Center for System Reliability

Life Prediction Algorithms

Laura Swiler

Sandia National Laboratories

Albuquerque, NM 87185

lpswile@sandia.gov, 505-844-8093

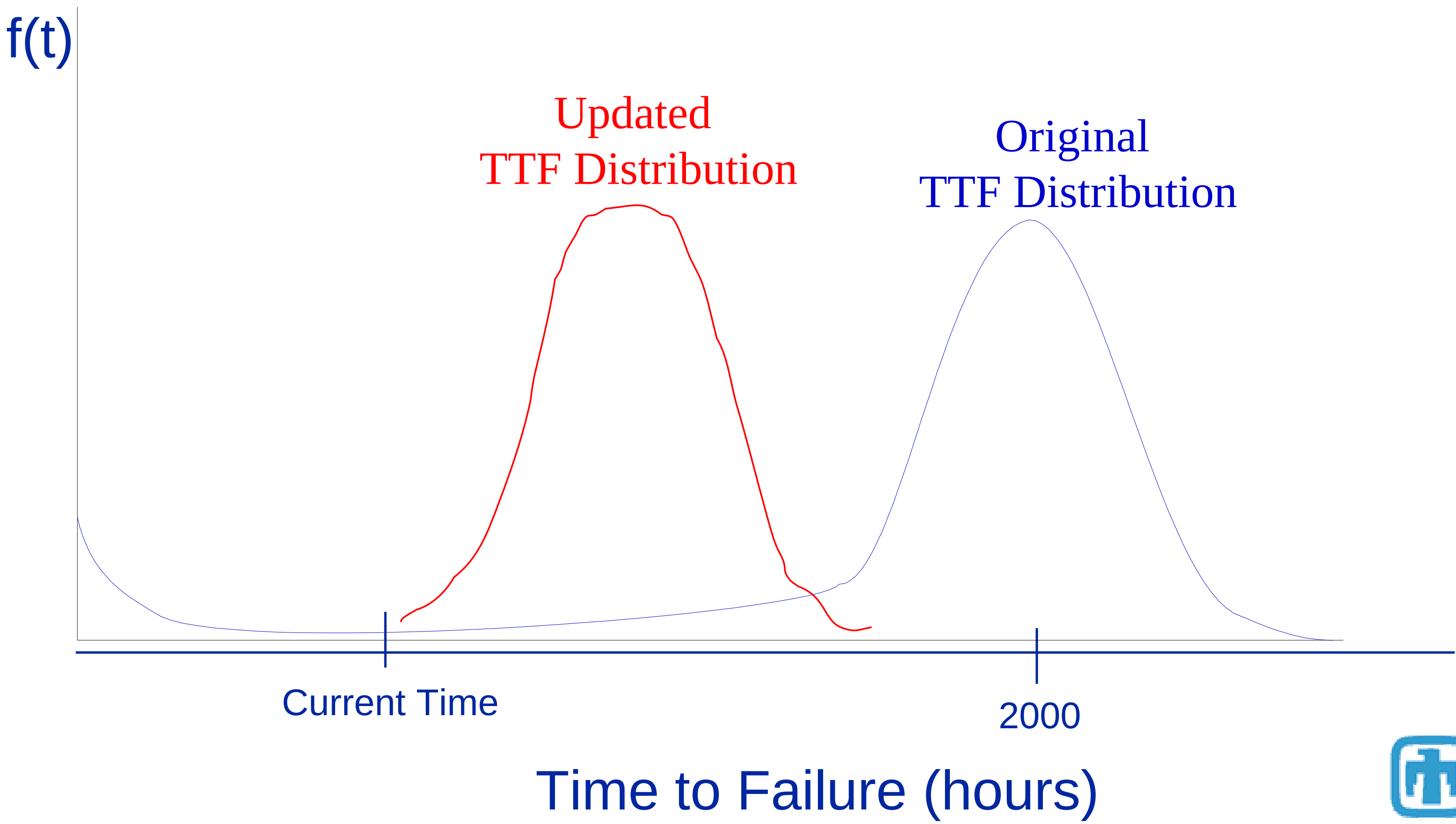
Sandia National Laboratories

Technologies that support life prediction

- **Sensor Feature Extraction/Sensor Fusion**
  - Time synchronous averaging, peak and level-shift detection, etc. Belief networks, neural networks, pattern classifiers, and statistical methods. These methods currently exist.
- **Component Health Estimation**
  - Need to have models which relate the available evidence to component TTF or RUL. Methods include trend analysis and case-based reasoning (e.g., IF the altitude is X and the speed is Y and the sensor reading is Z and the maintenance status is W, then the component time to failure is V.)
  - Classical reliability analysis, some analytical approaches in a few areas
- **Consequence Analysis**
  - Most prognostic systems focus solely on predicting remaining life
  - Understanding how potential maintenance actions affect system level decisions in terms of cost, availability, mission effectiveness, etc. is a complex problem
  - Simulation

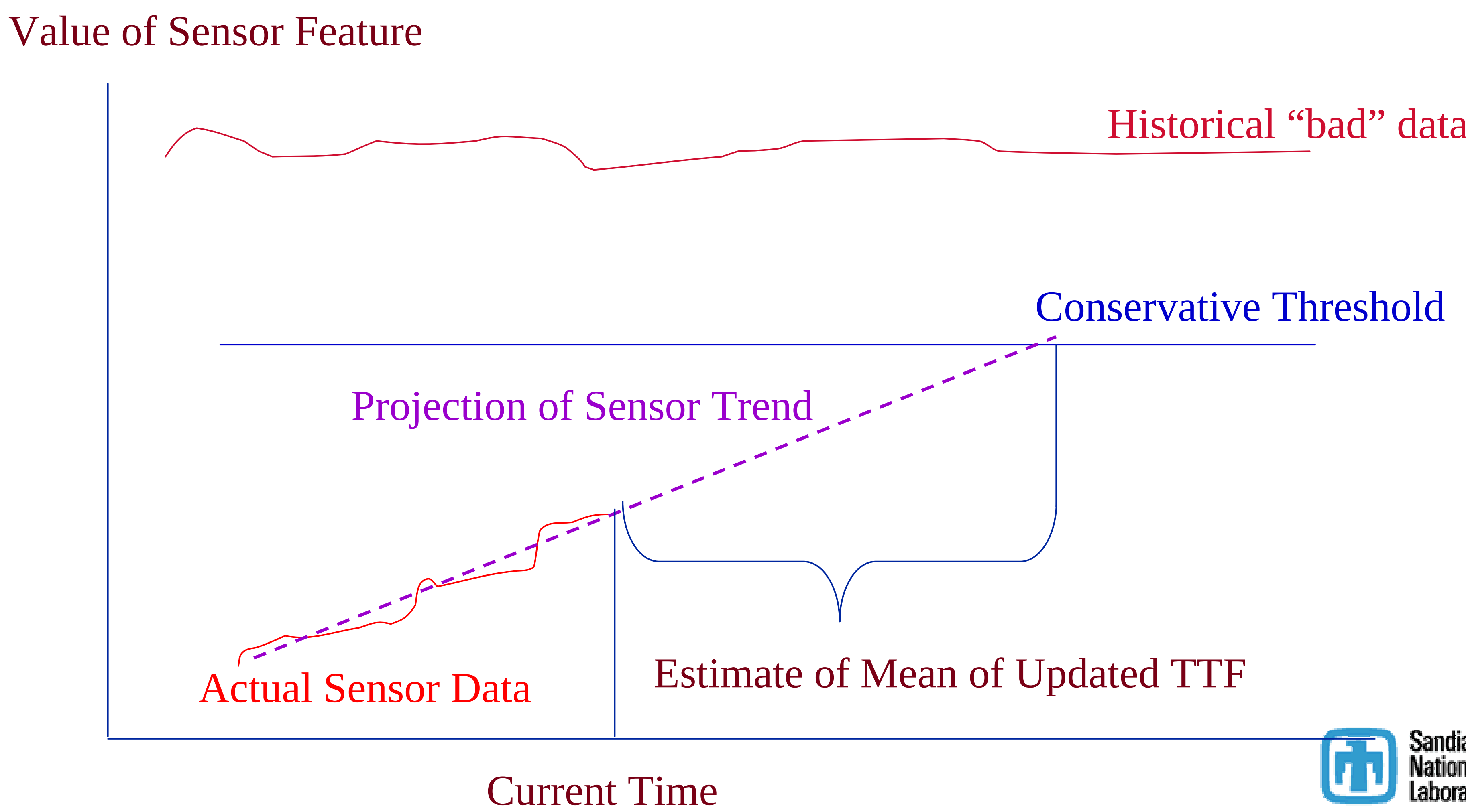
Prognostics Goal: Update TTF Distribution

Note: The updated TTF Distribution may be based on a more severe mission profile, sensor indications, inspection results, etc. or a combination of these.



Example Prognostics Approach

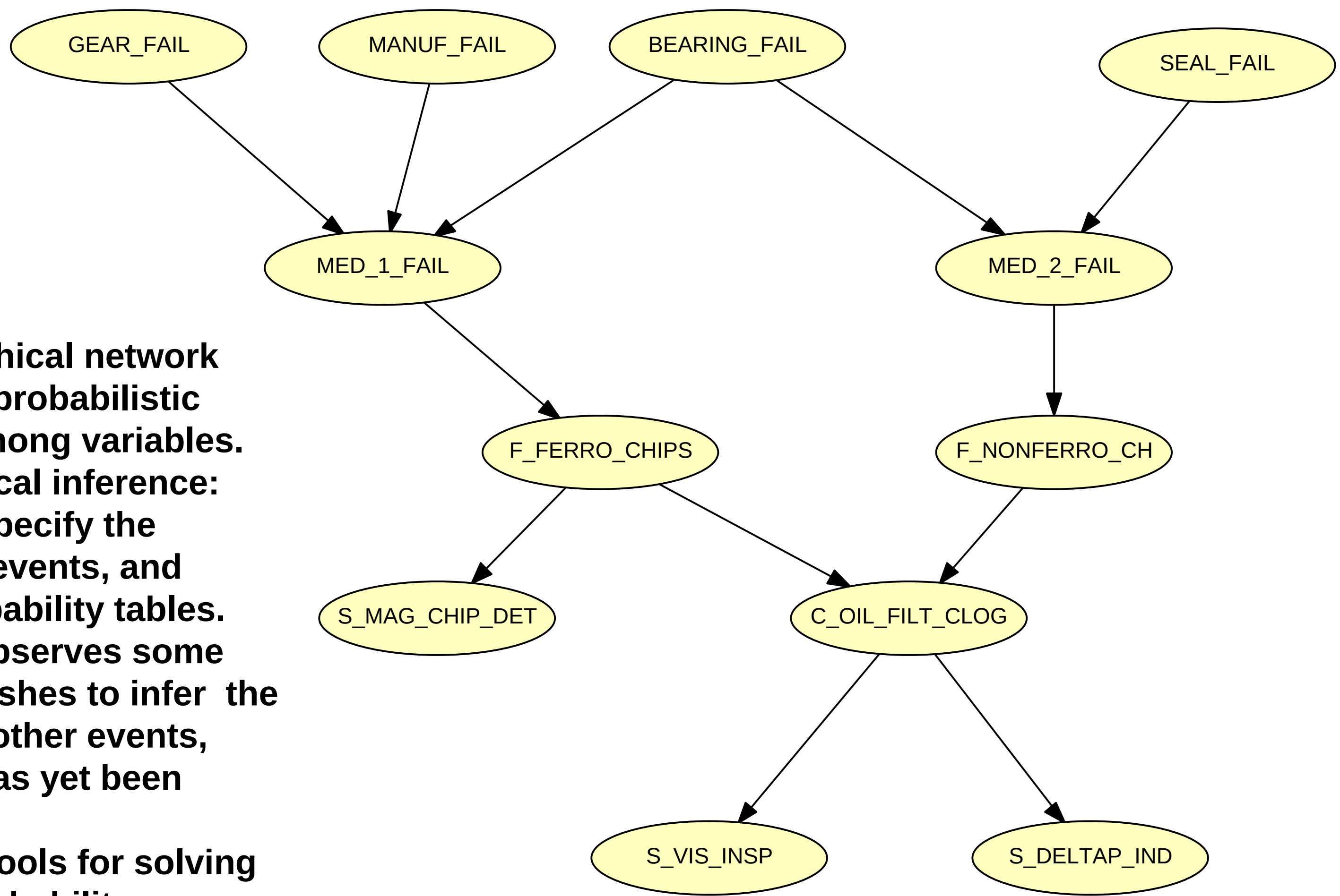
Center for System Reliability



Algorithms

- Fuzzy Logic
- Procedural rule-base expert systems
- Scripts, frames, case-based reasoning
- Neural networks, Bayesian networks
- Genetic Algorithms
- Statistical Process Control Methods
- Pattern classification, clustering algorithms
- Estimation methods – Kalman filters, Regression
- Bayesian updating

BBN for Lube Problems (Metal and Nonmetal chips) in Gearbox Oil



- **A BBN is a graphical network that represents probabilistic relationships among variables.**
- **Used for statistical inference: The user must specify the probabilities of events, and conditional probability tables. The user then observes some evidence and wishes to infer the probabilities of other events, which have not as yet been observed.**
- **Computational tools for solving the posterior probability distributions have been developed over the past ten years.**

BBN Specification of Conditional Probabilities

Prob(S_MAG_CHIP_DET|F_METAL_CHIPS)	Normal	Intermediate	Severe
Clean	.95	.05	.05
Few Chips	.04	.8	.1
Many Chips	.01	.15	.85

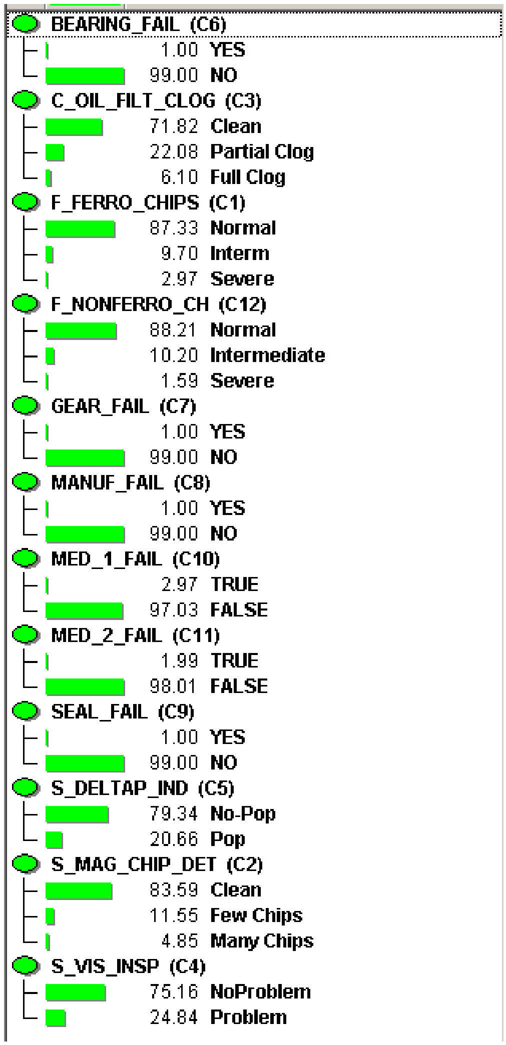
Conditional Probability: Prob(S_MAG_CHIP_DET|F_METAL_CHIPS)

Prob(S_DELTAP_IND|C_OIL_FILT)	Clean	Partial Clog	Full Clog
No Pop	.98	.4	.02
Pop	.02	.6	.98

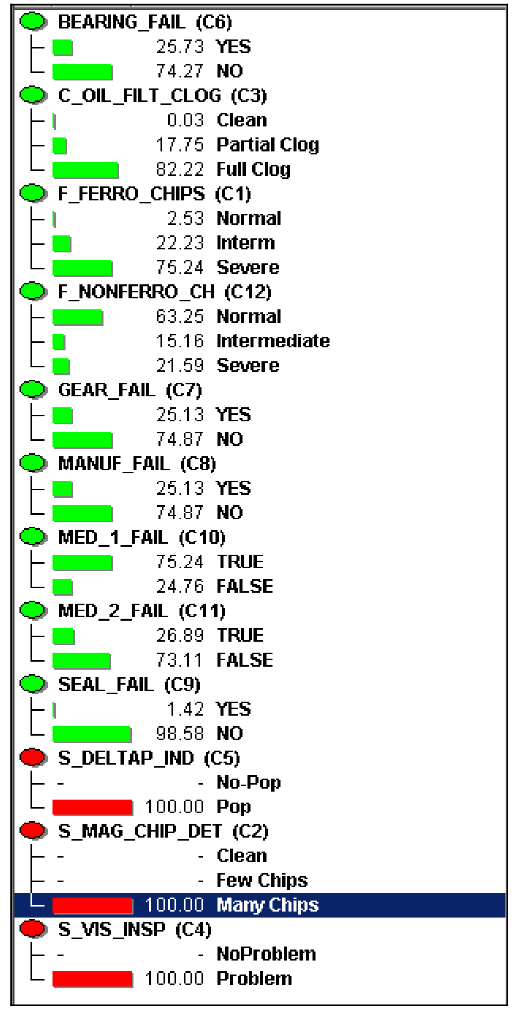
Conditional Probability: Prob(S_DELTAP_IND |C_OIL_FILT_CLOG)

- Specify conditional probabilities and prior probabilities of “root nodes”
- Can propagate evidence up or down the tree
- Observe data (leaf nodes), propagate evidence to determine the probability of being in a failure state

BBN for Lube Problems (Metal and Nonmetal chips) in Gearbox Oil

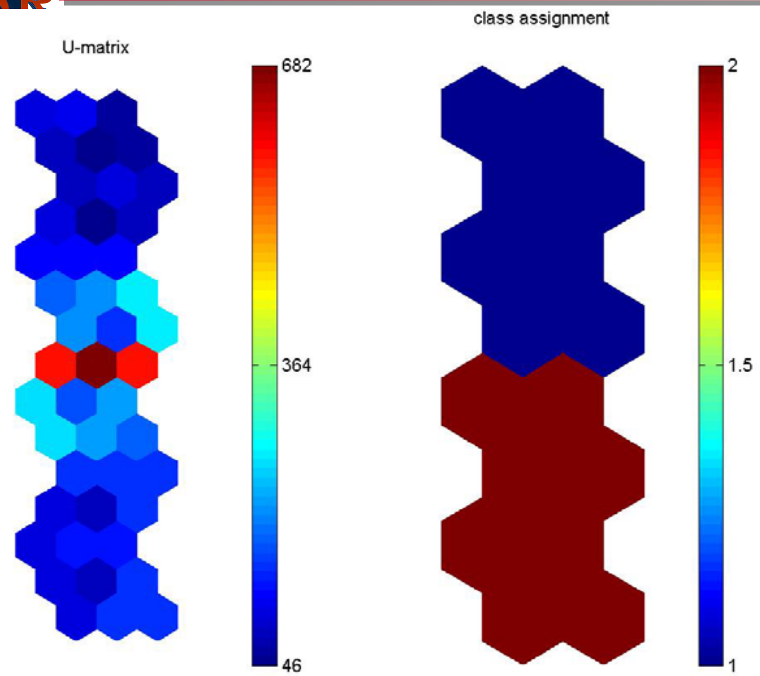


Prior Probabilities

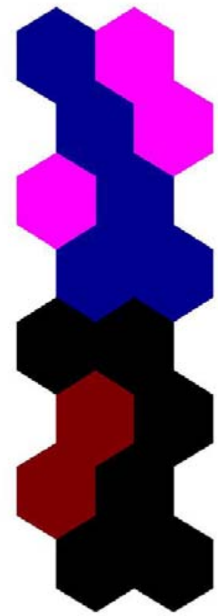


Updated probabilities with three evidence sources

Self-Organizing Maps

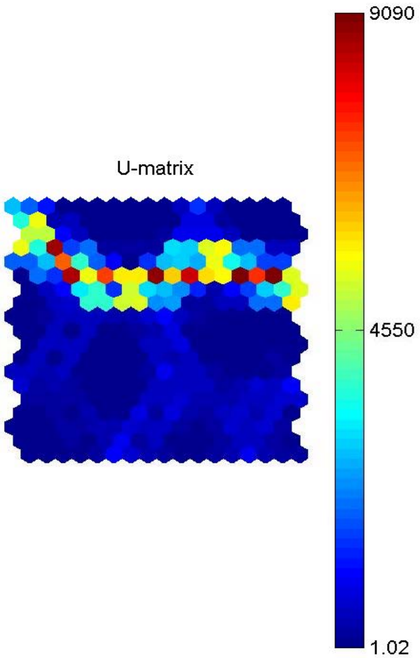


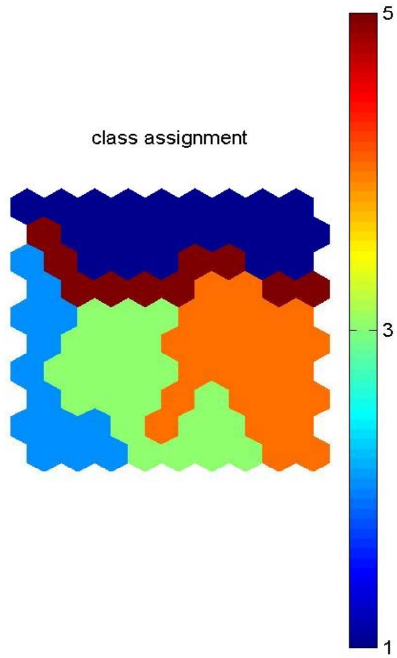
Cluster Map with normal data (pink) and oil leak data (black)

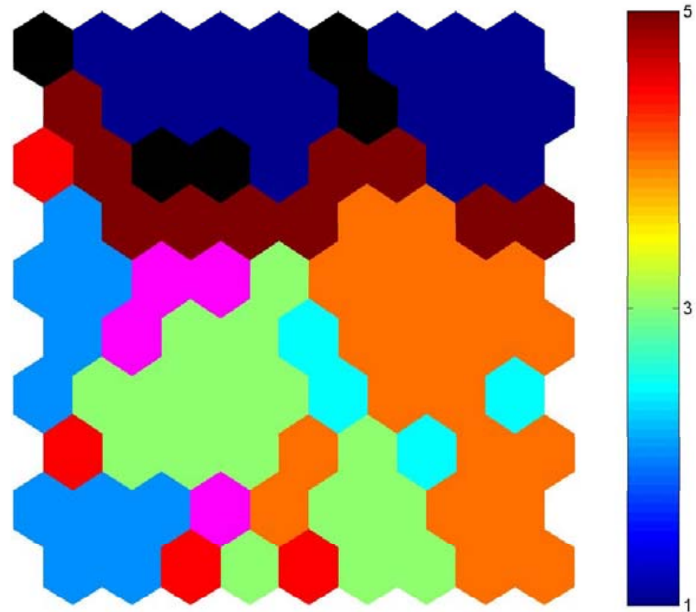


- SOMs are similar to neural networks, but they are based on the principle of competitive learning. Over the course of training, one cell becomes sensitized to a region of input signal values, and suppresses the sensitivity of the cells around it to the same input . Thus, each cell in the network is activated by a different constellation of sensor input values.
- The Self in Self Organizing Maps refers to the fact that the network trains itself, without any preconceived ideas of what the final outcome should be.
- Much of the SOM's power lies in its ability to reduce the dimensionality of an input vector space, while still retaining the distance relationships within that space.
- SOMS provide a mapping from input to output space, need some type of classification algorithm such as a clustering algorithm to classify the data.

Self-Organizing Maps







TESTING DATA

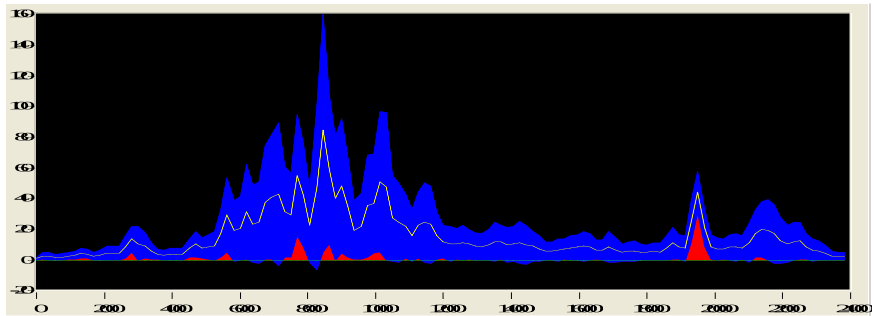
Class 1 (dark blue) represents oil-leak classification.
Class 2(light blue) represents tooth wear.
Class 3 (green) denotes normal data files.
Class 4 (orange) represents gear misalignment.
Class 5 (brown) is undesignated.

Sandia National Laboratories

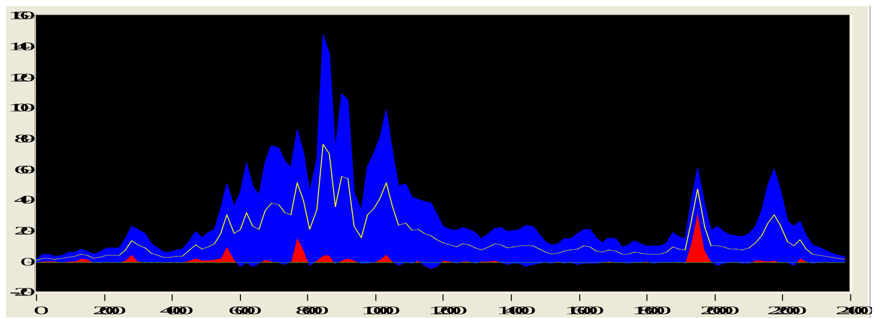
Frequency Domain Signal Comparison

Center for System Reliability

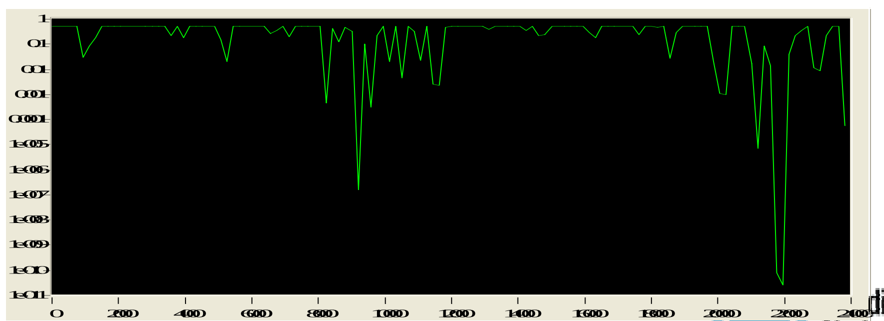
Establish Baseline Signature under fault-free conditions



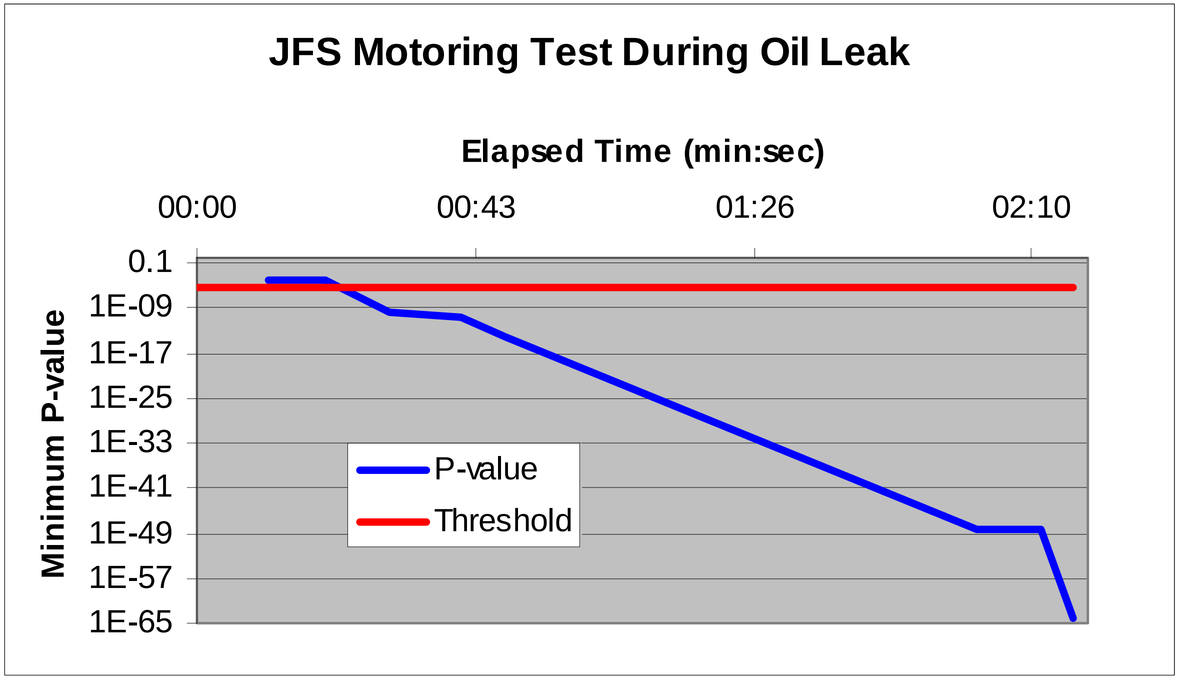
Establish Comparison Signature



Conduct Hypothesis Tests to determine existence of fault



Preliminary Results of Hypothesis Testing Algorithm



30 seconds => Problem Detected

False Positive rate set at 1/1000

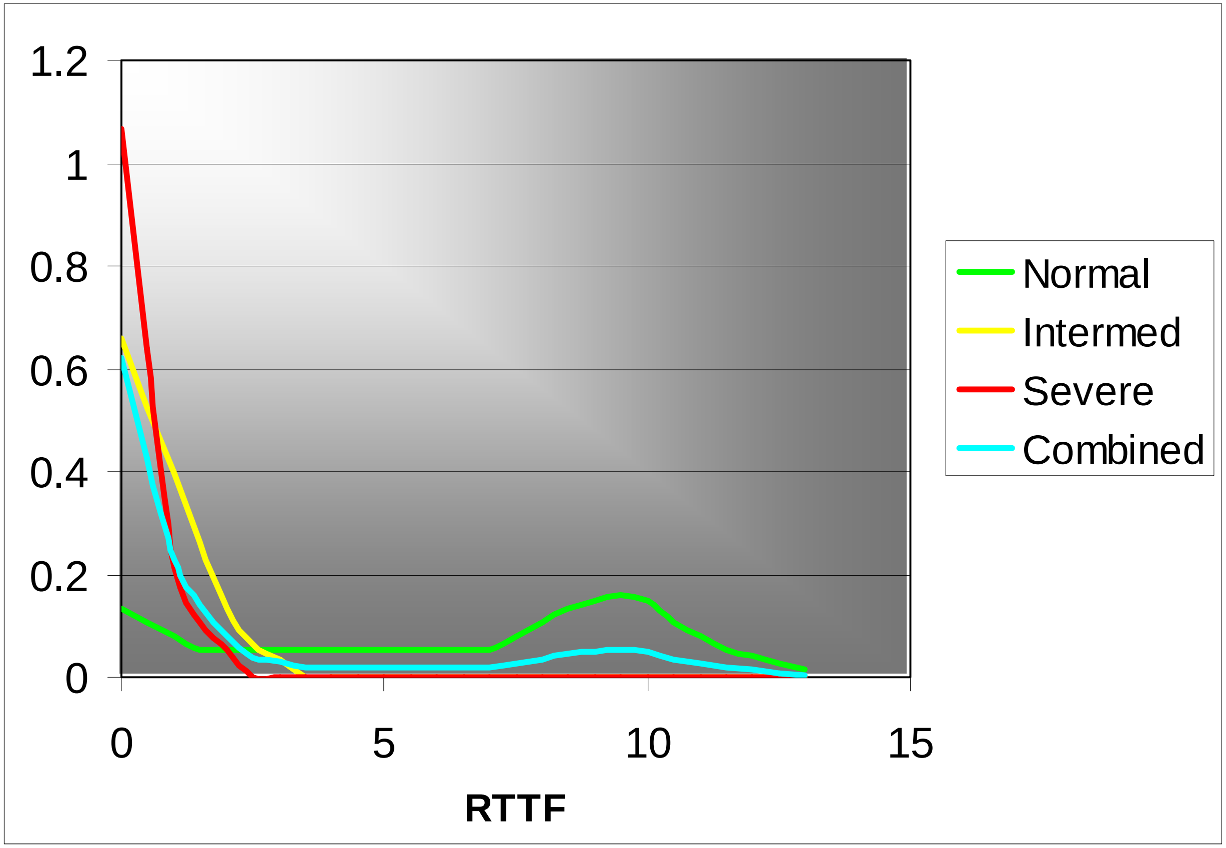
H0: Mean frequency amplitude within 10% of baseline

Estimation of Remaining Useful Life

- Each failure mode can be in a variety of states
- Each state has an associated Time-to-Failure distribution with pdf $f_i(t)$
- Remaining Time-to-Failure distributions, $r_i(t)$, are calculated by conditioning on the failure mode surviving to time t_{now}: $r_i(t) = \dfrac{f(t + t_{now})}{\int_{t_{now}}^{\infty} f(t)\,dt}$
- Overall distribution of RUL, g(t) calculated by weighting component states:

$$g(t) = \lim_{b \to a^+} \frac{P(a < t < b)}{b - a} = \lim_{b \to a^+} \frac{\sum_{i=1}^{n} s_i \int_a^b r_i(t)\,dt}{b - a}$$

Estimation of Remaining Useful Life



Note: Sandia has developed analytic formulas for calculating the CDF and PDF of a "wearout distribution." This is a three part distribution characterized by a percent of failures during burn-in, a percent of failures during constant failure rate period, and a normal end-of-life distribution.

Virtual System Simulator

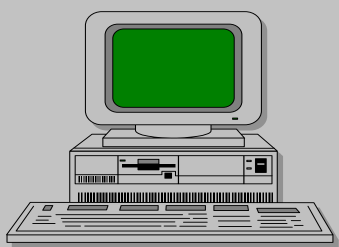
Center for System Reliability

PROGNOSTICS & HEALTH MGMT.

A software tool that simulates the behavior of a system including failures, maintenance, and sensor signals

Virtual System

Reliability Model



Virtual System

Planned Use Schedule

Simulated Failure and Repair Events

Simulated Sensor Data

Simulated Mission Profile

Scenario Generation

Performance Metrics:
Mission Completion Prob.
Maintenance Cost
Downtime
Availability
Parts Requirements

Motivation

- **Real system experiences failures and repairs too infrequently to support PHM**
- **Require capability for high-speed, realistic, reliability simulation of system to be monitored**
  - **- Support PHM design & testing**
  - **- Provide platform for realistic demos**
  - **- Analyze consequences of maintenance decisions**

Sandia National Laboratories

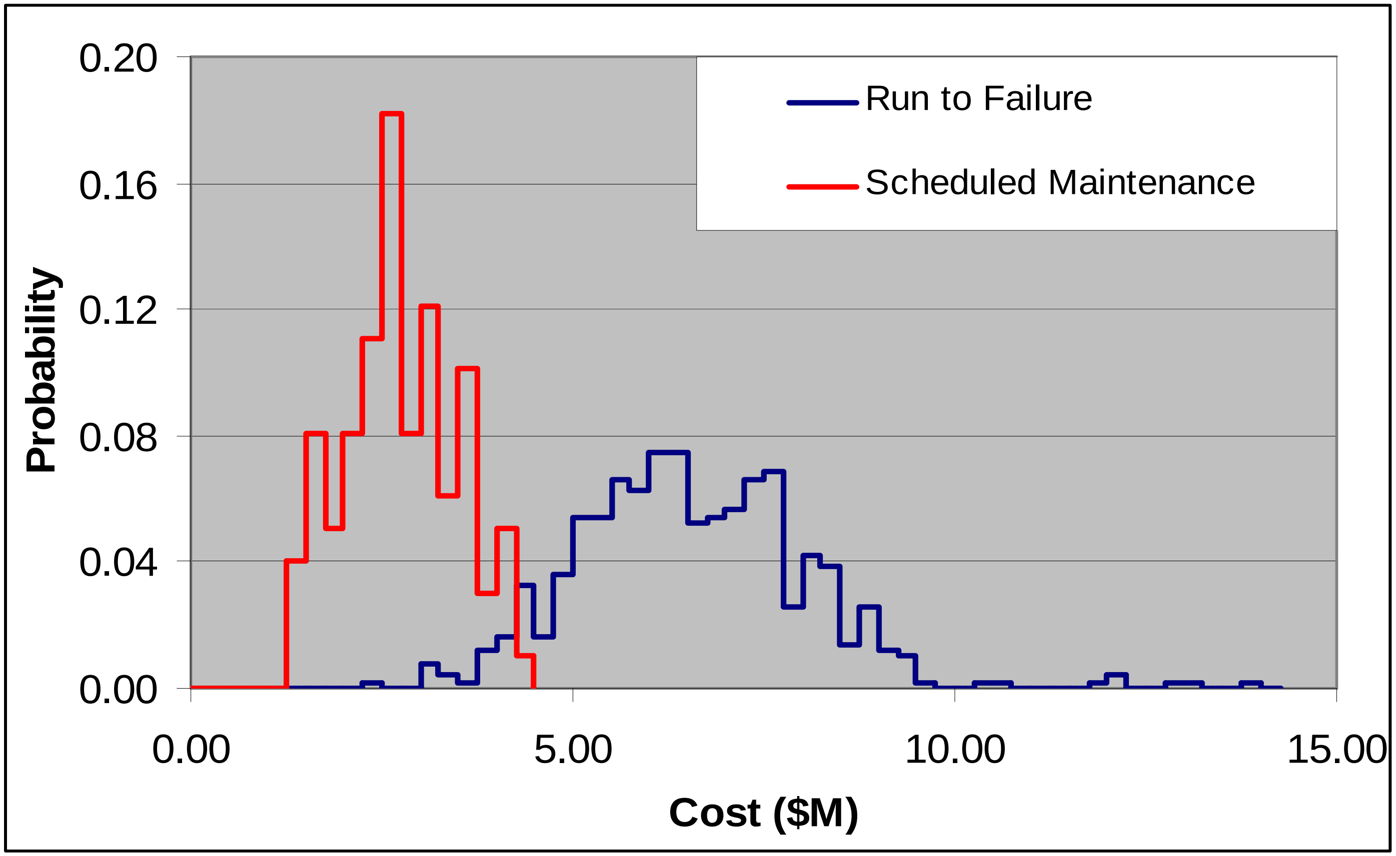
Example

- Based on data from pressurized water reactors (PWRs) in the United States during the period of 1990 – 1995
- Dataset represents 739 failures during 3,307,081 operational hours and 135,742 hours of outage time from 69 plants
- Assumed that each PWR required four weeks of scheduled outage time every 18 months for refueling.
- MTBF is 4170 hours and MTTR is 171 hours for the PWRs represented by the dataset.

Example Scenario

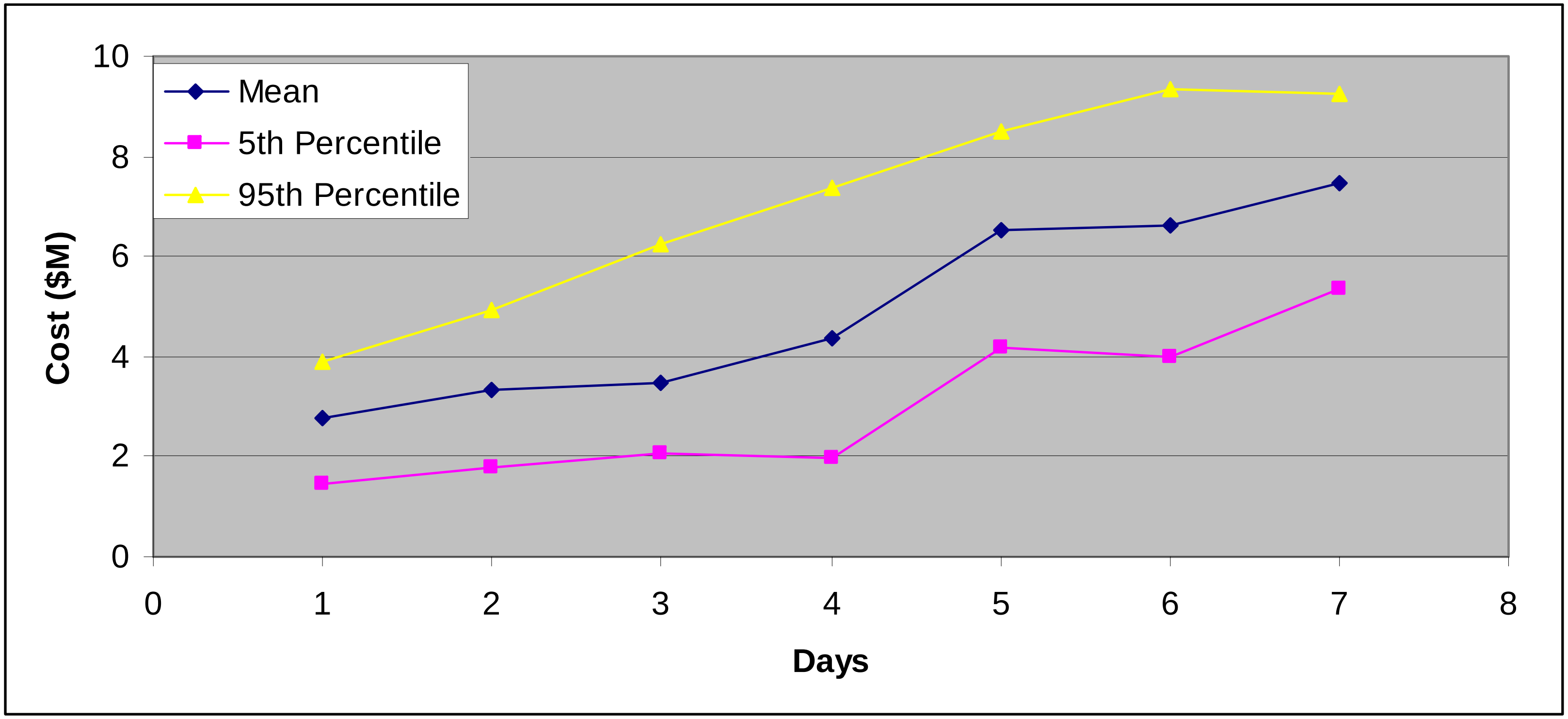
- On June 10, 2002, vibration sensors indicate that a turbine failure appears likely to occur in 1 to 2 weeks. In this case, excessive vibration would be expected to cause the turbine to trip.
- The Consequence Engine evaluated two cases:
  - 1) run to failure (trip)
  - 2) turbine maintenance scheduled within a day of the warning indication.
- The two cases are compared based on the cost of lost electricity generation using the wholesale price projections.
- The expected (i.e., mean) cost of lost generation for the run-to-failure scenario is about \$6.7M whereas the expected cost when maintenance is scheduled immediately is about \$2.9M

Example Scenario



Vary Maintenance Timing

Center for System Reliability



Cost of Lost Electricity Generation vs Days Delay in Maintenance

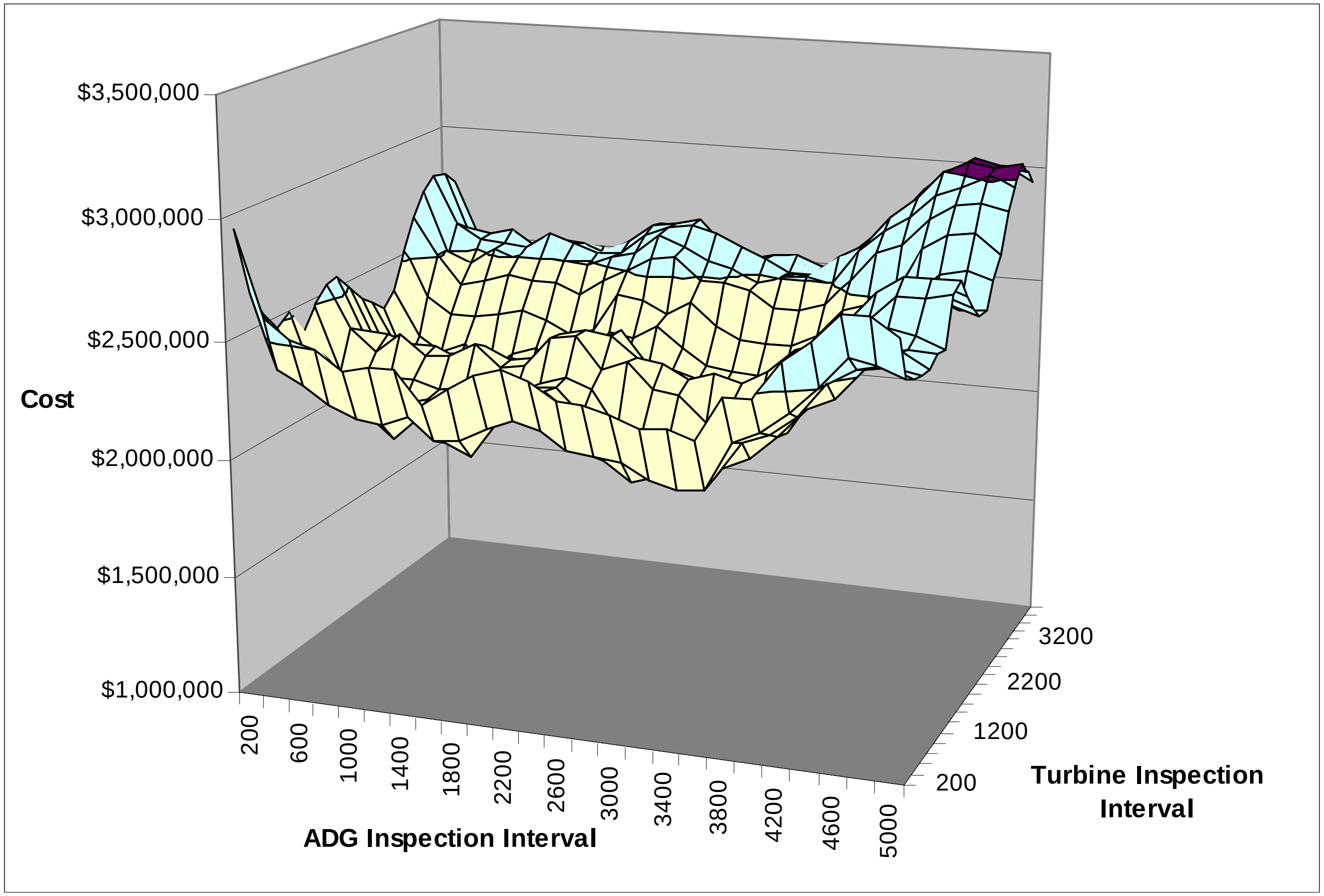
Sandia National Laboratories

Virtual System Simulator

- Discrete-event simulation capability
  - simulate failures, maintenance actions, downtime, etc.
- Spares model determines time at which a part will be available
- Capability to allow for different operational states (e.g., partially mission capable vs. up or down). We have implemented this through “success paths” in the underlying fault tree.
- Optimization capability: can optimize performance measures with respect to decision variables such as
  - Maintenance times, intervals, false positives, false negatives
  - Stocking levels, restock times, etc.

Mean Maintenance Cost

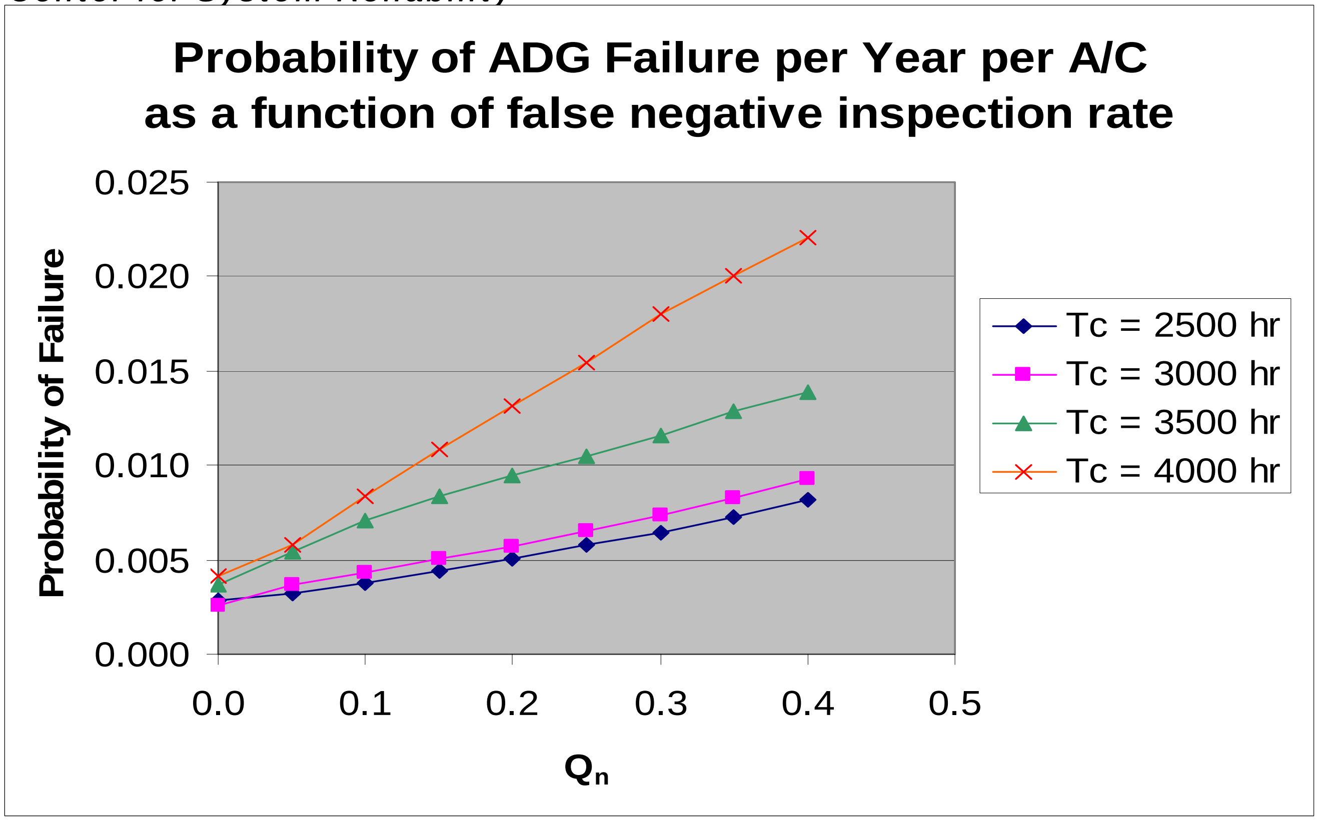
Center for System Reliability



Sandia National Laboratories

Consequence Example

Center for System Reliability



This graph can be used to determine the required precision of a prognostic system to maintain a certain reliability level. If, for example, an annual failure probability for the ADG per aircraft was desired to be 0.5% or less, the accuracy of a prognostic system with a 3500 hour time change interval would require a false negative probability of around 3%.

Sandia National Laboratories

Summary

Center for System Reliability

- It is probably only feasible to develop prognostics for a limited set of failure modes
- PHM requires much data tracked at the serial number level
- PHM requires data collection on a fleet of “good” parts to see normal signatures
- PHM also requires seeded fault testing and collection of field failure data to determine abnormal signatures
- PHM requires testing and verification of algorithms to minimize false positives and false negatives
- Development of features or metrics that can detect gradual aging and long-term trends is difficult. However, features to determine catastrophic failure modes are more feasible to develop, but lead-time is a critical issue.

State of PHM "Science"

- Sensor Feature Extraction/Sensor Fusion
  - There are many algorithms and approaches for data fusion, including neural networks, case-based reasoning tools, and statistical methods.
  - However, ALL of these methods rely heavily on having a large knowledge database which is often not available
- Component Health Estimation is the most difficult
  - We do not have a good way of linking physics-of-failure models to components such as electronic circuit boards, gearboxes, etc.
  - We do not understand how to integrate various types of evidence about a part (such as age, condition, current flight parameters, etc.) to update the age
- Consequence Analysis
  - Most prognostic systems focus solely on predicting remaining life
  - Understanding how potential maintenance actions affect system level decisions in terms of cost, availability, mission effectiveness, etc. is a complex problem