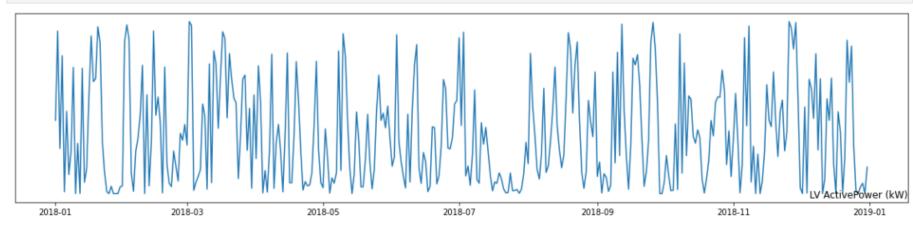
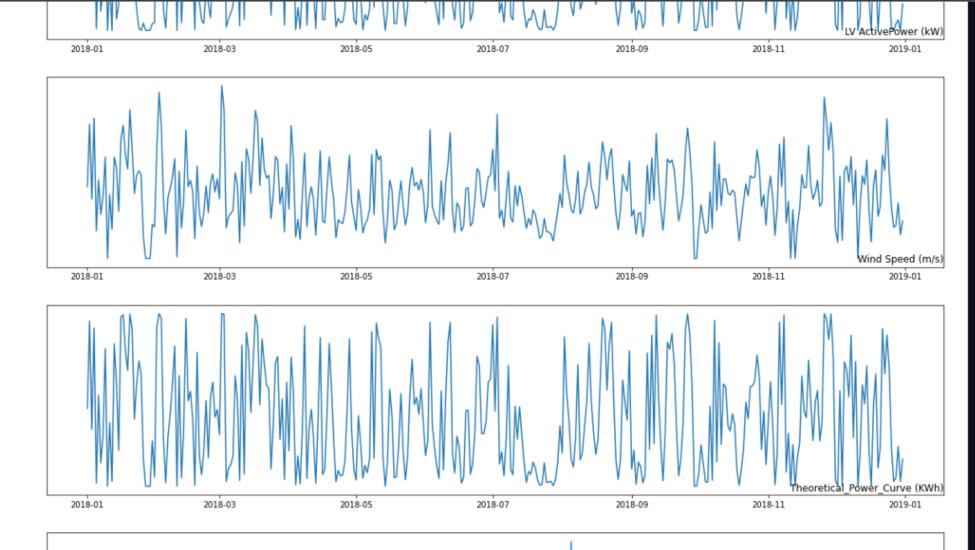
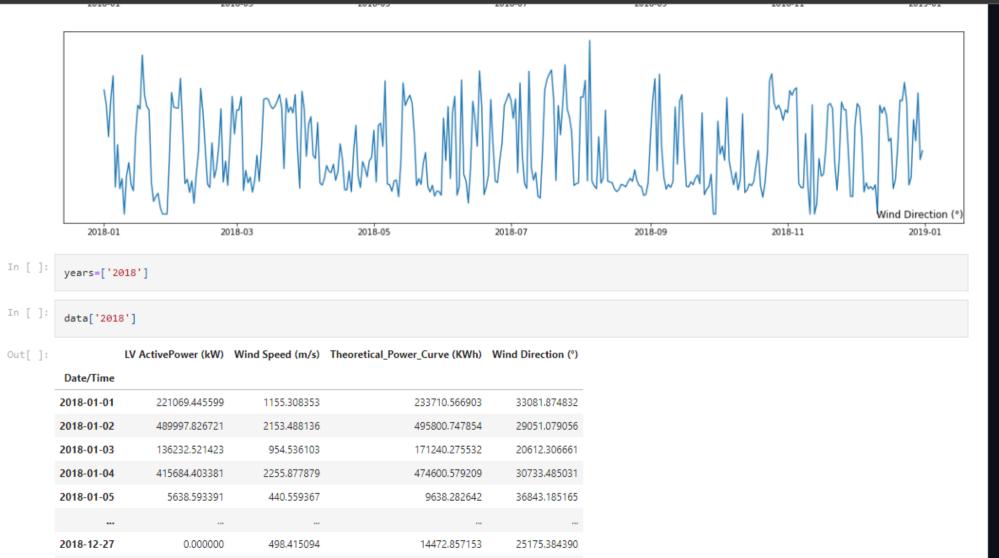
```
In [ ]:
         from pandas import DataFrame
         from pandas import Series
         from pandas import concat
         from pandas import read csv
         from pandas import datetime
         from sklearn.metrics import mean squared error
         from sklearn.preprocessing import MinMaxScaler
         from keras.models import Sequential
         from keras.layers import Dense
         from keras.layers import LSTM
         from math import sqrt
         from matplotlib import pyplot
         import numpy as np
         import pandas as pd
        Using TensorFlow backend.
In [ ]:
         window_size = 48
         batch_size_exp = 1
         epoch exp = 10
         neurons_exp = 50
         predict values exp = 6000
         lag exp=48
In [ ]:
         import pandas as pd
         data = pd.read csv('/content/drive/My Drive/T1.csv',index col="Date/Time")
In [ ]:
         data.to_csv('/content/cleaned_data.csv')
In [ ]:
         dataset = pd.read csv('/content/cleaned data.csv', parse dates=True,index col="Date/Time")
         data = dataset.resample('D').sum()
```

```
In [ ]:
         dataset = pd.read csv('/content/cleaned data.csv', parse dates=True,index col="Date/Time")
In [ ]:
         data = dataset.resample('D').sum()
In [ ]:
         from matplotlib import pyplot as plt
In [ ]:
         fig, ax = plt.subplots(figsize=(20,20))
         for i in range(len(data.columns)):
           plt.subplot(len(data.columns), 1, i+1)
           name = data.columns[i]
           plt.plot(data[name])
           plt.title(name, y=0, loc='right')
           plt.yticks([])
         plt.show()
         fig.tight_layout ()
```







```
data train = data.loc[:'2018-10-31',:]['Wind Direction (°)']
         data train
Out[]: Date/Time
        2018-01-01
                      33081.874832
        2018-01-02
                      29051.079056
        2018-01-03
                      20612.306661
        2018-01-04
                      30733,485031
        2018-01-05
                      36843.185165
        2018-10-27
                      27909.599655
        2018-10-28
                      29007.160919
        2018-10-29
                      27611.306152
        2018-10-30
                      24990.768890
        2018-10-31
                      27780.833587
        Freq: D, Name: Wind Direction (°), Length: 304, dtype: float64
In [ ]:
         data_test = data.loc['2018-11-01':'2018-12-31',:]['Wind Direction (°)']
         data_test
Out[]: Date/Time
        2018-11-01
                      26989.353104
        2018-11-02
                      32912.813599
        2018-11-03
                      31654.088837
        2018-11-04
                      33115.995506
        2018-11-05
                      33630.758800
                          . . .
        2018-12-27
                      25175.384390
        2018-12-28
                      19508.626114
        2018-12-29
                      32254.909293
        2018-12-30
                      14497.344503
        2018-12-31
                      16871.772377
        Freq: D, Name: Wind Direction (°), Length: 61, dtype: float64
         data train.shape
```

```
Out[]: (304,)
In [ ]:
         data_test.shape
Out[]: (61,)
In [ ]:
         data_train.head()
Out[]: Date/Time
        2018-01-01
                      33081.874832
        2018-01-02
                      29051.079056
        2018-01-03
                      20612.306661
        2018-01-04
                      30733.485031
        2018-01-05
                      36843.185165
        Freq: D, Name: Wind Direction (°), dtype: float64
In [ ]:
         data_train = np.array(data_train)
In [ ]:
         X_train, y_train = [],[]
         for i in range(3, len(data_train)-3):
           X_train.append(data_train[i-3:i])
           y_train.append(data_train[i:i+3])
In [ ]:
         X_train,y_train=np.array(X_train),np.array(y_train)
         X_train.shape, y_train.shape
Out[]: ((298, 3), (298, 3))
```

```
In [ ]:
         pd.DataFrame(X train).head()
Out[]:
         0 33081.874832 29051.079056 20612.306661
         1 29051.079056 20612.306661 30733.485031
         2 20612,306661 30733,485031 36843,185165
         3 30733.485031 36843.185165 7151.613260
         4 36843.185165 7151.613260 18498.549602
In [ ]:
          x scalar = MinMaxScaler()
          X_train = x_scalar.fit_transform(X_train)
In [ ]:
          v scalar = MinMaxScaler()
          y_train = y_scalar.fit_transform(y_train)
          pd.DataFrame(X_train).head()
Out[ ]:
         0 0.715178 0.628038 0.445605
         1 0.628038 0.445605 0.664409
         2 0.445605 0.664409 0.796491
         3 0.664409 0.796491 0.154607
         4 0.796491 0.154607 0.399909
In [ ]: X train.shape
```

```
In [ ]:
       X train = X train.reshape(298, 3, 1)
       X train.shape
Out[]: (298, 3, 1)
       reg = Sequential()
       reg.add(LSTM(units = 200, activation = 'relu', input shape=(3,1)))
       reg.add(Dense(3))
In [ ]:
       reg.compile(loss='mse', optimizer='adam')
       reg.fit(X train, y train, epochs = 100)
      Epoch 1/100
      Epoch 2/100
      298/298 [============ ] - 0s 368us/step - loss: 0.1229
      Epoch 3/100
      298/298 [=========== ] - 0s 363us/step - loss: 0.0717
      Epoch 4/100
      298/298 [========== ] - 0s 377us/step - loss: 0.0580
      Epoch 5/100
      298/298 [=========== ] - 0s 360us/step - loss: 0.0529
      Epoch 6/100
      298/298 [============ ] - 0s 374us/step - loss: 0.0519
      Epoch 7/100
      298/298 [=========== ] - 0s 348us/step - loss: 0.0509
      Epoch 8/100
      298/298 [=========== ] - 0s 397us/step - loss: 0.0504
      Epoch 9/100
      298/298 [============ ] - 0s 357us/step - loss: 0.0502
```

Out[]: (298, 3)

```
Epoch 12/100
298/298 [============ - - os 381us/step - loss: 0.0496
Epoch 13/100
298/298 [=========== ] - 0s 364us/step - loss: 0.0494
Epoch 14/100
298/298 [========= - - os 363us/step - loss: 0.0498
Epoch 15/100
298/298 [=========== ] - 0s 371us/step - loss: 0.0493
Epoch 16/100
298/298 [========== - - 0s 371us/step - loss: 0.0490
Epoch 17/100
298/298 [========== ] - 0s 352us/step - loss: 0.0488
Epoch 18/100
298/298 [============ - - os 362us/step - loss: 0.0487
Epoch 19/100
298/298 [=========== ] - 0s 354us/step - loss: 0.0486
Epoch 20/100
298/298 [============ ] - 0s 397us/step - loss: 0.0483
Epoch 21/100
298/298 [============ - - os 363us/step - loss: 0.0487
Epoch 22/100
298/298 [============ ] - 0s 356us/step - loss: 0.0485
Epoch 23/100
298/298 [=========== ] - 0s 332us/step - loss: 0.0485
Epoch 24/100
298/298 [========== ] - 0s 339us/step - loss: 0.0484
Epoch 25/100
298/298 [=========== ] - 0s 382us/step - loss: 0.0481
Epoch 26/100
298/298 [============ ] - 0s 355us/step - loss: 0.0478
Epoch 27/100
298/298 [=========== ] - 0s 351us/step - loss: 0.0478
Epoch 28/100
298/298 [============ ] - 0s 340us/step - loss: 0.0480
Epoch 29/100
298/298 [========== ] - 0s 373us/step - loss: 0.0476
Epoch 30/100
298/298 [============== ] - Os 341us/step - loss: 0.0476
Epoch 31/100
298/298 [============ ] - 0s 352us/step - loss: 0.0473
```

```
298/298 [============ ] - 0s 334us/step - loss: 0.0470
Epoch 37/100
298/298 [=========== ] - 0s 347us/step - loss: 0.0472
Epoch 38/100
298/298 [=========== - - os 373us/step - loss: 0.0468
Epoch 39/100
Epoch 40/100
298/298 [=========== ] - 0s 334us/step - loss: 0.0466
Epoch 41/100
298/298 [========== ] - 0s 327us/step - loss: 0.0466
Epoch 42/100
298/298 [=========== ] - 0s 362us/step - loss: 0.0465
Epoch 43/100
Epoch 44/100
298/298 [========== ] - 0s 351us/step - loss: 0.0465
Epoch 45/100
298/298 [=========== ] - 0s 360us/step - loss: 0.0464
Epoch 46/100
Epoch 47/100
298/298 [=========== - - os 350us/step - loss: 0.0462
Epoch 48/100
298/298 [============ - - os 361us/step - loss: 0.0462
Epoch 49/100
298/298 [============ ] - 0s 345us/step - loss: 0.0462
Epoch 50/100
298/298 [============= ] - 0s 352us/step - loss: 0.0464
Epoch 51/100
298/298 [=========== ] - 0s 339us/step - loss: 0.0459
Epoch 52/100
298/298 [============ - - os 350us/step - loss: 0.0462
Epoch 53/100
298/298 [============= ] - 0s 343us/step - loss: 0.0458
Epoch 54/100
298/298 [========== ] - 0s 338us/step - loss: 0.0459
Epoch 55/100
298/298 [=========== ] - 0s 339us/step - loss: 0.0462
Epoch 56/100
208/208 [------ loss: 0.0463
```

```
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298/298 [============ - - os 377us/step - loss: 0.0463
Epoch 57/100
298/298 [======== ] - 0s 337us/step - loss: 0.0465
Epoch 58/100
298/298 [============== ] - 0s 370us/step - loss: 0.0458
Epoch 59/100
298/298 [=========== ] - 0s 396us/step - loss: 0.0457
Epoch 60/100
Epoch 61/100
298/298 [============ ] - 0s 348us/step - loss: 0.0458
Epoch 62/100
298/298 [============ ] - 0s 351us/step - loss: 0.0460
Epoch 63/100
298/298 [=========== ] - 0s 345us/step - loss: 0.0460
Epoch 64/100
298/298 [======== ] - 0s 342us/step - loss: 0.0461
Epoch 65/100
298/298 [========= ] - 0s 374us/step - loss: 0.0457
Epoch 66/100
298/298 [========== ] - 0s 345us/step - loss: 0.0455
Epoch 67/100
298/298 [============== ] - 0s 391us/step - loss: 0.0455
Epoch 68/100
298/298 [=========== ] - 0s 348us/step - loss: 0.0458
Epoch 69/100
298/298 [============== ] - 0s 362us/step - loss: 0.0457
Epoch 70/100
298/298 [=========== ] - 0s 335us/step - loss: 0.0454
Epoch 71/100
298/298 [=========== ] - 0s 342us/step - loss: 0.0456
Epoch 72/100
298/298 [============ ] - 0s 342us/step - loss: 0.0461
Epoch 73/100
298/298 [======== ] - 0s 357us/step - loss: 0.0455
Epoch 74/100
298/298 [=========== ] - 0s 335us/step - loss: 0.0456
Epoch 75/100
```

```
Epoch 76/100
298/298 [========= ] - 0s 344us/step - loss: 0.0454
Epoch 77/100
298/298 [========== ] - 0s 370us/step - loss: 0.0454
Epoch 78/100
298/298 [========= - - 0s 364us/step - loss: 0.0458
Epoch 79/100
298/298 [========= ] - 0s 327us/step - loss: 0.0454
Epoch 80/100
298/298 [========== ] - 0s 380us/step - loss: 0.0454
Epoch 81/100
298/298 [=========== ] - 0s 352us/step - loss: 0.0453
Epoch 82/100
298/298 [============ ] - 0s 344us/step - loss: 0.0452
Epoch 83/100
298/298 [=========== ] - 0s 338us/step - loss: 0.0458
Epoch 84/100
298/298 [========= ] - 0s 350us/step - loss: 0.0453
Epoch 85/100
298/298 [============ ] - 0s 344us/step - loss: 0.0455
Epoch 86/100
298/298 [========== ] - 0s 352us/step - loss: 0.0458
Epoch 87/100
298/298 [========= - - 0s 372us/step - loss: 0.0452
Epoch 88/100
298/298 [========= - - 0s 363us/step - loss: 0.0455
Epoch 89/100
298/298 [========== ] - 0s 340us/step - loss: 0.0452
Epoch 90/100
298/298 [========= - - 0s 331us/step - loss: 0.0452
Epoch 91/100
298/298 [=========== ] - 0s 359us/step - loss: 0.0452
Epoch 92/100
298/298 [========= ] - 0s 356us/step - loss: 0.0451
298/298 [=========== ] - 0s 344us/step - loss: 0.0456
Epoch 94/100
298/298 [=========== - - 0s 341us/step - loss: 0.0452
Epoch 95/100
```

```
Epoch 97/100
       298/298 [=========== ] - 0s 358us/step - loss: 0.0453
       Epoch 98/100
       298/298 [=========== ] - 0s 348us/step - loss: 0.0452
       Epoch 99/100
       298/298 [=========== ] - 0s 372us/step - loss: 0.0452
       Epoch 100/100
       298/298 [========== ] - 0s 352us/step - loss: 0.0455
Out[]:
        data_test = np.array(data_test)
        X_test, y_test = [], []
        for i in range(3, len(data_test)-3):
          X_test.append(data_test[i-3:i])
          y test.append(data test[i:i+3])
        X_test, y_test=np.array(X_test), np.array(y_test)
        X_test = x_scalar.transform(X_test)
        y_test = y_scalar.transform(y_test)
        X_test.shape
Out[]: (55, 3)
        X_test = X_test.reshape(55, 3, 1)
        y_pred = reg.predict(X_test)
```

```
In [ ]:
        y pred = reg.predict(X test)
        v pred = v scalar.inverse transform(v pred)
        v true = v scalar.inverse transform(v test)
In [ ]:
        v true
Out[]: array([[33115.99550629, 33630.75879967, 8131.71406555],
               [33630.75879967, 8131.71406555, 7063.8345356],
               [ 8131.71406555, 7063.8345356, 6995.28148079],
               [ 7063.8345356 , 6995.28148079, 21468.86600792],
               [ 6995.28148079, 21468.86600792, 8157.80950069],
               [21468.86600792, 8157.80950069, 0, ],
               [ 8157.80950069, 0. , 29116.72072411].
               [ 0, , 29116.72072411, 0, ],
               [29116.72072411, 0. , 2793.34759331],
                        , 2793.34759331, 14737.10392174],
               [ 2793.34759331, 14737.10392174, 10112.13514081],
               [14737.10392174, 10112.13514081, 10613.06708145],
               [10112.13514081, 10613.06708145, 17370.42786407],
               [10613.06708145, 17370.42786407, 29016.88545227],
               [17370.42786407, 29016.88545227, 29461.56741333],
               [29016.88545227, 29461.56741333, 28115.14625549],
               [29461.56741333, 28115.14625549, 13706.64304161],
               [28115.14625549, 13706.64304161, 6312.51927948],
               [13706.64304161, 6312.51927948, 14784.38091278],
               [ 6312.51927948, 14784.38091278, 29879.50546265],
               [14784.38091278, 29879.50546265, 27907.6651001],
               [29879.50546265, 27907.6651001 , 27763.02044678],
               [27907.6651001 , 27763.02044678, 17034.9897837 ],
               [27763.02044678, 17034.9897837 , 4724.49790764],
               [17034.9897837 , 4724.49790764, 4672.6817627 ],
               [ 4724.49790764, 4672.6817627, 23593.9849329 ],
```

```
[ 0343.15305343, 0/13.111/5101, /321.3/515233],
       6713.11179161, 7321.37919235, 6543.93325424],
      [ 7321.37919235, 6543.93325424, 7789.27488327],
       6543,93325424, 7789,27488327,
                                          0.
                                    , 28994.74107689],
      7789.27488327, 0.
                    , 28994.74107689, 26877.00087738],
      [28994.74107689, 26877.00087738, 28466.81945801],
      [26877.00087738, 28466.81945801, 26306.70462036],
      [28466.81945801, 26306.70462036, 19395.79733944],
      [26306.70462036. 19395.79733944. 20196.71740341].
      [19395.79733944, 20196.71740341, 6770.31429863],
      [20196.71740341, 6770.31429863, 9318.74159431],
       6770.31429863, 9318.74159431, 18168.07575607],
      [ 9318.74159431, 18168.07575607, 30330.28541565],
      [18168.07575607, 30330.28541565, 30188.12014771],
      [30330.28541565, 30188.12014771, 35097.61787415],
      [30188.12014771, 35097.61787415, 29784.41993713],
      [35097.61787415, 29784.41993713, 7745.90272427],
      [29784.41993713, 7745.90272427, 9866.29644394],
      [ 7745.90272427, 9866.29644394, 25175.38438982],
      [ 9866.29644394, 25175.38438982, 19508.62611389],
      [25175.38438982, 19508.62611389, 32254.90929317],
     [19508.62611389, 32254.90929317, 14497.3445034 ]])
def evaluate model(y true, y predicted):
 scores = []
 #Calculate scores for each day
 for i in range(y true.shape[1]):
   mse = mean_squared_error(y_true[:, i], y_predicted[:, i])
   rmse = np.sqrt(mse)
   scores.append(rmse)
   #calculate score for whole prediction
   total score = 0
   for row in range(y true.shape[0]):
     for col in range(y predicted.shape[1]):
       total_score = total_score + (y_true[row, col] - y_predicted[row, col])**2
   total score = np.sqrt(total score/(y true.shape[0]*y predicted.shape[1]))
   return total score, scores
```

```
scores = []
           #Calculate scores for each day
           for i in range(y_true.shape[1]):
             mse = mean_squared_error(y_true[:, i], y_predicted[:, i])
             rmse = np.sqrt(mse)
             scores.append(rmse)
             #calculate score for whole prediction
             total score = 0
             for row in range(y_true.shape[0]):
               for col in range(y_predicted.shape[1]):
                 total_score = total_score + (y_true[row, col] - y_predicted[row, col])**2
             total_score = np.sqrt(total_score/(y_true.shape[0]*y_predicted.shape[1]))
             return total_score, scores
In [ ]:
         evaluate_model(y_true, y_pred)
Out[]: (10735.520841171958, [9883.835615418826])
In [ ]:
```

np.std(y\_true[0])

Out[]: 11900.88970862046

In [ ]: