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Using AI and Machine Learning to Protect Physical Assets

Herman Scheepers

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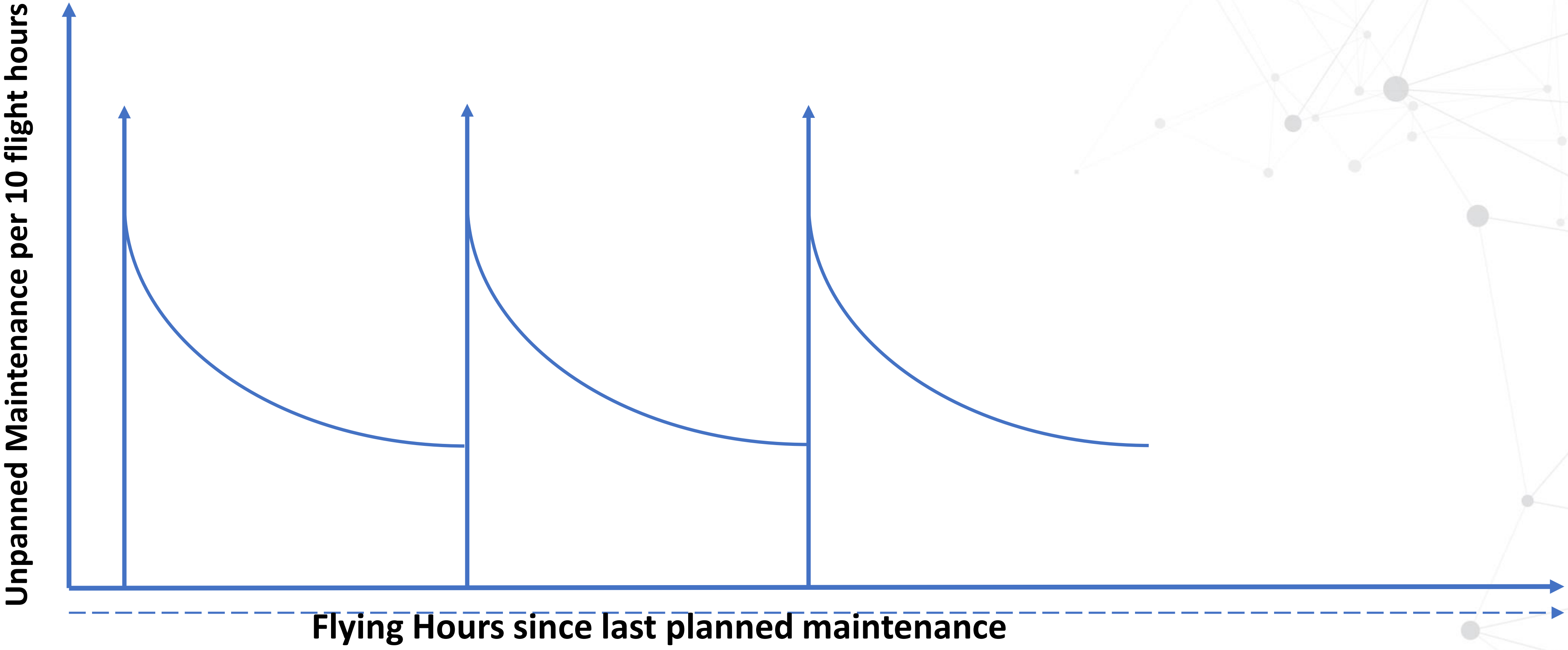
The Waddington Effect



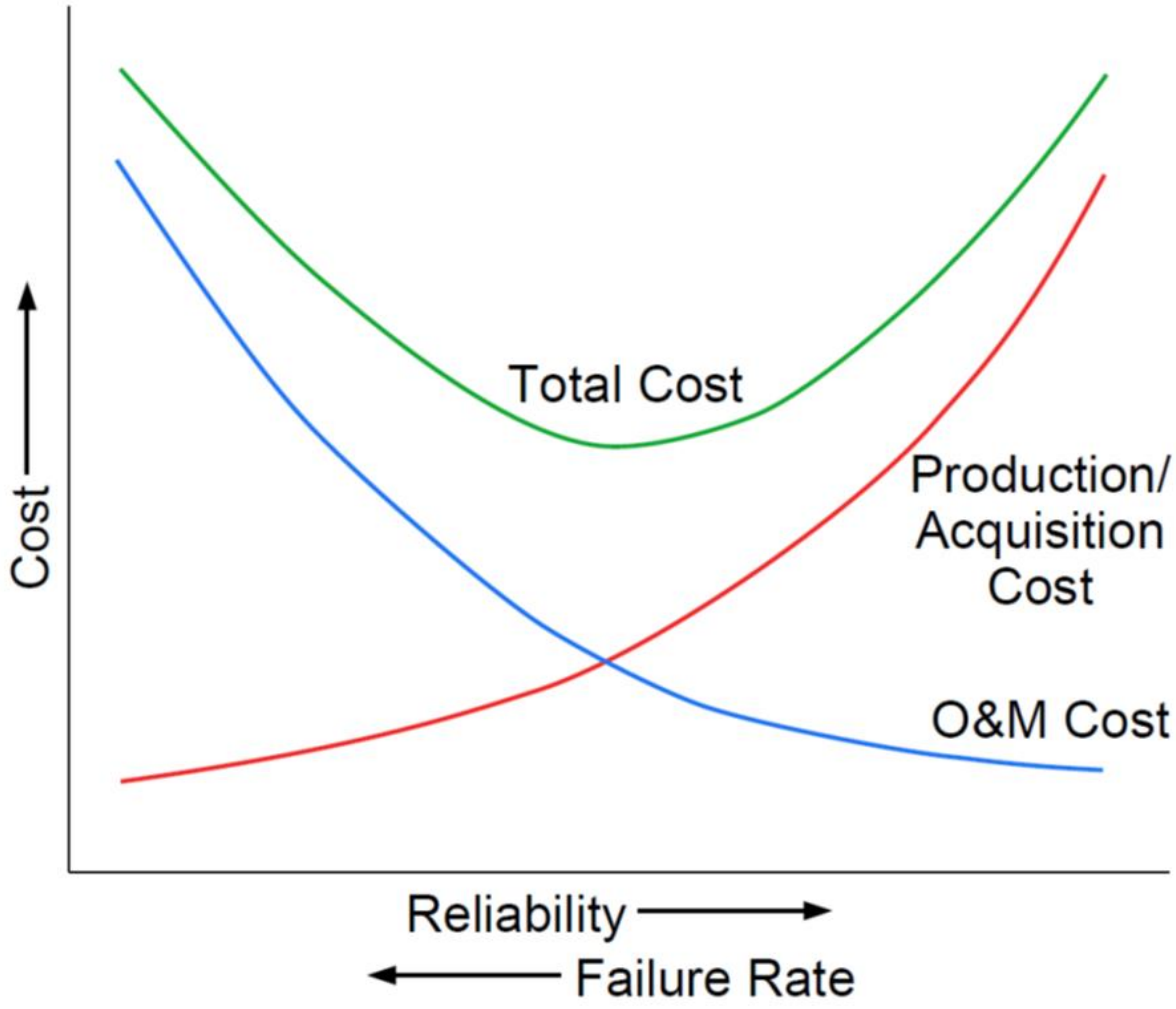
Nolan and Heap

- Each unit is inspected at regular intervals and remains in service until its failure resistance falls below a defined level- that is, until a **potential failure (PF)** is discovered.
- **On-condition** tasks discriminate between units that require corrective maintenance to forestall a functional failure and those units that will probably survive to the next inspection - they permit all units of the item to realize most of their useful lives.

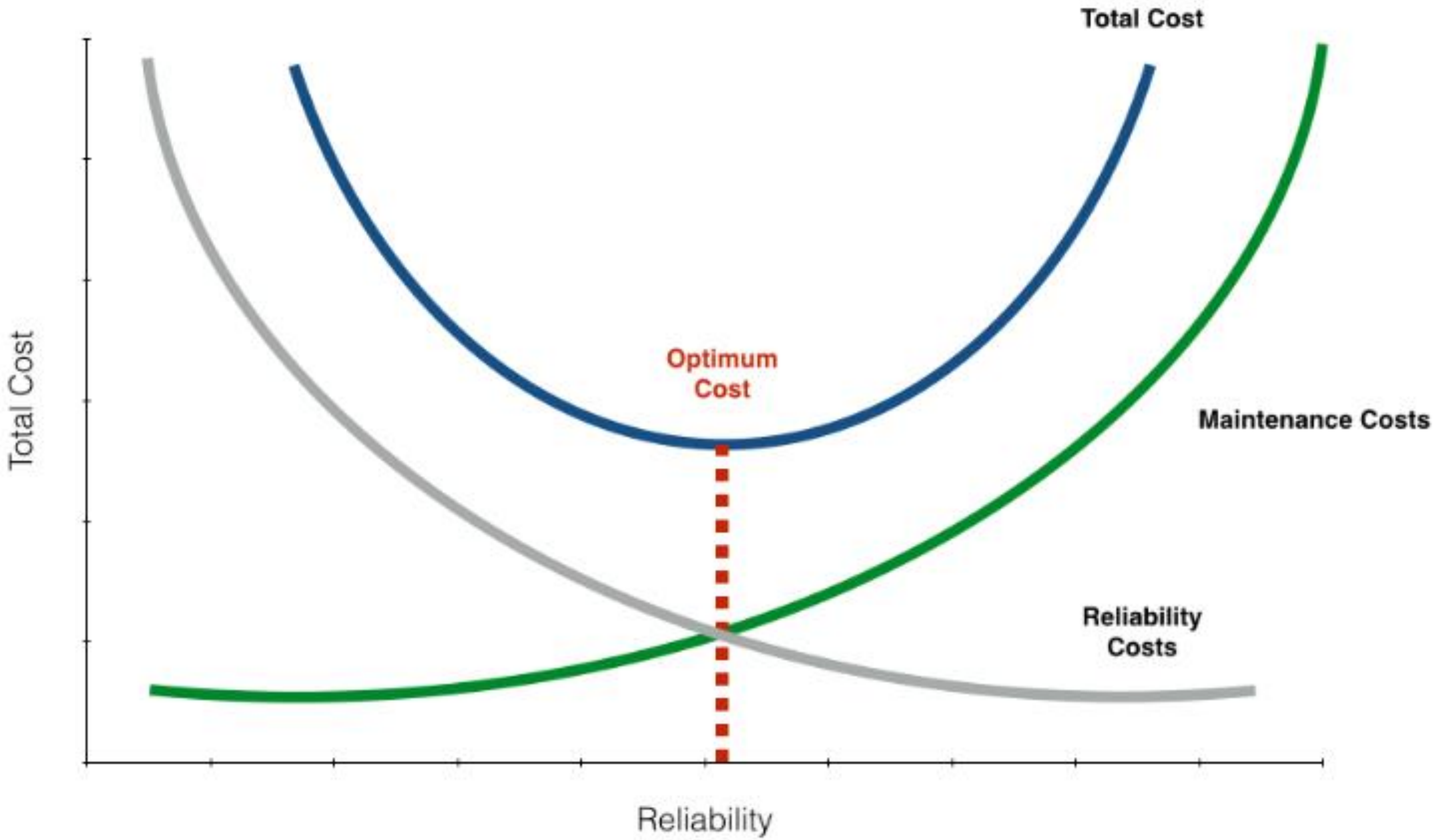
MSG3

- Maintenance only effective if task applicable
- No improvement in reliability by excessive maintenance
- Needless tasks can also introduce human error
- Few complex items exhibit wear out
- Monitoring generally more effective than hard-time overhaul - Condition-based maintenance (sometimes known as CBM)
- Reliability only improved by modification
- Maintenance may not be needed if failure cheaper

Cost of Reliability



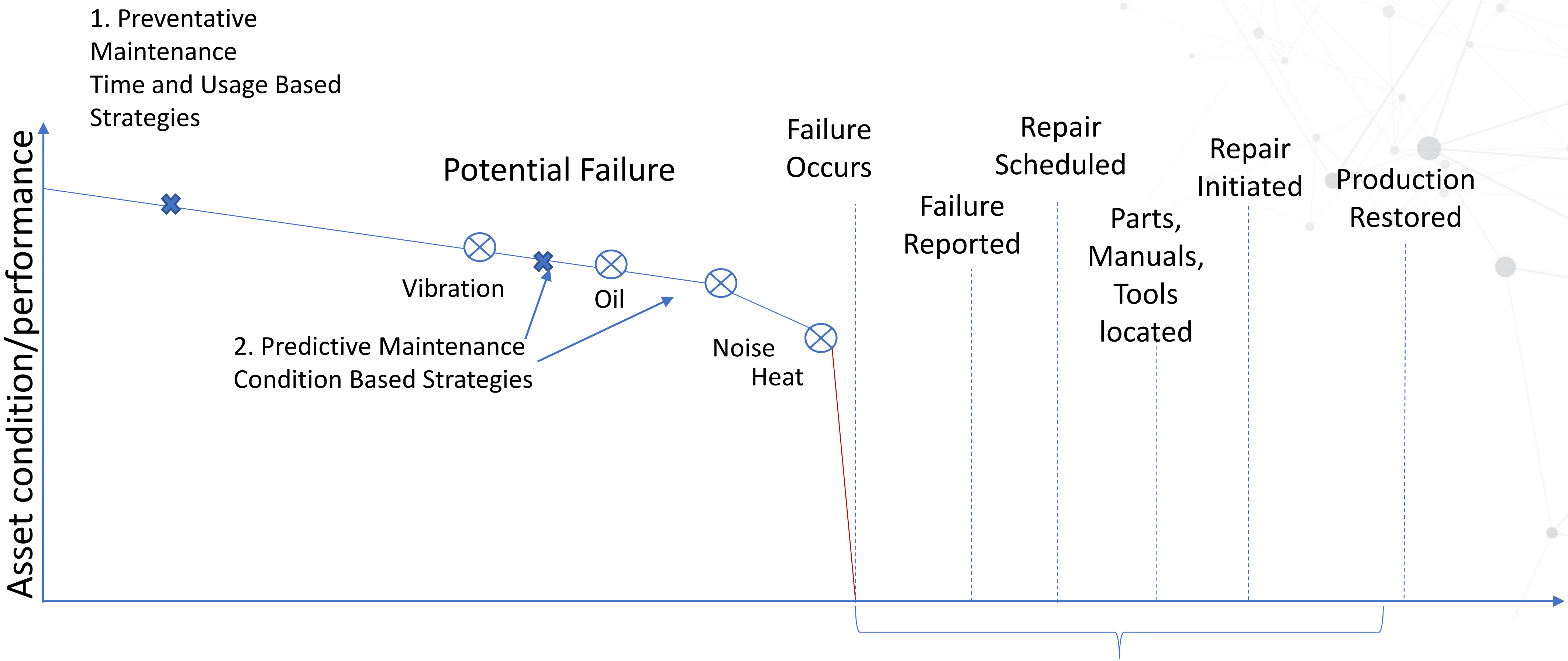
Cost Of Reliability



So HOW/WHY AI and Analytics?

- Maximise (or at least extract) from own and industry data
- Reduce risk
- Reduce maintenance without increasing risk
- Anomaly Detection for early warning
- Regression to predict remaining useful life
- Classification models to predict failure in a certain interval / time window
- Survival analysis
- Models may include deep learning / AI

It Can Save Money



Given the time it takes to restore service, in addition to other value leaks, would it not be a good idea to predict or pre-empt the failure using advanced analytics or condition monitoring? On-line where feasible.

Optimum Planned Maintenance

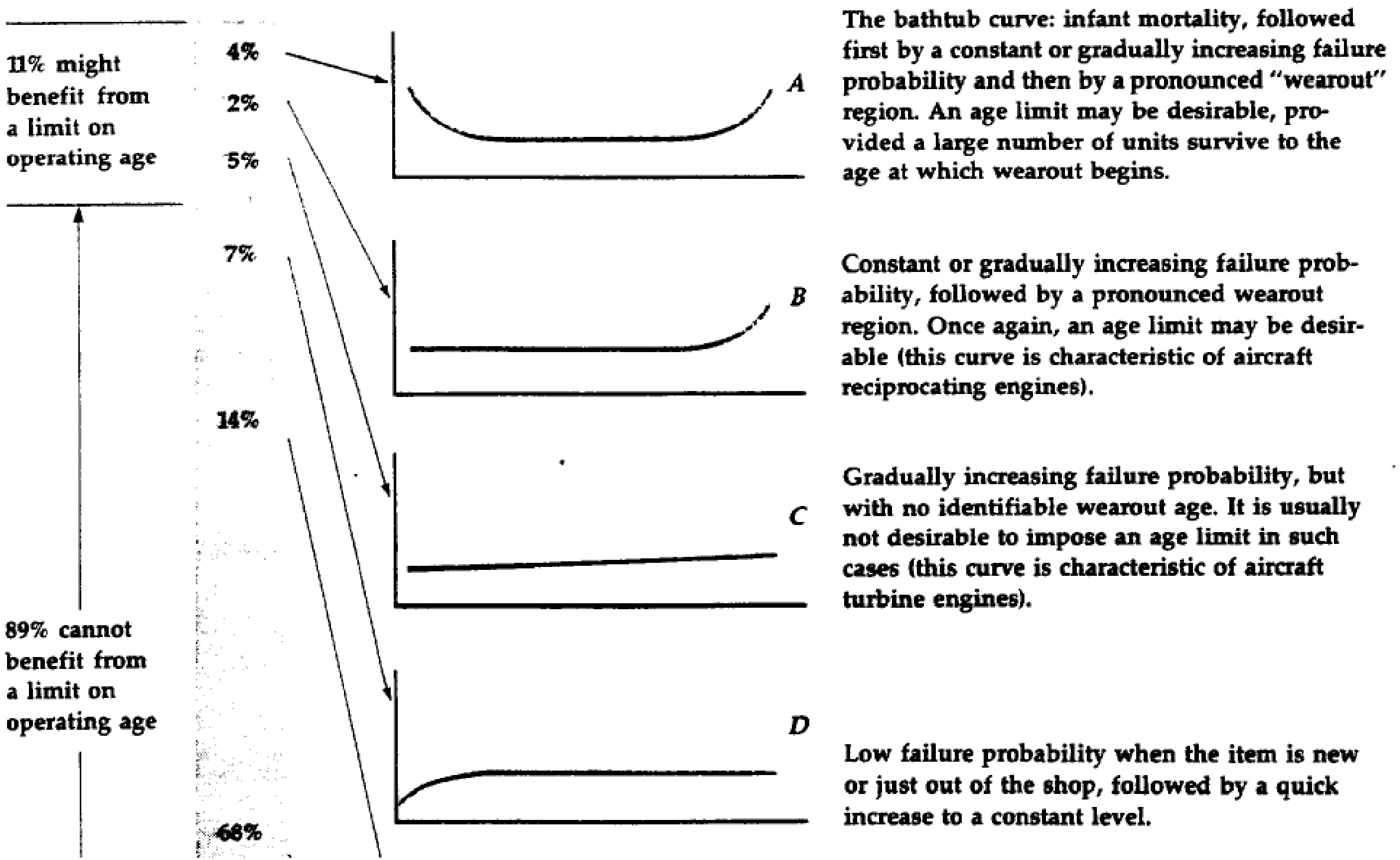
Function of:

- the probability density function (PDF) of failures, as well as the probability density function of the PF interval (duration of interval from potential failure to actual failure) for all or the dominant failure mode of a system (anything with defined boundaries)
- The cost of planned maintenance
- The probability density function of restoration time
- Direct and indirect costs associated with the failure

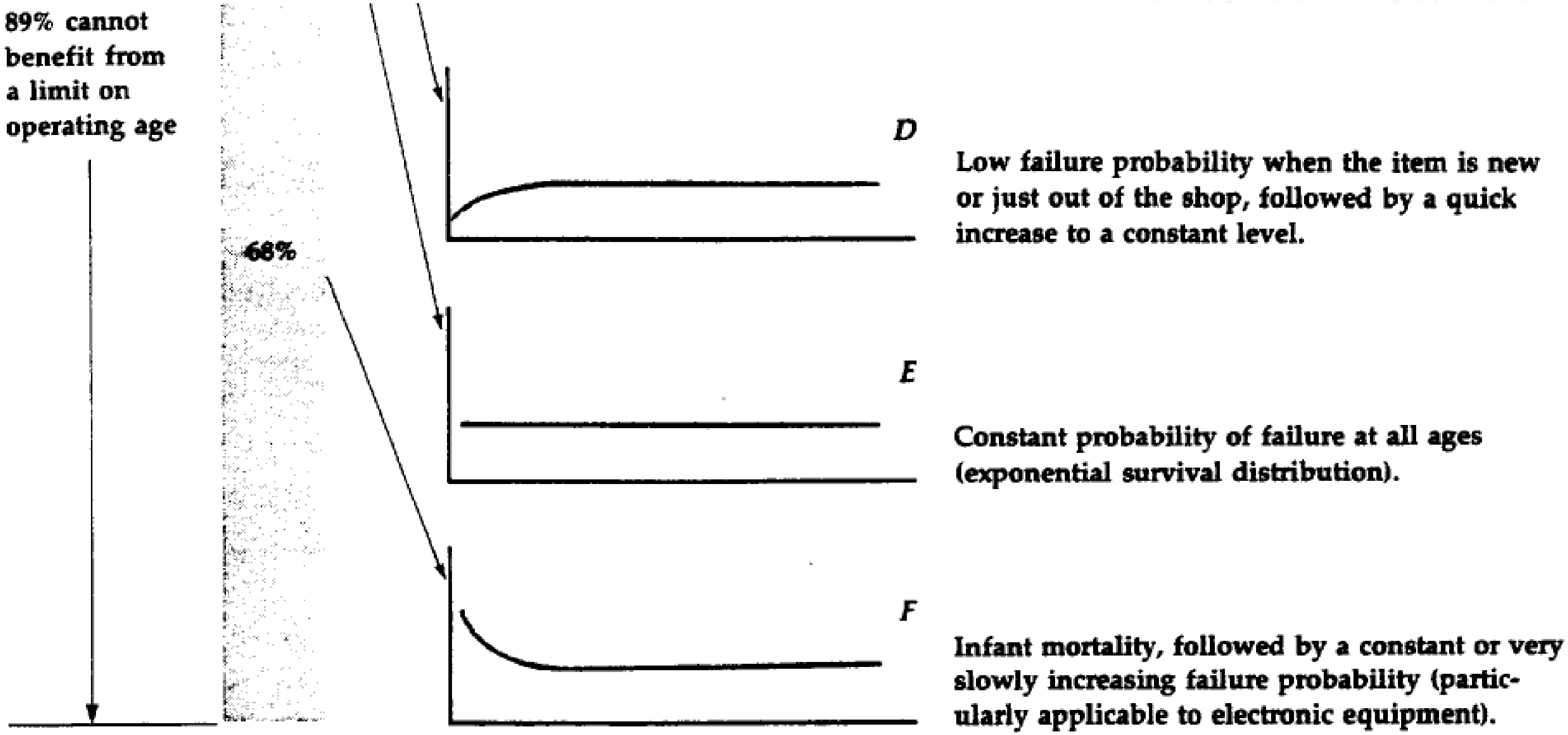
Decision Support

- Ideal scenario:
- Detect
- Diagnose
- Prognose
- Decide
- Decision can be immediate after detection

Failure rate curves



Most common was random



General

- International Organization for Standardization: "prognostic is the estimation of time to failure and risk for one or more existing and future failure modes
- process whose objective is to predict the remaining useful life (RUL) before a failure occurs given the current machine condition and past operation profile
- Must know the current condition
- Must define failure
- Must know history

Regression

- How long until asset fails?
- Historical data available for each type of event
- Events are known and labelled
- Asset master data available
- Known and relatively smooth failure progression
- One model for each failure mode
- Many models needed for many failure modes, unless a single dominant failure mode

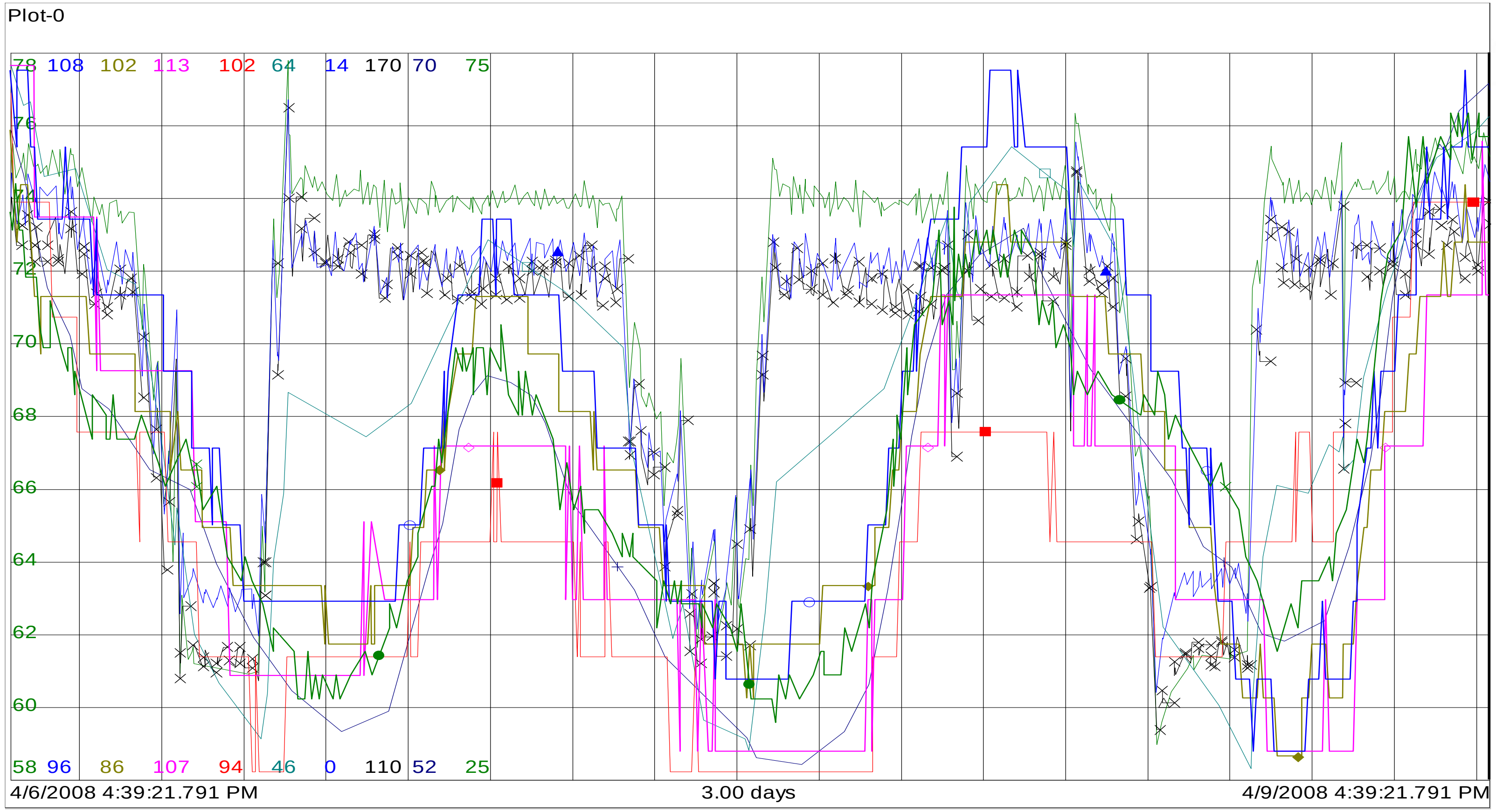
Classification

- Hard to predict exactly when individual asset will fail.
- Classify assets – at immediate risk or not
- Also needs labelled events and classification data
- Similar to regression

Anomaly Detection

- Commercially available
- Widely deployed in industry
- Practical, scalable, generic, and supports diagnosis
- Just need historian or IOT data representing normal operating conditions to train the model
- Can use data containing known failures to test model, but not absolutely essential
- Don’t need to know history or static data
- Domain knowledge vs data science
- Enhanced with diagnostics

Hard to interpret signal data



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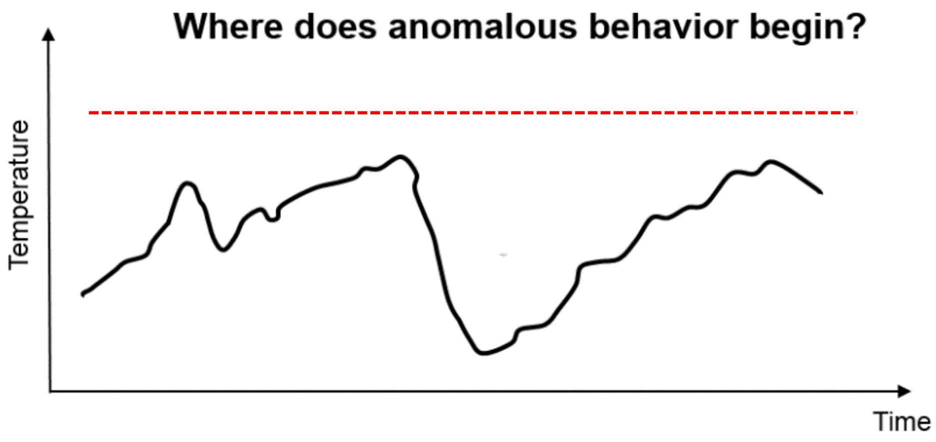
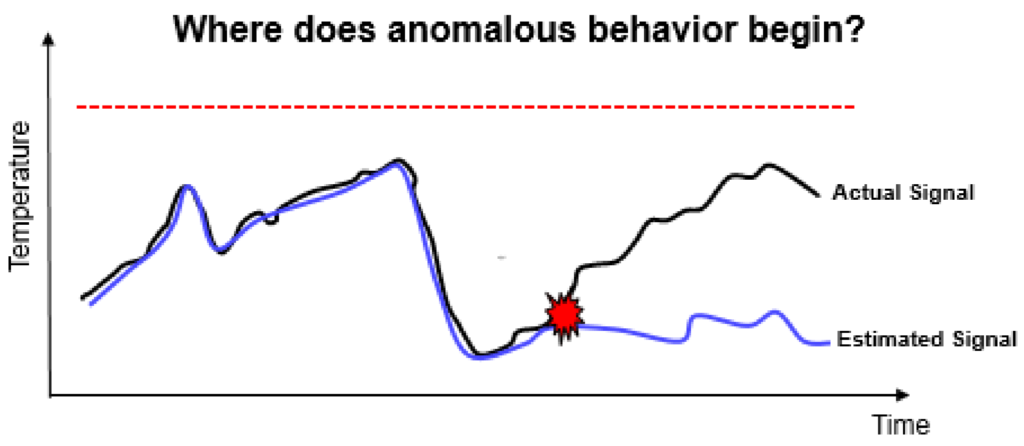
Easier to interpret model output

Traditional Monitoring



- Constant alert/alarm limits are typical
- Damage accumulates prior to reaching limit

Predictive Asset Monitoring



- Actual minus estimated (residual) signal detects anomaly as-soon-as-possible

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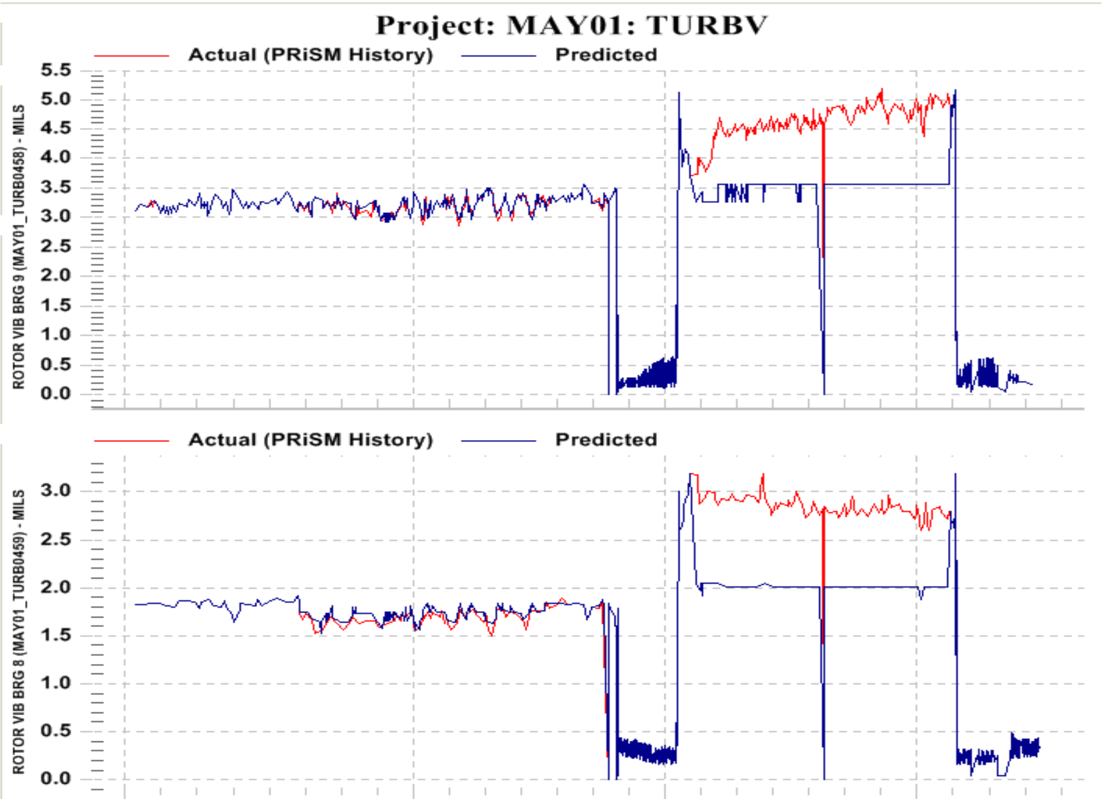
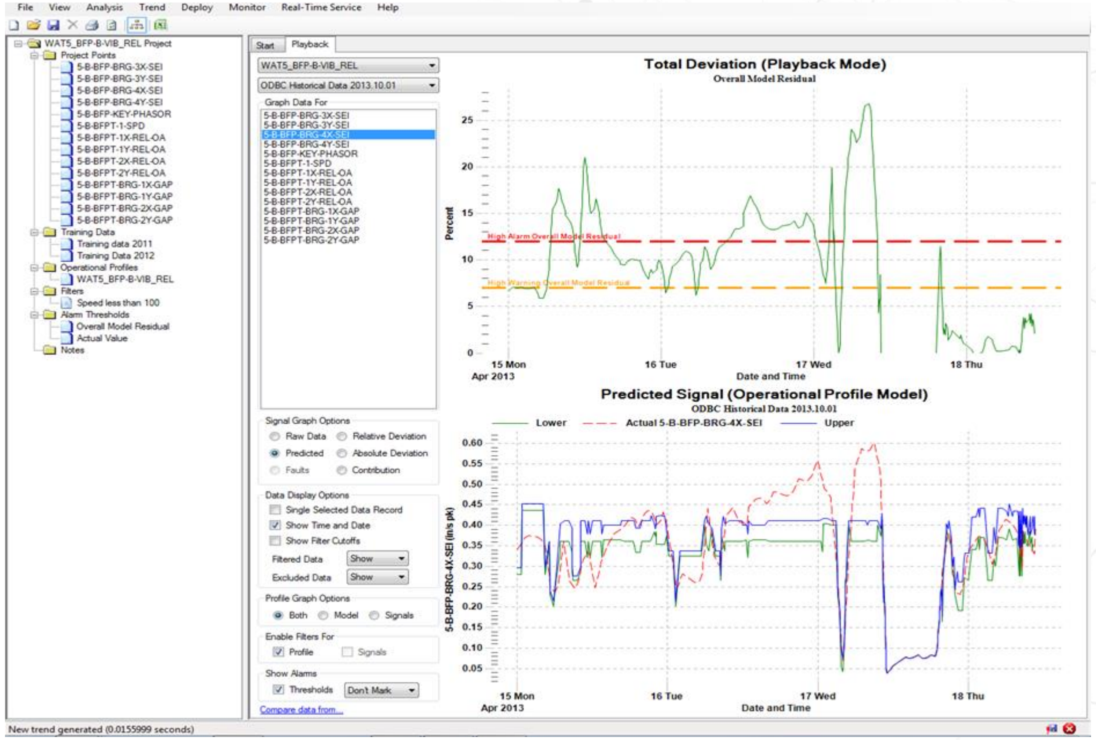
LP Rotor and Boiler Feedwater pump





Survival Models

- Actuarial, similar to models used in the insurance and medical fields – some include deep learning
- Conditional probability of failure at a certain ‘age’
- Weibull analysis
- Probability theory
- Parametric and non-parametric methods
- Can be used to calculate risk profile of a asset population
- Also need very good historical data and failure mode classification
- Used with ‘censored’ data

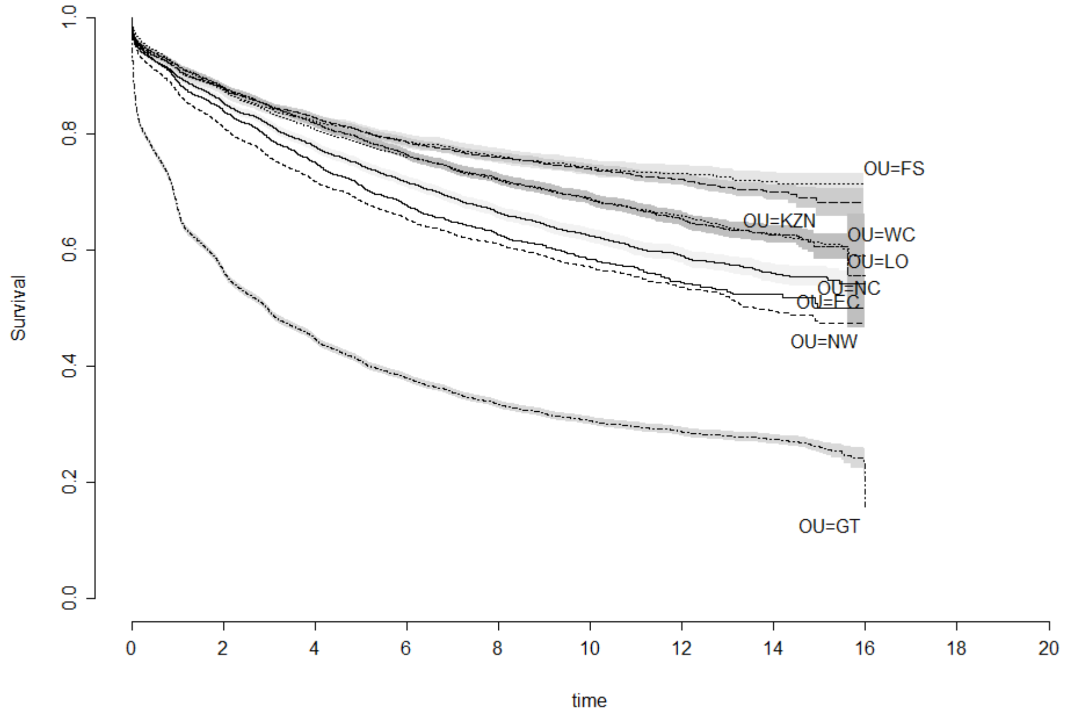
Practical Approach - Asset

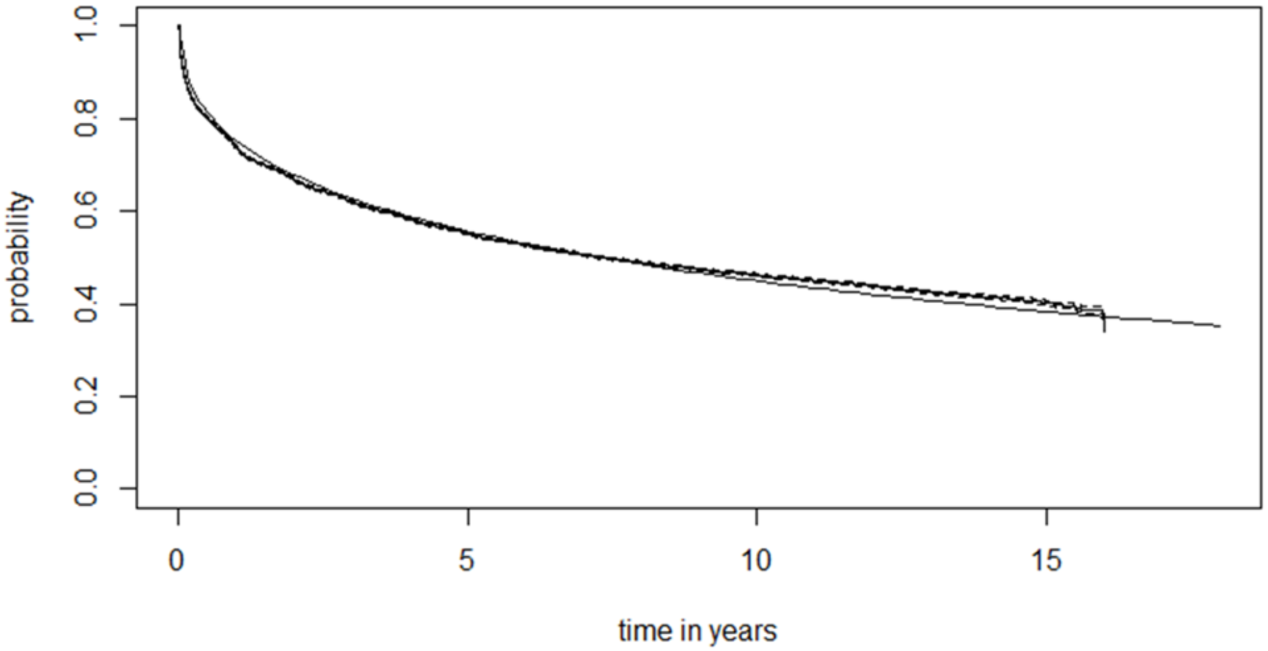
- Process manufacturing, steam / power generation
- Start with anomaly detection – early warning system that can detect incipient fault and classify it based on instrument (training then real time) and reference data: diagnostics
- Model time from potential failure to actual failure for specific problematic dominant failure modes with good data
- If the model proves useful (can support maintenance and operations decisions) – prognostics
- Start with **early warning** pilot / POC if unsure
- Move to diagnosis
- Prognostics models where practical

Practical Approach - Population

- Use survival models to compare asset types and calculate risk
- Identify infant mortality problems
- Determine if wear-out mode applies
- Calculate failure probability density function as input for statistical methods like RCM
- Visualise failure rate as a function of time
- Optimise planned maintenance frequencies
- Optimise spares inventories
- For all approaches start with good asset data practice
- Master data, maintenance, and instrumentation

Survival Function





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Questions

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