

MEASURE ENERGY CONSUMPTION

PHASE:4 PROJECT SUBMISSION

Analyzing the energy consumption data &
Creating visualizations.



MEASURE ENERGY CONSUMPTION

VISUALIZATIONS

- Visualization (graphics), the physical or imagining creation of images, diagrams, or animations to communicate a message.
- Data and information visualization, the practice of creating visual representations of complex data and information.
- Music visualization, animated imagery based on a piece of music.
- Mental image, the experience of images without the relevant external stimuli.

FEATURE ENGINEERING

The process of using domain knowledge to select and transform the most relevant variables from raw data when creating a predictive model using machine learning or statistical modeling.

MODEL TRAINING

Model training is the process of feeding engineered data to a parametrized machine learning algorithm in order to output a model with optimal learned trainable parameters that minimize an objective function.

MODEL EVALUATION

Model evaluation in machine learning is the process of determining a model's performance via a metrics-driven analysis. It can be performed in two ways:

Offline: The model is evaluated after training during experimentation or continuous retraining.

Online: The model is evaluated in production as part of model monitoring.

```
import numpy as np
```

```
import pandas as pd
```

```
import matplotlib.pyplot as plt
```

```
import tensorflow as tf
```

```
import sklearn.preprocessing
```

```
from sklearn.metrics import r2_score
```

```
from keras.layers import Dense, Dropout, SimpleRNN, LSTM
```

```
from keras.models import Sequential
```

```
AEP = pd.read_csv('../input/hourly-energy-consumption/AEP_hourly.csv', index_col=0, parse_dates=[0])
```

```
mau = ["#F8766D", "#D39200", "#93AA00", "#00BA38", "#00C19F", "#00B9E3", "#619CFF", "#DB72FB"]  
bieudo = AEP.plot(style='.', figsize=(15, 5), color=mau[0], title='AEP')
```

#Data transformation

```
def create_features(df, label=None):
    df = df.copy()
    df['date'] = df.index
    df['hour'] = df['date'].dt.hour
    df['dayofweek'] = df['date'].dt.dayofweek
    df['quarter'] = df['date'].dt.quarter
    df['month'] = df['date'].dt.month
    df['year'] = df['date'].dt.year
    df['dayofyear'] = df['date'].dt.dayofyear
    df['dayofmonth'] = df['date'].dt.day
    df['weekofyear'] = df['date'].dt.weekofyear

    X = df[['hour', 'dayofweek', 'quarter', 'month', 'year',
            'dayofyear', 'dayofmonth', 'weekofyear']]
    if label:
        y = df[label]
        return X, y
    return X

X, y = create_features(AEP, label='AEP_MW')
features_and_target = pd.concat([X, y], axis=1)
print(features_and_target)
plt.show()

plt.figure(figsize=(15, 6))
data_csv = AEP.dropna()
dataset = data_csv.values
dataset = dataset.astype('float32')
max_value = np.max(dataset)
min_value = np.min(dataset)
scalar = max_value - min_value
```

```
dataset=list(map(lambdax:(x-min_value)/scalar,dataset))
plt.plot(dataset)
print(max_value,min_value)
```

**hour dayofweek quarter month year dayofyear **
Datetime

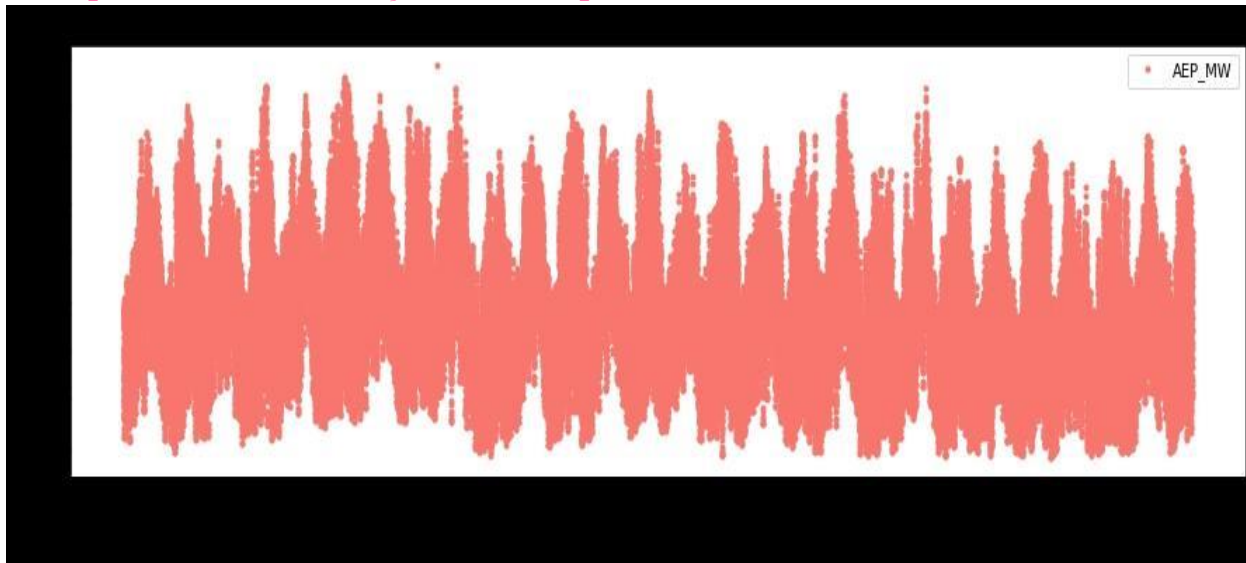
```
2004-12-31 01:00:00    1     4     4    12  2004    366
2004-12-31 02:00:00    2     4     4    12  2004    366
2004-12-31 03:00:00    3     4     4    12  2004    366
2004-12-31 04:00:00    4     4     4    12  2004    366
2004-12-31 05:00:00    5     4     4    12  2004    366
...
2018-01-01 20:00:00   20     0     1     1  2018     1
2018-01-01 21:00:00   21     0     1     1  2018     1
2018-01-01 22:00:00   22     0     1     1  2018     1
2018-01-01 23:00:00   23     0     1     1  2018     1
2018-01-02 00:00:00    0     1     1     1  2018     2
```

dayofmonth weekofyear AEP_MW
Datetime

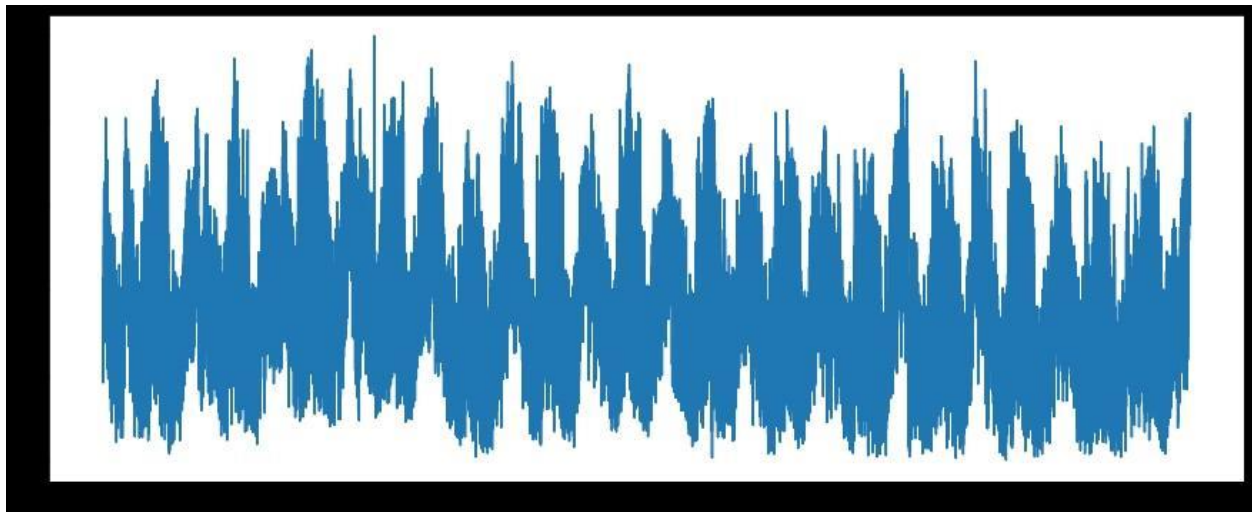
```
2004-12-31 01:00:00    31    53 13478.0
2004-12-31 02:00:00    31    53 12865.0
2004-12-31 03:00:00    31    53 12577.0
2004-12-31 04:00:00    31    53 12517.0
2004-12-31 05:00:00    31    53 12670.0
...
2018-01-01 20:00:00    1     1 21089.0
```

2018-01-01 21:00:00	1	1	20999.0
2018-01-01 22:00:00	1	1	20820.0
2018-01-01 23:00:00	1	1	20415.0
2018-01-02 00:00:00	2	1	19993.0

[121273 ROWS X 9 COLUMNS]



25695.0 9581.0




```
fpath='../input/hourly-energy-consumption/DOM_hourly.csv'
```

```
#Let's use datetime(2012-10-01 12:00:00,...) as index instead of numbers(0,1,...)
```

```
#This will be helpful for further data analysis as we are dealing with time series data
```

```
df=pd.read_csv(fpath,index_col='Datetime',parse_dates=['Datetime'])  
df.head()
```

```
#checking missing data
```

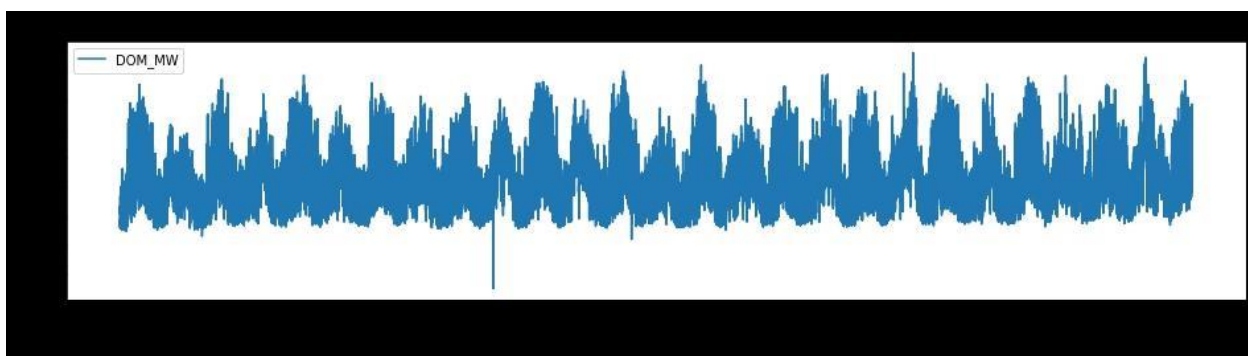
```
df.isna().sum()
```

```
#Data visualization
```

```
df.plot(figsize=(16,4),legend=True)
```

```
plt.title('DOM hourly power consumption data - BEFORE NORMALIZATION')
```

```
plt.show()
```



```
def normalize_data(df):
```

```
    scaler=sklearn.preprocessing.MinMaxScaler()  
    df['DOM_MW']=scaler.fit_transform(df['DOM_MW'].values.reshape(-1,1))  
    return df
```

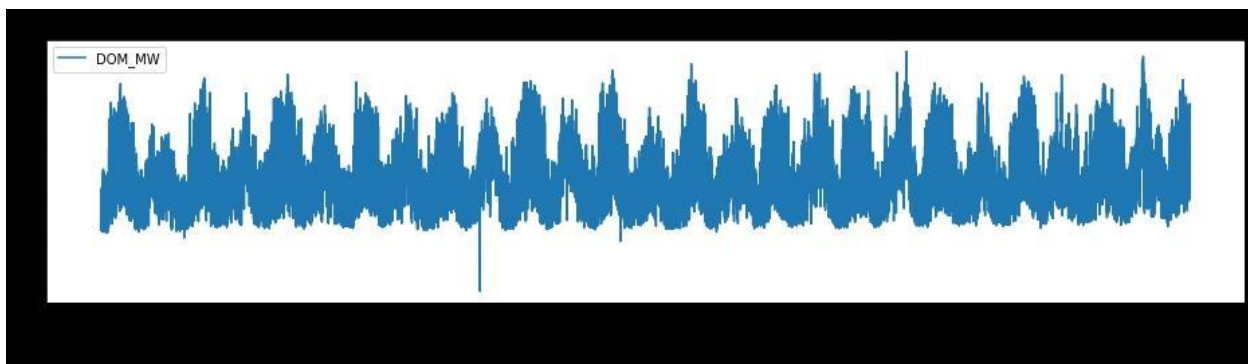
```
df_norm=normalize_data(df)  
df_norm.shape
```

```
#Visualize data after normalization
```

```
df_norm.plot(figsize=(16,4),legend=True)
```

```
plt.title('DOM hourly power consumption data - AFTER NORMALIZATION')
```

```
plt.show()
```



```
def load_data(stock, seq_len):
    X_train=[]
    y_train=[]
    for i in range(seq_len, len(stock)):
        X_train.append(stock.iloc[i-seq_len:i,0])
        y_train.append(stock.iloc[i,0])

    # 1 last 6189 days are going to be used in test
    X_test=X_train[110000:]
    y_test=y_train[110000:]

    # 2 first 110000 days are going to be used in training
    X_train=X_train[:110000]
    y_train=y_train[:110000]

    # 3 convert to numpy array
    X_train=np.array(X_train)
    y_train=np.array(y_train)

    X_test=np.array(X_test)
    y_test=np.array(y_test)

    # 4 reshape data to input into RNN models
    X_train=np.reshape(X_train,(110000,seq_len,1))

    X_test=np.reshape(X_test,(X_test.shape[0],seq_len,1)
    )

    return[X_train,y_train,X_test,y_test]
```

#create train, test data

```
seq_len=20#choose sequence length  
X_train,y_train,X_test,y_test=load_data(df,seq_len)
```

```
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 = (110000, 20, 1)

y_train.shape = (110000,)

X_test.shape = (6169, 20, 1)

y_test.shape = (6169,)

#RNN model

```
rnn_model=Sequential()  
rnn_model.add(SimpleRNN(40,activation="tanh",return_sequences=True,input_shape=(X_train.shape[1],1))  
rnn_model.add(Dropout(0.15))
```

```

rnn_model.add(SimpleRNN(40,activation="tanh",return_sequences=True))
rnn_model.add(Dropout(0.15))
rnn_model.add(SimpleRNN(40,activation="tanh",return_sequences=False))
rnn_model.add(Dropout(0.15))
rnn_model.add(Dense(1))
rnn_model.summary()
rnn_model.compile(optimizer="adam",loss="MSE")
rnn_model.fit(X_train,y_train,epochs=10,batch_size=1000)

```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
simple_rnn (SimpleRNN)	(None, 20, 40)	1680
dropout (Dropout)	(None, 20, 40)	0
simple_rnn_1 (SimpleRNN)	(None, 20, 40)	3240
dropout_1 (Dropout)	(None, 20, 40)	0
simple_rnn_2 (SimpleRNN)	(None, 40)	3240
dropout_2 (Dropout)	(None, 40)	0

dense (Dense) (None, 1) 41

=====

Total params: 8,201

Trainable params: 8,201

Non-trainable params: 0

Epoch 1/10

2022-08-19 16:26:37.061384: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:185] None of the MLIR Optimization Passes are enabled (registered 2)

110/110 [=====] - 10s 73ms/step - loss: 0.0820

Epoch 2/10

110/110 [=====] - 9s 81ms/step - loss: 0.0178

Epoch 3/10

110/110 [=====] - 8s 74ms/step - loss: 0.0096

Epoch 4/10

110/110 [=====] - 8s 73ms/step - loss: 0.0065

Epoch 5/10

110/110 [=====] - 8s 74ms/step - loss: 0.0050

Epoch 6/10

110/110 [=====] - 8s 73ms/step - loss: 0.0040

Epoch 7/10

110/110 [=====] - 9s 81ms/step - loss: 0.0035

Epoch 8/10

110/110 [=====] - 8s 73ms/step - loss: 0.0030

Epoch 9/10

110/110 [=====] - 8s 74ms/step - loss: 0.0027

Epoch 10/10

110/110 [=====] - 8s 75ms/step - loss: 0.0024

```
rnn_predictions=rnn_model.predict(X_test)
rnn_score=r2_score(y_test,rnn_predictions)
print("R2 Score of RNN model = ",rnn_score)
```

R2 SCORE OF RNN MODEL = 0.9466957722475382

```
def plot_predictions(test, predicted, title):
```

```

plt.figure(figsize=(16,4))
plt.plot(test,color='blue',label='Actual power consumption data')
plt.plot(predicted,alpha=0.7,color='orange',label='Predicted power consumption data')
plt.title(title)
plt.xlabel('Time')
plt.ylabel('Normalized power consumption scale')
plt.legend()
plt.show()
plot_predictions(y_test,rnn_predictions,"Predictions made by simple RNN model")

```

```
lstm_model=Sequential()
```

```

lstm_model.add(LSTM(40,activation="tanh",return_sequences=True,input_shape=(X_train.shape[1],1)))
lstm_model.add(Dropout(0.15))
lstm_model.add(LSTM(40,activation="tanh",return_sequences=True))
lstm_model.add(Dropout(0.15))
lstm_model.add(LSTM(40,activation="tanh",return_sequences=False))
lstm_model.add(Dropout(0.15))
lstm_model.add(Dense(1))
lstm_model.summary()
lstm_model.compile(optimizer="adam",loss="MSE")
lstm_model.fit(X_train,y_train,epochs=10,batch_size=1000)

```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 20, 40)	6720
dropout_3 (Dropout)	(None, 20, 40)	0
lstm_2 (LSTM)	(None, 20, 40)	12960
dropout_4 (Dropout)	(None, 20, 40)	0
lstm_3 (LSTM)	(None, 40)	12960
dropout_5 (Dropout)	(None, 40)	0
dense_1 (Dense)	(None, 1)	41
Total params: 32,681		
Trainable params: 32,681		
Non-trainable params: 0		

Epoch 1/10

110/110 [=====] - 26s 193ms/step - loss: 0.0211

Epoch 2/10

110/110 [=====] - 20s 185ms/step - loss: 0.0119

Epoch 3/10

110/110 [=====] - 21s 191ms/step - loss: 0.0080

Epoch 4/10

110/110 [=====] - 21s 186ms/step - loss: 0.0047

Epoch 5/10

110/110 [=====] - 20s 185ms/step - loss: 0.0037

Epoch 6/10

110/110 [=====] - 21s 194ms/step - loss: 0.0030

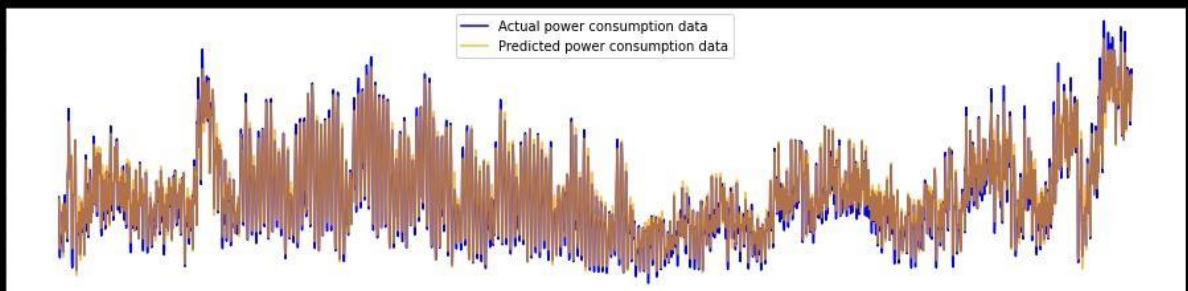
Epoch 7/10


```
110/110 [=====] - 20s 185ms/step - loss: 0.0026
Epoch 8/10
110/110 [=====] - 21s 192ms/step - loss: 0.0022
Epoch 9/10
110/110 [=====] - 20s 185ms/step - loss: 0.0020
Epoch 10/10
110/110 [=====] - 21s 191ms/step -
```

OUTPUT:

<KERAS.CALLBACKS.HISTORY AT 0X7F01D4E38810>

r2 score for the values predicted by the above trained LSTM model



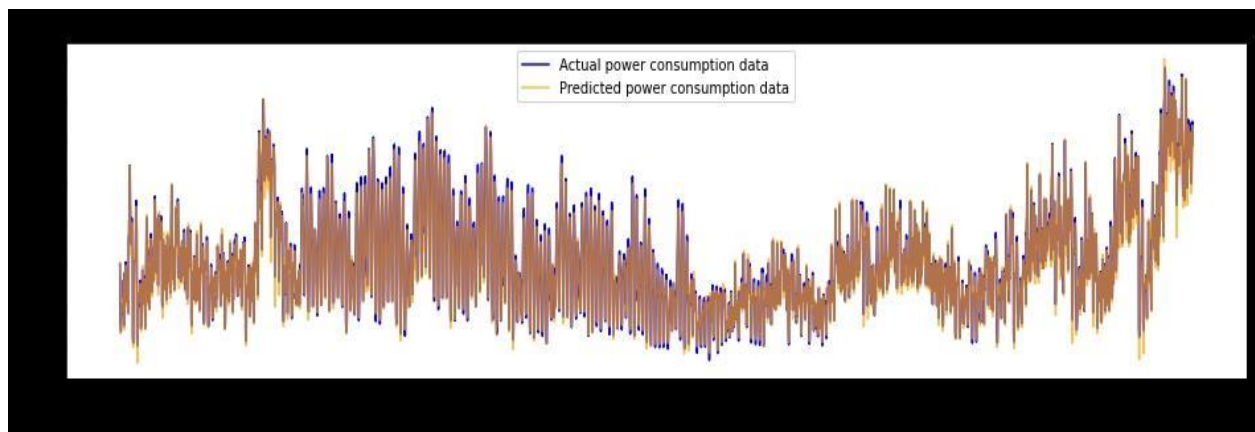
```
lstm_predictions=lstm_model.predict(X_test)
lstm_score=r2_score(y_test,lstm_predictions)
```

```
print("R^2 Score of LSTM model = ",lstm_score)
```

R^2 SCORE OF LSTM MODEL = 0.94996673239313

#actual values vs predicted values by plotting a graph

```
plot_predictions(y_test,lstm_predictions,"Predictions made by L  
STM model")
```



RNN, LSTM model by plotting data in *a* single graph

```
plt.figure(figsize=(15,8))
plt.plot(y_test,c="orange",linewidth=3,label="Original values")
plt.plot(lstm_predictions,c="red",linewidth=3,label="LSTM predictions")
plt.plot(rnn_predictions,alpha=0.5,c="blue",linewidth=3,label="RNN predictions")
plt.legend()
plt.title("Predictions vs actual data",fontsize=20)
plt.show()
```

