University Building ANN Model

November 23, 2020

```
[34]: # import the libraries
      import numpy as np
      import matplotlib.pyplot as plt
      import datetime
      import seaborn as sns
      import tensorflow as tf
      import pandas as pd
      from datetime import datetime
      print("TensorFlow version: ",tf.__version__) #print the version of tensorflow
     TensorFlow version: 2.3.0
[35]: from tensorflow.python.keras.layers import Dense
      from tensorflow.keras.layers import Dropout
      from tensorflow.python.keras.models import Sequential
      from tensorflow.python.keras.wrappers.scikit_learn import KerasRegressor
      from tensorflow import keras
      from tensorflow.keras import layers
      from tensorflow.keras import Sequential
      from tensorflow.keras.layers import Dense, Activation, Dropout
      from tensorflow.keras.callbacks import EarlyStopping
      from tensorflow.keras import regularizers
      from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
      from tensorflow.keras import regularizers
[36]: #Helper Functions
      def get_weekday2(year, month, day):
          dates = pd.DataFrame()
          dates['y'] = year
          dates['m'] = month
          dates['d'] = day
          dates['dates'] = dates['y'].astype('str') + '-' + dates['m'].astype('str')__
       →+ '-' + dates['d'].astype('str')
          return get_weekday(dates['dates'])
      #Get day of week based on date
      def get_weekday(dates):
```

```
return [1 if (datetime.strptime(d,"%Y-%m-%d").weekday() >= 5) else 0 for d_ \cup in dates]
```

1 Exploratory Data Analysis

```
[37]: data = pd.read_csv('https://raw.githubusercontent.com/A-Wadhwani/ME597-Project/
       →main/Datasets/Combined_PowerWeatherData2.csv')
      copy = data
      data
[37]:
             Year
                   Month
                              Square Feet
                                                 Туре
      0
             2016
                        8
                                   113866
                                           Classroom
      1
             2016
                        8
                                           Classroom
                                   113866
      2
             2016
                       8
                                   113866
                                           Classroom
      3
             2016
                        8
                                   113866
                                           Classroom
      4
                        8
                                           Classroom
             2016
                                   113866
      29987
             2019
                       12
                                    59548
                                           Classroom
      29988
             2019
                       12
                                    59548
                                           Classroom
      29989
             2019
                       12
                                    59548
                                           Classroom
                       12
      29990
             2019
                                    59548
                                           Classroom
      29991
             2019
                       12
                                    59548
                                           Classroom
      [29992 rows x 18 columns]
[38]: data.describe()
[38]:
                                   Month
                                                   Weekday
                                                              Square Feet
                     Year
             29992.000000
                            29992.000000
                                              29992.000000
                                                             29992.000000
      count
                                                  0.286977
                                                             95477.812017
              2018.172446
                                6.771239
      mean
      std
                 1.048141
                                3.404085
                                                  0.452358
                                                             41527.248371
      min
              2016.000000
                                1.000000
                                                  0.000000
                                                             10932.000000
      25%
              2017.000000
                                4.000000 ...
                                                  0.000000
                                                             59548.000000
      50%
              2019.000000
                                7.000000
                                                  0.000000
                                                            105545.000000
      75%
              2019.000000
                               10.000000
                                                  1.000000
                                                            121074.000000
      max
              2019.000000
                               12.000000
                                                  1.000000
                                                            238270.000000
      [8 rows x 15 columns]
[39]: #Creating column to denote each building type
      from sklearn.preprocessing import OrdinalEncoder
      encoder = OrdinalEncoder()
      data['Type'] = encoder.fit_transform(np.reshape(data['Type'].values, (-1,1)))
      data['Type'].describe()
```

```
[39]: count
               29992,000000
                   0.519405
     mean
      std
                   0.499632
     min
                   0.000000
      25%
                   0.000000
      50%
                   1.000000
      75%
                   1.000000
                   1.000000
      max
      Name: Type, dtype: float64
[40]: encoder.inverse_transform(np.reshape([0, 1], (-1,1)))
[40]: array([['Classroom'],
             ['Laboratory']], dtype=object)
[41]: #Removing unnecessary columns
      data = data.drop(['Year'], axis=1)
      data = data.drop(['University Name', 'Building Name'], axis=1)
      data.head()
         Month Day
[41]:
                                    Weekday
                                             Square Feet
                       DNI Mean ...
                                                           Type
                 10 310.769231
                                                            0.0
      0
             8
                                           0
                                                   113866
                                                            0.0
      1
             8
                     458.363636
                                           0
                                                   113866
                 11
      2
             8
                 12 419.000000
                                           0
                                                   113866
                                                            0.0
      3
                     498.666667
                                           1
                                                            0.0
                 13
                                                   113866
                      47.666667 ...
                                                   113866
                                                            0.0
      [5 rows x 15 columns]
[42]: #Select one building's data
      view = data[data['Square Feet'] == 113866]
      #See graphs for data vs Power Consumption
      sns.pairplot(view, x_vars = ['DNI Mean', 'Precipitable Water', 'Relative_
      →Humidity', 'Temperature', 'Pressure', 'Wind Speed'], y_vars=['Power_
       plt.show()
          E 12000
           10000
           8000
           6000
```

```
[43]: #Splitting into X and Y
      X = data.drop(["Power Consumption"],axis=1)
      y = data["Power Consumption"]
[44]: y = np.reshape(y.values, (-1,1))
[45]: # scaling inputs using RobustScaler
      from sklearn.preprocessing import RobustScaler
      x_scaler = RobustScaler()
      y_scaler = RobustScaler()
      x_f = x_scaler.fit_transform(X)
      y_f = y_scaler.fit_transform(y)
      x f = pd.DataFrame(x f)
[46]: x_f
[46]:
                   0
                             1
                                                               10
                                                                    11
                                                                              12
                                                                                   13
             0.166667 -0.400000 -0.498333 -0.033019 ... 0.000000 0.0 0.135244 -1.0
             0.166667 -0.333333 -0.095546 -0.051887 ... 0.000000 0.0 0.135244 -1.0
      1
      2
             0.166667 -0.266667 -0.202970 0.117925
                                                      ... 0.000000 0.0 0.135244 -1.0
      3
             0.166667 \; -0.200000 \quad 0.014441 \quad 0.221698 \quad \dots \quad 0.000000 \quad 1.0 \quad 0.135244 \; -1.0
             0.166667 -0.133333 -1.216342 -3.584906 ... 0.000000 1.0 0.135244 -1.0
      29987
             0.833333 0.733333 0.293846 0.146226 ... -0.725350 0.0 -0.747603 -1.0
      29988 0.833333 0.800000 0.458542 0.216981 ... -0.568777 1.0 -0.747603 -1.0
      29989 0.833333 0.866667 -1.241553 -3.570755 ... -0.689288 1.0 -0.747603 -1.0
      29990 0.833333 0.933333 0.472050 0.122642
                                                     ... -0.626293 0.0 -0.747603 -1.0
      29991 0.833333 1.000000 -0.041686 -0.485849 ... -0.578363 0.0 -0.747603 -1.0
      [29992 rows x 14 columns]
[47]: x_f = x_f.values
[48]: x_f.dtype
[48]: dtype('float64')
[49]: # split the data into train and test sets
      from sklearn.model_selection import train_test_split
      x_f_train, x_f_test, y_f_train, y_f_test = train_test_split(x_f,y_f, test_size_
      →= 0.25, shuffle=True,random_state=24)
[50]: # print the number of training and test damples
      print("Number of training samples: ",len(x_f_train))
      print("Number of testing samples: ",len(x_f_test))
```

Number of training samples: 22494 Number of testing samples: 7498

2 Building the Model

```
[68]: model = Sequential()
     model.add(Dense(512, input_shape=(14, ), activation='relu', name='dense_1'))
     model.add(Dense(256, activation='relu', name='dense_2'))
     model.add(Dense(128, activation='relu', name='dense_3'))
     model.add(Dense(64, activation='relu', name='dense_4'))
     model.add(Dense(32, activation='relu', name='dense_5'))
     model.add(Dense(16, activation='relu', name='dense_6'))
     model.add(Dense(1, activation='linear', name='dense_output'))
     model.summary()
    Model: "sequential_7"
    Layer (type)
                 Output Shape
                                                 Param #
    ______
    dense_1 (Dense)
                            (None, 512)
                                                  7680
                            (None, 256)
    dense_2 (Dense)
                                                  131328
    dense 3 (Dense)
                            (None, 128)
                                                  32896
                            (None, 64)
    dense_4 (Dense)
                                                  8256
                            (None, 32)
    dense_5 (Dense)
                                                  2080
    ______
    dense_6 (Dense)
                            (None, 16)
                                                  528
    dense_output (Dense) (None, 1) 17
    _____
    Total params: 182,785
    Trainable params: 182,785
    Non-trainable params: 0
[69]: opt = keras.optimizers.Adam(learning_rate = 0.001)
     model.compile(loss='mae', optimizer=opt, metrics=['mse', 'mae'])
     #Tensorboard tool callback
     log dir = ''
     \#log\_dir = "logs \setminus fit3 \setminus " + datetime.now().strftime("%M")
```

```
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir,_
 →histogram_freq=1, profile_batch = 100000000)
#Reduce Learning rate on Plateau
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=10, ___
\rightarrowverbose = 1)
#Earlystopping callback
early_stop = EarlyStopping(monitor = 'val_loss', min_delta= 1e-3, patience = 40, __
 →verbose = 1, restore_best_weights=True)
history = model.fit(x_f_train, y_f_train, callbacks = [tensorboard_callback,__
 →early_stop, reduce_lr],
             validation_data=(x_f_test, y_f_test), epochs=400,__
 →batch_size=90, verbose=1)
Epoch 1/400
0.2813 - mae: 0.3636 - val_loss: 0.2983 - val_mse: 0.2170 - val_mae: 0.2983
Epoch 2/400
0.1755 - mae: 0.2681 - val_loss: 0.2552 - val_mse: 0.1753 - val_mae: 0.2552
Epoch 3/400
0.1489 - mae: 0.2330 - val_loss: 0.2101 - val_mse: 0.1455 - val_mae: 0.2101
Epoch 4/400
0.1328 - mae: 0.2122 - val_loss: 0.2174 - val_mse: 0.1459 - val_mae: 0.2174
Epoch 5/400
0.1061 - mae: 0.1778 - val_loss: 0.1797 - val_mse: 0.1103 - val_mae: 0.1797
Epoch 6/400
0.1002 - mae: 0.1678 - val_loss: 0.1640 - val_mse: 0.1036 - val_mae: 0.1640
Epoch 7/400
0.0978 - mae: 0.1628 - val_loss: 0.1580 - val_mse: 0.1035 - val_mae: 0.1580
Epoch 8/400
0.0969 - mae: 0.1585 - val_loss: 0.1616 - val_mse: 0.1040 - val_mae: 0.1616
Epoch 9/400
0.0942 - mae: 0.1540 - val_loss: 0.1524 - val_mse: 0.0983 - val_mae: 0.1524
Epoch 10/400
0.0948 - mae: 0.1521 - val_loss: 0.1574 - val_mse: 0.1050 - val_mae: 0.1574
Epoch 11/400
```

```
0.0932 - mae: 0.1511 - val_loss: 0.1610 - val_mse: 0.1026 - val_mae: 0.1610
Epoch 12/400
0.0928 - mae: 0.1503 - val_loss: 0.1492 - val_mse: 0.0976 - val_mae: 0.1492
Epoch 13/400
0.0924 - mae: 0.1491 - val_loss: 0.1530 - val_mse: 0.0993 - val_mae: 0.1530
Epoch 14/400
0.0915 - mae: 0.1482 - val_loss: 0.1446 - val_mse: 0.0983 - val_mae: 0.1446
Epoch 15/400
0.0895 - mae: 0.1431 - val_loss: 0.1442 - val_mse: 0.0921 - val_mae: 0.1442
Epoch 16/400
0.0890 - mae: 0.1425 - val_loss: 0.1451 - val_mse: 0.0959 - val_mae: 0.1451
Epoch 17/400
0.0885 - mae: 0.1425 - val_loss: 0.1521 - val_mse: 0.0956 - val_mae: 0.1521
Epoch 18/400
0.0864 - mae: 0.1392 - val_loss: 0.1430 - val_mse: 0.0942 - val_mae: 0.1430
Epoch 19/400
0.0830 - mae: 0.1366 - val_loss: 0.1476 - val_mse: 0.0941 - val_mae: 0.1476
Epoch 20/400
0.0785 - mae: 0.1351 - val_loss: 0.1454 - val_mse: 0.0860 - val_mae: 0.1454
Epoch 21/400
0.0773 - mae: 0.1368 - val_loss: 0.1364 - val_mse: 0.0797 - val_mae: 0.1364
Epoch 22/400
0.0726 - mae: 0.1283 - val loss: 0.1287 - val mse: 0.0754 - val mae: 0.1287
Epoch 23/400
0.0705 - mae: 0.1258 - val_loss: 0.1370 - val_mse: 0.0802 - val_mae: 0.1370
Epoch 24/400
0.0704 - mae: 0.1237 - val_loss: 0.1253 - val_mse: 0.0775 - val_mae: 0.1253
Epoch 25/400
0.0686 - mae: 0.1216 - val_loss: 0.1236 - val_mse: 0.0742 - val_mae: 0.1236
Epoch 26/400
0.0679 - mae: 0.1204 - val_loss: 0.1297 - val_mse: 0.0775 - val_mae: 0.1297
Epoch 27/400
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```
0.0690 - mae: 0.1208 - val_loss: 0.1287 - val_mse: 0.0790 - val_mae: 0.1287
Epoch 28/400
0.0672 - mae: 0.1179 - val_loss: 0.1310 - val_mse: 0.0806 - val_mae: 0.1310
Epoch 29/400
0.0691 - mae: 0.1185 - val_loss: 0.1242 - val_mse: 0.0761 - val_mae: 0.1242
Epoch 30/400
0.0665 - mae: 0.1179 - val_loss: 0.1277 - val_mse: 0.0766 - val_mae: 0.1277
Epoch 31/400
0.0654 - mae: 0.1141 - val_loss: 0.1213 - val_mse: 0.0737 - val_mae: 0.1213
Epoch 32/400
0.0658 - mae: 0.1146 - val_loss: 0.1270 - val_mse: 0.0751 - val_mae: 0.1270
Epoch 33/400
0.0687 - mae: 0.1175 - val_loss: 0.1277 - val_mse: 0.0745 - val_mae: 0.1277
Epoch 34/400
0.0643 - mae: 0.1139 - val_loss: 0.1255 - val_mse: 0.0773 - val_mae: 0.1255
Epoch 35/400
0.0661 - mae: 0.1152 - val_loss: 0.1269 - val_mse: 0.0786 - val_mae: 0.1269
Epoch 36/400
0.0642 - mae: 0.1126 - val_loss: 0.1251 - val_mse: 0.0765 - val_mae: 0.1251
Epoch 37/400
0.0668 - mae: 0.1151 - val_loss: 0.1251 - val_mse: 0.0778 - val_mae: 0.1251
Epoch 38/400
0.0673 - mae: 0.1130 - val loss: 0.1299 - val mse: 0.0785 - val mae: 0.1299
Epoch 39/400
0.0640 - mae: 0.1103 - val_loss: 0.1234 - val_mse: 0.0722 - val_mae: 0.1234
Epoch 40/400
0.0639 - mae: 0.1092 - val_loss: 0.1237 - val_mse: 0.0752 - val_mae: 0.1237
Epoch 41/400
0.0650 - mae: 0.1125 - val_loss: 0.1193 - val_mse: 0.0739 - val_mae: 0.1193
Epoch 42/400
0.0631 - mae: 0.1100 - val_loss: 0.1247 - val_mse: 0.0769 - val_mae: 0.1247
Epoch 43/400
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```
0.0630 - mae: 0.1085 - val_loss: 0.1205 - val_mse: 0.0709 - val_mae: 0.1205
Epoch 44/400
0.0602 - mae: 0.1046 - val_loss: 0.1156 - val_mse: 0.0685 - val_mae: 0.1156
Epoch 45/400
0.0634 - mae: 0.1082 - val_loss: 0.1174 - val_mse: 0.0729 - val_mae: 0.1174
Epoch 46/400
0.0612 - mae: 0.1043 - val_loss: 0.1219 - val_mse: 0.0708 - val_mae: 0.1219
Epoch 47/400
0.0603 - mae: 0.1030 - val_loss: 0.1145 - val_mse: 0.0717 - val_mae: 0.1145
Epoch 48/400
0.0628 - mae: 0.1056 - val_loss: 0.1186 - val_mse: 0.0723 - val_mae: 0.1186
Epoch 49/400
0.0597 - mae: 0.1007 - val_loss: 0.1206 - val_mse: 0.0771 - val_mae: 0.1206
Epoch 50/400
0.0581 - mae: 0.0977 - val_loss: 0.1225 - val_mse: 0.0750 - val_mae: 0.1225
Epoch 51/400
0.0615 - mae: 0.1028 - val_loss: 0.1213 - val_mse: 0.0776 - val_mae: 0.1213
Epoch 52/400
0.0621 - mae: 0.1012 - val_loss: 0.1198 - val_mse: 0.0765 - val_mae: 0.1198
Epoch 53/400
0.0618 - mae: 0.1007 - val_loss: 0.1156 - val_mse: 0.0769 - val_mae: 0.1156
Epoch 54/400
0.0582 - mae: 0.0972 - val_loss: 0.1184 - val_mse: 0.0715 - val_mae: 0.1184
Epoch 55/400
0.0597 - mae: 0.0976 - val_loss: 0.1112 - val_mse: 0.0678 - val_mae: 0.1112
Epoch 56/400
0.0617 - mae: 0.1002 - val_loss: 0.1126 - val_mse: 0.0737 - val_mae: 0.1126
Epoch 57/400
0.0612 - mae: 0.0991 - val_loss: 0.1177 - val_mse: 0.0769 - val_mae: 0.1177
Epoch 58/400
0.0585 - mae: 0.0964 - val_loss: 0.1160 - val_mse: 0.0789 - val_mae: 0.1160
Epoch 59/400
```

```
0.0565 - mae: 0.0920 - val_loss: 0.1123 - val_mse: 0.0698 - val_mae: 0.1123
Epoch 60/400
0.0584 - mae: 0.0937 - val_loss: 0.1181 - val_mse: 0.0756 - val_mae: 0.1181
Epoch 61/400
0.0586 - mae: 0.0941 - val_loss: 0.1135 - val_mse: 0.0753 - val_mae: 0.1135
Epoch 62/400
0.0569 - mae: 0.0917 - val_loss: 0.1198 - val_mse: 0.0756 - val_mae: 0.1198
0.0591 - mae: 0.0928 - val_loss: 0.1184 - val_mse: 0.0814 - val_mae: 0.1184
Epoch 64/400
0.0598 - mae: 0.0935 - val_loss: 0.1099 - val_mse: 0.0718 - val_mae: 0.1099
Epoch 65/400
0.0590 - mae: 0.0915 - val_loss: 0.1180 - val_mse: 0.0769 - val_mae: 0.1180
Epoch 66/400
0.0590 - mae: 0.0913 - val_loss: 0.1117 - val_mse: 0.0690 - val_mae: 0.1117
Epoch 67/400
0.0570 - mae: 0.0887 - val_loss: 0.1155 - val_mse: 0.0776 - val_mae: 0.1155
Epoch 68/400
0.0556 - mae: 0.0880 - val_loss: 0.1110 - val_mse: 0.0791 - val_mae: 0.1110
Epoch 69/400
0.0573 - mae: 0.0891 - val_loss: 0.1116 - val_mse: 0.0725 - val_mae: 0.1116
Epoch 70/400
0.0574 - mae: 0.0874 - val_loss: 0.1141 - val_mse: 0.0804 - val_mae: 0.1141
Epoch 71/400
0.0551 - mae: 0.0843 - val_loss: 0.1086 - val_mse: 0.0690 - val_mae: 0.1086
Epoch 72/400
0.0523 - mae: 0.0820 - val_loss: 0.1147 - val_mse: 0.0789 - val_mae: 0.1147
Epoch 73/400
0.0561 - mae: 0.0867 - val_loss: 0.1135 - val_mse: 0.0754 - val_mae: 0.1135
Epoch 74/400
0.0558 - mae: 0.0867 - val_loss: 0.1094 - val_mse: 0.0815 - val_mae: 0.1094
Epoch 75/400
```

```
0.0582 - mae: 0.0856 - val_loss: 0.1058 - val_mse: 0.0662 - val_mae: 0.1058
Epoch 76/400
0.0550 - mae: 0.0838 - val_loss: 0.1146 - val_mse: 0.0811 - val_mae: 0.1146
Epoch 77/400
0.0554 - mae: 0.0834 - val_loss: 0.1104 - val_mse: 0.0740 - val_mae: 0.1104
Epoch 78/400
0.0555 - mae: 0.0842 - val_loss: 0.1052 - val_mse: 0.0670 - val_mae: 0.1052
Epoch 79/400
0.0560 - mae: 0.0838 - val_loss: 0.1091 - val_mse: 0.0739 - val_mae: 0.1091
Epoch 80/400
0.0516 - mae: 0.0777 - val_loss: 0.1075 - val_mse: 0.0783 - val_mae: 0.1075
Epoch 81/400
0.0585 - mae: 0.0861 - val_loss: 0.1055 - val_mse: 0.0712 - val_mae: 0.1055
Epoch 82/400
0.0585 - mae: 0.0856 - val_loss: 0.1076 - val_mse: 0.0693 - val_mae: 0.1076
Epoch 83/400
0.0568 - mae: 0.0845 - val_loss: 0.1148 - val_mse: 0.0891 - val_mae: 0.1148
Epoch 84/400
0.0547 - mae: 0.0795 - val_loss: 0.1049 - val_mse: 0.0747 - val_mae: 0.1049
Epoch 85/400
0.0525 - mae: 0.0784 - val_loss: 0.1132 - val_mse: 0.0827 - val_mae: 0.1132
Epoch 86/400
0.0539 - mae: 0.0803 - val_loss: 0.1086 - val_mse: 0.0708 - val_mae: 0.1086
Epoch 87/400
0.0530 - mae: 0.0805 - val_loss: 0.1112 - val_mse: 0.0842 - val_mae: 0.1112
Epoch 88/400
0.0538 - mae: 0.0798 - val_loss: 0.1130 - val_mse: 0.0820 - val_mae: 0.1130
Epoch 89/400
0.0566 - mae: 0.0829 - val_loss: 0.1111 - val_mse: 0.0728 - val_mae: 0.1111
Epoch 90/400
0.0552 - mae: 0.0825 - val_loss: 0.1067 - val_mse: 0.0819 - val_mae: 0.1067
Epoch 91/400
```

```
0.0550 - mae: 0.0794 - val_loss: 0.1056 - val_mse: 0.0794 - val_mae: 0.1056
Epoch 92/400
0.0526 - mae: 0.0773 - val_loss: 0.1151 - val_mse: 0.0845 - val_mae: 0.1151
Epoch 93/400
0.0524 - mae: 0.0762 - val_loss: 0.1047 - val_mse: 0.0711 - val_mae: 0.1047
Epoch 94/400
0.0500 - mae: 0.0734 - val_loss: 0.1018 - val_mse: 0.0651 - val_mae: 0.1018
0.0538 - mae: 0.0785 - val_loss: 0.1071 - val_mse: 0.0764 - val_mae: 0.1071
Epoch 96/400
0.0528 - mae: 0.0788 - val_loss: 0.1126 - val_mse: 0.0870 - val_mae: 0.1126
Epoch 97/400
0.0554 - mae: 0.0797 - val_loss: 0.1088 - val_mse: 0.0769 - val_mae: 0.1088
Epoch 98/400
0.0506 - mae: 0.0761 - val_loss: 0.1052 - val_mse: 0.0786 - val_mae: 0.1052
Epoch 99/400
0.0539 - mae: 0.0762 - val_loss: 0.1117 - val_mse: 0.0703 - val_mae: 0.1117
Epoch 100/400
0.0490 - mae: 0.0747 - val_loss: 0.1076 - val_mse: 0.0696 - val_mae: 0.1076
Epoch 101/400
0.0552 - mae: 0.0793 - val_loss: 0.1317 - val_mse: 0.1118 - val_mae: 0.1317
Epoch 102/400
0.0540 - mae: 0.0796 - val loss: 0.1029 - val mse: 0.0766 - val mae: 0.1029
Epoch 103/400
0.0515 - mae: 0.0737 - val_loss: 0.1075 - val_mse: 0.0731 - val_mae: 0.1075
Epoch 104/400
- mae: 0.0742
Epoch 00104: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
0.0507 - mae: 0.0742 - val_loss: 0.1054 - val_mse: 0.0741 - val_mae: 0.1054
Epoch 105/400
0.0440 - mae: 0.0610 - val_loss: 0.0983 - val_mse: 0.0733 - val_mae: 0.0983
Epoch 106/400
```

```
0.0435 - mae: 0.0575 - val_loss: 0.0971 - val_mse: 0.0739 - val_mae: 0.0971
Epoch 107/400
0.0424 - mae: 0.0562 - val_loss: 0.0977 - val_mse: 0.0753 - val_mae: 0.0977
Epoch 108/400
0.0419 - mae: 0.0554 - val_loss: 0.0978 - val_mse: 0.0766 - val_mae: 0.0978
Epoch 109/400
0.0434 - mae: 0.0549 - val loss: 0.0979 - val mse: 0.0724 - val mae: 0.0979
Epoch 110/400
0.0418 - mae: 0.0543 - val_loss: 0.0973 - val_mse: 0.0751 - val_mae: 0.0973
Epoch 111/400
0.0416 - mae: 0.0539 - val_loss: 0.0978 - val_mse: 0.0762 - val_mae: 0.0978
Epoch 112/400
0.0419 - mae: 0.0537 - val_loss: 0.0969 - val_mse: 0.0726 - val_mae: 0.0969
Epoch 113/400
0.0419 - mae: 0.0533 - val_loss: 0.0972 - val_mse: 0.0707 - val_mae: 0.0972
Epoch 114/400
0.0410 - mae: 0.0530 - val_loss: 0.0978 - val_mse: 0.0748 - val_mae: 0.0978
Epoch 115/400
0.0410 - mae: 0.0529 - val_loss: 0.0965 - val_mse: 0.0674 - val_mae: 0.0965
Epoch 116/400
0.0400 - mae: 0.0527 - val_loss: 0.0983 - val_mse: 0.0742 - val_mae: 0.0983
Epoch 117/400
0.0403 - mae: 0.0525 - val loss: 0.0980 - val mse: 0.0795 - val mae: 0.0980
Epoch 118/400
0.0406 - mae: 0.0520 - val_loss: 0.0978 - val_mse: 0.0720 - val_mae: 0.0978
Epoch 119/400
0.0398 - mae: 0.0516 - val_loss: 0.0973 - val_mse: 0.0712 - val_mae: 0.0973
Epoch 120/400
0.0393 - mae: 0.0513 - val_loss: 0.0968 - val_mse: 0.0695 - val_mae: 0.0968
Epoch 121/400
0.0397 - mae: 0.0513 - val_loss: 0.0983 - val_mse: 0.0739 - val_mae: 0.0983
Epoch 122/400
```

```
0.0391 - mae: 0.0510 - val_loss: 0.0981 - val_mse: 0.0736 - val_mae: 0.0981
Epoch 123/400
0.0388 - mae: 0.0512 - val_loss: 0.0995 - val_mse: 0.0769 - val_mae: 0.0995
Epoch 124/400
0.0376 - mae: 0.0502 - val_loss: 0.0985 - val_mse: 0.0743 - val_mae: 0.0985
Epoch 125/400
- mae: 0.0500
Epoch 00125: ReduceLROnPlateau reducing learning rate to 4.0000001899898055e-05.
0.0375 - mae: 0.0502 - val_loss: 0.0974 - val_mse: 0.0697 - val_mae: 0.0974
Epoch 126/400
0.0359 - mae: 0.0477 - val_loss: 0.0974 - val_mse: 0.0726 - val_mae: 0.0974
Epoch 127/400
0.0362 - mae: 0.0470 - val_loss: 0.0975 - val_mse: 0.0725 - val_mae: 0.0975
Epoch 128/400
0.0363 - mae: 0.0467 - val_loss: 0.0974 - val_mse: 0.0723 - val_mae: 0.0974
Epoch 129/400
0.0359 - mae: 0.0465 - val loss: 0.0975 - val mse: 0.0728 - val mae: 0.0975
Epoch 130/400
0.0358 - mae: 0.0463 - val_loss: 0.0977 - val_mse: 0.0736 - val_mae: 0.0977
Epoch 131/400
0.0360 - mae: 0.0461 - val_loss: 0.0973 - val_mse: 0.0704 - val_mae: 0.0973
Epoch 132/400
0.0355 - mae: 0.0460 - val_loss: 0.0976 - val_mse: 0.0718 - val_mae: 0.0976
Epoch 133/400
0.0352 - mae: 0.0458 - val_loss: 0.0975 - val_mse: 0.0707 - val_mae: 0.0975
Epoch 134/400
0.0354 - mae: 0.0458 - val_loss: 0.0978 - val_mse: 0.0722 - val_mae: 0.0978
Epoch 135/400
- mae: 0.0458
Epoch 00135: ReduceLROnPlateau reducing learning rate to 8.000000525498762e-06.
0.0350 - mae: 0.0457 - val_loss: 0.0979 - val_mse: 0.0741 - val_mae: 0.0979
Epoch 136/400
```

```
0.0353 - mae: 0.0452 - val_loss: 0.0976 - val_mse: 0.0725 - val_mae: 0.0976
Epoch 137/400
0.0351 - mae: 0.0450 - val_loss: 0.0976 - val_mse: 0.0722 - val_mae: 0.0976
Epoch 138/400
0.0349 - mae: 0.0449 - val_loss: 0.0976 - val_mse: 0.0726 - val_mae: 0.0976
Epoch 139/400
0.0350 - mae: 0.0449 - val_loss: 0.0976 - val_mse: 0.0725 - val_mae: 0.0976
Epoch 140/400
0.0349 - mae: 0.0448 - val_loss: 0.0975 - val_mse: 0.0721 - val_mae: 0.0975
0.0349 - mae: 0.0448 - val_loss: 0.0976 - val_mse: 0.0721 - val_mae: 0.0976
Epoch 142/400
0.0348 - mae: 0.0448 - val_loss: 0.0976 - val_mse: 0.0724 - val_mae: 0.0976
Epoch 143/400
0.0347 - mae: 0.0448 - val_loss: 0.0976 - val_mse: 0.0723 - val_mae: 0.0976
Epoch 144/400
0.0348 - mae: 0.0447 - val_loss: 0.0976 - val_mse: 0.0719 - val_mae: 0.0976
Epoch 145/400
- mae: 0.0450
Epoch 00145: ReduceLROnPlateau reducing learning rate to 1.6000001778593287e-06.
0.0347 - mae: 0.0447 - val_loss: 0.0976 - val_mse: 0.0724 - val_mae: 0.0976
Epoch 146/400
- mae: 0.0444Restoring model weights from the end of the best epoch.
0.0347 - mae: 0.0446 - val_loss: 0.0976 - val_mse: 0.0723 - val_mae: 0.0976
Epoch 00146: early stopping
```

3 Testing accuracy of Model with validation data

```
[62]: y_f_result = model.predict(x_f_test)
y_result = y_scaler.inverse_transform(y_f_result)
y_actual = y_scaler.inverse_transform(y_f_test)

compare = pd.DataFrame()
compare['Expected'] = y_actual.reshape(1,-1)[0]
```

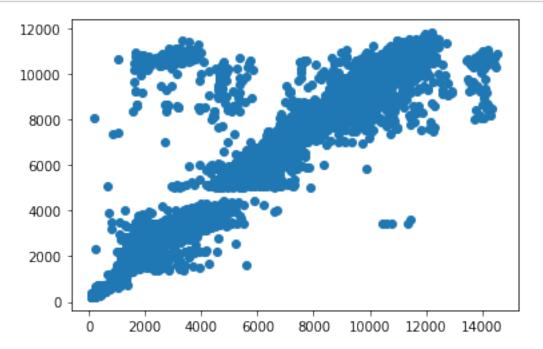
```
compare['Result'] = y_result.reshape(1,-1)[0]
compare['Difference'] = compare['Expected'] - compare['Result']
compare['Percentage Error'] = 100 * compare['Difference']/compare['Expected']

#Print out percentile descriptions of model accuracy
compare['Percentage Error'].describe(percentiles=[0.001, 0.01, 0.05, 0.25, 0.5, 0.75, 0.95, 0.99, 0.999])
```

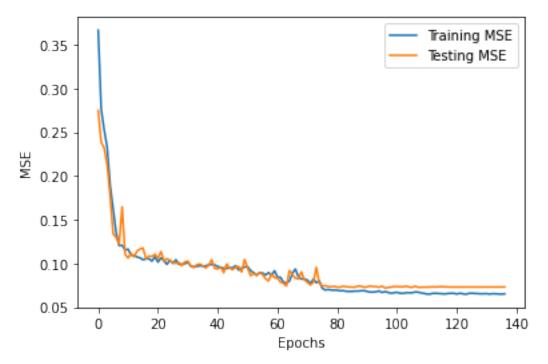
```
[62]: count
               7498.000000
      mean
                -10.916233
                 67.227989
      std
      min
              -3923.573845
      0.1%
               -545.837426
      1%
               -238.477236
      5%
                -73.881641
      25%
                 -9.409581
      50%
                 -0.973565
      75%
                  5.432740
      95%
                 21.019523
      99%
                 35.267476
      99.9%
                 60.016162
                 71.264463
      max
```

Name: Percentage Error, dtype: float64

```
[63]: plt.scatter(compare['Expected'], compare['Result'])
plt.show()
```



```
[59]: plt.plot(history.history['mse'],label='Training MSE')
   plt.plot(history.history['val_mse'],label='Testing MSE')
   plt.xlabel('Epochs')
   plt.ylabel('MSE')
   plt.legend()
   plt.show()
```



```
[70]: model.save('Trained_Models/Building_Model' + datetime.now().

⇒strftime("%Y%m%d-%H%M%S") + '.h5')
```

4 Building Model Analysis

```
[71]: def clean_data(location, skiprows = 0):
    df_weather = pd.read_csv(location, skiprows=skiprows)
    df_weather = df_weather.drop(columns=['Hour', 'Minute'])
    df_weather = df_weather[df_weather.DNI != 0]

#Take mean, max and min for each DNI in DataFrame and mean for everything
    →else

max_dni = df_weather.groupby(['Year', 'Month', 'Day']).max().
    →reset_index()['DNI']
```

```
min_dni = df_weather.groupby(['Year', 'Month', 'Day']).min().
       →reset_index()['DNI']
         df_weather = pd.DataFrame(df_weather.groupby(['Year', 'Month', 'Day']).
       →mean().reset index())
         df_weather.insert(4, 'DNI Max', max_dni)
         df_weather.insert(5, 'DNI Min', min_dni)
         return df_weather
[72]: def training prep(data, square feet, building type):
         data = data.loc[:, ['Year', 'Month', 'Day', 'DNI', 'DNI Max', 'DNI Min', __
       →'Wind Speed', 'Precipitable Water', 'Wind Direction', 'Relative Humidity', □
       →'Temperature', 'Pressure']]
         data.loc[:, 'Weekday'] = get weekday2(data['Year'], data['Month'],
      →data['Day'])
         data = data.drop(['Year'], axis=1)
         data.loc[:, 'Square Feet'] = square_feet
         data.loc[:, 'Type'] = building_type
         return data
[73]: #Taking data for University of Michigan Research Building
      michigan_data = training_prep(clean_data('https://raw.githubusercontent.com/
      →A-Wadhwani/ME597-Project/main/Datasets/AnnArbor_Weather.csv'), 100000, 2)
      michigan_data.head()
[73]:
        Month Day
                           DNI DNI Max ...
                                               Pressure Weekday Square Feet
                                                                                Type
            1
                 1
                     52.111111
                                     178 ...
                                             993.888889
                                                                0
                                                                        100000
      0
                                                                                   2
                 2 396.000000
                                     751 ... 1011.400000
                                                                0
                                                                        100000
                                                                                   2
      1
            1
                                                               0
                                                                                   2
      2
                 3 299.700000
                                     752 ...
                                             997.400000
            1
                                                                        100000
                                                                                   2
      3
                 4 281.900000
                                     576 ...
                                             997.300000
                                                                0
                                                                        100000
             1
                                                                                   2
                 5
                     10.000000
                                             986.000000
                                                                1
                                                                        100000
             1
                                     21 ...
      [5 rows x 14 columns]
[74]: #Applying transform to data
      mi_test = x_scaler.transform(michigan_data)
[75]: #Testing model:
      mi_result = y_scaler.inverse_transform(model.predict(mi_test))
      compare = pd.DataFrame()
      compare['Month'] = michigan_data['Month']
      compare['Result'] = mi_result.reshape(1,-1)[0]
      compare.head()
```

```
[75]:
         Month
                      Result
      0
             1
                10769.524414
      1
             1
                 9488.891602
      2
             1
               10889.340820
      3
                 9792.707031
                 7874.032227
      compare = pd.DataFrame(compare.groupby(['Month']).sum().reset_index())
      actual = [212259, 240083, 218423, 233777, 240106, 272017, 300123, 295701, 1
       →288447, 254802, 228097, 220258]
      compare['Actual'] = actual
      compare['Difference'] = compare['Actual'] - compare['Result']
      compare['Percentage Error'] = 100 * compare['Difference']/compare['Actual']
      compare.head(12)
[76]:
          Month
                        Result Actual
                                            Difference
                                                        Percentage Error
              1
                 329494.250000
                                212259 -117235.250000
                                                              -55.232169
      0
      1
                 277154.531250
                                240083
                                        -37071.531250
                                                              -15.441131
      2
              3
                 274379.218750
                                218423
                                        -55956.218750
                                                              -25.618281
      3
              4
                 226625.281250
                                233777
                                           7151.718750
                                                                3.059205
      4
                 196259.890625
                                240106
                                          43846.109375
                                                               18.261147
      5
              6
                 153253.062500
                                272017
                                         118763.937500
                                                               43.660484
      6
              7
                 142121.968750 300123
                                        158001.031250
                                                               52.645426
      7
              8
                 141248.828125
                                295701
                                        154452.171875
                                                               52.232550
      8
                 141370.921875
                                        147076.078125
              9
                                288447
                                                               50.988944
      9
             10
                 164804.406250
                                254802
                                          89997.593750
                                                               35.320599
                 222006.390625
      10
                                228097
                                           6090.609375
                                                                2.670184
             11
      11
                 237003.234375
                                220258
                                        -16745.234375
                                                               -7.602554
[77]:
      compare.describe()
                                                          Difference Percentage Error
[77]:
                 Month
                               Result
                                               Actual
             12.000000
      count
                            12.000000
                                            12.000000
                                                           12.000000
                                                                              12.000000
      mean
              6.500000
                        208810.171875
                                       250341.083333
                                                        41530.917969
                                                                              12.912034
      std
              3.605551
                         62929.816406
                                         31378.512646
                                                        91700.318958
                                                                              35.169540
     min
              1.000000
                        141248.828125
                                       212259.000000 -117235.250000
                                                                             -55.232169
      25%
              3.750000
                        150470.289062
                                       226137.250000
                                                       -21826.808594
                                                                              -9.562199
      50%
              6.500000
                        209133.140625
                                       240094.500000
                                                        25498.914062
                                                                              10.660176
      75%
                        246347.230469
                                                       125841.972656
              9.250000
                                       276124.500000
                                                                              45.492599
             12.000000
                        329494.250000
                                       300123.000000
                                                       158001.031250
                                                                              52.645426
      max
```

5 Comparison against UIUC data

```
[113]: uiuc_test = pd.read_csv('https://raw.githubusercontent.com/A-Wadhwani/
       →ME597-Project/main/Datasets/UIUC_PowerWeatherData.csv')
       #Adding other relevant data, including square feet and type
      uiuc_test['Square Feet'] = 100000
       #Laboratory
      uiuc_test['Type'] = 1
      uiuc_actual = uiuc_test['Power Consumption']
      uiuc_test = uiuc_test.drop(['Building Name', 'University Name', 'Year', 'Power_
       uiuc_test.head()
[113]:
                Day
                                                         Weekday
                                                                   Square Feet
         Month
                       DNI Mean
                                 DNI Max ...
                                                Pressure
                                                                                Type
                                      898 ...
                                                                        100000
      0
             10
                   1
                     597.916667
                                             988.333333
                                                                0
      1
             10
                     332.250000
                                      772 ...
                                             986.250000
                                                                0
                                                                        100000
                                                                                   1
      2
                                                                0
            10
                  3 408.000000
                                      923 ...
                                             991.555556
                                                                        100000
                      617.250000
      3
             10
                                      931 ...
                                             999.416667
                                                                0
                                                                        100000
                                             990.500000
             10
                  5
                     309.400000
                                      810 ...
                                                                1
                                                                        100000
                                                                                   1
      [5 rows x 14 columns]
[114]: #Applying transform to data
      uiuc_test = x_scaler.transform(uiuc_test)
[115]: #Testing model:
      uiuc_result = y_scaler.inverse_transform(model.predict(uiuc_test))
      compare = pd.DataFrame()
      compare['Actual'] = uiuc actual
      compare['Result'] = uiuc result.reshape(1,-1)[0]
      compare['Difference'] = compare['Actual'] - compare['Result']
      compare['Percentage Error'] = 100 * compare['Difference']/compare['Actual']
      compare.describe()
[115]:
                   Actual
                                Result
                                         Difference Percentage Error
               51.000000
                             51.000000
                                          51.000000
                                                            51.000000
      count
             6189.156863 7997.752441 -1808.595081
                                                           -29.337230
      mean
      std
              228.978372
                            682.941345
                                         680.797346
                                                            11.350610
             5069.000000 5545.342773 -3601.576172
                                                           -57.893846
      min
      25%
             6142.000000 7724.354980 -2041.887695
                                                           -33.842293
      50%
             6243.000000 7895.011230 -1771.775879
                                                           -28.423119
      75%
             6301.000000 8197.769531 -1541.850098
                                                           -24.538141
              6518.000000 9866.675781
                                        506.657227
      max
                                                             8.371732
```

```
[116]: plt.hist(compare['Percentage Error'])
    plt.show()
```

