Supporting the Elicitation of Engineering Knowledge for Reliability and Maintenance Modelling

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Predictive Maintenance

- Aims to predict when certain maintenance actions will be needed
- Logical development of Condition Based Maintenance (CBM)
- Availability contracts make increased availability beneficial for both parties

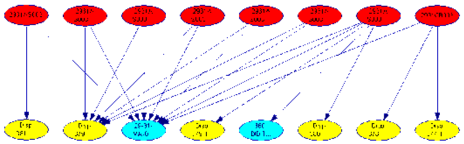
Prognostics

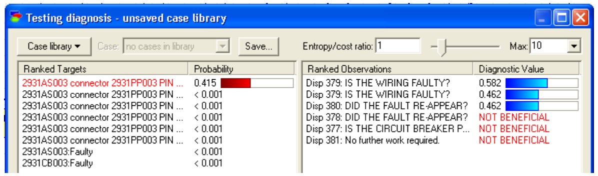
- Several reasons why prognostics is becoming popular:
  - Development of affordable sensors and telecoms
  - Affordable data storage
  - Collected health and usage data
  - Machine learning and data mining
- US Military requires prognostics to be included in all new platforms.

Some Approaches to Prognosis

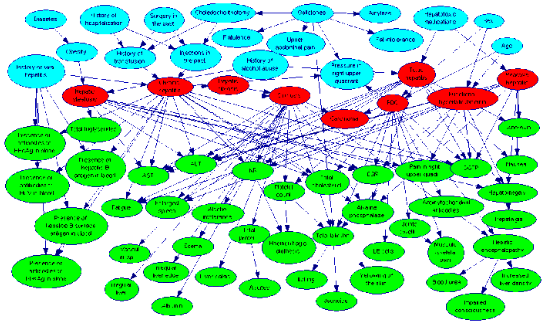
- Data-driven approaches, e.g. neural networks
- Physics of Failure Modelling
- Statistical Modelling, e.g. proportional hazards model
- Probabilistic Graphical Modelling

Bayesian Networks

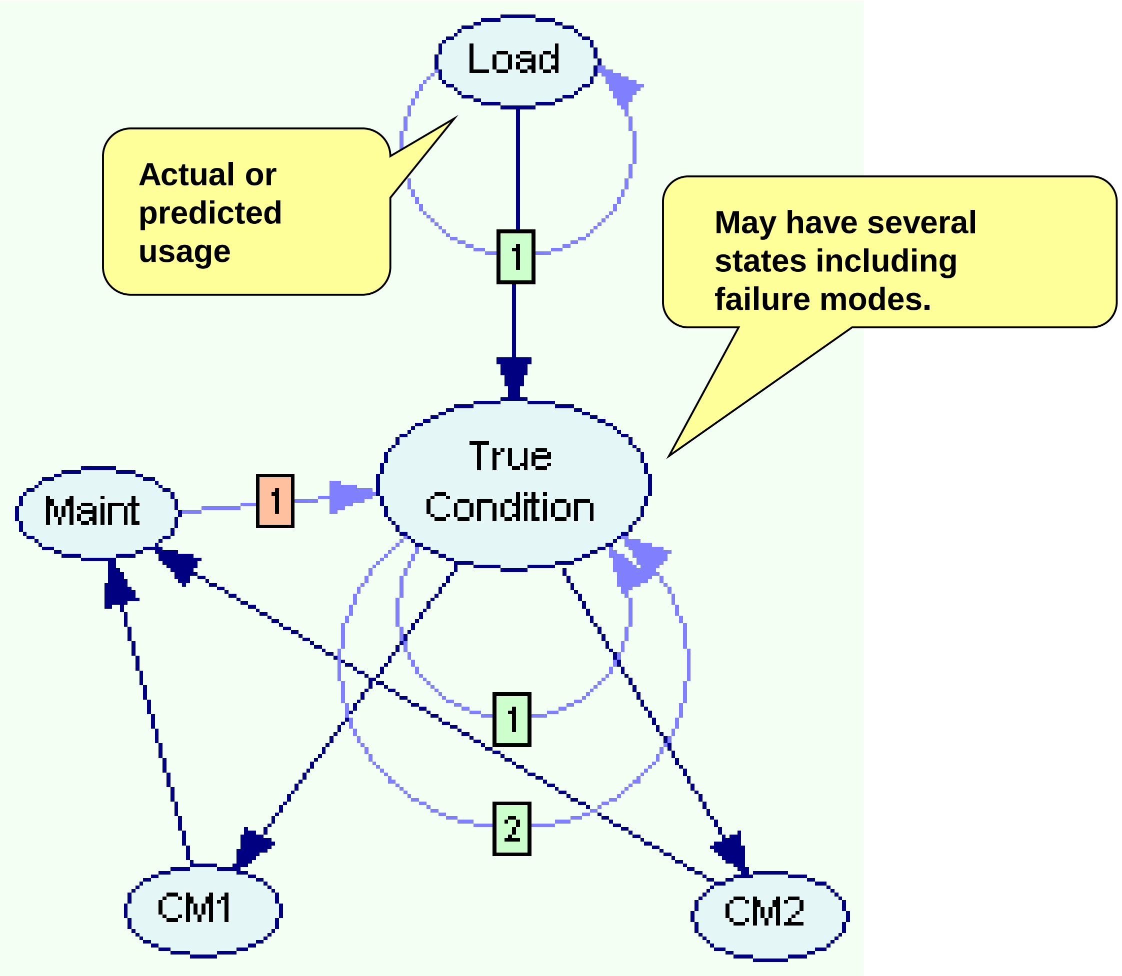


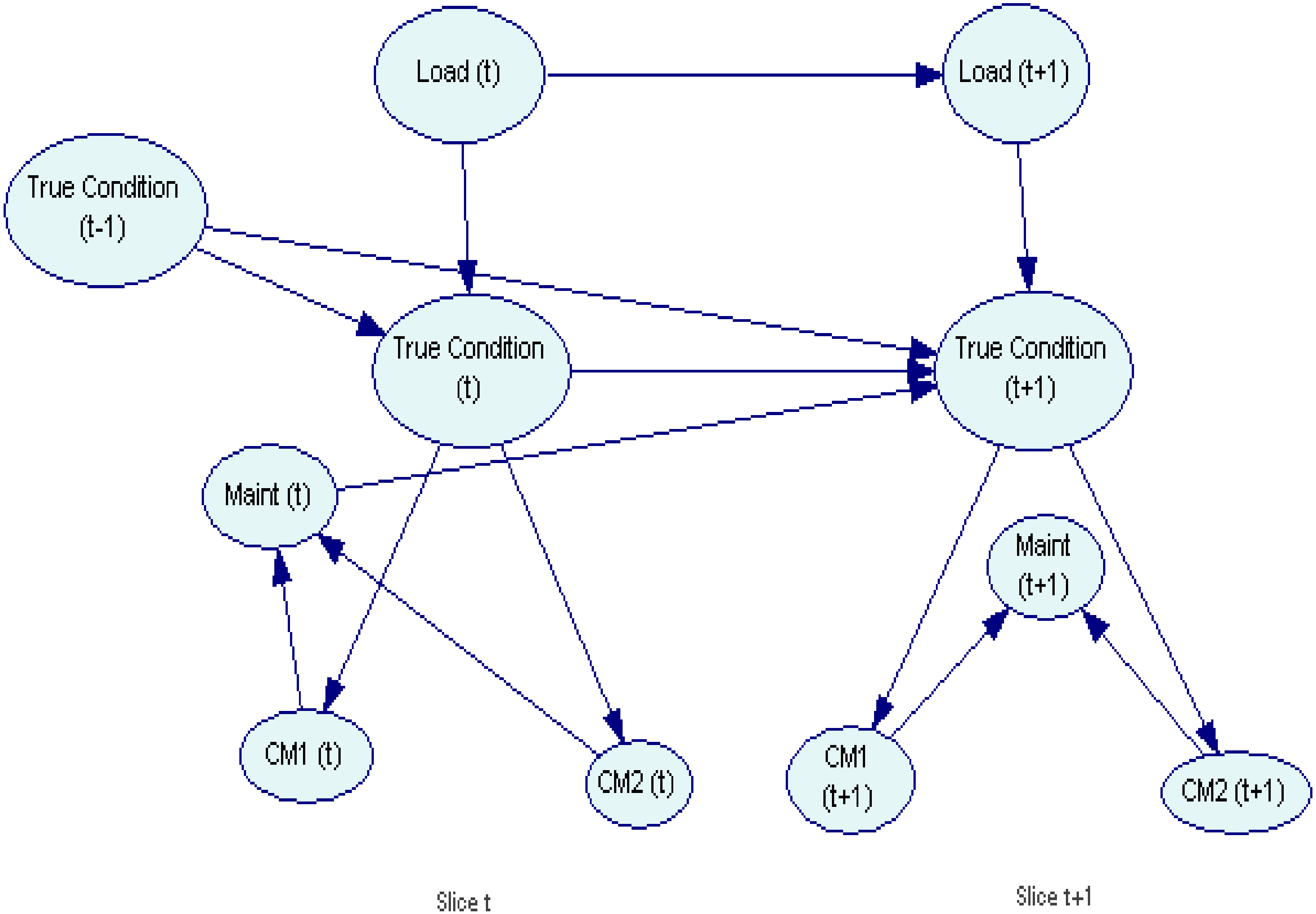


- BN is a popular modelling tool for domains involving uncertainty
  - The graphical representation of dependencies between variables is intuitive for domain experts.
  - Allows for flexibility in combining knowledge and data from different sources
    - Human expertise
    - Learning models from data (both graph structure and parameters)
- BNs are proven in industrial applications for diagnosis:
  - Aircraft diagnosis (Boeing)
  - Land Vehicles (GM)
  - Printers (HP)



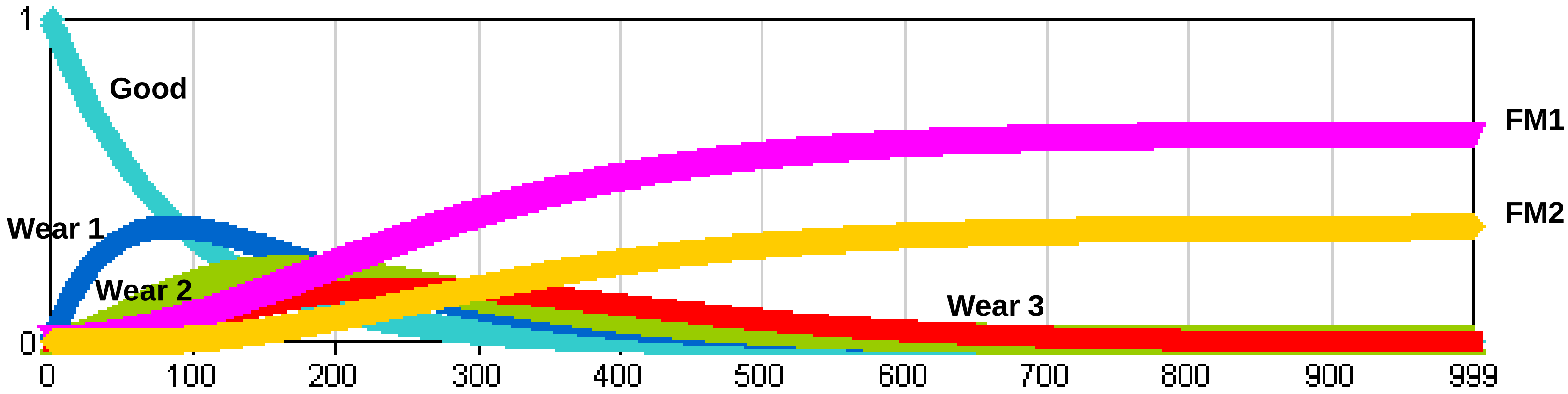
A Simple Prognostic DBN



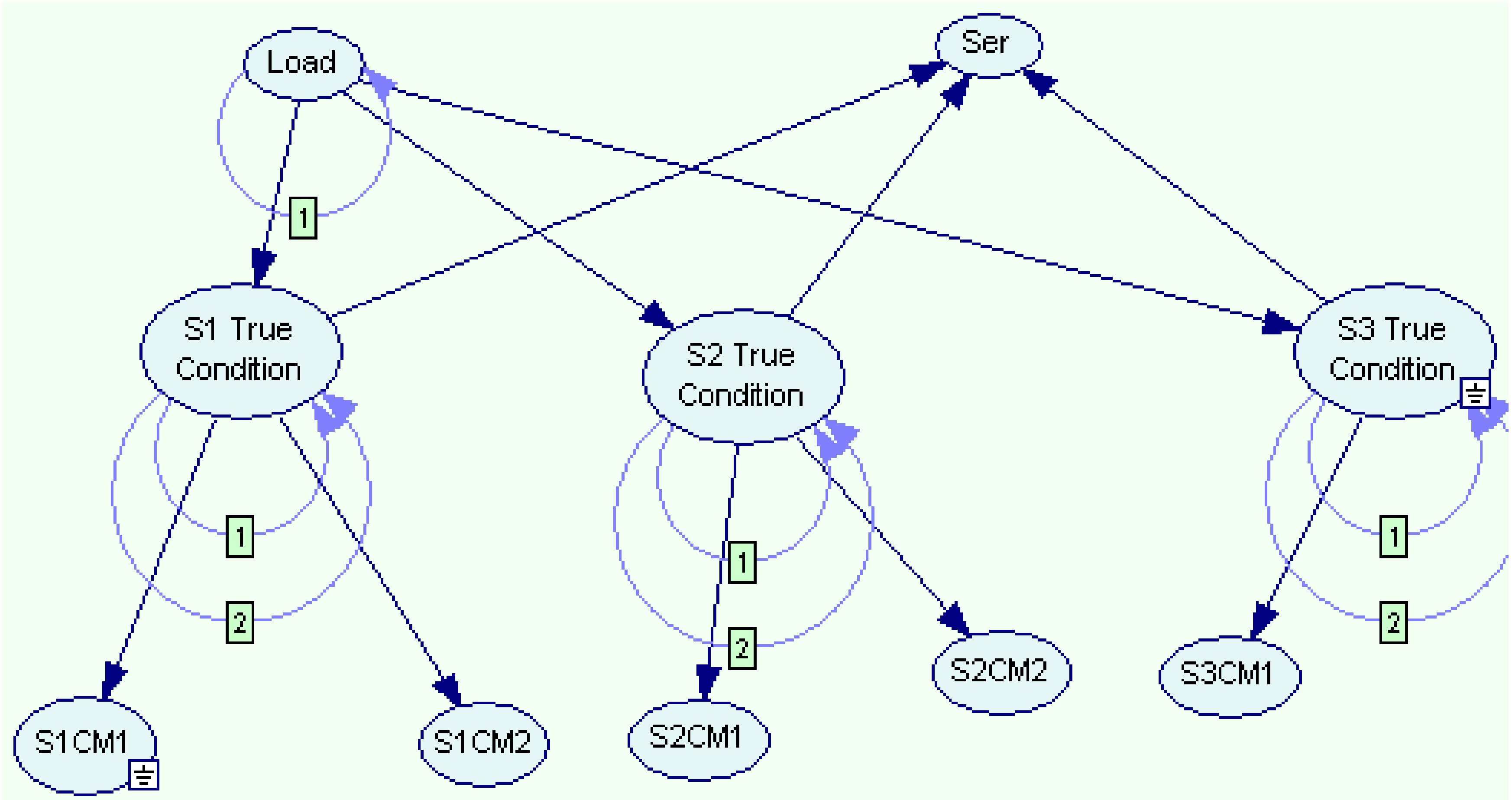


The DBN unrolled over two time slices.

Example Output

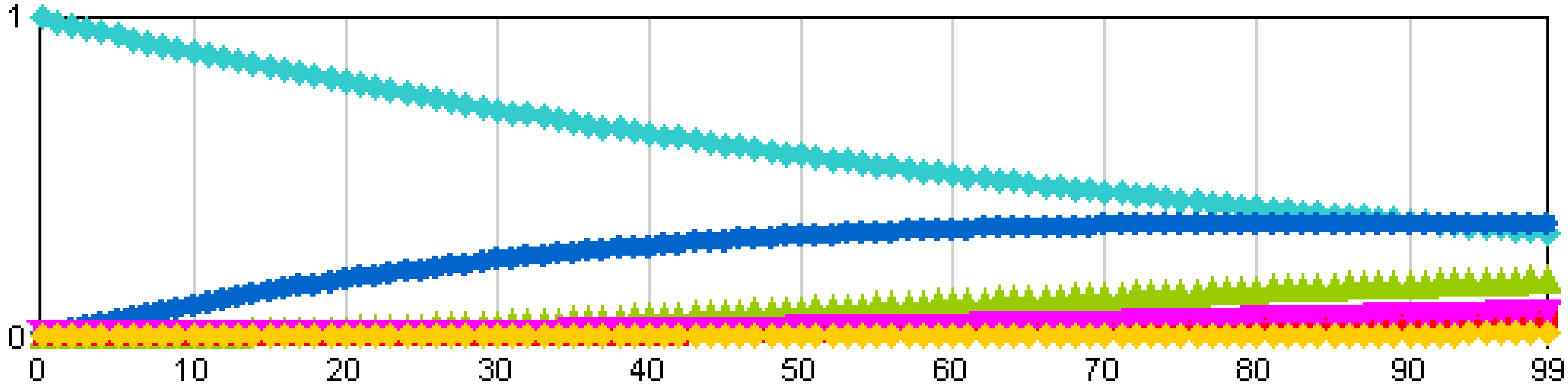


Probability distribution of the True Condition node vs Time given no maintenance

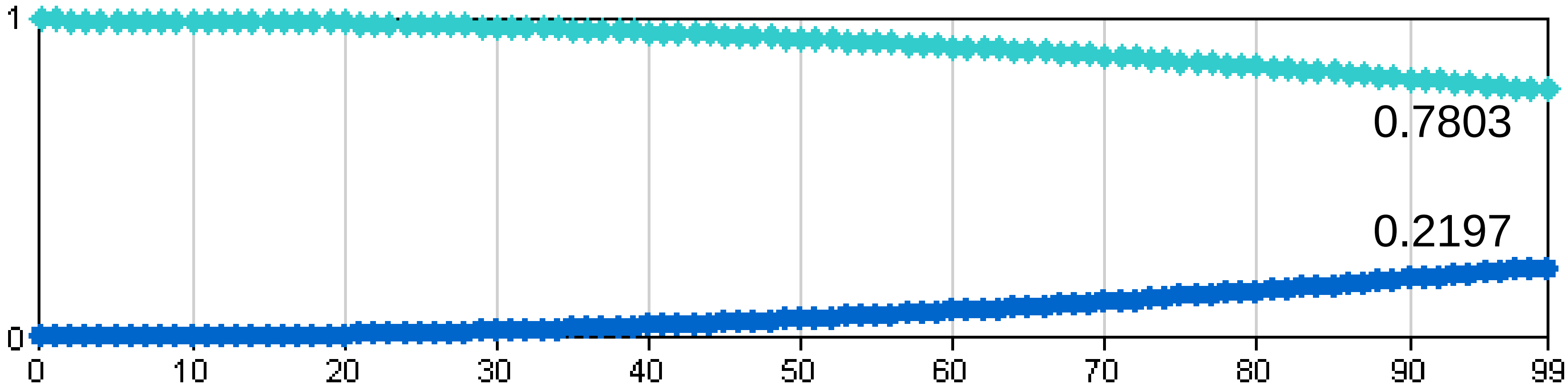


System Comprising 3 Components in a Series Reliability Arrangement

Base Case



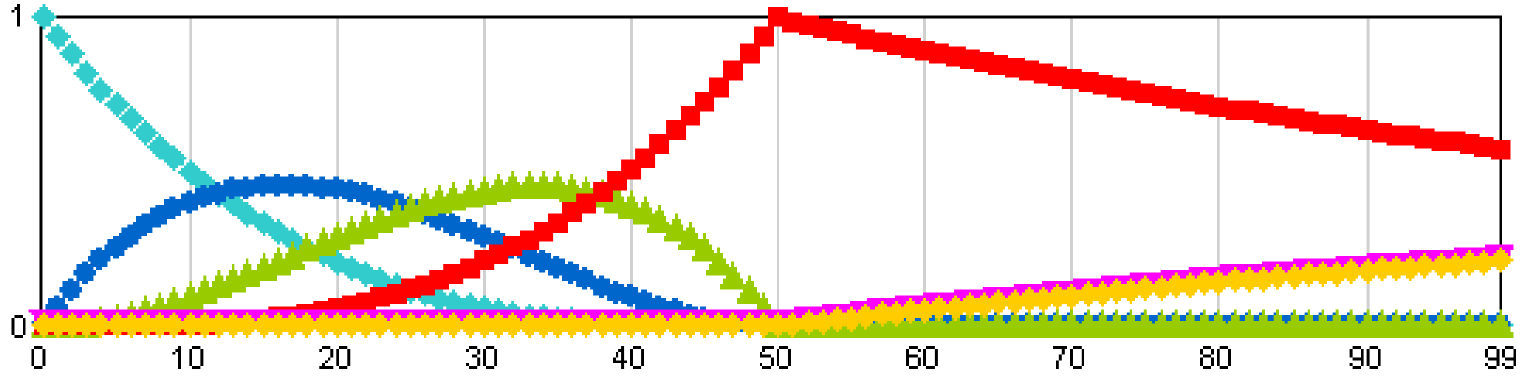
Prob Distribution of Component State vs Time



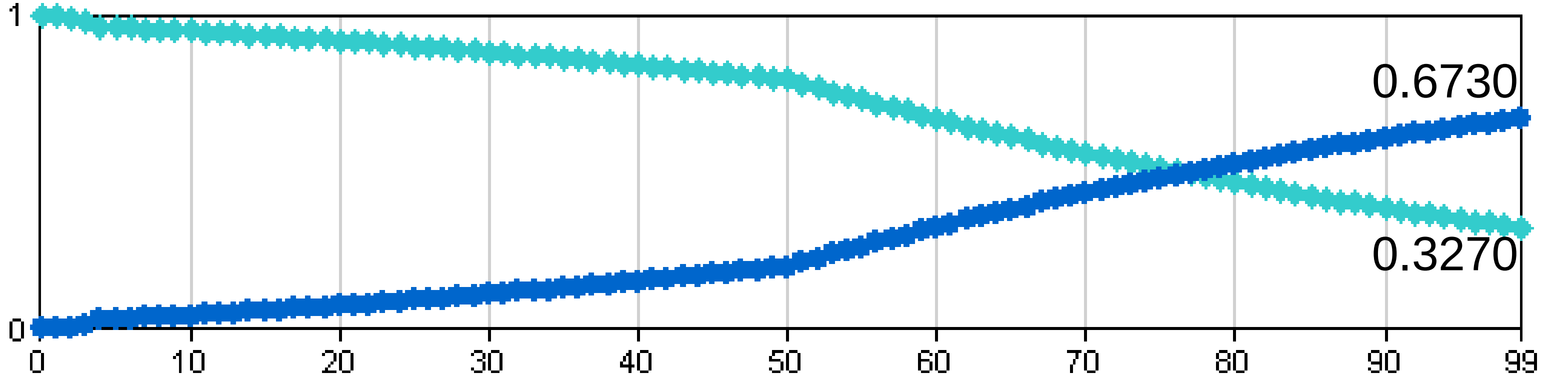
Prob Distribution of System State vs Time

Observation from S1CM1 of

Wear State 3 at time 50

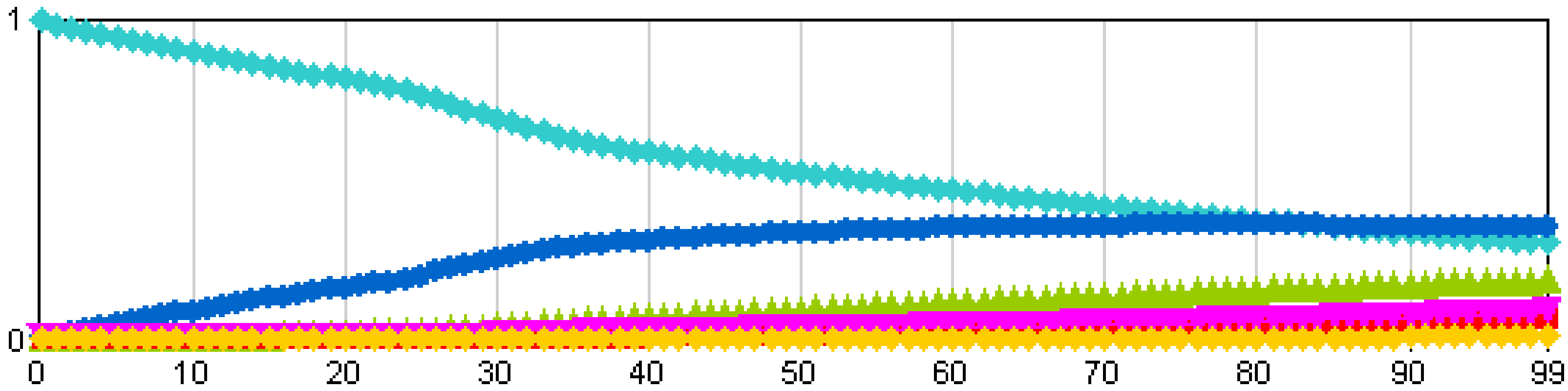


Prob Distribution of Component State vs Time

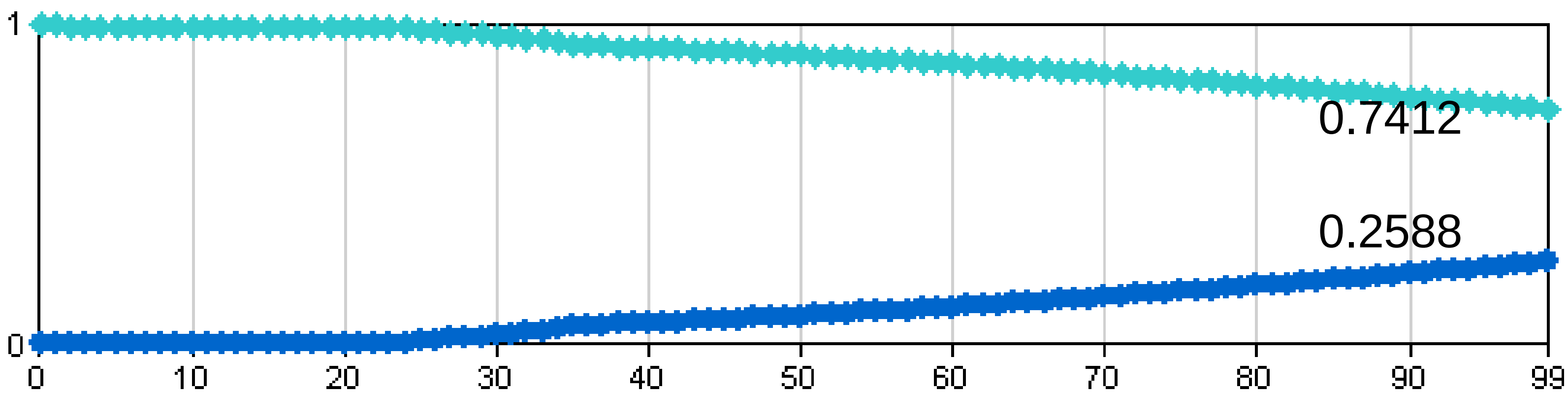


Prob Distribution of System State vs Time

Normal Load until time 24, then Abnormal Load from time 25 to 36.



Prob Distribution of Component State vs Time



Prob Distribution of System State vs Time

KT Box Tools

Failure & Degradation Elicitation Support Tool - FADES

Predictive Maintenance Probabilistic Decision Support – PMPDS

PMPDS

Aim:

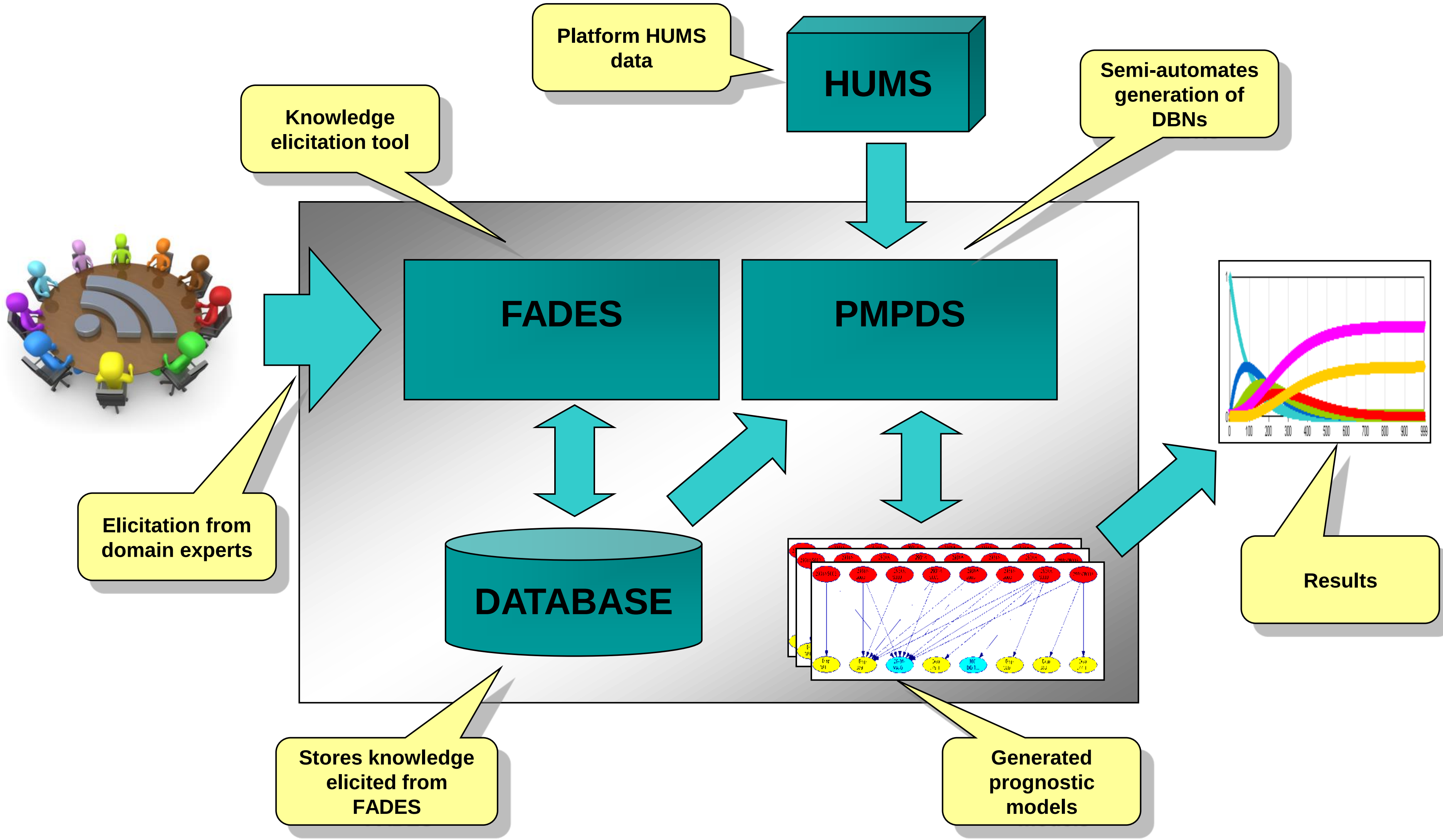
- Reduce the cost of developing prognostic models by automating some aspects of model construction
- Development of a modelling framework and a software tool which semi-automates the creation of dynamic Bayesian networks (DBNs) to undertake prognostic modelling and support predictive maintenance decisions

FADES

Aim:

- To facilitate the elicitation and storage of knowledge from engineering and maintenance personnel in order to support modelling and decision-making in the prognostics and predictive maintenance domain.

How the Tools are Linked



Required Information

Identification of failure modes and degradation mechanisms (may be available from Failure Mode and Effects Analysis)

Elicitation of failure patterns (e.g. bath-tube curve, constant, slow rise, etc).

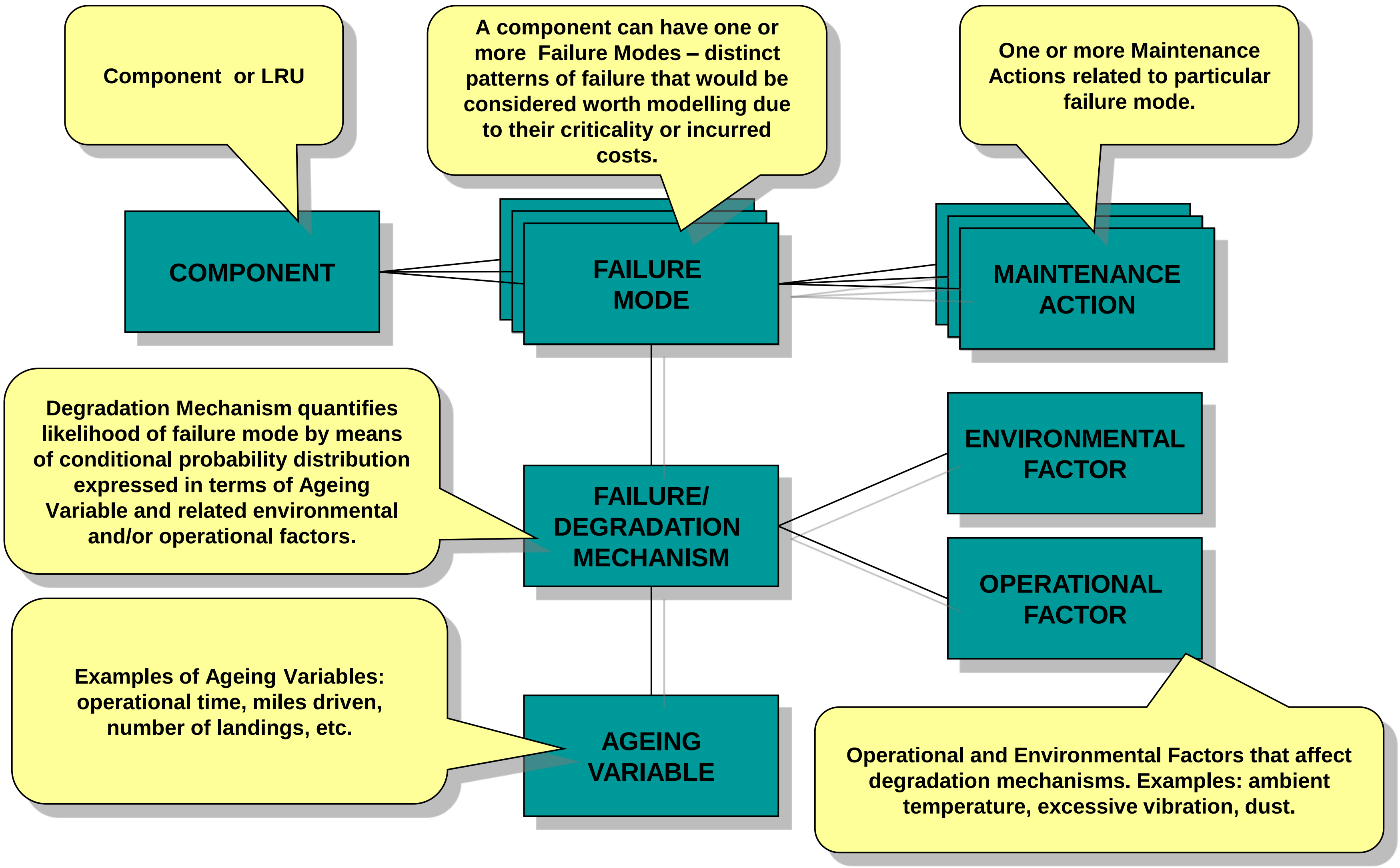
Elicitation of failure rates/frequencies
(Allowing derivation of transition probabilities in DBN between different component states from one time slice to the next:

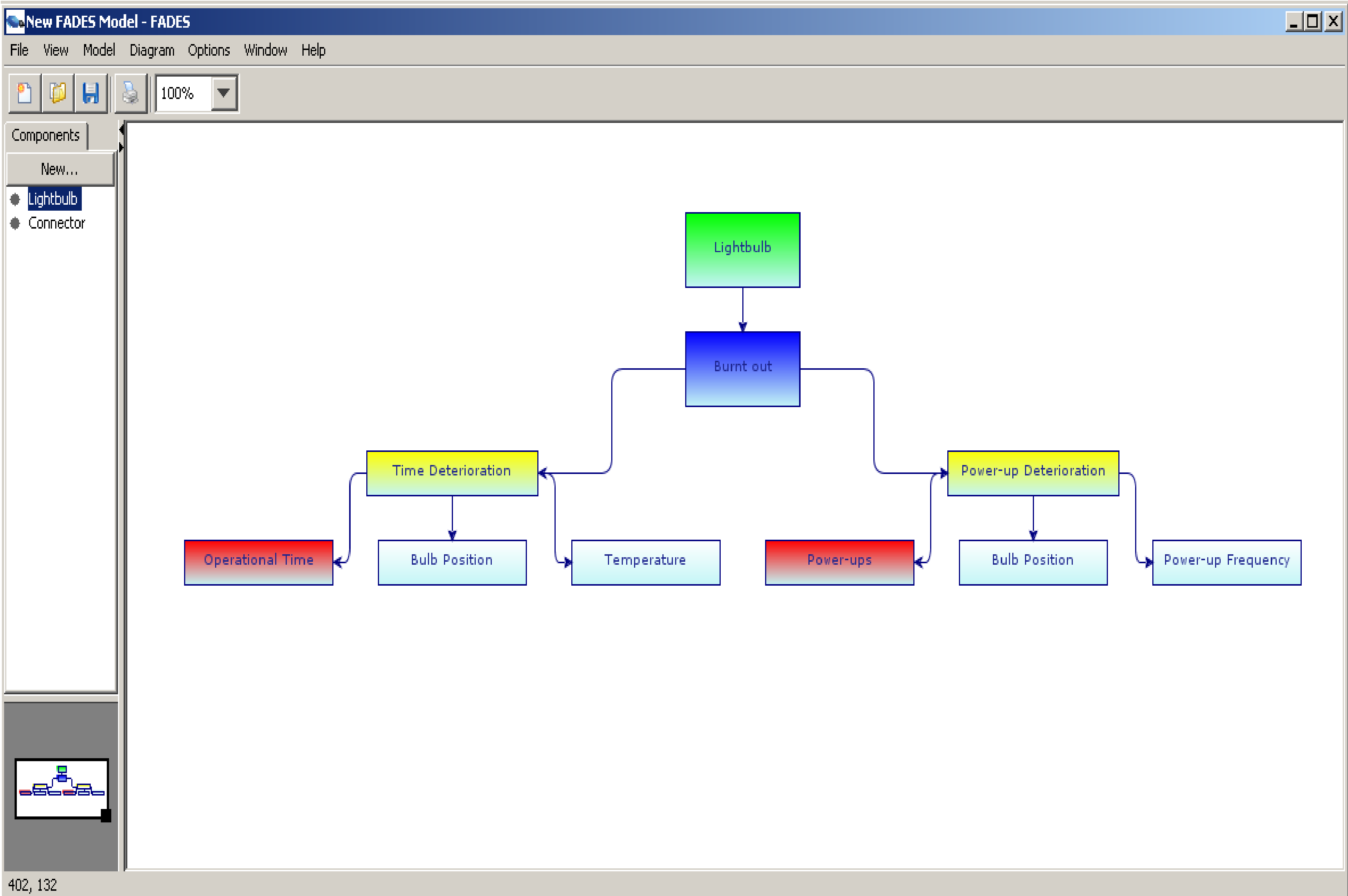
$$P(S_{t+1} \mid S_t, M_t, E_{t+1}, O_{t+1})$$

Identification of symptoms and condition monitoring/HUMS variables relevant to the identified failure modes

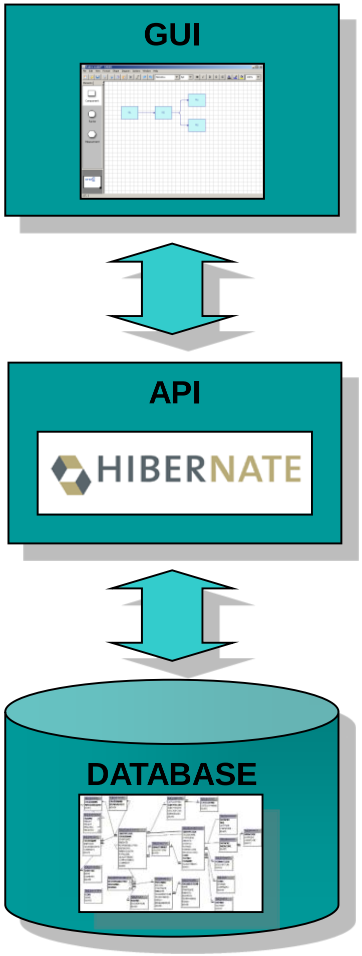
Identification of possible maintenance actions for the various failure modes

FADES Approach




New FADES Model - FADES
File View Model Diagram Options Window Help
100%
Components
New...
Lightbulb
Connector
Lightbulb
Burnt out
Time Deterioration
Power-up Deterioration
Operational Time
Bulb Position
Temperature
Power-ups
Bulb Position
Power-up Frequency
402, 132

FADES Design



•FADES software incorporates the following elements that constitute the complete system:

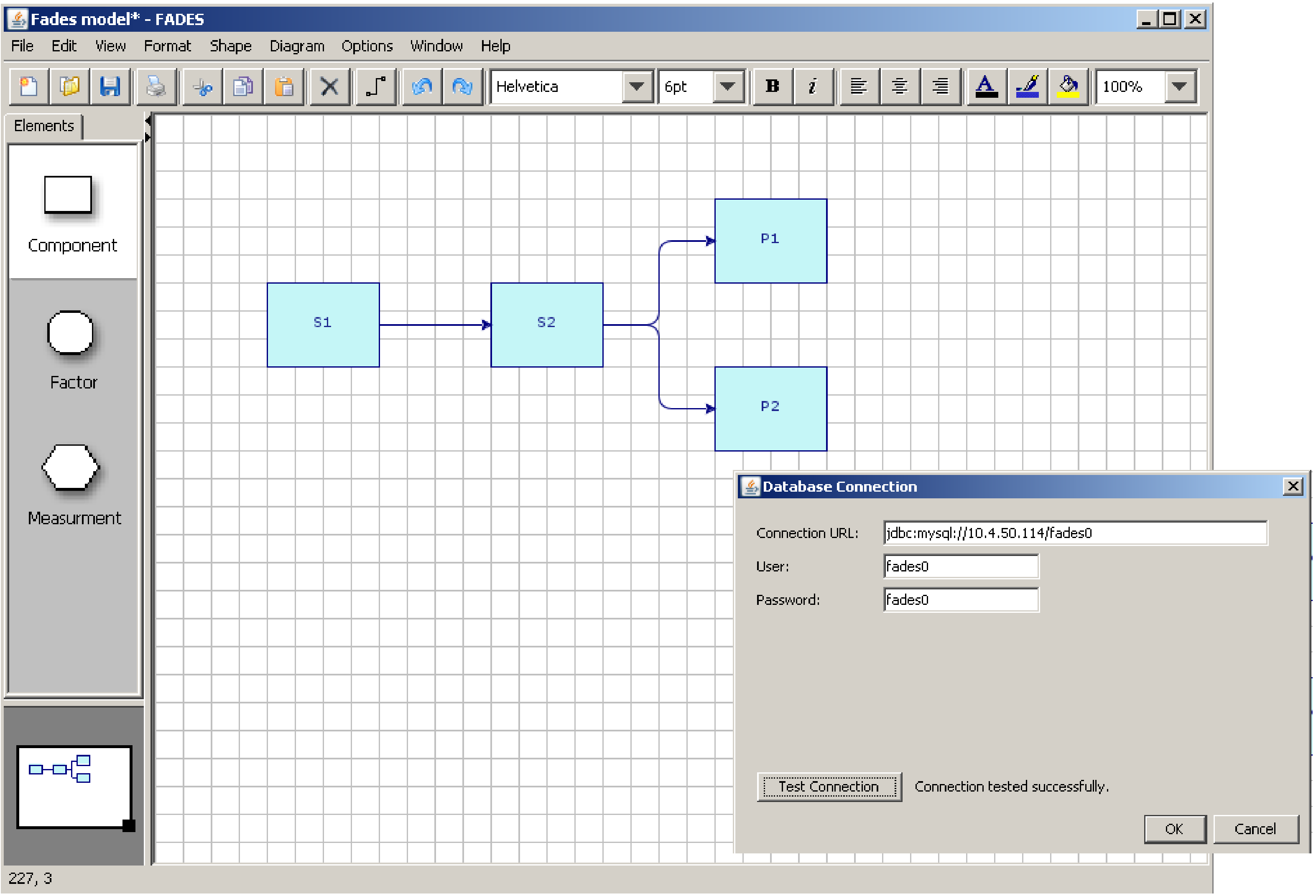
- Graphical User Interface (GUI) written in Java,
- Hibernate relational persistence that enables Application Programming Interface (API), and
- Relational database (currently MySQL).

•The GUI and Hibernate API were implemented and tested using the unit testing approach.

•FADES has been designed in a modular form to allow for future customisation and flexibility in further development and upgrading individual elements of the system.

- For example, the Hibernate API is being used by PMPDS tool and allows for abstraction of the modelling concepts from details of the database implementation. Furthermore, this API can be customised to provide access to non-FADES database as long as the necessary information is stored in the database.

FADES User Interface

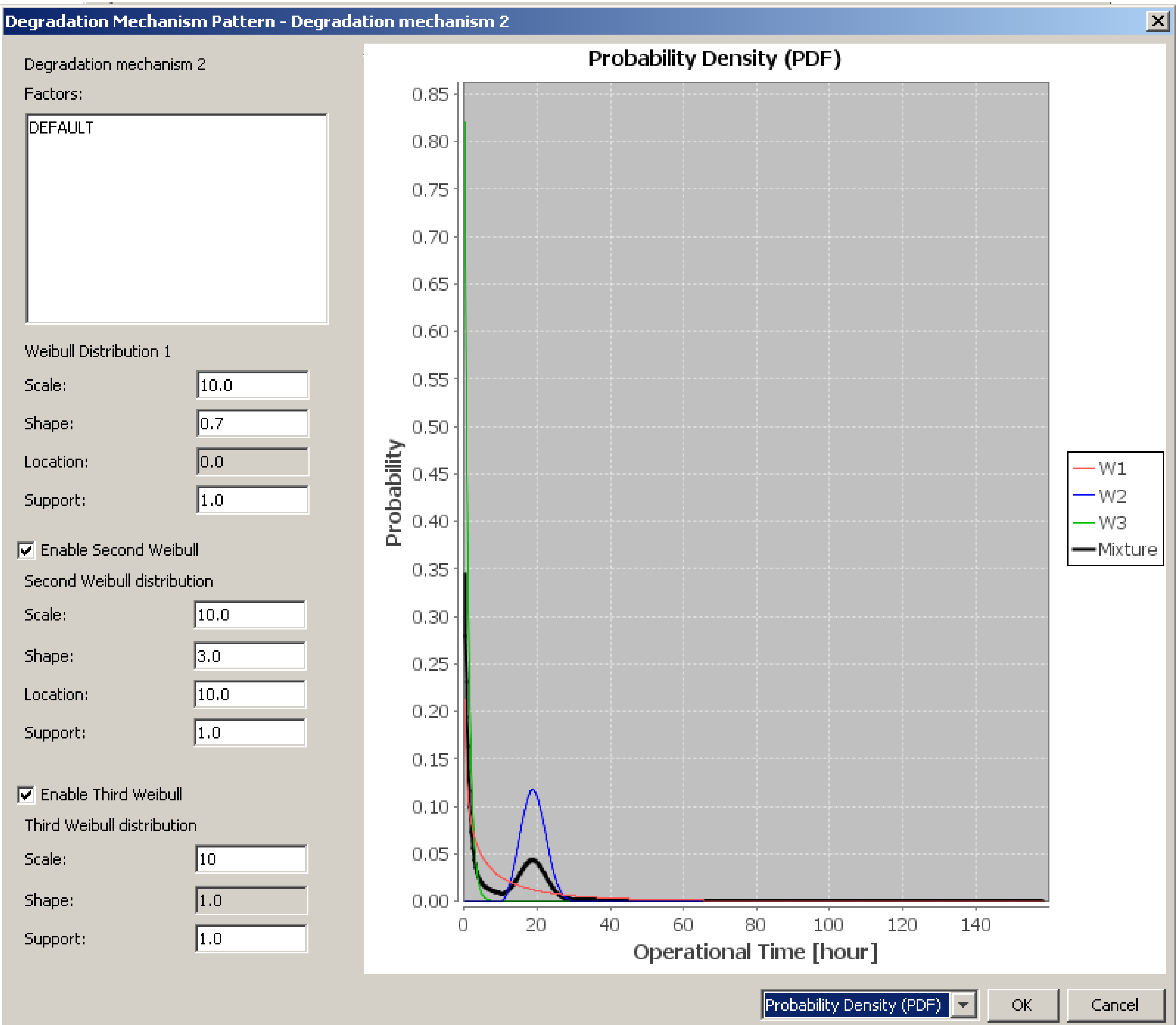


Currently use Weibull distributions to represent failure times. A mixture of up to three Weibull distributions can be visualised within FADES.

The pdf of the 3-parameter Weibull distribution is defined as follows:

$$f(t) = \frac{k}{\lambda}\left(\frac{t-\theta}{\lambda}\right)^{k-1} e^{-\left(\frac{t-\theta}{\lambda}\right)^{k}}$$

where λ is the scale parameter, k is the shape parameter, and θ is the location or offset parameter.


Degradation Mechanism Pattern - Degradation mechanism 2
Degradation mechanism 2
Factors:
DEFAULT
Weibull Distribution 1
Scale: 10.0
Shape: 0.7
Location: 0.0
Support: 1.0
Enable Second Weibull
Second Weibull distribution
Scale: 10.0
Shape: 3.0
Location: 10.0
Support: 1.0
Enable Third Weibull
Third Weibull distribution
Scale: 10
Shape: 1.0
Support: 1.0
Probability Density (PDF)
Probability
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
20
40
60
80
100
120
140
Operational Time [hour]
W1
W2
W3
Mixture
Probability Density (PDF)
OK
Cancel

We interpret the failure rates elicited for the various failure and degradation mechanisms in the absence of abnormal environmental and operational factors as *baseline* rates.

We then need to quantify the effects of the environmental and operational factors that were identified by subject matters as being relevant to the particular failure mode.

Can either elicit ratios of failure rates to baseline rates, i.e. *multiplicative factors*, or elicit a whole new distribution in same way as for baseline rates.

Prognosis

- To predict future health of the system, we should know planned future usage
- Usage patterns can be very different
  - Microprocessor manufacturing machine
  - Airliner
  - Military land vehicle
- Prognostic models are especially challenging for military systems
  - Irregular usage
  - Usage beyond design specification

Planned future usage can be captured in the form of hard evidence entered on the operational variables (and also possibly on environmental variables) in the DBN.

Such an evidence set defines an operational scenario.

Maintenance Nodes

If a fixed maintenance policy is assumed, the CPTs of the Maintenance nodes will correspond to the logical choice of a maintenance action (including the choice of taking no action) given the observed values of the parent Condition Monitoring/HUMS variables.

Or we could have a probability distribution over the choice of actions to reflect the attitudes of different maintainers, for example.

Or we could extend the representation to an influence diagram and treat the Maintenance nodes as decisions to be optimized given the relative costs and benefits of the various possible outcomes.

Additional Knowledge Required for IDs

- Cost of each possible maintenance action
- Expected cost of failure and unplanned maintenance

These costs could be multi-dimensional, e.g. monetary cost and downtime, with weights then needed to define a multi-objective cost function.

Conclusions

- Dynamic Bayesian networks offer another valuable approach for prognostic modelling.
- Elicitation is a major task for building such models.
- FADES is intended to support the elicitation process and provide a means of storing and sharing the results.
- We will continue to develop the tool and include a wider range of options to support the elicitation process.