In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error,r2_score
import matplotlib.pyplot as plt
```

In [2]:
```
data = pd.read_csv(r"C:\\Users\\ASUS\\Desktop\\ML1 project\\household_power_co
nsumption.csv",nrows=5000)
data.shape
```

Out[2]:
```
(5000, 9)
```

In [3]:
```
data.head(5)
```

Out[3]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Su
0	16/12/2006	17:24:00	4.216	0.418	234.84	18.4	
1	16/12/2006	17:25:00	5.360	0.436	233.63	23.0	
2	16/12/2006	17:26:00	5.374	0.498	233.29	23.0	
3	16/12/2006	17:27:00	5.388	0.502	233.74	23.0	
4	16/12/2006	17:28:00	3.666	0.528	235.68	15.8	

In [4]:
```
data.tail(5)
```

Out[4]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity
4995	20/12/2006	4:39:00	0.414	0.258	246.66	2.0
4996	20/12/2006	4:40:00	0.392	0.250	246.06	1.8
4997	20/12/2006	4:41:00	0.388	0.248	246.52	1.8
4998	20/12/2006	4:42:00	0.310	0.144	247.00	1.4
4999	20/12/2006	4:43:00	0.308	0.144	247.21	1.4

In [5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 9 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Date                   5000 non-null   object
 1   Time                   5000 non-null   object
 2   Global_active_power    5000 non-null   float64
 3   Global_reactive_power  5000 non-null   float64
 4   Voltage                5000 non-null   float64
 5   Global_intensity       5000 non-null   float64
 6   Sub_metering_1         5000 non-null   int64
 7   Sub_metering_2         5000 non-null   int64
 8   Sub_metering_3         5000 non-null   int64
dtypes: float64(4), int64(3), object(2)
memory usage: 351.7+ KB
```

In [6]:
```
data.dtypes
```

Out[6]:
```
Date                      object
Time                      object
Global_active_power      float64
Global_reactive_power    float64
Voltage                  float64
Global_intensity         float64
Sub_metering_1             int64
Sub_metering_2             int64
Sub_metering_3             int64
dtype: object
```

In [7]:
```
data['date_time'] = pd.to_datetime(data['Date'] + ' ' + data['Time'], format
='%d/%m/%Y %H:%M:%S')
data.drop(columns=['Date', 'Time'], inplace=True)
data.set_index('date_time', inplace=True)
data.head(5)
```

Out[7]:

date_time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1
2006-12-16 17:24:00	4.216	0.418	234.84	18.4	0
2006-12-16 17:25:00	5.360	0.436	233.63	23.0	0
2006-12-16 17:26:00	5.374	0.498	233.29	23.0	0
2006-12-16 17:27:00	5.388	0.502	233.74	23.0	0
2006-12-16 17:28:00	3.666	0.528	235.68	15.8	0

In [8]:
```
data.describe()
```

Out[8]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000
mean	1.718148	0.120149	240.972194	7.287000	0.787000
std	1.301801	0.109505	3.961620	5.500968	5.147012
min	0.194000	0.000000	229.080000	0.800000	0.000000
25%	0.380000	0.000000	238.157500	1.800000	0.000000
50%	1.626000	0.104000	241.410000	6.800000	0.000000
75%	2.502000	0.176000	244.050000	10.400000	0.000000
max	7.840000	0.646000	249.370000	33.600000	38.000000

In [9]:
```
data.isnull().sum()
```

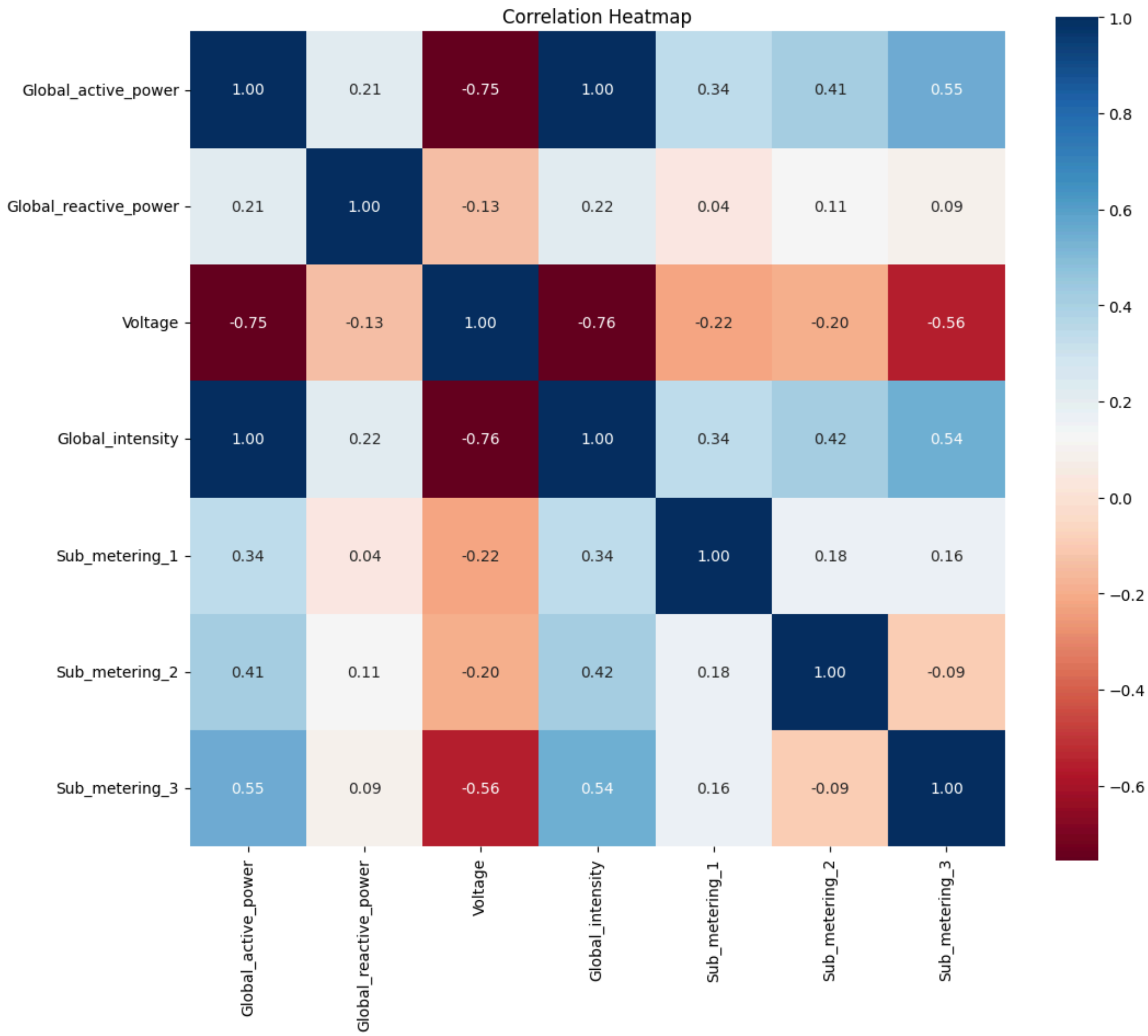
Out[9]:
```
Global_active_power      0
Global_reactive_power    0
Voltage                  0
Global_intensity         0
Sub_metering_1           0
Sub_metering_2           0
Sub_metering_3           0
dtype: int64
```

In [10]:
```
data.replace('?', np.nan, inplace=True)
data = data.apply(pd.to_numeric, errors='coerce')
data.dropna(axis=0, inplace=True)
```

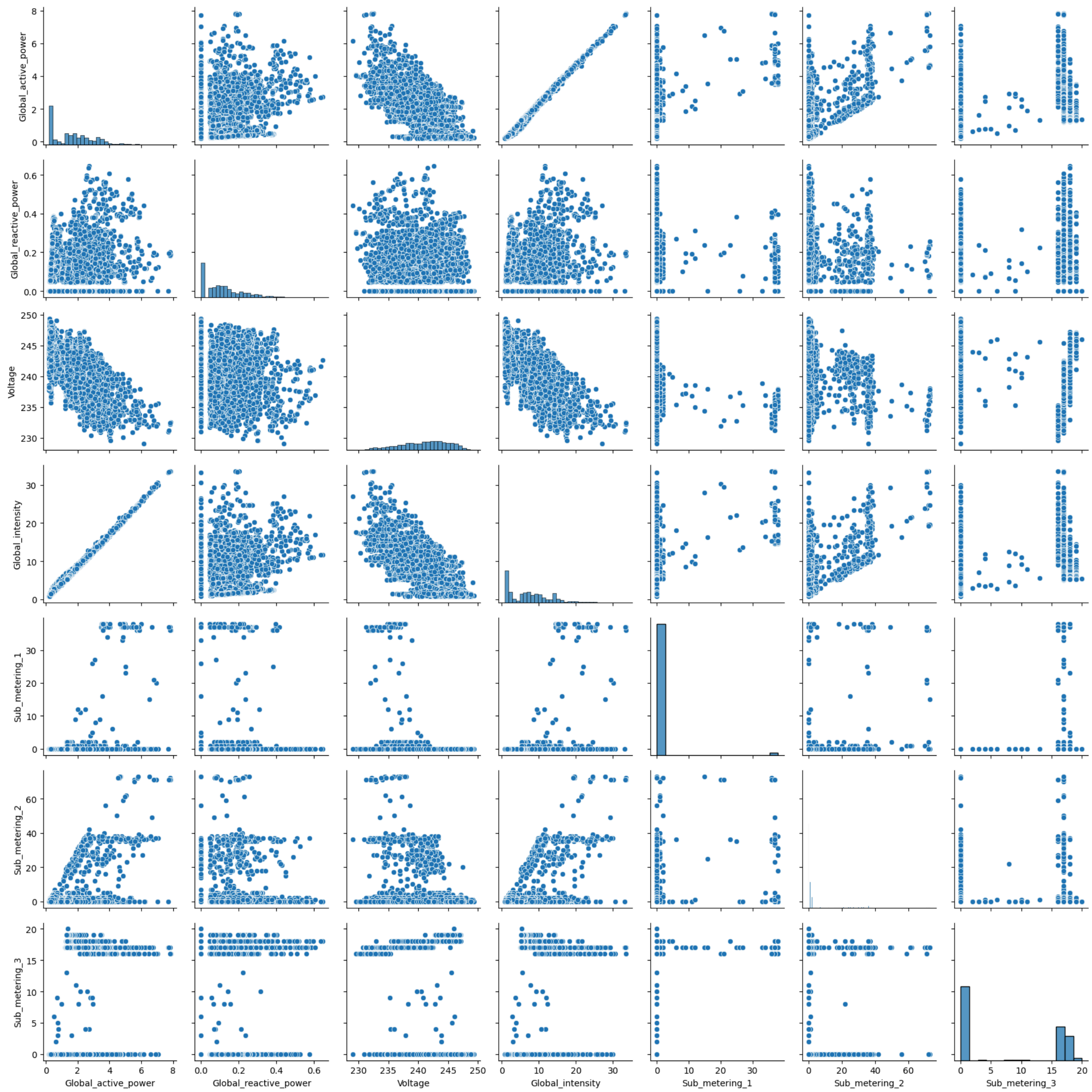
In [11]:
```
data.isnull().sum()
```

Out[11]:
```
Global_active_power      0
Global_reactive_power    0
Voltage                  0
Global_intensity         0
Sub_metering_1           0
Sub_metering_2           0
Sub_metering_3           0
dtype: int64
```

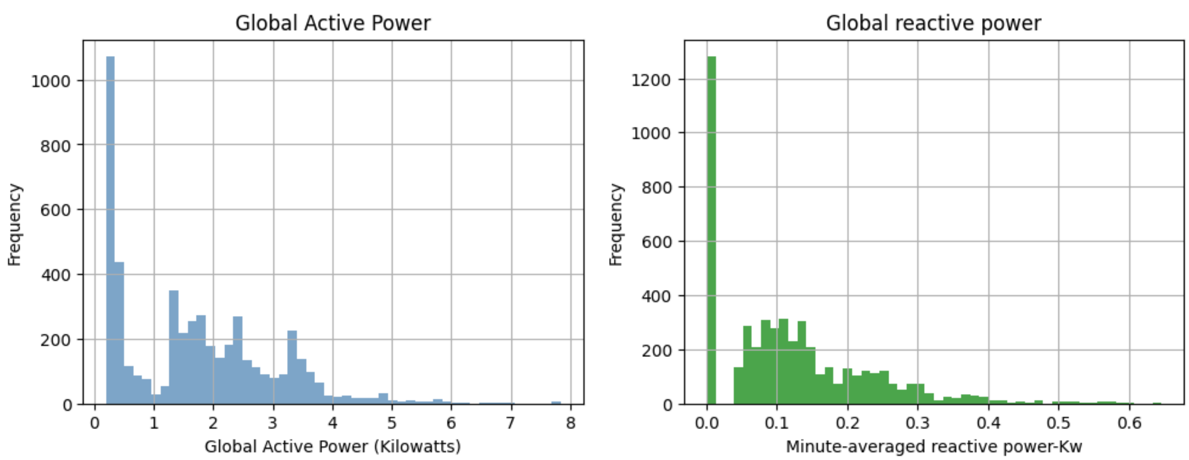
In [12]:
```
plt.figure(figsize=(12,10))
sns.heatmap(data.corr(),annot=True,fmt=".2f",cmap='RdBu',square=True)
plt.title("Correlation Heatmap")
plt.show()
```



In [13]:
```
sns.pairplot(data, height=2.5)
plt.tight_layout()
plt.show()
```



In [14]:
```
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.hist(data['Global_active_power'],bins=50,color='steelblue',alpha=0.7)
plt.title('Global Active Power')
plt.xlabel('Global Active Power (Kilowatts)')
plt.ylabel('Frequency')
plt.grid(True)

plt.subplot(1,2,2)
plt.hist(data['Global_reactive_power'],bins=50,color='green',alpha=0.7)
plt.title('Global reactive power')
plt.xlabel('Minute-averaged reactive power-Kw')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



In [15]:
```
X = data.drop(columns=['Global_active_power'])  # Features
y = data['Global_active_power']  # Target variable

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

In [16]:
```
print(X_train.shape)
print(X_test.shape)
```

```
(4000, 6)
(1000, 6)
```

In [17]:
```
X_train.describe()
```

Out[17]:

	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub
count	4000.000000	4000.00000	4000.00000	4000.000000	4000.000000	
mean	0.120554	240.99829	7.22545	0.755250	2.905000	
std	0.109299	3.92977	5.46814	5.044275	9.069732	
min	0.000000	229.08000	0.80000	0.000000	0.000000	
25%	0.000000	238.21750	1.80000	0.000000	0.000000	
50%	0.104000	241.41000	6.60000	0.000000	0.000000	
75%	0.178000	244.05000	10.40000	0.000000	1.000000	
max	0.636000	249.37000	33.60000	38.000000	73.000000	

In [18]:
```
# Linear Regression
linear_reg_model = LinearRegression()
linear_reg_model.fit(X_train, y_train)

y_pred_lin_train = linear_reg_model.predict(X_train)
y_pred_lin_test = linear_reg_model.predict(X_test)

train_lin_mse = mean_squared_error(y_train, y_pred_lin_train)
test_lin_mse = mean_squared_error(y_test, y_pred_lin_test)

train_lin_r2 = r2_score(y_train, y_pred_lin_train)
test_lin_r2 = r2_score(y_test, y_pred_lin_test)

print("Train MSE: %.6f , Test MSE: %.6f"%(train_lin_mse,test_lin_mse))
print("Train R2_score: %.6f , Test R2_score: %.6f"%(train_lin_r2,test_lin_r2))
```

```
Train MSE: 0.003912 , Test MSE: 0.004393
Train R2_score: 0.997664 , Test R2_score: 0.997516
```

In [19]:
```
# Decision Tree regression
tree = DecisionTreeRegressor()
tree.fit(X_train, y_train)

y_pred_tree_train = tree.predict(X_train)
y_pred_tree_test = tree.predict(X_test)

train_tree_mse = mean_squared_error(y_train, y_pred_tree_train)
test_tree_mse = mean_squared_error(y_test, y_pred_tree_test)

train_tree_r2 = r2_score(y_train, y_pred_tree_train)
test_tree_r2 = r2_score(y_test, y_pred_tree_test)

print("Train MSE: %.6f , Test MSE: %.6f"%(train_tree_mse,test_tree_mse))
print("Train R2_score: %.6f , Test R2_score: %.6f"%(train_tree_r2,test_tree_r
2))
```

```
Train MSE: 0.000001 , Test MSE: 0.004681
Train R2_score: 1.000000 , Test R2_score: 0.997353
```

In [20]:
```
# Hyperparameter Tuning on Decision Tree Regression
param_grid_tree = {
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

grid_search_tree = GridSearchCV(tree, param_grid=param_grid_tree, cv=5, scorin
g='neg_mean_squared_error')
grid_search_tree.fit(X_train, y_train)

best_params_dt = grid_search_tree.best_params_
best_score_dt = -grid_search_tree.best_score_

print("Best Parameters (Decision Tree):", best_params_dt)
print("Best Negative MSE (Decision Tree):", best_score_dt)
```

```
Best Parameters (Decision Tree): {'max_depth': 10, 'min_samples_leaf': 4, 'mi
n_samples_split': 2}
Best Negative MSE (Decision Tree): 0.0035151518385264577
```

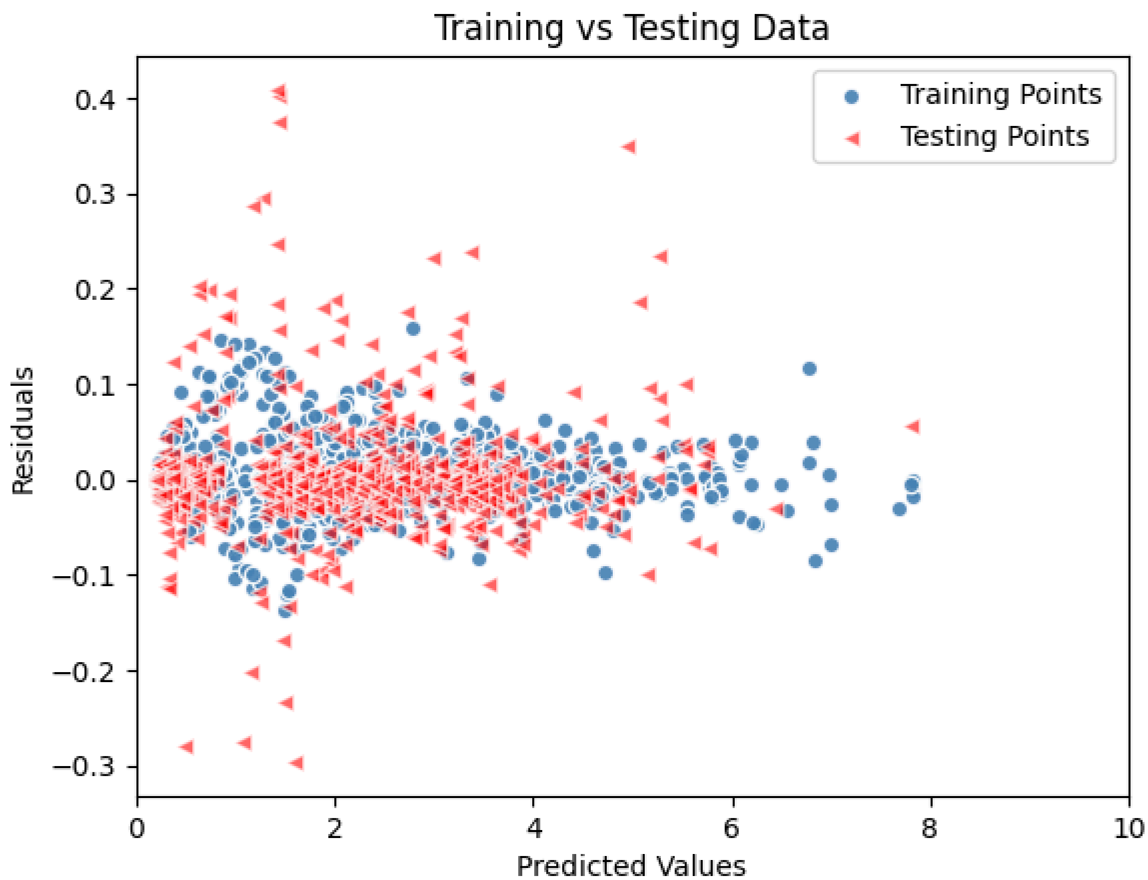
In [21]:
```
best_tree_model = DecisionTreeRegressor(max_depth=10, min_samples_leaf=4, min_
samples_split=5)
best_tree_model.fit(X_train, y_train)

y_pred_tree_test_best = best_tree_model.predict(X_test)

test_tree_mse_best = mean_squared_error(y_test, y_pred_tree_test_best)
test_tree_r2_best = r2_score(y_test, y_pred_tree_test_best)

print("Best Decision Tree Mean Squared Error:", test_tree_mse)
print("Best Decision Tree R2 Score:", test_tree_r2)
```

```
Best Decision Tree Mean Squared Error: 0.004681355
Best Decision Tree R2 Score: 0.9973529744288679
```

In [22]:
```
random_model = RandomForestRegressor()
random_model.fit(X_train, y_train)

y_pred_random_train = random_model.predict(X_train)
y_pred_random_test = random_model.predict(X_test)

train_ran_mse = mean_squared_error(y_train, y_pred_random_train)
test_ran_mse = mean_squared_error(y_test, y_pred_random_test)

train_ran_r2 = r2_score(y_train, y_pred_random_train)
test_ran_r2 = r2_score(y_test, y_pred_random_test)

print("Train MSE: %.6f , Test MSE: %.6f"%(train_ran_mse,test_ran_mse))
print("Train R2_score: %.6f , Test R2_score: %.6f"%(train_ran_r2,test_ran_r2))
```

```
Train MSE: 0.000355 , Test MSE: 0.002834
Train R2_score: 0.999788 , Test R2_score: 0.998397
```

In [23]:
```
plt.scatter(y_pred_random_train,y_pred_random_train-y_train,
            color='steelblue',edgecolors='white',
            marker='o',alpha=0.9,
            label='Training Points')
plt.scatter(y_pred_random_test,y_pred_random_test-y_test,
            color='red',edgecolors='white',
            marker='<',alpha=0.6,
            label='Testing Points')
plt.title('Training vs Testing Data')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.legend(loc='upper right')
plt.xlim([0,10])
plt.show()
```



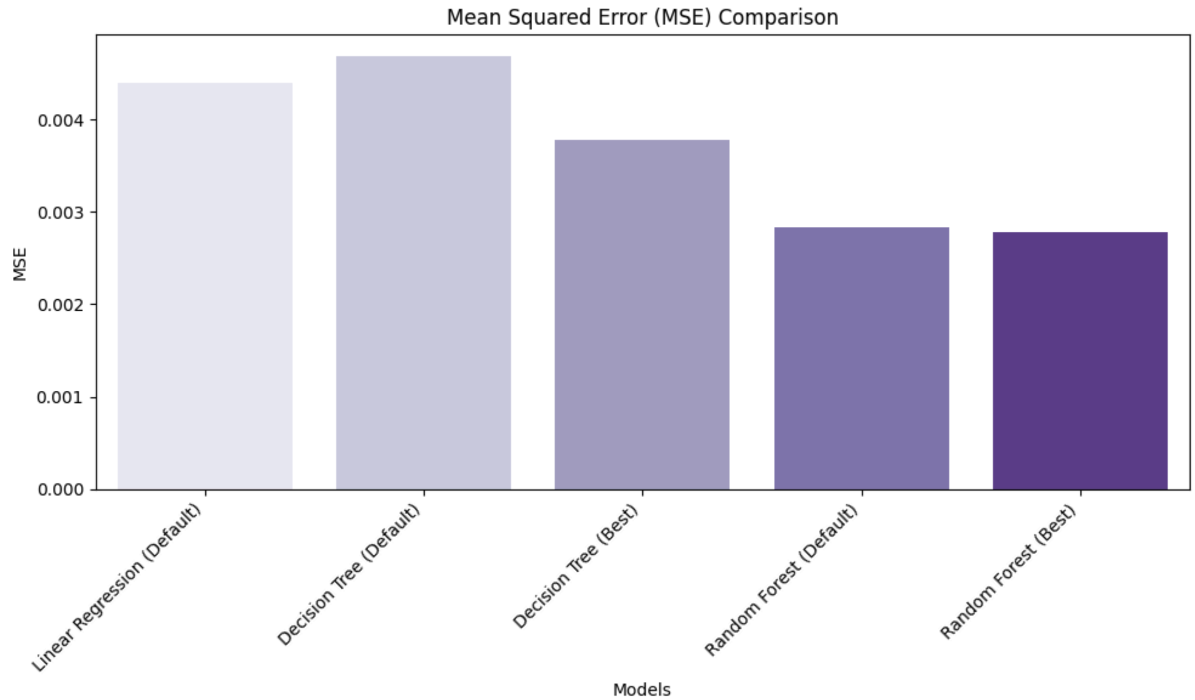
In [29]:
```
# Hyperparameter Tuning on Random Forest Regression
param_grid_rf = {
    'n_estimators': [5, 50],
    'max_depth': [None, 10],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1]
}

grid_search_rf = GridSearchCV(estimator=random_model, param_grid=param_grid_r
f, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_search_rf.fit(X_train, y_train)

best_params_rf = grid_search_rf.best_params_
best_score_rf = -grid_search_rf.best_score_

print("Best Parameters (Random Forest):", best_params_rf)
print("Best Negative MSE (Random Forest):", best_score_rf)
```

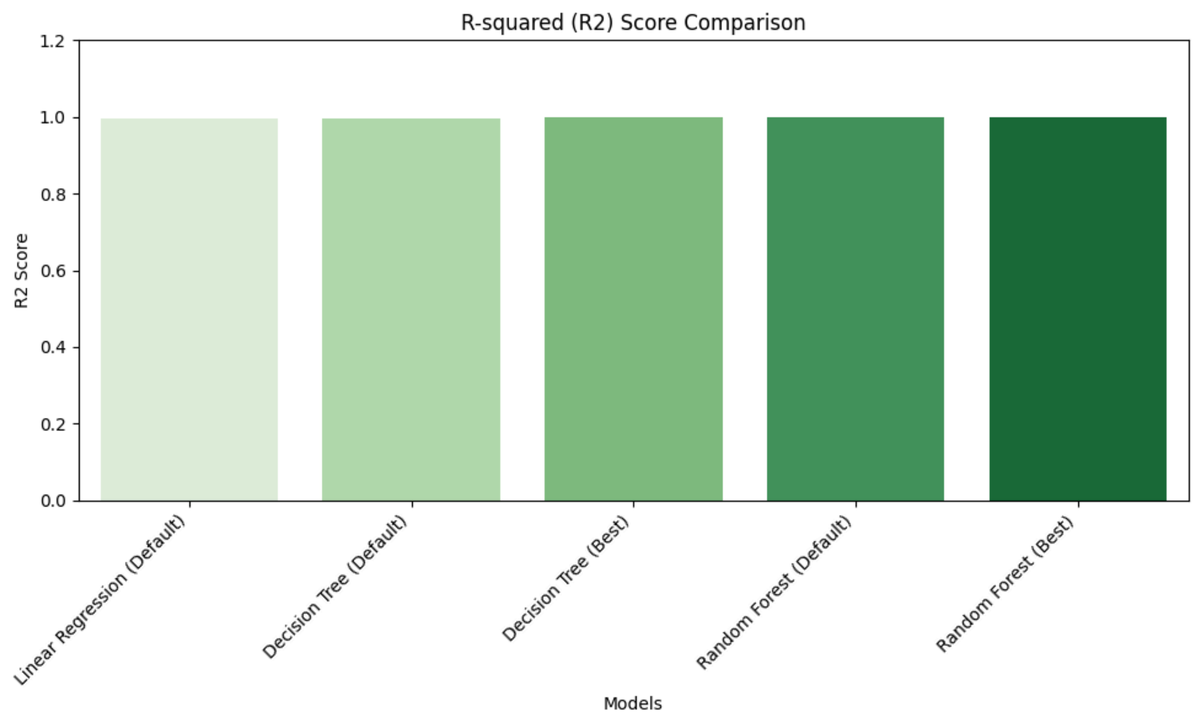
```
Best Parameters (Random Forest): {'max_depth': None, 'min_samples_leaf': 1,
'min_samples_split': 5, 'n_estimators': 50}
Best Negative MSE (Random Forest): 0.0026500304459620666
```

In [30]:
```
best_params_rf = {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_spli
t': 5, 'n_estimators': 50}

best_rf_model = RandomForestRegressor(**best_params_rf)

best_rf_model.fit(X_train, y_train)
y_pred_rf_test_best = best_rf_model.predict(X_test)

test_ran_mse_best = mean_squared_error(y_test, y_pred_rf_test_best)
test_ran_r2_best = r2_score(y_test, y_pred_rf_test_best)

print("Best Random Forest Mean Squared Error:", test_ran_mse_best)
print("Best Random Forest R2 Score:", test_ran_r2_best)
```

```
Best Random Forest Mean Squared Error: 0.00277626922729103
Best Random Forest R2 Score: 0.9984301862095513
```

In [32]:
```
models = ['Linear Regression (Default)', 'Decision Tree (Default)','Decision Tree (Best)', 'Random Forest (Default)','Random Forest (Best)']

mse_values = [test_lin_mse, test_tree_mse,test_tree_mse_best, test_ran_mse, test_ran_mse_best]
r2_values = [test_lin_r2, test_tree_r2,test_tree_r2_best, test_ran_r2, test_ran_r2_best]

plt.figure(figsize=(10,6))
sns.barplot(x=models, y=mse_values, hue=models, palette='Purples', dodge=False)
plt.title('Mean Squared Error (MSE) Comparison')
plt.xlabel('Models')
plt.ylabel('MSE')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()


plt.figure(figsize=(10, 6))
sns.barplot(x=models, y=r2_values, hue=models, palette='Greens', dodge=False)
plt.title('R-squared (R2) Score Comparison')
plt.xlabel('Models')
plt.ylabel('R2 Score')
plt.xticks(rotation=45, ha='right')
plt.ylim(0, 1.2)
plt.tight_layout()
plt.show()
```


Mean Squared Error (MSE) Comparison
MSE
0.000
0.001
0.002
0.003
0.004
Linear Regression (Default)
Decision Tree (Default)
Decision Tree (Best)
Random Forest (Default)
Random Forest (Best)
Models


R-squared (R2) Score Comparison
R2 Score
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Linear Regression (Default)
Decision Tree (Default)
Decision Tree (Best)
Random Forest (Default)
Random Forest (Best)
Models