WindPrediction

December 15, 2021

1 Load Libraries

```
In [1]: import numpy as np  # linear algebra

        import pandas as pd  # data processing, CSV file I/O (e.g. pd.read_csv), data manipulati
        import matplotlib.pyplot as plt  # this is used for the plot the graph

        from sklearn.preprocessing import MinMaxScaler

        from sklearn.preprocessing import LabelEncoder

        from sklearn.metrics import mean_squared_error,r2_score,mean_absolute_error

        ## for Deep-learing:
        import keras
        from keras.layers import Dense
        from keras.models import Sequential
        from keras.layers import LSTM
        from keras.layers import Dropout

        from keras.utils import plot_model
        from IPython.display import Image

        import timeit
```

```
Using TensorFlow backend.
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/tensorflow/python/
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/tensorflow/python/
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/tensorflow/python/
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/tensorflow/python/
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/tensorflow/python/
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/tensorflow/python/
```

```
np_resource = np.dtype([("resource", np.ubyte, 1)])
```

2 Load Data

```
In [2]: #fileToRead = '../Data/OilRefineryData.xlsx'
        fileToRead = '../Data/WindPowerForecasting.xlsx'
        rawData = pd.read_excel(fileToRead)
        #Display data info
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/ipykernel_launcher
  This is separate from the ipykernel package so we can avoid doing imports until
```

```
In [3]: rawData.head(10)
```

```
Out[3]:          TIMESTAMP  TARGETVAR       U10       V10      U100      V100
        0   20120101 1:00   0.000000  2.124600 -2.681966  2.864280 -3.666076
        1   20120101 2:00   0.054879  2.521695 -1.796960  3.344859 -2.464761
        2   20120101 3:00   0.110234  2.672210 -0.822516  3.508448 -1.214093
        3   20120101 4:00   0.165116  2.457504 -0.143642  3.215233 -0.355546
        4   20120101 5:00   0.156940  2.245898  0.389576  2.957678  0.332701
        5   20120101 6:00   0.168781  1.986038  0.796304  2.655406  0.882648
        6   20120101 7:00   0.114745  1.319787  1.440681  1.946708  1.941323
        7   20120101 8:00   0.085424 -0.122061  2.358907 -0.235427  4.323885
        8   20120101 9:00   0.153181 -1.380191  2.903624 -3.048145  6.041520
        9  20120101 10:00   0.139273 -1.710881  2.013933 -4.213648  4.877628
```

3 Check for Missing Data

```
In [4]: rawData.isnull().sum()
```

```
Out[4]: TIMESTAMP     0
        TARGETVAR    35
        U10           0
        V10           0
        U100          0
        V100          0
        dtype: int64
```

4 Deal with Missing Data

It is clear that here are many missing values in the data. The solution is to fill the N/A values with the folowing: 1. Mean of each feature for numerical features.

This step ca be implemented using the command:

pandas.DataFrame.fillna(DataFrame.mean(),inplace=True)

2. Fill N/A with neighbor values for string features.

This is achieved by the following command:

pandas.DataFrame.fillna(method='bfill')

```
In [5]: fixedRawData = rawData
        for col in rawData.columns:
            #print('Filling column ', col)
            if(rawData[col].dtype == 'object'):
                fixedRawData[col] = rawData[col].fillna(method='bfill')
            else:
                fixedRawData[col] = rawData[col].fillna(fixedRawData[col].mean())
```

```
In [6]: print('Missing Data:')
        fixedRawData.isnull().sum()
```

```
Missing Data:
```

```
Out[6]: TIMESTAMP    0
        TARGETVAR    0
        U10          0
        V10          0
        U100         0
        V100         0
        dtype: int64
```

5 Normalization

```
In [11]: NormOrScale = 0
         if(NormOrScale == 0):
             normalizedData=(fixedRawData-fixedRawData.mean())/fixedRawData.std()
         elif(NormOrScale == 1):
             normalizedData=(fixedRawData-fixedRawData.min())/(fixedRawData.max()-fixedRawData.m
```

```
In [12]: del normalizedData['TIMESTAMP']
         featureNames = normalizedData.columns
         normalizedData
```

```
Out[12]:          TARGETVAR       U10      U100       V10      V100
         0     -1.047630e+00  0.465135  0.303671 -0.832710 -0.618776
         1     -8.579996e-01  0.620467  0.416316 -0.529624 -0.379867
         2     -6.667253e-01  0.679344  0.454661 -0.195909 -0.131143
         3     -4.770848e-01  0.595357  0.385933  0.036584  0.039598
         4     -5.053360e-01  0.512583  0.325564  0.219194  0.176472
         ...            ...       ...       ...       ...       ...
         16795 -1.534514e-15 -1.102634 -1.341183 -0.789087 -1.330735
         16796 -1.534514e-15 -1.248584 -1.306854 -1.113995 -1.354609
```

```
16797 -1.534514e-15 -1.257667 -1.188111 -1.285914 -1.212264
16798 -1.534514e-15 -1.124088 -1.008011 -1.480033 -1.255134
16799 -1.534514e-15 -0.858808 -0.778210 -1.748151 -1.440478

[16800 rows x 5 columns]
```

6 Reframe Data

For prediction of timeseries data, the model has to estimate features from the previous values. So, if the desired output is $x(t)$, the input feature should be $x(t-1)$.

Series to supervised function is designed to take samples of $\{t-n, t-n-1, ..., t-1\}$ as input for the machine learning. The output will be samples at $\{t, t+1, ..., t+n\}$.

For the current application, the COVID-19 data are sampled daily and hence the input is previous day and the output is the current day.

6.1 Reframe Data Function

```
In [13]: # ## Splitting Train and Test data

         # ## Resample the data
         def Reframe(data, n_in=1, n_out=1, dropnan=True):
             n_vars = 1 if type(data) is list else data.shape[1]
             dff = pd.DataFrame(data)
             cols, names = list(), list()
             # input sequence (t-n, ... t-1)
             for i in range(n_in, 0, -1):
                 cols.append(dff.shift(i))
                 names += [('var%d(t-%d)' % (j + 1, i)) for j in range(n_vars)]
             # forecast sequence (t, t+1, ... t+n)
             for i in range(0, n_out):
                 cols.append(dff.shift(-i))
                 if i == 0:
                     names += [('var%d(t)' % (j + 1)) for j in range(n_vars)]
                 else:
                     names += [('var%d(t+%d)' % (j + 1, i)) for j in range(n_vars)]
             # put it all together
             returnedData = pd.concat(cols, axis=1)
             returnedData.columns = names
             # drop rows with NaN values
             if dropnan:
                 returnedData.dropna(inplace=True)
             return returnedData
```

7 Application of Reframe Data

7.1 Get Numerical Data

```
In [14]: #cleanData2.head()
         values = normalizedData.values

In [15]: normalizedData.head()

Out[15]:    TARGETVAR       U10      U100       V10      V100
         0  -1.047630  0.465135  0.303671 -0.832710 -0.618776
         1  -0.858000  0.620467  0.416316 -0.529624 -0.379867
         2  -0.666725  0.679344  0.454661 -0.195909 -0.131143
         3  -0.477085  0.595357  0.385933  0.036584  0.039598
         4  -0.505336  0.512583  0.325564  0.219194  0.176472

In [16]: values.shape

Out[16]: (16800, 5)
```

7.2 Apply Reframe Data

Apply reframe function on the values of Data

```
In [17]: # frame as supervised learning
         reframed = Reframe(values, 1, 1)
         reframed.head(20)

Out[17]:     var1(t-1)  var2(t-1)  var3(t-1)  var4(t-1)  var5(t-1)   var1(t)   var2(t)  \
         1   -1.047630   0.465135   0.303671  -0.832710  -0.618776 -0.858000  0.620467
         2   -0.858000   0.620467   0.416316  -0.529624  -0.379867 -0.666725  0.679344
         3   -0.666725   0.679344   0.454661  -0.195909  -0.131143 -0.477085  0.595357
         4   -0.477085   0.595357   0.385933   0.036584   0.039598 -0.505336  0.512583
         5   -0.505336   0.512583   0.325564   0.219194   0.176472 -0.464420  0.410933
         6   -0.464420   0.410933   0.254713   0.358485   0.285841 -0.651138  0.150314
         7   -0.651138   0.150314   0.088598   0.579163   0.496383 -0.752453 -0.413695
         8   -0.752453  -0.413695  -0.422882   0.893626   0.970209 -0.518325 -0.905839
         9   -0.518325  -0.905839  -1.082166   1.080174   1.311800 -0.566385 -1.035196
         10  -0.566385  -1.035196  -1.355354   0.775484   1.080334 -0.757974 -1.201092
         11  -0.757974  -1.201092  -1.650035   0.574058   0.850377 -0.536835 -1.281442
         12  -0.536835  -1.281442  -1.796380   0.297372   0.421528 -0.568333 -1.232089
         13  -0.568333  -1.232089  -1.723805   0.119429   0.129876 -0.280300 -1.202823
         14  -0.280300  -1.202823  -1.681480   0.008288  -0.061035 -0.214705 -1.156241
         15  -0.214705  -1.156241  -1.583164  -0.070182  -0.256800 -0.198144 -1.051128
         16  -0.198144  -1.051128  -1.224532  -0.342784  -0.812383 -0.221525 -0.748776
         17  -0.221525  -0.748776  -0.715838  -0.809665  -1.396119 -0.171841 -0.457507
         18  -0.171841  -0.457507  -0.360920  -1.138859  -1.652608 -0.003958 -0.269099
         19  -0.003958  -0.269099  -0.131915  -1.253939  -1.684535  0.735445 -0.220612
         20   0.735445  -0.220612  -0.075659  -1.190492  -1.621113  1.493683 -0.197234
```

```
     var3(t)   var4(t)   var5(t)
1   0.416316 -0.529624 -0.379867
2   0.454661 -0.195909 -0.131143
3   0.385933  0.036584  0.039598
4   0.325564  0.219194  0.176472
5   0.254713  0.358485  0.285841
6   0.088598  0.579163  0.496383
7  -0.422882  0.893626  0.970209
8  -1.082166  1.080174  1.311800
9  -1.355354  0.775484  1.080334
10 -1.650035  0.574058  0.850377
11 -1.796380  0.297372  0.421528
12 -1.723805  0.119429  0.129876
13 -1.681480  0.008288 -0.061035
14 -1.583164 -0.070182 -0.256800
15 -1.224532 -0.342784 -0.812383
16 -0.715838 -0.809665 -1.396119
17 -0.360920 -1.138859 -1.652608
18 -0.131915 -1.253939 -1.684535
19 -0.075659 -1.190492 -1.621113
20 -0.092244 -1.256856 -1.518000
```

8 Split Data into Train and Test

```
In [18]: # split into train and test sets
         values = reframed.values
         # 1- Take train either specific samples
         #n_train_time = 100

         # 2- OR 80% train and 20% test
         n_train_time = int(np.round(0.8*len(values)))

         train = values[:n_train_time, :]
         test = values[n_train_time:, :]
         ##test = values[n_train_time:n_test_time, :]
         # split into input and outputs
         train_X, train_y = train[:, 0:len(normalizedData.columns)], train[:, len(normalizedData
         test_X, test_y = test[:, 0:len(normalizedData.columns)], test[:, len(normalizedData.col
```

9 Reshape Input

Input has to be 3D [samples, timesteps, features]

```
In [19]: train_X = train_X.reshape((train_X.shape[0], 1, train_X.shape[1]))
         test_X = test_X.reshape((test_X.shape[0], 1, test_X.shape[1]))
         print('Train input Shape: ',train_X.shape, '  Train Y shape: ', train_y.shape)
```

```
print('Test X shape: ', test_X.shape,'  Test y Shape: ' ,test_y.shape)
# We reshaped the input into the 3D format as expected by LSTMs, namely [samples, times
```

```
Train input Shape:  (13439, 1, 5)   Train Y shape:  (13439, 5)
Test X shape:  (3360, 1, 5)   Test y Shape:  (3360, 5)
```

10 Design the LSTM

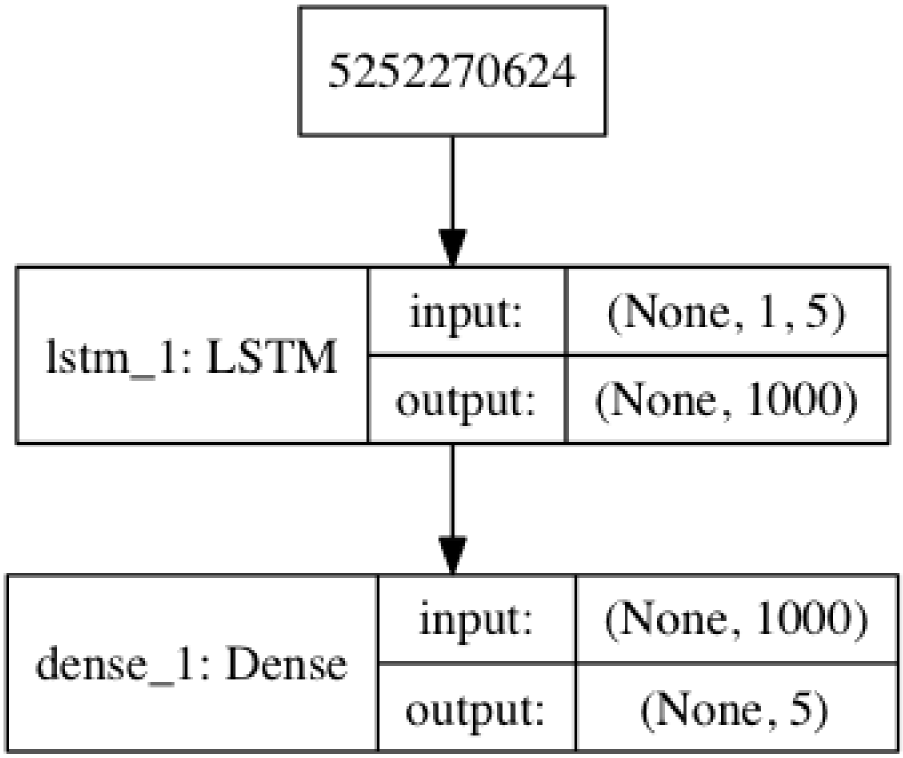
In [20]:
```
# # LSTM Network
model = Sequential()
# model.add(LSTM(1000, return_sequences=True, input_shape=(train_X.shape[1], train_X.sh
# model.add(Dropout(0.2))

model.add(LSTM(1000,input_shape=(train_X.shape[1], train_X.shape[2])))
# model.add(Dropout(0.2))

model.add(Dense(len(normalizedData.columns)))

model.compile(loss='mean_squared_error', optimizer='adam')

model.summary()
```

```
WARNING:tensorflow:From /Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-pac
Instructions for updating:
Colocations handled automatically by placer.
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 1000)              4024000
_________________________________________________________________
dense_1 (Dense)              (None, 5)                 5005
=================================================================
Total params: 4,029,005
Trainable params: 4,029,005
Non-trainable params: 0
_________________________________________________________________
```

11 Draw the LSTM Network

In [21]:
```
from keras.utils import plot_model
plot_model(model,'model.png',show_shapes=True, show_layer_names=True)
from IPython.display import Image
Image('model.png')
```

Out[21]:

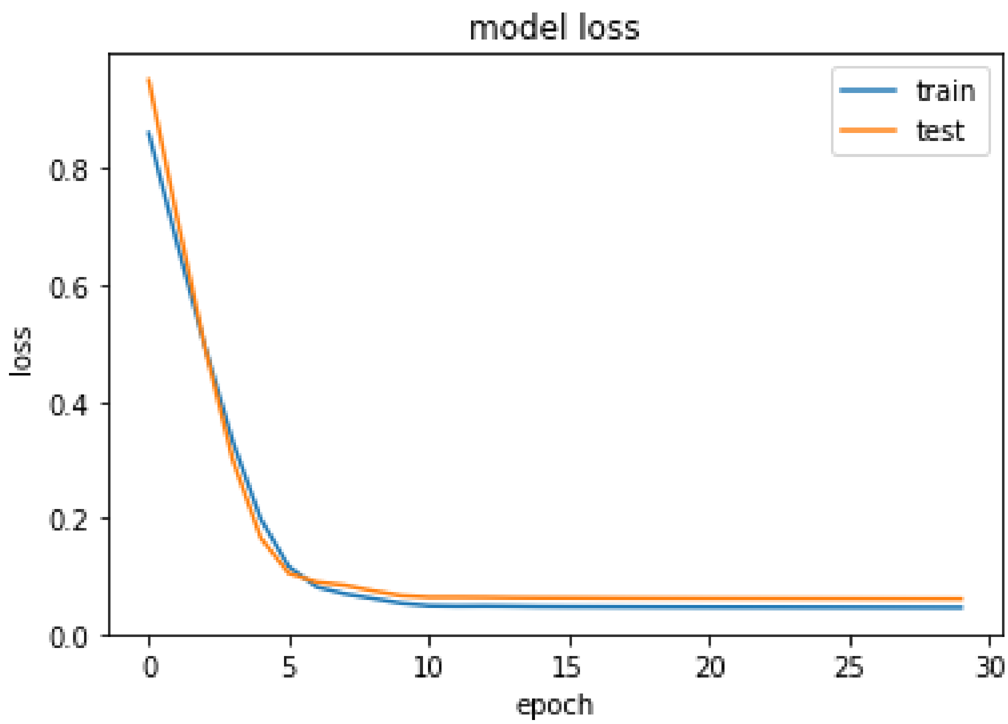



```
In [22]: # Train the network: fit network
         print("Training the LSTM Deep network")
         tic=timeit.default_timer()

         history = model.fit(train_X, train_y, epochs=30, batch_size=2500, validation_data=(test
                             shuffle=False)
         toc=timeit.default_timer()
         elapsedTime = toc - tic #elapsed time in seconds

         # summarize history for loss
         plt.plot(history.history['loss'])
         plt.plot(history.history['val_loss'])
         plt.title('model loss')
         plt.ylabel('loss')
         plt.xlabel('epoch')
         plt.legend(['train', 'test'], loc='upper right')
         plt.show()
```

```
Training the LSTM Deep network
WARNING:tensorflow:From /Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-pac
Instructions for updating:
Use tf.cast instead.
Train on 13439 samples, validate on 3360 samples
```

```
Epoch 1/30
13439/13439 [==============================] - 6s 425us/step - loss: 0.8613 - val_loss: 0.9523
Epoch 2/30
13439/13439 [==============================] - 4s 280us/step - loss: 0.6743 - val_loss: 0.7190
Epoch 3/30
13439/13439 [==============================] - 4s 277us/step - loss: 0.4965 - val_loss: 0.4950
Epoch 4/30
13439/13439 [==============================] - 4s 278us/step - loss: 0.3318 - val_loss: 0.3002
Epoch 5/30
13439/13439 [==============================] - 4s 281us/step - loss: 0.1991 - val_loss: 0.1664
Epoch 6/30
13439/13439 [==============================] - 4s 282us/step - loss: 0.1171 - val_loss: 0.1056
Epoch 7/30
13439/13439 [==============================] - 4s 275us/step - loss: 0.0822 - val_loss: 0.0905
Epoch 8/30
13439/13439 [==============================] - 4s 278us/step - loss: 0.0703 - val_loss: 0.0851
Epoch 9/30
13439/13439 [==============================] - 4s 276us/step - loss: 0.0623 - val_loss: 0.0756
Epoch 10/30
13439/13439 [==============================] - 4s 284us/step - loss: 0.0542 - val_loss: 0.0673
Epoch 11/30
13439/13439 [==============================] - 4s 287us/step - loss: 0.0498 - val_loss: 0.0646
Epoch 12/30
13439/13439 [==============================] - 4s 282us/step - loss: 0.0491 - val_loss: 0.0646
Epoch 13/30
13439/13439 [==============================] - 4s 286us/step - loss: 0.0493 - val_loss: 0.0644
Epoch 14/30
13439/13439 [==============================] - 4s 284us/step - loss: 0.0489 - val_loss: 0.0637
Epoch 15/30
13439/13439 [==============================] - 4s 297us/step - loss: 0.0484 - val_loss: 0.0634
Epoch 16/30
13439/13439 [==============================] - 4s 296us/step - loss: 0.0481 - val_loss: 0.0633
Epoch 17/30
13439/13439 [==============================] - 4s 276us/step - loss: 0.0480 - val_loss: 0.0631
Epoch 18/30
13439/13439 [==============================] - 4s 280us/step - loss: 0.0478 - val_loss: 0.0629
Epoch 19/30
13439/13439 [==============================] - 4s 280us/step - loss: 0.0477 - val_loss: 0.0628
Epoch 20/30
13439/13439 [==============================] - 4s 276us/step - loss: 0.0476 - val_loss: 0.0626
Epoch 21/30
13439/13439 [==============================] - 4s 277us/step - loss: 0.0474 - val_loss: 0.0625
Epoch 22/30
13439/13439 [==============================] - 4s 278us/step - loss: 0.0473 - val_loss: 0.0624
Epoch 23/30
13439/13439 [==============================] - 4s 277us/step - loss: 0.0472 - val_loss: 0.0623
Epoch 24/30
13439/13439 [==============================] - 4s 275us/step - loss: 0.0471 - val_loss: 0.0622
```

```
Epoch 25/30
13439/13439 [==============================] - 4s 278us/step - loss: 0.0470 - val_loss: 0.0621
Epoch 26/30
13439/13439 [==============================] - 4s 278us/step - loss: 0.0470 - val_loss: 0.0620
Epoch 27/30
13439/13439 [==============================] - 4s 278us/step - loss: 0.0469 - val_loss: 0.0619
Epoch 28/30
13439/13439 [==============================] - 4s 278us/step - loss: 0.0468 - val_loss: 0.0618
Epoch 29/30
13439/13439 [==============================] - 4s 278us/step - loss: 0.0467 - val_loss: 0.0617
Epoch 30/30
13439/13439 [==============================] - 4s 278us/step - loss: 0.0466 - val_loss: 0.0617
```




```
In [25]: toPredict = 'U10'
         #indexOfToPredict = rawData.loc[rawData.columns ==toPredict.lower()]
         indexOfToPredict = normalizedData.columns.get_loc(toPredict)
         print("We are going to predict \"",toPredict,"\" which has index=", indexOfToPredict)
```

```
We are going to predict " U10 " which has index= 1
```

```
In [26]: def mean_absolute_percentage_error(y_true, y_pred):
             y_true, y_pred = np.array(y_true), np.array(y_pred)
             return np.mean(np.abs((y_true - y_pred) / y_true))
```

11.0.1 Deal with Value Zero as MAPE has division

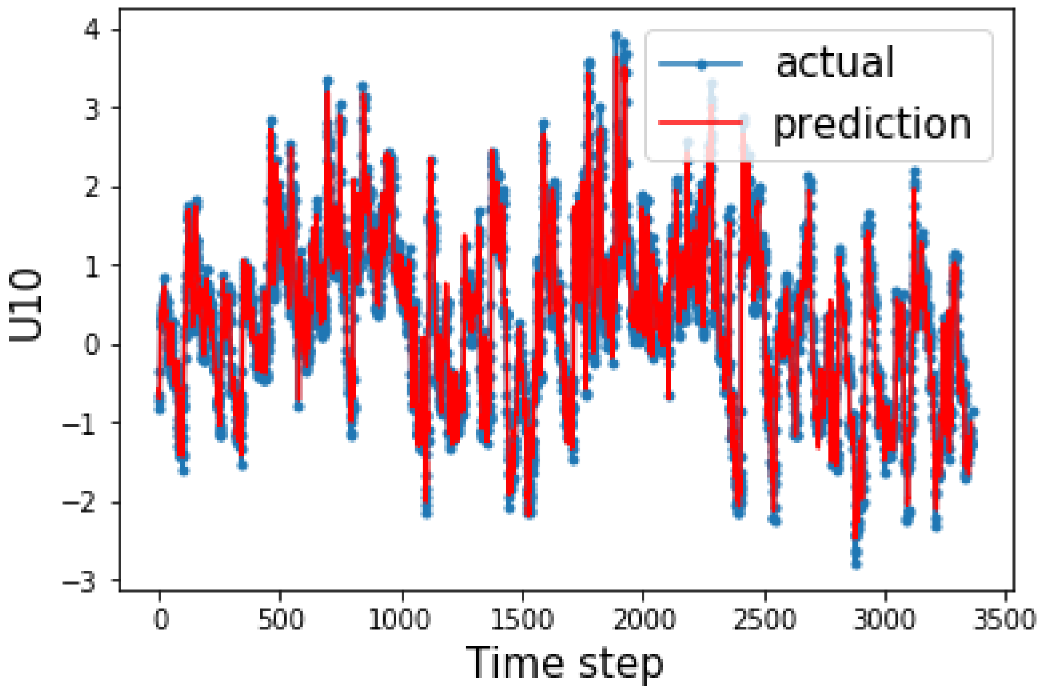
```
In [27]: flag = False
         for i in range(0,len(test_y[:,indexOfToPredict])):
             if(test_y[i,indexOfToPredict]==0):
                 indexToRemove = i
                 flag = True
         if(flag):
             print("Index to repair Because it has 'ZERO': ", indexToRemove)
             test_y[indexToRemove,indexOfToPredict] = 0.0001
         else:
             print('No Zero value exist in the data.')
```

```
No Zero value exist in the data.
```

```
In [28]: # calculate Errors
         yhat = model.predict(test_X)
         rmse_lstm = np.sqrt(mean_squared_error(test_y[:,indexOfToPredict],yhat[:,indexOfToPredi
         mae_lstm =  mean_absolute_error(test_y[:,indexOfToPredict],yhat[:,indexOfToPredict])
         mape_lstm = mean_absolute_percentage_error(test_y[:,indexOfToPredict],yhat[:,indexOfToP
         print('Test MAE For LSTM: %.3f' % mae_lstm)
         #print('Test MAPE For LSTM: %.3f' % mape_lstm)
         print('Test RMSE For LSTM: %.3f' % rmse_lstm)
         print('Training elapsed Time: %.3f '% elapsedTime,' Seconds')
```

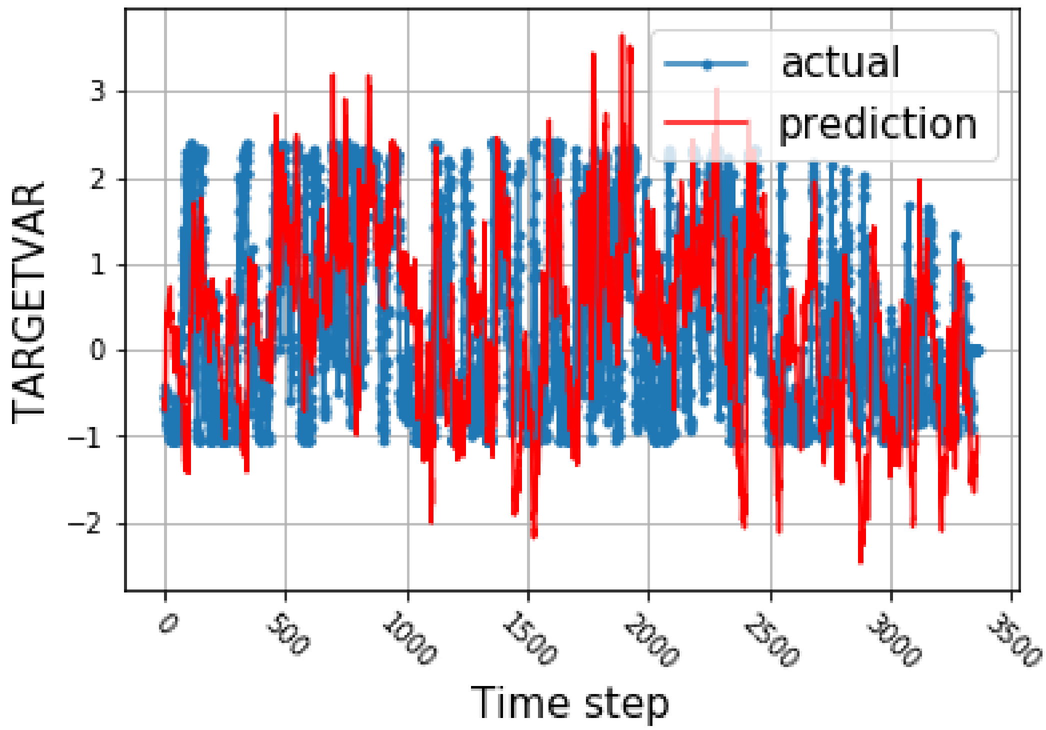
```
Test MAE For LSTM: 0.168
Test RMSE For LSTM: 0.235
Training elapsed Time: 115.836   Seconds
```

```
In [31]: plt.plot(test_y[:,indexOfToPredict], marker='.', label="actual")
         plt.plot(yhat[:,1], 'r', label="prediction")
         plt.ylabel(toPredict, size=15)
         plt.xlabel('Time step', size=15)
         plt.legend(fontsize=15)
         plt.show()
```

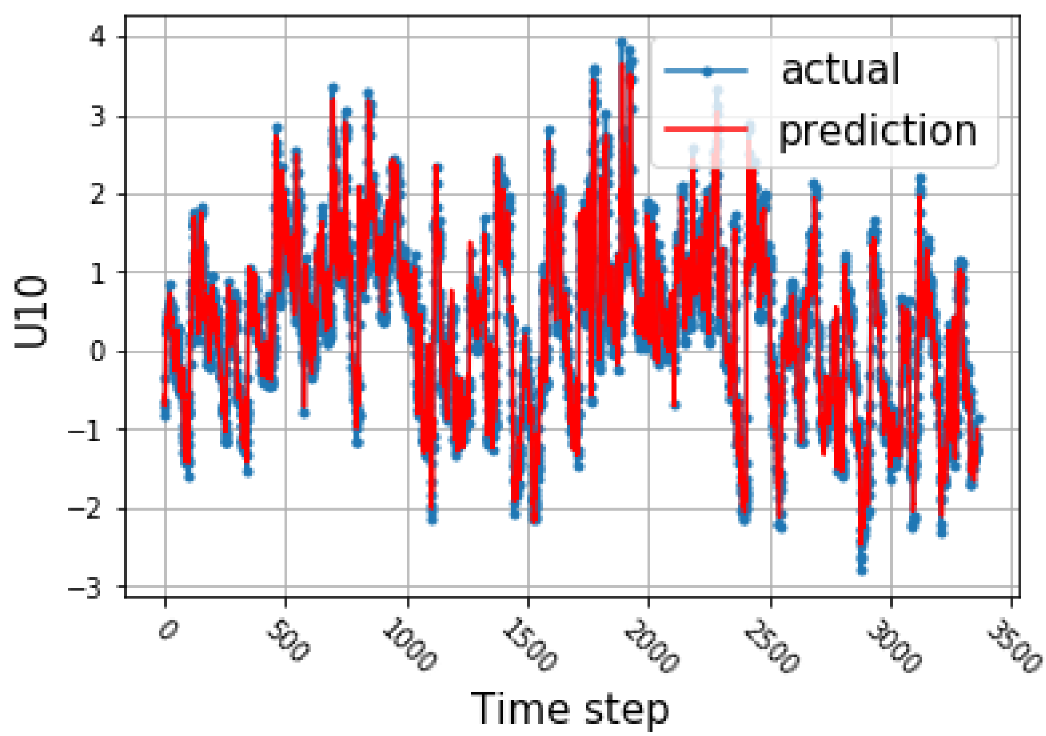



```
In [32]: toPredict = normalizedData.columns
         print(len(toPredict))
         for col in toPredict:
             indexOfToPredict = normalizedData.columns.get_loc(col)
             plt.plot(test_y[:,indexOfToPredict], marker='.', label="actual")
             plt.plot(yhat[:,1], 'r', label="prediction")
             plt.ylabel(col, size=15)
             plt.xlabel('Time step', size=15)
             plt.xticks(rotation = -45)
             plt.grid()
             plt.legend(fontsize=15)
             plt.show()
```

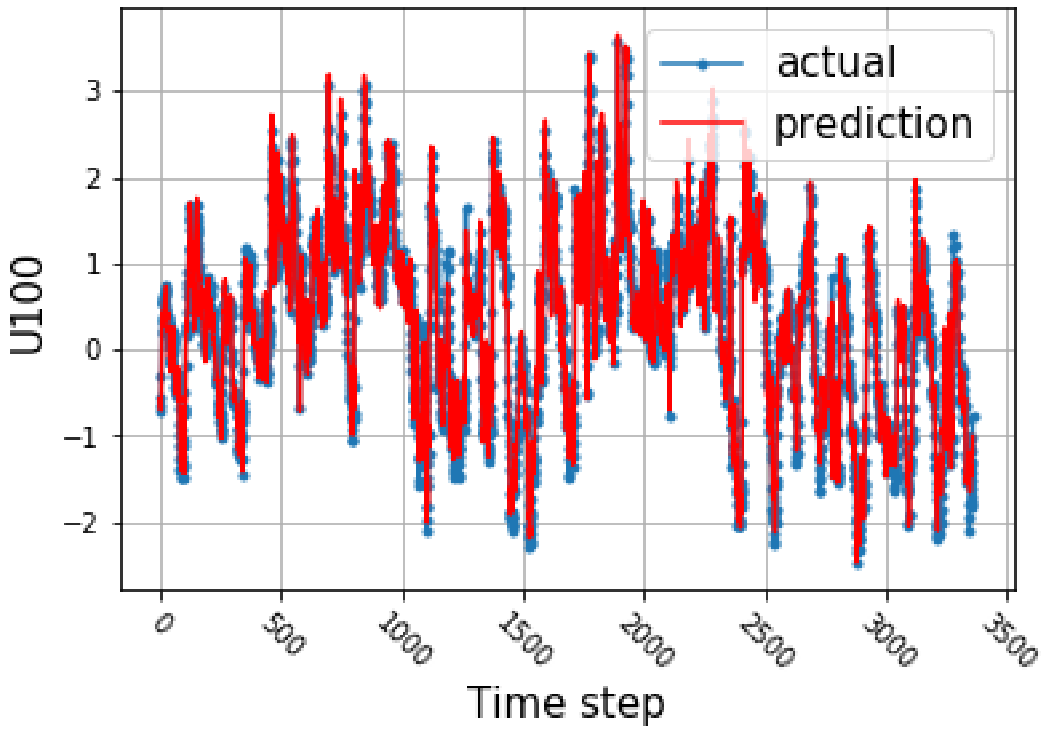
5

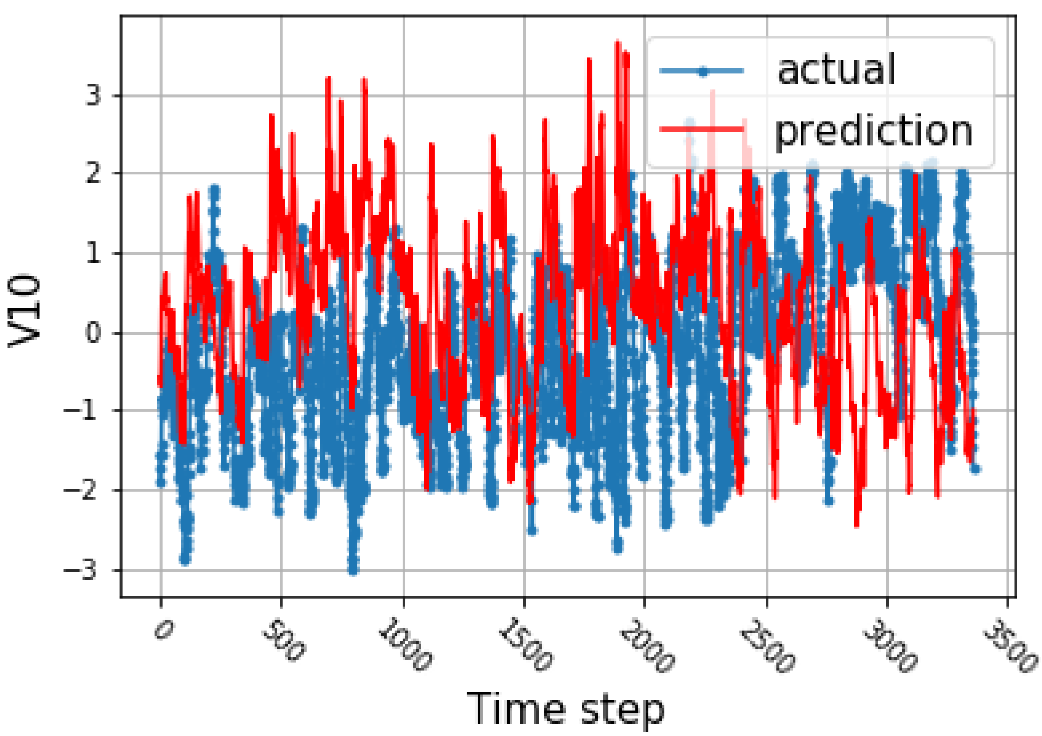


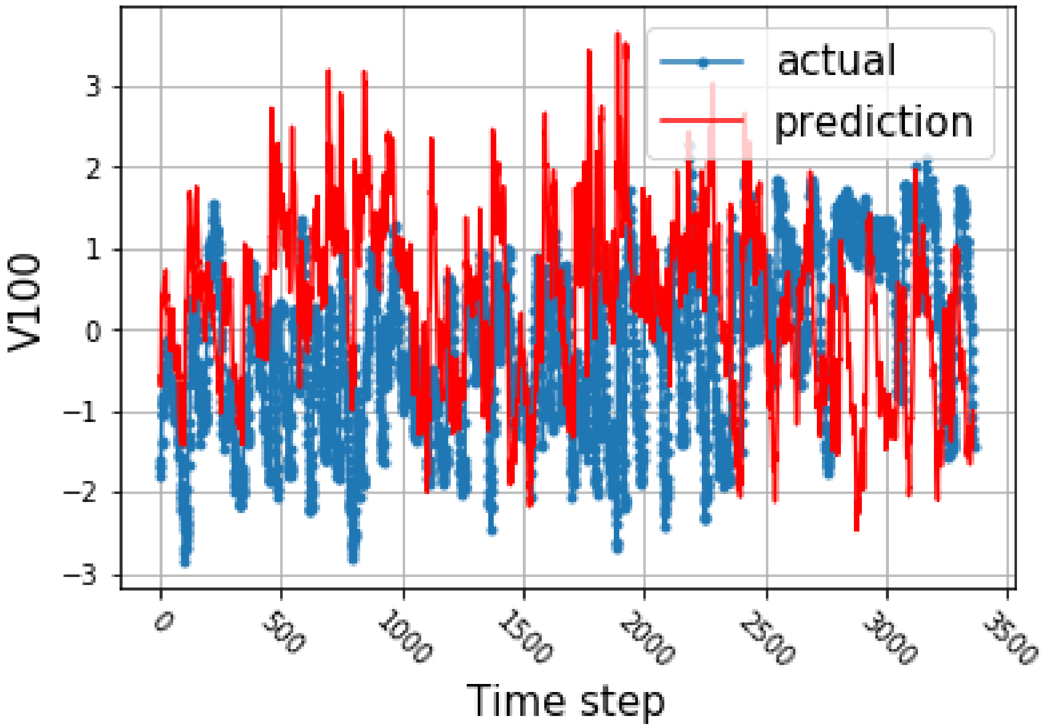
actual
prediction
TARGETVAR
Time step



actual
prediction
U10
Time step


actual
prediction
U100
Time step


actual
prediction
V10
Time step


actual
prediction
V100
3
2
1
0
−1
−2
−3
0
500
1000
1500
2000
2500
3000
3500
Time step