fd001-eda

June 14, 2024

1 Predictive Maintenance of Turbofan Jet Engine: Exploratory Data Analysis

1.1 1. Data Inspection

[1]:
```python
import warnings
warnings.filterwarnings("ignore")

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```python
# Open dataset description README.md
with open("data/README.md", "r") as f:
    print(f.read())
```

```
Data Set: FD001
Train trajectories: 100
Test trajectories: 100
Conditions: ONE (Sea Level)
Fault Modes: ONE (HPC Degradation)

Data Set: FD002
Train trajectories: 260
Test trajectories: 259
Conditions: SIX
Fault Modes: ONE (HPC Degradation)

Data Set: FD003
Train trajectories: 100
Test trajectories: 100
Conditions: ONE (Sea Level)
Fault Modes: TWO (HPC Degradation, Fan Degradation)

Data Set: FD004
Train trajectories: 248
Test trajectories: 249
```

```
Conditions: SIX
Fault Modes: TWO (HPC Degradation, Fan Degradation)



Experimental Scenario

Data sets consists of multiple multivariate time series. Each data set is
further divided into training and test subsets. Each time series is from a
different engine ï¿½ i.e., the data can be considered to be from a fleet of
engines of the same type. Each engine starts with different degrees of initial
wear and manufacturing variation which is unknown to the user. This wear and
variation is considered normal, i.e., it is not considered a fault condition.
There are three operational settings that have a substantial effect on engine
performance. These settings are also included in the data. The data is
contaminated with sensor noise.

The engine is operating normally at the start of each time series, and develops
a fault at some point during the series. In the training set, the fault grows in
magnitude until system failure. In the test set, the time series ends some time
prior to system failure. The objective of the competition is to predict the
number of remaining operational cycles before failure in the test set, i.e., the
number of operational cycles after the last cycle that the engine will continue
to operate. Also provided a vector of true Remaining Useful Life (RUL) values
for the test data.

The data are provided as a zip-compressed text file with 26 columns of numbers,
separated by spaces. Each row is a snapshot of data taken during a single
operational cycle, each column is a different variable. The columns correspond
to:
1)      unit number
2)      time, in cycles
3)      operational setting 1
4)      operational setting 2
5)      operational setting 3
6)      sensor measurement  1
7)      sensor measurement  2
…
26)     sensor measurement  21


Reference: A. Saxena, K. Goebel, D. Simon, and N. Eklund, ï¿½Damage Propagation
Modeling for Aircraft Engine Run-to-Failure Simulationï¿½, in the Proceedings of
the Ist International Conference on Prognostics and Health Management (PHM08),
Denver CO, Oct 2008.
```

For this assignment, we will be using **FD001** dataset since it is widely researched. Thus, it is suitable for benchmarking purposes.

[3]:
```
# Define the columns of our dataset.
INDEX_COLUMNS = ["unit", "time_cycles"]
OP_SETTING_COLUMNS = ["op_setting_{}".format(i) for i in range(1, 4)]
SENSOR_COLUMNS = ["sensor_{}".format(i) for i in range(1, 22)]
col_names = INDEX_COLUMNS + OP_SETTING_COLUMNS + SENSOR_COLUMNS
```

[4]:
```
# Load training data
train_data = pd.read_csv(
    "data/train_FD001.txt", sep="\s+", header=None, names=col_names
)
train_data.head()
```

[4]:
```
   unit  time_cycles  op_setting_1  op_setting_2  op_setting_3  sensor_1  \
0     1            1       -0.0007       -0.0004         100.0    518.67
1     1            2        0.0019       -0.0003         100.0    518.67
2     1            3       -0.0043        0.0003         100.0    518.67
3     1            4        0.0007        0.0000         100.0    518.67
4     1            5       -0.0019       -0.0002         100.0    518.67

   sensor_2  sensor_3  sensor_4  sensor_5  …  sensor_12  sensor_13  \
0    641.82   1589.70   1400.60     14.62  …     521.66    2388.02
1    642.15   1591.82   1403.14     14.62  …     522.28    2388.07
2    642.35   1587.99   1404.20     14.62  …     522.42    2388.03
3    642.35   1582.79   1401.87     14.62  …     522.86    2388.08
4    642.37   1582.85   1406.22     14.62  …     522.19    2388.04

   sensor_14  sensor_15  sensor_16  sensor_17  sensor_18  sensor_19  \
0    8138.62     8.4195       0.03        392       2388      100.0
1    8131.49     8.4318       0.03        392       2388      100.0
2    8133.23     8.4178       0.03        390       2388      100.0
3    8133.83     8.3682       0.03        392       2388      100.0
4    8133.80     8.4294       0.03        393       2388      100.0

   sensor_20  sensor_21
0      39.06    23.4190
1      39.00    23.4236
2      38.95    23.3442
3      38.88    23.3739
4      38.90    23.4044

[5 rows x 26 columns]
```

[5]:
```
# Load test data
test_data = pd.read_csv("data/test_FD001.txt", sep="\s+", header=None,␣
 ↪names=col_names)
```

```python
test_data.head()
```

```
[5]:    unit  time_cycles  op_setting_1  op_setting_2  op_setting_3  sensor_1  \
0     1            1        0.0023        0.0003         100.0    518.67
1     1            2       -0.0027       -0.0003         100.0    518.67
2     1            3        0.0003        0.0001         100.0    518.67
3     1            4        0.0042        0.0000         100.0    518.67
4     1            5        0.0014        0.0000         100.0    518.67

   sensor_2  sensor_3  sensor_4  sensor_5  …  sensor_12  sensor_13  \
0    643.02   1585.29   1398.21     14.62  …     521.72    2388.03
1    641.71   1588.45   1395.42     14.62  …     522.16    2388.06
2    642.46   1586.94   1401.34     14.62  …     521.97    2388.03
3    642.44   1584.12   1406.42     14.62  …     521.38    2388.05
4    642.51   1587.19   1401.92     14.62  …     522.15    2388.03

   sensor_14  sensor_15  sensor_16  sensor_17  sensor_18  sensor_19  \
0    8125.55     8.4052       0.03        392       2388      100.0
1    8139.62     8.3803       0.03        393       2388      100.0
2    8130.10     8.4441       0.03        393       2388      100.0
3    8132.90     8.3917       0.03        391       2388      100.0
4    8129.54     8.4031       0.03        390       2388      100.0

   sensor_20  sensor_21
0      38.86    23.3735
1      39.02    23.3916
2      39.08    23.4166
3      39.00    23.3737
4      38.99    23.4130

[5 rows x 26 columns]
```

```python
[6]: # Load the true RUL values for the test data
test_rul = pd.read_csv("data/RUL_FD001.txt", sep="\s+", header=None,␣
 ↪names=["rul"])

# Add a unit column to the test RUL
test_rul["unit"] = test_rul.index + 1
test_rul.head()
```

```
[6]:    rul  unit
0  112     1
1   98     2
2   69     3
3   82     4
4   91     5
```

[7]:
```python
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20631 entries, 0 to 20630
Data columns (total 26 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   unit          20631 non-null  int64
 1   time_cycles   20631 non-null  int64
 2   op_setting_1  20631 non-null  float64
 3   op_setting_2  20631 non-null  float64
 4   op_setting_3  20631 non-null  float64
 5   sensor_1      20631 non-null  float64
 6   sensor_2      20631 non-null  float64
 7   sensor_3      20631 non-null  float64
 8   sensor_4      20631 non-null  float64
 9   sensor_5      20631 non-null  float64
 10  sensor_6      20631 non-null  float64
 11  sensor_7      20631 non-null  float64
 12  sensor_8      20631 non-null  float64
 13  sensor_9      20631 non-null  float64
 14  sensor_10     20631 non-null  float64
 15  sensor_11     20631 non-null  float64
 16  sensor_12     20631 non-null  float64
 17  sensor_13     20631 non-null  float64
 18  sensor_14     20631 non-null  float64
 19  sensor_15     20631 non-null  float64
 20  sensor_16     20631 non-null  float64
 21  sensor_17     20631 non-null  int64
 22  sensor_18     20631 non-null  int64
 23  sensor_19     20631 non-null  float64
 24  sensor_20     20631 non-null  float64
 25  sensor_21     20631 non-null  float64
dtypes: float64(22), int64(4)
memory usage: 4.1 MB
```

[8]:
```python
train_data.describe()
```

[8]:

	unit	time_cycles	op_setting_1	op_setting_2	op_setting_3 \
count	20631.000000	20631.000000	20631.000000	20631.000000	20631.0
mean	51.506568	108.807862	-0.000009	0.000002	100.0
std	29.227633	68.880990	0.002187	0.000293	0.0
min	1.000000	1.000000	-0.008700	-0.000600	100.0
25%	26.000000	52.000000	-0.001500	-0.000200	100.0
50%	52.000000	104.000000	0.000000	0.000000	100.0
75%	77.000000	156.000000	0.001500	0.000300	100.0
max	100.000000	362.000000	0.008700	0.000600	100.0

```
       sensor_1      sensor_2      sensor_3      sensor_4      sensor_5  ...  \
count  20631.00  20631.000000  20631.000000  20631.000000  2.063100e+04  ...
mean     518.67    642.680934   1590.523119   1408.933782  1.462000e+01  ...
std        0.00      0.500053      6.131150      9.000605  1.776400e-15  ...
min      518.67    641.210000   1571.040000   1382.250000  1.462000e+01  ...
25%      518.67    642.325000   1586.260000   1402.360000  1.462000e+01  ...
50%      518.67    642.640000   1590.100000   1408.040000  1.462000e+01  ...
75%      518.67    643.000000   1594.380000   1414.555000  1.462000e+01  ...
max      518.67    644.530000   1616.910000   1441.490000  1.462000e+01  ...

          sensor_12     sensor_13     sensor_14     sensor_15     sensor_16  \
count  20631.000000  20631.000000  20631.000000  20631.000000  2.063100e+04
mean     521.413470   2388.096152   8143.752722      8.442146  3.000000e-02
std        0.737553      0.071919     19.076176      0.037505  1.387812e-17
min      518.690000   2387.880000   8099.940000      8.324900  3.000000e-02
25%      520.960000   2388.040000   8133.245000      8.414900  3.000000e-02
50%      521.480000   2388.090000   8140.540000      8.438900  3.000000e-02
75%      521.950000   2388.140000   8148.310000      8.465600  3.000000e-02
max      523.380000   2388.560000   8293.720000      8.584800  3.000000e-02

          sensor_17  sensor_18  sensor_19     sensor_20     sensor_21
count  20631.000000    20631.0    20631.0  20631.000000  20631.000000
mean     393.210654     2388.0      100.0     38.816271     23.289705
std        1.548763        0.0        0.0      0.180746      0.108251
min      388.000000     2388.0      100.0     38.140000     22.894200
25%      392.000000     2388.0      100.0     38.700000     23.221800
50%      393.000000     2388.0      100.0     38.830000     23.297900
75%      394.000000     2388.0      100.0     38.950000     23.366800
max      400.000000     2388.0      100.0     39.430000     23.618400

[8 rows x 26 columns]
```

1.2 2. Distribution of Engine Lifetime in Train Sets and Last Time Cycle in Test Sets

[9]:
```python
# Find the lifetime of each engine unit
train_units_lifetime = train_data.groupby("unit")["time_cycles"].max().
 ↪reset_index()
test_units_lifetime = test_data.groupby("unit")["time_cycles"].max().
 ↪reset_index()

# Add a column to indicate if the data is from the training or test set
train_units_lifetime["dataset"] = "train"
test_units_lifetime["dataset"] = "test"
```

```
units_lifetime = train_units_lifetime._append(test_units_lifetime,␣
↪ignore_index=True)
```

[10]:
```
units_lifetime.groupby("dataset")["time_cycles"].describe()
```

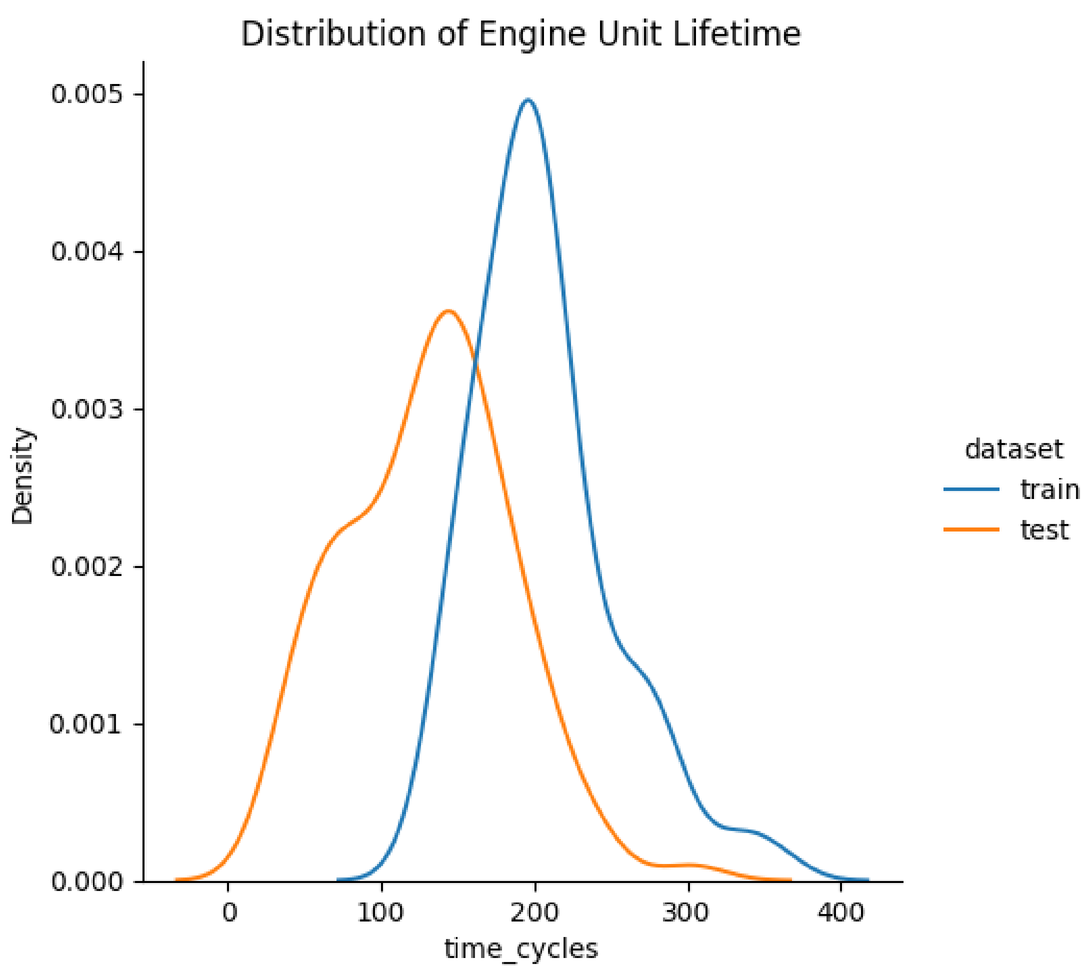
[10]:

	count	mean	std	min	25%	50%	75%	max
dataset								
test	100.0	130.96	53.593479	31.0	88.75	133.5	164.25	303.0
train	100.0	206.31	46.342749	128.0	177.00	199.0	229.25	362.0

[11]:
```
# Plot the distribution of the lifetime of the engine units
plt.figure(figsize=(8, 6))
sns.displot(units_lifetime, x="time_cycles", hue="dataset", kind="kde")
plt.title("Distribution of Engine Unit Lifetime")
```

[11]: Text(0.5, 1.0, 'Distribution of Engine Unit Lifetime')

<Figure size 800x600 with 0 Axes>



Observations:

- Engine units in the test set have shorter lifetimes than train set.
- On average, engine lifetimes in the test set are 70 cycles shorter than train set.

1.3 3. Distribution of RUL in Train and Test Sets

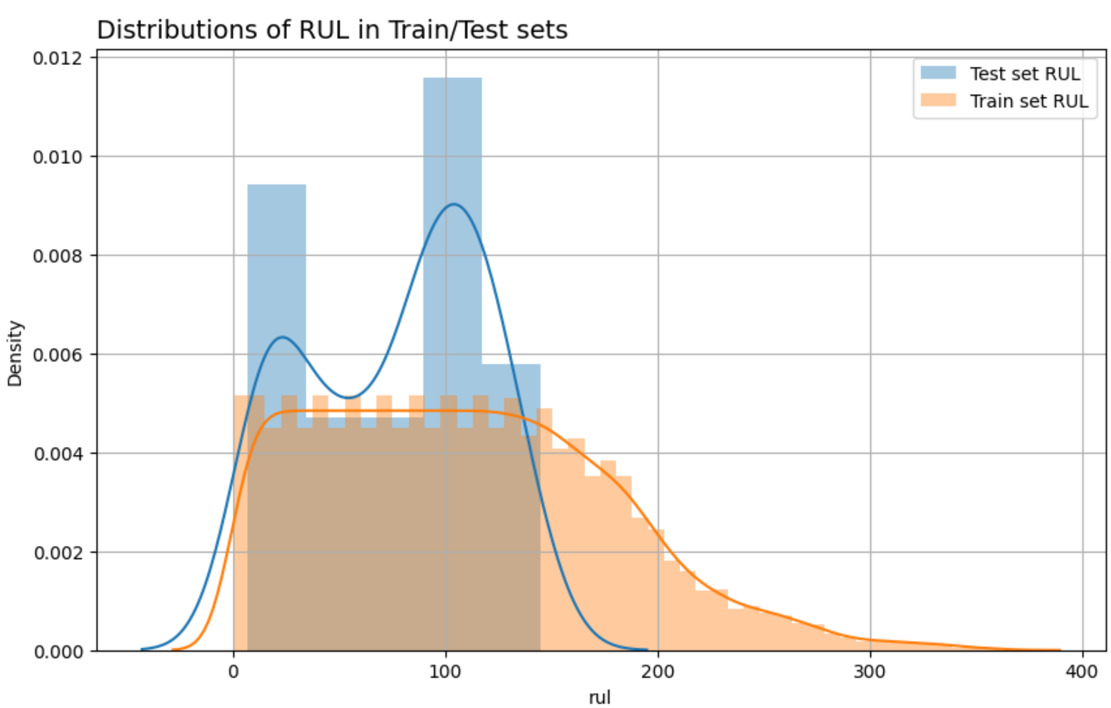
[12]:
```
def calculate_RUL(X, upper_threshold=None):
    lifetime = X.groupby(["unit"])["time_cycles"].transform(max)
    rul = lifetime - X["time_cycles"]

    if upper_threshold:
        rul = np.where(rul > upper_threshold, upper_threshold, rul)

    return rul
```

[13]:
```
train_data["rul"] = calculate_RUL(train_data)

fig, ax = plt.subplots(figsize=(10, 6))
ax.set_title("Distributions of RUL in Train/Test sets", loc="left", size=14)
sns.distplot(test_rul["rul"], label="Test set RUL")
sns.distplot(train_data["rul"], label="Train set RUL")
ax.legend()
ax.grid()
plt.show()
```



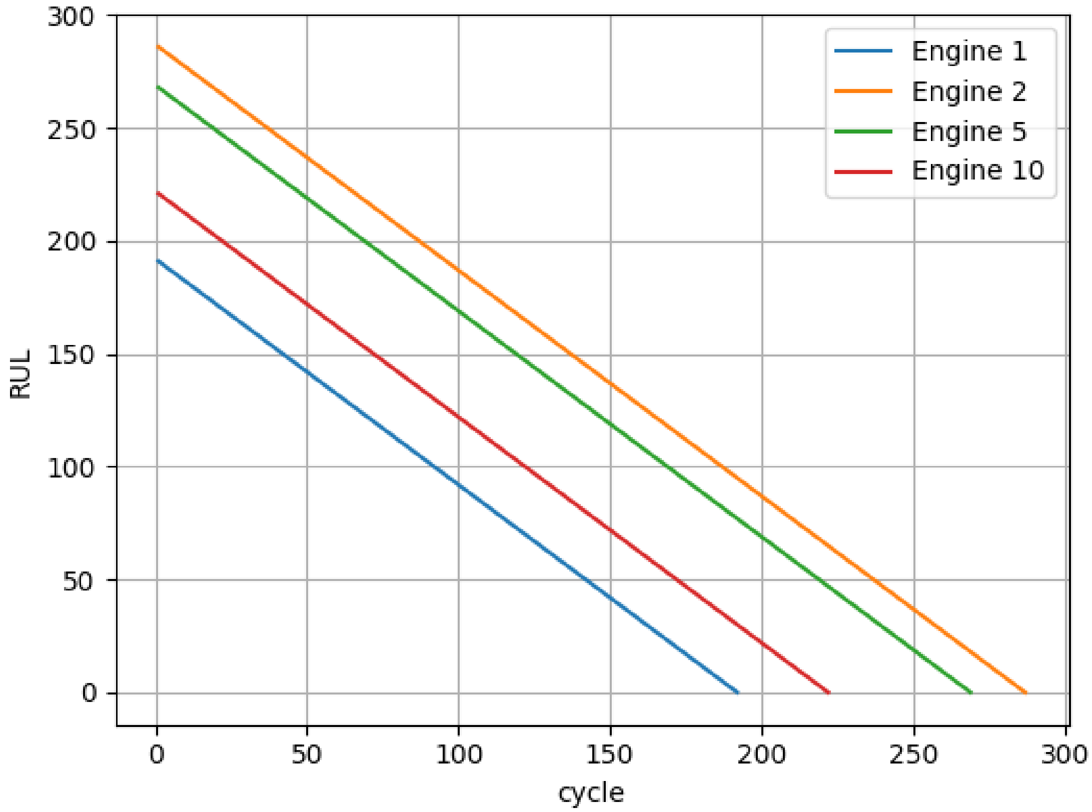
Observations:

- As expected, the Train set contains units with RUL way higher than in Test set.
- This is because the Train set have the full lifetime data of an engine while the Test set only contains data until a period of time before its end of life.
- Hence, our target is to predict the RUL at the last cycle of each engine in the Test set.

To address this issue, we need to limit the maximum value of RUL. The motivation is that a degradation process will only be noticeable in the data after a unit has operated for some time.

[14]:
```
# Before applying limit
for _unit in [1, 2, 5, 10]:
    plt.plot(
        train_data[train_data["unit"] == _unit]["time_cycles"],
        train_data[train_data["unit"] == _unit]["rul"],
        label=f"Engine {_unit}",
    )

plt.legend()
plt.xlabel("cycle")
plt.ylabel("RUL")
plt.grid()
plt.show()
```

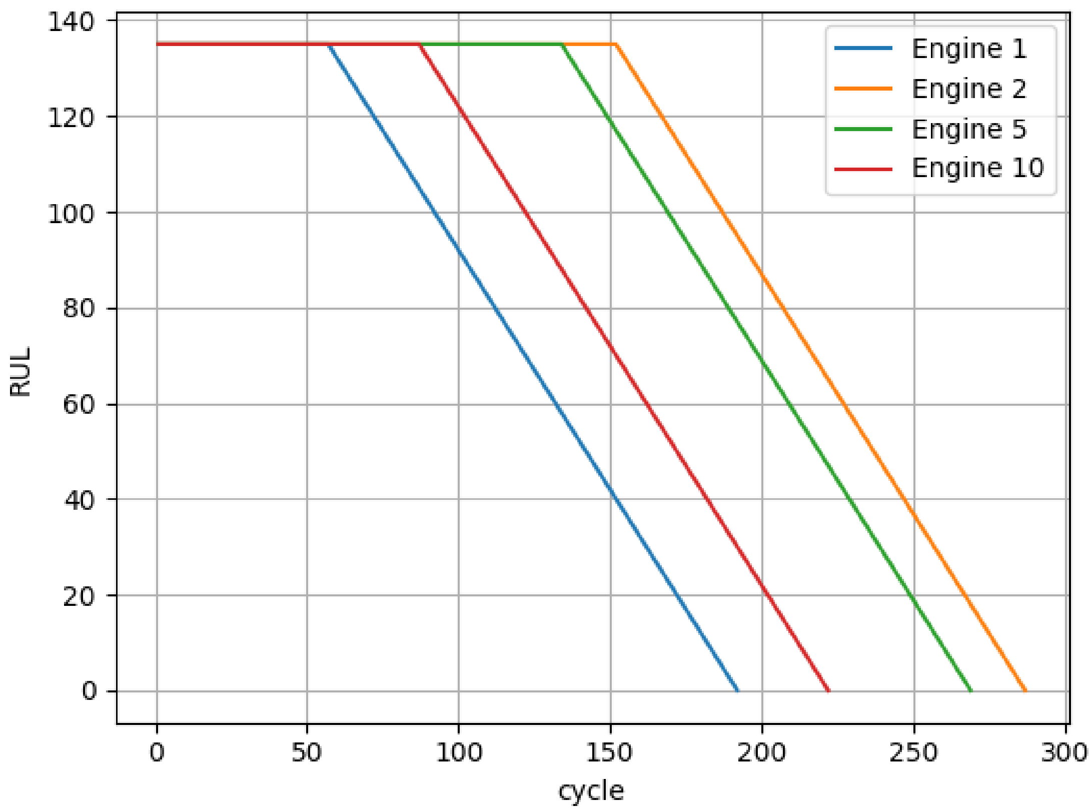


[15]:

```
# After applying limit
train_data["rul"] = calculate_RUL(train_data, upper_threshold=135)

for _unit in [1, 2, 5, 10]:
    plt.plot(
        train_data[train_data["unit"] == _unit]["time_cycles"],
        train_data[train_data["unit"] == _unit]["rul"],
        label=f"Engine {_unit}",
    )

plt.legend()
plt.xlabel("cycle")
plt.ylabel("RUL")
plt.grid()
plt.show()
```

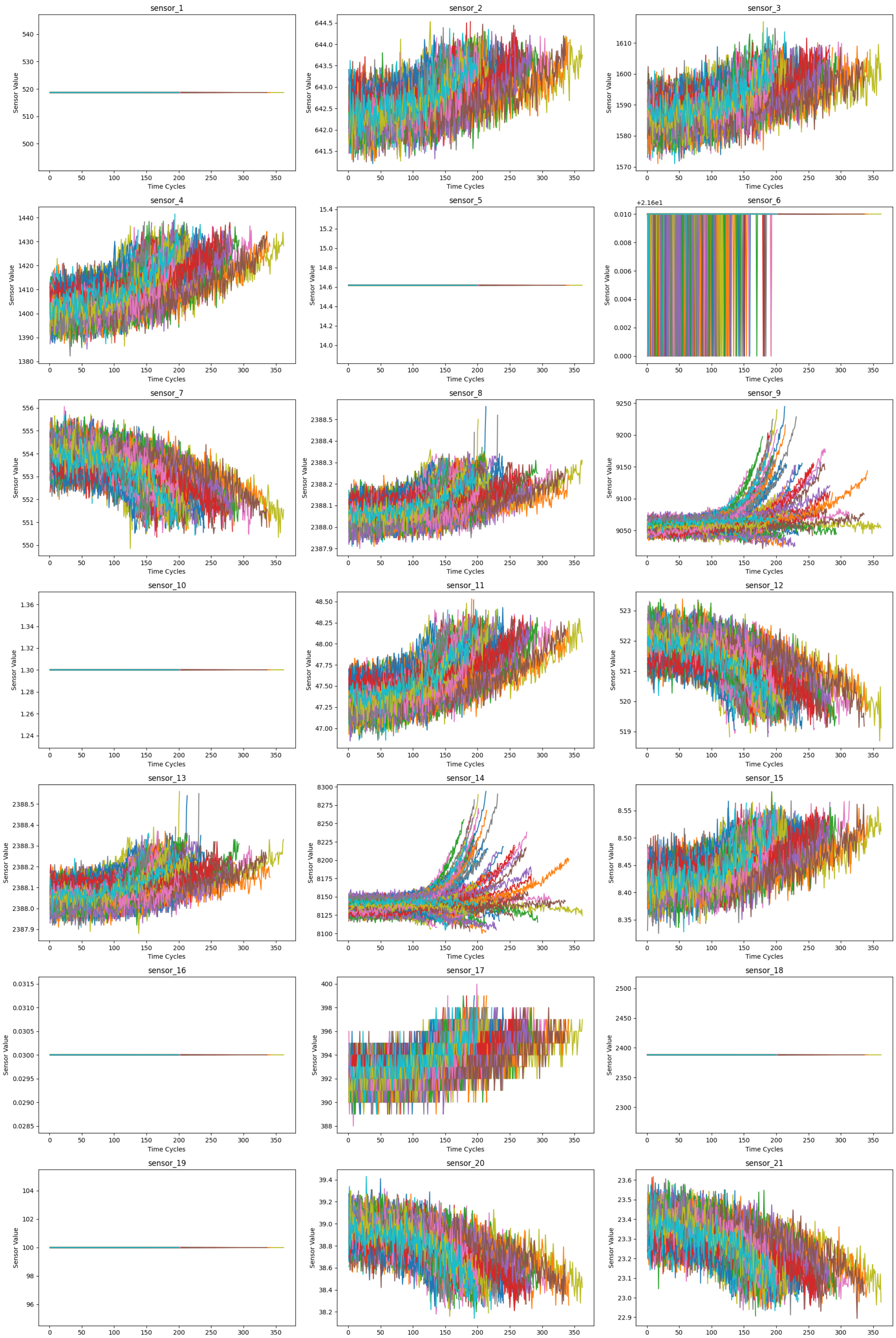


1.4 4. Wear / Degradation Patterns

[16]:
```
fig, axes = plt.subplots(7, 3, figsize=(20, 30))
axes = axes.flatten()

for i, col in enumerate(SENSOR_COLUMNS):
    for unit in train_data["unit"].unique():
        unit_data = train_data[train_data["unit"] == unit]
        axes[i].plot(unit_data["time_cycles"], unit_data[col])
    axes[i].set_title(SENSOR_COLUMNS[i])
    axes[i].set_xlabel("Time Cycles")
    axes[i].set_ylabel("Sensor Value")

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


sensor_1
sensor_2
sensor_3
sensor_4
sensor_5
sensor_6
+2.16e1
sensor_7
sensor_8
sensor_9
sensor_10
sensor_11
sensor_12
sensor_13
sensor_14
sensor_15
sensor_16
sensor_17
sensor_18
sensor_19
sensor_20
sensor_21
Sensor Value
Time Cycles

Observations:

- Sensor 1, 5, 10, 16, 18, 19 are constant throughout cycles.
- Due to low variance, they are considered useless features and can be dropped.
- For others, we can really see how the sensor values changed with respect to time cycles. Some increase and some decrease.

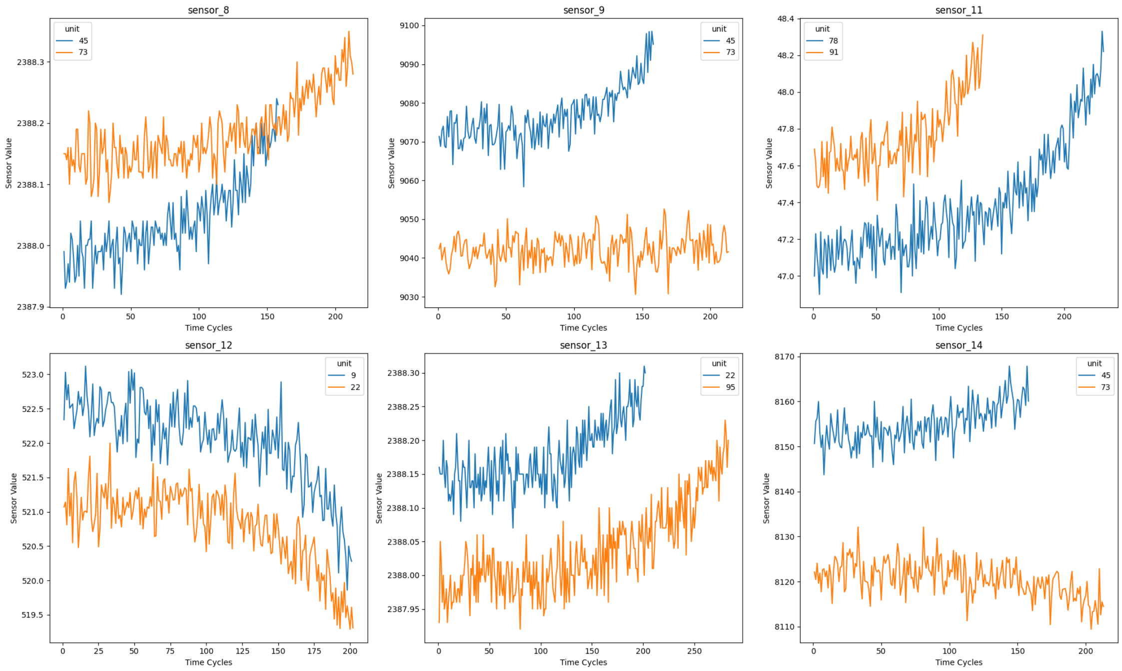
1.5 5. Difference between Each Unit of Engines

[17]:
```
SELECTED_SENSORS = [
    "sensor_8",
    "sensor_9",
    "sensor_11",
    "sensor_12",
    "sensor_13",
    "sensor_14",
]

first_avg_values = (
    train_data[train_data["time_cycles"] <= 20]
    .groupby("unit")[SELECTED_SENSORS]
    .mean()
    .reset_index()
)

fig, ax = plt.subplots(2, 3, figsize=(20, 12))
for i, sensor in enumerate(SELECTED_SENSORS):
    avg_sorted = first_avg_values.sort_values(sensor)
    engine_a, engine_b = avg_sorted["unit"].iloc[0], avg_sorted["unit"].iloc[-1]
    sns.lineplot(
        data=train_data[train_data["unit"].isin([engine_a, engine_b])],
        x="time_cycles",
        y=sensor,
        hue="unit",
        ax=ax.flatten()[i],
        palette="tab10",
    )
    ax.flatten()[i].set_title(sensor)
    ax.flatten()[i].set_xlabel("Time Cycles")
    ax.flatten()[i].set_ylabel("Sensor Value")

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



Observations:

- We can see the difference between engines based on the sensor time series.
- This suggests that we might need to scale the sensor time series with respect to start of every individual engines time series.
- Scaling with respect to individual engines starting values allows us to bring all the engines time series to the same scale.