Turbine Engine Diagnosis

On the Reconstruction of Performance Parameters from Engine and FADEC Measurements

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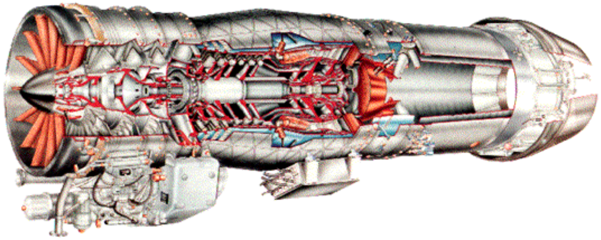
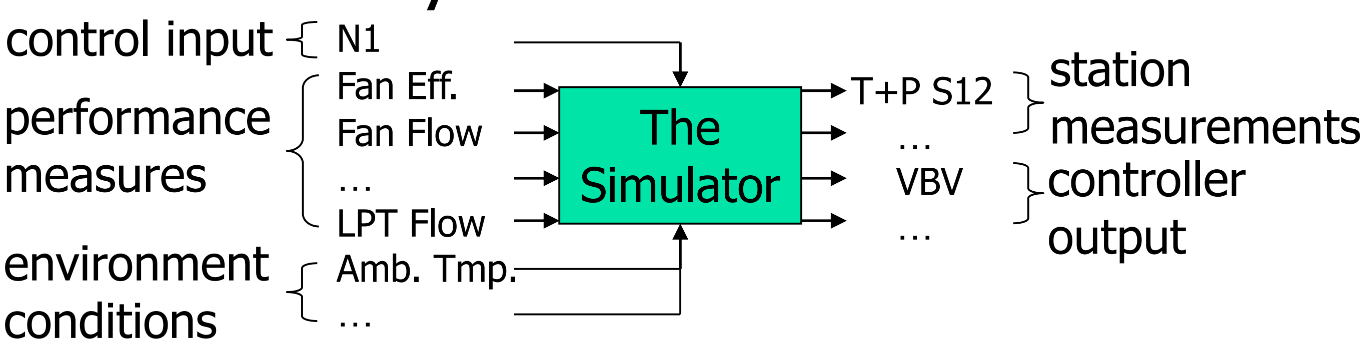
The Challenge

- Diagnosis of a twin-spool turbofan, based on pressure and temperature measurements at different stations, FADEC variables (VBV, VSV, WFM, etc.), environmental conditions.
- Technique: reconstruction of station performance measures (efficiency measures, flow measures) at said stations.

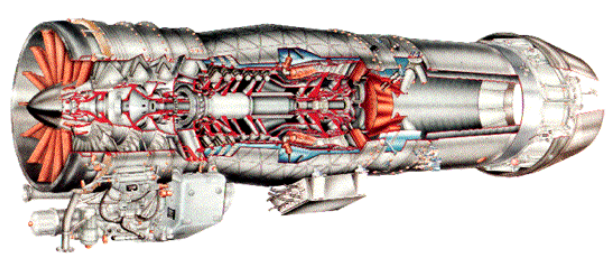


The Information

- Black box (OEM-supplied) thermodynamic steady-state simulator

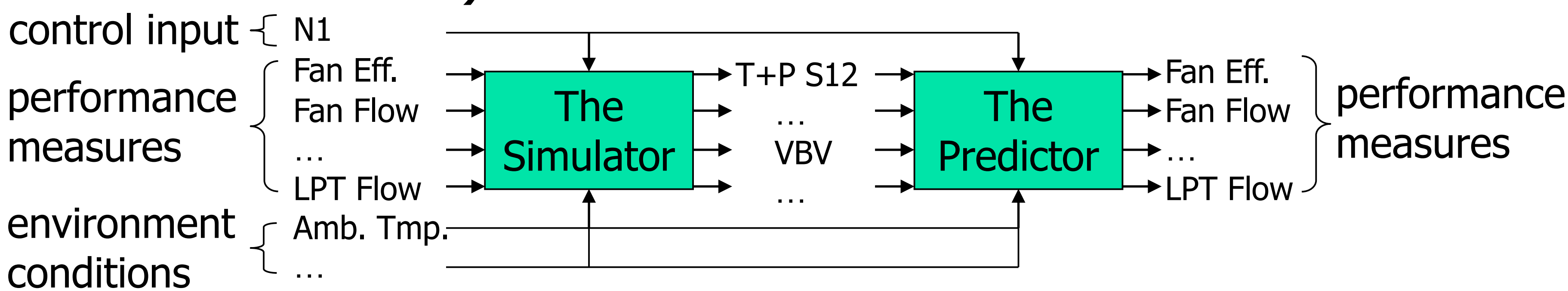


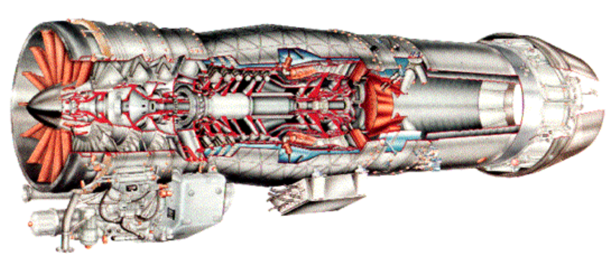
- Limited test-cell measurements of engine, used for parameter range estimation.



The Mission

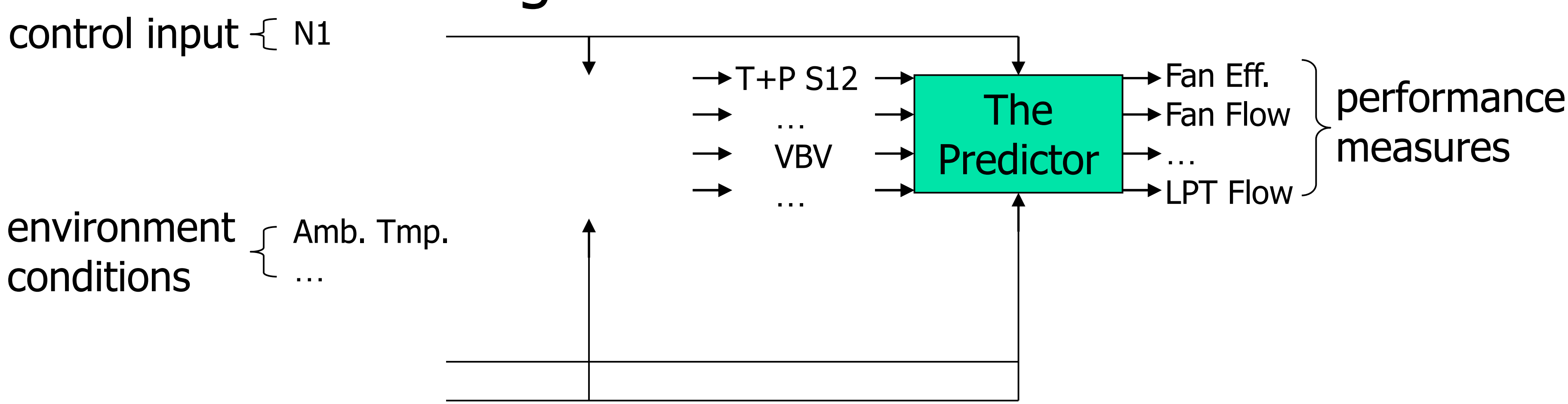
- Producing a simulator reconstructor (The Perdictor)

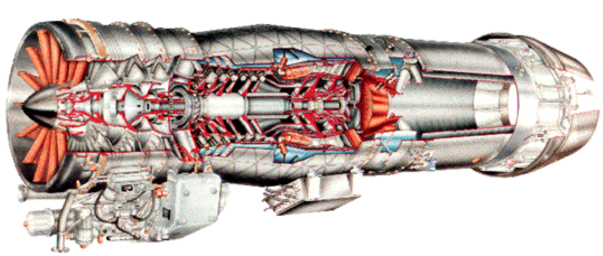




The Goal

- The Predictor as a **diagnostic tool** for the real engine





Is this a well-posed problem?

1. Existence ?
2. Uniqueness ?
3. Continuity ?

(Hadamard, 1902, 1923;
Tikhonov & Arsenin, 1977;
Morozov, 1993;
Kirsch, 1996;
Haykin, 1999)

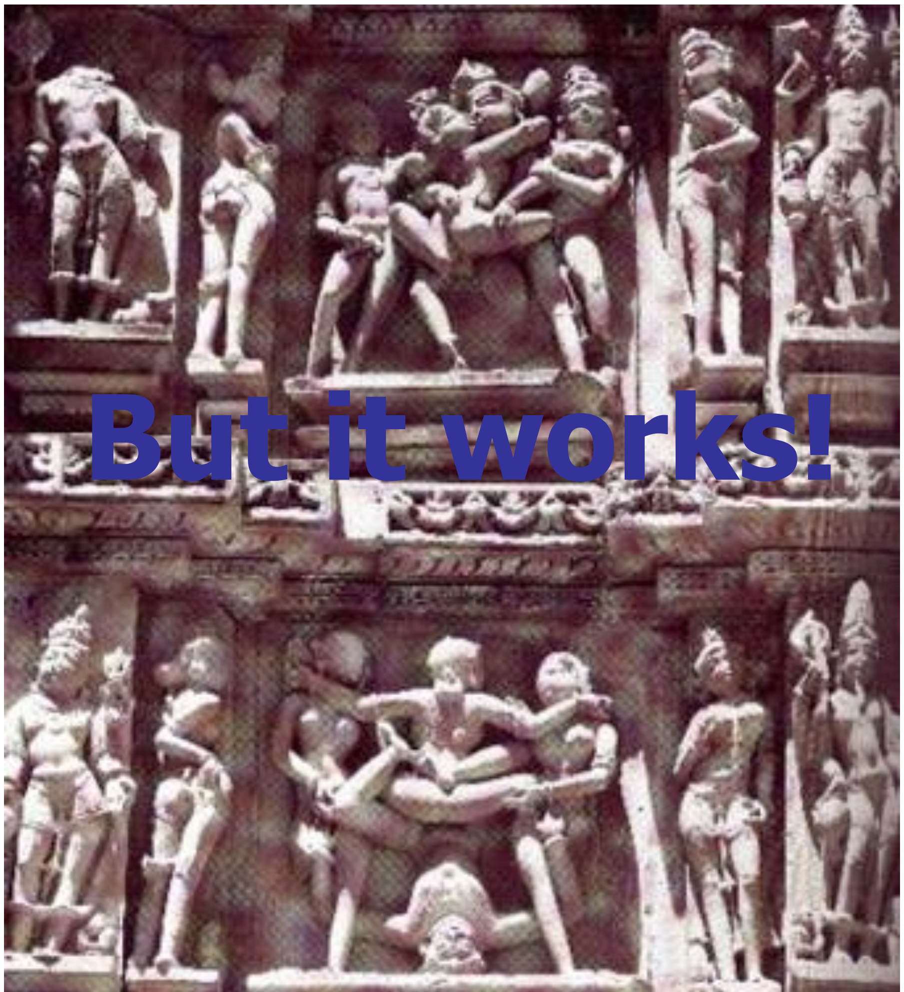
Generally: NO!

In practice:

- Prior knowledge about simulation type/problem nature
- Restraints on parameter combinations/distributions
- Parameters limited to localized working conditions

For Practical Purposes: WE'LL TRY!

There exist more well-posed examples..

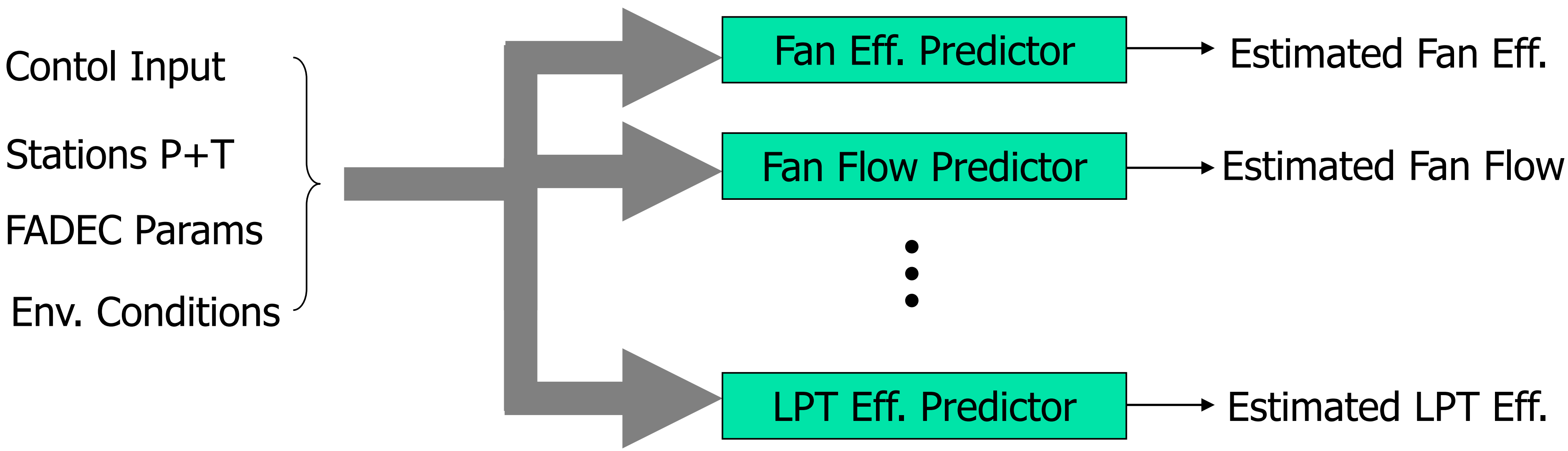


But it works!

(Kandariya Visvanatha Mahadeva Temple, Khajoraho, India, 10th-11th century AD)

Predictor Implementation

- The Predictor (non-linear regression) was realized on feed-forward neural networks.
- Different predictor/NN for each performance parameter.

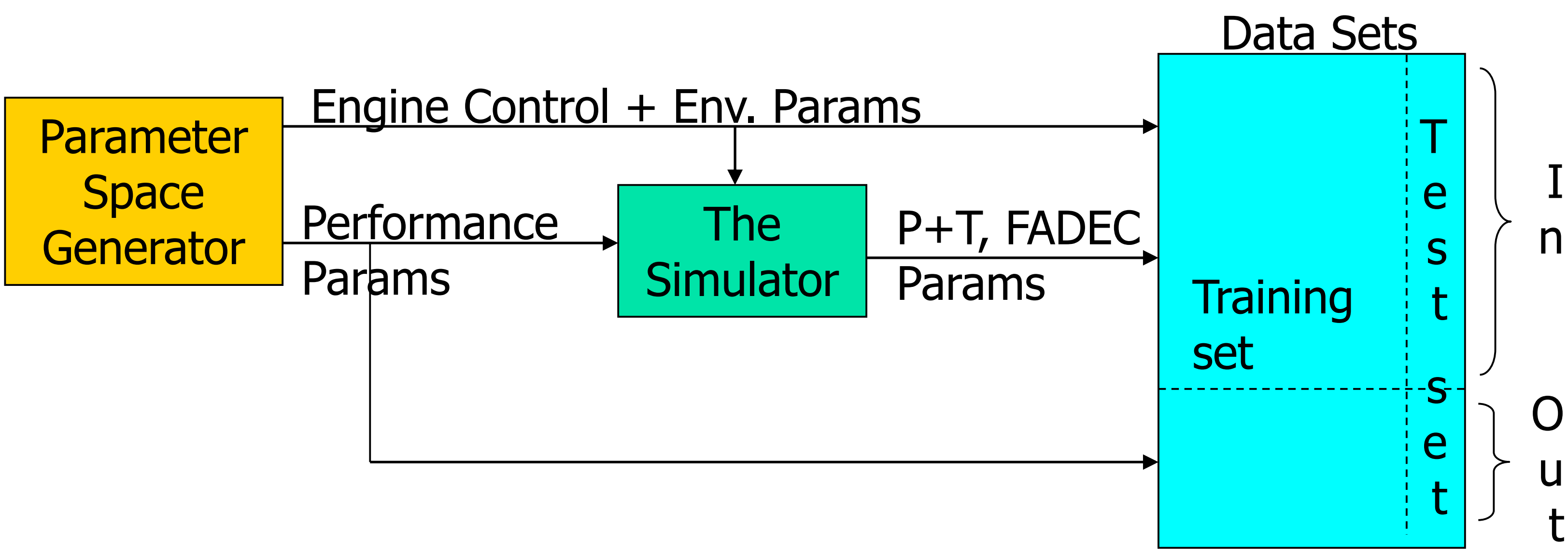


Data Sets

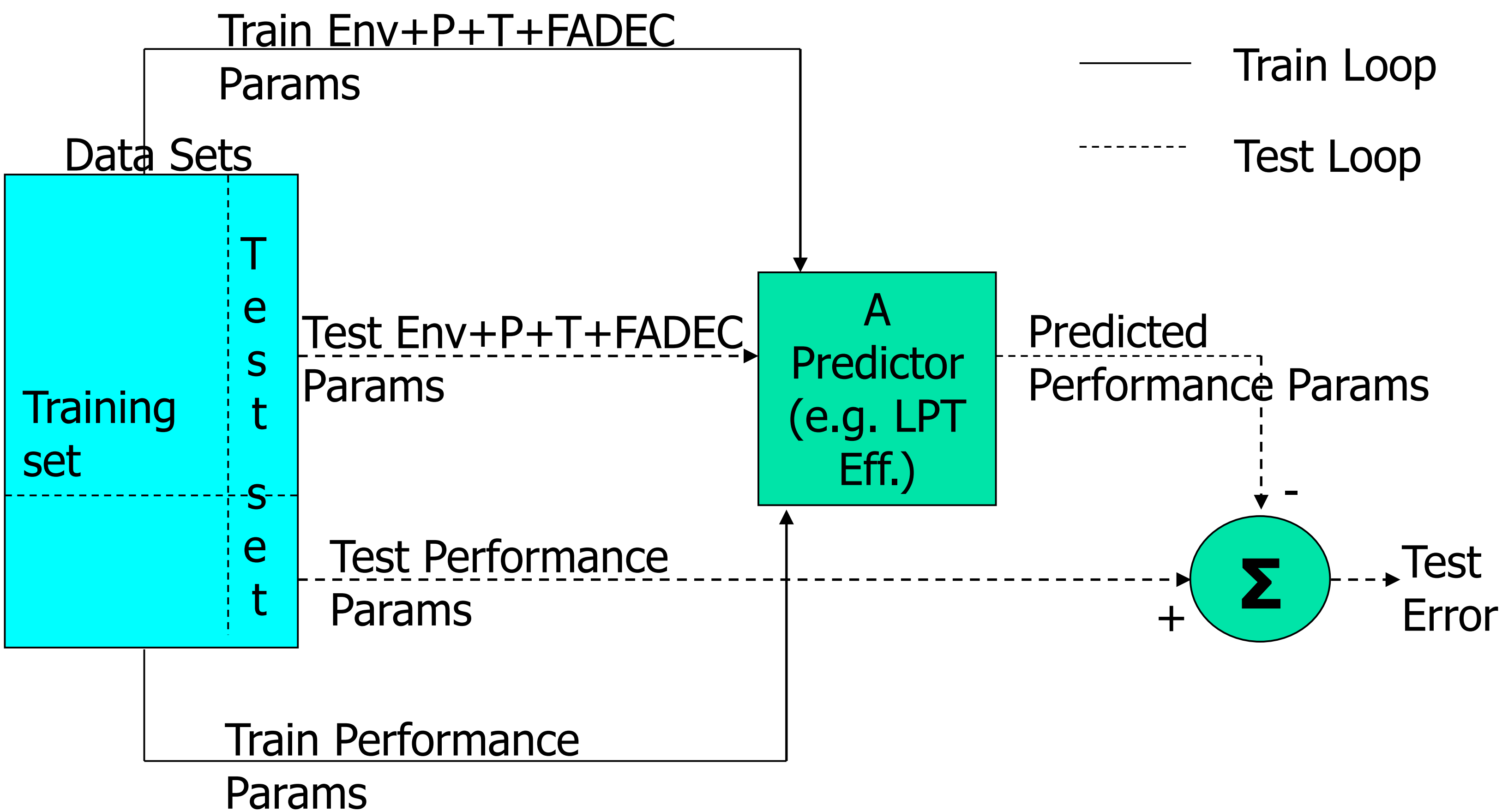
- Two sets for training and testing of The Predictor.
- Sets to span spaces to be encountered:
  - Performance parameters (engine integrity states) in all stations/cocktails thereof
  - Engine operating states
  - Environmental conditions
- Working with a simulator, manufacturing synthetic data with no limits on size, distribution (independence) and quality.

Data Sets

- Data sets were produced using extensive execution of the simulator under controlled input conditions, as to span the working conditions to be encountered.



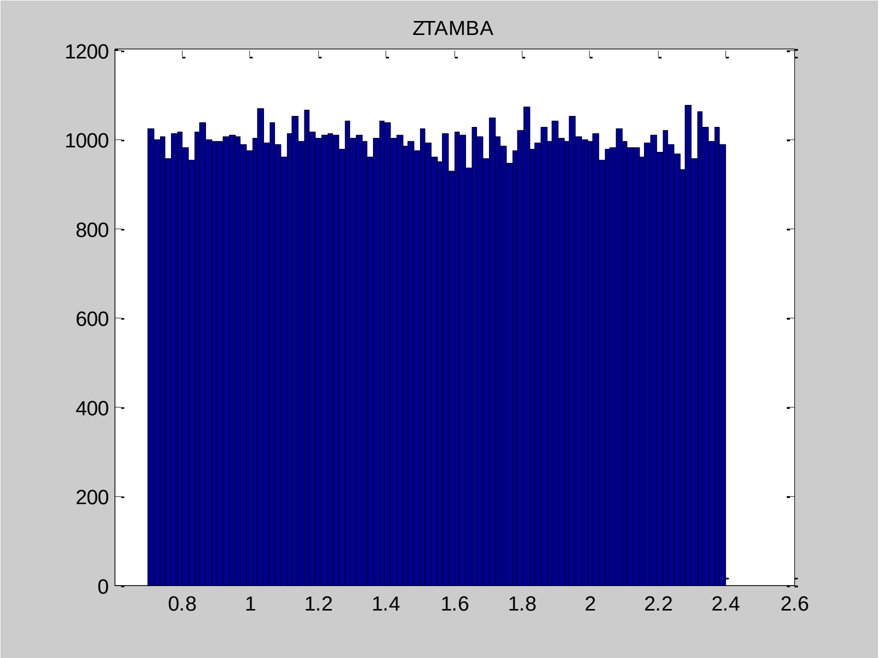
Predictor Training/Testing



Data Sets Distribution Strategy

- Environment and engine control (e.g. N1) inputs were chosen to be uniformly distributed in ranges obtained from test-cell data.

e.g. ambient temperature histogram

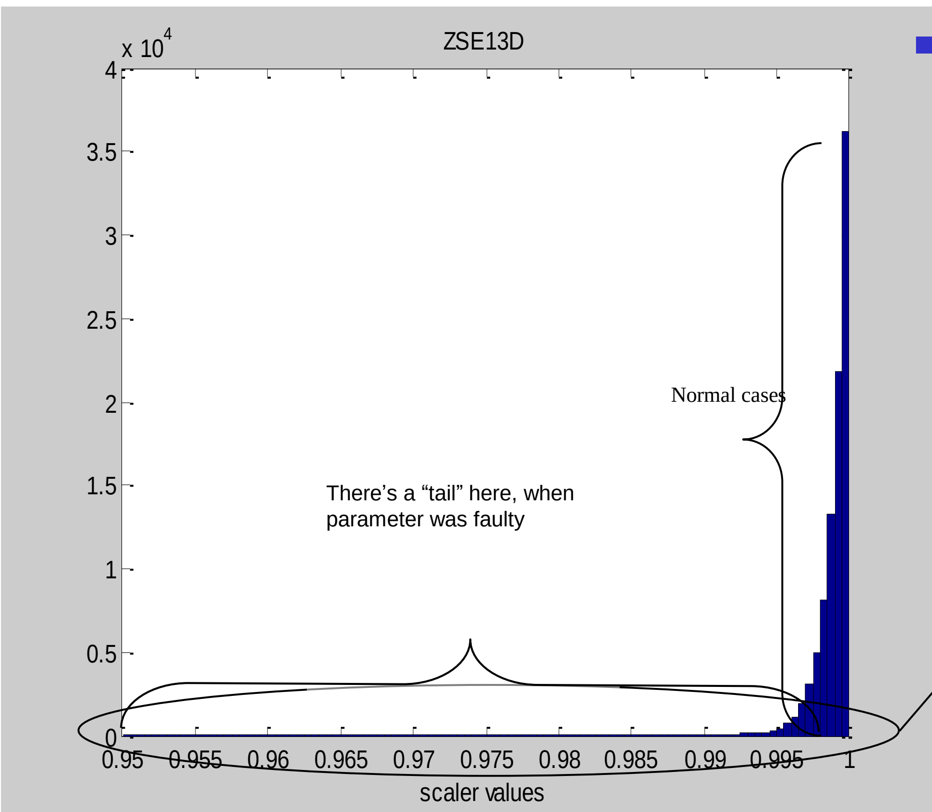


Data Sets Distribution Strategy

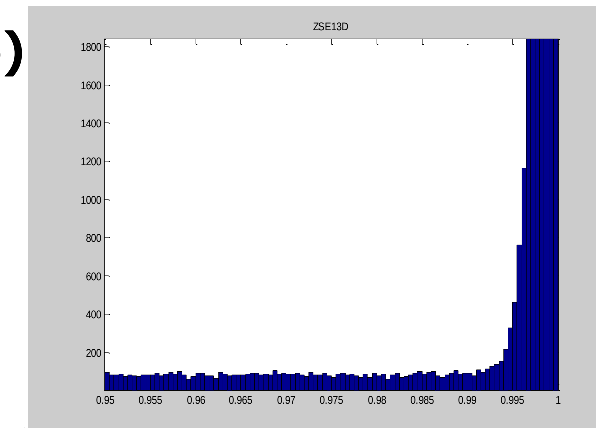
- Performance parameters (efficiencies and flows) were chosen from two distributions, representing either "normal behavior" or "faulty behavior"
- "normal behavior" consisted of most values near their nominal expected value (scaler = 1.0), with exponential distribution with parameter $\mu = 0.001$ to the "left" of 1, accounting for less than ideal performance.
- "faulty behavior" was chosen from a uniform distribution in the scaler range 0.95 – 1.0.
- Modeled parameter was uniform at interval 0.95-1.0 according to target reconstruction range.

Data Sets Distribution Strategy

- e.g. Fan isentropic efficiency HISTOGRAM



- **(Pf = 0.5)**



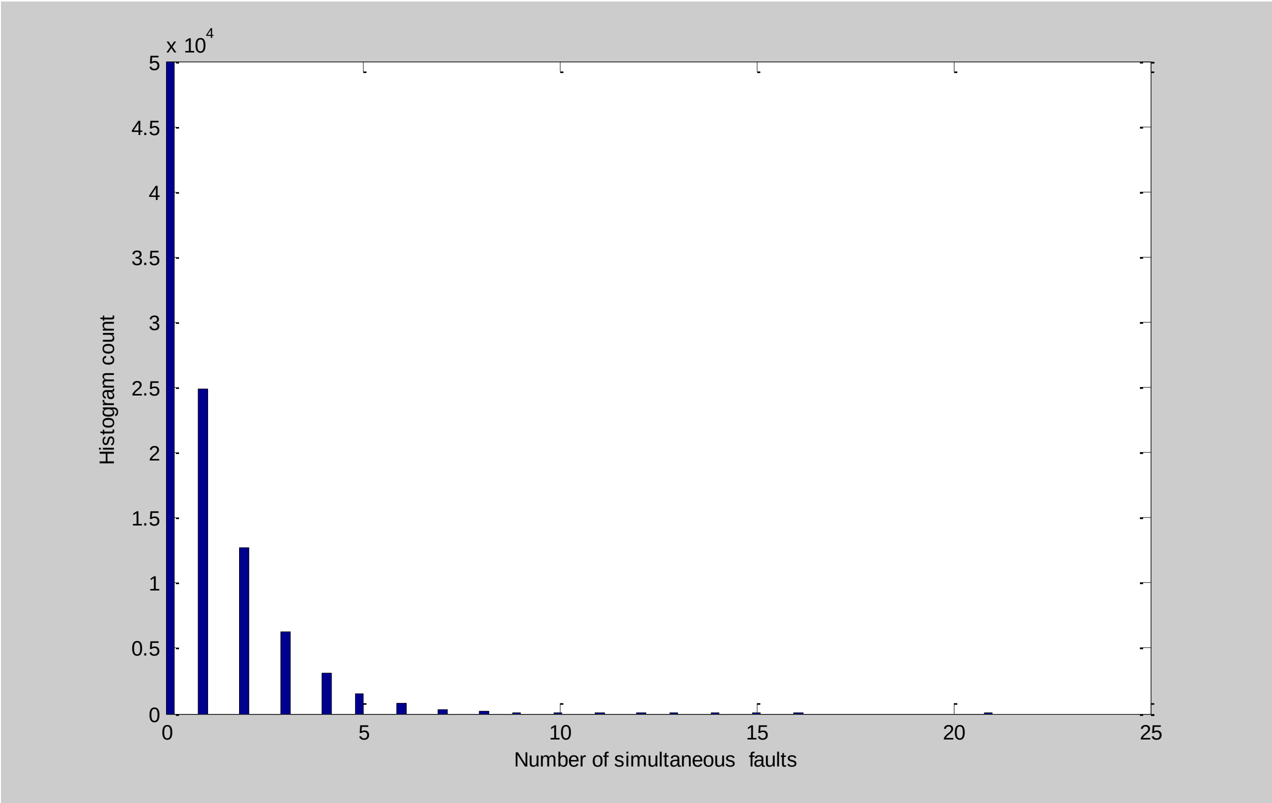
See fault distribution strategy presented below

Fault Distribution Strategy

- Test set fault distribution assumed fault occurrence independence, resulting in sets with decreasing frequency of occurrence of multiple simultaneous faults.
- The number of simultaneous faulted parameters (not including the modeled parameter) was chosen at each data point, such that if a probability for a single faulted parameter is P_f, then the probability for n faults was P_f^n. Pessimistic values used for P_f were 0.1 and 0.5.

Fault Distribution Strategy

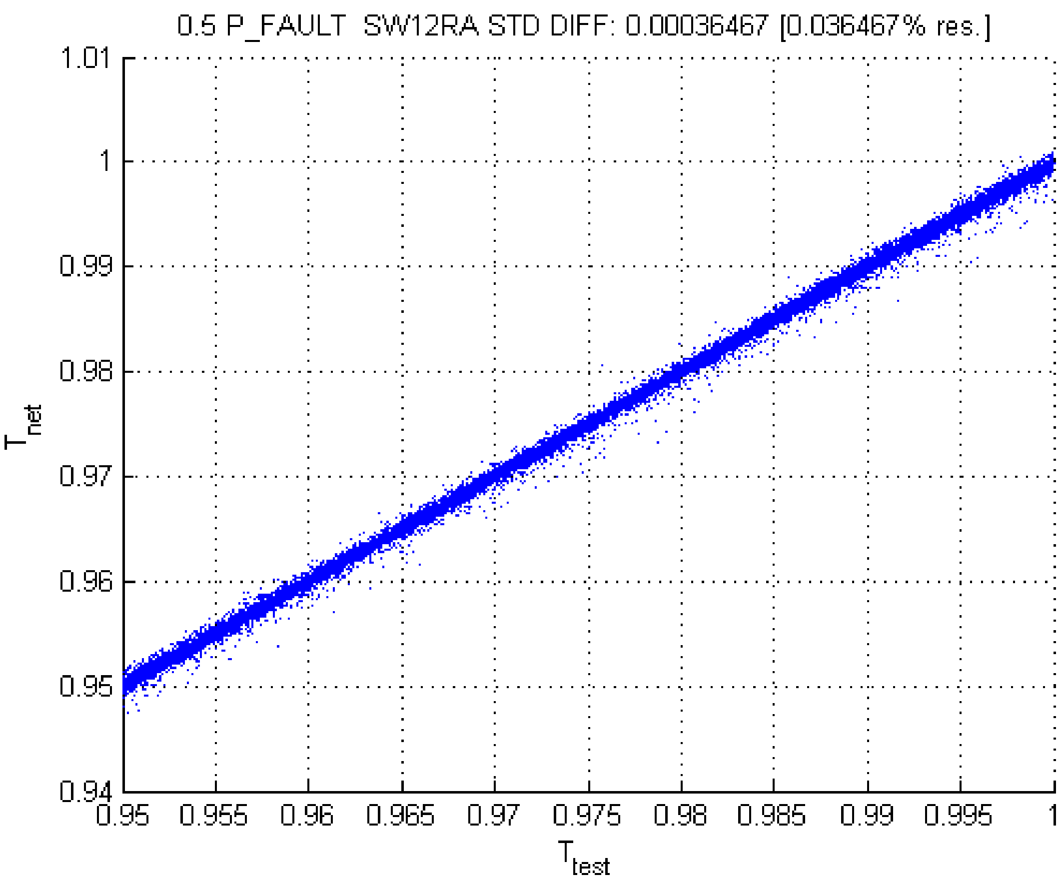
- Fault distribution HISTOGRAM for $P_f = 0.5$



Average fault number is 1 (for $P_f = 0.1$ average is ~0.11)

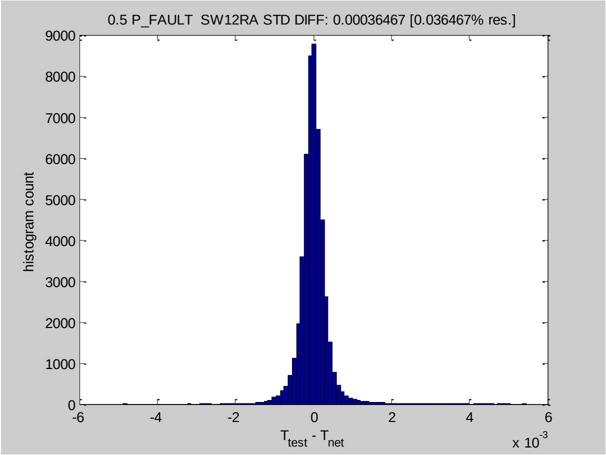
Results

- e.g. Fan flow scaler ($P_f = 0.5$)



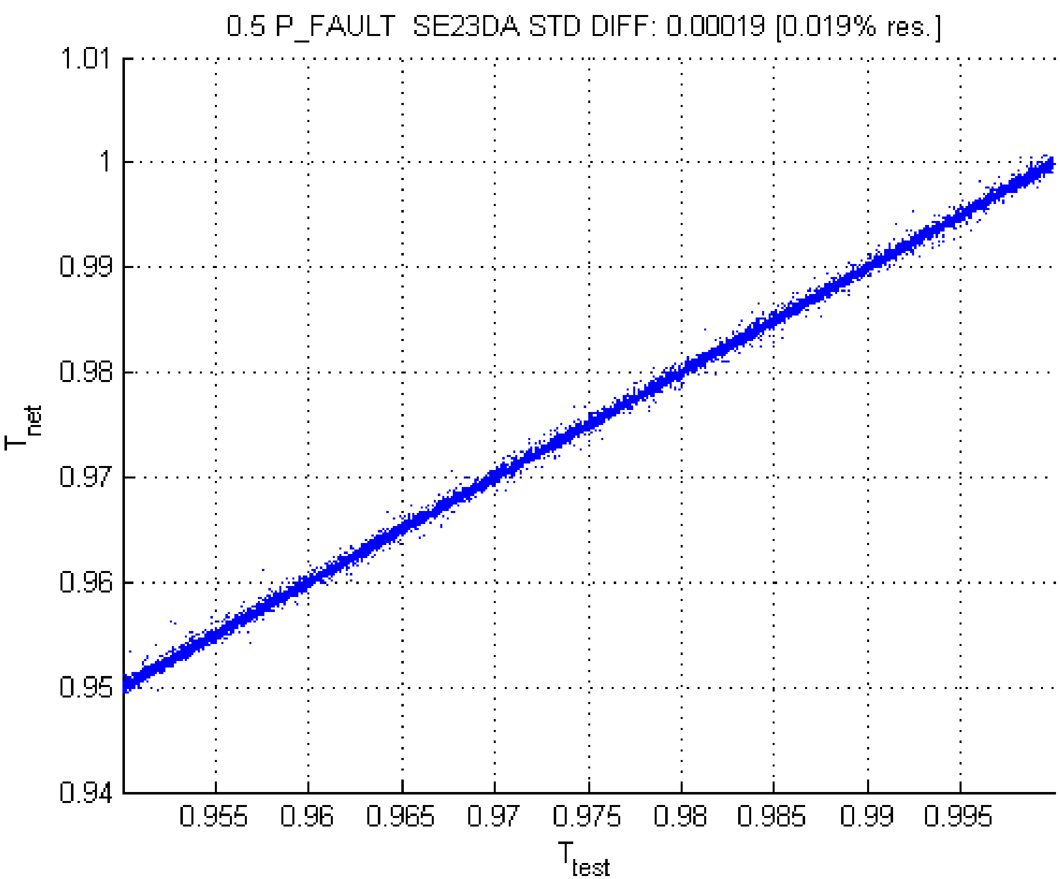
Graph shows reconstructed parameter value VS original value

90th Percentile Error: 0.050%



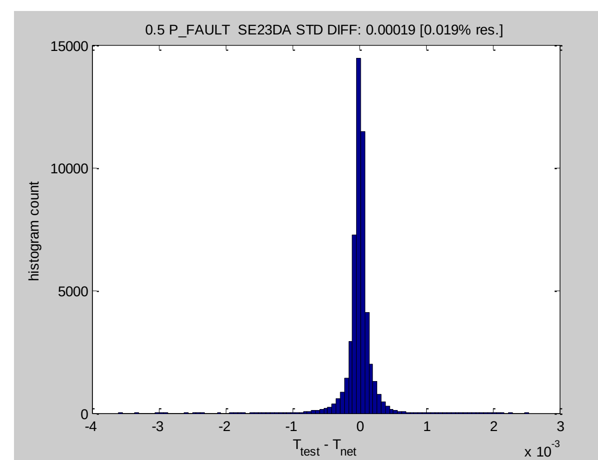
Results

- e.g. Booster isentropic eff. scaler (P_f = 0.5)



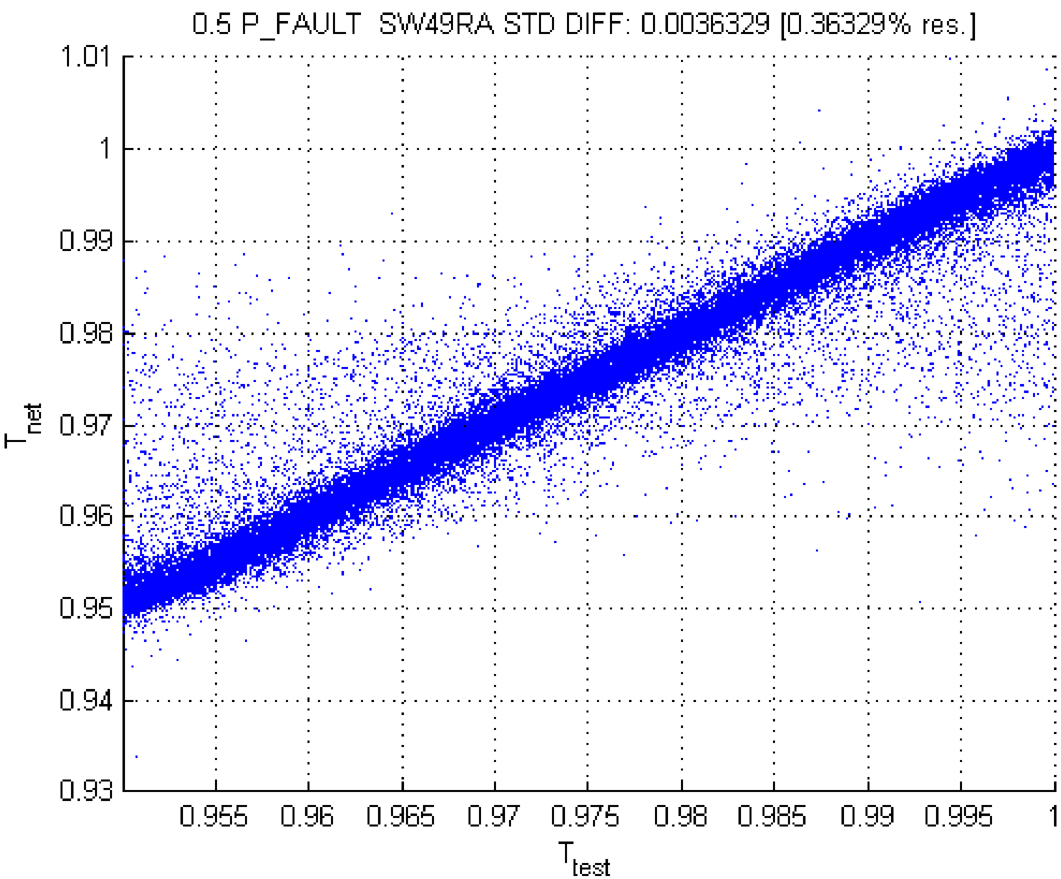
Graph shows reconstructed parameter value VS original value

90th Percentile Error: 0.025%



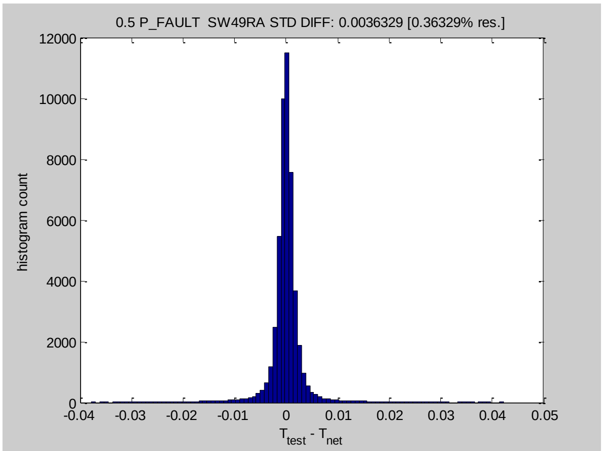
Results

- e.g. LPT flow scaler ($P_f = 0.5$)



Graph shows reconstructed parameter value VS original value

90th Percentile Error: 0.377%



Conclusions

- The regression attempt has produced results whose 90th percentile deviation averaged 0.156%, exceeding requirements for detecting plausible fault performance degradations of 1% – 2%.
- The less precise regression has been achieved for LPT efficiency and flow parameters
- This feasibility study proved the capability of utilizing machine learning techniques to reproduce actual engine status from accessible measurements, at least in the simulator context.

ANY QUESTIONS?