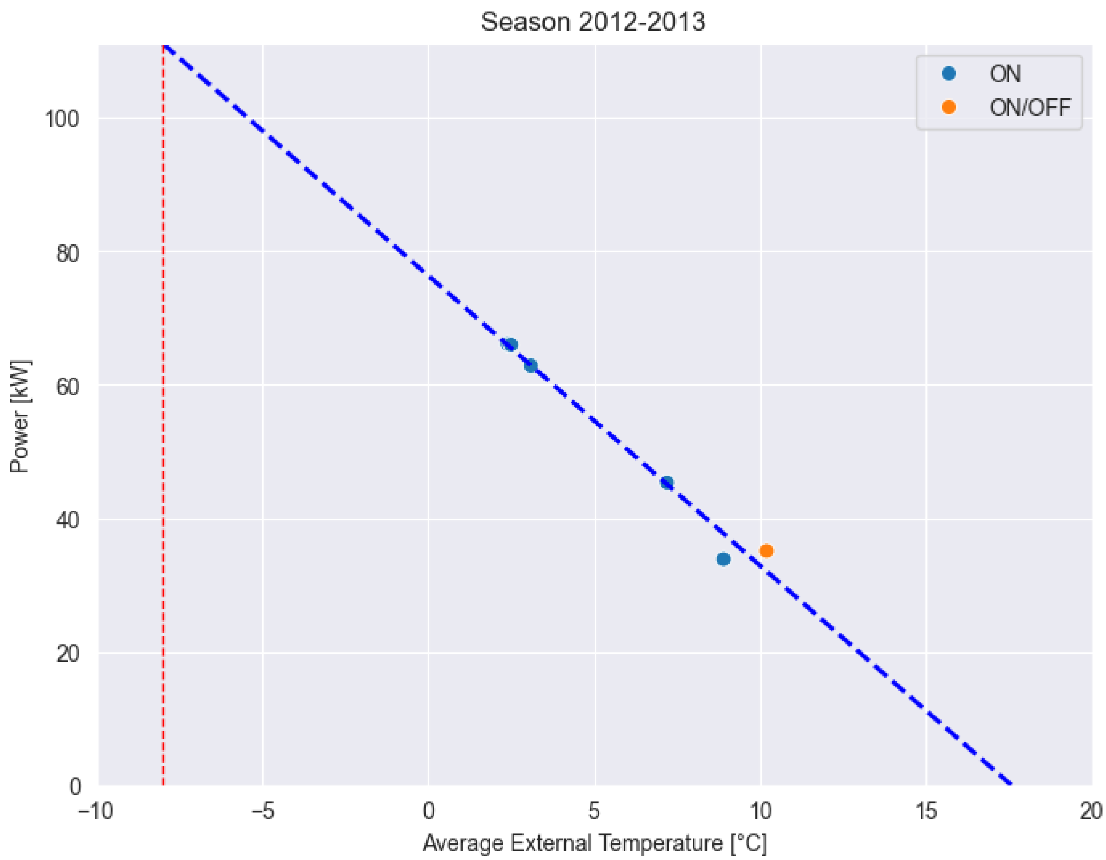
```python
    plt.figure(figsize=(8, 6))
    sns.scatterplot(x='T_media', y='potenza', hue='tipo_misura',␣
↪data=season_data, s=50)

    # calculate T_max when y = 0
    max_t_plot = -model.intercept_ / model.coef_[0]
    # calculate P_max when T = -8
    max_p_plot = model.predict([[-8.0]])[0]
    # Generate values for plotting the regression line
    X_plot = np.linspace(-8.0, max_t_plot, 100).reshape(-1, 1)
    y_plot = model.predict(X_plot)

    # Plot the regression line
    plt.plot(X_plot, y_plot, color='blue', linestyle='--', linewidth=2)
    # add vertical line at T = -8
    plt.axvline(x=-8, color='red', linestyle='--', linewidth=1)

    # Set plot limits
    plt.xlim(-10, 20)
    plt.ylim(0, max_p_plot)

    # Set labels and title
    plt.xlabel('Average External Temperature [°C]')
    plt.ylabel('Power [kW]')
    plt.title(f"Season {season}")

    plt.legend()
    plt.show()
```

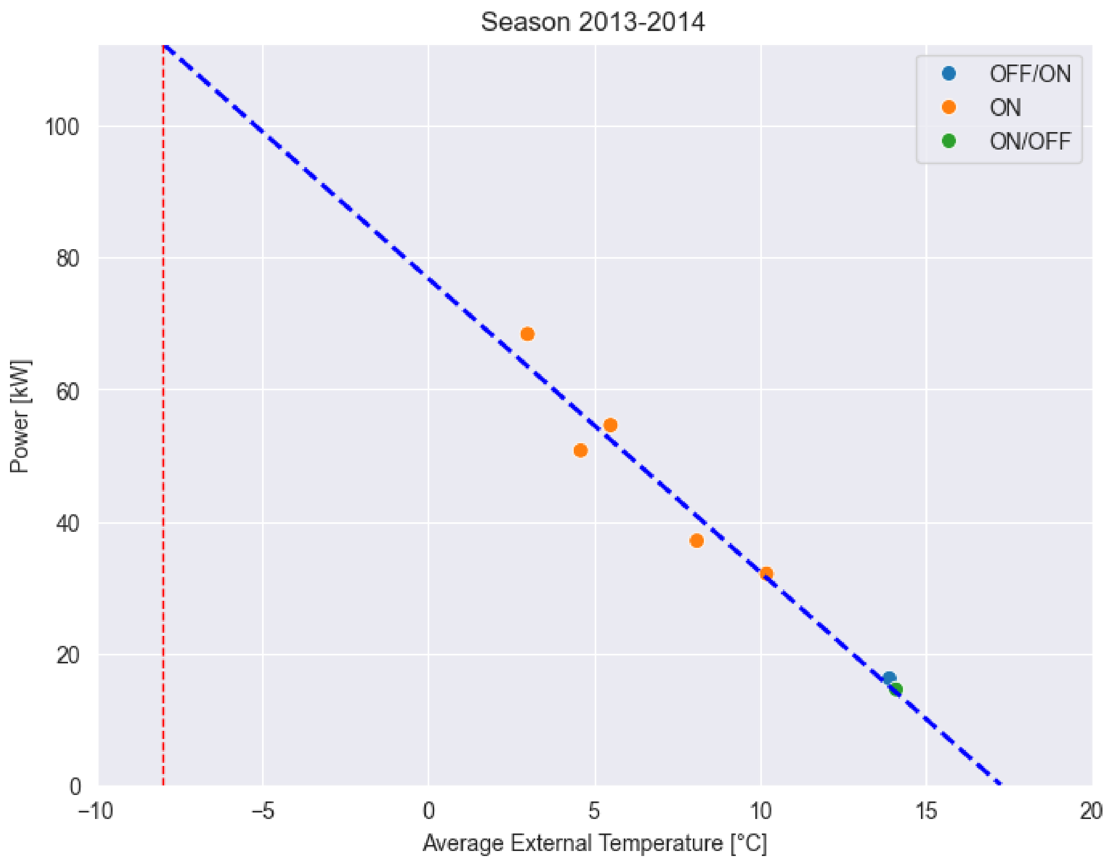
1. **`season_data = data[data['Stagione'] == season]`**
   - This line filters the input DataFrame (`data`) to create a new DataFrame (`season_data`) containing only the rows where the value in the `'Stagione'` column matches the given `season`.
   - This helps us focus the visualization on data relevant to the specified season.
2. **`plt.figure(figsize=(8, 6))`**
   - This line initializes a new figure for plotting, with a specified size of 8 by 6 inches.
   - It ensures that the plot has a consistent and appropriate size for visualization.
3. **`sns.scatterplot(x='T_media', y='potenza', hue='tipo_misura', data=season_data, s=50)`**
   - This line creates a scatter plot of the filtered data (`season_data`).
   - **`x='T_media'`** and **`y='potenza'`** specify the x-axis and y-axis variables, representing average temperature and power, respectively.
   - **`hue='tipo_misura'`** adds a color dimension to distinguish between different measurement types.
   - **`s=50`** sets the marker size for the scatter plot points.
4. **`X_plot = np.linspace(season_data['T_media'].min(), season_data['T_media'].max(), 100).reshape(-1, 1)`**
   - This line generates 100 equally spaced values between the minimum and maximum of

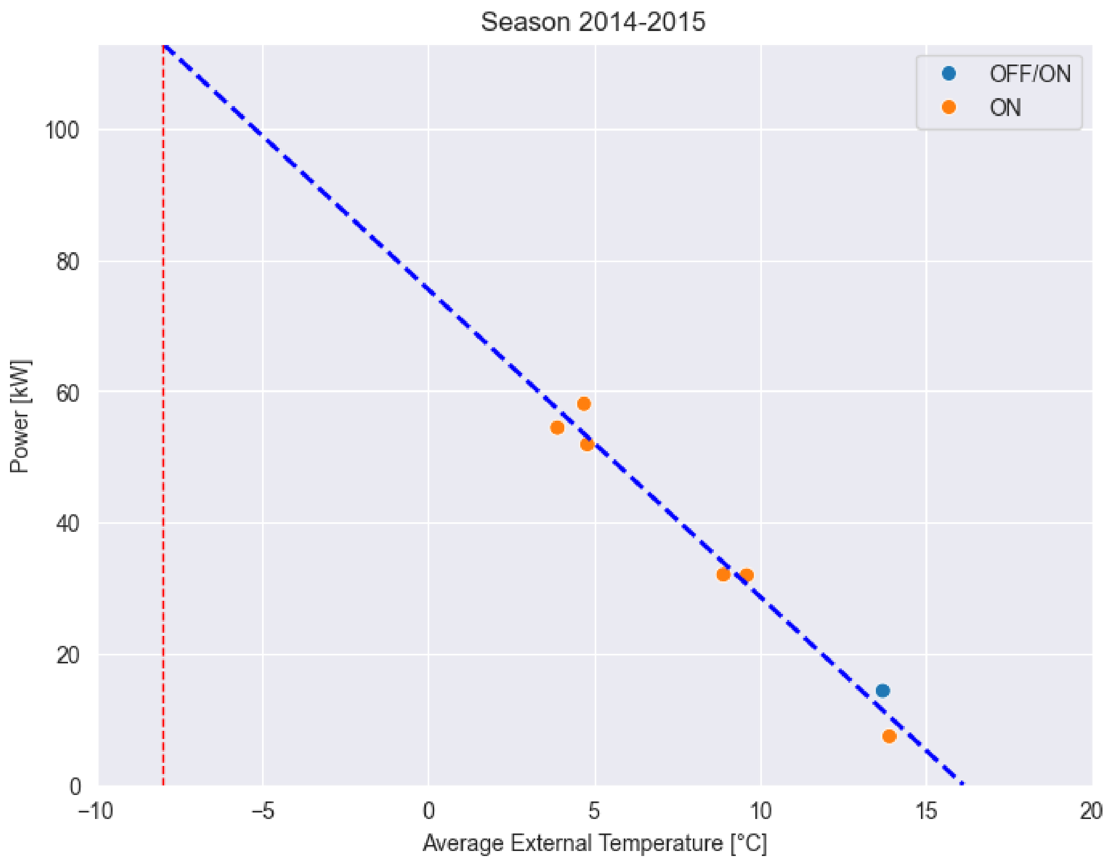
'T_media' in the season data.
   - **.reshape(-1, 1)** reshapes the generated values into a two-dimensional array suitable for prediction.
5. **y_plot = model.predict(X_plot)**
   - This line uses the linear regression model (model) to predict power values (y_plot) for the generated temperature values (X_plot).
   - It allows us to plot the regression line that fits the data.
6. **plt.plot(X_plot, y_plot, color='blue', linestyle='--', linewidth=2)**
   - This line plots the regression line on the figure.
   - **color='blue'** sets the line color, **linestyle='--'** creates a dashed line, and **linewidth=2** controls the line thickness.
7. **plt.xlim(0, 20) and plt.ylim(0, 70)**
   - These lines set the limits for the x-axis (temperature) and y-axis (power).
   - This helps keep the plot focused on a meaningful range for analysis.
8. **plt.xlabel('Average External Temperature [°C]') and plt.ylabel('Power [kW]')**
   - These lines set the labels for the x and y axes to provide context for the data being plotted.
9. **plt.title(f"Season {season}")**
   - This line sets the title for the plot.
   - It dynamically includes the season name to clarify which data is being visualized.
10. **plt.legend()**
    - This line adds a legend to the plot.
    - It provides information about the different measurement types indicated by the hue parameter in the scatter plot.
11. **plt.show()**
    - This line displays the plot.

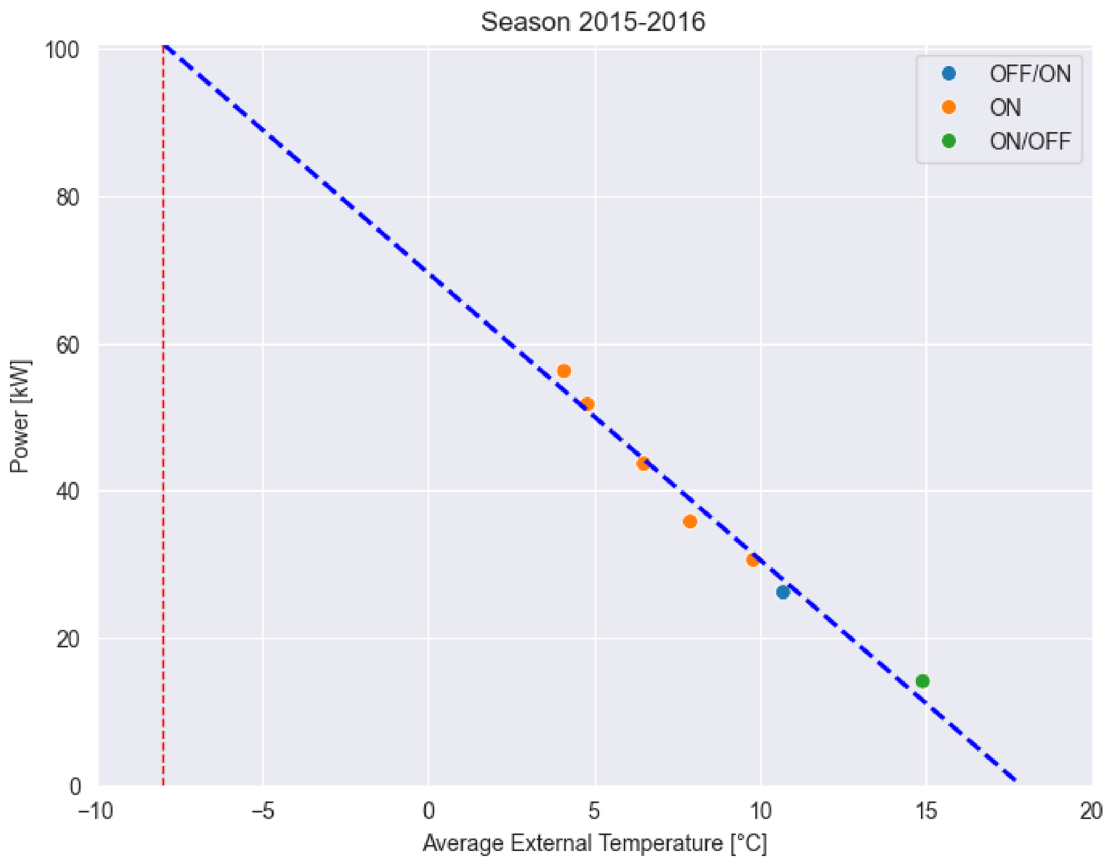
1.2.4 Call the function to plot the regression line for each season

[10]:
```
for season in seasons:
    plot_regression(df1, models[season], season)
```


Season 2012-2013
ON
ON/OFF
Power [kW]
100
80
60
40
20
0
−10
−5
0
5
10
15
20
Average External Temperature [°C]


Season 2013-2014
OFF/ON
ON
ON/OFF
Power [kW]
100
80
60
40
20
0
−10
−5
0
5
10
15
20
Average External Temperature [°C]


Season 2014-2015
OFF/ON
ON
Power [kW]
Average External Temperature [°C]
0
20
40
60
80
100
−10
−5
0
5
10
15
20



1.3 Overall model

1.3.1 Define the dataframe

[11]:
```
df_tot = df[df['tipo_misura'] != 'OFF']
```

1.3.2 Define the independent and dependent variables

[12]:
```
X_tot = df_tot[['T_media']].values
y_tot = df_tot['potenza'].values
```

1.3.3 Fit the model

[13]:
```
lm_tot = LinearRegression().fit(X_tot, y_tot)
```

1.3.4 Calculate the R^2 of the overall model

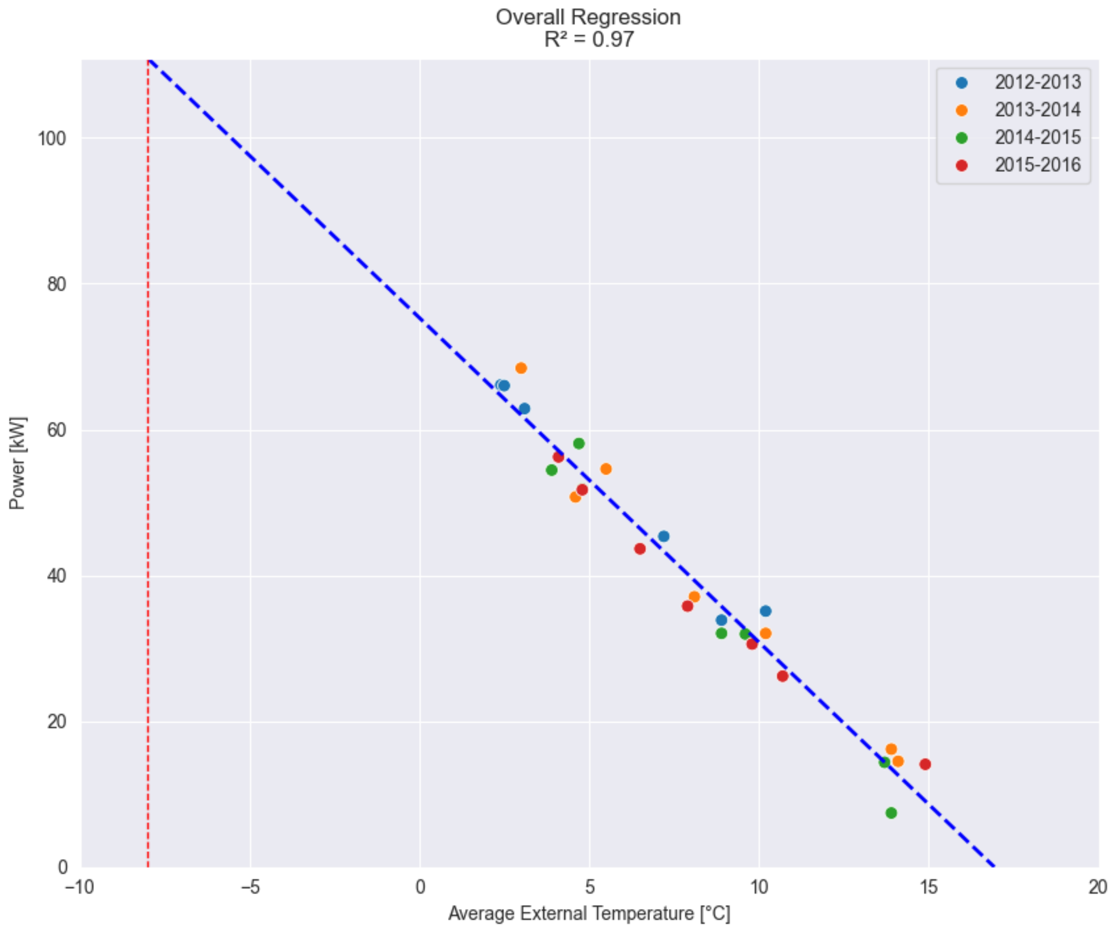
[14]:
```
r2_tot = lm_tot.score(X_tot, y_tot)
print(f"Summary of the overall model: R² = {r2_tot:.2f}")
```

```
Summary of the overall model: R² = 0.97
```

1.3.5 Plot the overall regression

Create a scatter plot of the data points and the regression line for the overall model Color the data points based on the season.

[15]:
```
# Plot the overall regression
plt.figure(figsize=(10, 8))
sns.scatterplot(x='T_media', y='potenza', hue='Stagione', data=df_tot, s=50)

# calculate T_max when y = 0
max_t_plot = -lm_tot.intercept_ / lm_tot.coef_[0]
# calculate P_max when T = -8
max_p_plot = lm_tot.predict([[-8.0]])[0]
# Generate values for plotting the regression line
X_plot = np.linspace(-8.0, max_t_plot, 100).reshape(-1, 1)
y_plot = lm_tot.predict(X_plot)
plt.plot(X_plot, y_plot, color='blue', linestyle='--', linewidth=2)
# add vertical line at T = -8
plt.axvline(x=-8, color='red', linestyle='--', linewidth=1)

# Set plot limits
plt.xlim(-10, 20)
plt.ylim(0, max_p_plot)

# Set labels and title
plt.xlabel('Average External Temperature [°C]')
plt.ylabel('Power [kW]')
plt.title(f"Overall Regression\nR² = {r2_tot:.2f}")

plt.legend()
plt.show()
```



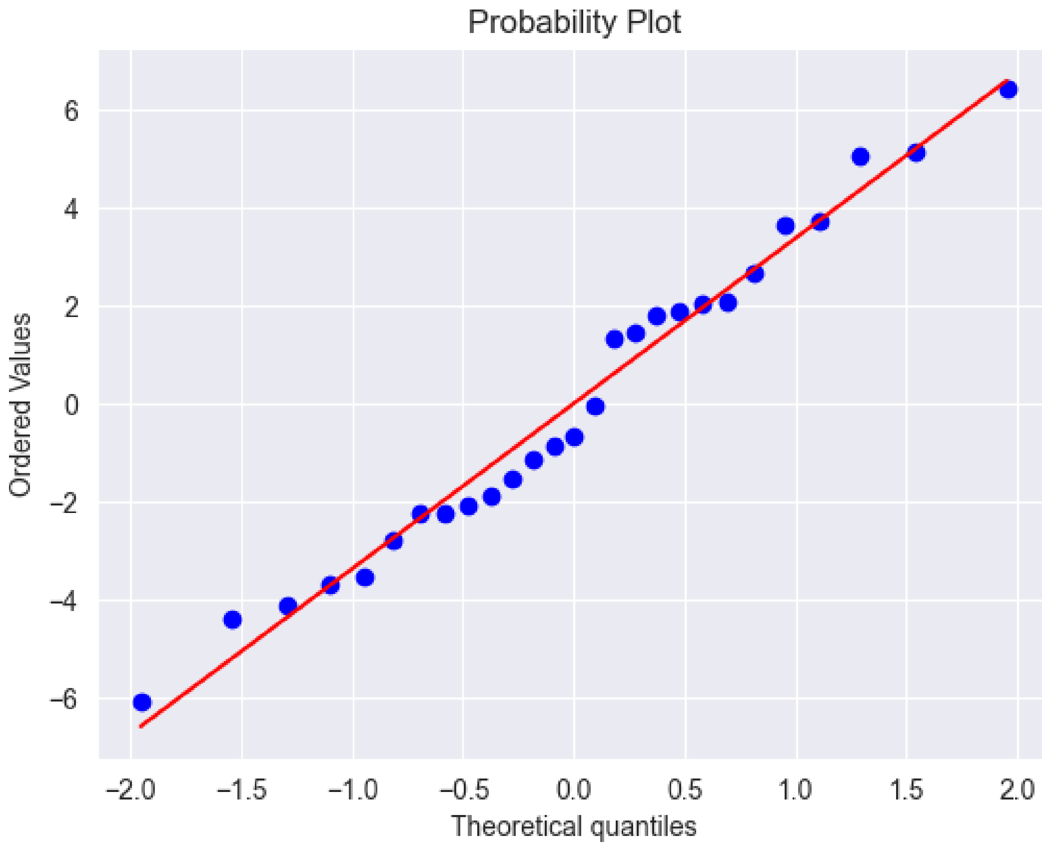
1.3.6 Assign the predicted values to a new column of the pre-retrofit dataframe

[16]:
```
df_tot['pred'] = lm_tot.predict(df_tot[['T_media']].values)
```

1.4 Model evaluation

1.4.1 QQ plot

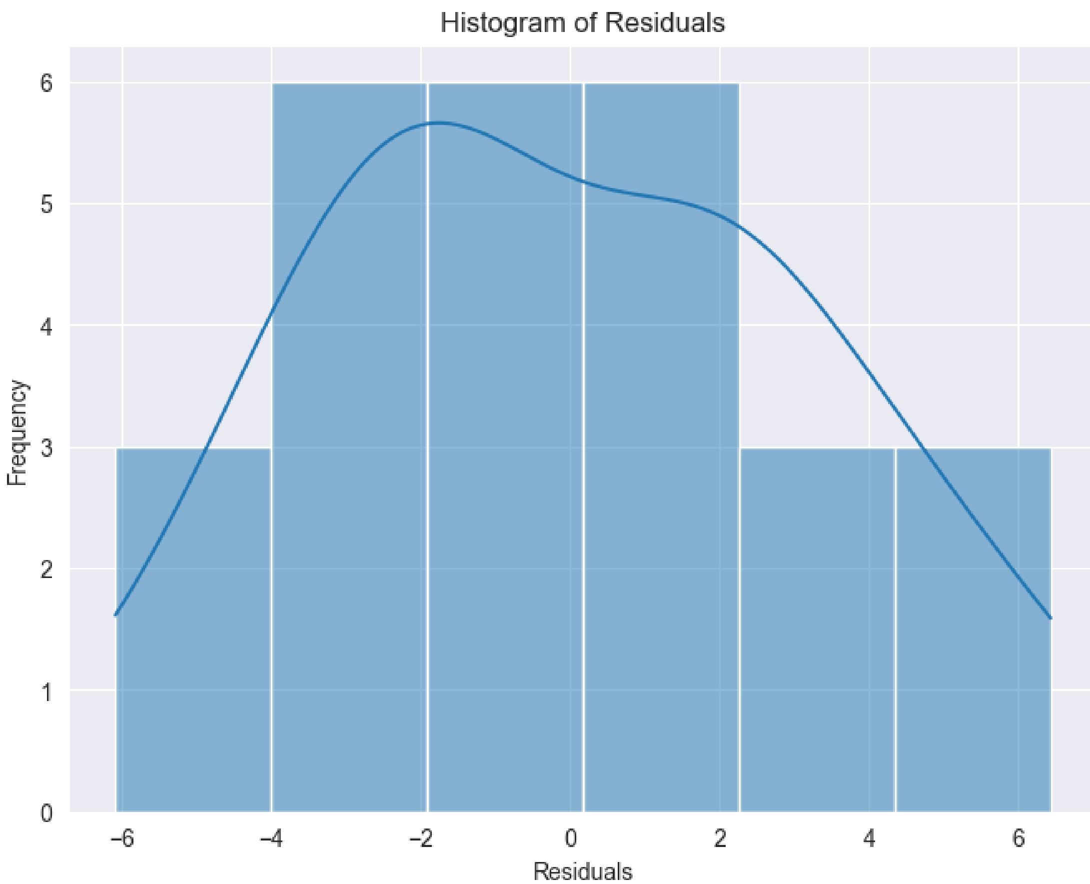
[17]:
```
import scipy.stats as stats

residuals = df_tot['potenza'] - df_tot['pred']
stats.probplot(residuals, dist="norm", plot=plt)
plt.show()
```



1. **`stats.probplot(residuals, dist="norm", plot=plt)`**
   - This line generates a Q-Q plot to visually assess whether the residuals follow a normal distribution.
   - **`stats.probplot()`** is a function from the `scipy.stats` library used to create probability plots.
   - **`residuals`** represents the residual values from a regression model.
   - **`dist="norm"`** specifies that the distribution to compare against is the normal distribution.
   - **`plot=plt`** tells the function to use `matplotlib` (`plt`) for plotting the Q-Q plot, providing a visual comparison of the residuals to a normal distribution.

1.4.2 Plot histogram of residuals

[18]:
```
plt.figure(figsize=(8, 6))
sns.histplot(residuals, kde=True)
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.title('Histogram of Residuals')
plt.show()
```



1.4.3 Calculate MAPE, RMSE, and CVRMSE

[19]:
```
# Calculate Mean Absolute Percentage Error (MAPE)
mape = mean_absolute_percentage_error(df_tot['potenza'], df_tot['pred']) * 100
print(f"MAPE: {mape:.2f}%")

# Calculate Root Mean Squared Error (RMSE)
rmse = sqrt(mean_squared_error(df_tot['potenza'], df_tot['pred']))
print(f"RMSE: {rmse:.2f}")

# Calculate Coefficient of Variation of RMSE (CVRMSE)
cvrmse = (rmse / df_tot['potenza'].mean()) * 100
print(f"CVRMSE: {cvrmse:.2f}%")
```

```
MAPE: 10.41%
RMSE: 3.20
CVRMSE: 7.93%
```

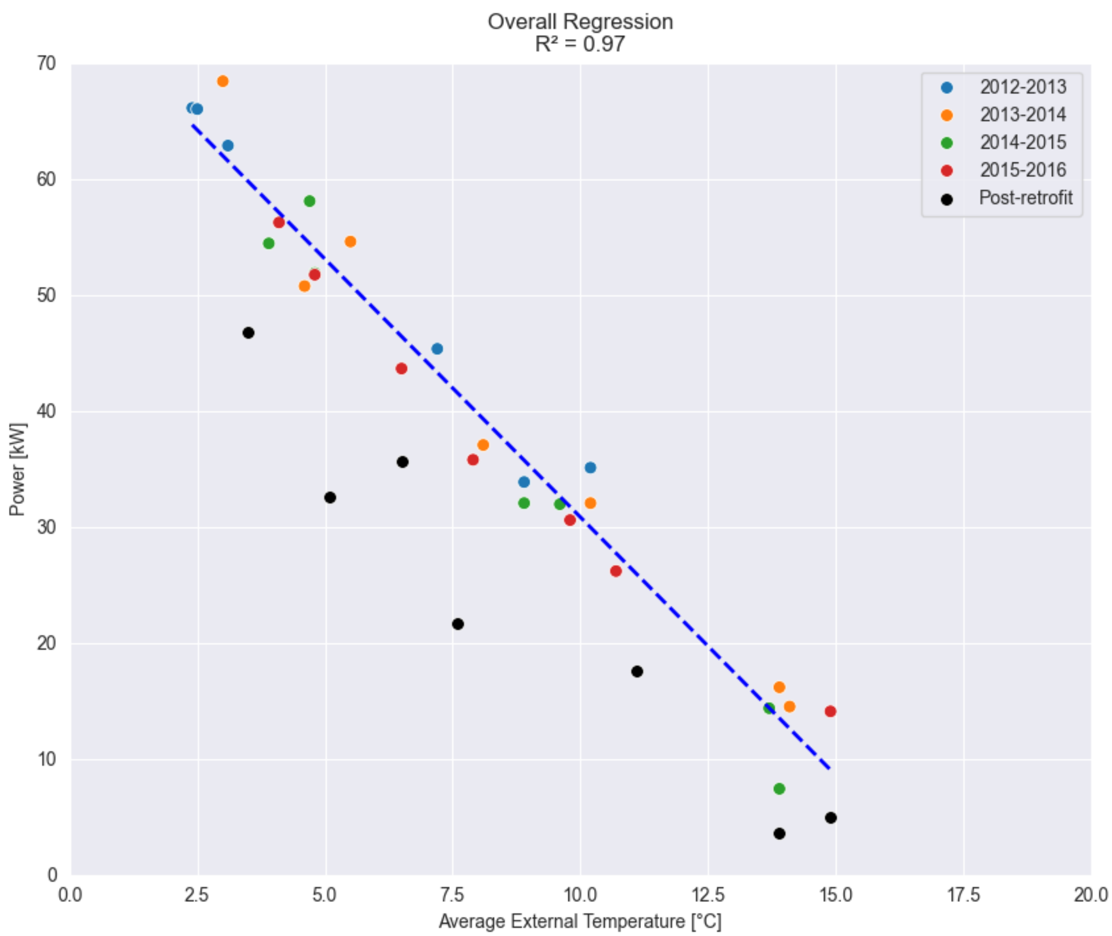
1.5 Saving calculations on post-retrofit data

1.5.1 import the post-retrofit data

[20]:
```
df_post = pd.read_csv('../data/post_retrofit.csv')

df_post['DATA_misura'] = pd.to_datetime(df_post['DATA_misura'], format="%d/%m/
↪%Y")
df_post['DATA_inizio'] = pd.to_datetime(df_post['DATA_inizio'], format="%d/%m/
↪%Y")

df_post['giorni_letture'] = (df_post['DATA_misura'] - df_post['DATA_inizio']).
↪dt.days
df_post['ore_tot'] = df_post['giorni_letture'] * 24
df_post['ore_ON'] = df_post['ore_tot'] - df_post['giorni_off'] * 24
df_post['potenza'] = (df_post['consumo_gasm_smc'] * cf) / df_post['ore_ON']
df_post['potenza'] = df_post['potenza'].replace([np.inf, -np.inf], np.nan)
df_post = df_post.dropna(subset=['potenza'])
df_post_clean = df_post[df_post['tipo_misura'] != 'OFF']
```

1.5.2 Plot model and post-retrofit data

[21]:
```
plt.figure(figsize=(10, 8))
sns.scatterplot(x='T_media', y='potenza', hue='Stagione', data=df_tot, s=50)
sns.scatterplot(x='T_media', y='potenza', color='black', data=df_post_clean,␣
↪s=50, label="Post-retrofit")

X_plot = np.linspace(df_tot['T_media'].min(), df_tot['T_media'].max(), 100).
↪reshape(-1, 1)
y_plot = lm_tot.predict(X_plot)
plt.plot(X_plot, y_plot, color='blue', linestyle='--', linewidth=2)

plt.xlim(0, 20)
plt.ylim(0, 70)

plt.xlabel('Average External Temperature [°C]')
plt.ylabel('Power [kW]')
plt.title(f"Overall Regression\nR² = {r2_tot:.2f}")

plt.legend()
plt.show()
```



1.5.3 Assign the predicted values to a new column of the post-retrofit dataframe

[22]:
```
df_post_clean['pred'] = lm_tot.predict(df_post_clean[['T_media']].values)
```

1.6 Energy saving assessment

1.6.1 Calculate the estimated consumption in post retrofit

[23]:
```
df_post_clean['consumo_stimato_smc'] = df_post_clean['pred'] *␣
  ↪df_post_clean['ore_ON'] / cf
```

1.6.2 Calculate the energy saving

[24]:
```
energy_saving = df_post_clean['consumo_stimato_smc'].sum() -␣
  ↪df_post_clean['consumo_gasm_smc'].sum()
print(f"Energy saving: {energy_saving:.2f} smc")
```

```
Energy saving: 4959.75 smc
```

[25]:

```
energy_saving_percentage = (energy_saving /␣
  ↪df_post_clean['consumo_stimato_smc'].sum()) * 100
print(f"Energy saving percentage: {energy_saving_percentage:.2f}%")
```

```
Energy saving percentage: 33.47%
```