Degradation modelling and maintenance scheduling: exploring the role of big-data analytics

Richard Dwight
School of Mechanical, Materials, Mechatronic and Biomedical Engineering
Faculty of Engineering and Information Sciences
University of Wollongong
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Planned topics to cover

1. Outline work undertaken in degradation modelling within an asset management decision framework

2. Relate to big-data analytics and our work on CM for rail systems

3. Characterise the problem of maintenance scheduling

4. Projection of the prospects for BDA (Free thinking)

Asset Management & Systems Engineering Group at UOW

http://eis.uow.edu.au/mmm/engineering-asset-management/index.html

ENGINEERING ASSET MANAGEMENT GROUP

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Asset Management & Systems Engineering Group at UOW

Link to Smart Infrastructure-UOW

Complexity and Uncertainty

- Complexity
  - Difficulty of understanding interconnected and interdependent components often forming System of Systems
- Uncertainty
  - Difficulty of predicting due to lack of information, knowledge and understanding

Topic 1

- Degradation Modelling and Asset Management Decisions

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Degradation Modelling- small data

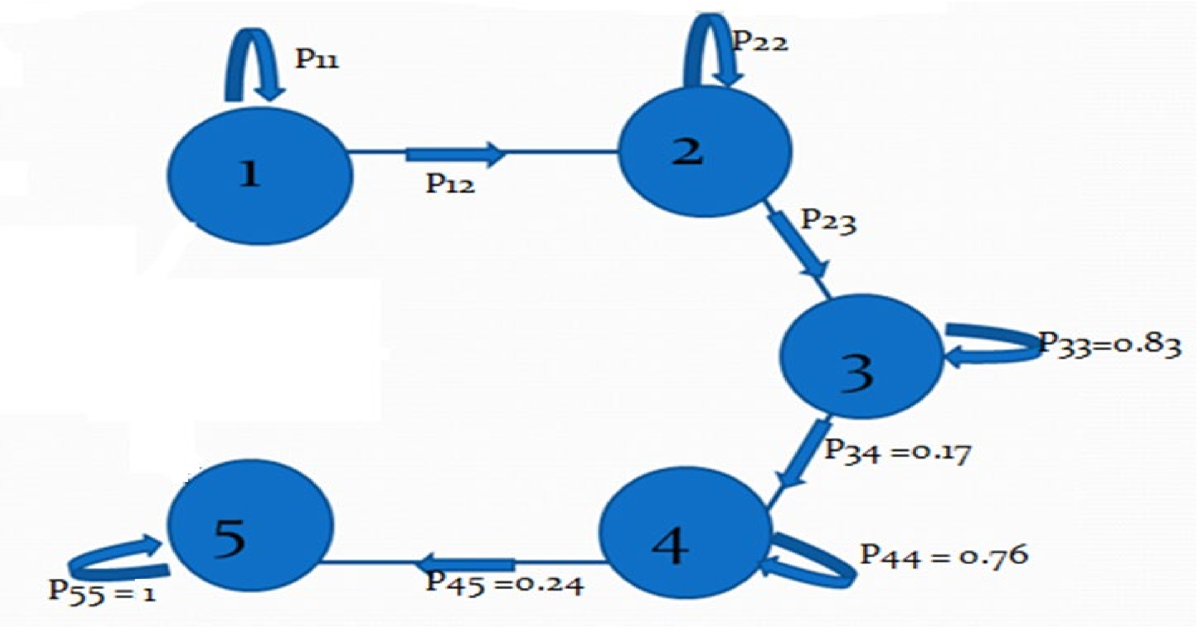
- Deterministic Approach

  Based on statistical and regression analysis

- Stochastic Approach

  Bridge element ratings, or duration at a particular rating, are assumed to be random variables and modelled by an underlying probability distribution

Need transition-probabilities (in form of a matrix)



MCMC Simulation Method

- According to Bayes' rule for a given set of condition rating data $Y = \{y_1, y_2, y_3, ..., y_n\}$, unknown transition probability θ
can be expressed as:

$$P(\theta/Y) \propto P(\theta)\, P(Y/\theta)$$

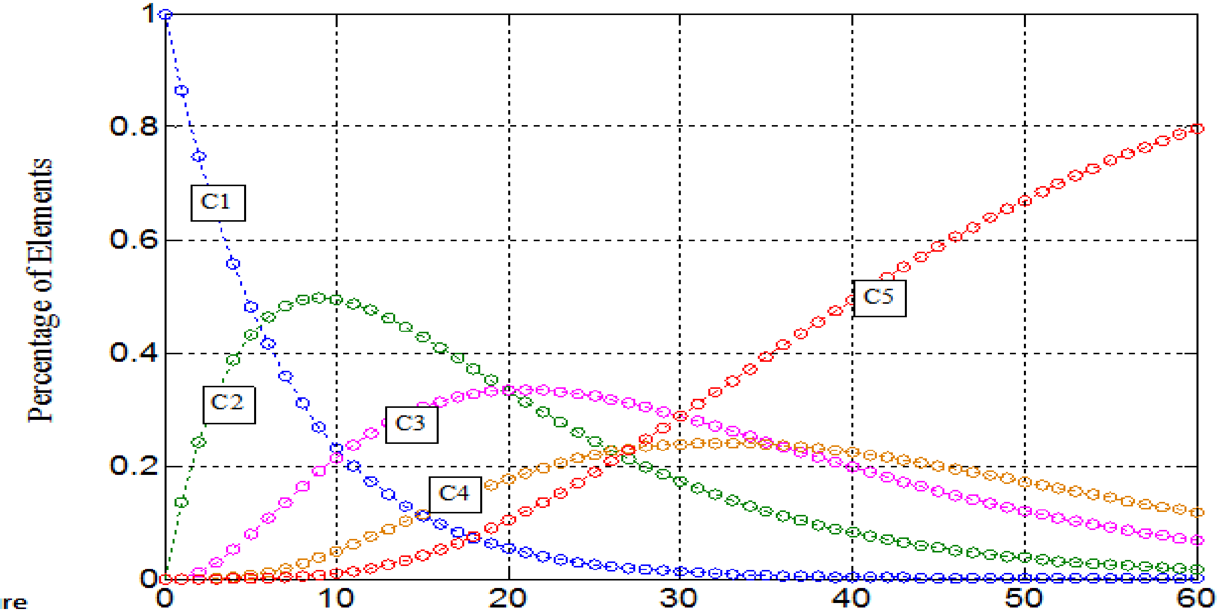
Where:

$P(\theta /Y)$ = posterior or target distribution

$P(\theta)$ = prior distribution

$P(Y/ \theta)$ = sampling distribution or likelihood function

Condition Prediction



Years into Future	0	10	20	30	40	50	60
Cond. 1 (Like New)	100	23	5	1	0	0	0
Cond. 2 (Very good)	0	50	33	17	8	4	1
Cond. 3 (Satisfactory)	0	22	33	29	20	12	7
Cond. 4 (Marginally acceptable)	0	5	19	24	22	17	12
Cond. 5 (Critical)	0	0	10	29	50	67	80

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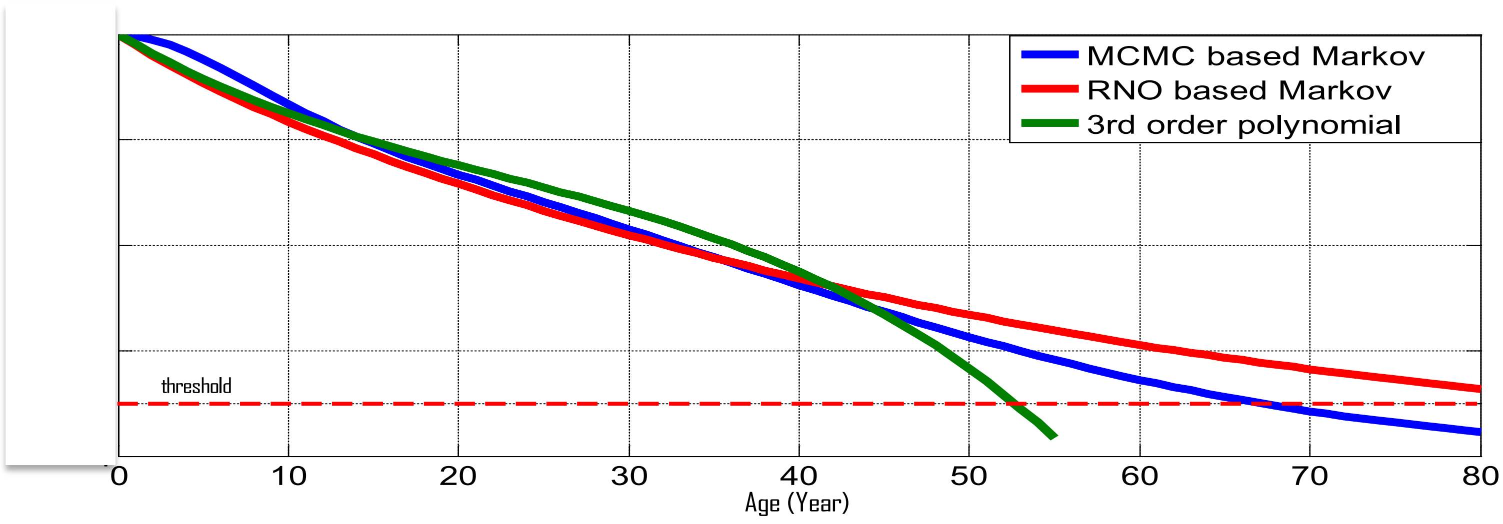
Comparison: Non-homogeneous Markov analysis for deck group using proposed approach:

Method	χ^2 values with 4 DOF ($\leq \chi^2_{0.05,4} = 9.49$)
	Full dataset
3rd order polynomial-based Regression-based Non-linear Optimisation	25.42
MCMC	0.51

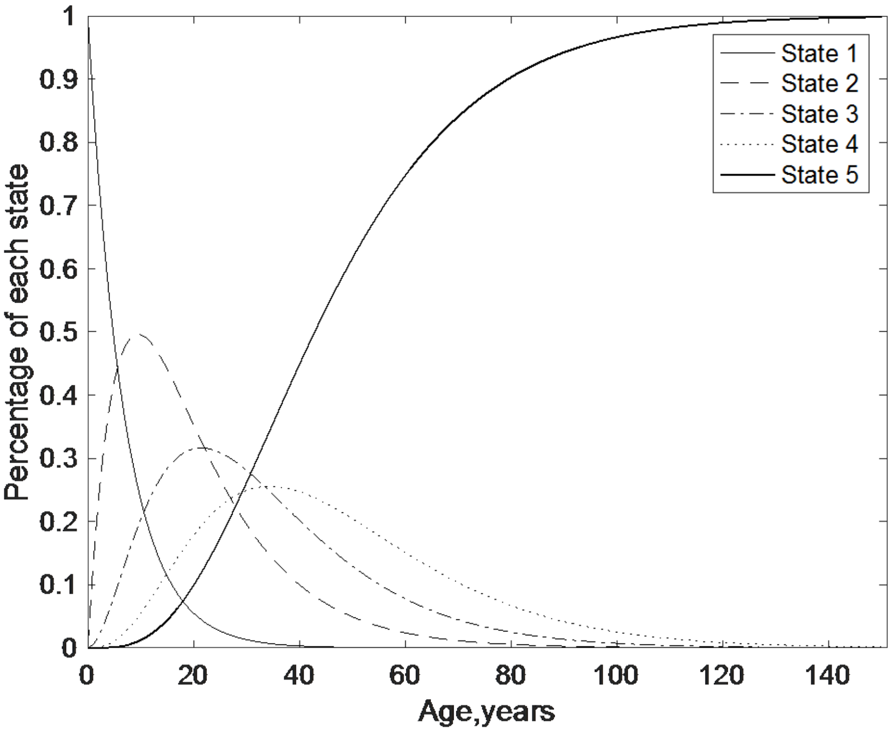
Prediction Results for Average Performance

Average condition prediction results for a typical timber bridge deck



Buried pipeline example

Age (years)	Structure conditions (Markov states)			
	1	2	3	4
3	9	0	1	0
5	3	0	0	0
8	1	0	0	0
9	0	1	0	0
20	12	2	0	0
26	12	2	0	4
30	24	2	0	1
36	14	3	1	4
40	7	1	0	4
41	2	0	0	0
46	18	3	7	17
50	1	0	0	0
51	38	9	16	14
56	95	20	25	76
60	2	0	0	6
61	15	2	0	1
66	1	0	0	0
70	1	0	2	2
80	0	0	0	4

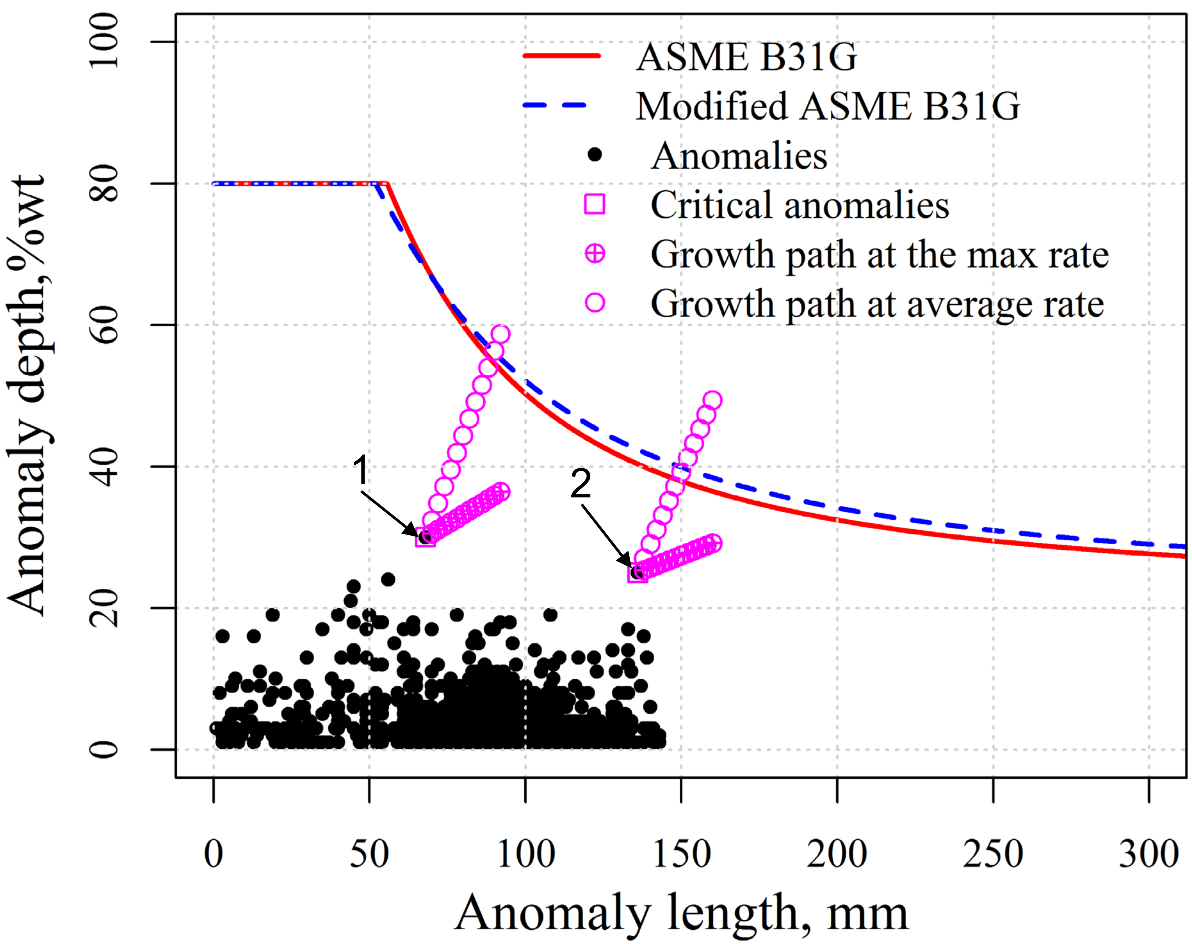


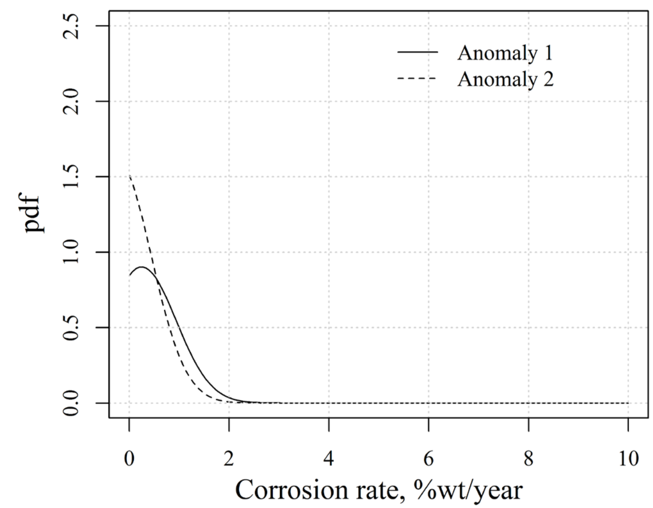
Degradation modelling where measurement data is available – bigger data

- Investigated various approaches

Models	comments
Markov process based models	population-based
Winer process based models	Not representing the mono-growth process
Gamma process based models	Simple and mono-growth-allowable
Inverse Gaussian process based models	Simple and mono-growth-allowable
Dynamic linear models	Allowing varying corrosion rates with time

2 data sets-DI decision





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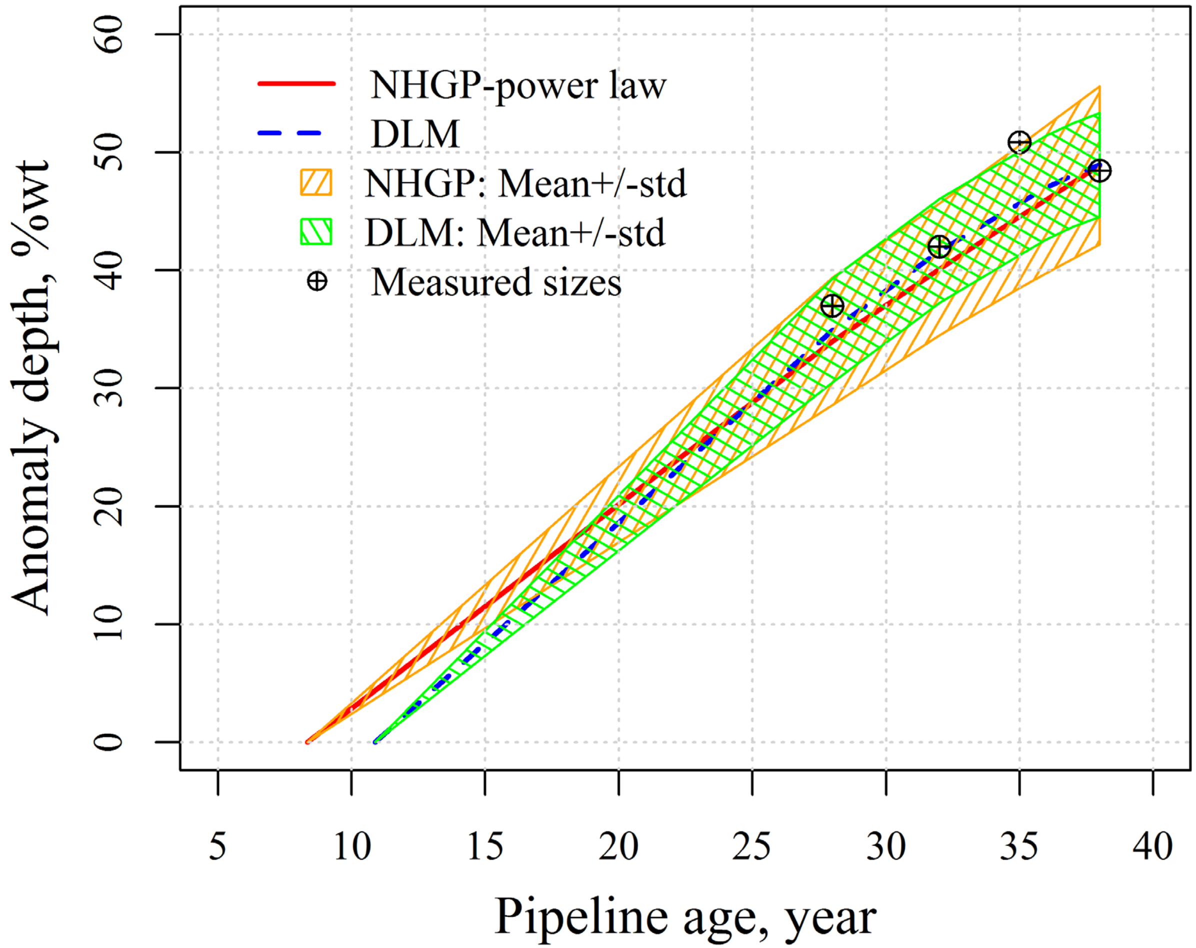
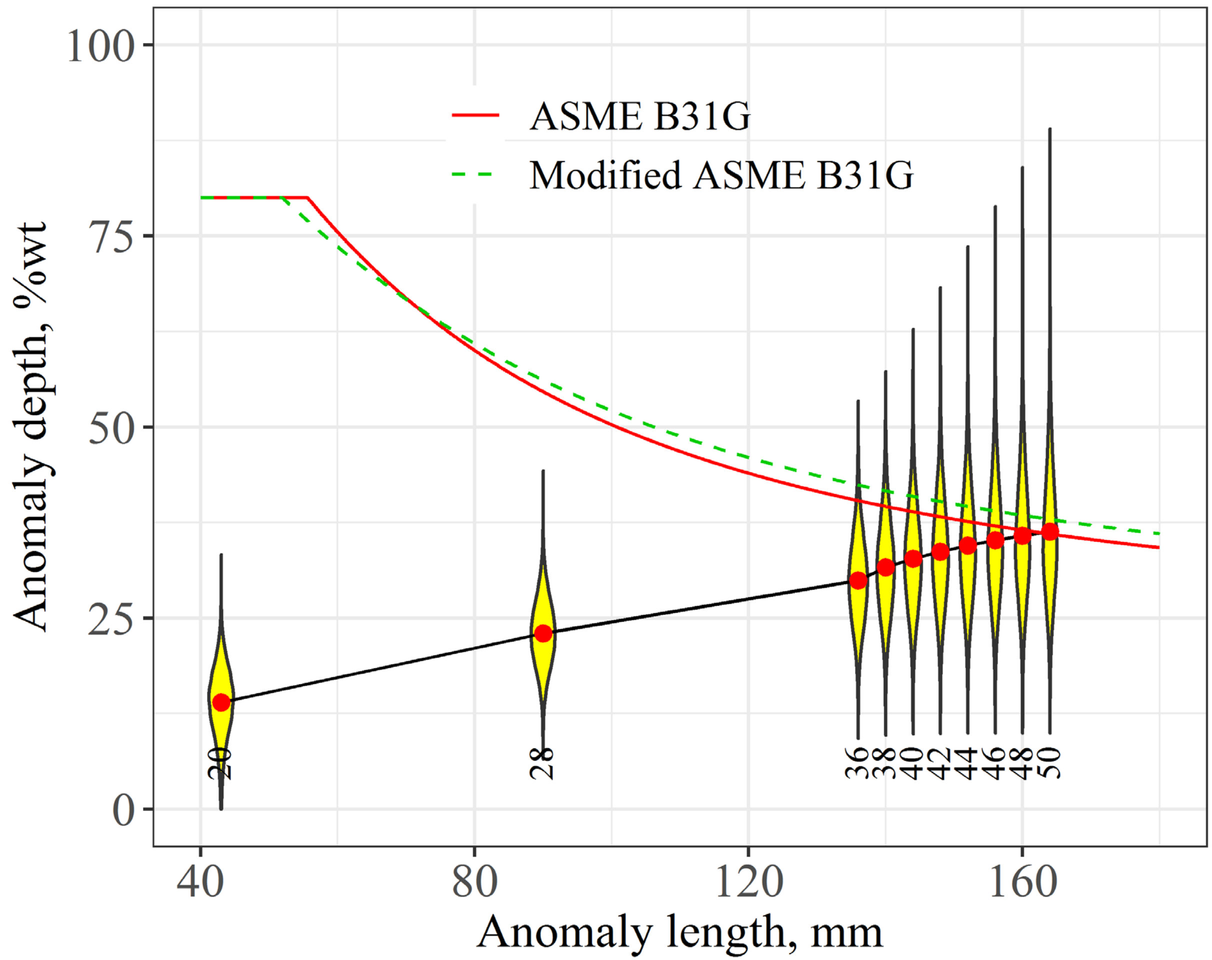
Multiple data sets-Condition projections



Multiple data sets-DI decision



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General Outcomes for this work

- Dynamic-linear-model is more flexible than gamma-process based models

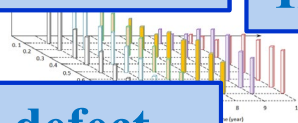
- Hierarchical Bayesian structure allows consideration of the correlation of multiple anomalies

- Measurement error is critical in ensuring the accuracy of the models

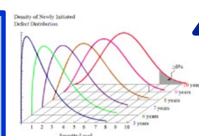
Degradation modelling in context…

Collect and process condition data

Collect other data: This & similar systems



Run known- defect deterioration model

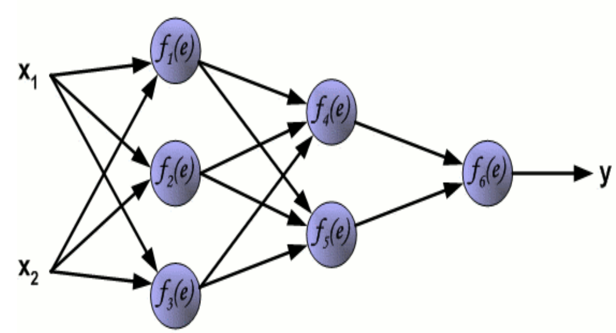


Run new-defect prediction model

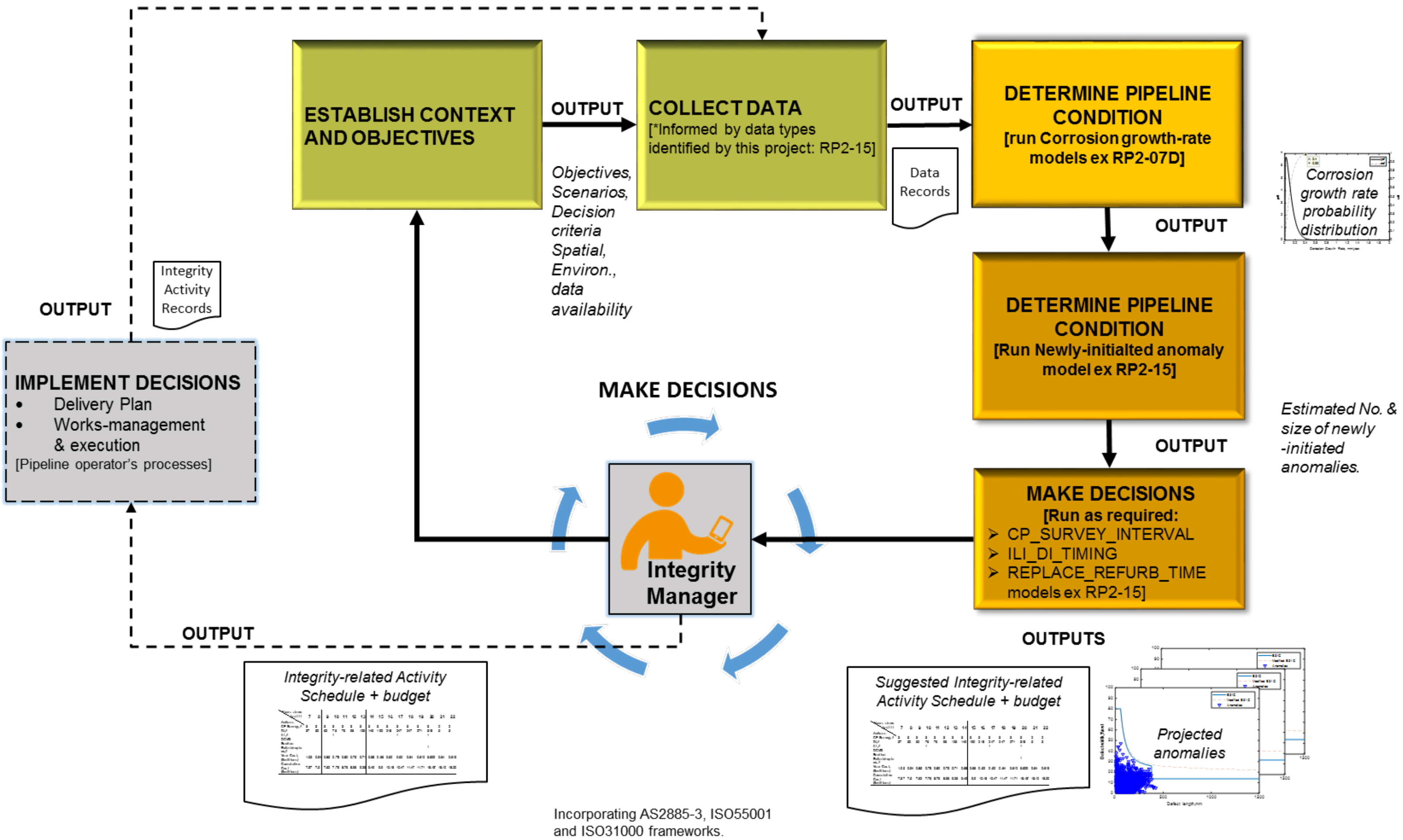
Run decision analysis: integrity & cost models

Implement plans

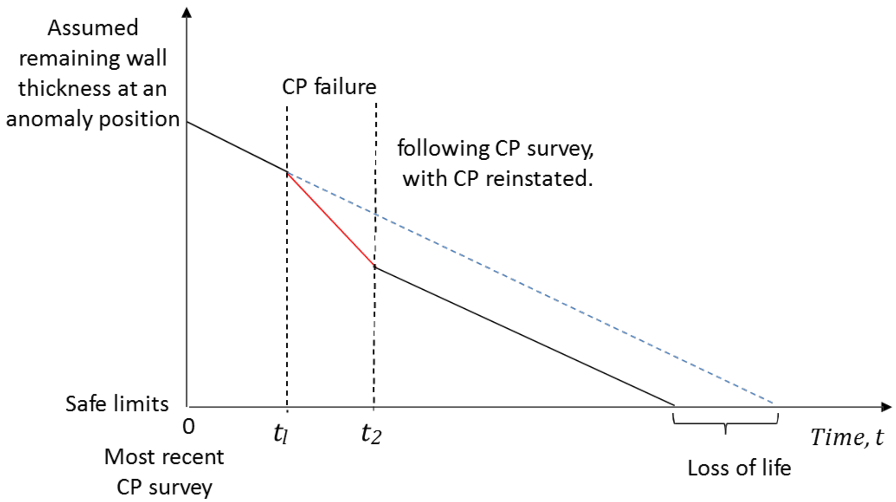
Monitor Implementation



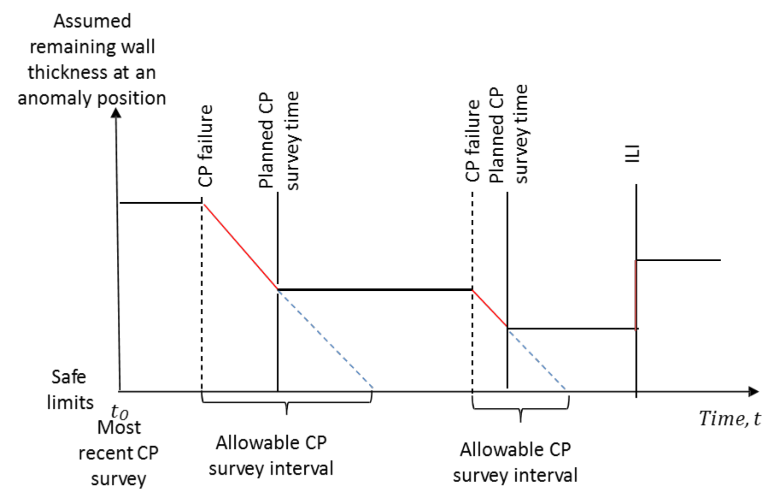
One process delivered to industry



Protective system inspection interval



OR



Probability of Ineffective CP, $P_{fCP}(t)$,

$$T_{CP} * \dot{c}(T_{CP}) = \sum_{i=1}^{N_{AN}} P_{fCP}(t) * \Delta L_{i,red} * C_{DI}(i) * WACC$$

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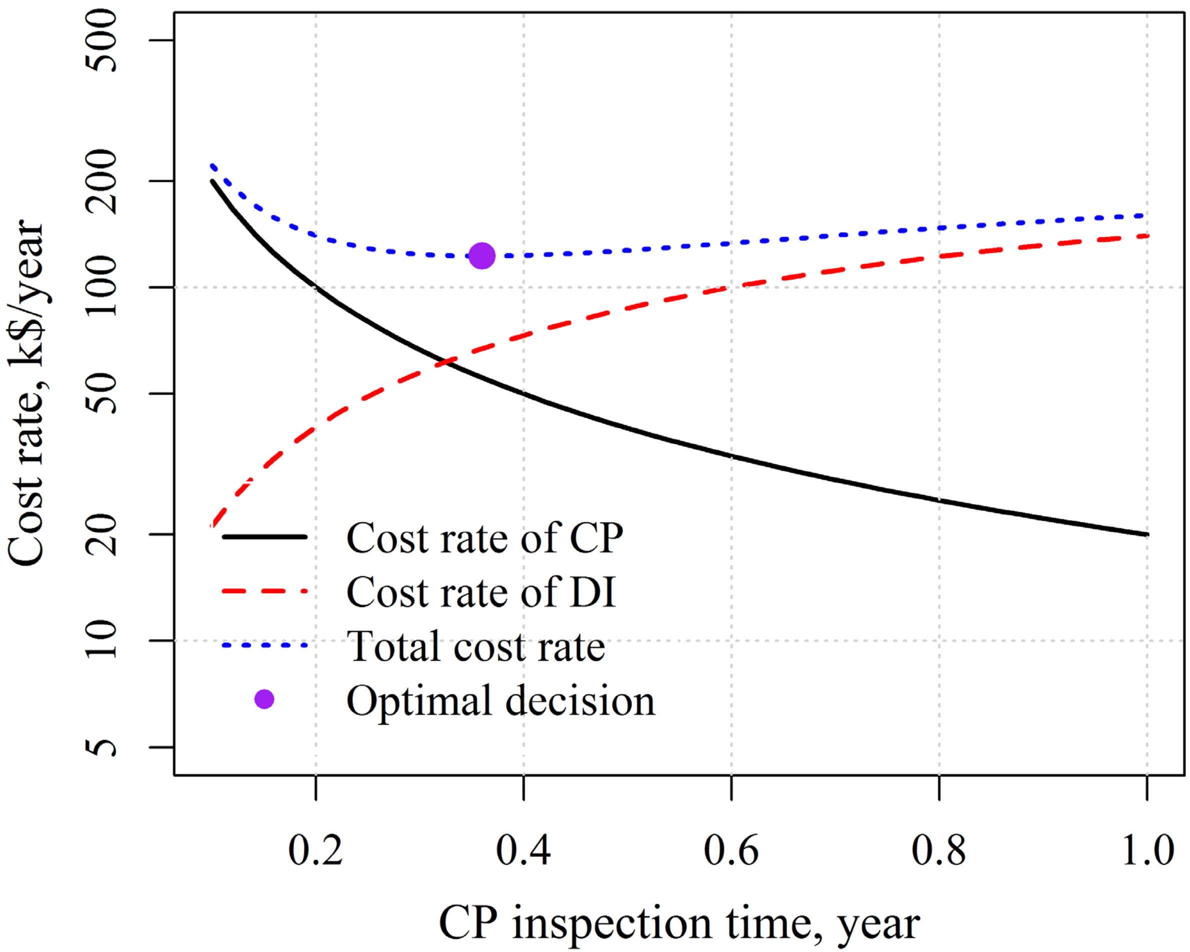
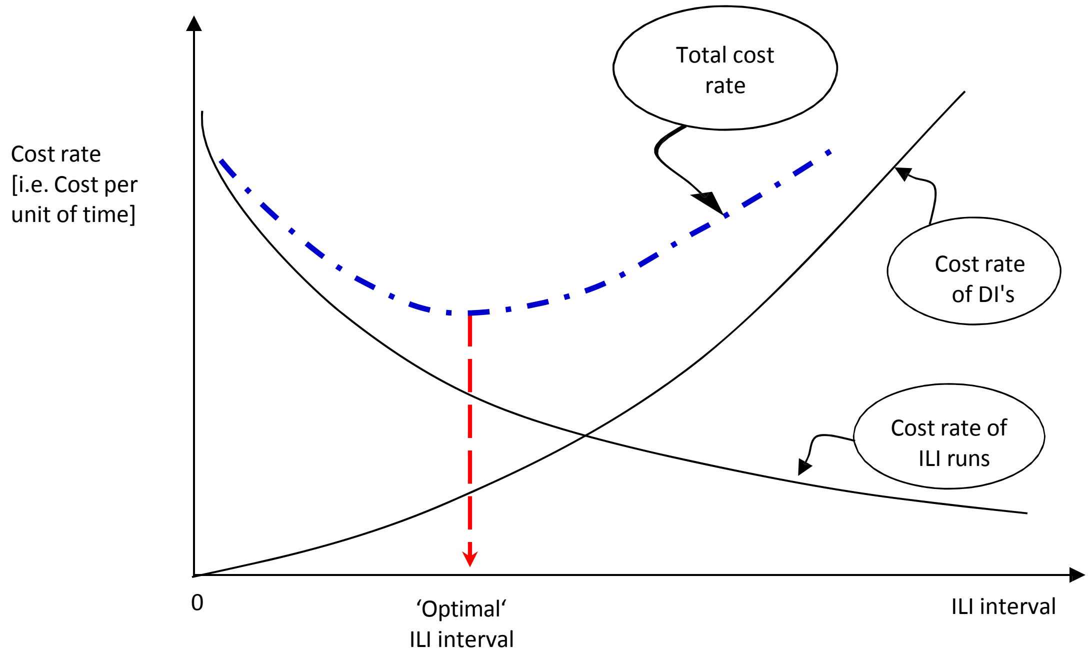
Protective system inspection interval



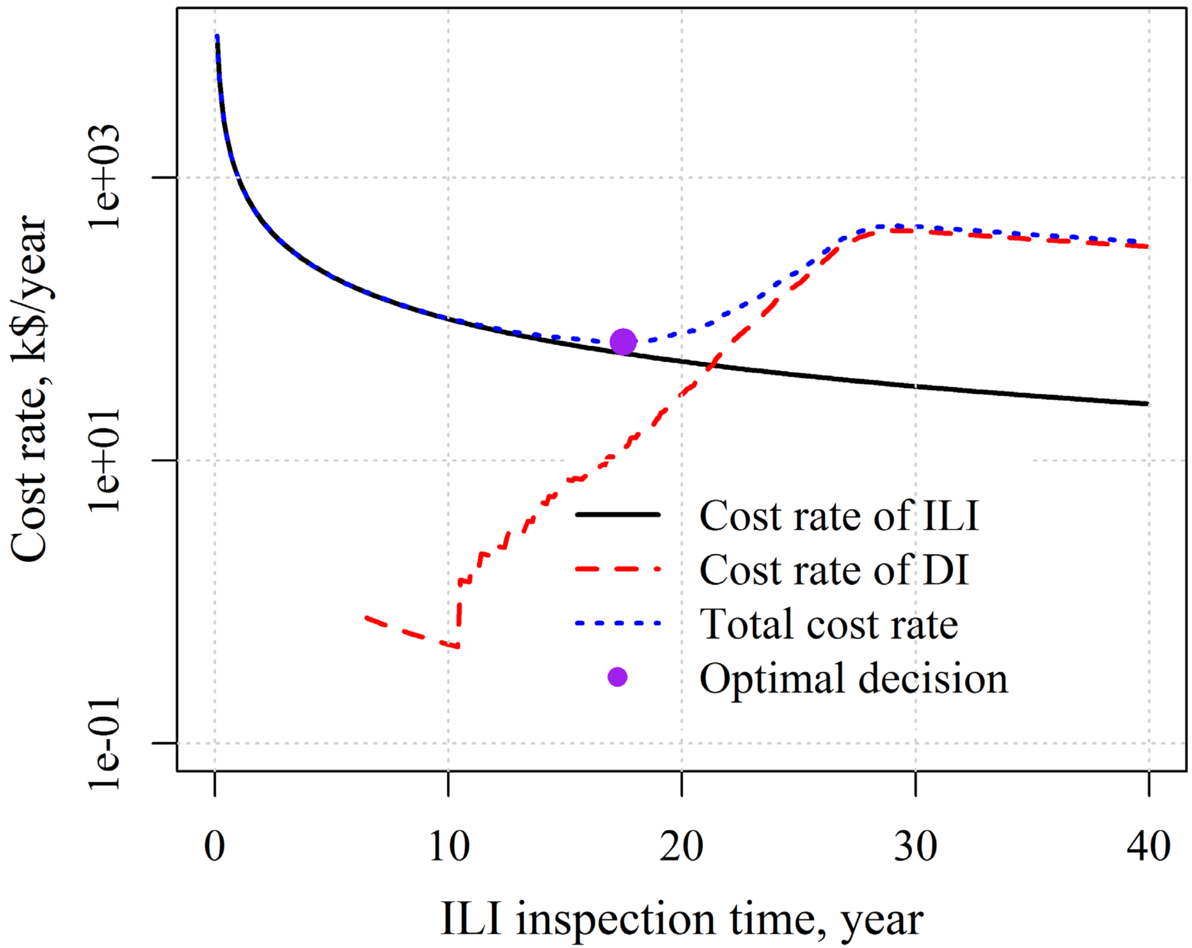
Anomaly measurement timing model

$$T_{ILI} \times \dot{c}(T_{ILI}) = C_{ILI} + N_{DI}(T_{ILI}) \times C_{DI}$$

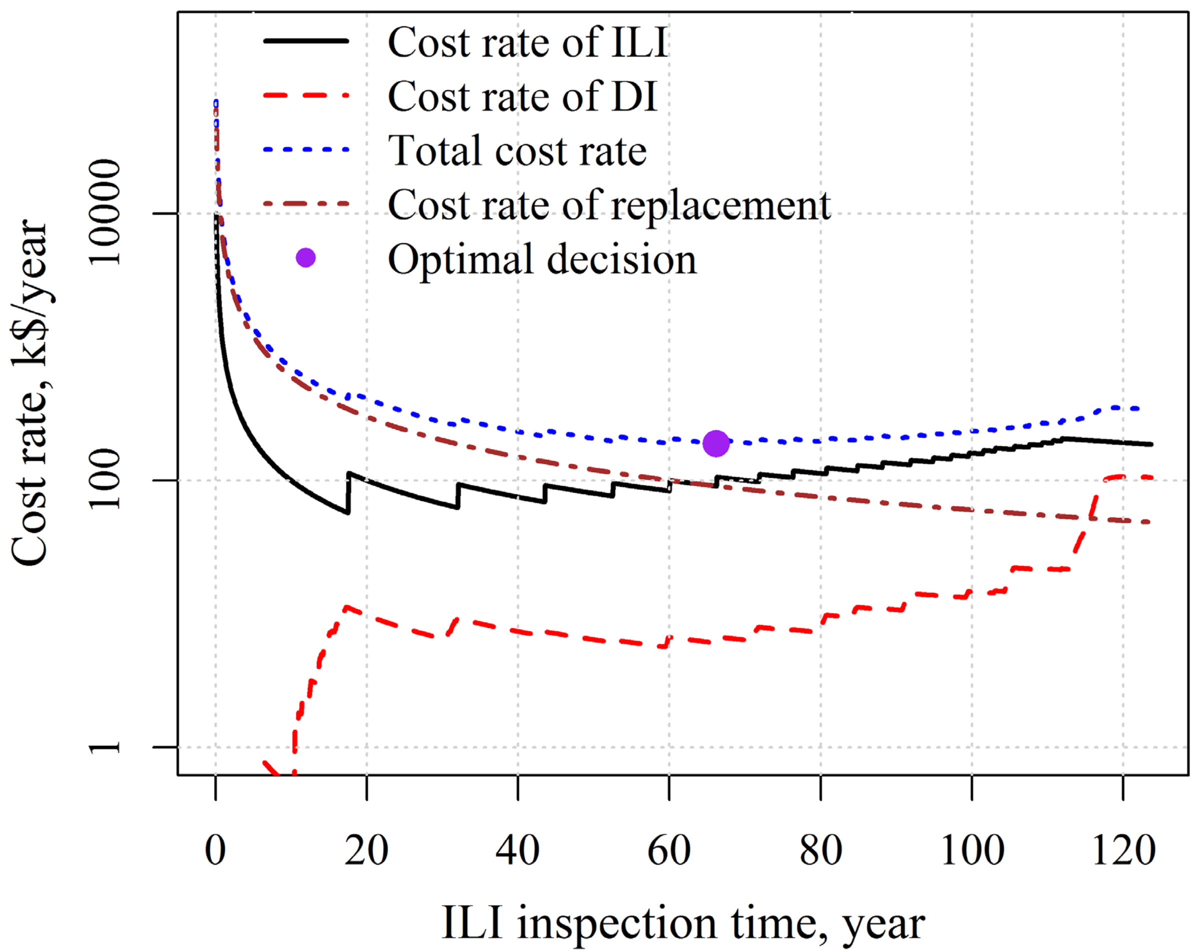


- Anomalies depicted as coloured dots removed by DI progressively as they reach safe limit.

Anomaly measurement timing



Replacement/Refurbishment timing



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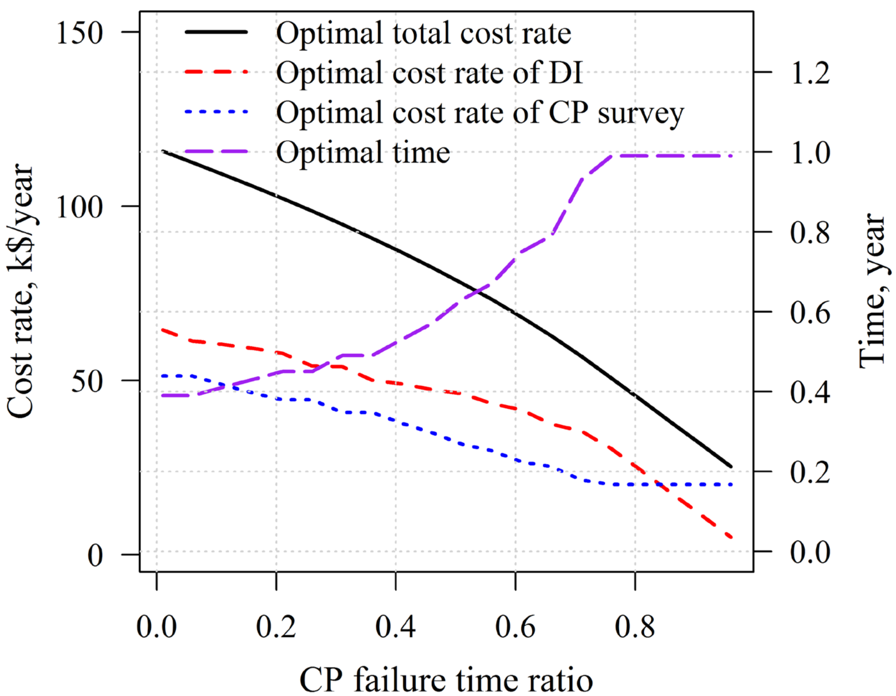
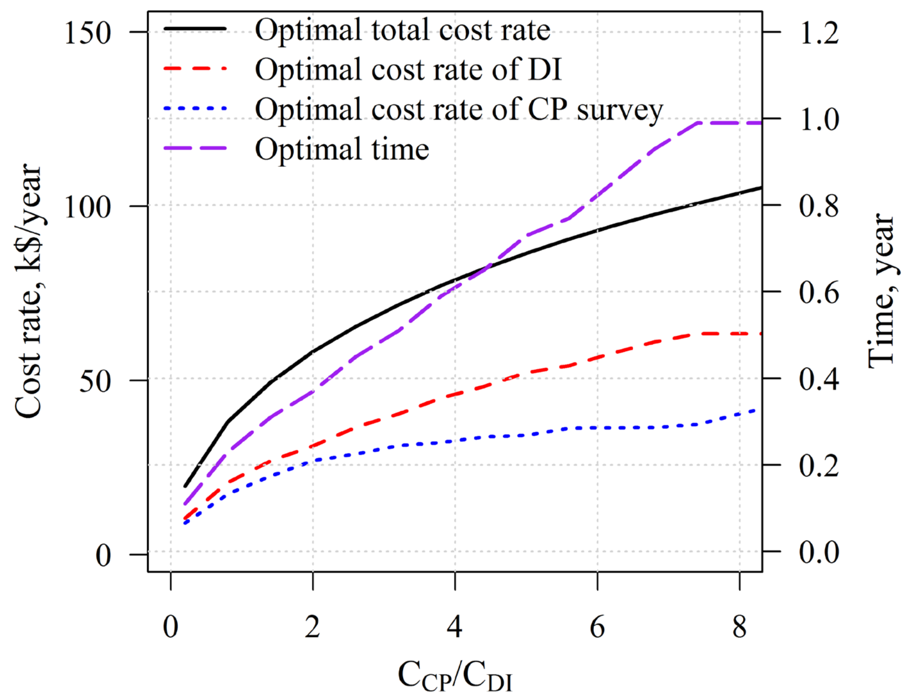
Sensitivity analysis and scenario testing





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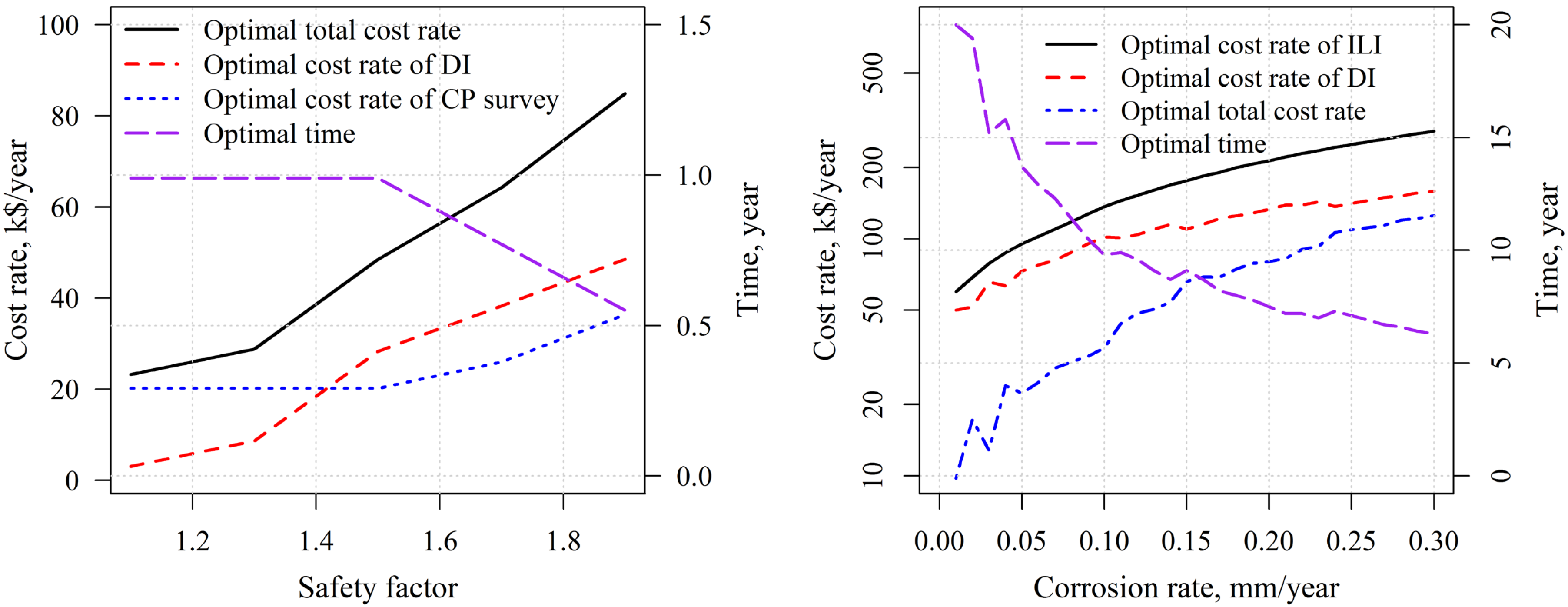
Sensitivity analysis and scenario testing



Outcomes of note:

1. Data-centric LCC-focused
   integrity management decision process
   delivered to industry.

2. Starts from the decision to be made and accounts
   for a range of practical data situations.

Topic 2

- Relate to big-data analytics

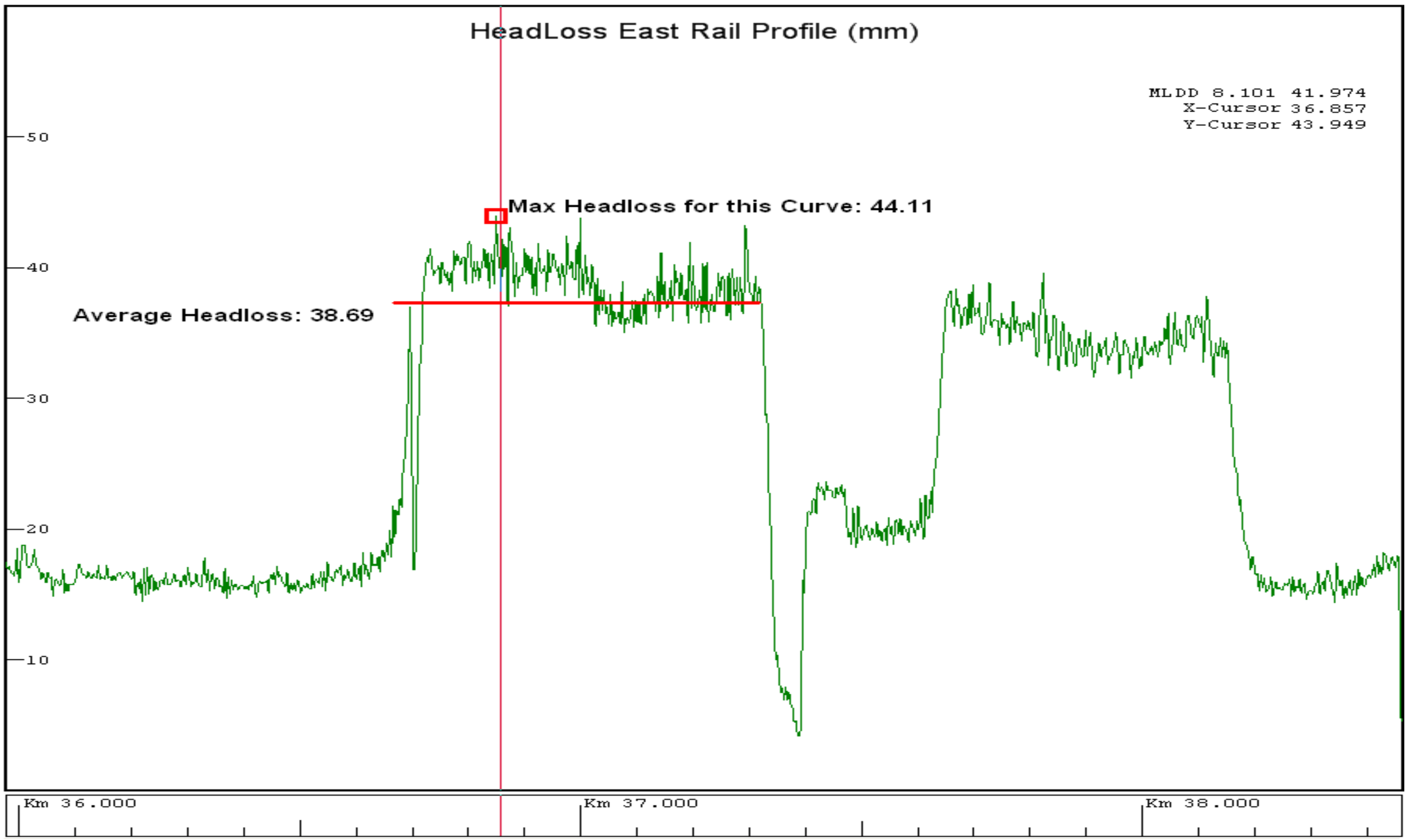
Types of Data Set to be Dealt With

Train Monitoring Systems

- In Motion Weighbridges
- Hot Box Detectors
- Automatic Equipment Identifier
- Dragging Equipment Detector
- Wheel Impact Detector
- Acoustic Bearing Monitor
- Angle of Attack
- Ground-borne Noise Systems

Types of Data Set to be Dealt With

Sample Raw Data



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Integration of Asset Condition Data into Asset Management Systems - Situation

- A set of **condition monitoring equipment is deployed** across Railway Networks
- Use of condition monitoring equipment is **not fully utilized** in daily maintenance activities.
- One reason is that condition equipment **uses proprietary databases**
- **Scheduling for maintenance** of rolling stock via CMMS **without real-time asset condition data**
- Separate condition monitoring database **not integrated** with asset management system

Objective of our current work: to propose enhancements to integrate asset condition data with asset management systems using Big Data techniques

Challenges: Condition Assessment

- Should be a predictive tool
- Will play a role in mitigating potential risks
- Integrity issues in source data systems
- Lack of Standards either between vendors and railway organisations, and other associated Operators.
  (difficult to validate existing algorithms used in wayside systems due to proprietary nature of algorithms).
- No single user access to the multitude of Wayside sensor data.
- Consolidation and reporting of Consist Data in motion is an identified primary requirement
  for both internal and external stakeholders
- Stakeholder committees required that articulate a vision and direction for all stakeholders.

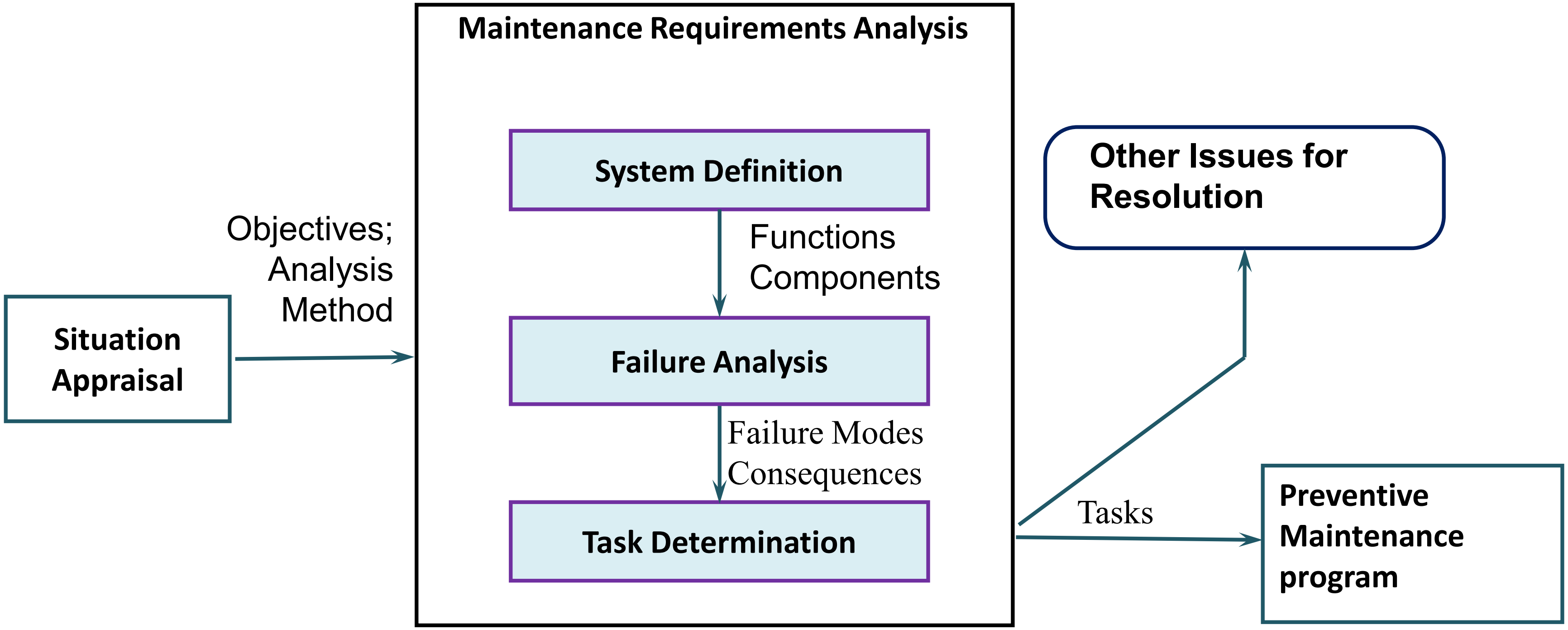
Topic 3

- Characterise the problem of maintenance scheduling

Where is Data Analytics Leading Though?

- Having data is fine if it is useful.
- Need to consider new ways of using data
- Data must be used by Decision Support Systems
  that allow the capability for dynamic requirements analysis
  across the network informed by resource capacity
  and operating schedule.

Maintenance Requirements Analysis Process



Source: Dwight and Gordon

Great hope

- The emergence of **cost effective sensor technologies** and **data acquisition storage** and **analysis systems** allows the **condition** of components within an asset such as a train to be **known in real time**.

- Perhaps the silver bullet is arriving?

- If it does then the whole **basis for the maintenance system** for items such as fleets of trains **may be invalid**.

How does degradation modelling, sensor technology, and BDA address fleet-maintenance cost-drivers?

Cost drivers:

- Groupability
  - Routine nature of the work and work schedule
  - Prediction accuracy
- Time systems are out of service
- Component time in service

Conflicts:

- Extending time in service v grouping

- CBM v Routing nature of the work schedule

Forces **move to dynamic integrated Maintenance Requirements Analysis**.
For a fleet, global and local updates to mtce program will be beneficial.

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Topic 4

- Projection of the prospects for BDA (Free thinking)

Thoughts

- Big data (analytics) is a solution…but for which problems?
- Lots of **data** may be **an opportunity** rather than a problem. Nothing much has changed on that front.
- Asset management decisions require condition information.
- **Condition information is improving**…when will we get there…and where is there..
- **Big data** sets are **useful when** the they **contain the required information** is likely to be held within the data.
- **The fundamentals remain**: failure mechanism, prediction, task selection based on cost.
- **Condition monitoring** provides a window to **some aspects** of asset condition.
- **Asset condition is relative** to competing assets or asset states.
- Need to **define the value of** obtained by having **condition information**. What is the information sought…

  (partly need to know when the asset will cease to deliver the required functions…)

  Finally it is about minimising the cost of service delivery
- Amazed that **things** (even IoT) generating huge amounts of unused data are being installed.
- Pipeline like situations with many data points offering information on degradation rates is an application of BDA. Searching for relationships that inform corrosion rates.
- Is the shift to CBM as advanced as some imply?

The Future Research Direction

Where Is This Leading?

- Knowing condition is fine if it is useful.
- Need to consider new ways of scheduling maintenance (e.g. via Flexsim).
- Dynamic integrated maintenance requirements analysis across the fleet informed by resource capacity and operating schedule required.
- Fundamental rethink of the maintenance system in the wake of sensor technology (BD?) may be worthwhile.

Acknowledgements

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– Ongoing research on LCC based track-form decisions and maintenance scheduling for rolling stock under Australasian Centre for Rail Innovation and other sources.

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Thank you for the opportunity!

Richard Dwight: radwight@uow.edu.au

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