In [ ]:
```
# STUDENT: MOLTO, JOAQUIN (PID: 6119985)
# COURSE: EEL6812 - ADVANCED TOPICS IN NEURAL NETWORKS (DEEP LEARNING)
# ASSIGNMENT #3: RECURRENT NEURAL NETWORK AND LONG SHORT-TERM MEMORY NETWORKS
# DUE DATE: 04/26/2024
```

RETRIEVING DATA FROM **GEFCOM2014(E,V2)** AND PREPARING IT FOR THE RNN/LSTM

In [ ]:
```
# THE FIRST PORTION OF THIS JUPYTER NOTEBOOK (.IPYNB) WAS PROVIDED BY DR. BARRETO F
# IT WILL BE USED AS A HELPER IN DEVELOPING THE RNN AND LSTM SOLUTIONS PER THE PROB
```

In [ ]:
```
# IMPORT NECESSARY LIBRARIES
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
# plt.style.use('./rose-pine-moon.mplstyle')
import os
import shutil
import matplotlib.pyplot as plt
%matplotlib inline
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import ModelCheckpoint, LambdaCallback, EarlyStoppi
import sklearn
from sklearn.metrics import mean_absolute_error

!wget https://www.dropbox.com/s/pqenrr2mcvl0hk9/GEFCom2014.zip # retrieve the zip f
```

In [ ]:
```
!unzip GEFCom2014.zip # OS-level command to unzip the file brought into the Google
```

```
Archive:  GEFCom2014.zip
replace GEFCom2014 Data/GEFCom2014-S_V2.zip? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
 extracting: GEFCom2014 Data/GEFCom2014-S_V2.zip
 extracting: GEFCom2014 Data/GEFCom2014-W_V2.zip
  inflating: GEFCom2014 Data/READ ME_V2.txt
  inflating: GEFCom2014 Data/Provisional_Leaderboard_V2.xlsx
 extracting: GEFCom2014 Data/GEFCom2014-L_V2.zip
 extracting: GEFCom2014 Data/GEFCom2014-E_V2.zip
 extracting: GEFCom2014 Data/GEFCom2014-P_V2.zip
```

In [ ]:
```
!ls -l # UNIX command to list files in directory, passing the -l flag (long)
```

```
total 1117280
-rw-r--r-- 1 root root    402234 Apr 28 04:14  best_model.keras
-rw-r--r-- 1 root root   1573348 Apr 28 04:22  GEF14.csv
drwxrwxr-x 2 root root      4096 Apr 28 04:23 'GEFCom2014 Data'
-rw-rw-r-- 1 root root   2348089 Feb 11  2016  GEFCom2014-E_V2.zip
-rw-r--r-- 1 root root   2452214 Jan 25  2016  GEFCom2014-E.xlsx
-rw-r--r-- 1 root root 126360077 Apr 28 00:52  GEFCom2014.zip
-rw-r--r-- 1 root root 126360077 Apr 28 01:16  GEFCom2014.zip.1
-rw-r--r-- 1 root root 126360077 Apr 28 01:57  GEFCom2014.zip.2
-rw-r--r-- 1 root root 126360077 Apr 28 02:00  GEFCom2014.zip.3
-rw-r--r-- 1 root root 126360077 Apr 28 02:17  GEFCom2014.zip.4
-rw-r--r-- 1 root root 126360077 Apr 28 03:52  GEFCom2014.zip.5
-rw-r--r-- 1 root root 126360077 Apr 28 03:56  GEFCom2014.zip.6
-rw-r--r-- 1 root root 126360077 Apr 28 04:21  GEFCom2014.zip.7
-rw-r--r-- 1 root root 126360077 Apr 28 04:23  GEFCom2014.zip.8
-rw-r--r-- 1 root root     40905 Apr 28 00:50  rose-pine-moon.mplstyle
drwxr-xr-x 1 root root      4096 Apr 25 13:25  sample_data
```

In [ ]:
```
!ls -l 'GEFCom2014 Data'/
```

```
total 123420
-rw-rw-r-- 1 root root  2348089 Feb 11  2016  GEFCom2014-E_V2.zip
-rw-rw-r-- 1 root root  2599214 Feb 11  2016  GEFCom2014-L_V2.zip
-rw-rw-r-- 1 root root  3338992 Feb 11  2016  GEFCom2014-P_V2.zip
-rw-rw-r-- 1 root root 36734790 Feb 11  2016  GEFCom2014-S_V2.zip
-rw-rw-r-- 1 root root 81149634 Feb 11  2016  GEFCom2014-W_V2.zip
-rw-rw-r-- 1 root root   195932 Feb 11  2016  Provisional_Leaderboard_V2.xlsx
-rw-rw-r-- 1 root root      389 Feb 11  2016 'READ ME_V2.txt'
```

We want to use **GEFCom2014-E_V2.zip** for this project

In [ ]:
```
!mv  'GEFCom2014 Data'/GEFCom2014-E_V2.zip  ./ # let's bring it to the top level be
```

In [ ]:
```
!unzip GEFCom2014-E_V2.zip
```

```
Archive:  GEFCom2014-E_V2.zip
replace GEFCom2014-E.xlsx? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
  inflating: GEFCom2014-E.xlsx
```

In [ ]:
```
!ls -l # we can now verify that we loaded the file GEFCom2014-E.xlsx
```

```
total 1117280
-rw-r--r-- 1 root root    402234 Apr 28 04:14  best_model.keras
-rw-r--r-- 1 root root   1573348 Apr 28 04:22  GEF14.csv
drwxrwxr-x 2 root root      4096 Apr 28 04:23 'GEFCom2014 Data'
-rw-rw-r-- 1 root root   2348089 Feb 11  2016  GEFCom2014-E_V2.zip
-rw-r--r-- 1 root root   2452214 Jan 25  2016  GEFCom2014-E.xlsx
-rw-r--r-- 1 root root 126360077 Apr 28 00:52  GEFCom2014.zip
-rw-r--r-- 1 root root 126360077 Apr 28 01:16  GEFCom2014.zip.1
-rw-r--r-- 1 root root 126360077 Apr 28 01:57  GEFCom2014.zip.2
-rw-r--r-- 1 root root 126360077 Apr 28 02:00  GEFCom2014.zip.3
-rw-r--r-- 1 root root 126360077 Apr 28 02:17  GEFCom2014.zip.4
-rw-r--r-- 1 root root 126360077 Apr 28 03:52  GEFCom2014.zip.5
-rw-r--r-- 1 root root 126360077 Apr 28 03:56  GEFCom2014.zip.6
-rw-r--r-- 1 root root 126360077 Apr 28 04:21  GEFCom2014.zip.7
-rw-r--r-- 1 root root 126360077 Apr 28 04:23  GEFCom2014.zip.8
-rw-r--r-- 1 root root     40905 Apr 28 00:50  rose-pine-moon.mplstyle
drwxr-xr-x 1 root root      4096 Apr 25 13:25  sample_data
```

In [ ]:
```
GEFDF = pd.read_excel('GEFCom2014-E.xlsx', skiprows=range(1, 17545), dtype = {'A':n
```

In [ ]:
```
print(GEFDF) # we can "see" the Pandas DataFrame (called GEFDF) that has been obtai
```

```
             Date  Hour    load          T
0      2006-01-01     1  3010.0  22.666667
1      2006-01-01     2  2853.0  20.666667
2      2006-01-01     3  2758.0  21.333333
3      2006-01-01     4  2705.0  19.000000
4      2006-01-01     5  2709.0  19.333333
...           ...   ...     ...        ...
78883  2014-12-31    20  4012.0  18.000000
78884  2014-12-31    21  3856.0  16.666667
78885  2014-12-31    22  3671.0  17.000000
78886  2014-12-31    23  3499.0  15.333333
78887  2014-12-31    24  3345.0  15.333333

[78888 rows x 4 columns]
```

In [ ]:
```
# WRITING OUT THE GEFDF DATAFRAME TO A TEXT (CSV) FILE
GEFDF.to_csv('GEF14.csv',  encoding='utf-8', index=False, header=True, columns=['Ho
with open('GEF14.csv') as f:
    lines = f.readlines()
    last = len(lines) - 1
    lines[last] = lines[last].replace('\r','').replace('\n','')
with open('GEF14.csv', 'w') as wr:
    wr.writelines(lines)
```

In [ ]:
```
!ls -l ./ # verifying we have created the csv file GEF14.csv
```

```
total 1117280
-rw-r--r-- 1 root root    402234 Apr 28 04:14  best_model.keras
-rw-r--r-- 1 root root   1573348 Apr 28 04:23  GEF14.csv
drwxrwxr-x 2 root root      4096 Apr 28 04:23 'GEFCom2014 Data'
-rw-rw-r-- 1 root root   2348089 Feb 11  2016  GEFCom2014-E_V2.zip
-rw-r--r-- 1 root root   2452214 Jan 25  2016  GEFCom2014-E.xlsx
-rw-r--r-- 1 root root 126360077 Apr 28 00:52  GEFCom2014.zip
-rw-r--r-- 1 root root 126360077 Apr 28 01:16  GEFCom2014.zip.1
-rw-r--r-- 1 root root 126360077 Apr 28 01:57  GEFCom2014.zip.2
-rw-r--r-- 1 root root 126360077 Apr 28 02:00  GEFCom2014.zip.3
-rw-r--r-- 1 root root 126360077 Apr 28 02:17  GEFCom2014.zip.4
-rw-r--r-- 1 root root 126360077 Apr 28 03:52  GEFCom2014.zip.5
-rw-r--r-- 1 root root 126360077 Apr 28 03:56  GEFCom2014.zip.6
-rw-r--r-- 1 root root 126360077 Apr 28 04:21  GEFCom2014.zip.7
-rw-r--r-- 1 root root 126360077 Apr 28 04:23  GEFCom2014.zip.8
-rw-r--r-- 1 root root     40905 Apr 28 00:50  rose-pine-moon.mplstyle
drwxr-xr-x 1 root root      4096 Apr 25 13:25  sample_data
```

In [ ]:

```
# THIS CODE CELL IS ESSENTIALLY THE SAME AS IN THE EXAMPLE FROM CH. 10 IN BOOK
import os
fname = os.path.join("GEF14.csv")

with open(fname) as f:
    data = f.read()

lines = data.split("\n")
header = lines[0].split(",")
lines = lines[1:]
print(header)
print(len(lines))
```

```
['Hour', 'load', 'T']
78888
```

In [ ]:

```
# VERY SIMILAR TO THE CORRESPONDING CØDE CELL FROM CHAPTER 10 IN BOOK
# eload (electric load) is the timeseries we will predict
# tempf (temperature in Fahrenheit) is the temperature at the same time
# import numpy as np
eload = np.zeros((len(lines),))
tempf = np.zeros((len(lines),))
raw_data = np.zeros((len(lines), len(header)-2))   #chgd )-1  to )-2 to also
# remove the HOUR column, in addition to the DATE column
print(len(lines))

for m in range(78888):
    thisline  = lines[m]
    values = [float(x) for x in thisline.split(",")[1:]]
    eload[m] = values[0]         #Captures JUST E LOAD
    tempf[m] = values[1]            #Captures JUST TEMPF
    raw_data[m] = values[0]         #Like this, raw_data Captures JUST E LOAD
    # raw_data[m, :] = values[:]   # Like this, raw_data CAPTURES BOTH
```

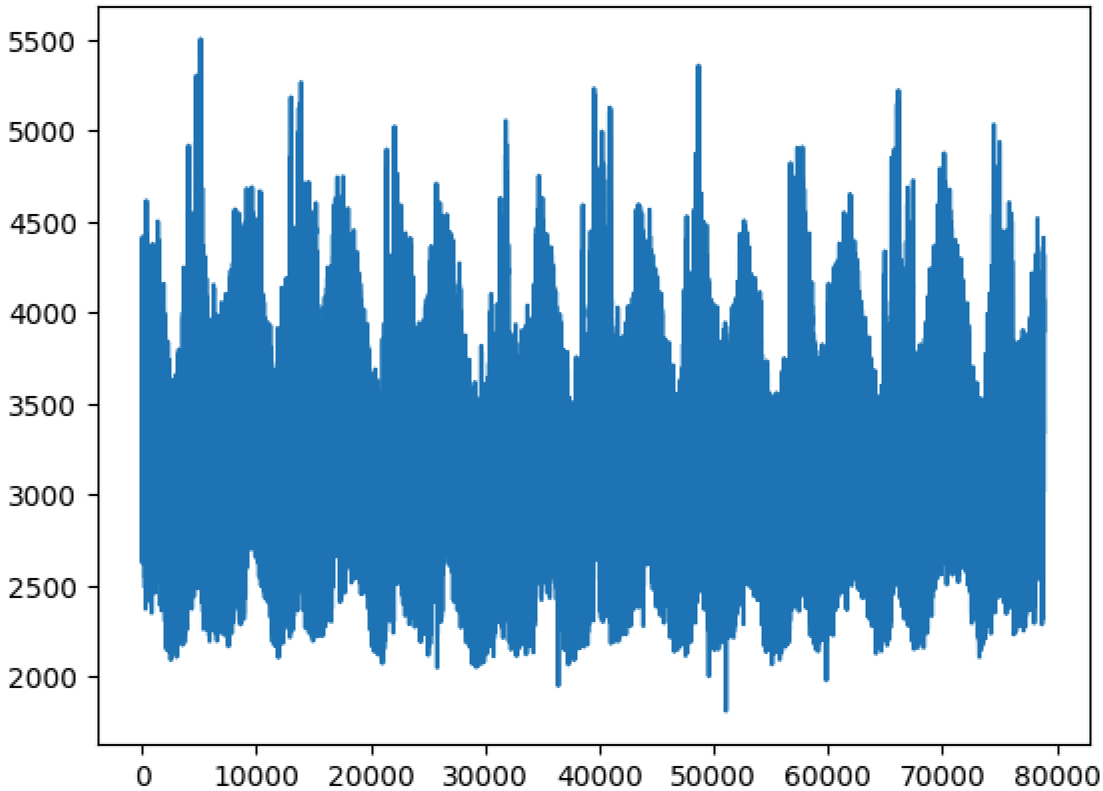
```
78888
```

In [ ]:

```
plt.plot(range(len(eload)), eload)
```

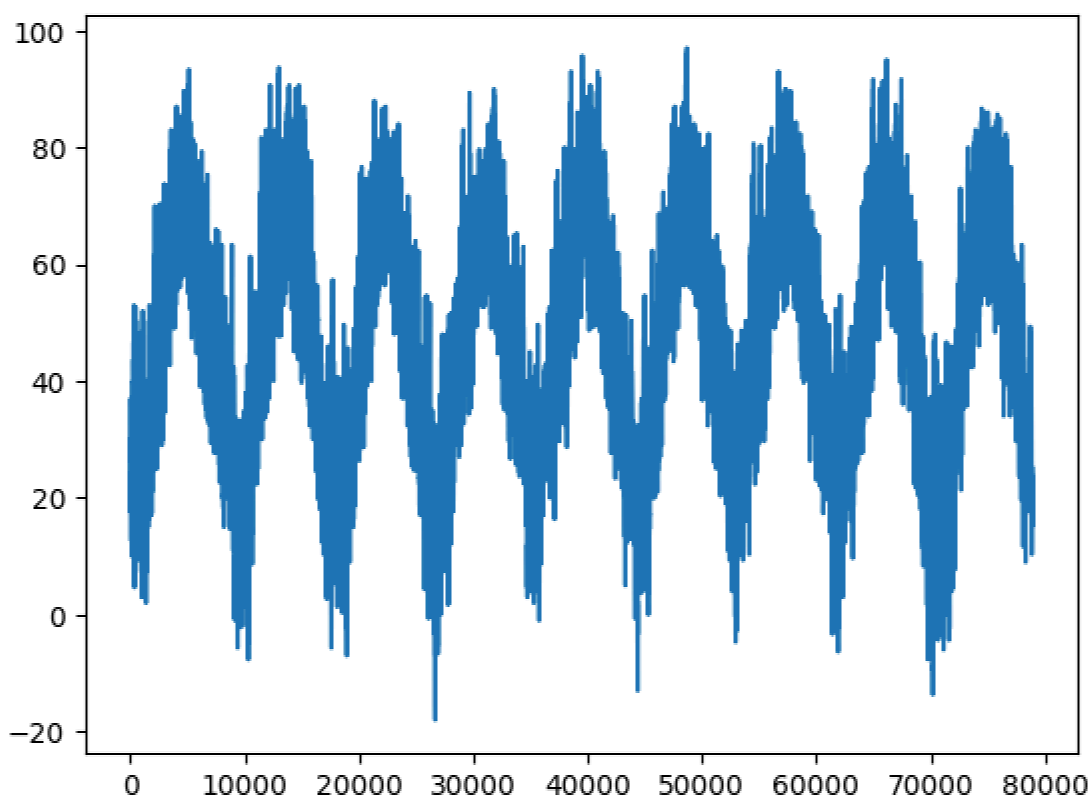
Out[ ]:

```
[<matplotlib.lines.Line2D at 0x7d8545080a90>]
```



In [ ]:
```
plt.plot(range(len(tempf)), tempf)
```

Out[ ]: [<matplotlib.lines.Line2D at 0x7d85425f3670>]



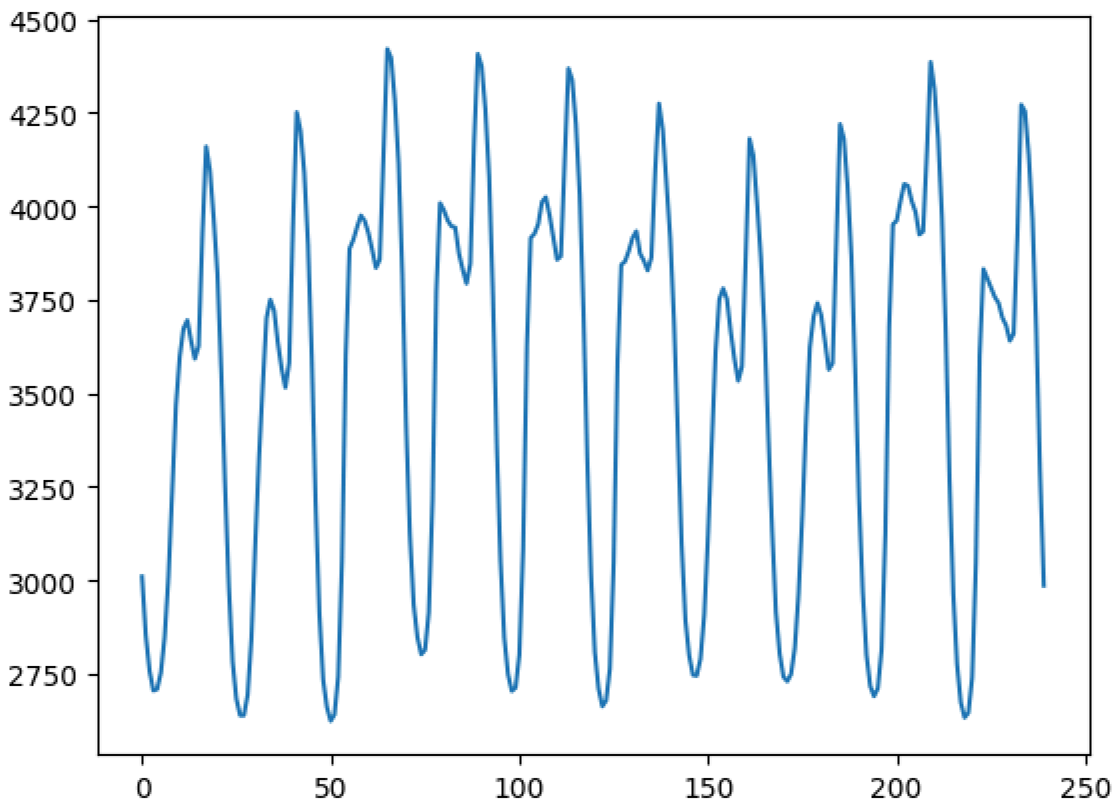
In [ ]:
```
num_train_samples = int(0.5 * len(raw_data))
num_val_samples = int(0.25 * len(raw_data))
```

```
num_test_samples = len(raw_data) - num_train_samples - num_val_samples
print("num_train_samples:", num_train_samples)
print("num_val_samples:", num_val_samples)
print("num_test_samples:", num_test_samples)
```

```
num_train_samples: 39444
num_val_samples: 19722
num_test_samples: 19722
```

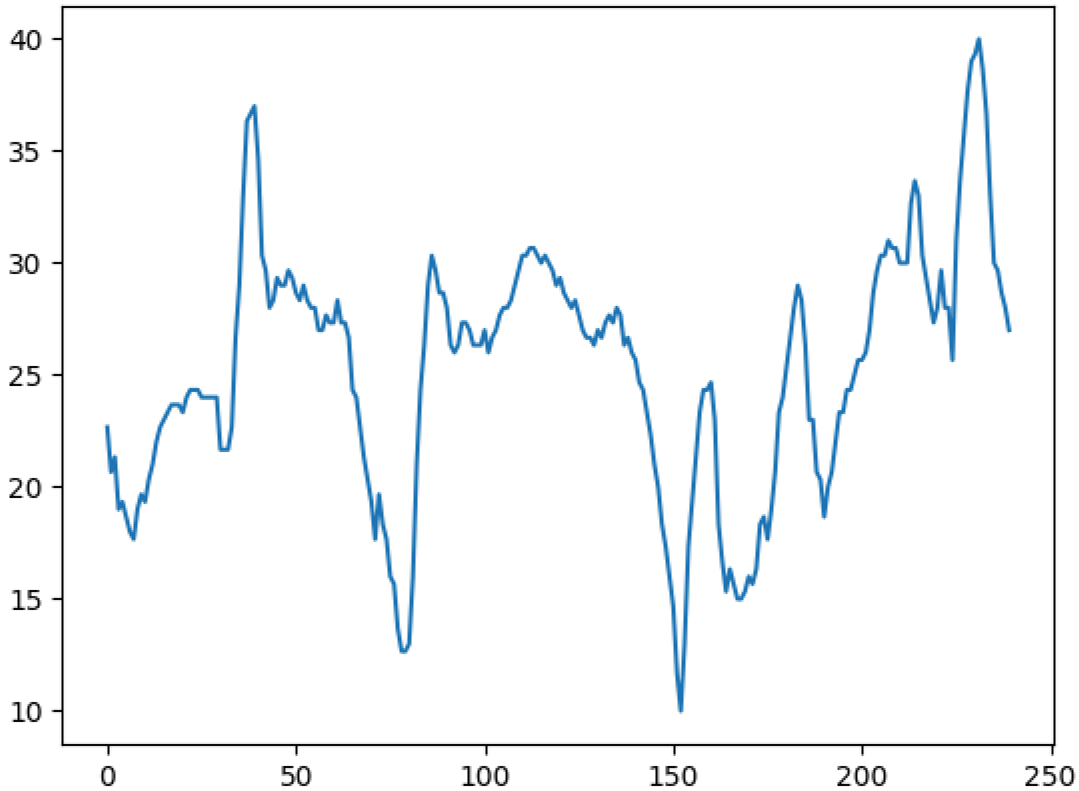
In [ ]:
```
# Display the ELOAD for the first 10 days
plt.plot(range(240),eload[:240])
```

Out[ ]: [<matplotlib.lines.Line2D at 0x7d8544256ec0>]



In [ ]:
```
# Display the tempf for the first 10 days
plt.plot(range(240),tempf[:240])
```

Out[ ]: [<matplotlib.lines.Line2D at 0x7d85437a13f0>]



Normalize the Data $(\dfrac{X-\mu}{\sigma})$

- This will ensure the underlying patterns behind the data are still present

while downscaling its magnitude; making it more palatable to the Neural Network

In [ ]:
```
mean = raw_data[:num_train_samples].mean(axis=0)
raw_data -= mean # Value - Mean / Standard Deviation
std = raw_data[:num_train_samples].std(axis=0)
raw_data /= std
```

Instantiating TensorFlow (TF) Datasets for Training [TR], Validation [TT], and Testing [TS]

In [ ]:
```
# LETS JUST USE ELOAD TO FORECAST ELOAD
# THIS TIME, ( 1-input case)
# NOTE: THIS CODE HAS TO BE MODIFIED FOR THE 2-INPUT CASE, WHICH ALSO TAKES INTO CO
from tensorflow import keras

horizon = 3       # num. of hours ahead for forecast
sampling_rate = 1 # this should be kept as 1, as the sampling is already hourly
sequence_length = 15
delay = sampling_rate * (sequence_length + horizon - 1)
batch_size = 128

train_dataset = keras.utils.timeseries_dataset_from_array(
    raw_data[:-delay],
    targets=raw_data[delay:], # this would used "Normalized Targets"
    # targets=eload[delay:], # this would used "Not-normalized eload targets"
```

```
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=True,                    # changed to false JUST FOR VERIFICATION
    batch_size= num_train_samples,
    start_index=0,
    end_index=num_train_samples)

val_dataset = keras.utils.timeseries_dataset_from_array(
    raw_data[:-delay],    # changed from raw_data to just eload not really
    targets=raw_data[delay:],  # this would used "Normalized Targets"
    # targets=eload[delay:], # this would used "Not-normalized eload targets"
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=True,
    batch_size=num_val_samples,
    start_index=num_train_samples,
    end_index=num_train_samples + num_val_samples)

test_dataset = keras.utils.timeseries_dataset_from_array(
    raw_data[:-delay],     # changed from raw_data to just eload
    targets=raw_data[delay:],  # this would used "Normalized Targets"
    # targets=eload[delay:], # this would used "Not-normalized eload targets"
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=False,
    batch_size=num_test_samples,
    start_index=num_train_samples + num_val_samples)
```

Inspecting the Output of one of the Datasets

In [ ]:
```
for samples, targets in train_dataset:
    print("samples shape:", samples.shape)
    print("targets shape:", targets.shape)
    break
```

```
samples shape: (39430, 15, 1)
targets shape: (39430, 1)
```

END OF DATA PREPARATION

[PART II.] DESIGNING THE "1-INPUT (ELOAD)" PREDICTORS

- This part of the project calls for the creation of a model that will predict the future amount of electrical energy demand or "load" (*eload*) with a prediction horizon of 3 hours into the future and 6 hours into the future. Therefore, we will have two "1-input" models for this part:

1. 1N_3HR
2. 1IN_6HR

- Per the instructions, we need AT LEAST ONE Long Short-Term Memory (LSTM) layer in our Recurrent Neural Network (RNN). Whether to use Recurrent Dropout or not is optional; however, it might improve generalization and performance. However, this comes at the cost of slow computation time due to the incompatibility with CuDNN (CUDA Deep Neural Network) Library.

In [ ]:
```
max_value = float('-inf') # initialize variable for maximum value as negative infin
min_value = float('inf') # initialize variable for maximum value as positive infini

# Iterate over each batch in the dataset
for _, targets in test_dataset:
    # Find the maximum and minimum in the targets
    current_max = tf.reduce_max(targets * std + mean)
    current_min = tf.reduce_min(targets * std + mean)

    # Update the maximum and minimum values across all batches
    max_value = max(max_value, current_max.numpy())  # Update the overall max
    min_value = min(min_value, current_min.numpy())  # Update the overall min
full_range = max_value - min_value
print("MAX ELOAD IN TEST_DATASET:", max_value)
print("MIN ELOAD IN TEST_DATASET:", min_value)
print("FULL-RANGE OF ELOAD IN TEST_DATASET:", full_range)
```

```
MAX ELOAD IN TEST_DATASET: 5224.0
MIN ELOAD IN TEST_DATASET: 1979.0
FULL-RANGE OF ELOAD IN TEST_DATASET: 3245.0
```

[PART IIA.] DESIGNING THE "1-INPUT (ELOAD)" PREDICTOR FOR "3-HOUR HORIZON"

In [ ]:
```
# INITIALIZE THE SIZE/DIMENSIONS OF INPUT AND OUTPUT
output_units = 1 # will only output 1 prediction
```

In [ ]:
```
model = Sequential([
    LSTM(100, return_sequences=True),
    Dropout(0.1),  # Apply dropout separately
    LSTM(100),
    Dense(output_units)
])
```

In [ ]:
```
# COMPILE THE MODEL
model.compile(optimizer='adam', loss='mse',metrics=['mae'])
```

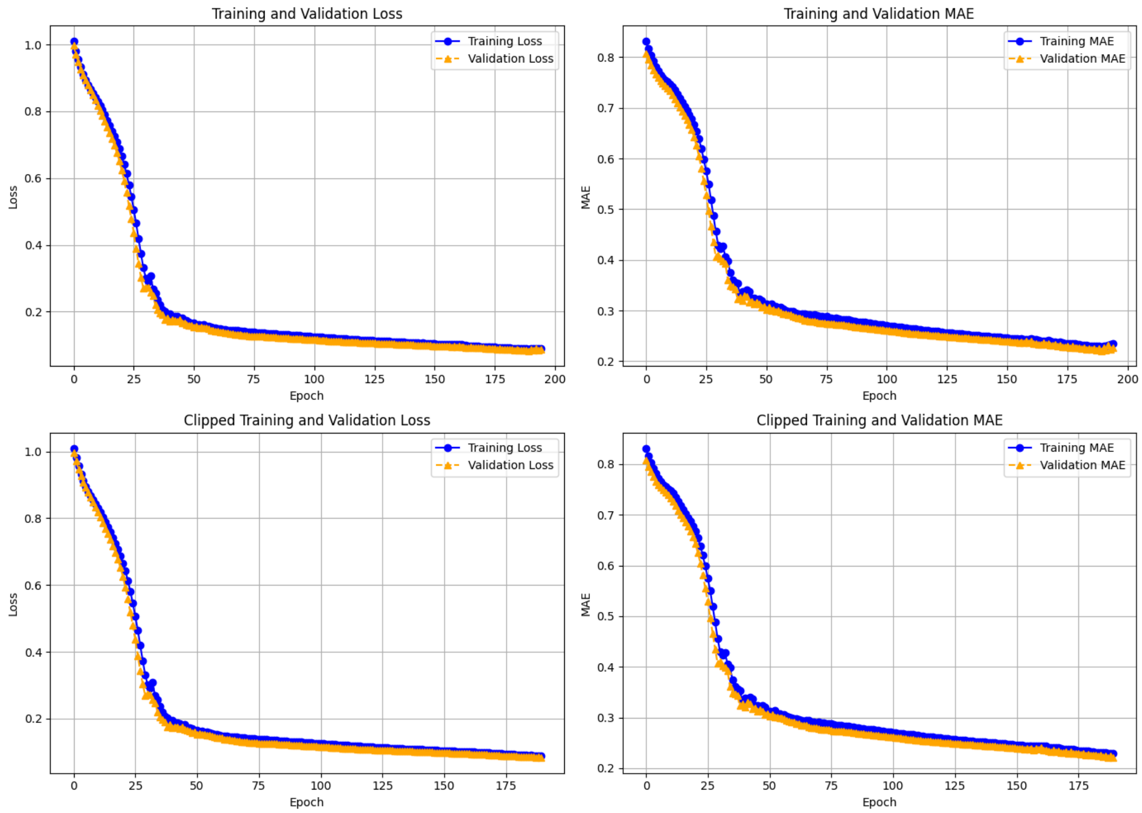
In [ ]:
```
# CALLBACKS FOR MONITORING AND PLOTTING
val_loss_checkpoint = ModelCheckpoint('best_model.keras', monitor='val_loss', verbo
# CALLBACK FOR EARLY STOPPING
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights
```

In [ ]:
```
# Function to store metrics and plot them after training
def plot_metrics(history):
    fig, axes = plt.subplots(2, 2, figsize=(14, 10))  # Create a figure with subplo
```

```
    # Plot for full history
    axes[0, 0].plot(history['loss'], color='blue', linestyle='-', marker='o', label
    axes[0, 0].plot(history['val_loss'], color='orange', linestyle='--', marker='^'
    axes[0, 0].set_title('Training and Validation Loss')
    axes[0, 0].set_xlabel('Epoch')
    axes[0, 0].set_ylabel('Loss')
    axes[0, 0].legend()
    axes[0, 0].grid(True)

    axes[0, 1].plot(history['mae'], color='blue', linestyle='-', marker='o', label=
    axes[0, 1].plot(history['val_mae'], color='orange', linestyle='--', marker='^',
    axes[0, 1].set_title('Training and Validation MAE')
    axes[0, 1].set_xlabel('Epoch')
    axes[0, 1].set_ylabel('MAE')
    axes[0, 1].legend()
    axes[0, 1].grid(True)

    # Find the epoch with the best validation loss
    best_epoch = np.argmin(history['val_loss'])

    # Plot for clipped history up to best validation loss
    axes[1, 0].plot(history['loss'][:best_epoch+1], color='blue', linestyle='-', ma
    axes[1, 0].plot(history['val_loss'][:best_epoch+1], color='orange', linestyle='
    axes[1, 0].set_title('Clipped Training and Validation Loss')
    axes[1, 0].set_xlabel('Epoch')
    axes[1, 0].set_ylabel('Loss')
    axes[1, 0].legend()
    axes[1, 0].grid(True)

    axes[1, 1].plot(history['mae'][:best_epoch+1], color='blue', linestyle='-', mar
    axes[1, 1].plot(history['val_mae'][:best_epoch+1], color='orange', linestyle='-
    axes[1, 1].set_title('Clipped Training and Validation MAE')
    axes[1, 1].set_xlabel('Epoch')
    axes[1, 1].set_ylabel('MAE')
    axes[1, 1].legend()
    axes[1, 1].grid(True)

    plt.tight_layout()
    plt.show()
```

In [ ]:

```
# TRAIN THE MODEL WITH CALLBACKS
history = model.fit(train_dataset, epochs=200, validation_data=val_dataset,
                    callbacks=[val_loss_checkpoint, early_stopping])

# AFTER THE TRAINING IS COMPLETE, PLOT THE METRICS USING THE HISTORY OBJECT
plot_metrics(history.history)
```



In [ ]:
```
# PRINT THE MODEL SUMMARY
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, None, 50)          10400

 dropout_1 (Dropout)         (None, None, 50)          0

 lstm_3 (LSTM)               (None, 50)                20200

 dense_1 (Dense)             (None, 1)                 51

=================================================================
Total params: 30651 (119.73 KB)
Trainable params: 30651 (119.73 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [ ]:
```
predictions = model.predict(test_dataset) # this will return the predictions in the
```

```
1/1 [==============================] - 1s 1s/step
```

De-Normalize the Data $(X * \sigma + \mu)$

- Return the predictions array back to its original form when analyzing the MAE and $PMAE$

In [ ]:
```
predictions_original_scale = predictions * std + mean
```

In [ ]:
```
for samples, targets in test_dataset.take(1):
    print("Samples: \n", samples.numpy() * std + mean)
    print("Targets: \n", targets.numpy() * std + mean)
```

In [ ]:
```
target_values = []
for batch in test_dataset:
  targets = batch[1]
  target_values.extend(targets * std + mean)
target_values = np.array(target_values)
print("targets_values shape: ", target_values.shape)
```

```
targets_values shape:  (19691, 1)
```

$$MAE = \sum_{i=1}^{n} \frac{|y_i - x_i|}{n}$$

Where:

MAE=Mean Absolute Error \ x_i=ith Input Sample/Pattern \ y_i=ith Target Respective to Input \ n=Total Number of Data Points

In [ ]:
```
mae = mean_absolute_error(target_values, predictions_original_scale)
print("MAE on the Test Set:", mae)
```

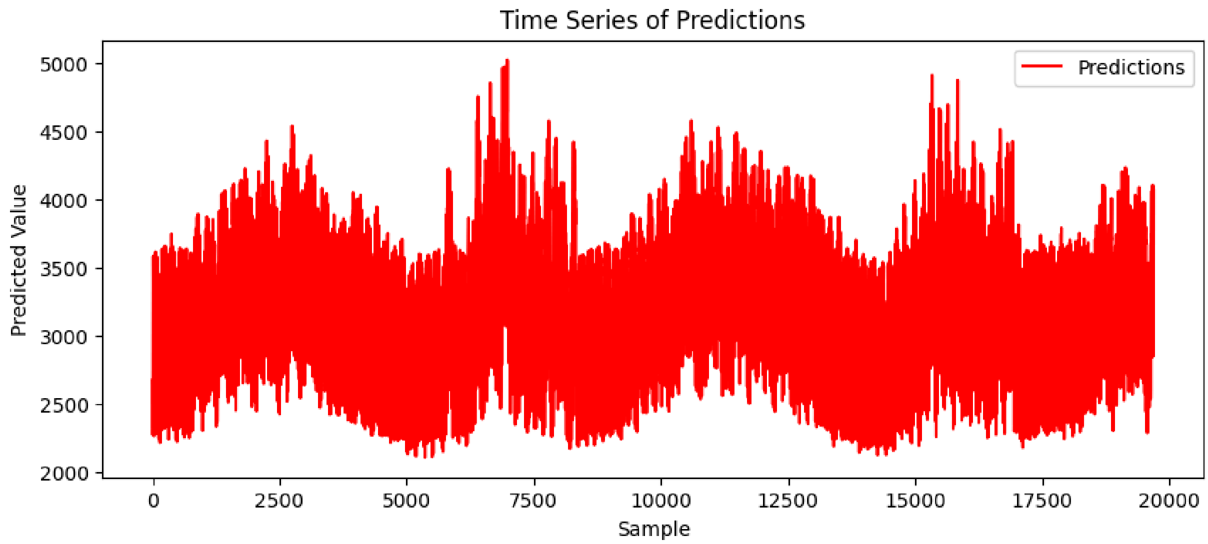
```
MAE on the Test Set: 132.68647274418277
```

$$PMAE = \frac{MAE_{[TS]}}{FR_{[TS]}}$$

In [ ]:
```
pmae = (mae / full_range) * 100
print("Percentage Mean Absolute Error (PMAE):", pmae)
```

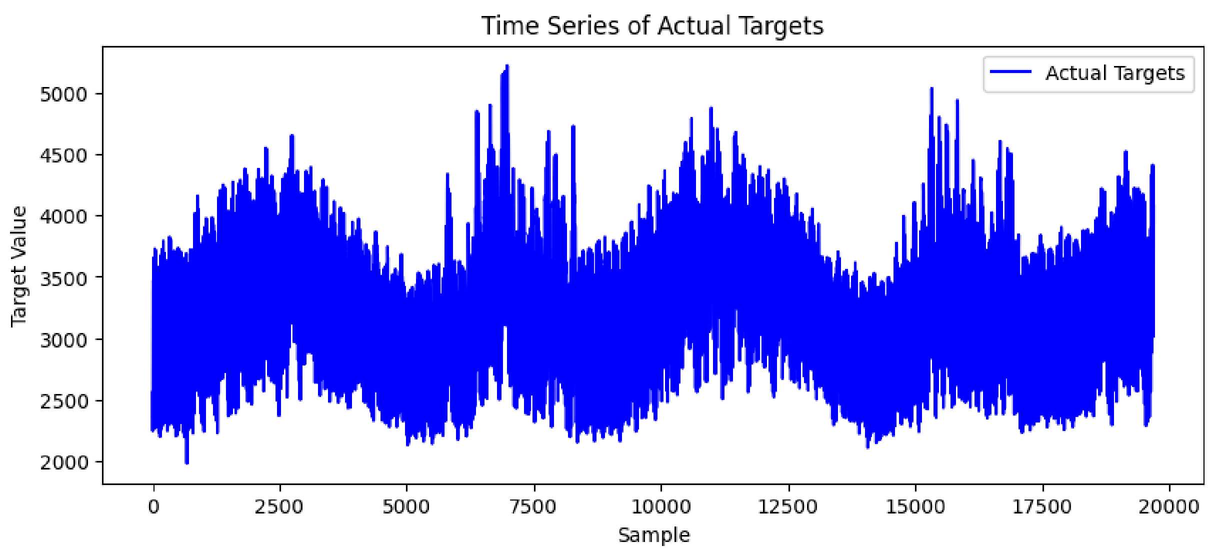
```
Percentage Mean Absolute Error (PMAE): 4.088951394273737
```

In [ ]:
```
# TIMESERIES PLOT OF PREDICTED VALUES BY MODEL
plt.figure(figsize=(10, 4))
plt.plot(predictions_original_scale, 'r', label='Predictions')
plt.title('Time Series of Predictions')
plt.xlabel('Sample')
plt.ylabel('Predicted Value')
plt.legend()
plt.show()
```



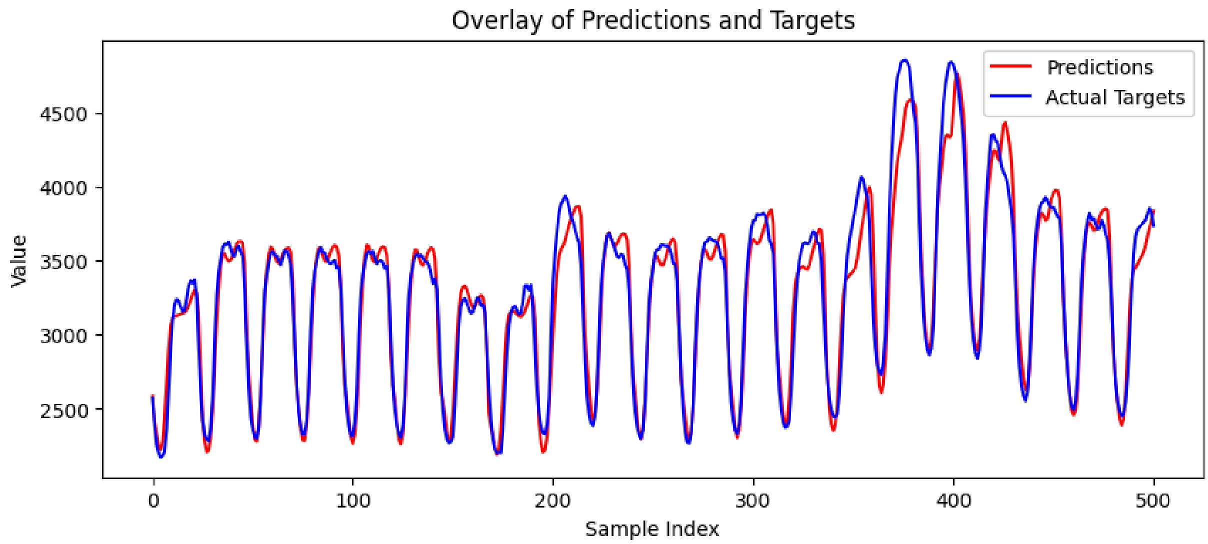
In [ ]:

```
# TIMESERIES PLOT OF CORRESPONDING TARGETS
plt.figure(figsize=(10, 4))
plt.plot(target_values, 'b', label='Actual Targets')
plt.title('Time Series of Actual Targets')
plt.xlabel('Sample')
plt.ylabel('Target Value')
plt.legend()
plt.show()
```



In [ ]:

```
# OVERLAY PLOT OF PREDICTIONS (RED SOLID LINE) AND TARGETS (BLUE SOLID LINE) (6,000
plt.figure(figsize=(10, 4))
plt.plot(predictions_original_scale[6000:6501], 'r', label='Predictions', linestyle
plt.plot(target_values[6000:6501], 'b', label='Actual Targets', linestyle='-')
plt.title('Overlay of Predictions and Targets')
plt.xlabel('Sample Index')
plt.ylabel('Value')
plt.legend()
plt.show()
```


Overlay of Predictions and Targets
Predictions
Actual Targets
4500
4000
3500
3000
2500
Value
0
100
200
300
400
500
Sample Index