5.2. 냉난방 부하예측 ML모델 개발

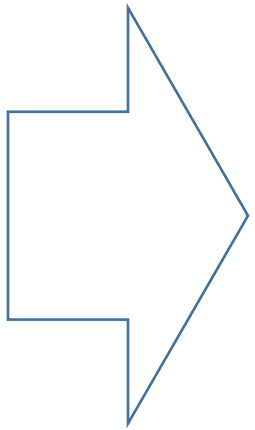
박경규

냉난방 부하 예측모델

건물 에너지 소비는 전체 에너지 사용의 약 40%를 차지합니다.
설계 단계에서 건물의 냉난방 부하를 예측하는 것은 에너지 효율화를 위해 매우 중요합니다.
건물 에너지 성능에 대한 데이터셋을 기반으로 건물의 냉난방 부하를 예측하는 다양한 모델을 개발합니다.

Input

- Relative Compactness
- Surface Area - m^2
- Wall Area - m^2
- Roof Area - m^2
- Overall Height - m
- Orientation - 2:North, 3:East, 4:South, 5:West
- Glazing Area - 0%, 10%, 25%, 40% (of floor area)
- Glazing Area Distribution (Variance)
  - 1:Uniform, 2:North, 3:East, 4:South, 5:West
- Heating Load - kWh
- Cooling Load - kWh



Output

- 난방부하
- 냉방부하

냉난방 부하 예측모델

energy_efficiency_modeling.ipynb

```
[1]  import os
     import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
     import warnings
     warnings.filterwarnings('ignore')
```

```
[2]  data = pd.read_csv('building_energy_efficiency.csv')
```

```
[3]  data.head()
```

	Relative Compactness	Surface Area	Wall Area	Roof Area	Overall Height	Orientation	Glazing Area	Glazing Area Distribution	Heating Load	Cooling Load
0	0.7638	514.5	294.0	110.25	7.0	2	0.0	0	15.55	21.33
1	0.9800	514.5	294.0	110.25	7.0	3	0.0	0	15.55	21.33
2	0.9800	514.5	294.0	110.25	7.0	4	0.0	0	15.55	21.33
3	0.9800	514.5	294.0	110.25	7.0	5	0.0	0	15.55	21.33
4	0.9000	563.5	318.5	122.50	7.0	2	0.0	0	20.84	28.28

냉난방 부하 예측모델

```
[4]  data.shape
```

```
(768, 10)
```

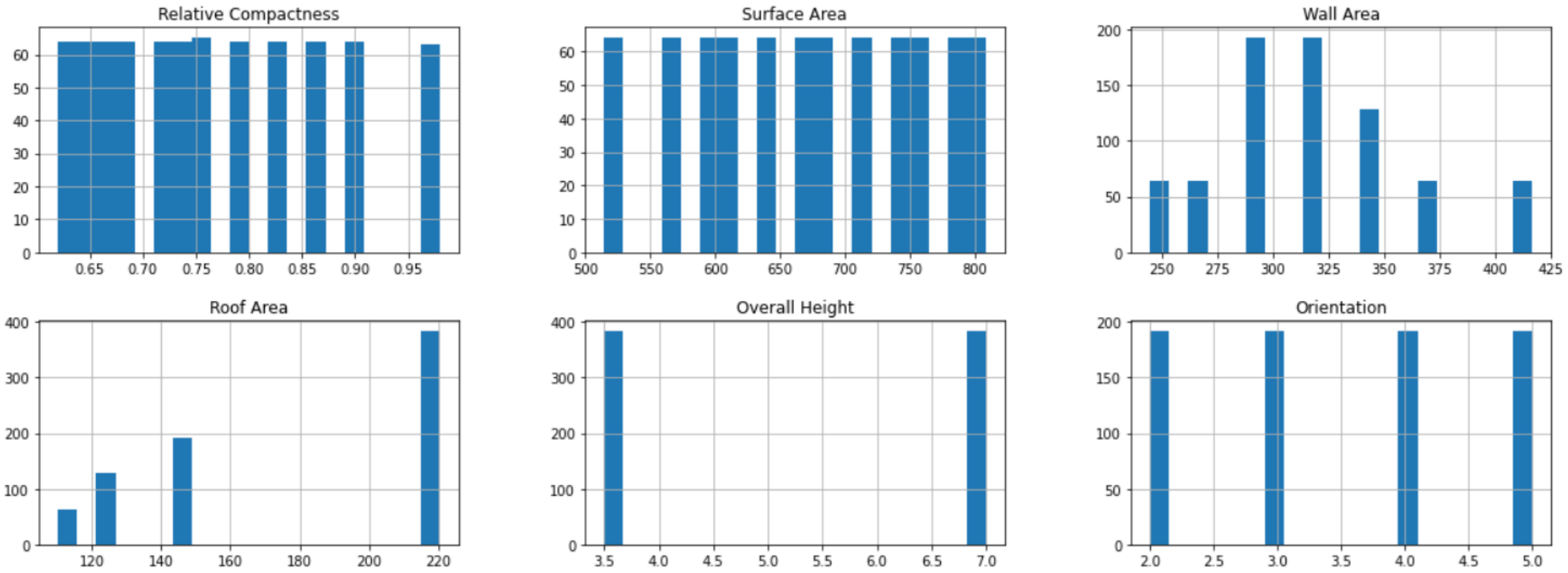
```
[5]  data.isnull().sum()
```

```
Relative Compactness          0
Surface Area                  0
Wall Area                     0
Roof Area                     0
Overall Height                0
Orientation                   0
Glazing Area                  0
Glazing Area Distribution     0
Heating Load                  0
Cooling Load                  0
dtype: int64
```

냉난방 부하 예측모델

각 데이터의 분포 체크

```
[6]  data.hist(bins=20, figsize=(20,15))
     plt.show()
```

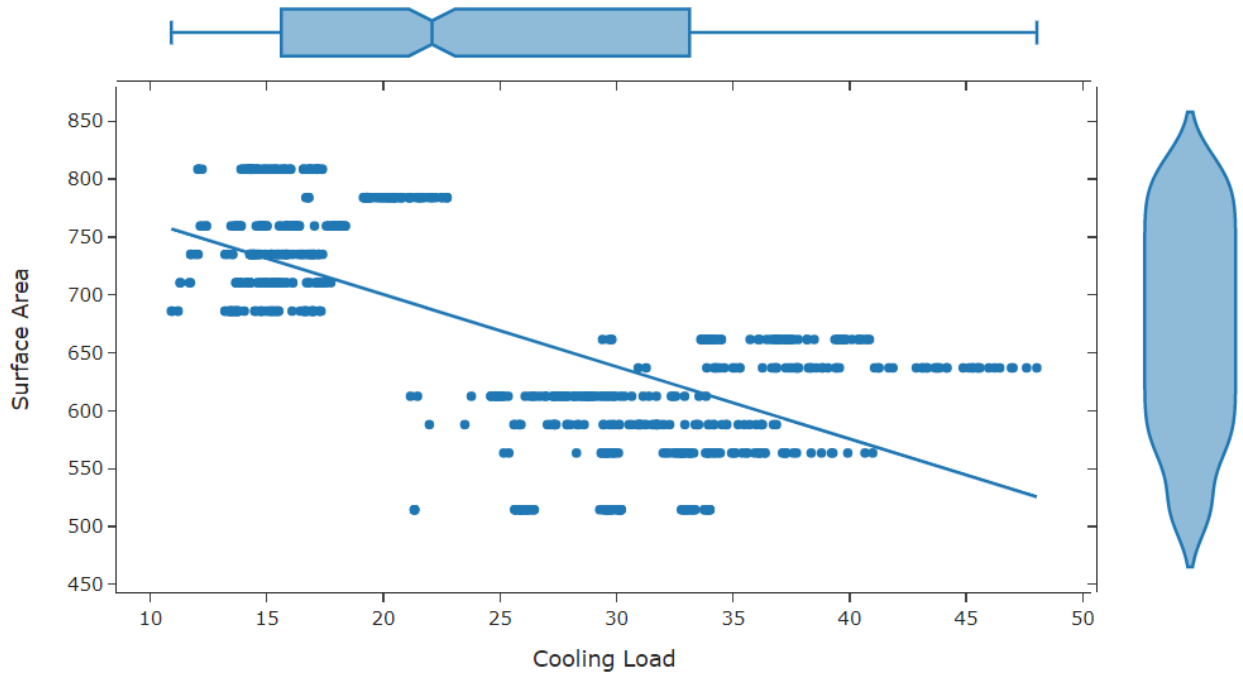


냉난방 부하 예측모델

상관관계 분석

```
[7]  import plotly.express as px

     yprop = 'Surface Area'
     xprop = 'Cooling Load'
     h= None
     px.scatter(data, x=xprop, y=yprop, color=h, marginal_y="violin", marginal_x="box", trendline="ols",
```



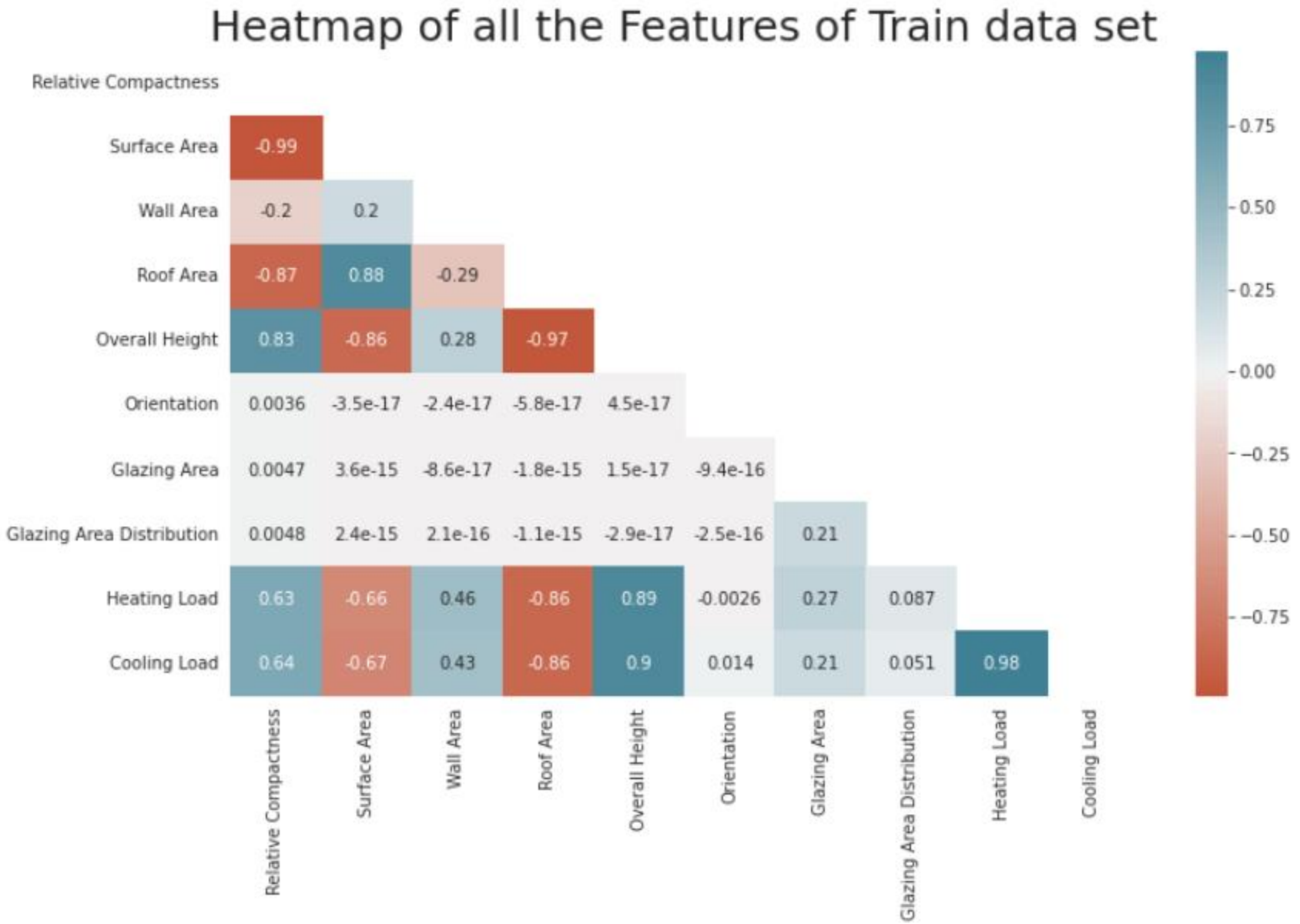
냉난방 부하 예측모델

명확한 상관관계를 찾기위해 상관관계 행렬 확인

```
[9]  import matplotlib.pyplot as plt
     import matplotlib.style as style
     import seaborn as sns
     style.use('ggplot')
     sns.set_style('whitegrid')

     plt.subplots(figsize = (12,7))
     ## Plotting heatmap. # Generate a mask for the upper triangle (taken from seabor
     mask = np.zeros_like(data.corr(), dtype=np.bool)
     mask[np.triu_indices_from(mask)] = True
     sns.heatmap(data.corr(), cmap=sns.diverging_palette(20, 220, n=200), annot=True,
     plt.title("Heatmap of all the Features of Train data set", fontsize = 25);
```

냉난방 부하 예측모델


Heatmap of all the Features of Train data set
Relative Compactness
Surface Area -0.99
Wall Area -0.2 0.2
Roof Area -0.87 0.88 -0.29
Overall Height 0.83 -0.86 0.28 -0.97
Orientation 0.0036 -3.5e-17 -2.4e-17 -5.8e-17 4.5e-17
Glazing Area 0.0047 3.6e-15 -8.6e-17 -1.8e-15 1.5e-17 -9.4e-16
Glazing Area Distribution 0.0048 2.4e-15 2.1e-16 -1.1e-15 -2.9e-17 -2.5e-16 0.21
Heating Load 0.63 -0.66 0.46 -0.86 0.89 -0.0026 0.27 0.087
Cooling Load 0.64 -0.67 0.43 -0.86 0.9 0.014 0.21 0.051 0.98
Relative Compactness
Surface Area
Wall Area
Roof Area
Overall Height
Orientation
Glazing Area
Glazing Area Distribution
Heating Load
Cooling Load
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

냉난방 부하 예측모델

```
[11] from scipy.stats import randint as sp_randint
     from catboost import CatBoostRegressor
     from sklearn.model_selection import GridSearchCV
     from keras.layers import Dense
     from keras.models import Sequential
     from sklearn.tree import DecisionTreeRegressor
     from sklearn.neighbors import KNeighborsRegressor
     from sklearn.neural_network import MLPRegressor
     from sklearn.ensemble import GradientBoostingRegressor,AdaBoostRegressor
     from sklearn.ensemble import BaggingRegressor, RandomForestRegressor
     from sklearn.model_selection import GridSearchCV
     from sklearn.model_selection import train_test_split
     from sklearn.multioutput import MultiOutputRegressor
     from sklearn.preprocessing import MinMaxScaler
     from sklearn.svm import SVC
     from sklearn.svm import SVR
     from sklearn.metrics import accuracy_score, f1_score
     from sklearn.metrics import r2_score
     from sklearn.metrics import roc_auc_score
```

냉난방 부하 예측모델

```
[12] X = data[['Relative Compactness', 'Surface Area', 'Wall Area',
               'Roof Area', 'Overall Height', 'Orientation',
               'Glazing Area', 'Glazing Area Distribution']]
     Y = data[['Heating Load', 'Cooling Load']]
     Y1= data[['Heating Load']]
     Y2= data[['Cooling Load']]
```

냉난방 부하 예측모델

- 데이터 세트를 훈련 및 테스트 세트로 분할.
- 특징 스케일링 또는 데이터 정규화는 데이터의 독립 변수 또는 특징의 범위를 정규화하는 데 사용되는 방법입니다.
- 따라서 독립 변수에서 값이 많이 다를 때 모든 값이 비교 가능한 범위에 유지되도록 특성 스케일링을 사용합니다.

```
[13] X_train, X_test, y1_train, y1_test, y2_train, y2_test = train_test_split(
         X, Y1, Y2, test_size=0.33, random_state = 20)

     MinMax = MinMaxScaler(feature_range= (0,1))
     X_train = MinMax.fit_transform(X_train)
     X_test = MinMax.transform(X_test)
```

냉난방 부하 예측모델

모델링

각 모델의 결과를 저장할 DataFrame을 만듭니다.

```
[14] Acc = pd.DataFrame(index=None, columns=['model',
                                             'train_Heating','test_Heating',
                                             'train_Cooling','test_Cooling'])
```

```
[15] regressors = [['SVR',SVR()],
                   ['DecisionTreeRegressor',DecisionTreeRegressor()],
                   ['KNeighborsRegressor', KNeighborsRegressor()],
                   ['RandomForestRegressor', RandomForestRegressor()],
                   ['MLPRegressor',MLPRegressor()],
                   ['AdaBoostRegressor',AdaBoostRegressor()],
                   ['GradientBoostingRegressor',GradientBoostingRegressor()]]
```

냉난방 부하 예측모델

```
[16]  for mod in regressors:
          name = mod[0]
          model = mod[1]

          model.fit(X_train, y1_train)
          actr1 = r2_score(y1_train, model.predict(X_train))
          acte1 = r2_score(y1_test, model.predict(X_test))

          model.fit(X_train, y2_train)
          actr2 = r2_score(y2_train, model.predict(X_train))
          acte2 = r2_score(y2_test, model.predict(X_test))

          Acc = Acc.append(pd.Series({'model':name, 'train_Heating':actr1,
                                      'test_Heating':acte1,'train_Cooling':actr2,
                                      'test_Cooling':acte2}),ignore_index=True )

      Acc.sort_values(by='test_Cooling')
```

냉난방 부하 예측모델

	model	train_Heating	test_Heating	train_Cooling	test_Cooling
4	MLPRegressor	0.865059	0.872689	0.815817	0.835746
0	SVR	0.930662	0.910593	0.892578	0.887385
2	KNeighborsRegressor	0.945989	0.904490	0.926869	0.888896
5	AdaBoostRegressor	0.958150	0.955481	0.943954	0.941024
1	DecisionTreeRegressor	1.000000	0.997228	1.000000	0.948199
3	RandomForestRegressor	0.999405	0.997419	0.995561	0.964753
6	GradientBoostingRegressor	0.998173	0.997641	0.979423	0.976044

냉난방 부하 예측모델

모델 파라미터 튜닝

- Boosting machine learning 알고리즘은 단순한 알고리즘보다 더 나은 정확도를 제공하기 때문에 많이 사용됩니다.
- 알고리즘의 성능은 하이퍼파라미터에 따라 다릅니다.
- 최적의 parameter는 더 높은 정확도를 달성하는 데 도움이 될 수 있습니다.
- 수동으로 hyper parameter를 찾는 것은 지루하고 계산 비용이 많이 듭니다.
- 하이퍼파라미터 튜닝의 자동화가 중요합니다.
- RandomSearch, GridSearchCV, Bayesian optimization은 하이퍼파라미터를 최적화하는 데 사용됩니다.

냉난방 부하 예측모델

```
[17] param_grid = [{"learning_rate": [0.01, 0.02, 0.1],
                    "n_estimators":[150, 200, 250], "max_depth": [4, 5, 6],
                    "min_samples_split":[1, 2, 3], "min_samples_leaf":[2, 3],
                    "subsample":[1.0, 2.0]}]

     GBR = GradientBoostingRegressor()
     grid_search_GBR = GridSearchCV(GBR, param_grid, cv=10,
                                    scoring='neg_mean_squared_error')
     grid_search_GBR.fit(X_train, y2_train)

     print("R-Squared::{}".format(grid_search_GBR.best_score_))
     print("Best Hyperparameters::₩n{}".format(grid_search_GBR.best_params_))
```

```
R-Squared::-1.056051894122206 8
Best Hyperparameters::
{'learning_rate': 0.1, 'max_depth': 5, 'min_samples_leaf': 3, 'min_samples_split': 3,
```

냉난방 부하 예측모델

A. Decision Tree Regressor parameters turning

```
[18] DTR = DecisionTreeRegressor()
     param_grid = {"criterion": ["mse", "mae"],"min_samples_split": [14, 15, 16, 17],
                   "max_depth": [5, 6, 7],"min_samples_leaf": [4, 5, 6],
                   "max_leaf_nodes": [29, 30, 31, 32],}

     grid_cv_DTR = GridSearchCV(DTR, param_grid, cv=5)

     grid_cv_DTR.fit(X_train,y2_train)
     print("R-Squared::{}".format(grid_cv_DTR.best_score_))
     print("Best Hyperparameters::₩n{}".format(grid_cv_DTR.best_params_))
```

```
R-Squared::0.9599150110108299
Best Hyperparameters::
{'criterion': 'mse', 'max_depth': 6, 'max_leaf_nodes': 32, 'min_samples_leaf': 5
```

냉난방 부하 예측모델

```
[19] DTR = DecisionTreeRegressor()
     param_grid = {"criterion": ["mse", "mae"],"min_samples_split": [14, 15, 16, 17],
                   "max_depth": [5, 6, 7],"min_samples_leaf": [4, 5, 6],
                   "max_leaf_nodes": [29, 30, 31, 32],}

     grid_cv_DTR = GridSearchCV(DTR, param_grid, cv=5)

     grid_cv_DTR.fit(X_train,y2_train)
     print("R-Squared::{}".format(grid_cv_DTR.best_score_))
     print("Best Hyperparameters::₩n{}".format(grid_cv_DTR.best_params_))
```

```
R-Squared::0.9598595926917322
Best Hyperparameters::
{'criterion': 'mse', 'max_depth': 6, 'max_leaf_nodes': 31, 'min_samples_leaf': 5
```

냉난방 부하 예측모델

B. Tune Random Forests Parameters

```
[20]  from sklearn.model_selection import GridSearchCV
      param_grid = [{'n_estimators': [350, 400, 450], 'max_features': [1, 2],
                     'max_depth': [85, 90, 95]}]

      RFR = RandomForestRegressor(n_jobs=-1)
      grid_search_RFR = GridSearchCV(RFR, param_grid, cv=10,
                                     scoring='neg_mean_squared_error')
      grid_search_RFR.fit(X_train, y2_train)

      print("R-Squared::{}".format(grid_search_RFR.best_score_))
      print("Best Hyperparameters::₩n{}".format(grid_search_RFR.best_params_))
```

```
R-Squared::-2.7105394110927175
Best Hyperparameters::
{'max_depth': 85, 'max_features': 1, 'n_estimators': 350}
```

냉난방 부하 예측모델

C. Gradient Boosting Regression - Hyperparameter Tuning

```
[22] GBR = GradientBoostingRegressor(learning_rate=0.1,n_estimators=250,
                                     max_depth=5, min_samples_split=3,
                                     min_samples_leaf=2, subsample=1.0)

     GBR.fit(X_train,y1_train)
     print("R-Squared on train dataset={}".format(GBR.score(X_test,y1_test)))

     GBR.fit(X_train,y2_train)
     print("R-Squaredon test dataset={}".format(GBR.score(X_test,y2_test)))
```

```
R-Squared on train dataset=0.9986725708412564
R-Squaredon test dataset=0.9915616795439752
```

냉난방 부하 예측모델

D. CatBoostRegressor

```
[23]  import warnings
      warnings.filterwarnings("ignore")
      from sklearn import datasets
      from sklearn.model_selection import train_test_split
      from sklearn.model_selection import GridSearchCV
      from catboost import CatBoostRegressor

      model_CBR = CatBoostRegressor()
      parameters = {'depth':[8, 10],'iterations':[10000],'learning_rate':[0.02,0.03],
                    'border_count':[5],'random_state': [42, 45]}

      grid = GridSearchCV(estimator=model_CBR, param_grid = parameters, cv = 2, n_jobs=-1)
      grid.fit(X_train, y2_train)
      print(" Results from Grid Search " )
      print("₩n The best estimator across ALL searched params:₩n", grid.best_estimator_)
      print("₩n The best score across ALL searched params:₩n", grid.best_score_)
      print("₩n The best parameters across ALL searched params:₩n", grid.best_params_)
```

냉난방 부하 예측모델

E. MLPRegressor

```
[24] MLPR = MLPRegressor(hidden_layer_sizes = [180,100,20],activation ='relu',
                         solver='lbfgs',max_iter = 10000,random_state = 0)
     MLPR.fit(X_train,y1_train)
     print("R-Squared on train dataset={}".format(MLPR.score(X_test,y1_test)))

     MLPR.fit(X_train,y2_train)
     print("R-Squaredon test dataset={}".format(MLPR.score(X_test,y2_test)))
```

```
R-Squared on train dataset=0.9978104168656019
R-Squaredon test dataset=0.9905898640304825
```

냉난방 부하 예측모델

모델 성능 Summary

```
[25] Acc1 = pd.DataFrame(index=None, columns=['model','train_Heating','test_Heating',
                                              'train_Cooling','test_Cooling'])
```

```
[26] regressors1 = [['DecisionTreeRegressor',
                     DecisionTreeRegressor(criterion= 'mse', max_depth= 6,
                                           max_leaf_nodes= 30, min_samples_leaf= 5,
                                           min_samples_split= 17)],
                    ['RandomForestRegressor',
                     RandomForestRegressor(n_estimators = 450, max_features = 1,
                                           max_depth= 90, bootstrap= True)],
                    ['MLPRegressor',
                     MLPRegressor(hidden_layer_sizes = [180,100,20],activation ='relu'
                                  solver='lbfgs',max_iter = 10000,random_state = 0)],
                    ['GradientBoostingRegressor',
                     GradientBoostingRegressor(learning_rate=0.1,n_estimators=250,
                                               max_depth=5, min_samples_split=2,
                                               min_samples_leaf=3, subsample=1.0)]]
```

냉난방 부하 예측모델

```
[27]  for mod in regressors1:
          name = mod[0]
          model = mod[1]

          model.fit(X_train,y1_train)
          actr1 = r2_score(y1_train, model.predict(X_train))
          acte1 = r2_score(y1_test, model.predict(X_test))

          model.fit(X_train,y2_train)
          actr2 = r2_score(y2_train, model.predict(X_train))
          acte2 = r2_score(y2_test, model.predict(X_test))

          Acc1 = Acc1.append(pd.Series({'model':name, 'train_Heating':actr1,
                                        'test_Heating':acte1,'train_Cooling':actr2,
                                        'test_Cooling':acte2}),ignore_index=True )
      Acc1.sort_values(by='test_Cooling')
```

냉난방 부하 예측모델

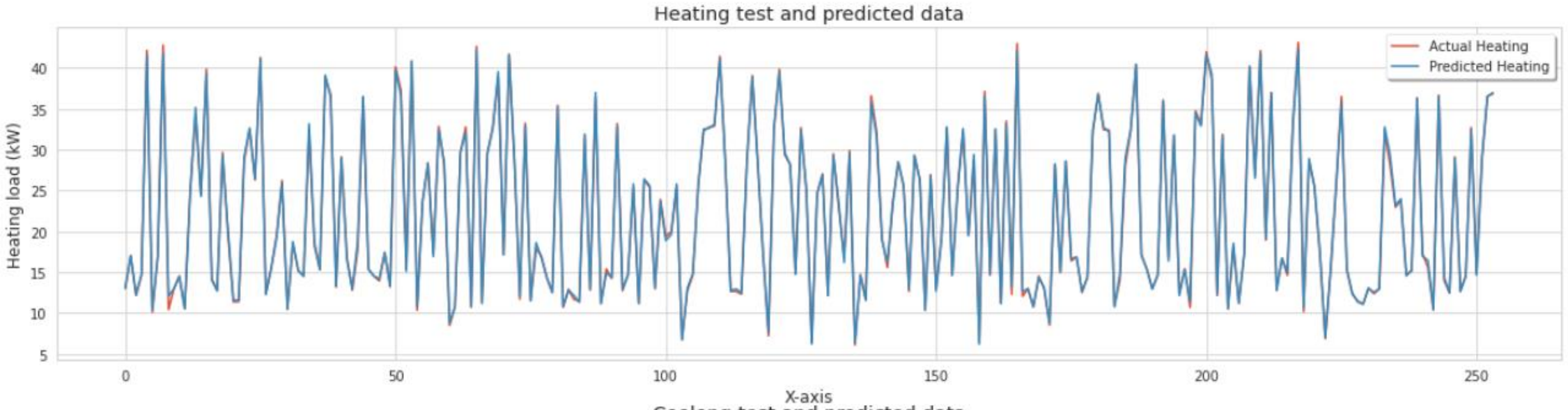
	model	train_Heating	test_Heating	train_Cooling	test_Cooling
0	DecisionTreeRegressor	0.994803	0.995168	0.967655	0.959112
1	RandomForestRegressor	0.998754	0.991773	0.996188	0.974144
2	MLPRegressor	0.999816	0.997810	0.999640	0.990590
3	GradientBoostingRegressor	0.999735	0.998553	0.998988	0.991933

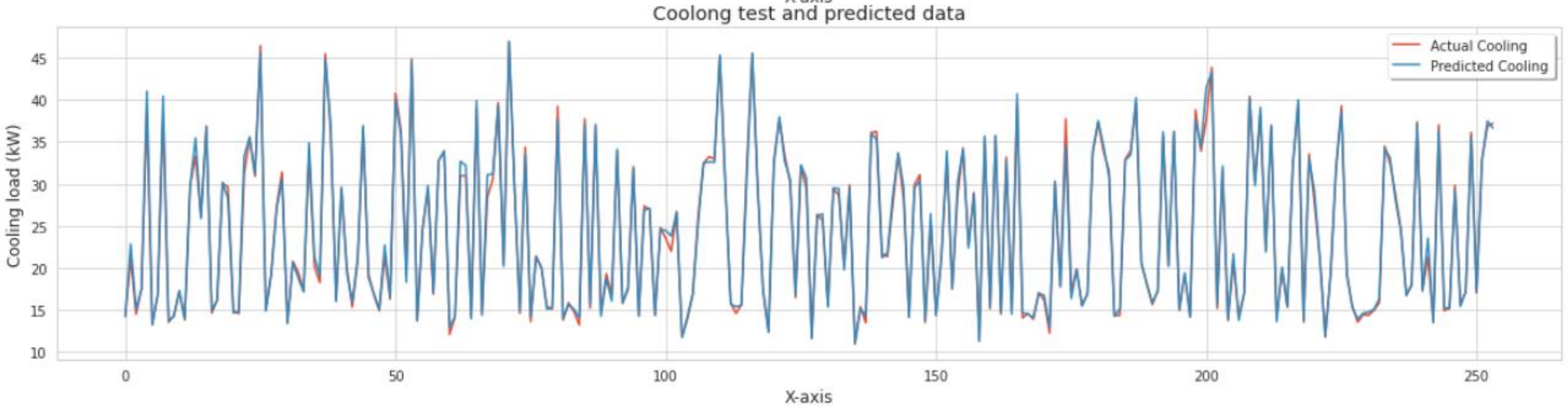
냉난방 부하 예측모델

```
[30]  x_ax = range(len(y1_test))
      plt.figure(figsize=(20,10))
      plt.subplot(2,1,1)
      plt.plot(x_ax, y1_test, label="Actual Heating")
      plt.plot(x_ax, y1_pred, label="Predicted Heating")
      plt.title("Heating test and predicted data")
      plt.xlabel('X-axis')
      plt.ylabel('Heating load (kW)')
      plt.legend(loc='best',fancybox=True, shadow=True)
      plt.grid(True)

      plt.subplot(2,1,2)
      plt.plot(x_ax, y2_test, label="Actual Cooling")
      plt.plot(x_ax, y2_pred, label="Predicted Cooling")
      plt.title("Coolong test and predicted data")
      plt.xlabel('X-axis')
      plt.ylabel('Cooling load (kW)')
      plt.legend(loc='best',fancybox=True, shadow=True)
      plt.grid(True)
```

냉난방 부하 예측모델


Heating test and predicted data
Actual Heating
Predicted Heating
Heating load (kW)
X-axis
0
50
100
150
200
250
5
10
15
20
25
30
35
40


Coolong test and predicted data
Actual Cooling
Predicted Cooling
Cooling load (kW)
X-axis
0
50
100
150
200
250
10
15
20
25
30
35
40
45

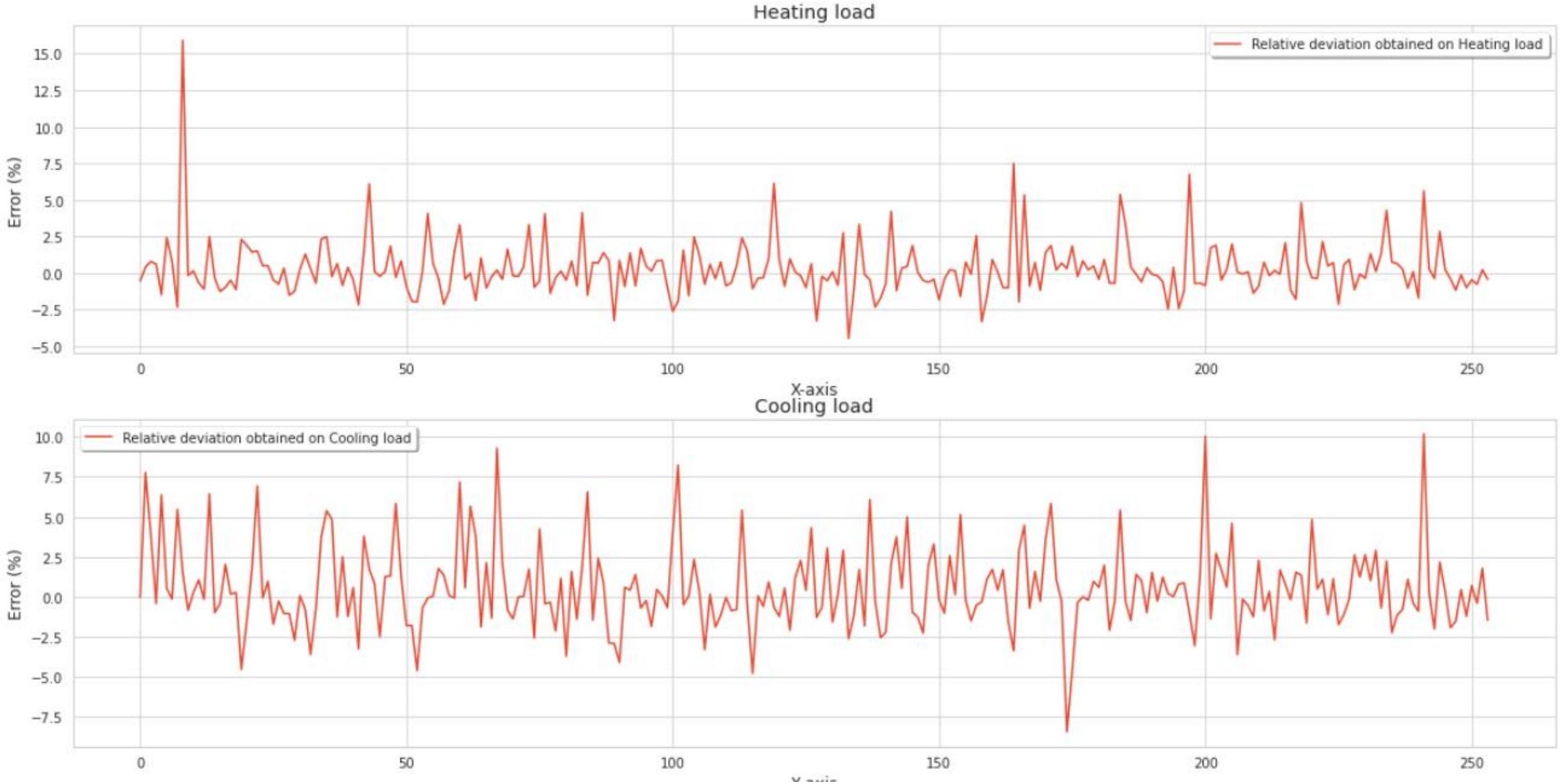
냉난방 부하 예측모델

```
[31] def AAD(y1_test, y1_pred):
         AAD =[]
         for i in range(len(y1_pred)):
             AAD.append((y1_pred[i] - y1_test.values[i])/y1_test.values[i]*100)
         return AAD

     x_ax = range(len(y1_test))
     plt.figure(figsize=(20,10))
     plt.subplot(2,1,1)
     plt.plot(x_ax, AAD(y1_test, y1_pred), label="Relative deviation obtained on Heating load")
     plt.title("Heating load")
     plt.xlabel('X-axis')
     plt.ylabel('Error (%)')
     plt.legend(loc='best',fancybox=True, shadow=True)
     plt.grid(True)

     plt.subplot(2,1,2)
     plt.plot(x_ax, AAD(y2_test, y2_pred), label="Relative deviation obtained on Cooling load")
     plt.title("Cooling load")
     plt.xlabel('X-axis')
     plt.ylabel('Error (%)')
     plt.legend(loc='best',fancybox=True, shadow=True)
     plt.grid(True)
```

냉난방 부하 예측모델


Heating load
Relative deviation obtained on Heating load
Error (%)
15.0
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
0
50
100
150
200
250
X-axis
Cooling load
Relative deviation obtained on Cooling load
Error (%)
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
0
50
100
150
200
250

THANK YOU

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