

Identifying Key Factors in Turbofan Engine Health Degradation using Functional Analysis

A Case Study Using NASA's NC-MAPSS DS02 Data

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Background

Objective: To develop an interpretable method for assessing the state of health in turbofan engines

Key Findings: Identification of critical parameters and flight regime points conducive to effective prognostics

Methodology: Elastic registration, data standardization, and functional principal components analysis (FPCA)

Benchmark: NASA's New Commercial Modular Aero-Propulsion System Simulation (NC-MAPSS) DS02 dataset.

Impact of Prognostics: Implementing accurate and interpretable prognostics can greatly improve safety by enabling early detection of degradation and can reduce maintenance costs through condition-based maintenance strategies.



Background: NASA's NC-MAPSS DS02 Benchmark Dataset

- NASA's NC-MAPSS standardizes aerospace research, providing a reliable basis for developing and validating engine health prognostic models.
- Dataset Details: Features 32 engine-related time-series parameters, aggregated into 26.9 GB of H5 files, capturing real-world flight conditions and turbofan degradation.
- The DS02 dataset contains subset features a specific usage case that simulates three key degradation types: High-Pressure Turbine Efficiency (HPT_eff_mod), Low-Pressure Turbine Efficiency (LPT_eff_mod) and Flow (LPT_flow_mod).



Chao, M.A., Kulkarni, C., Goebel, K., & Fink, O. (2021). Aircraft engine run-to-failure dataset under real flight conditions for prognostics and diagnostics. Data, 6(1), 5.

Approach



B-Spline Interpolation and Universal Flight Domain Results







Elastic Registration and Standardization Results (Equivalency Ratio, Φ)

Elastic Registration

$$\gamma^{*}(t) = argmin_{\gamma}D\left(f(t), g(\gamma(t))\right)$$

 $= argmin_{\gamma}$

 $\int_0^1 || (q(t) - (q_g \circ \gamma))(t)) ||^2 dt$ Where $(q_g \circ \gamma)(t)$ is the composition of the B-Spline function with the time warping function that minimizes the distance metric.



$$z = \frac{x - \mu}{\sigma}$$





FPCA Projection Results (Equivalency Ratio, Φ)

Multivariate Principal Component Analysis[

 $\max_{\beta^T\beta=1}\frac{1}{N}\beta^T X^T X\beta$

Found solving the eigenvalue problem, $V\beta = \lambda_1\beta$, where $V = \frac{1}{N}(X^T X)$

Functional Principal <u>Component Analysis</u> $V_f(s) = \int_T v(s,t)f(t)d(t)$ Where $v(s,t) = \sum_{i=1}^N x_i(s)x_i(t)$ $\int_T v(s,t)\beta_j(t)d(t) = \lambda_j\beta_j(s)$



Standardized and Aligned Data



OMP/k-NN Results



Data Preprocessing Results



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ESF-kNN Testing Results



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Spearman Correlation Results Comparison





Conclusion

- Effectively built a predictive State of Health (SoH) estimation method for turbofan engines, incorporating advanced preprocessing and data transformation techniques.
- Created an innovative use of feature engineering, selection and state estimation called Elastic-Sparse-Functional k-NN or (ESF-kNN)
- The method achieved a remarkable reduction in feature space complexity from 6200 critical variables to just 9 (0.145%), while maintained moderate levels of predictive accuracy while greatly increasing interpretability.
- This method can aid in root cause analysis, refining data collection techniques and undertaking big data analysis.



Extra Slides





OMP Information Results





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Engine Parameters

Index	Symbol	Description	Units	Symbol	Description	Units
1	Nf	Physical fan speed	rpm	accel_in	Accel limiter input	rpm/s
2	Nc	Physical core speed	rpm	accel_out	Accel limiter output	rpm/s
3	epr	Engine pressure ratio (P50/P2)		BPR	Bypass ratio	
4	P21	Total pressure at fan outlet	nsia	DD	Decel limiter output	rpm/s
5	T21	Total temperature at fan outlet	°D	farB	Burner fuel-air ratio	
5	121 D24	Total temperature at fail outlet	K	far_HPT	HPT fuel-air ratio	
0	P24	Total pressure at LPC outlet	psia	far_LPT	LPT fuel-air ratio	
7	124	Total temperature at LPC outlet	°R	Fdrag	Drag force	lbf
8	P30	Total pressure at HPC outlet	psia	htBleed	Bleed enthalpy	
9	T30	Total temperature at HPC outlet	°R	Nf_dot	Fan acceleration	rpm/s
10	P40	Total pressure at burner outlet	psia	Nc_dot	Core acceleration	rpm/s
11	T40	Total temperature at burner outlet	°R	Nf_dmd	Demanded fan speed	rpm
12	P45	Total pressure at HPT outlet	psia	P2	Pressure at fan inlet	psia
13	T48	Total temperature at HPT outlet	°R	PCNfRdmd	Demanded corrected fan speed	pct
14	P50	Total pressure at LPT outlet	nsia	PCNfR_filtered	Output of penfr filter for gain scheduling	pct
15	T 50	Total temperature at LPT outlet	°D.	PR_HPC	Pressure ratio of HPC	
15	150		K	PR_HPT	Pressure ratio of HPT	
16	W21	Fan flow	pps	PR_LPT	Pressure ratio of LPT	
17	Fn	Net thrust	lbf	tau_HPC	Torque of HPC	ft-lb
18	Fg	Gross thrust	lbf	tau_HPT	Torque of HPT	ft-lb
19	SmFan	Fan stall margin		tau_LPT	Torque of LPT	ft-lb
20	SmLPC	LPC stall margin		TRA	Throttle resolver angle	deg
21	SmHPC	HPC stall margin		12	Total temperature at fan inlet	°R
22	NRf	Corrected fan speed	rpm	W22	Flow out of LPC	Ibm/s
23	NRc	Corrected core speed	rpm	W25	Flow into HPC	Ibm/s
20	P15	Total pressure in bypass-duct	neia	W31	HP1 coolant bleed	Ibm/s
24	DCM/D	Demonstration of the speed	psia	W32	HP1 coolant bleed	Ibm/s
25	PUNIK	Percent corrected fan speed	pct	W48	Flow out of HPT	Ibm/s
26	Ps30	Static pressure at HPC outlet	psia	W50	Flow out of LPT	Ibm/s
27	phi	Ratio of fuel flow to Ps30	pps/psi	Wf_dot	Derivative of fuel flow	lbm/s ²
				x1,,x5	Solver outputs	



