Instructions:

To complete the following task using Python, please download an Integrated Development Environment (IDE) of your choice. Ensure that your solution includes both the written code (input) and its corresponding output. Once completed, upload your solution in PDF format or any other format you prefer. The questions are worth 50 points each.

Question 2: Predicting Building Energy Efficiency

Objective:

Apply regression techniques using Scikit-learn to analyze and predict the energy efficiency of buildings, focusing on heating and cooling load requirements. This involves the use of various regression models, feature engineering, and model evaluation.

Dataset:

The dataset for this assignment, Energy Efficiency Dataset, can be found at the UCI Machine Learning Repository. It includes architectural features and energy efficiency metrics of buildings. The dataset columns are renamed for clarity as follows:

```
column_names = {'X1':'Relative_Compactness', 'X2': 'Surface_Area',
'X3': 'Wall_Area', 'X4': 'Roof_Area',
'X5': 'Overall_Height', 'X6': 'Orientation',
'X7': 'Glazing_Area', 'X8': 'Glazing_Area_Distribution',
'Y1': 'Cooling_Load', 'Y2': 'Cooling_Load'}
```

All of the imports

In [ ]:
```
import pandas as pd
import numpy as np
import datetime as dt
import matplotlib.pyplot as plt
import seaborn as sns
from ucimlrepo import fetch_ucirepo
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.utils import resample
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
```

```
from sklearn.linear_model import ElasticNet
from sklearn.ensemble import RandomForestRegressor
from sklearn.datasets import make_regression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import root_mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
```

Task 1

Data Preprocessing:

- Perform exploratory data analysis (EDA) after loading the dataset.
- Conduct feature engineering if necessary.

In [ ]:
```
# fetch dataset
energy_efficiency = fetch_ucirepo(id=242)

# data (as pandas dataframes)
X1 = energy_efficiency.data.features
y1 = energy_efficiency.data.targets

# metadata
print("Source data metadata:")
print(energy_efficiency.metadata)

# variable information
print("")
print("Source data variable information:")
print(energy_efficiency.variables)

# X descriptive statistics
print("")
print("Feature descriptive statistics:")
print(X1.describe())

print("")
print("Target descriptive statistics:")
print(y1.describe())
```

```
Source data metadata:
```


```
{'uci_id': 242, 'name': 'Energy efficiency', 'repository_url': 'https://archive.ics.
uci.edu/dataset/242/energy+efficiency', 'data_url': 'https://archive.ics.uci.edu/sta
tic/public/242/data.csv', 'abstract': 'This study looked into assessing the heating
load and cooling load requirements of buildings (that is, energy efficiency) as a fu
nction of building parameters.', 'area': 'Computer Science', 'tasks': ['Classificati
on', 'Regression'], 'characteristics': ['Multivariate'], 'num_instances': 768, 'num_
features': 8, 'feature_types': ['Integer', 'Real'], 'demographics': [], 'target_co
l': ['Y1', 'Y2'], 'index_col': None, 'has_missing_values': 'no', 'missing_values_sym
bol': None, 'year_of_dataset_creation': 2012, 'last_updated': 'Sat Jan 27 2024', 'da
taset_doi': '10.24432/C51307', 'creators': ['Athanasios Tsanas', 'Angeliki Xifara'],
'intro_paper': {'title': 'Accurate quantitative estimation of energy performance of
residential buildings using statistical machine learning tools', 'authors': 'A. Tsan
as, Angeliki Xifara', 'published_in': 'Energy and Buildings, vol. 49', 'year': 2012,
'url': 'https://www.semanticscholar.org/paper/Accurate-quantitative-estimation-of-en
ergy-of-using-Tsanas-Xifara/719e65379c5959141180a45f540f707d583b8ce2', 'doi': None},
'additional_info': {'summary': 'We perform energy analysis using 12 different buildi
ng shapes simulated in Ecotect. The buildings differ with respect to the glazing are
a, the glazing area distribution, and the orientation, amongst other parameters. We
simulate various settings as functions of the afore-mentioned characteristics to obt
ain 768 building shapes. The dataset comprises 768 samples and 8 features, aiming to
predict two real valued responses. It can also be used as a multi-class classificati
on problem if the response is rounded to the nearest integer.', 'purpose': None, 'fu
nded_by': None, 'instances_represent': None, 'recommended_data_splits': None, 'sensi
tive_data': None, 'preprocessing_description': None, 'variable_info': 'The dataset c
ontains eight attributes (or features, denoted by X1...X8) and two responses (or out
comes, denoted by y1 and y2). The aim is to use the eight features to predict each o
f the two responses.\r\n\r\nSpecifically:\r\nX1\tRelative Compactness\r\nX2\tSurface
Area\r\nX3\tWall Area\r\nX4\tRoof Area\r\nX5\tOverall Height\r\nX6\tOrientation\r\nX
7\tGlazing Area\r\nX8\tGlazing Area Distribution\r\ny1\tHeating Load\r\ny2\tCooling
Load', 'citation': None}}
```


```
Source data variable information:
  name     role        type demographic                description units  \
0   X1  Feature  Continuous        None       Relative Compactness  None
1   X2  Feature  Continuous        None               Surface Area  None
2   X3  Feature  Continuous        None                  Wall Area  None
3   X4  Feature  Continuous        None                  Roof Area  None
4   X5  Feature  Continuous        None             Overall Height  None
5   X6  Feature     Integer        None                Orientation  None
6   X7  Feature  Continuous        None               Glazing Area  None
7   X8  Feature     Integer        None  Glazing Area Distribution  None
8   Y1   Target  Continuous        None               Heating Load  None
9   Y2   Target  Continuous        None               Cooling Load  None

  missing_values
0             no
1             no
2             no
3             no
4             no
5             no
6             no
7             no
8             no
9             no
```

```
Feature descriptive statistics:
               X1          X2          X3          X4         X5          X6  \
count  768.000000  768.000000  768.000000  768.000000  768.00000  768.000000
mean     0.764167  671.708333  318.500000  176.604167    5.25000    3.500000
std      0.105777   88.086116   43.626481   45.165950    1.75114    1.118763
min      0.620000  514.500000  245.000000  110.250000    3.50000    2.000000
25%      0.682500  606.375000  294.000000  140.875000    3.50000    2.750000
50%      0.750000  673.750000  318.500000  183.750000    5.25000    3.500000
75%      0.830000  741.125000  343.000000  220.500000    7.00000    4.250000
max      0.980000  808.500000  416.500000  220.500000    7.00000    5.000000

               X7         X8
count  768.000000  768.00000
mean     0.234375    2.81250
std      0.133221    1.55096
min      0.000000    0.00000
25%      0.100000    1.75000
50%      0.250000    3.00000
75%      0.400000    4.00000
max      0.400000    5.00000

Target descriptive statistics:
               Y1          Y2
count  768.000000  768.000000
mean    22.307201   24.587760
std     10.090196    9.513306
min      6.010000   10.900000
25%     12.992500   15.620000
50%     18.950000   22.080000
75%     31.667500   33.132500
max     43.100000   48.030000
```

In [ ]:

```python
column_names = {'X1':'Relative_Compactness', 'X2': 'Surface_Area',
'X3': 'Wall_Area', 'X4': 'Roof_Area',
'X5': 'Overall_Height', 'X6': 'Orientation',
'X7': 'Glazing_Area', 'X8': 'Glazing_Area_Distribution',
'Y1': 'Heating_Load', 'Y2': 'Cooling_Load'}
print("")
print("Renaming the columns per:")
print(column_names)
X = X1.rename(columns=column_names)
y = y1.rename(columns=column_names)
print("")
print("New X:")
print(X)
print("")
print("New y:")
print(y)
```

```
Renaming the columns per:
{'X1': 'Relative_Compactness', 'X2': 'Surface_Area', 'X3': 'Wall_Area', 'X4': 'Roof_
Area', 'X5': 'Overall_Height', 'X6': 'Orientation', 'X7': 'Glazing_Area', 'X8': 'Gla
zing_Area_Distribution', 'Y1': 'Heating_Load', 'Y2': 'Cooling_Load'}

New X:
     Relative_Compactness  Surface_Area  Wall_Area  Roof_Area  Overall_Height  \
0                    0.98         514.5      294.0     110.25             7.0
1                    0.98         514.5      294.0     110.25             7.0
2                    0.98         514.5      294.0     110.25             7.0
3                    0.98         514.5      294.0     110.25             7.0
4                    0.90         563.5      318.5     122.50             7.0
..                    ...           ...        ...        ...             ...
763                  0.64         784.0      343.0     220.50             3.5
764                  0.62         808.5      367.5     220.50             3.5
765                  0.62         808.5      367.5     220.50             3.5
766                  0.62         808.5      367.5     220.50             3.5
767                  0.62         808.5      367.5     220.50             3.5

     Orientation  Glazing_Area  Glazing_Area_Distribution
0              2           0.0                          0
1              3           0.0                          0
2              4           0.0                          0
3              5           0.0                          0
4              2           0.0                          0
..           ...           ...                        ...
763            5           0.4                          5
764            2           0.4                          5
765            3           0.4                          5
766            4           0.4                          5
767            5           0.4                          5

[768 rows x 8 columns]

New y:
     Heating_Load  Cooling_Load
0           15.55         21.33
1           15.55         21.33
2           15.55         21.33
3           15.55         21.33
4           20.84         28.28
..            ...           ...
763         17.88         21.40
764         16.54         16.88
765         16.44         17.11
766         16.48         16.61
767         16.64         16.03

[768 rows x 2 columns]
```

I did not see any need for feature engineering. The data looks good, there are no missing values, and I cannot see any new calculated values. I did consider vectorizing several of the columns but felt that it was not necessary.

Task 2

Model Development:

- Implement various regression models (Linear Regression, Ridge, Lasso, and Elastic Net).
- Implement Random Forest Regression (Bonus Question - 5pts)
- Perform hyperparameter tuning for optimization.

Before we start, lets split the data into Test and Training data.

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

print('X_train shape:', X_train.shape)
print('y_train shape:', y_train.shape)
print('X_test shape:', X_test.shape)
print('y_test shape:', y_test.shape)
```

```
X_train shape: (614, 8)
y_train shape: (614, 2)
X_test shape: (154, 8)
y_test shape: (154, 2)
```

Task 2.1.1

Linear Regression Heating

Perform a hyperparameter search.

In [ ]:
```
param_grid = {'fit_intercept': [True, False]}
grid = GridSearchCV(LinearRegression(), param_grid, cv=7)
grid.fit(X_train, y_train['Heating_Load'])
grid.best_params_
```

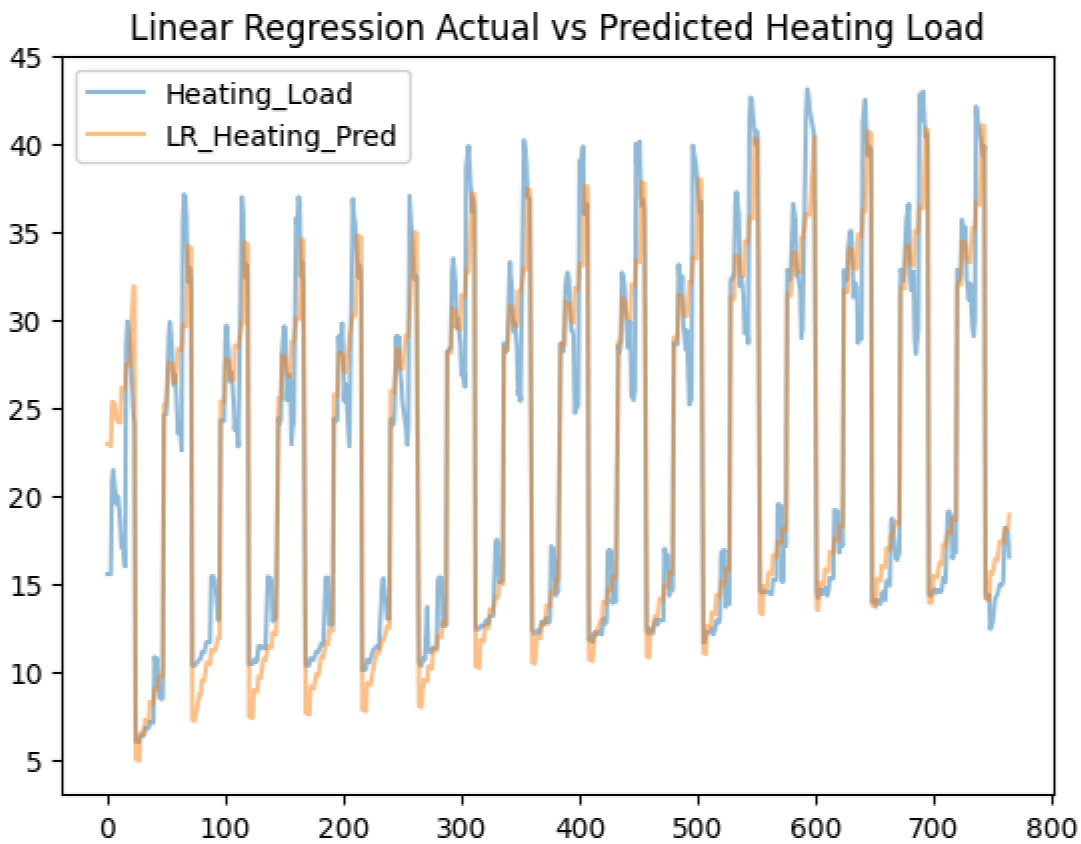
```
True
```

In [ ]:
```
modelLRHeat = LinearRegression(fit_intercept=grid.best_params_['fit_intercept'])
modelLRHeat.fit(X_train, y_train['Heating_Load'])
y_train['LR_Heating_Pred'] = modelLRHeat.predict(X_train)
y_test['LR_Heating_Pred'] = modelLRHeat.predict(X_test)

print("")
print("Linear regression heating intercept:")
print(modelLRHeat.intercept_)
print("Linear regression heating coefficients:")
print(modelLRHeat.coef_)
```

```
Linear regression heating intercept:
89.71793630044306
Linear regression heating coefficients:
[-6.74615065e+01  2.70325996e+12 -2.70325996e+12 -5.40651992e+12
  4.16039296e+00 -3.43839226e-02  2.03578843e+01  1.96642418e-01]
```

In [ ]:
```
x = y_train[['Heating_Load', 'LR_Heating_Pred']].sort_index().plot(alpha=0.5, title
```



In [ ]:
```
paramsLRHeat = pd.Series(modelLRHeat.coef_, index=X_train.columns)
paramsLRHeat
```

Out[ ]:
```
Relative_Compactness        -6.746151e+01
Surface_Area                 2.703260e+12
Wall_Area                   -2.703260e+12
Roof_Area                   -5.406520e+12
Overall_Height               4.160393e+00
Orientation                 -3.438392e-02
Glazing_Area                 2.035788e+01
Glazing_Area_Distribution    1.966424e-01
dtype: float64
```

In [ ]:
```
np.random.seed(1)
errLRHeat = np.std([modelLRHeat.fit(*resample(X_train, y_train['Heating_Load'])).co
              for i in range(1000)], 0)
```

In [ ]:
```
print(pd.DataFrame({'effect': paramsLRHeat.round(0),
                    'error': errLRHeat.round(0)}))
```

```
                                 effect         error
Relative_Compactness      -6.700000e+01  7.000000e+00
Surface_Area               2.703260e+12  1.038923e+12
Wall_Area                 -2.703260e+12  1.038923e+12
Roof_Area                 -5.406520e+12  2.077845e+12
Overall_Height             4.000000e+00  0.000000e+00
Orientation               -0.000000e+00  0.000000e+00
Glazing_Area               2.000000e+01  1.000000e+00
Glazing_Area_Distribution  0.000000e+00  0.000000e+00
```

Task 2.1.2

Linear Regression Cooling

Perform a hyperparameter search.

In [ ]:
```
param_grid = {'fit_intercept': [True, False]}
grid = GridSearchCV(LinearRegression(), param_grid, cv=7)
grid.fit(X_train, y_train['Cooling_Load'])
grid.best_params_
```

Out[ ]:
```
{'fit_intercept': True}
```

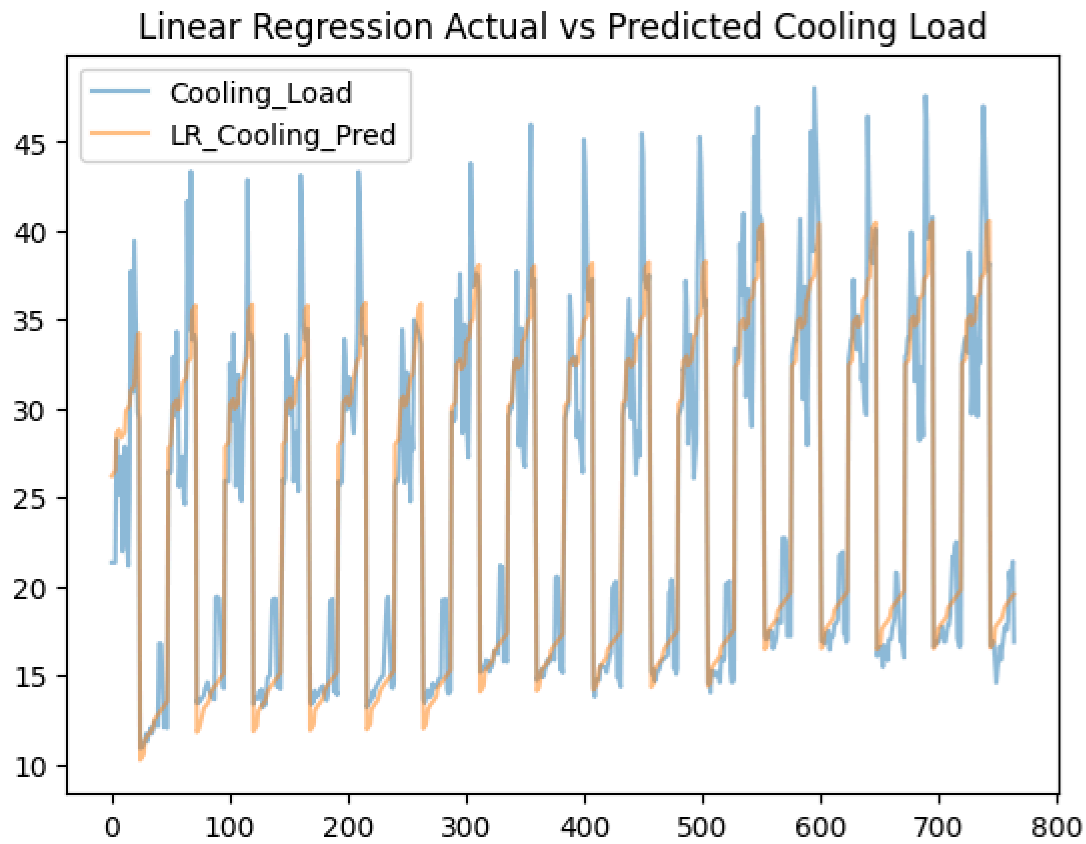
In [ ]:
```
modelLRCool = LinearRegression(fit_intercept=grid.best_params_['fit_intercept'])
modelLRCool.fit(X_train, y_train['Cooling_Load'])
y_train['LR_Cooling_Pred'] = modelLRCool.predict(X_train)
y_test['LR_Cooling_Pred'] = modelLRCool.predict(X_test)

print("")
print("Linear regression cooling intercept:")
print(modelLRCool.intercept_)
print("Linear regression cooling coefficients:")
print(modelLRCool.coef_)
```

```
Linear regression cooling intercept:
99.36310688741688
Linear regression cooling coefficients:
[-7.22275652e+01  2.17833249e+12 -2.17833249e+12 -4.35666497e+12
  4.44973868e+00  1.04135174e-01  1.51861664e+01  4.93585819e-02]
```

In [ ]:
```
y_train[['Cooling_Load', 'LR_Cooling_Pred']].sort_index().plot(alpha=0.5, title="Li
```

Out[ ]:
```
<Axes: title={'center': 'Linear Regression Actual vs Predicted Cooling Load'}>
```



In [ ]:
```python
paramsLRCool = pd.Series(modelLRCool.coef_, index=X_train.columns)
paramsLRCool
```

Out[ ]:
```
Relative_Compactness        -7.222757e+01
Surface_Area                 2.178332e+12
Wall_Area                   -2.178332e+12
Roof_Area                   -4.356665e+12
Overall_Height               4.449739e+00
Orientation                  1.041352e-01
Glazing_Area                 1.518617e+01
Glazing_Area_Distribution    4.935858e-02
dtype: float64
```

In [ ]:
```python
np.random.seed(1)
errLRCool = np.std([modelLRCool.fit(*resample(X_train, y_train['Cooling_Load'])).co
              for i in range(1000)], 0)
```

In [ ]:
```python
print(pd.DataFrame({'effect': paramsLRCool.round(0),
                    'error': errLRCool.round(0)}))
```

```
                                effect         error
Relative_Compactness     -7.200000e+01  8.000000e+00
Surface_Area              2.178332e+12  1.164205e+12
Wall_Area                -2.178332e+12  1.164205e+12
Roof_Area                -4.356665e+12  2.328410e+12
Overall_Height            4.000000e+00  0.000000e+00
Orientation               0.000000e+00  0.000000e+00
Glazing_Area              1.500000e+01  1.000000e+00
Glazing_Area_Distribution  0.000000e+00  0.000000e+00
```

Task 2.2.1

Ridge Heating

In [ ]:
```
param_grid = {'alpha': [1, 0.1, 0.01, 0.001, 0.0001, 0.00001]}
grid = GridSearchCV(Ridge(), param_grid, cv=7)
grid.fit(X_train, y_train['Heating_Load'])
grid.best_params_
```

Out[ ]:
```
{'alpha': 0.001}
```

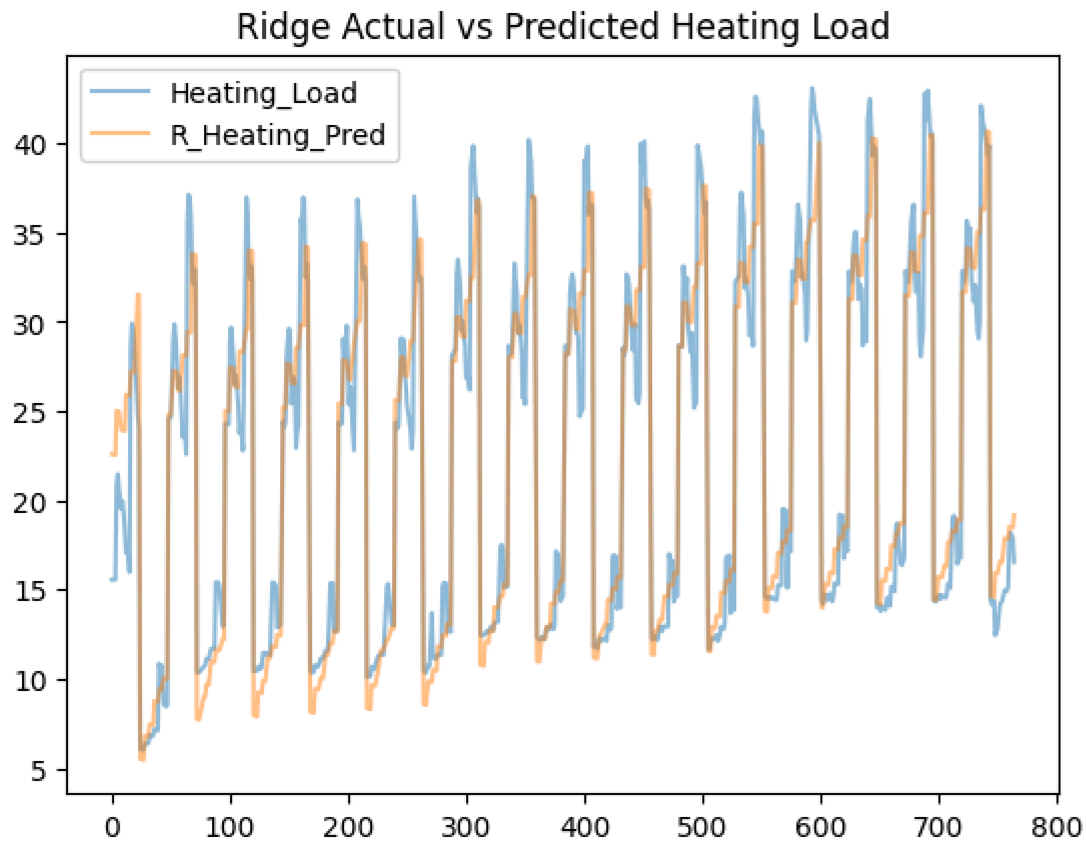
In [ ]:
```
modelRHeat = Ridge(alpha=grid.best_params_['alpha'])
modelRHeat.fit(X_train, y_train['Heating_Load'])
y_train['R_Heating_Pred'] = modelRHeat.predict(X_train)
y_test['R_Heating_Pred'] = modelRHeat.predict(X_test)

print("")
print("Ridge heating intercept:")
print(modelRHeat.intercept_)
print("Ridge heating coefficients:")
print(modelRHeat.coef_)
```

```
Ridge heating intercept:
87.29532168939392
Ridge heating coefficients:
[-6.67405915e+01 -6.50772394e-02  3.66975676e-02 -5.08883664e-02
  4.14922128e+00 -2.06610289e-02  2.02461180e+01  2.04228682e-01]
```

In [ ]:
```
y_train[['Heating_Load', 'R_Heating_Pred']].sort_index().plot(alpha=0.5, title="Rid
```

Out[ ]:
```
<Axes: title={'center': 'Ridge Actual vs Predicted Heating Load'}>
```



In [ ]:
```python
paramsRHeat = pd.Series(modelRHeat.coef_, index=X_train.columns)
paramsRHeat
```

Out[ ]:
```
Relative_Compactness        -66.740592
Surface_Area                 -0.065077
Wall_Area                     0.036698
Roof_Area                    -0.050888
Overall_Height                4.149221
Orientation                  -0.020661
Glazing_Area                 20.246118
Glazing_Area_Distribution     0.204229
dtype: float64
```

In [ ]:
```python
np.random.seed(1)
errRHeat = np.std([modelRHeat.fit(*resample(X_train, y_train['Heating_Load'])).coef
             for i in range(1000)], 0)
```

In [ ]:
```python
print(pd.DataFrame({'effect': paramsRHeat.round(0),
                    'error': errRHeat.round(0)}))
```

```
                           effect  error
Relative_Compactness        -67.0    7.0
Surface_Area                 -0.0    0.0
Wall_Area                     0.0    0.0
Roof_Area                    -0.0    0.0
Overall_Height                4.0    0.0
Orientation                  -0.0    0.0
Glazing_Area                 20.0    1.0
Glazing_Area_Distribution     0.0    0.0
```

Task 2.2.2

Ridge Cooling

In [ ]:
```
param_grid = {'alpha': [1, 0.1, 0.01, 0.001, 0.0001, 0.00001]}
grid = GridSearchCV(Ridge(), param_grid, cv=7)
grid.fit(X_train, y_train['Cooling_Load'])
grid.best_params_
```

Out[ ]:
```
{'alpha': 0.001}
```

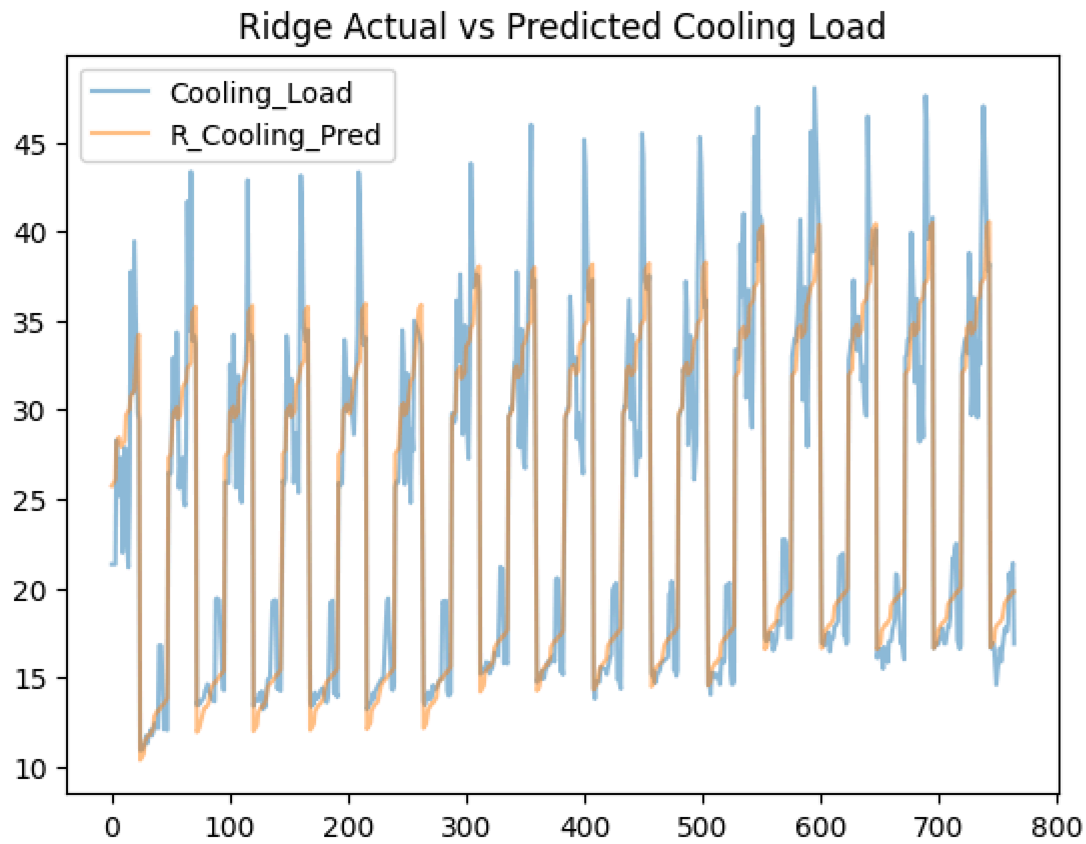
In [ ]:
```
modelRCool = Ridge(alpha=grid.best_params_['alpha'])
modelRCool.fit(X_train, y_train['Cooling_Load'])
y_train['R_Cooling_Pred'] = modelRCool.predict(X_train)
y_test['R_Cooling_Pred'] = modelRCool.predict(X_test)

print("")
print("Ridge cooling intercept:")
print(modelRCool.intercept_)
print("Ridge cooling coefficients:")
print(modelRCool.coef_)
```

```
Ridge cooling intercept:
96.48548770986395
Ridge cooling coefficients:
[-7.13767085e+01 -6.51703572e-02  2.07462305e-02 -4.29591941e-02
  4.44628175e+00  1.15266507e-01  1.50961863e+01  5.55912128e-02]
```

In [ ]:
```
y_train[['Cooling_Load', 'R_Cooling_Pred']].sort_index().plot(alpha=0.5, title="Rid
```

Out[ ]:
```
<Axes: title={'center': 'Ridge Actual vs Predicted Cooling Load'}>
```



In [ ]:
```
paramsRCool = pd.Series(modelRCool.coef_, index=X_train.columns)
paramsRCool
```

Out[ ]:
```
Relative_Compactness        -71.376708
Surface_Area                 -0.065170
Wall_Area                     0.020746
Roof_Area                    -0.042959
Overall_Height                4.446282
Orientation                   0.115267
Glazing_Area                 15.096186
Glazing_Area_Distribution     0.055591
dtype: float64
```

In [ ]:
```
np.random.seed(1)
errRCool = np.std([modelRCool.fit(*resample(X_train, y_train['Cooling_Load'])).coef
              for i in range(1000)], 0)
```

In [ ]:
```
print(pd.DataFrame({'effect': paramsRCool.round(0),
                    'error': errRCool.round(0)}))
```

```
                           effect  error
Relative_Compactness        -71.0    8.0
Surface_Area                 -0.0    0.0
Wall_Area                     0.0    0.0
Roof_Area                    -0.0    0.0
Overall_Height                4.0    0.0
Orientation                   0.0    0.0
Glazing_Area                 15.0    1.0
Glazing_Area_Distribution     0.0    0.0
```

Task 2.3.1

Lasso Heating

In [ ]:
```
param_grid = {'alpha': [1, 0.1]}
grid = GridSearchCV(Lasso(), param_grid, cv=7)
grid.fit(X_train, y_train['Heating_Load'])
grid.best_params_
```

Out[ ]:
```
{'alpha': 0.1}
```

With the value of 0.001 included, the result did not converge. Using 0.01 worked but later steps had convergence errors.

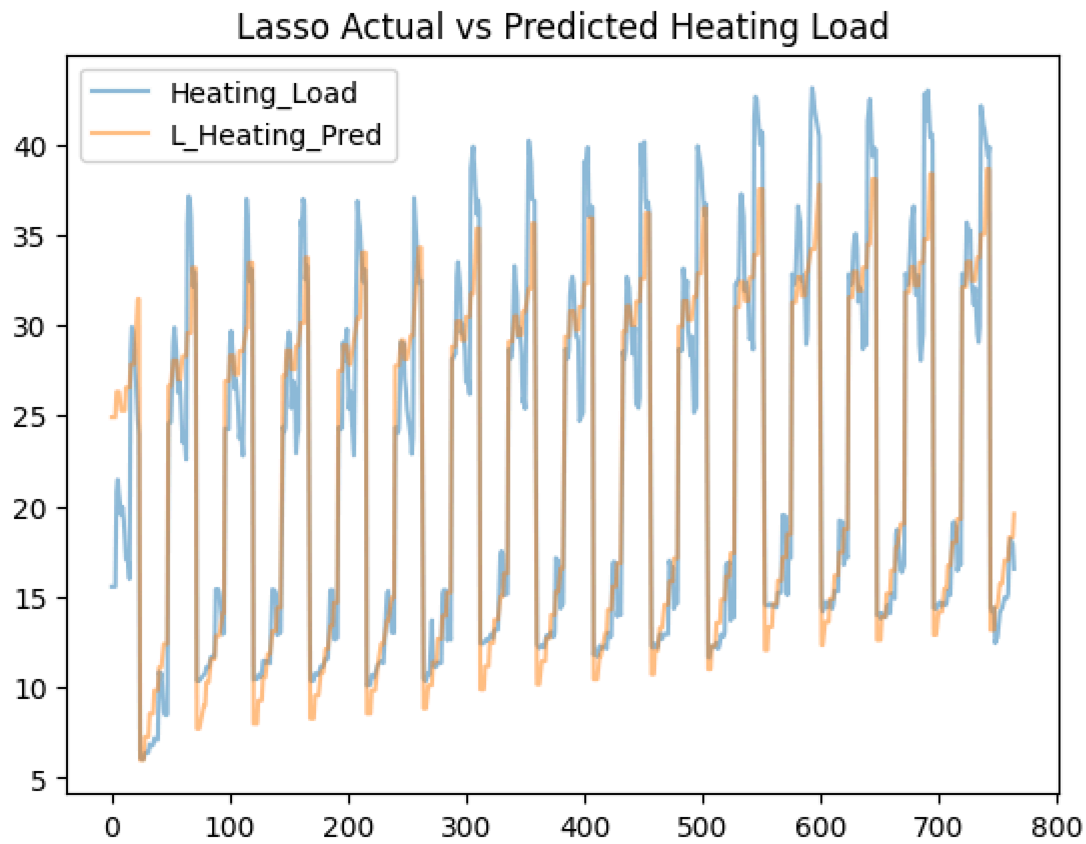
In [ ]:
```
modelLHeat = Lasso(alpha=grid.best_params_['alpha'])
modelLHeat.fit(X_train, y_train['Heating_Load'])
y_train['L_Heating_Pred'] = modelLHeat.predict(X_train)
y_test['L_Heating_Pred'] = modelLHeat.predict(X_test)

print("")
print("Lasso heating intercept:")
print(modelLHeat.intercept_)
print("Lasso heating coefficients:")
print(modelLHeat.coef_)
```

```
Lasso heating intercept:
-26.48249713602111
Lasso heating coefficients:
[-0.00000000e+00  4.96633944e-03  4.73190985e-02 -0.00000000e+00
  4.98997459e+00 -0.00000000e+00  1.44716271e+01  2.79426489e-01]
```

In [ ]:
```
y_train[['Heating_Load', 'L_Heating_Pred']].sort_index().plot(alpha=0.5, title="Las
```

Out[ ]:
```
<Axes: title={'center': 'Lasso Actual vs Predicted Heating Load'}>
```



In [ ]:
```
paramsLHeat = pd.Series(modelLHeat.coef_, index=X_train.columns)
paramsLHeat
```

Out[ ]:
```
Relative_Compactness        -0.000000
Surface_Area                 0.004966
Wall_Area                    0.047319
Roof_Area                   -0.000000
Overall_Height               4.989975
Orientation                 -0.000000
Glazing_Area                14.471627
Glazing_Area_Distribution    0.279426
dtype: float64
```

In [ ]:
```
np.random.seed(1)
errLHeat = np.std([modelLHeat.fit(*resample(X_train, y_train['Heating_Load'])).coef
              for i in range(1000)], 0)
```

In [ ]:
```
print(pd.DataFrame({'effect': paramsLHeat.round(0),
                    'error': errLHeat.round(0)}))
```

```
                           effect  error
Relative_Compactness         -0.0    0.0
Surface_Area                  0.0    0.0
Wall_Area                     0.0    0.0
Roof_Area                    -0.0    0.0
Overall_Height                5.0    0.0
Orientation                  -0.0    0.0
Glazing_Area                 14.0    1.0
Glazing_Area_Distribution     0.0    0.0
```

Task 2.3.2

Lasso Cooling

In [ ]:
```
param_grid = {'alpha': [1, 0.1]}
grid = GridSearchCV(Lasso(), param_grid, cv=7)
grid.fit(X_train, y_train['Cooling_Load'])
grid.best_params_
```

Out[ ]:
```
{'alpha': 0.1}
```

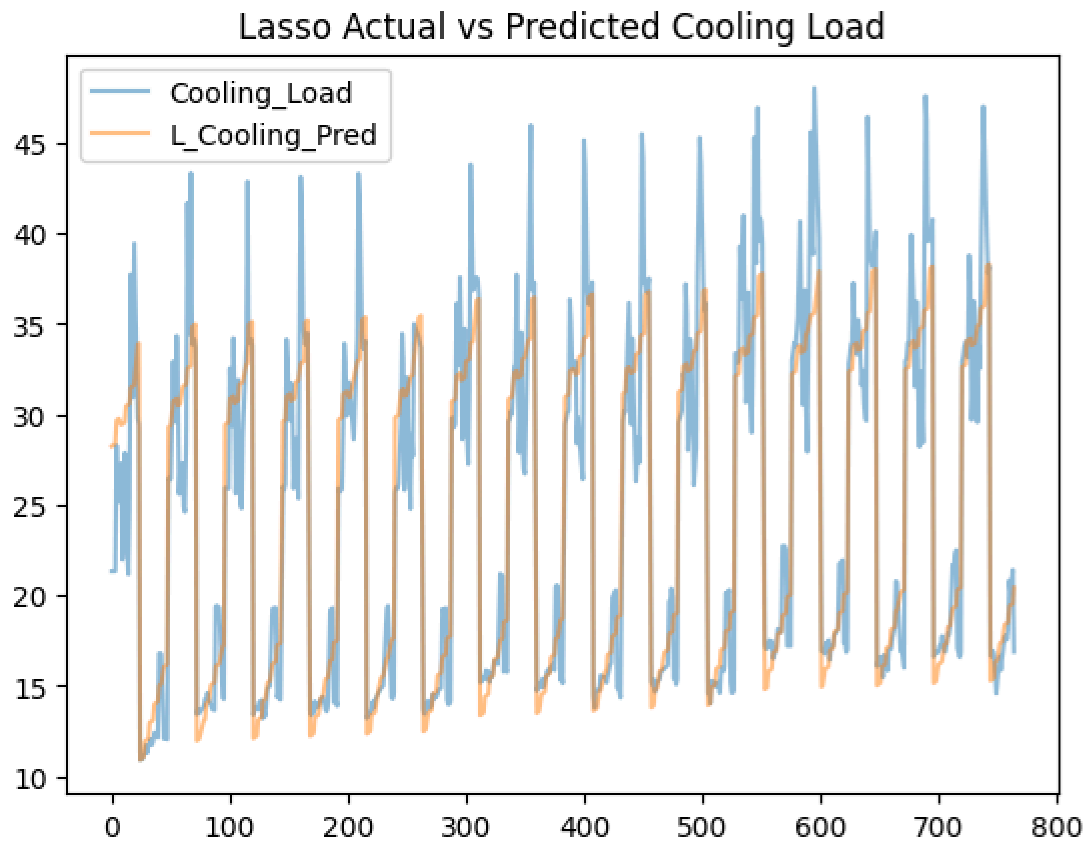
In [ ]:
```
modelLCool = Lasso(alpha=grid.best_params_['alpha'])
modelLCool.fit(X_train, y_train['Cooling_Load'])
y_train['L_Cooling_Pred'] = modelLCool.predict(X_train)
y_test['L_Cooling_Pred'] = modelLCool.predict(X_test)

print("")
print("Lasso cooling intercept:")
print(modelLCool.intercept_)
print("Lasso cooling coefficients:")
print(modelLCool.coef_)
```

```
Lasso cooling intercept:
-25.410809931200188
Lasso cooling coefficients:
[-0.          0.01613122  0.02576576 -0.          5.38188424  0.04955085
  9.32690516  0.13041771]
```

In [ ]:
```
y_train[['Cooling_Load', 'L_Cooling_Pred']].sort_index().plot(alpha=0.5, title="Las
```

Out[ ]:
```
<Axes: title={'center': 'Lasso Actual vs Predicted Cooling Load'}>
```



In [ ]:
```
paramsLCool = pd.Series(modelLCool.coef_, index=X_train.columns)
paramsLCool
```

Out[ ]:
```
Relative_Compactness        -0.000000
Surface_Area                 0.016131
Wall_Area                    0.025766
Roof_Area                   -0.000000
Overall_Height               5.381884
Orientation                  0.049551
Glazing_Area                 9.326905
Glazing_Area_Distribution    0.130418
dtype: float64
```

In [ ]:
```
np.random.seed(1)
errLCool = np.std([modelLCool.fit(*resample(X_train, y_train['Cooling_Load'])).coef
              for i in range(1000)], 0)
```

In [ ]:
```
print(pd.DataFrame({'effect': paramsLCool.round(0),
                    'error': errLCool.round(0)}))
```

```
                           effect  error
Relative_Compactness         -0.0    0.0
Surface_Area                  0.0    0.0
Wall_Area                     0.0    0.0
Roof_Area                    -0.0    0.0
Overall_Height                5.0    0.0
Orientation                   0.0    0.0
Glazing_Area                  9.0    1.0
Glazing_Area_Distribution     0.0    0.0
```

Task 2.4.1

Elastic Net Heating

In [ ]:
```
param_grid = {'alpha': [1, 0.1]}
grid = GridSearchCV(ElasticNet(), param_grid, cv=7)
grid.fit(X_train, y_train['Heating_Load'])
grid.best_params_
```

Out[ ]:
```
{'alpha': 0.1}
```

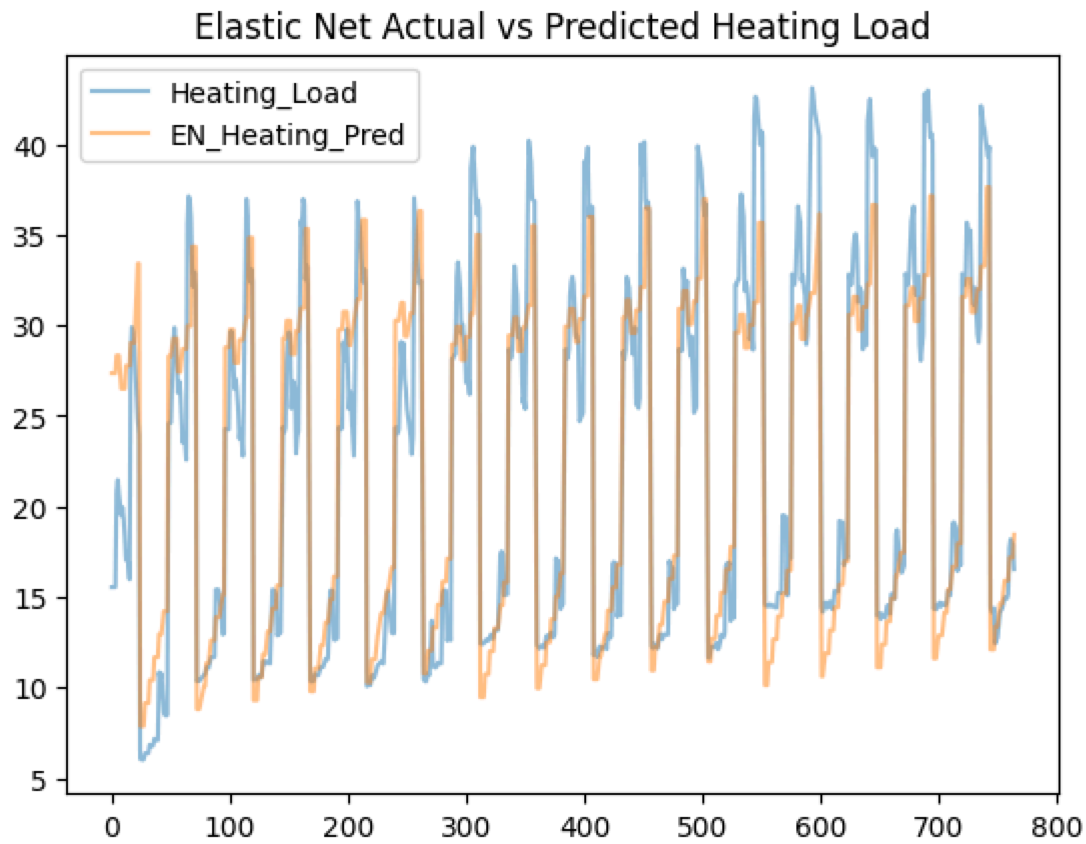
In [ ]:
```
modelENHeat = ElasticNet(alpha=grid.best_params_['alpha'], random_state=65)
modelENHeat.fit(X_train, y_train['Heating_Load'])
y_train['EN_Heating_Pred'] = modelENHeat.predict(X_train)
y_test['EN_Heating_Pred'] = modelENHeat.predict(X_test)

print("")
print("Elastic Net heating intercept:")
print(modelLHeat.intercept_)
print("Elastic Net heating coefficients:")
print(modelLHeat.coef_)
```

```
Elastic Net heating intercept:
-26.961154755654604
Elastic Net heating coefficients:
[-0.00000000e+00  8.94092109e-03  4.48575435e-02 -7.46251489e-03
  4.94617189e+00 -4.33822678e-02  1.63010167e+01  2.20869612e-01]
```

In [ ]:
```
y_train[['Heating_Load', 'EN_Heating_Pred']].sort_index().plot(alpha=0.5, title="El
```

Out[ ]:
```
<Axes: title={'center': 'Elastic Net Actual vs Predicted Heating Load'}>
```



In [ ]:
```
paramsENHeat = pd.Series(modelENHeat.coef_, index=X_train.columns)
paramsENHeat
```

Out[ ]:
```
Relative_Compactness        -0.000000
Surface_Area                -0.006056
Wall_Area                    0.057786
Roof_Area                   -0.011224
Overall_Height               4.104711
Orientation                 -0.000000
Glazing_Area                 4.406504
Glazing_Area_Distribution    0.492566
dtype: float64
```

In [ ]:
```
np.random.seed(1)
errENHeat = np.std([modelENHeat.fit(*resample(X_train, y_train['Heating_Load'])).co
              for i in range(1000)], 0)
```

In [ ]:
```
print(pd.DataFrame({'effect': paramsENHeat.round(0),
                    'error': errENHeat.round(0)}))
```

```
                           effect  error
Relative_Compactness         -0.0    0.0
Surface_Area                 -0.0    0.0
Wall_Area                     0.0    0.0
Roof_Area                    -0.0    0.0
Overall_Height                4.0    0.0
Orientation                  -0.0    0.0
Glazing_Area                  4.0    0.0
Glazing_Area_Distribution     0.0    0.0
```

Task 2.4.2

Elastic Net Cooling

In [ ]:
```
param_grid = {'alpha': [1, 0.1]}
grid = GridSearchCV(ElasticNet(), param_grid, cv=7)
grid.fit(X_train, y_train['Cooling_Load'])
grid.best_params_
```

Out[ ]:
```
{'alpha': 0.1}
```

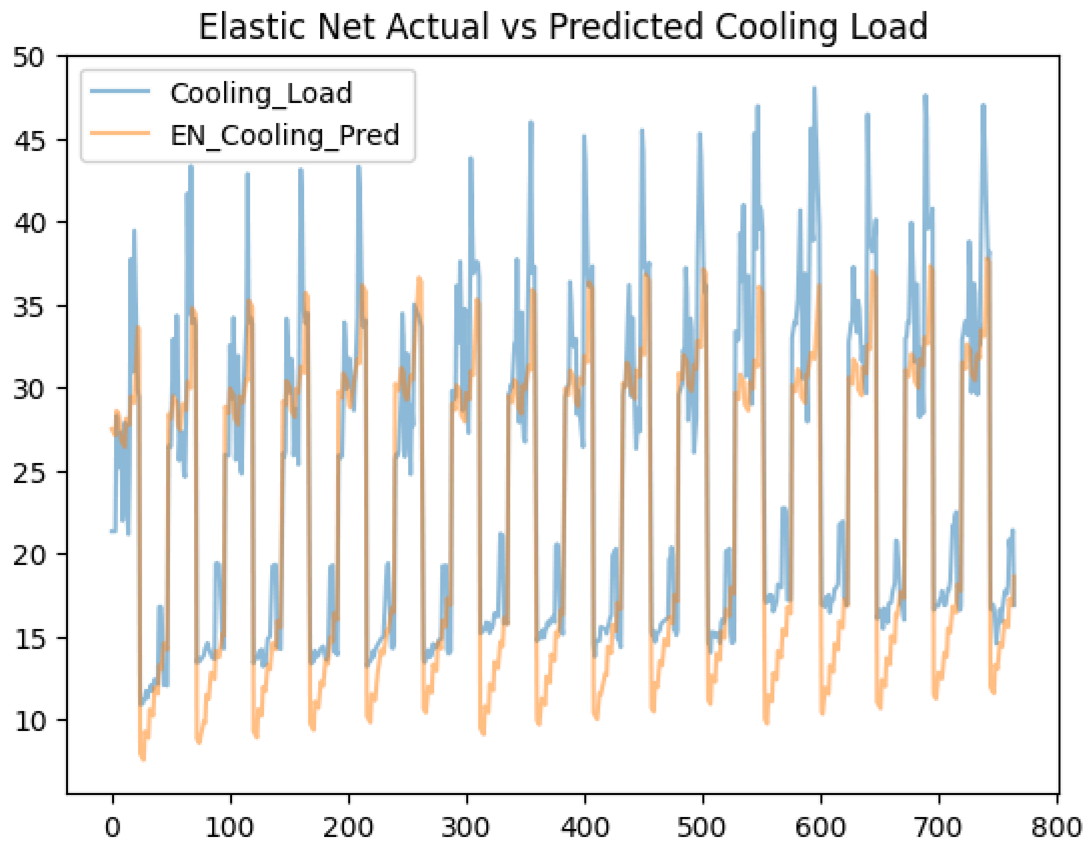
In [ ]:
```
modelENCool = ElasticNet(alpha=grid.best_params_['alpha'], random_state=65)
modelENCool.fit(X_train, y_train['Cooling_Load'])
y_train['EN_Cooling_Pred'] = modelENHeat.predict(X_train)
y_test['EN_Cooling_Pred'] = modelENHeat.predict(X_test)

print("")
print("Elastic Net cooling intercept:")
print(modelLCool.intercept_)
print("Elastic Net cooling coefficients:")
print(modelLCool.coef_)
```

```
Elastic Net cooling intercept:
-25.410809931200188
Elastic Net cooling coefficients:
[-0.          0.01613122  0.02576576 -0.          5.38188424  0.04955085
  9.32690516  0.13041771]
```

In [ ]:
```
y_train[['Cooling_Load', 'EN_Cooling_Pred']].sort_index().plot(alpha=0.5, title="El
```

Out[ ]:
```
<Axes: title={'center': 'Elastic Net Actual vs Predicted Cooling Load'}>
```



In [ ]:
```
paramsENCool = pd.Series(modelENCool.coef_, index=X_train.columns)
paramsENCool
```

Out[ ]:
```
Relative_Compactness        -0.000000
Surface_Area                -0.000000
Wall_Area                    0.041551
Roof_Area                   -0.004378
Overall_Height               4.404607
Orientation                  0.086316
Glazing_Area                 3.101857
Glazing_Area_Distribution    0.268356
dtype: float64
```

In [ ]:
```
np.random.seed(1)
errENCool = np.std([modelENCool.fit(*resample(X_train, y_train['Cooling_Load'])).co
              for i in range(1000)], 0)
```

In [ ]:
```
print(pd.DataFrame({'effect': paramsENCool.round(0),
                    'error': errENCool.round(0)}))
```

```
                           effect  error
Relative_Compactness         -0.0    0.0
Surface_Area                 -0.0    0.0
Wall_Area                     0.0    0.0
Roof_Area                    -0.0    0.0
Overall_Height                4.0    0.0
Orientation                   0.0    0.0
Glazing_Area                  3.0    0.0
Glazing_Area_Distribution     0.0    0.0
```

Task 2.5.1

Random Forest Regression Heating

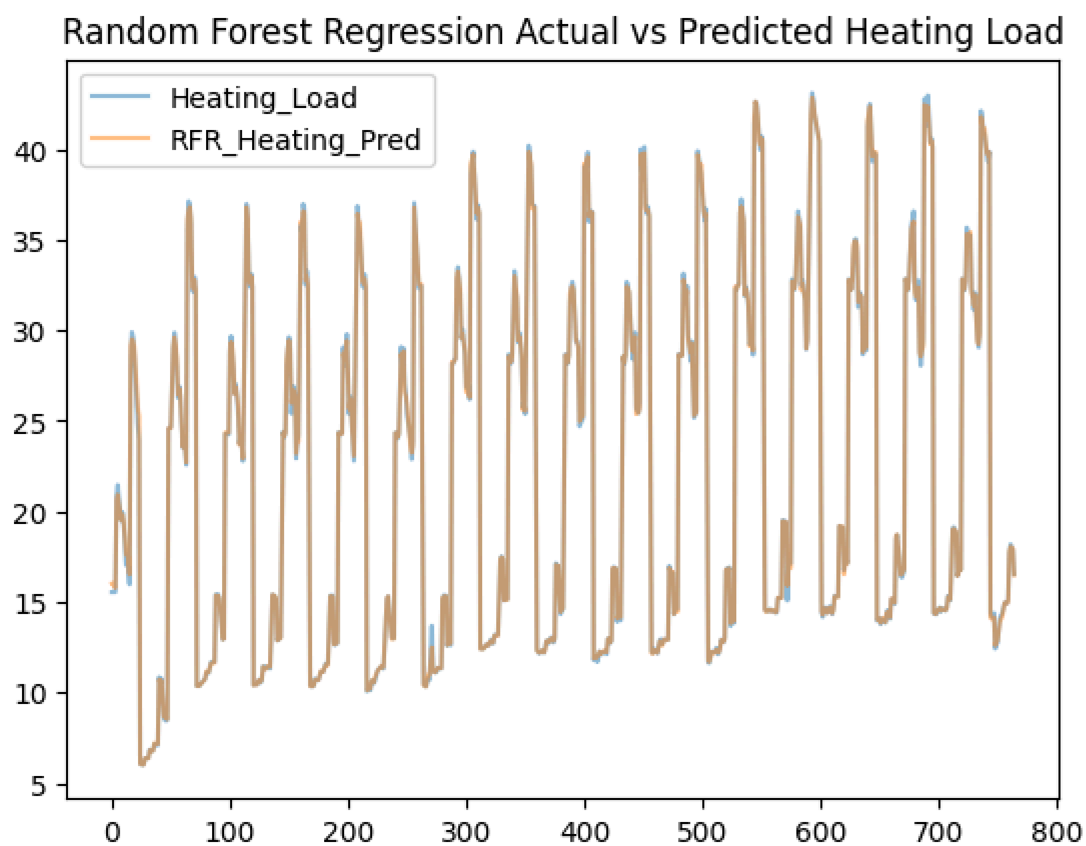
In [ ]:
```
param_grid = {'n_estimators': [1, 10, 50, 100, 200]}
grid = GridSearchCV(RandomForestRegressor(), param_grid, cv=7)
grid.fit(X_train, y_train['Heating_Load'])
grid.best_params_
```

Out[ ]:
```
{'n_estimators': 200}
```

In [ ]:
```
modelRFRHeat = RandomForestRegressor(grid.best_params_['n_estimators'])
modelRFRHeat.fit(X_train, y_train['Heating_Load'])
y_train['RFR_Heating_Pred'] = modelRFRHeat.predict(X_train)
y_test['RFR_Heating_Pred'] = modelRFRHeat.predict(X_test)
# No intercept or coefficients
```

In [ ]:
```
y_train[['Heating_Load', 'RFR_Heating_Pred']].sort_index().plot(alpha=0.5, title="R
```

Out[ ]:
```
<Axes: title={'center': 'Random Forest Regression Actual vs Predicted Heating Loa
d'}>
```



Task 2.5.2

Random Forest Regression Cooling

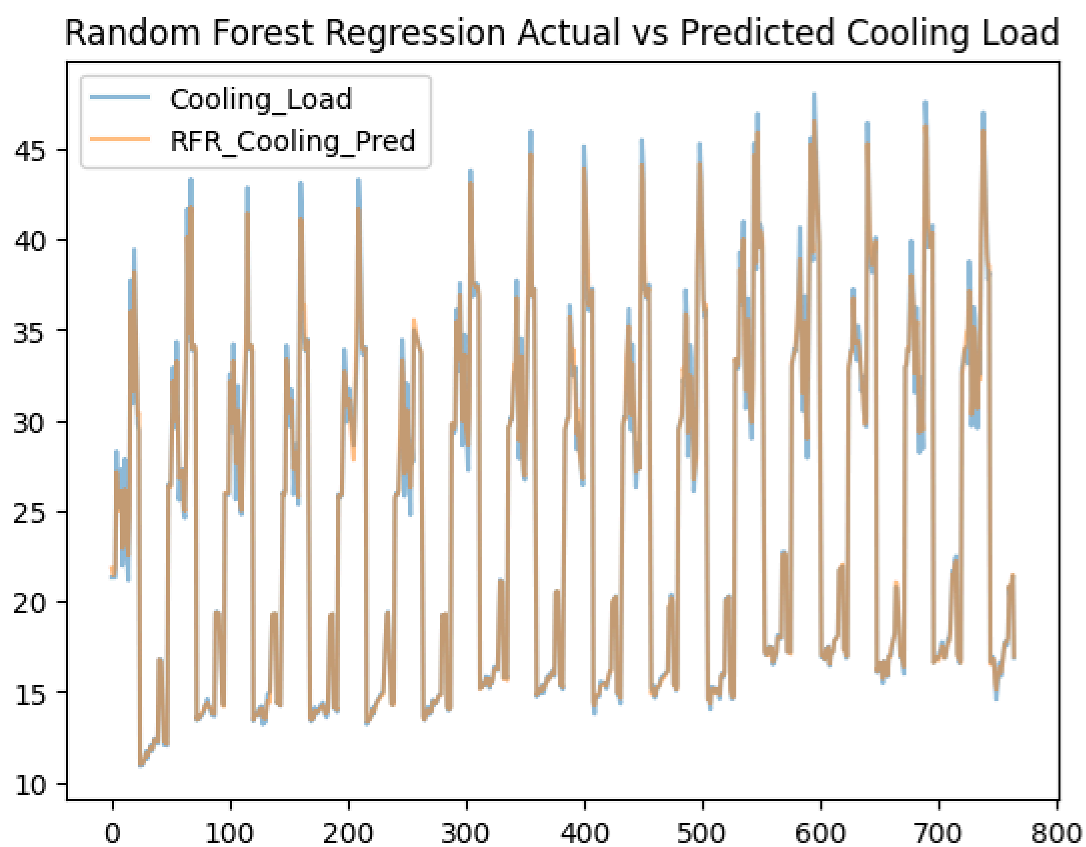
In [ ]:
```
param_grid = {'n_estimators': [1, 10, 50, 100, 200]}
grid = GridSearchCV(RandomForestRegressor(), param_grid, cv=7)
grid.fit(X_train, y_train['Cooling_Load'])
grid.best_params_
```

Out[ ]:
```
{'n_estimators': 100}
```

In [ ]:
```
modelRFRCool = RandomForestRegressor(grid.best_params_['n_estimators'])
modelRFRCool.fit(X_train, y_train['Cooling_Load'])
y_train['RFR_Cooling_Pred'] = modelRFRCool.predict(X_train)
y_test['RFR_Cooling_Pred'] = modelRFRCool.predict(X_test)
# No intercept or coefficients
```

In [ ]:
```
y_train[['Cooling_Load', 'RFR_Cooling_Pred']].sort_index().plot(alpha=0.5, title="R
```

Out[ ]:
```
<Axes: title={'center': 'Random Forest Regression Actual vs Predicted Cooling Loa
d'}>
```



Task 3

Model Evaluations

Task 3.1

Evaluate models using RMSE, MAE, and R^2 score

In [ ]:
```
meh = pd.DataFrame(np.array([[mean_squared_error(y_train['Heating_Load'],  y_train[
                             ,[root_mean_squared_error(y_train['Heating_Load'],  y_
                             ,[mean_absolute_error(y_train['Heating_Load'],  y_trai
                             ,[r2_score(y_train['Heating_Load'],  y_train['LR_Heati
                               ])
                             , columns=["Lin Reg","Ridge","Lasso", "Elastic Net", "
                             , index=["MSE","RMSE","MAE","R2"])

mec = pd.DataFrame(np.array([[mean_squared_error(y_train['Cooling_Load'],  y_train[
                             ,[root_mean_squared_error(y_train['Cooling_Load'],  y_
                             ,[mean_absolute_error(y_train['Cooling_Load'],  y_trai
                             ,[r2_score(y_train['Cooling_Load'],  y_train['LR_Cooli
                               ])
                             , columns=["Lin Reg","Ridge","Lasso", "Elastic Net", "
                             , index=["MSE","RMSE","MAE","R2"])
print("")
print("Performance of model with training data")
print("The Heating data:")
print(meh)
print("")
print("The Cooling data:")
print(mec)
```

```
Performance of model with training data
The Heating data:
       Lin Reg     Ridge     Lasso  Elastic Net  Random Forest Regressor
MSE   8.045089  7.946340  9.060286    13.064293                 0.031529
RMSE  2.836387  2.818925  3.010031     3.614456                 0.177565
MAE   2.019194  1.991271  2.155065     2.659659                 0.117113
R2    0.920289  0.921268  0.910231     0.870559                 0.999688

The Cooling data:
       Lin Reg     Ridge      Lasso  Elastic Net  Random Forest Regressor
MSE   9.939724  9.931788  11.123164    18.930985                 0.373874
RMSE  3.152733  3.151474   3.335141     4.350975                 0.611452
MAE   2.198225  2.209375   2.391760     3.396784                 0.380178
R2    0.890300  0.890388   0.877239     0.791068                 0.995874
```

Based on the information above, I would have to select the Random Forest Regressor. It seems to be much better than the other models. However, it may be overfitting the data. I would want to get more data and verify if it is really that good or not. Otherwise, I would probably just go with the Linear Regression model. It seems good enough. Better to stick with the simpler model if the more complex ones do not add any value.

Task 3.2

Assess performance on training and testing datasets.

In [ ]:
```
meh_test = pd.DataFrame(np.array([[mean_squared_error(y_test['Heating_Load'],  y_te
                             ,[root_mean_squared_error(y_test['Heating_Load'],  y_t
                             ,[mean_absolute_error(y_test['Heating_Load'],  y_test[
                             ,[r2_score(y_test['Heating_Load'],  y_test['LR_Heating
                               ])
```

```
                            , columns=["Lin Reg","Ridge","Lasso", "Elastic Net", "
                            , index=["MSE","RMSE","MAE","R2"])

mec_test = pd.DataFrame(np.array([[mean_squared_error(y_test['Cooling_Load'],  y_te
                            ,[root_mean_squared_error(y_test['Cooling_Load'],  y_t
                            ,[mean_absolute_error(y_test['Cooling_Load'],  y_test[
                            ,[r2_score(y_test['Cooling_Load'],  y_test['LR_Cooling
                              ])
                            , columns=["Lin Reg","Ridge","Lasso", "Elastic Net", "
                            , index=["MSE","RMSE","MAE","R2"])
print("Performance of model with test data")
print("")
print("The Heating data:")
print(meh_test)
print("")
print("The delta between using training and test data")
print(meh - meh_test)
print("")
print("The Cooling data:")
print(mec_test)
print("")
print("The delta between using training and test data")
print(mec - mec_test)
```

```
Performance of model with test data

The Heating data:
        Lin Reg      Ridge      Lasso  Elastic Net  Random Forest Regressor
MSE   11.075499  10.836508  11.355348    14.650100                 0.213841
RMSE   3.327987   3.291885   3.369770     3.827545                 0.462429
MAE    2.482320   2.404288   2.543646     2.915634                 0.327338
R2     0.894188   0.896472   0.891515     0.860038                 0.997957

The delta between using training and test data
       Lin Reg     Ridge     Lasso  Elastic Net  Random Forest Regressor
MSE  -3.030410 -2.890168 -2.295061    -1.585807                -0.182311
RMSE -0.491601 -0.472960 -0.359739    -0.213089                -0.284864
MAE  -0.463126 -0.413018 -0.388581    -0.255976                -0.210225
R2    0.026101  0.024796  0.018716     0.010521                 0.001731

The Cooling data:
        Lin Reg      Ridge      Lasso  Elastic Net  Random Forest Regressor
MSE   11.182752  11.049192  11.493701    17.818479                 2.529660
RMSE   3.344062   3.324032   3.390236     4.221194                 1.590490
MAE    2.390682   2.381975   2.527897     3.429176                 0.908479
R2     0.875025   0.876518   0.871550     0.800867                 0.971729

The delta between using training and test data
       Lin Reg     Ridge     Lasso  Elastic Net  Random Forest Regressor
MSE  -1.243028 -1.117404 -0.370537     1.112507                -2.155786
RMSE -0.191329 -0.172559 -0.055095     0.129781                -0.979038
MAE  -0.192457 -0.172600 -0.136137    -0.032392                -0.528301
R2    0.015275  0.013870  0.005689    -0.009799                 0.024144
```

Reviewing the data above, the deltas between the Training data and the Test data do not seem appreciable. However, the MSE scores seem to have the biggest delta. In addition, the deltas for the Cooling data are smaller than the deltas for the deltas for the Heating data. Therefore, it seems that the Cooling model is high bias while the heating model is high variance.

I did not run a cross validation since that did not seem to be the point of this question.

Task 4

Target Variable Analysis:

- Develop separate models for Heating Load and Cooling Load as target variables.
- Compare the effectiveness of models for each target.

I performed all of the analysis with heating and cooling separate. It did not make sens to me that I would combine them. So the above analysis covers the effectiveness of the separate models.