Step 4.2: Feature Selection

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

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.svm import SVR

from sklearn.metrics import mean_squared_error,r2_score

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [2]:
```
# Load the Data set
df=pd.read_csv('Group_14_Clean_Data.csv')
df.head()
```

Out[2]:

	X1	Y1	X2	Y2	X3	Y3	X4	Y4	X5
0	316.5855	223.9277	182.3434	551.5497	7.8641	243.1339	361.0877	115.9284	78.6087
1	530.3136	68.7031	31.5983	175.2582	516.1441	63.4652	67.0954	369.4486	14.0930
2	27.3967	399.0488	565.6854	394.0466	120.2245	558.1293	546.4520	27.3256	314.1051
3	346.1526	59.6375	226.2742	280.9095	402.2161	218.7181	207.0407	339.5676	280.2195
4	317.9144	551.8542	335.4745	40.0240	316.6285	365.6434	416.3060	562.1028	211.3577

5 rows × 49 columns

In [3]:
```
# Define features and target variable

X = df.drop(columns=['Powerall'])
y = df['Powerall']
```

In [4]:
```
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [5]:
```
# Perform scaling after splitting
scaler = StandardScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [ ]:

```

```

Explanation of Lasso Regression for Feature Selection

Why Choose Lasso Regression?

Lasso Regression (Least Absolute Shrinkage and Selection Operator) is a powerful method for feature selection due to the following reasons:

1. Automatic Feature Selection:

- Lasso applies L1 regularization, which adds a penalty proportional to the absolute value of the coefficients. This results in some coefficients shrinking to exactly zero.
- Features with zero coefficients are automatically excluded, making Lasso an efficient way to reduce dimensionality and retain only the most important features.

2. Handles Multicollinearity:

- Lasso can handle multicollinearity (high correlation among features) by retaining only one of the highly correlated features, reducing redundancy in the dataset.

3. Simple and Effective:

- Unlike wrapper methods that require multiple iterations of model building, Lasso selects features in a single step, saving computational resources.

4. Interpretable Results:

- The selected features and their coefficients provide a clear understanding of their impact on the target variable.

Reason of ussing Lasso:

- The dataset contains a large number of features (positions and power outputs for multiple WECs).
- Not all features are equally important for predicting Powerall.
- Lasso identifies the most relevant features, improving model performance and interpretability while reducing overfitting.

In [15]:

```
from sklearn.linear_model import LassoCV

lasso = LassoCV(cv=3, random_state=42)
lasso.fit(X_train_scaled, y_train)
```

```python
# Identify important features
lasso_importances = pd.Series(data=lasso.coef_, index=X.columns)
important_features = lasso_importances[lasso_importances != 0].index
print("Selected Features by Lasso:", important_features.tolist())
```

```
Selected Features by Lasso: ['P1', 'P2', 'P3', 'P4', 'P5', 'P6', 'P7', 'P8', 'P9',
'P10', 'P11', 'P12', 'P13', 'P14', 'P15', 'P16']
```

In [16]:
```python
# Rebuild dataset with selected features
X_train_selected = X_train[important_features]
X_test_selected = X_test[important_features]
```

In [17]:
```python
# Scale selected features
scaler_selected = StandardScaler()
X_train_selected_scaled = scaler_selected.fit_transform(X_train_selected)
X_test_selected_scaled = scaler_selected.transform(X_test_selected)
```

In [18]:
```python
# Initialize models
models_selected= {
    "Linear_Regression": LinearRegression(),
    "K_Nearest_Neighbors": KNeighborsRegressor(n_neighbors=5),
    "Random_Forest": RandomForestRegressor(n_estimators=50,max_depth= 10,random_sta
    "SVM_Linear_Kernel": SVR(kernel="linear"),
    "SVM_RBF_Kernel": SVR(kernel='rbf',C=100,gamma=0.1),
    "Gradient_Boosting": GradientBoostingRegressor(n_estimators=50, max_depth=3, ra
}
```

In [19]:
```python
# Rebuild models with selected features
results_selected = {}
for model_name, model in models_selected.items():
    model.fit(X_train_selected_scaled, y_train)
    y_train_pred = model.predict(X_train_selected_scaled)
    y_test_pred = model.predict(X_test_selected_scaled)

    train_rmse = np.sqrt(mean_squared_error(y_train, y_train_pred))
    test_rmse = np.sqrt(mean_squared_error(y_test, y_test_pred))
    train_r2 = r2_score(y_train, y_train_pred)
    test_r2 = r2_score(y_test, y_test_pred)

    results_selected[model_name] = {"Train_RMSE": train_rmse, "Test_RMSE": test_rms
                                    "Train_R2": train_r2, "Test_R2": test_r2}
```

In [24]:
```python
# Convert results to DataFrame
results_selected_df = pd.DataFrame(results_selected).T
results_selected_df
```

Out[24]:

	Train_RMSE	Test_RMSE	Train_R2	Test_R2
Linear_Regression	370.009543	230.190600	0.999955	0.999983
K_Nearest_Neighbors	13283.319359	16353.409818	0.942151	0.914315
Random_Forest	20786.467203	22968.382043	0.858341	0.830976
SVM_Linear_Kernel	370.072019	229.977084	0.999955	0.999983
SVM_RBF_Kernel	17172.558568	17325.680147	0.903316	0.903824
Gradient_Boosting	18371.891596	18898.750074	0.889340	0.885566

After feature selection, the results highlight the following:

1. Linear Regression and SVM (Linear Kernel): Top performers with near-perfect R^2 scores (0.9999) and minimal RMSE values (370.01 Train, 230.19 Test). Best suited for this dataset due to its linear relationships.
2. K-Nearest Neighbors: Moderate performance with R^2 (0.9143 Test) and higher RMSE (16,353 Test).
3. Random Forest and Gradient Boosting: Reasonable but less accurate, with lower R^2 (0.8309 Test) and higher RMSE values.
4. SVM (RBF Kernel): Decent performance (0.9038 Test R^2) but outperformed by linear models.

Linear Regression and SVM (Linear Kernel) are the best models after feature selection. Future work should focus on optimizing these models.

Step 4.3: Hyperparameter Tuning

In [25]:

```
from sklearn.model_selection import RandomizedSearchCV

# Define parameter grids for each model
param_grids = {
    "K_Nearest_Neighbors": {
        "n_neighbors": [3, 5, 10, 20],
        "weights": ['uniform', 'distance']
    },
    "Random_Forest": {
        "n_estimators": [50, 100, 200],
        "max_depth": [None, 10, 20]
    },
    "SVM_Linear_Kernel": {
        "C": [0.1, 1, 10]
    },
    "SVM_RBF_Kernel": {
        "C": [0.1, 1, 10],
```

```
        "gamma": ['scale', 'auto']
    },
    "Gradient_Boosting": {
        "n_estimators": [50, 100, 200],
        "learning_rate": [0.01, 0.1, 0.2]
    }
}
```

In [29]:
```
warnings.simplefilter(action='ignore', category=UserWarning)
```

In [31]:
```
# Perform Random Search for each model
tuned_models = {}
best_params = {}

for model_name, model in models_original.items():
    if model_name in param_grids:  # Skip Linear Regression (no hyperparameters)
        print(f"Tuning {model_name}...")
        rand_search = RandomizedSearchCV(
            estimator=model,
            param_distributions=param_grids[model_name],
            scoring='neg_mean_squared_error',
            cv=3,
            random_state=42,
            n_iter=10
        )
        rand_search.fit(X_train_scaled, y_train)
        tuned_models[model_name] = rand_search.best_estimator_
        best_params[model_name] = rand_search.best_params_
        print(f"Best Parameters for {model_name}: {rand_search.best_params_}")
```

```
Tuning K_Nearest_Neighbors...
Best Parameters for K_Nearest_Neighbors: {'weights': 'distance', 'n_neighbors': 10}
Tuning Random_Forest...
Best Parameters for Random_Forest: {'n_estimators': 200, 'max_depth': None}
Tuning SVM_Linear_Kernel...
Best Parameters for SVM_Linear_Kernel: {'C': 10}
Tuning SVM_RBF_Kernel...
Best Parameters for SVM_RBF_Kernel: {'gamma': 'scale', 'C': 10}
Tuning Gradient_Boosting...
Best Parameters for Gradient_Boosting: {'n_estimators': 200, 'learning_rate': 0.2}
```

In [32]:
```
# Store results for tuned models
tuned_results = {}

for model_name, model in tuned_models.items():
    y_train_pred = model.predict(X_train_scaled)
    y_test_pred = model.predict(X_test_scaled)

    train_rmse = np.sqrt(mean_squared_error(y_train, y_train_pred))
    test_rmse = np.sqrt(mean_squared_error(y_test, y_test_pred))
    train_r2 = r2_score(y_train, y_train_pred)
    test_r2 = r2_score(y_test, y_test_pred)

    tuned_results[model_name] = {"Train_RMSE": train_rmse, "Test_RMSE": test_rmse,
                                 "Train_R2": train_r2, "Test_R2": test_r2}
```

In [33]:
```python
# Convert results to DataFrame
tuned_results_df = pd.DataFrame(tuned_results).T
print(tuned_results_df)
```

```
                      Train_RMSE     Test_RMSE  Train_R2   Test_R2
K_Nearest_Neighbors     0.003368  19117.054832  1.000000  0.882907
Random_Forest        6125.410789  16396.287382  0.987699  0.913865
SVM_Linear_Kernel     370.071964    229.977465  0.999955  0.999983
SVM_RBF_Kernel      47754.606530  48428.936874  0.252324  0.248553
Gradient_Boosting    6720.336957   7247.047816  0.985193  0.983173
```

In [34]:
```python
# Visualize performance before and after tuning
original_results_df = pd.DataFrame(results).T
```

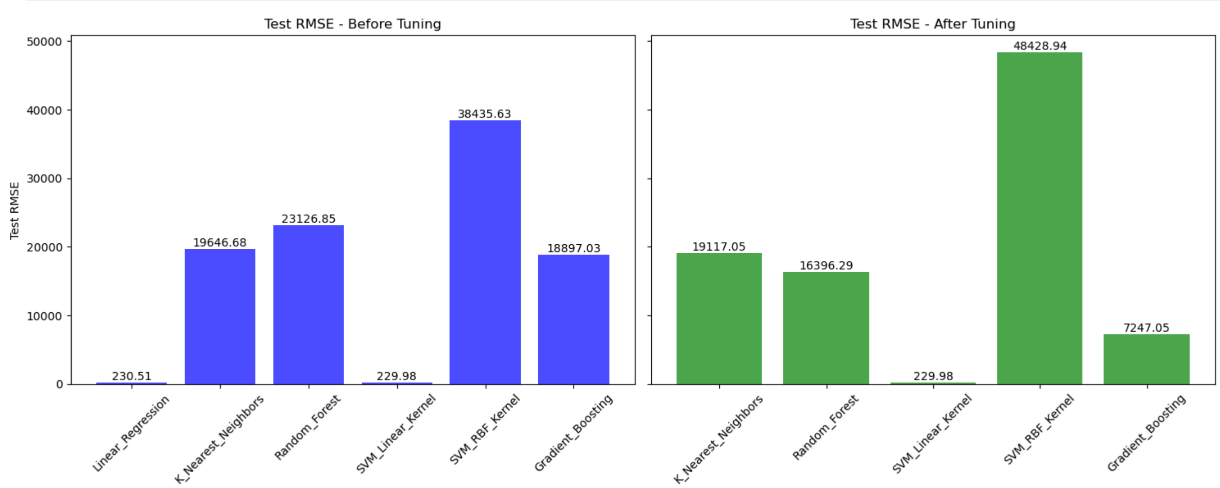
In [35]:
```python
# Set up a figure with two subplots
fig, axes = plt.subplots(1, 2, figsize=(15, 6), sharey=True)

# Plot Original Results
axes[0].bar(original_results_df.index, original_results_df["Test_RMSE"], color='blu
axes[0].set_title("Test RMSE - Before Tuning")
axes[0].set_ylabel("Test RMSE")
axes[0].tick_params(axis='x', rotation=45)

# Plot Tuned Results
axes[1].bar(tuned_results_df.index, tuned_results_df["Test_RMSE"], color='green', a
axes[1].set_title("Test RMSE - After Tuning")
axes[1].tick_params(axis='x', rotation=45)

for i, val in enumerate(original_results_df["Test_RMSE"]):
    axes[0].text(i, val, f"{val:.2f}", ha='center', va='bottom', fontsize=10)
for i, val in enumerate(tuned_results_df["Test_RMSE"]):
    axes[1].text(i, val, f"{val:.2f}", ha='center', va='bottom', fontsize=10)

# Adjust layout
plt.tight_layout()
plt.show()
```



In [36]:
```python
# Set up a figure with two subplots
fig, axes = plt.subplots(1, 2, figsize=(15, 6), sharey=True)
```

```
# Plot Original Results
axes[0].bar(original_results_df.index, original_results_df["Test_R2"], color='blue'
axes[0].set_title("Test R² - Before Tuning")
axes[0].set_ylabel("Test R²")
axes[0].tick_params(axis='x', rotation=45)

# Plot Tuned Results
axes[1].bar(tuned_results_df.index, tuned_results_df["Test_R2"], color='green', alp
axes[1].set_title("Test R² - After Tuning")
axes[1].tick_params(axis='x', rotation=45)

for i, val in enumerate(original_results_df["Test_R2"]):
    axes[0].text(i, val, f"{val:.2f}", ha='center', va='bottom', fontsize=10)
for i, val in enumerate(tuned_results_df["Test_R2"]):
    axes[1].text(i, val, f"{val:.2f}", ha='center', va='bottom', fontsize=10)

# Adjust layout
plt.tight_layout()
plt.show()
```