```
import tensorflow as tf
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential

import numpy as np
import pandas as pd
import sklearn
import os
import seaborn as sns
from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import random
np.random.seed(34)
```

```
from google.colab import drive

drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
dataset_path = '/content/drive/MyDrive/CMaps'
train_data_path = f'{dataset_path}/train_FD001.txt'
columns=["id","cycle","op1","op2","op3","sensor1","sensor2","sensor3","sensor4","sensor5","sensor6","sensor7","sensor8",
         "sensor9","sensor10","sensor11","sensor12","sensor13","sensor14","sensor15","sensor16","sensor17","sensor18","sensor19"
         ,"sensor20","sensor21"]
train_data = pd.read_csv(train_data_path, sep= "\s+", header = None,names=columns )
print("DataFrame Shape:",train_data.shape)
missing_values = train_data.isnull().sum()
print("Missing Values:")
print(missing_values)
```

```
DataFrame Shape: (20631, 26)
Missing Values:
id          0
cycle       0
op1         0
op2         0
op3         0
sensor1     0
sensor2     0
sensor3     0
sensor4     0
sensor5     0
sensor6     0
sensor7     0
sensor8     0
sensor9     0
sensor10    0
sensor11    0
sensor12    0
sensor13    0
sensor14    0
sensor15    0
sensor16    0
sensor17    0
sensor18    0
sensor19    0
sensor20    0
sensor21    0
dtype: int64
```

```
train_data.head()
```

	id	cycle	op1	op2	op3	sensor1	sensor2	sensor3	sensor4	sensor5	...	sensor12	sensor13	sensor14	sensor15	sensor16	s
0	1	1	-0.0007	-0.0004	100.0	518.67	641.82	1589.70	1400.60	14.62	...	521.66	2388.02	8138.62	8.4195	0.03	
1	1	2	0.0019	-0.0003	100.0	518.67	642.15	1591.82	1403.14	14.62	...	522.28	2388.07	8131.49	8.4318	0.03	
2	1	3	-0.0043	0.0003	100.0	518.67	642.35	1587.99	1404.20	14.62	...	522.42	2388.03	8133.23	8.4178	0.03	
3	1	4	0.0007	0.0000	100.0	518.67	642.35	1582.79	1401.87	14.62	...	522.86	2388.08	8133.83	8.3682	0.03	
4	1	5	-0.0019	-0.0002	100.0	518.67	642.37	1582.85	1406.22	14.62	...	522.19	2388.04	8133.80	8.4294	0.03	

```
print(train_data.shape)
```

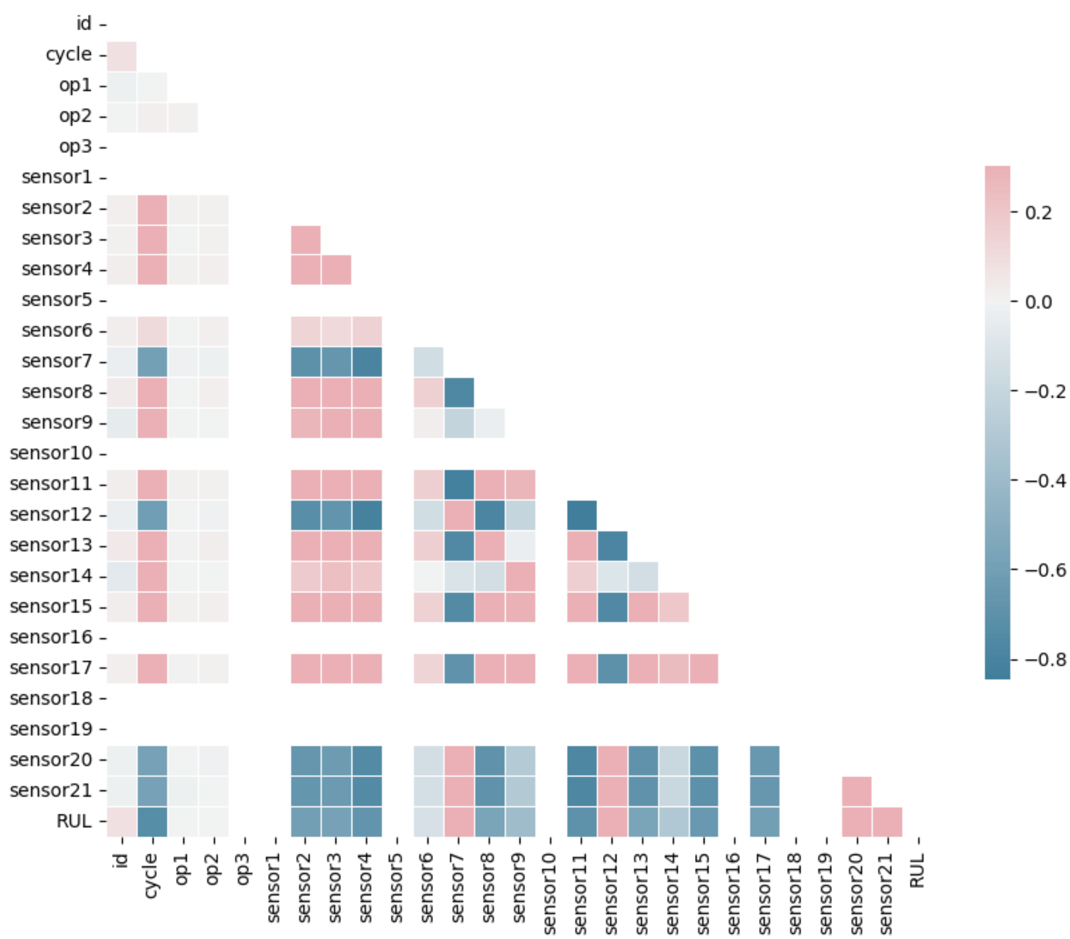
```
(20631, 26)
```

```
def add_rul(g):
    g['RUL'] = max(g['cycle']) - g['cycle']
    return g
train = train_data.groupby('id').apply(add_rul)
```

```
<ipython-input-115-951723a8a72b>:4: FutureWarning: Not prepending group keys to the result index of transform-like apply. In the future,
To preserve the previous behavior, use

        >>> .groupby(..., group_keys=False)

To adopt the future behavior and silence this warning, use

        >>> .groupby(..., group_keys=True)
  train = train_data.groupby('id').apply(add_rul)
```

```
corr = train.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(10, 10))
cmap = sns.diverging_palette(230, 10, as_cmap=True)
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

```
<Axes: >
```



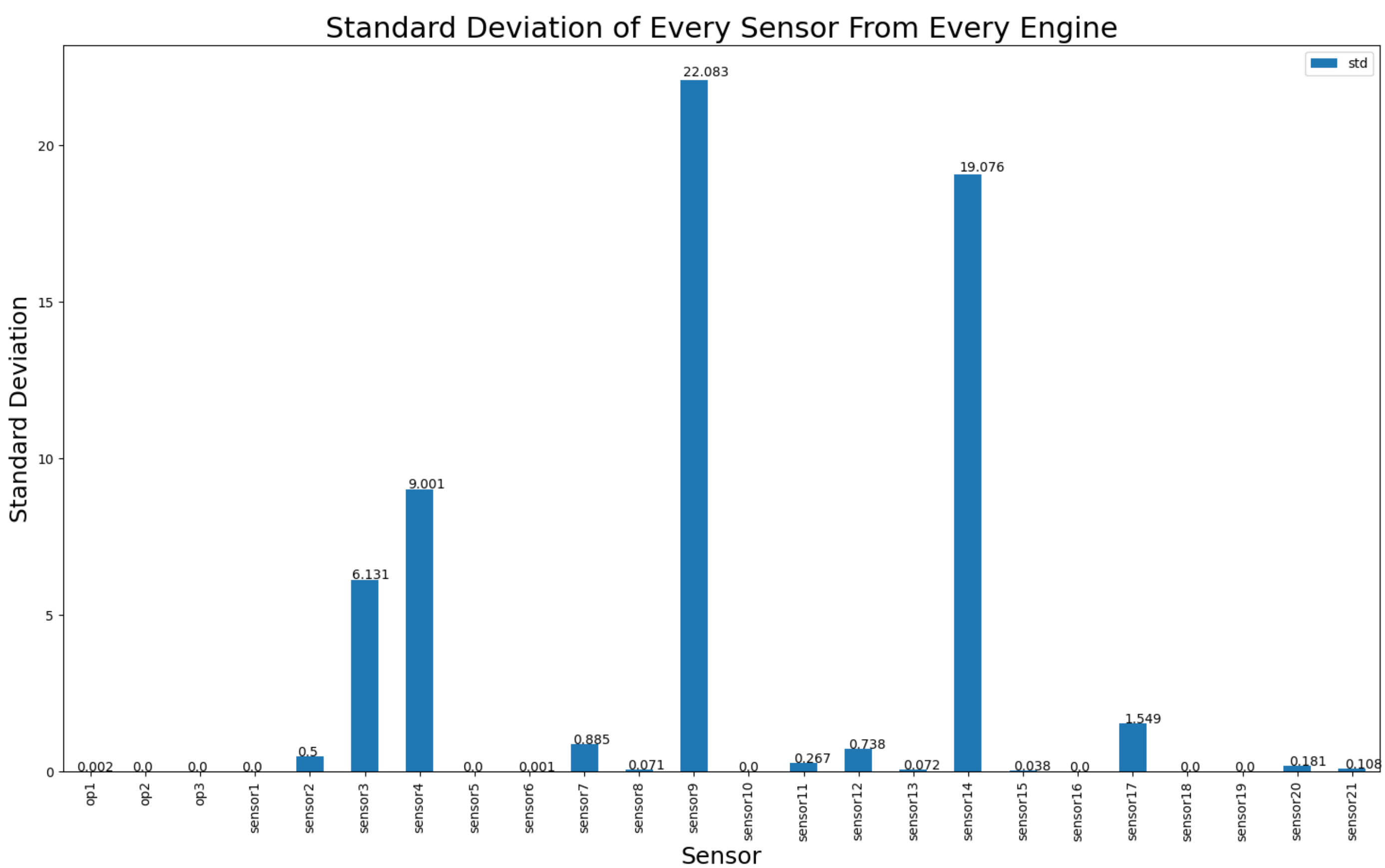
```
# Import necessary libraries
import pandas as pd
import numpy as np
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Load your dataset
data = train.copy()

# Select the target variable 'RUL' and the features of interest
features = ['op1', 'op2', 'op3', 'sensor1', 'sensor2', 'sensor3', 'sensor4',
            'sensor5', 'sensor6', 'sensor7', 'sensor8', 'sensor9', 'sensor10',
            'sensor11', 'sensor12', 'sensor13', 'sensor14', 'sensor15',
            'sensor16', 'sensor17', 'sensor18', 'sensor19', 'sensor20', 'sensor21']
target_variable = 'RUL'

# Normalize the feature variables
scaler = StandardScaler()
X = data[features]
X_scaled = scaler.fit_transform(X)  # Normalize the feature data
y = data[target_variable]

# Rename the columns for readability in the summary
X_with_names = pd.DataFrame(X_scaled, columns=features)  # Remove 'const'

# Add a constant term (intercept) to the model
X_with_names = sm.add_constant(X_with_names)

# Create a Linear Regression model
model = sm.OLS(y, X_with_names)

# Fit the model to the training data
results = model.fit()

# Print the summary of the regression results
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    RUL   R-squared:                      -1.870
Model:                            OLS   Adj. R-squared:                 -1.872
Method:                 Least Squares   F-statistic:                    -839.5
Date:                Fri, 15 Dec 2023   Prob (F-statistic):               1.00
Time:                        23:49:39   Log-Likelihood:            -1.2747e+05
No. Observations:               20631   AIC:                         2.550e+05
Df Residuals:                   20614   BIC:                         2.551e+05
Df Model:                          16
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
op1            0.1119      0.813      0.138      0.891      -1.483       1.706
op2            0.4528      0.813      0.557      0.578      -1.141       2.047
op3         2.089e-15   8.76e-16      2.384      0.017    3.71e-16    3.81e-15
sensor1     5.891e-16   4.44e-16      1.328      0.184    -2.8e-16    1.46e-15
sensor2       -3.4090      1.320     -2.582      0.010      -5.997      -0.821
sensor3       -2.7037      1.230     -2.198      0.028      -5.114      -0.293
sensor4       -6.8838      1.739     -3.958      0.000     -10.293      -3.475
sensor5    -9.377e-16   3.07e-15     -0.305      0.760   -6.96e-15    5.09e-15
sensor6       -0.7092      0.825     -0.859      0.390      -2.327       0.908
sensor7        6.0910      1.691      3.601      0.000       2.776       9.406
sensor8       -0.9395      1.764     -0.533      0.594      -4.398       2.519
sensor9       -7.7186      3.433     -2.248      0.025     -14.448      -0.989
sensor10   -4.124e-16   5.03e-16     -0.819      0.413    -1.4e-15    5.74e-16
sensor11      -9.9388      1.991     -4.992      0.000     -13.841      -6.037
sensor12       7.8355      1.865      4.201      0.000       4.180      11.491
sensor13      -0.8532      1.762     -0.484      0.628      -4.308       2.601
sensor14      -5.2231      3.376     -1.547      0.122     -11.841       1.394
sensor15      -4.4783      1.476     -3.034      0.002      -7.372      -1.585
sensor16   -2.161e-28   1.88e-28     -1.150      0.250   -5.84e-28    1.52e-28
sensor17      -2.8623      1.300     -2.201      0.028      -5.411      -0.314
sensor18            0          0        nan        nan           0           0
sensor19            0          0        nan        nan           0           0
sensor20       3.5898      1.422      2.524      0.012       0.803       6.377
sensor21       4.4471      1.433      3.103      0.002       1.638       7.256
==============================================================================
Omnibus:                     3258.323   Durbin-Watson:                   0.013
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5724.588
Skew:                           1.027   Prob(JB):                         0.00
Kurtosis:                       4.562   Cond. No.                     2.31e+39
```

```
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 3.49e-74. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Columns with 0 SD dropped

```
subset_stats = train_data.agg(['mean', 'std']).T[2:]
ax = subset_stats.plot.bar(figsize=(18, 10), y="std")
ax.set_title("Standard Deviation of Every Sensor From Every Engine", fontsize=22)
ax.set_xlabel("Sensor", fontsize=18)
ax.set_ylabel("Standard Deviation", fontsize=18)

# Annotate each bar with its standard deviation value
for p in ax.patches:
    # Round the standard deviation value to 3 decimal places
    annotation_text = str(round(p.get_height(), 3))

    # Position the annotation slightly above and to the right of the bar
    annotation_position = (p.get_x() * 1.005, p.get_height() * 1.005)

    # Add the annotation to the plot
    ax.annotate(annotation_text, annotation_position)
```



```
import numpy as np

def process_targets(data_length, early_rul=None):
    if early_rul is None:
        return np.arange(data_length - 1, -1, -1)
    else:
        early_rul_duration = data_length - early_rul
        if early_rul_duration <= 0:
            return np.arange(data_length - 1, -1, -1)
        else:
            return np.append(early_rul * np.ones(shape=(early_rul_duration,)), np.arange(early_rul - 1, -1, -1))

def process_input_data_with_targets(input_data, target_data=None, window_length=1, shift=1):
    num_batches = int(np.floor((len(input_data) - window_length) / shift)) + 1
    num_features = input_data.shape[1]
    output_data = np.full((num_batches, window_length, num_features), np.nan)

    if target_data is None:
        for batch in range(num_batches):
            output_data[batch, :, :] = input_data[(0 + shift * batch):(0 + shift * batch + window_length), :]
        return output_data
    else:
        output_targets = np.full(num_batches, np.nan)
        for batch in range(num_batches):
            output_data[batch, :, :] = input_data[(0 + shift * batch):(0 + shift * batch + window_length), :]
            output_targets[batch] = target_data[(shift * batch + (window_length - 1))]
        return output_data, output_targets

def process_test_data(test_data_for_an_engine, window_length, shift, num_test_windows=1):
    max_num_test_batches = int(np.floor((len(test_data_for_an_engine) - window_length) / shift)) + 1
    if max_num_test_batches < num_test_windows:
        required_len = (max_num_test_batches - 1) * shift + window_length
    else:
        required_len = (num_test_windows - 1) * shift + window_length

    batched_test_data_for_an_engine = process_input_data_with_targets(
        test_data_for_an_engine[-required_len:, :],
        target_data=None,
        window_length=window_length,
        shift=shift
    )
    return batched_test_data_for_an_engine, min(max_num_test_batches, num_test_windows)
```

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
test_data_path = f'{dataset_path}/test_FD001.txt'
true_rul_path = f'{dataset_path}/RUL_FD001.txt'
# Load data
test_data = pd.read_csv(test_data_path, sep="\s+", header=None, names=columns)
true_rul = pd.read_csv(true_rul_path, sep='\s+', header=None)

# Parameters
window_length = 30
shift = 1
early_rul = 125
num_test_windows = 5

# Columns to drop
columns_to_be_dropped = ['id', 'op1', 'op2', 'op3', 'sensor1', 'sensor5', 'sensor6', 'sensor7', 'sensor10',
                          'sensor16', 'sensor18', 'sensor19']

# Extract first columns
train_data_first_column = train_data["id"]
test_data_first_column = test_data["id"]

# Scale data
scaler = StandardScaler()
train_data_scaled = scaler.fit_transform(train_data.drop(columns=columns_to_be_dropped))
test_data_scaled = scaler.transform(test_data.drop(columns=columns_to_be_dropped))

# Create dataframes
train_data = pd.DataFrame(data=np.c_[train_data_first_column, train_data_scaled])
test_data = pd.DataFrame(data=np.c_[test_data_first_column, test_data_scaled])

# Get unique machine counts
num_train_machines = len(train_data[0].unique())
num_test_machines = len(test_data[0].unique())

# Process training data
processed_train_data = []
processed_train_targets = []

for i in range(1, num_train_machines + 1):
    temp_train_data = train_data[train_data[0] == i].drop(columns=[0]).values

    if len(temp_train_data) < window_length:
        raise AssertionError("Train engine {} doesn't have enough data for window_length of {}".format(i, window_length))

    temp_train_targets = process_targets(data_length=temp_train_data.shape[0], early_rul=early_rul)
    data_for_a_machine, targets_for_a_machine = process_input_data_with_targets(
        temp_train_data, temp_train_targets, window_length=window_length, shift=shift
    )

    processed_train_data.append(data_for_a_machine)
    processed_train_targets.append(targets_for_a_machine)

processed_train_data = np.concatenate(processed_train_data)
processed_train_targets = np.concatenate(processed_train_targets)

# Process test data
processed_test_data = []
num_test_windows_list = []

for i in range(1, num_test_machines + 1):
    temp_test_data = test_data[test_data[0] == i].drop(columns=[0]).values

    if len(temp_test_data) < window_length:
        raise AssertionError("Test engine {} doesn't have enough data for window_length of {}".format(i, window_length))

    test_data_for_an_engine, num_windows = process_test_data(
        temp_test_data, window_length=window_length, shift=shift, num_test_windows=num_test_windows
    )

    processed_test_data.append(test_data_for_an_engine)
    num_test_windows_list.append(num_windows)

processed_test_data = np.concatenate(processed_test_data)
true_rul = true_rul[0].values
```

```
# Shuffle training data
index = np.random.permutation(len(processed_train_targets))
processed_train_data, processed_train_targets = processed_train_data[index], processed_train_targets[index]

# Display shapes
print("Processed training data shape:", processed_train_data.shape)
print("Processed training RULs shape:", processed_train_targets.shape)
print("Processed test data shape:", processed_test_data.shape)
print("True RUL shape:", true_rul.shape)
```

```
Processed training data shape: (17731, 30, 14)
Processed training RULs shape: (17731,)
Processed test data shape: (497, 30, 14)
True RUL shape: (100,)
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers
import tensorflow as tf

def create_compiled_model():
    model = Sequential([
        layers.LSTM(256, input_shape=(window_length, 14), return_sequences=True, activation="tanh"),
        layers.LSTM(128, activation="tanh", return_sequences=True),
        layers.LSTM(64, activation="tanh"),
        layers.Dense(128, activation="relu"),
        layers.Dense(64, activation="relu"),
        layers.Dense(32, activation="relu"),
        layers.Dense(1)
    ])

    model.compile(loss="mse", optimizer=tf.keras.optimizers.Adam(learning_rate=0.001))
    return model
```

```
processed_train_data, processed_val_data, processed_train_targets, processed_val_targets = train_test_split(processed_train_data,
                                                                                                            processed_train_targets,
                                                                                                            test_size = 0.2,
                                                                                                            random_state = 83)
```

```
model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_15 (LSTM)              (None, 30, 256)           277504

 lstm_16 (LSTM)              (None, 30, 128)           197120

 lstm_17 (LSTM)              (None, 64)                49408

 dense_15 (Dense)            (None, 128)               8320

 dense_16 (Dense)            (None, 64)                8256

 dense_17 (Dense)            (None, 32)                2080

 dense_18 (Dense)            (None, 1)                 33

=================================================================
Total params: 542721 (2.07 MB)
Trainable params: 542721 (2.07 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
print(processed_train_data.shape)
print(processed_val_data.shape)
print(processed_train_targets.shape)
print(processed_val_targets.shape)
print(true_rul.shape)
```

```
(14184, 30, 14)
(3547, 30, 14)
(14184,)
(3547,)
(100,)
```

```
from tensorflow.keras import callbacks
def scheduler(epoch, lr):
    if epoch < 5:
        return lr
    else:
        return lr * tf.math.exp(-0.1)

lr_scheduler = callbacks.LearningRateScheduler(scheduler, verbose=1)

model = create_compiled_model()
history = model.fit(
    processed_train_data, processed_train_targets,
    epochs=10,
    validation_data=(processed_val_data, processed_val_targets),
    callbacks=[lr_scheduler],
    batch_size=128,
    verbose=2
)
```

```
Epoch 1: LearningRateScheduler setting learning rate to 0.0010000000474974513.
Epoch 1/10
111/111 - 66s - loss: 3051.0122 - val_loss: 1759.7078 - lr: 0.0010 - 66s/epoch - 590ms/step

Epoch 2: LearningRateScheduler setting learning rate to 0.0010000000474974513.
Epoch 2/10
111/111 - 51s - loss: 1747.6793 - val_loss: 1756.3828 - lr: 0.0010 - 51s/epoch - 461ms/step

Epoch 3: LearningRateScheduler setting learning rate to 0.0010000000474974513.
Epoch 3/10
111/111 - 53s - loss: 1741.1545 - val_loss: 1653.6035 - lr: 0.0010 - 53s/epoch - 482ms/step

Epoch 4: LearningRateScheduler setting learning rate to 0.0010000000474974513.
Epoch 4/10
111/111 - 52s - loss: 616.4809 - val_loss: 310.1664 - lr: 0.0010 - 52s/epoch - 472ms/step

Epoch 5: LearningRateScheduler setting learning rate to 0.0010000000474974513.
Epoch 5/10
111/111 - 53s - loss: 262.9413 - val_loss: 197.0415 - lr: 0.0010 - 53s/epoch - 473ms/step

Epoch 6: LearningRateScheduler setting learning rate to 0.0009048374486155808.
Epoch 6/10
111/111 - 51s - loss: 198.0380 - val_loss: 172.2691 - lr: 9.0484e-04 - 51s/epoch - 463ms/step

Epoch 7: LearningRateScheduler setting learning rate to 0.0008187307976186275.
Epoch 7/10
111/111 - 54s - loss: 173.1290 - val_loss: 190.4802 - lr: 8.1873e-04 - 54s/epoch - 490ms/step

Epoch 8: LearningRateScheduler setting learning rate to 0.0007408182718791068.
Epoch 8/10
111/111 - 58s - loss: 164.0929 - val_loss: 160.9714 - lr: 7.4082e-04 - 58s/epoch - 519ms/step

Epoch 9: LearningRateScheduler setting learning rate to 0.0006703201215714216.
Epoch 9/10
111/111 - 51s - loss: 186.0141 - val_loss: 188.5288 - lr: 6.7032e-04 - 51s/epoch - 461ms/step

Epoch 10: LearningRateScheduler setting learning rate to 0.0006065307534299791.
Epoch 10/10
111/111 - 51s - loss: 179.1188 - val_loss: 165.6290 - lr: 6.0653e-04 - 51s/epoch - 460ms/step
```

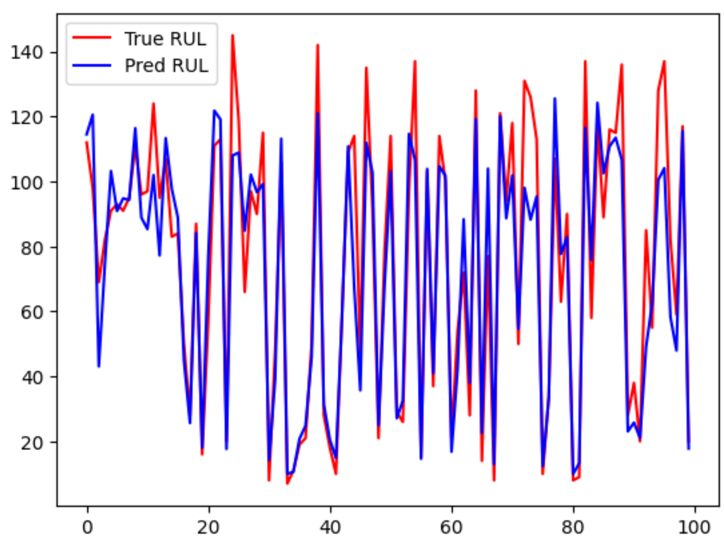
```
# Predict RUL for test data
rul_pred = model.predict(processed_test_data).reshape(-1)

# Split predictions into individual engines
preds_for_each_engine = np.split(rul_pred, np.cumsum(num_test_windows_list)[:-1])

# Calculate the weighted average RUL for each engine
mean_pred_for_each_engine = [
    np.average(ruls_for_each_engine, weights=np.repeat(1 / num_windows, num_windows))
    for ruls_for_each_engine, num_windows in zip(preds_for_each_engine, num_test_windows_list)
]

# Calculate RMSE
RMSE = np.sqrt(mean_squared_error(true_rul, mean_pred_for_each_engine))

print("RMSE:", RMSE)
```

```
16/16 [==============================] - 3s 95ms/step
RMSE: 14.313829841369941
```

```
tf.keras.models.save_model(model, "FD001_LSTM_piecewise_RMSE_"+ str(np.round(RMSE, 4)) + ".h5")
#We will now compute the RMSE by taking only last example of each engine.

indices_of_last_examples = np.cumsum(num_test_windows_list) - 1
preds_for_last_example = np.concatenate(preds_for_each_engine)[indices_of_last_examples]

RMSE_new = np.sqrt(mean_squared_error(true_rul, preds_for_last_example))
print("RMSE (Taking only last examples): ", RMSE_new)
def compute_s_score(rul_true, rul_pred):
    """
    Both rul_true and rul_pred should be 1D numpy arrays.
    """
    diff = rul_pred - rul_true
    return np.sum(np.where(diff < 0, np.exp(-diff/13)-1, np.exp(diff/10)-1))
s_score = compute_s_score(true_rul, preds_for_last_example)
print("S-score: ", s_score)
```

```
RMSE (Taking only last examples):  14.766835291811162
S-score:  280.10231252596407
<ipython-input-126-c11554ff9415>:1: UserWarning: You are saving your model as an HDF5 file via `model.save()`. This file format is consi
  tf.keras.models.save_model(model, "FD001_LSTM_piecewise_RMSE_"+ str(np.round(RMSE, 4)) + ".h5")
```

```
# Plot true and predicted RUL values
plt.plot(true_rul, label = "True RUL", color = "red")
plt.plot(preds_for_last_example, label = "Pred RUL", color = "blue")
plt.legend()
plt.show()
```



```
# Set a seed for random number generation
np.random.seed(42)  # Use any integer seed you prefer

import pandas as pd
import numpy as np
# Define the columns for engine ID and cycle (replace with actual column names)
engine_id_column = 'id'
cycle_column = 'cycle'
# Define initial engine ID and engine ID until which the attack should happen
engineId = 1
engineIdEnd = 37
# Define the cycle start (period of the attack)
cycleStart = 1
# Define the sensors where noise should be added
sensors = ['sensor2', 'sensor8', 'sensor14']  # Update with your column names
# Define the noise to be added (biased noise)
bound = [-0.06, -0.04, -0.02, -0.002,0]
rmse_plot=[]
for x in bound:
    df = pd.read_csv(test_data_path, sep="\s+", header=None, names=columns)
    # Iterate through engine IDs
    for l in range(engineId, engineIdEnd + 1):
        Table = df[(df[engine_id_column] == l) & (df[cycle_column] > cycleStart)].copy()
        # Iterate through selected sensors
        for sensor in sensors:
            # Generate random noise
            noise = np.random.uniform(-x, x)
            Table[sensor] = np.round(Table[sensor] * (1 + noise), 2)
        # Update the original DataFrame with modified values
        df.loc[(df[engine_id_column] == l) & (df[cycle_column] > cycleStart)] = Table
    # Parameters
    window_length = 30
    shift = 1
    early_rul = 125
    num_test_windows = 5
    columns_to_be_dropped = ['id', 'op1', 'op2', 'op3', 'sensor1', 'sensor5', 'sensor6', 'sensor7', 'sensor10',
                             'sensor16', 'sensor18', 'sensor19']
    new_test_data_first_column = df["id"]
    new_test_data_scaled = scaler.transform(df.drop(columns=columns_to_be_dropped))
    new_test_data = pd.DataFrame(data=np.c_[new_test_data_first_column, new_test_data_scaled])
    new_num_test_machines = len(new_test_data[0].unique())
    # Process test data
    new_processed_test_data = []
    new_num_test_windows_list = []
    for i in range(1, new_num_test_machines + 1):
        new_temp_test_data = new_test_data[new_test_data[0] == i].drop(columns=[0]).values
        if len(new_temp_test_data) < window_length:
            raise AssertionError(
                "Test engine {} doesn't have enough data for window_length of {}".format(i, window_length))

        new_test_data_for_an_engine, new_num_windows = process_test_data(
            new_temp_test_data, window_length=window_length, shift=shift,num_test_windows=num_test_windows
        )
        new_processed_test_data.append(new_test_data_for_an_engine)
        new_num_test_windows_list.append(new_num_windows)
    new_processed_test_data = np.concatenate(new_processed_test_data)
    new_rul_pred = model.predict(new_processed_test_data).reshape(-1)
    new_preds_for_each_engine = np.split(new_rul_pred, np.cumsum(num_test_windows_list)[:-1])
    new_mean_pred_for_each_engine = [
        np.average(new_ruls_for_each_engine, weights=np.repeat(1 / new_num_windows, new_num_windows))
        for new_ruls_for_each_engine, new_num_windows in zip(new_preds_for_each_engine, new_num_test_windows_list)
    ]
    # Calculate RMSE
    RMSE = np.sqrt(mean_squared_error(true_rul,new_mean_pred_for_each_engine))
    rmse_plot.append(RMSE)
    print(f'RMSE for the bound {x} is: {RMSE}')
```

```
16/16 [==============================] - 3s 151ms/step
RMSE for the bound -0.06 is: 34.405310328590396
16/16 [==============================] - 2s 100ms/step
RMSE for the bound -0.04 is: 39.69423892929466
16/16 [==============================] - 1s 58ms/step
RMSE for the bound -0.02 is: 40.05883892335657
16/16 [==============================] - 1s 57ms/step
RMSE for the bound -0.002 is: 33.34105106091056
16/16 [==============================] - 1s 57ms/step
RMSE for the bound 0 is: 14.313829841369941
```

```
import matplotlib.pyplot as plt
# Create a plot
plt.figure(figsize=(10, 6))
plt.plot(bound, rmse_plot, marker='o')

# Adding title and labels
plt.title('RMSE vs Noise Bound')
plt.xlabel('Noise Bound')
plt.ylabel('RMSE')

# Show grid
plt.grid(True)

# Display the plot
plt.show()
```

RMSE vs Noise Bound