Remaining Useful Life (RUL) Prediction of Turbofan Engines Through Machine Learning

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1. Research Background

Prognostics is a research field that focuses on estimating the health state of an engine and, simultaneously, obtain a reasonable approximation of time left before failure. The Remaining useful life (RUL) provides an up-to-date estimate of the health status, and it is measured in operation cycles. The estimation of RUL of degrading engines aims to decrease the cost of maintenance. Also, it helps manufacturers to increase the safety and reliability of their systems.

2. Methodology

The prediction the RUL values of a series of simulated turbofan engines [Figure 1] was directly extracted from the cycles, three operational settings and the measurements of 21 sensors (temperature, pressure, etc.) placed around different components of each engine. Also, a predictive maintenance algorithm was developed [Figure 2]. This process was conducted on four training data sets.

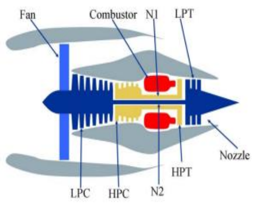

Figure 1. Turbofan engine components

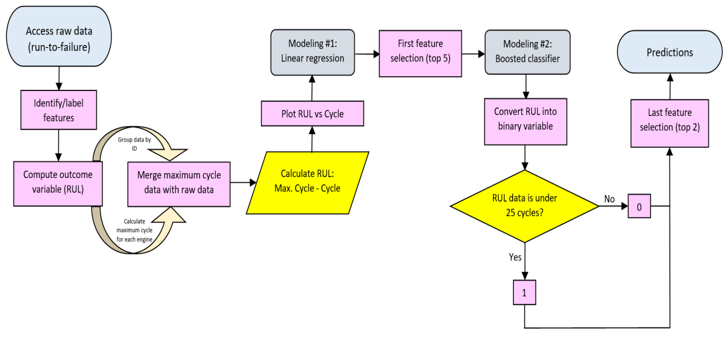

Figure 2. Predictive maintenance algorithm flowchart

3. Target Identification, Feature Selection and RUL Predictions

Table 1. Description of sensors

Sensor Measurement #	Description	Units
1	Total temperature at fan inlet	°R
2	Total temperature at LPC outlet	°R
3	Total temperature at HPC outlet	°R
4	Total temperature at LPT outlet	°R
5	Pressure at fan inlet	psia
6	Total pressure in bypass-duct	psia
7	Total pressure at HPC outlet	psia
8	Physical fan speed	rpm
9	Physical core speed	rpm
10	Engine pressure ratio	--
11	Static pressure at HPC outlet	psia
12	Ratio of fuel flow to Sensor Measurement #11	pps/psi
13	Corrected fan speed	rpm
14	Corrected core speed	rpm
15	Bypass Ratio	--
16	Burner fuel-air ratio	--
17	Bleed Enthalpy	--
18	Demanded fan speed	rpm
19	Demanded corrected fan speed	rpm
20	HPT coolant bleed	lbm/s
21	LPT coolant bleed	lbm/s

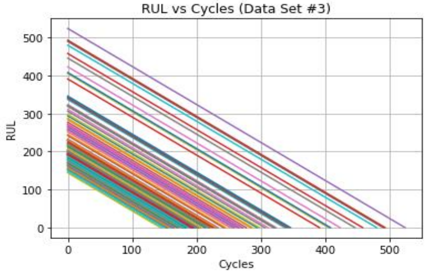

Figure 3. RUL vs Cycles (each linear relationship represents an engine)

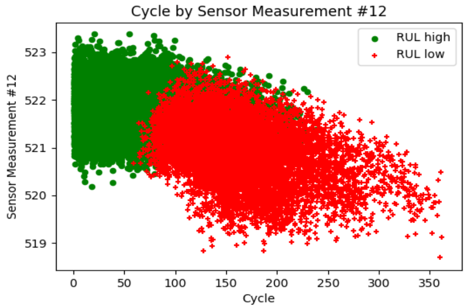

Figure 4. Sensor Measurement #12 vs Cycle (best pair of features on Model #1)

Model #1

- Type of ML model: **Linear regression**
- Root Mean Square Error: **35.44 RMSE**
- Target: **RUL**
- Top 5 features:
  1) **Cycle**
  2) **Ratio of fuel flow to static pressure at HPC outlet**
  3) **Static pressure at HPC outlet**
  4) **Total temperature at LPT outlet**
  5) **Corrected core speed**

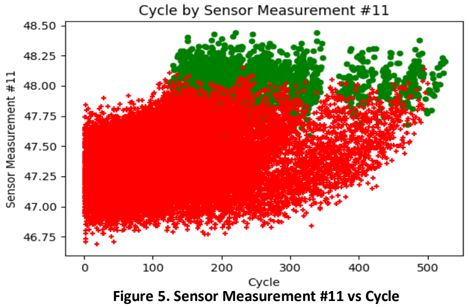

Figure 5. Sensor Measurement #11 vs Cycle (best pair of features on Model #2)

Model #2

- Type of ML model: **Boosted classifier**
- Model's accuracy: **98.5%**
- Target: **RUL**
- Features (top 2): **Cycle and Static pressure at HPC outlet**
- The red crosses are 0 values (RUL > 25 cycles) and the green points are 1 values (RUL ≤ 25 cycles).

4. Conclusions and Future Work

Conclusions:

- Based on the results of the four data sets obtained from C-MAPSS (Commercial Modular Aero-Propulsion System Simulation), the operation cycle and the sensor measurements #4 and #11 are usually the best predictors (features) for RUL in turbofan engines.
- In addition, the best ML model to predict RUL is a boosted classifier.

Future work:

- Implement test data sets (data before failure begins) on the developed algorithm.
- Acquire more updated data sets (training/test) in order to test them through the predictive maintenance algorithm.
- Compare the predictions attained from boosting with other ML models (SVMs, Random Forest, etc.).

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6. References

(1) A. Saxena and K. Goebel (2008). "Turbofan Engine Degradation Simulation Data Set", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA

(2) Khelif, R., Chebel-Morello, B., Malinowski, S., Laajili, E., Fnaiech, F., & Zerhouni, N. (2017). Direct Remaining Useful Life Estimation Based on Support Vector Regression. IEEE Transactions on Industrial Electronics, 64(3), 2276–2285. doi:10.1109/tie.2016.2623060

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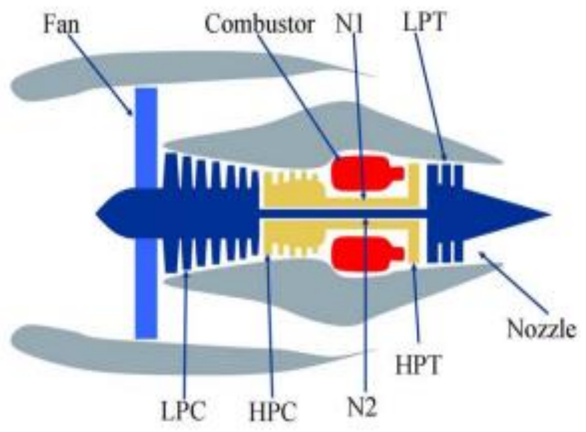

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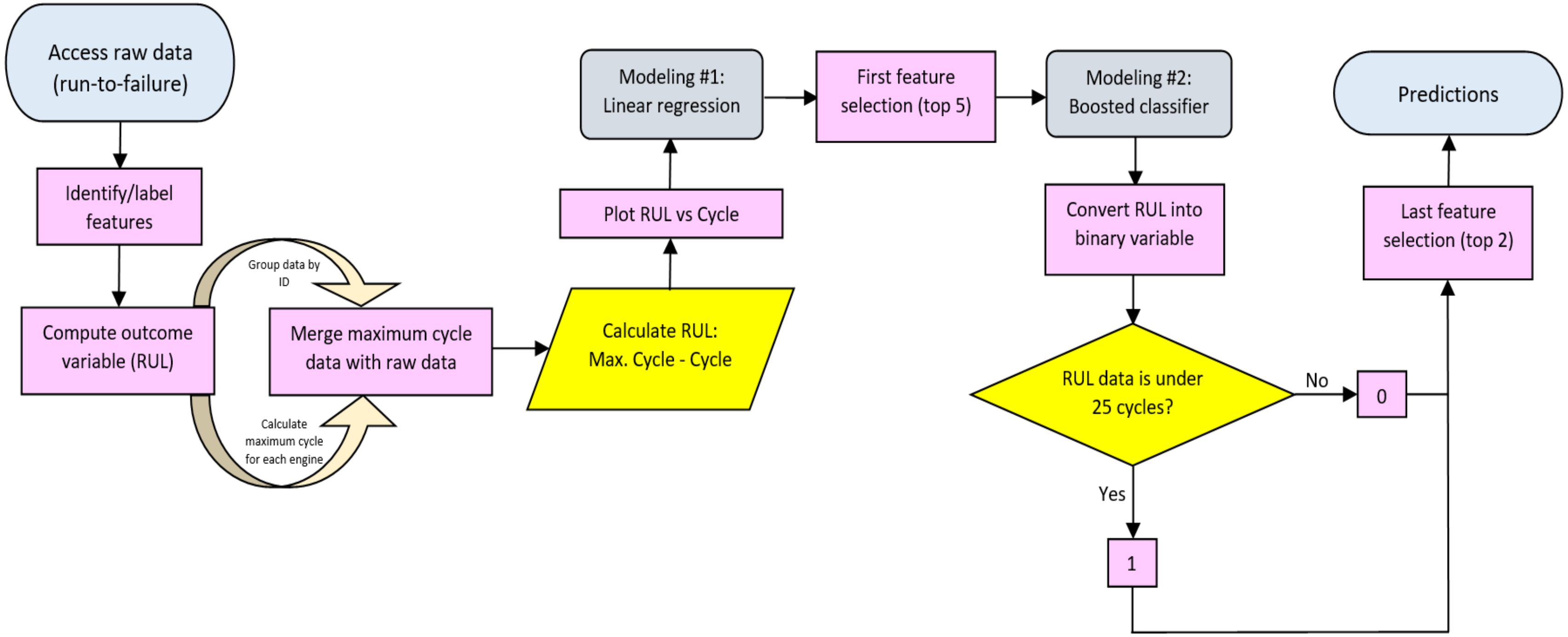

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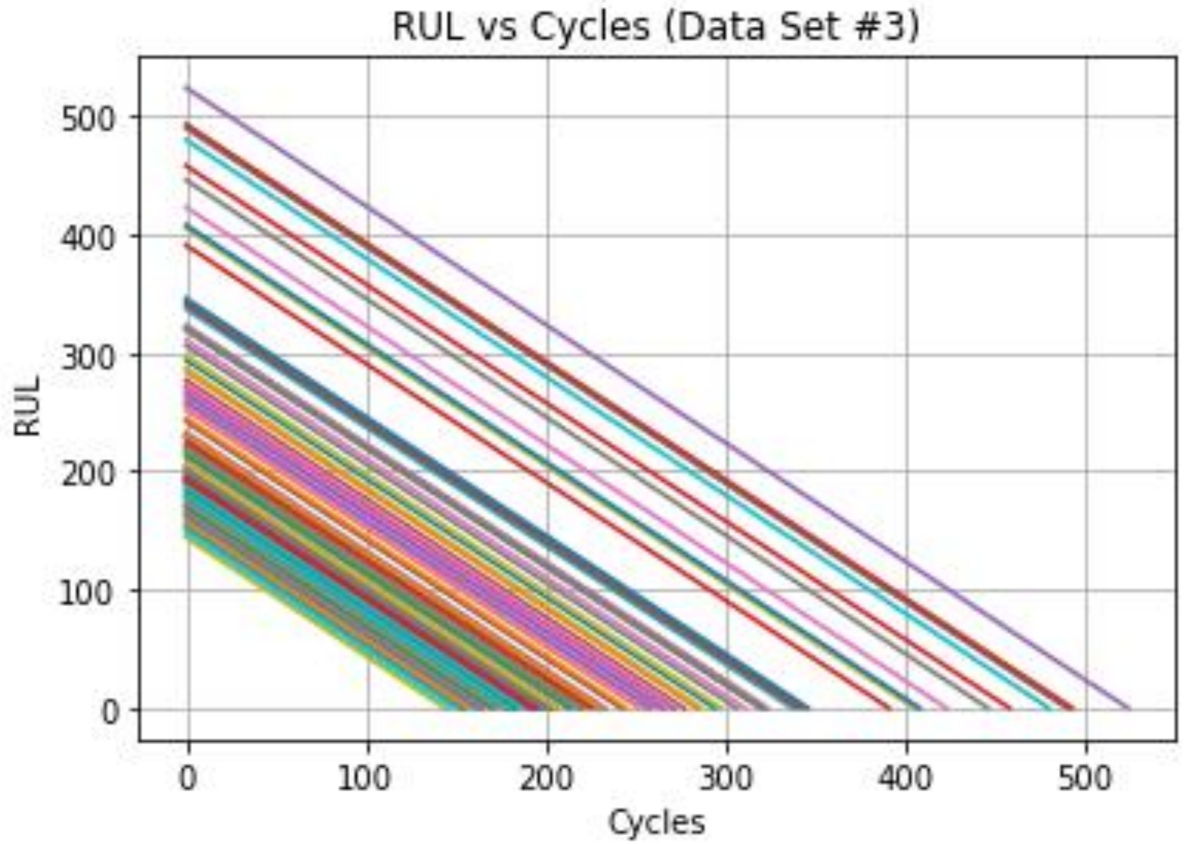

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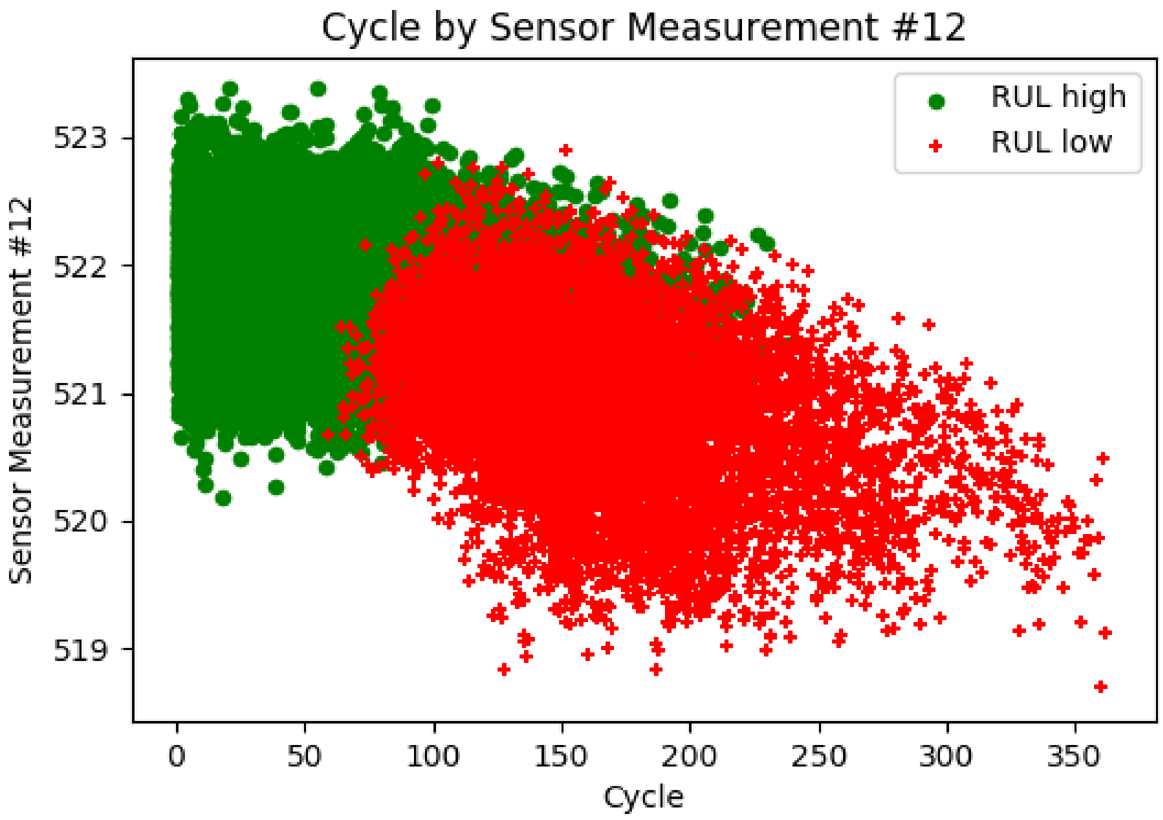

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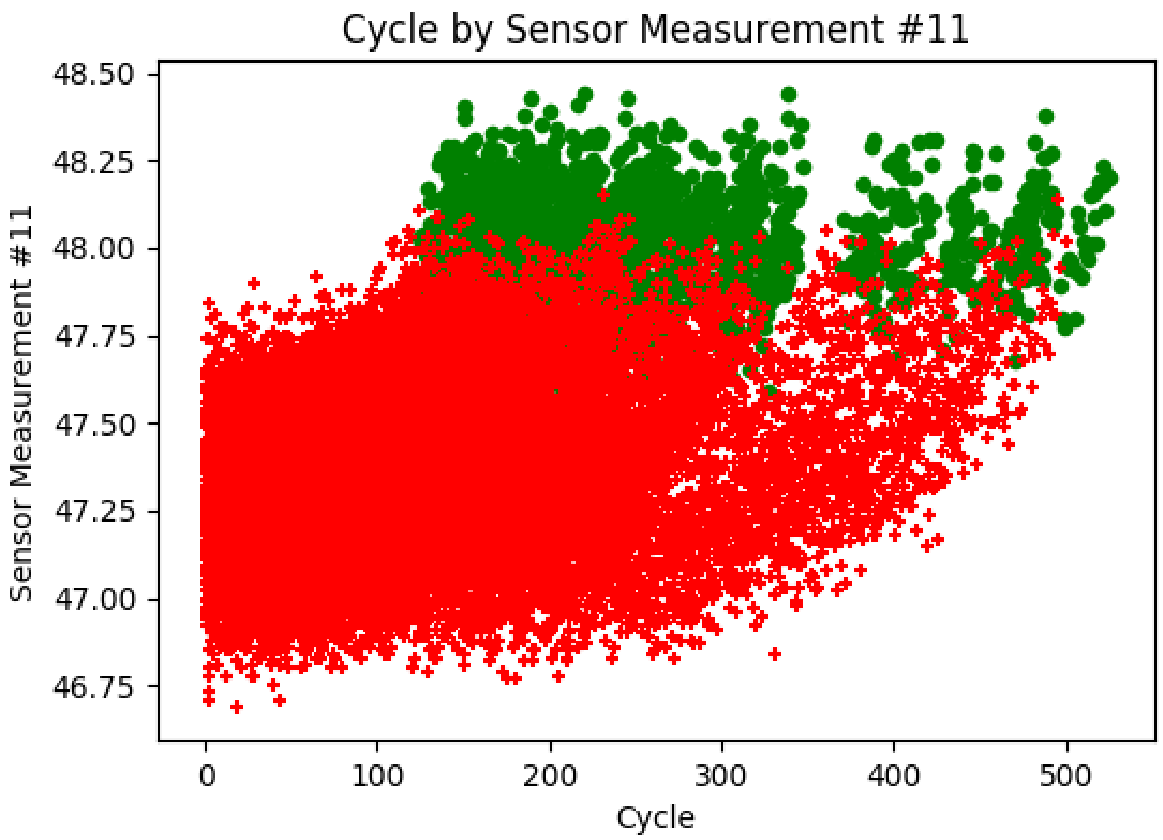

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