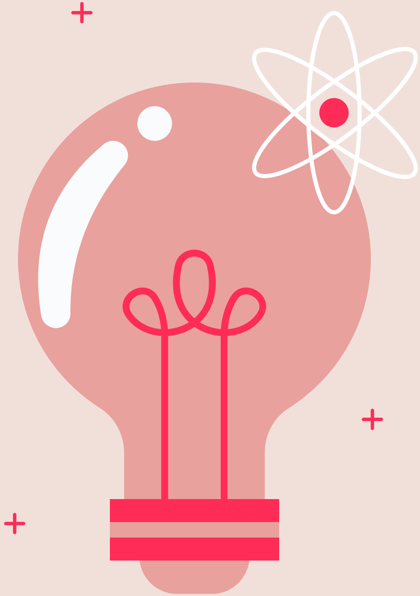
DAMAGE PROPAGATION

AIRCRAFT ENGINE



By - Tushar Bajaj

OVERVIEW OF RESEARCH PAPER

AIRCRAFT ENGINE

Modeled within the modules of aircraft gas turbine engines

RESPONSE SURFACE

Response surfaces of all sensors are generated via a thermo-dynamical simulation model

FLOW AND EFFICIENCY

An exponential rate of change for flow and efficiency loss was imposed for each data set

Health Index

A health index was defined as the minimum of several superimposed operational margins at any given time

PHM Data Competition

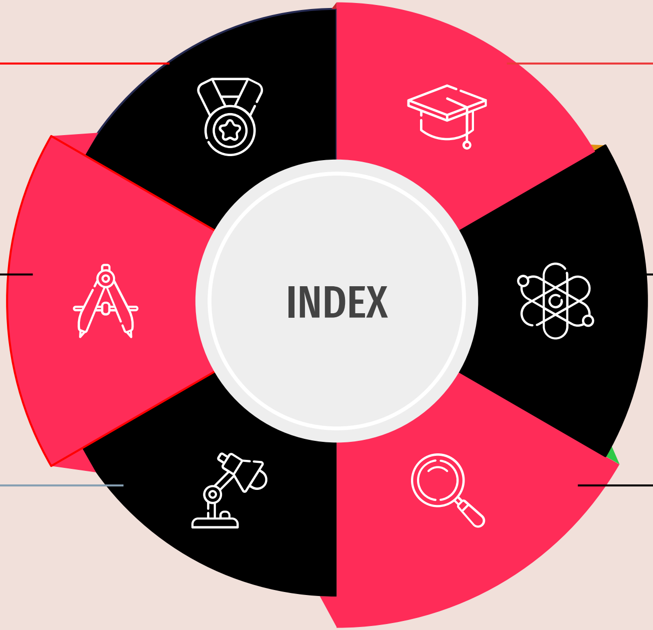
The data generated were used as challenge data for the Prognostics and Health Management (PHM) data competition at PHM'08

CONTENT

PROGNOSTICS

SYSTEM MODEL

Damage Propagation Modeling



Competition Data

Performance Evaluation

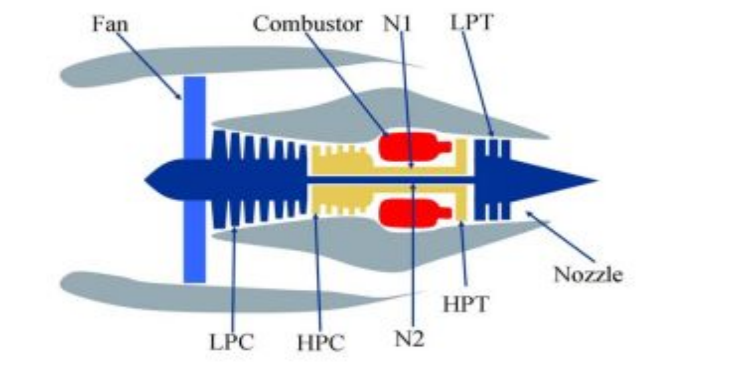
Conclusions

PROGNOSTICS

- **Prognostics** here exclusively defined as the estimation of remaining useful component life.
- The remaining useful life (RUL) estimates are in units of time (e.g., hours or cycles).
- Prognostics is currently at the core of systems health management. Reliably estimating remaining life holds the promise for considerable cost savings
- It also allows planners to account for upcoming maintenance and set in motion logistics process that supports a smooth transition from faulty equipment to fully functional
- A system model can be used to generate run-to-failure data that can then be utilized to develop, train, and test prognostic algorithms

SYSTEM MODEL

- **C-MAPSS** software is coded in the MATLAB and Simulink environment
- C-MAPSS simulates an engine model of the 90,000 lb thrust class and the package includes an atmospheric model capable of simulating operations at (i) altitudes ranging from sea level to 40,000 ft, (ii) Mach numbers from 0 to 0.90, and (iii) sea-level temperatures from –60 to 103 °F.
- CMAPSS can be operated either in open-loop (without any controller) or in close loop (with the engine and its control system) configurations.



Simplified diagram of engine simulated in C-MAPSS [11].

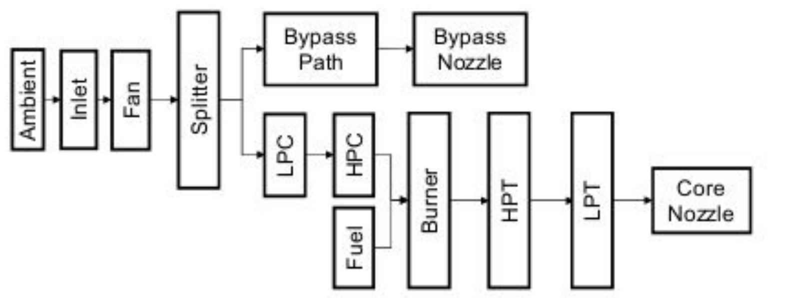


Figure 2. A layout showing various modules and their connections as modeled in the simulation [11].

C-MAPSS INPUTS AND OUTPUTS

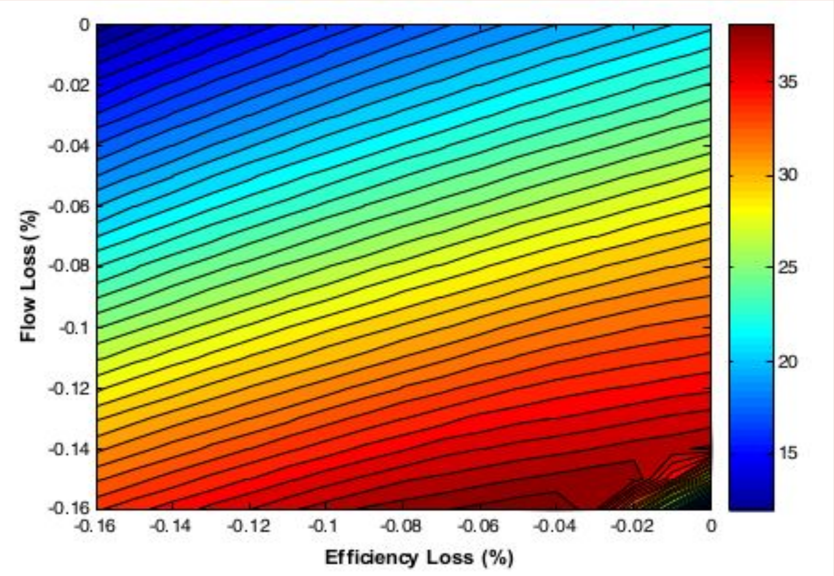
Name	*Symbol*
Fuel flow	W_f
Fan efficiency modifier	fan_eff_mod
Fan flow modifier	fan_flow_mod
Fan pressure-ratio modifier	fan_PR_mod
LPC efficiency modifier	LPC_eff_mod
LPC flow modifier	LPC_flow_mod
LPC pressure-ratio modifier	LPC_PR_mod
HPC efficiency modifier	HPC_eff_mod
HPC flow modifier	HPC_flow_mod
HPC pressure-ratio modifier	HPC_PR_mod
HPT efficiency modifier	HPT_eff_mod
HPT flow modifier	HPT_flow_mod
LPT efficiency modifier	LPT_eff_mod
HPT flow modifier	LPT_flow_mod

INPUTS

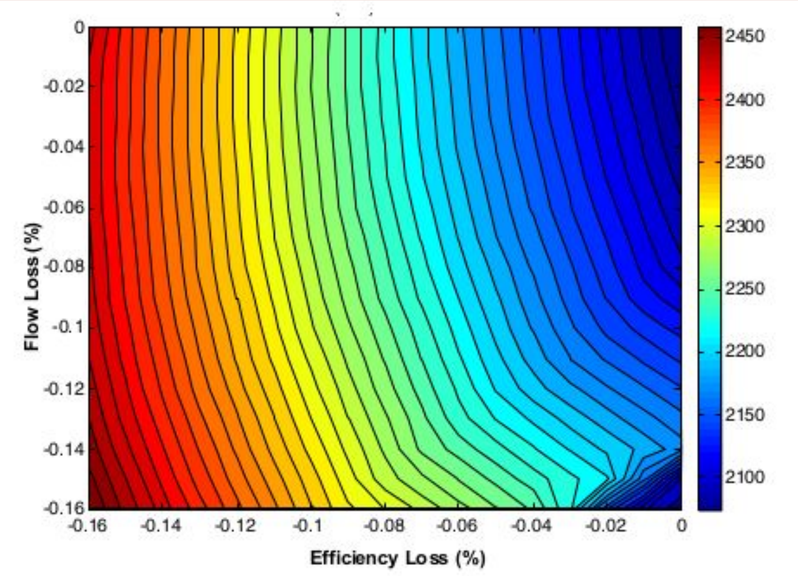
Symbol	*Description*	*Units*
Parameters available to participants as sensor data		
T2	Total temperature at fan inlet	°R
T24	Total temperature at LPC outlet	°R
T30	Total temperature at HPC outlet	°R
T50	Total temperature at LPT outlet	°R
P2	Pressure at fan inlet	psia
P15	Total pressure in bypass-duct	psia
P30	Total pressure at HPC outlet	psia
Nf	Physical fan speed	rpm
Nc	Physical core speed	rpm
epr	Engine pressure ratio (P50/P2)	--
Ps30	Static pressure at HPC outlet	psia
phi	Ratio of fuel flow to Ps30	pps/psi
NRf	Corrected fan speed	rpm
NRc	Corrected core speed	rpm
BPR	Bypass Ratio	--
farB	Burner fuel-air ratio	--
htBleed	Bleed Enthalpy	--

OUTPUTS

C-MAPSS RESPONSE SURFACES



Response surface of HPC stall margin as a function of efficiency and flow losses simulating degradation in HPC module



Response surface for Exhaust Gas Temperature (EGT) as a function of efficiency and flow losses.

DAMAGE PROPAGATION MODELING

Arrhenius:

$$t_f = Ae^{\frac{\Delta H}{kT}},$$

Coffin-Manson model:

$$N_f = Af^{-\alpha}\Delta T^{-\beta}G(T_{\max}),$$

Eyring Model:

$$t_f = AT^{\alpha}e^{\left(\frac{\Delta H}{kT}+\left(B+\frac{C}{T}\right)S_1+\left(D+\frac{E}{T}\right)S_2\right)},$$

DAMAGE PROPAGATION MODELING FOR THE CHALLENGE PROBLEM

For the purpose of a physics inspired data-generation approach, we assume a generalized equation for wear, which ignores micro-level processes but retains macro-level degradation characteristics.

$$w = Ae^{B(t)},$$

Assuming further an upper wear threshold, **thw** , that denotes an operational limit
The generalized wear equation can be rewritten as a time varying health index, **h(t)**, by subtracting wear from the upper wear threshold and normalizing it with respect to the upper wear threshold as

$$h(t) = 1 - Ae^{B(t)} / th_w.$$

$$h(t) = 1 - \exp\{at^b\}.$$

Generally, the system will be observed with some non- zero initial degradation, d.

$$h(t) = 1 - d - \exp\{at^{b}\}.$$

Specifically, for aircraft engine modules like the compressor and turbine sections, the health is described both by efficiency (e) and flow (f).

$$e(t) = 1 - d_e - \exp\{a_e(t).t^{b_e(t)}\},$$
$$f(t) = 1 - d_f - \exp\{a_f(t)t^{b_f(t)}\}$$

The terms e(t) and f(t) are then aggregated to form the overall health index H(t).

$$H(t) = g(e(t), f(t))$$

where, the function g is the minimum of all operative margins considered,

i.e.

$$g(e(t), f(t)) = \min(m_{Fan}, m_{HPC}, m_{HPT}, m_{EGT}),$$

DATA GENERATION

Choose initial deterioration,

$$e_0 \in [0.99, 1]$$
$$f_0 \in [0.99, 1]$$

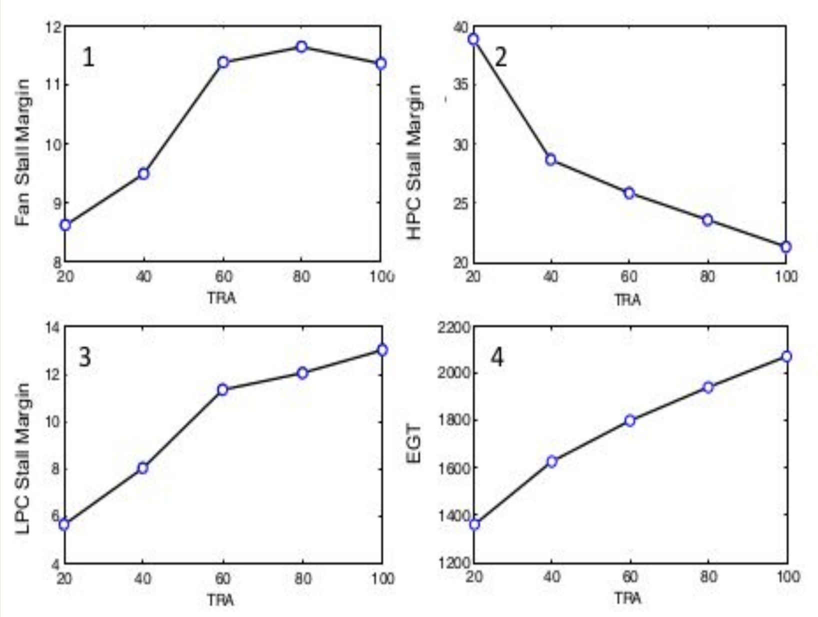
Impose an exponential rate of change for flow and efficiency loss for each data set

$$f_i, e_i \leq 1\%,$$
$$a_k \in [0.001, 0.003],$$
$$b_k \in [1.4, 1.6], \quad k = 1,2.$$

Stop when health H= 0

HEALTH INDEX CALCULATION

- The safe operation region for an engine is determined via operability margins - how far the engine is operating from various operational limits like stall and temperature limits.
- These margins can be calculated by computing the distance between current engine state and pre-defined limits
- Each of these margins are normalized to the range [0,1], where one signifies a perfectly healthy system and zero denotes a system whose stall margin has reduced by a specified limit.
- For the challenge data this limit was set at 15% for HPC, LPC and fan stall margins and about 2% for the EGT margin.



PERFORMANCE EVALUATION

- Performance evaluation is concerned with employing metrics that help assess if the prognosis meets specifications for the task at hand.
- In specific situations where failures may not pose life threatening situations and early predictions may instead involve significant economic burden
- For an engine degradation scenario an early prediction is preferred over late predictions.
- Therefore, the scoring algorithm for this challenge was asymmetric around the true time of failure such that late predictions were more heavily penalized than early predictions

$$s = \begin{cases} \sum_{i=1}^{n} e^{-\left(\frac{d}{a_1}\right)} - 1 \text{ for } d < 0 \\ \sum_{i=1}^{n} e^{\left(\frac{d}{a_2}\right)} - 1 \text{ for } d \geq 0, \end{cases}$$

where

s is the computed score,

n is the number of UUTs,

$d = \hat{t}_{RUL} - t_{RUL}$ (Estimated RUL – True RUL),

$a_1 = 10$, and $a_2 = 13$.

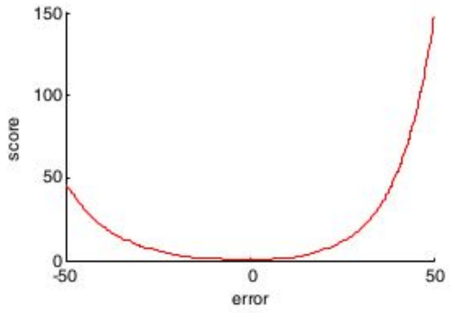


Figure 9. Score as a function of error.

THANKS!