Domain Knowledge and Data Analytics: Towards a Holistic Approach to Power System Condition Monitoring and Asset Management

Dr Bruce Stephen

Advanced Electrical Systems Group
Institute for Energy and Environment
Department of Electronic and Electrical Engineering
University of Strathclyde
Glasgow G1 1RD
United Kingdom

bruce.stephen@strath.ac.uk

Future Power System Operational Challenges

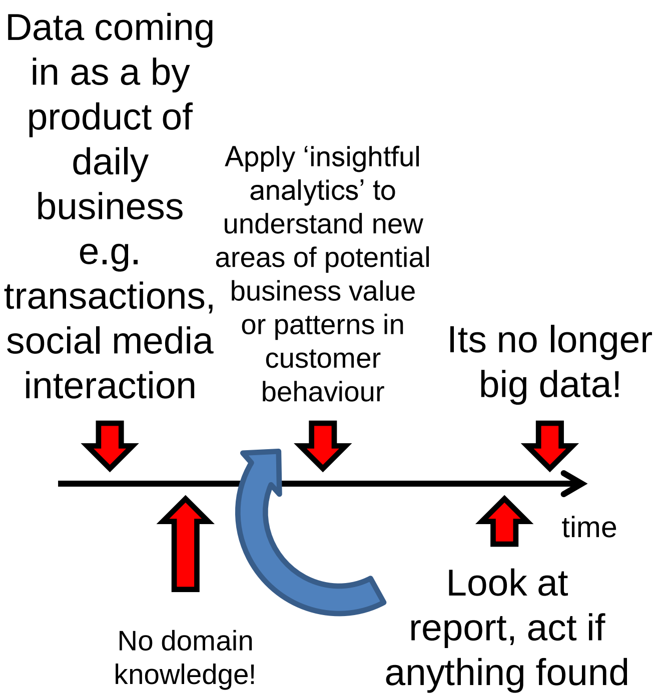
- Power utility companies face ongoing pressure for ever higher quality of service from customers and regulatory bodies
  - High quality of service means intensive maintenance and therefore high cost – how can this be optimised to direct resource to most critical plant at the least disruptive time?
- Falling cost and availability of sensors and digital storage permit intensive monitoring of critical plant
  - Condition monitoring data shows asset behaviour at a resolution previously unknown – how to understand this and integrate it with domain knowledge?
- Installing new sensors on operational plant presents a risk
  - How to calibrate? What data expected? How to show compliance?

Understanding and acting on anticipated plant degradation is the underpinning of Reliability Centred Maintenance. A combination of:

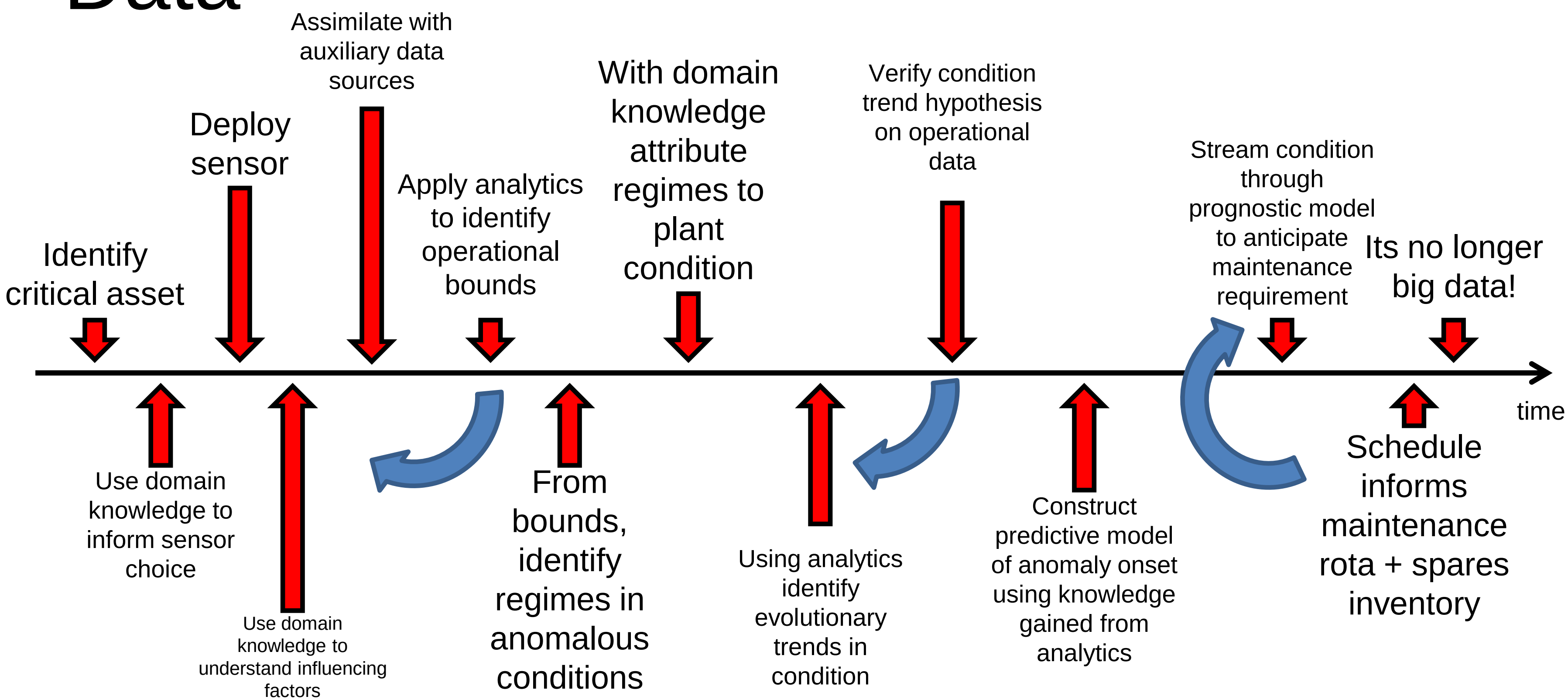
- Domain expertise
- Advanced data analytics
- Realistic operational testing

is required to transition from the research environment to business as usual

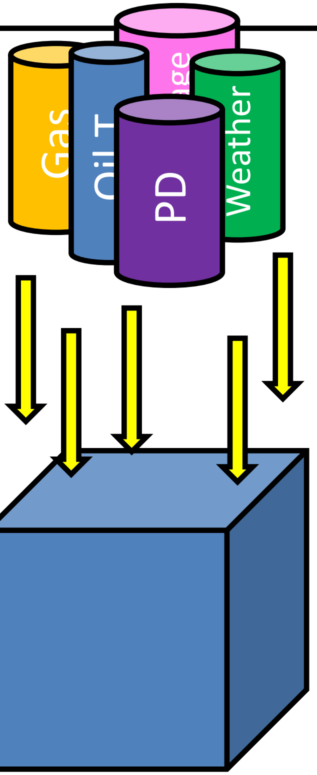
Journey to Big (e-Business) Data



Journey to Big (Asset Management) Data

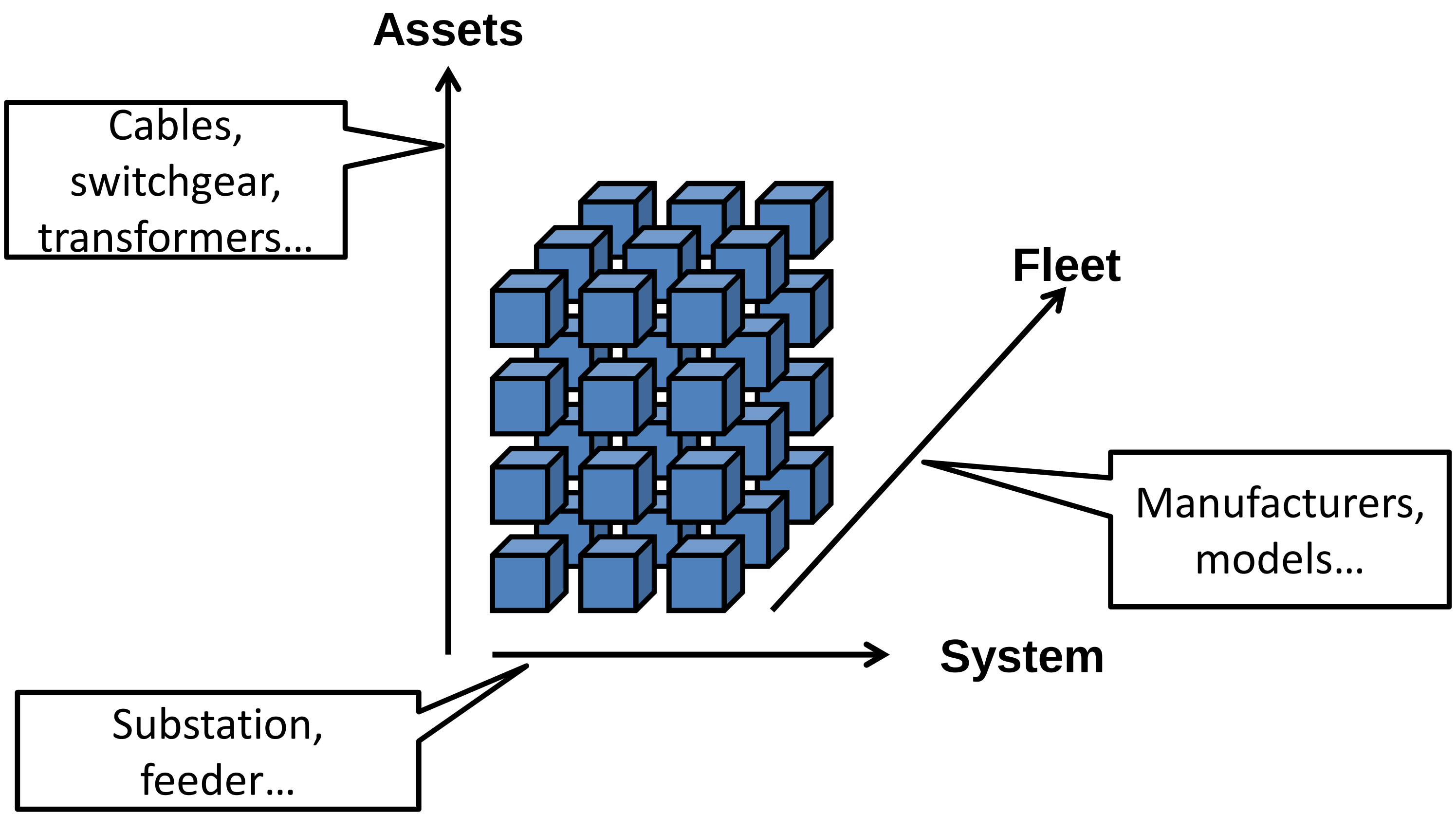


Condition Monitoring Challenge

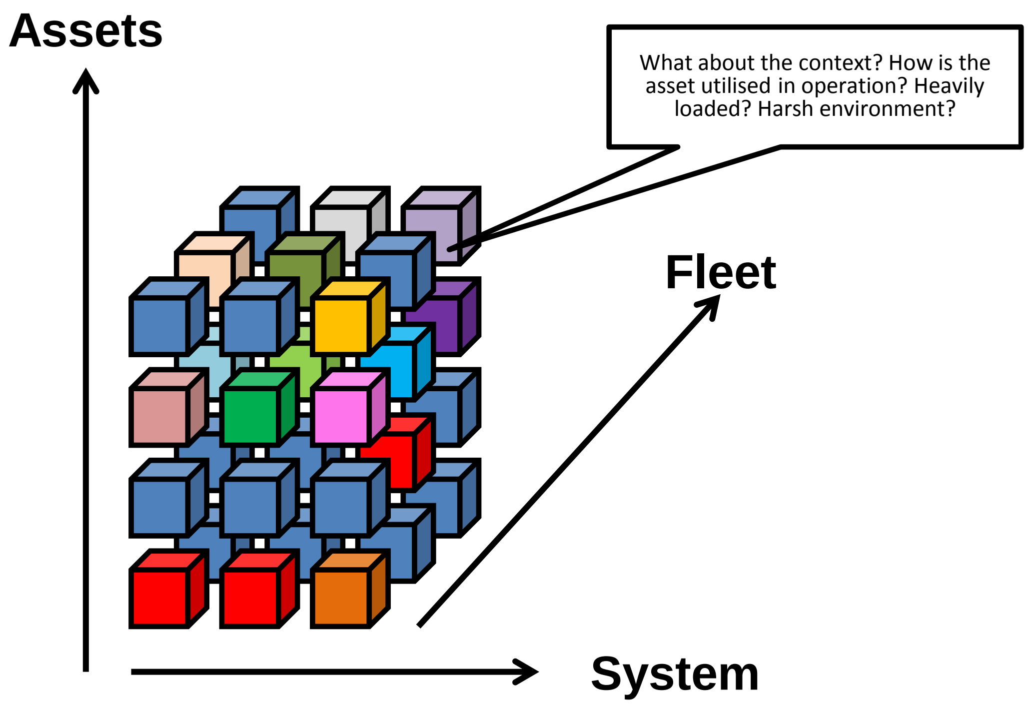


Even for one plant item, condition monitoring data comes from a variety of sensors at a variety of rates. Should these be dealt with in isolation?

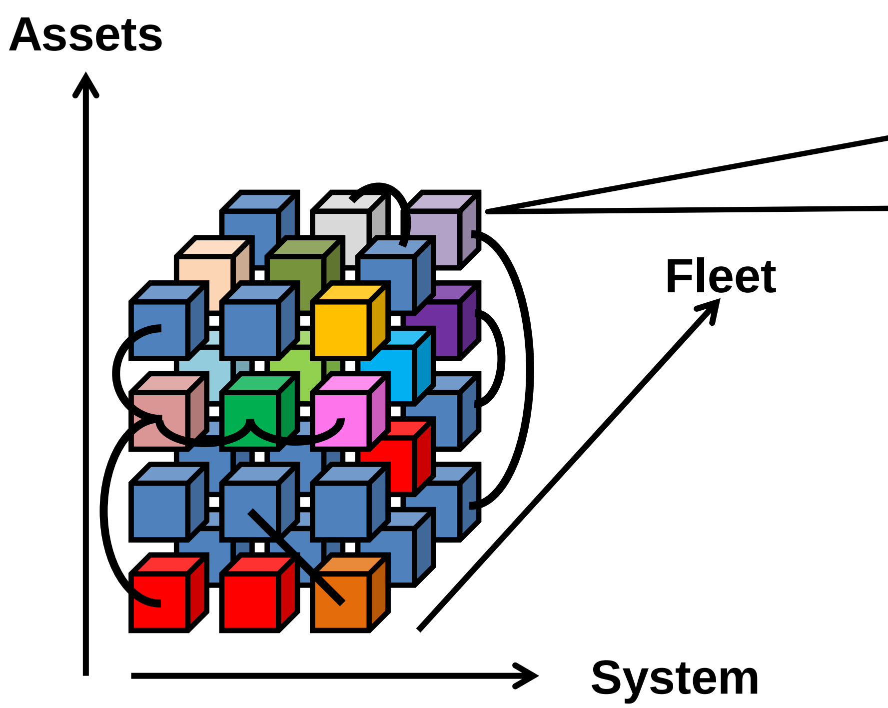
Condition Monitoring Challenge



Condition Monitoring Challenge



Condition Monitoring Challenge



Interlinking relations – how to understand this? Domain knowledge of the physical system and analysis of the statistical co-behaviours of sensor measurements

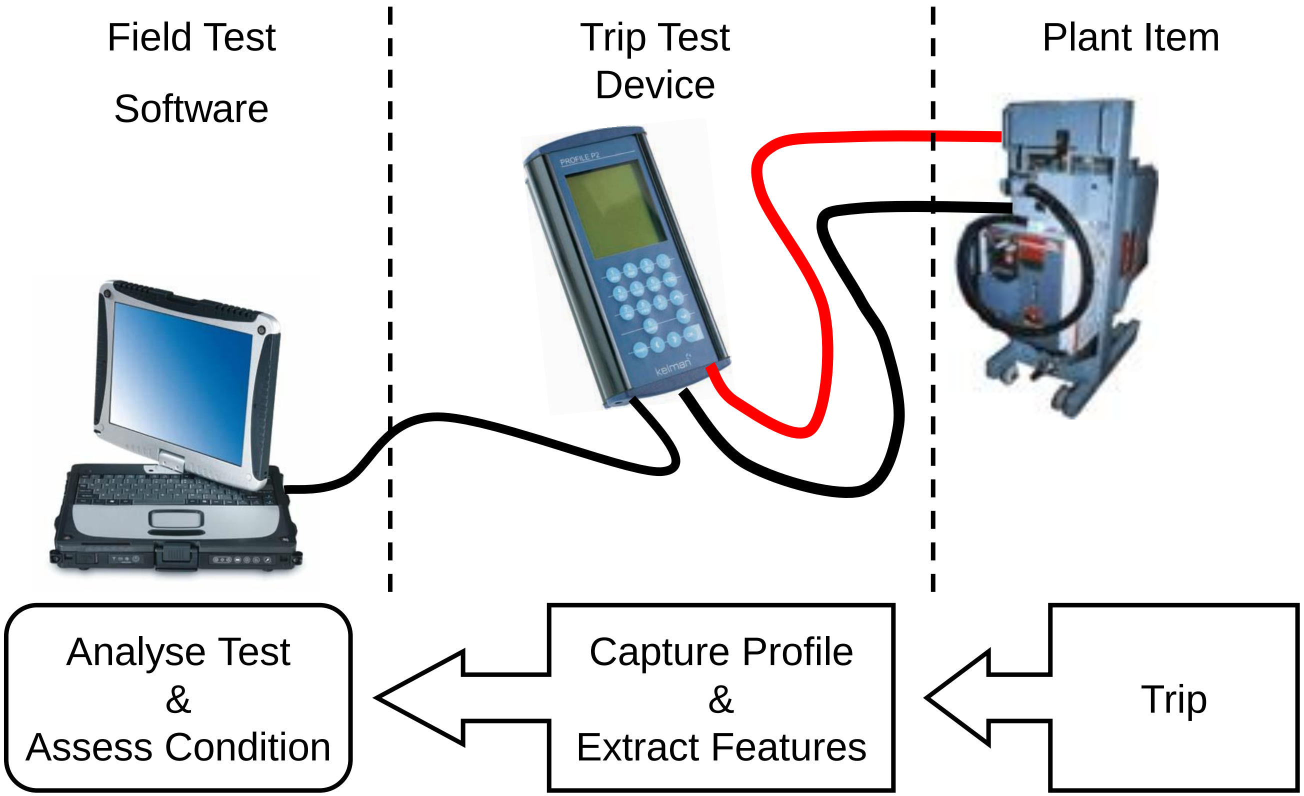
Practical Experience and Tacit Findings

DOMAIN KNOWLEDGE

Domain Knowledge

- Engineering knowledge is often obtained through practical application
  - Resides in the mind of the expert…
- How can domain knowledge be formalised?
- How can new data be utilised?
- Example: Switchgear on distribution networks amounts to numerous heterogeneous plant items
  - Each has a different optimal behaviour
  - Routine maintenance indirectly captures this through trip testing

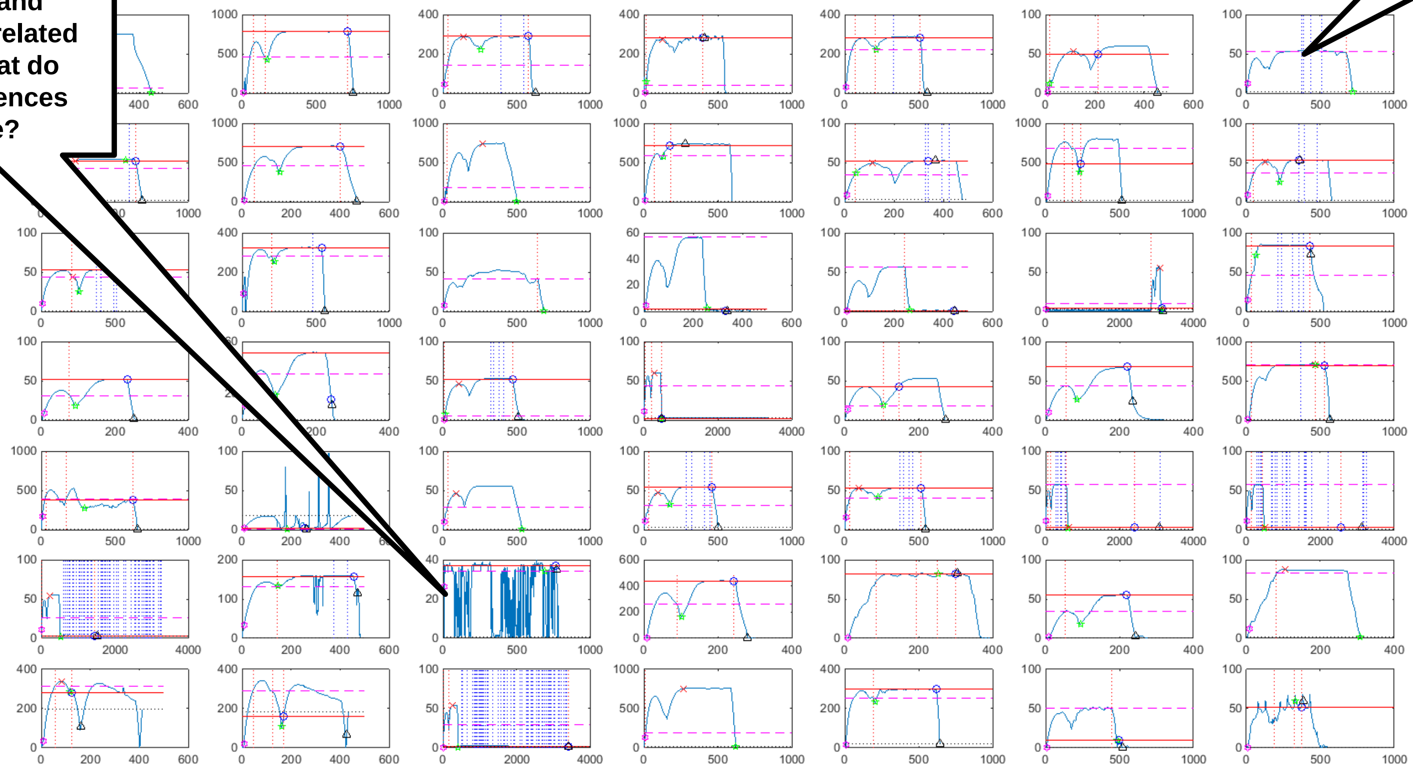
Example: Trip Current Testing



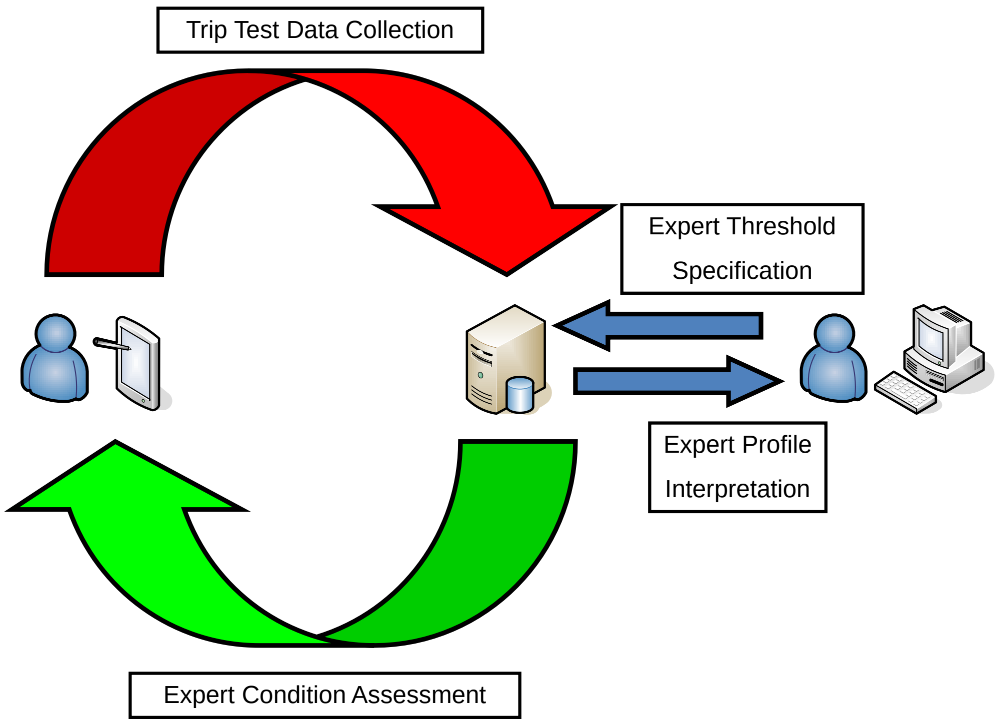
Example: Trip Current Testing

Trip test on 11kV CB produces a trace that can be used to diagnose faults through expert interpretation – how to capture this formally?

Differences in behaviour can pick up vibration, electrical and mechanical related faults – what do these differences look like?

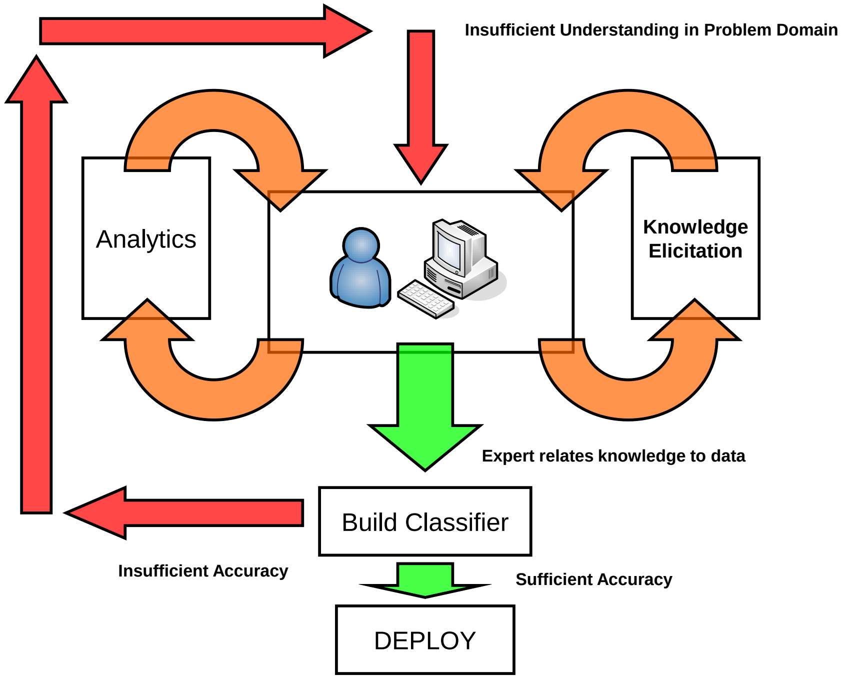


Example: Trip Current Testing



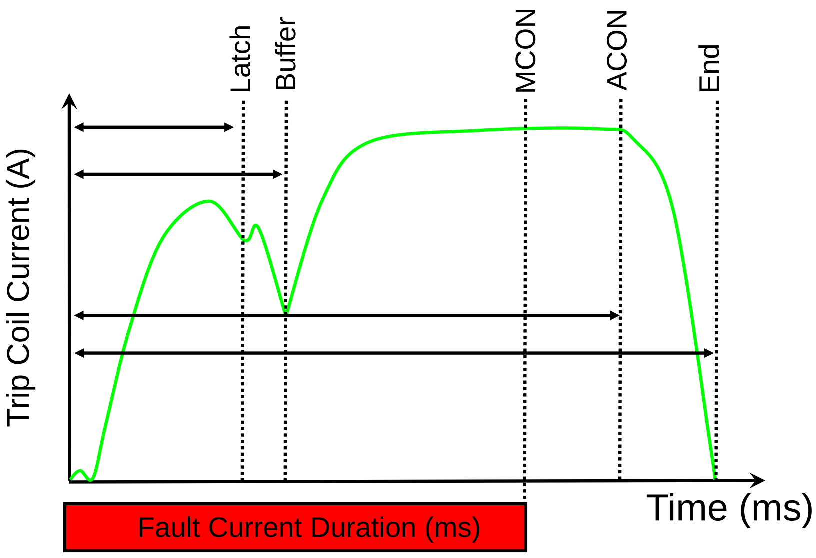
Integrating Domain Knowledge

- Whether classifying behaviour or tracking its evolution, CM data may be overwhelmingly large
- Expert knowledge may be grounded in practical experience, hence not generalizable
- Solution is to incrementally apply analytics to reduce data to a manageable set of unknowns then match up knowledge



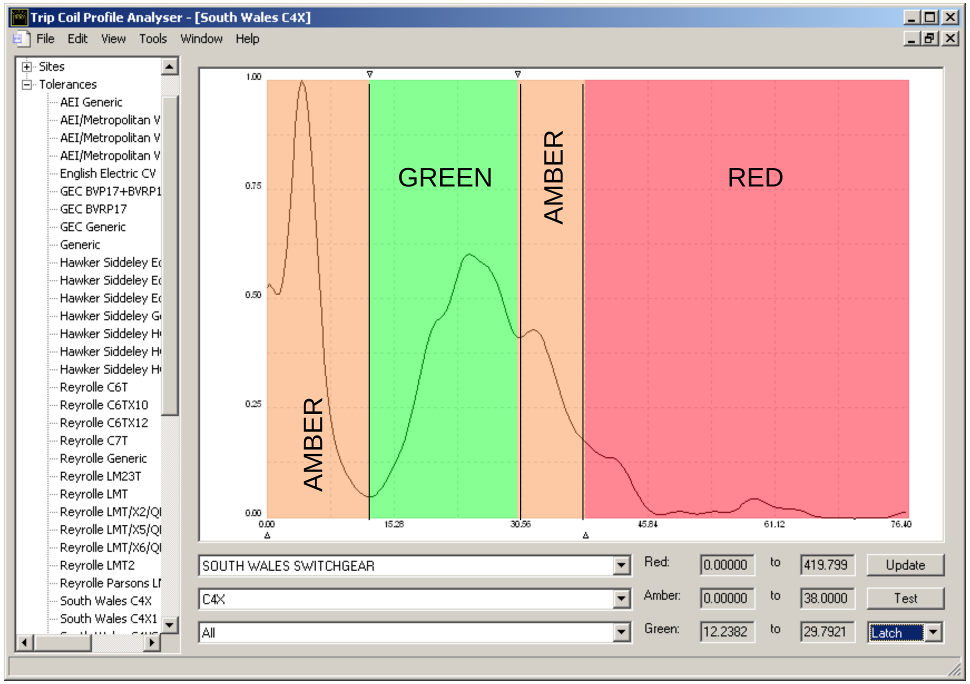
Solution for Trip Current Testing

- Look at how expert chosen features of the test are distributed according to manufacturer and model
- Allow experts to set bounds informed by modes in the implied probability density
  - Not by guesswork or memory!
- Reduce this to a simple ‘traffic light’ indicator based on past experience of <u>general</u> performance



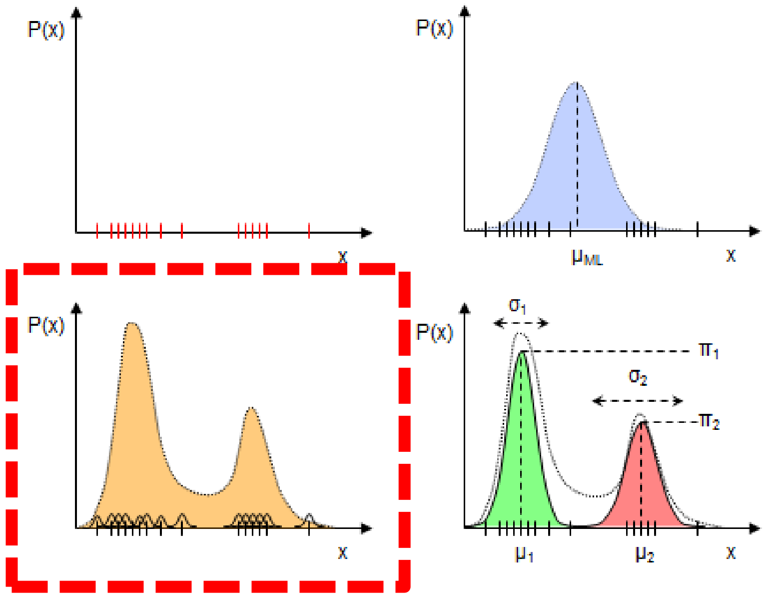
Solution for Trip Current Testing

- Look at how expert chosen features of the test are distributed according to manufacturer and model
- Allow experts to set bounds informed by modes in the implied probability density
  - Not by guesswork or memory!
- Reduce this to a simple ‘traffic light’ indicator based on past experience of <u>general</u> performance



Bridging the Knowledge/Data Gap

- Implied probability distribution of switchgear trip times (and other features) is not of a known form
- A number of methods (right) for estimating this – a high fidelity, non-parametric approach is to use a Kernel Density Estimate
  - Place a kernel (simple probability distribution) on each data point and sum all probabilities to get an approximation of the trip time probability distribution
- The expert then decides what the modes in the distribution mean



$$P(x)=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_n^d}K\left(\frac{x-x_i}{h_n}\right)$$

Beyond Orthodox Statistics…

ADVANCED ANALYTICS

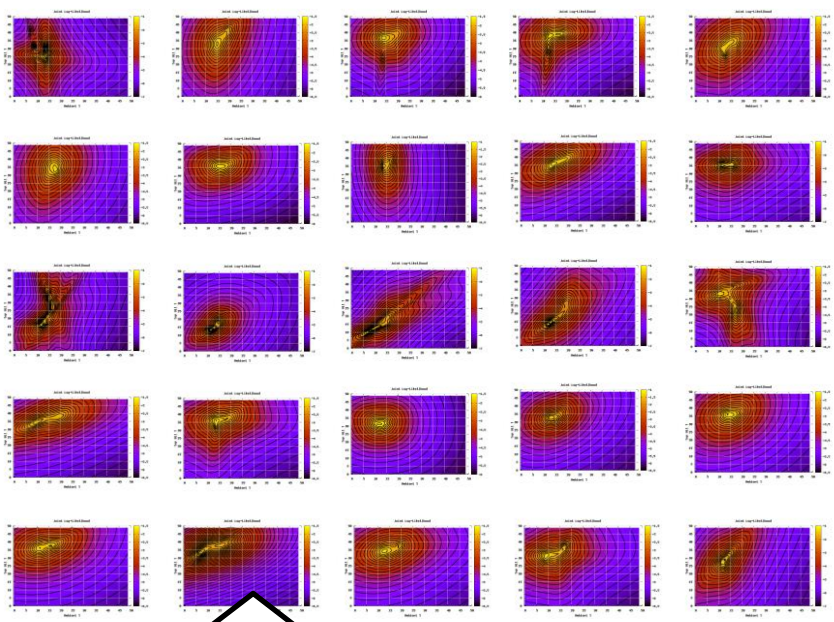
Understanding Condition Monitoring Data

- Condition monitoring data will collect plant behaviour at a higher resolution than domain experts are used to seeing
- This may pick up several operating regimes such as start up, shut down, faults and transitions between all of these
  - Simple statistics would average over these leading to an unrepresentative view of plant performance
  - Sensor values may not change, but the dependency relation between them might
- Other domains exploit advances in Machine Learning, how might appropriate models be selected for Power?

Grid Transformers

- Monitoring transmission network assets (132kV and above in UK) is particularly important:
  - Large number of customers served
  - Large specialised – nobody carries a large inventory of replacements
- Large body of knowledge in understanding plant aging and fault onset

Capturing expected behaviour

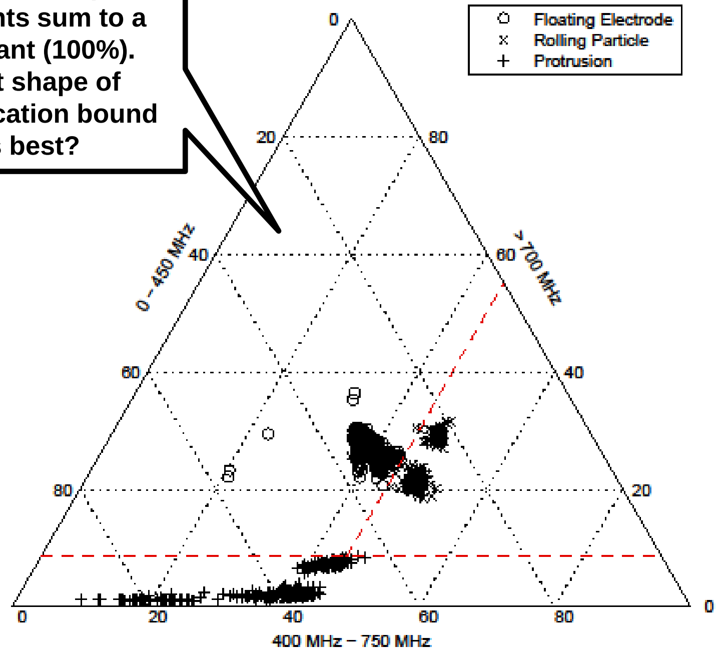


The daily joint probability of ambient temperature and top oil temperature in a grid transformer over 25 days – shows what to expect but is a complex shaped relation every day

- Oil temperature can be an important indicator of transformer health
- Relation between ambient temperature and oil temperature (left) changes
  - May be related to loading, wind speed or precipitation
- How to express plant behaviour formally so that a change can be detected? Probabilistically.

Transformer PD Classification

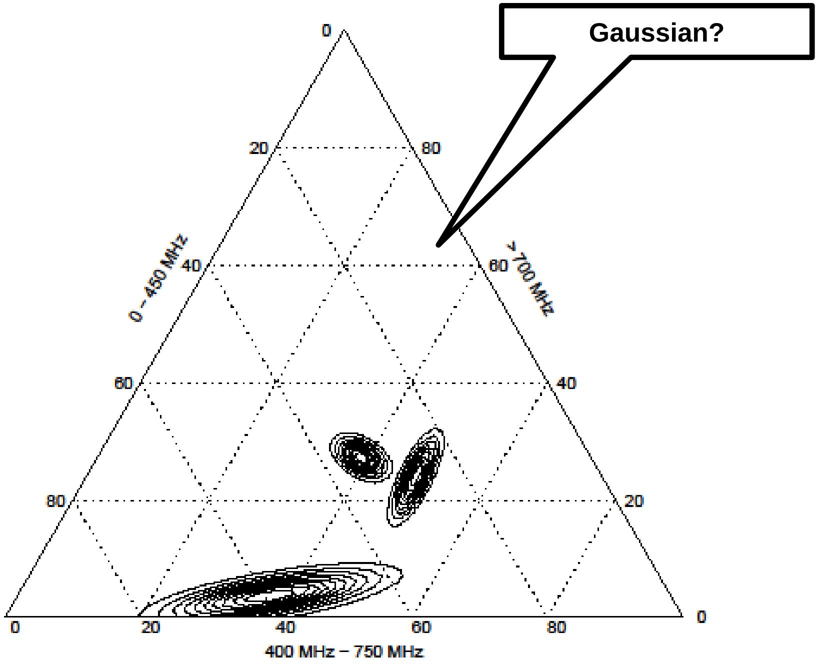
3 frequency bands means a 3-simplex: all points sum to a constant (100%). What shape of classification bound is best?



- Partial discharge (PD) is a known indicator of incipient degradation in electrical plant insulation
- Lots of domain knowledge and good physical models of behaviour
- Ultimately end up with a volume of data (owing to sub-second sampling) that is unmanageable
- <u>Know</u> that the frequency *composition* is important – but *compositional* data poses problems when using conventional classification techniques

Baker, P., Stephen, B. & Judd, M. (2013) Compositional modelling of partial discharge pulse spectral characteristics. IEEE Transactions on Instrumentation and Measurement, 62 (7). 1909 - 1916. ISSN 0018-9456

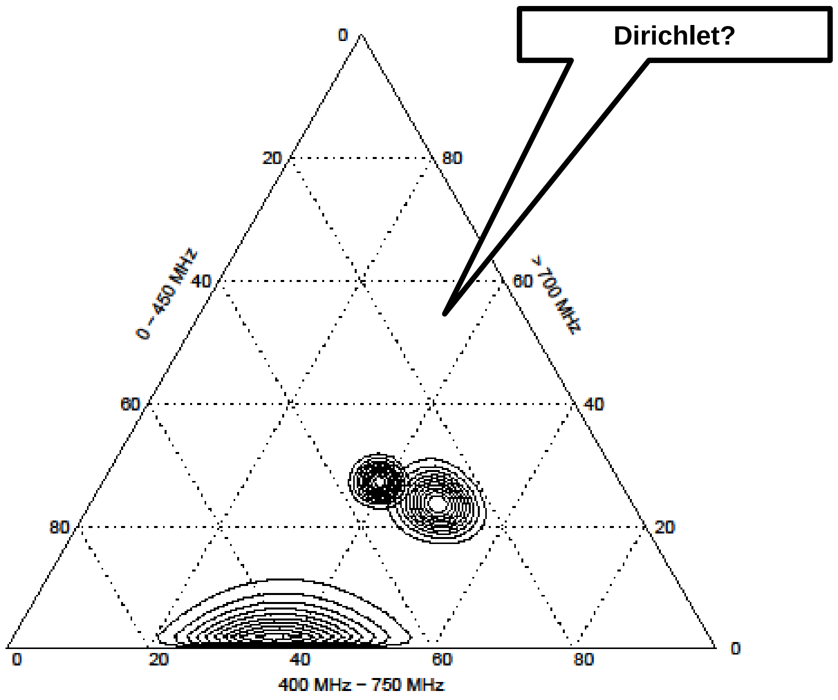
Transformer PD Classification



- Partial discharge (PD) is a known indicator of incipient degradation in electrical plant insulation
- Lots of domain knowledge and good physical models of behaviour
- Ultimately end up with a volume of data (owing to sub-second sampling) that is unmanageable
- <u>Know</u> that the frequency *composition* is important – but *compositional* data poses problems when using conventional classification techniques

Baker, P., Stephen, B. & Judd, M. (2013) Compositional modelling of partial discharge pulse spectral characteristics. IEEE Transactions on Instrumentation and Measurement, 62 (7). 1909 - 1916. ISSN 0018-9456

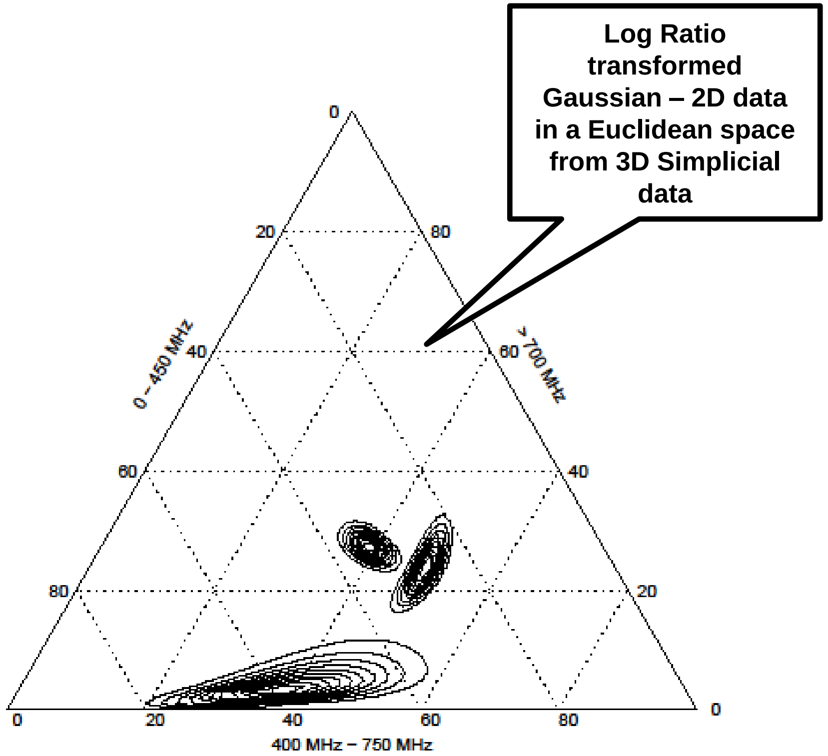
Transformer PD Classification



- Partial discharge (PD) is a known indicator of incipient degradation in electrical plant insulation
- Lots of domain knowledge and good physical models of behaviour
- Ultimately end up with a volume of data (owing to sub-second sampling) that is unmanageable
- Know that the frequency *composition* is important – but *compositional* data poses problems when using conventional classification techniques

Baker, P., Stephen, B. & Judd, M. (2013) Compositional modelling of partial discharge pulse spectral characteristics. IEEE Transactions on Instrumentation and Measurement, 62 (7). 1909 - 1916. ISSN 0018-9456

Transformer PD Classification



- Partial discharge (PD) is a known indicator of incipient degradation in electrical plant insulation
- Lots of domain knowledge and good physical models of behaviour
- Ultimately end up with a volume of data (owing to sub-second sampling) that is unmanageable
- <u>Know</u> that the frequency *composition* is important – but *compositional* data poses problems when using conventional classification techniques

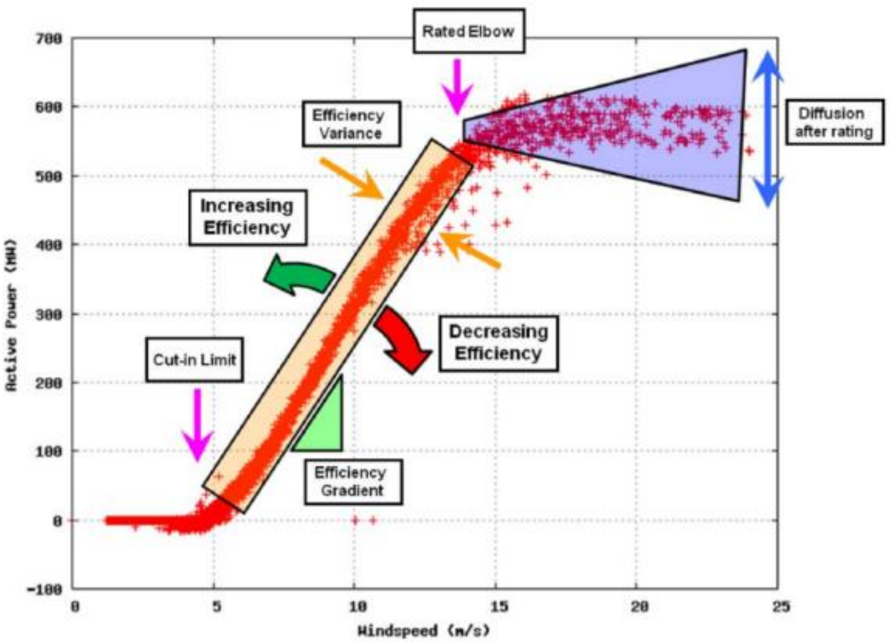
Baker, P., Stephen, B. & Judd, M. (2013) Compositional modelling of partial discharge pulse spectral characteristics. IEEE Transactions on Instrumentation and Measurement, 62 (7). 1909 - 1916. ISSN 0018-9456

Generation Assets

- Anticipating generation plant failure allows
  - Schedule maintenance outside unit commitment times
  - Schedule maintenance at times with low revenue potential
- Wind Turbines (WT) are at risk from a variety of factors
  - Can’t monitor everything, how to get a general view of plant health?

WT Fault Detection/Diagnosis

- Although wind turbines have various specialised sensors, the power curve (relation between windspeed and power) can yield various health indicators…
- …Failing plant results in less power for the same windspeed…
- How to factor in variability? Power curve essentially stochastic not deterministic
- Express as joint probability capturing the complex form using a Copula



Stephen, B., Galloway, S.J., McMillan, D., Hill, D.C. & Infield, D.G. (2011) A copula model of wind turbine performance. IEEE Transactions on Power Systems, 26 (2). pp. 965-966. ISSN 0885-8950

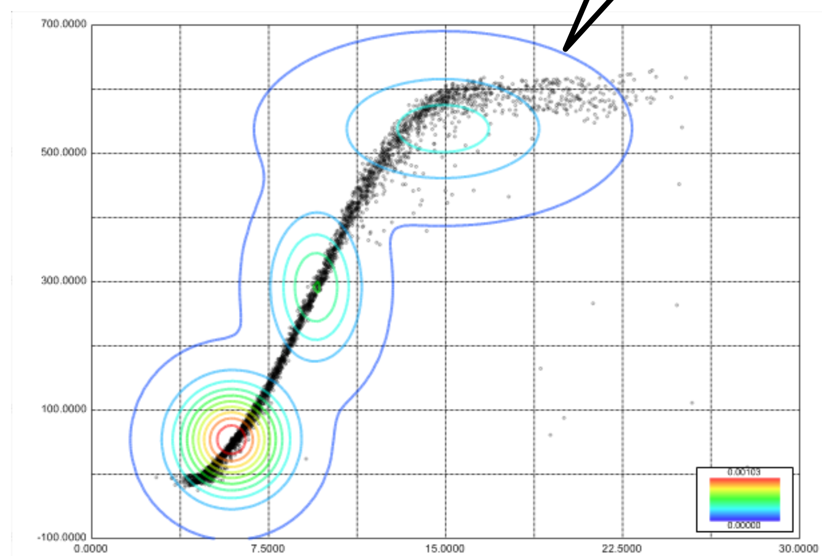
Gill, S., Stephen, B. & Galloway, S., "Wind Turbine Condition Assessment Through Power Curve Copula Modeling," in IEEE Transactions on Sustainable Energy, vol. 3, no. 1, pp. 94-101, Jan. 2012.

Wang Y, Infield DG, Stephen B, Galloway SJ. Copula-based model for wind turbine power curve outlier rejection. Wind Energy 2013; 17: 1677–1688.

WT Fault Detection/Diagnosis

Bivariate Gaussian Mixture model with no dependence assumed

- Although wind turbines have various specialised sensors, the power curve (relation between windspeed and power) can yield various health indicators…
- …Failing plant results in less power for the same windspeed…
- How to factor in variability? Power curve essentially stochastic not deterministic
- Express as joint probability capturing the complex form using a Copula



Stephen, B., Galloway, S.J., McMillan, D., Hill, D.C. & Infield, D.G. (2011) A copula model of wind turbine performance. IEEE Transactions on Power Systems, 26 (2). pp. 965-966. ISSN 0885-8950

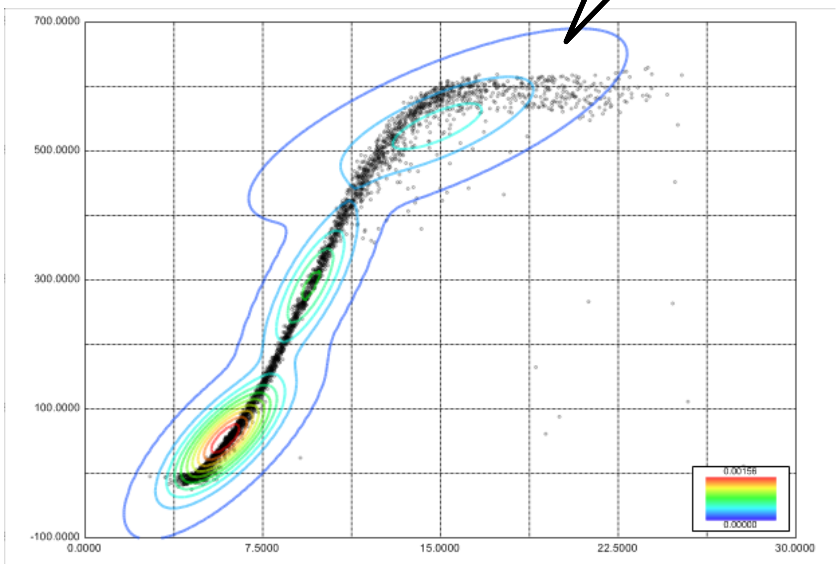
Gill, S., Stephen, B. & Galloway, S., "Wind Turbine Condition Assessment Through Power Curve Copula Modeling," in IEEE Transactions on Sustainable Energy, vol. 3, no. 1, pp. 94-101, Jan. 2012.

Wang Y, Infield DG, Stephen B, Galloway SJ. Copula-based model for wind turbine power curve outlier rejection. Wind Energy 2013; 17: 1677–1688.

WT Fault Detection/Diagnosis

Bivariate Gaussian Mixture model with full covariance assumed – still not a great fit

- Although wind turbines have various specialised sensors, the power curve (relation between windspeed and power) can yield various health indicators…
- …Failing plant results in less power for the same windspeed…
- How to factor in variability? Power curve essentially stochastic not deterministic
- Express as joint probability capturing the complex form using a Copula



Stephen, B., Galloway, S.J., McMillan, D., Hill, D.C. & Infield, D.G. (2011) A copula model of wind turbine performance. IEEE Transactions on Power Systems, 26 (2). pp. 965-966. ISSN 0885-8950

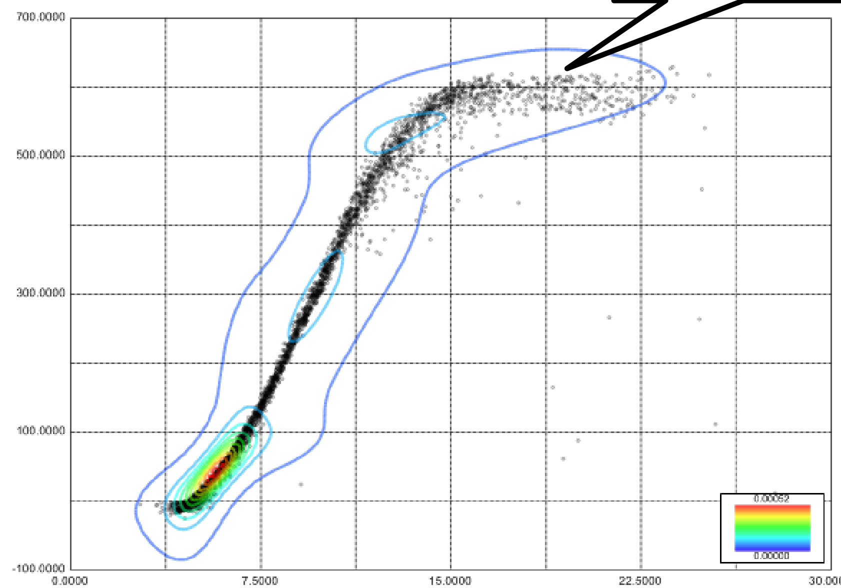
Gill, S., Stephen, B. & Galloway, S., "Wind Turbine Condition Assessment Through Power Curve Copula Modeling," in IEEE Transactions on Sustainable Energy, vol. 3, no. 1, pp. 94-101, Jan. 2012.

Wang Y, Infield DG, Stephen B, Galloway SJ. Copula-based model for wind turbine power curve outlier rejection. Wind Energy 2013; 17: 1677–1688.

WT Fault Detection/Diagnosis

Gaussian Mixture model approximating the PDFs of windspeed and active power. Dependency structure added using a Frank Copula – better fit.

- Although wind turbines have various specialised sensors, the power curve (relation between windspeed and power) can yield various health indicators…
- …Failing plant results in less power for the same windspeed…
- How to factor in variability? Power curve essentially stochastic not deterministic
- Express as joint probability capturing the complex form using a Copula



Stephen, B., Galloway, S.J., McMillan, D., Hill, D.C. & Infield, D.G. (2011) A copula model of wind turbine performance. IEEE Transactions on Power Systems, 26 (2). pp. 965-966. ISSN 0885-8950

Gill, S., Stephen, B. & Galloway, S., "Wind Turbine Condition Assessment Through Power Curve Copula Modeling," in IEEE Transactions on Sustainable Energy, vol. 3, no. 1, pp. 94-101, Jan. 2012.

Wang Y, Infield DG, Stephen B, Galloway SJ. Copula-based model for wind turbine power curve outlier rejection. Wind Energy 2013; 17: 1677–1688.

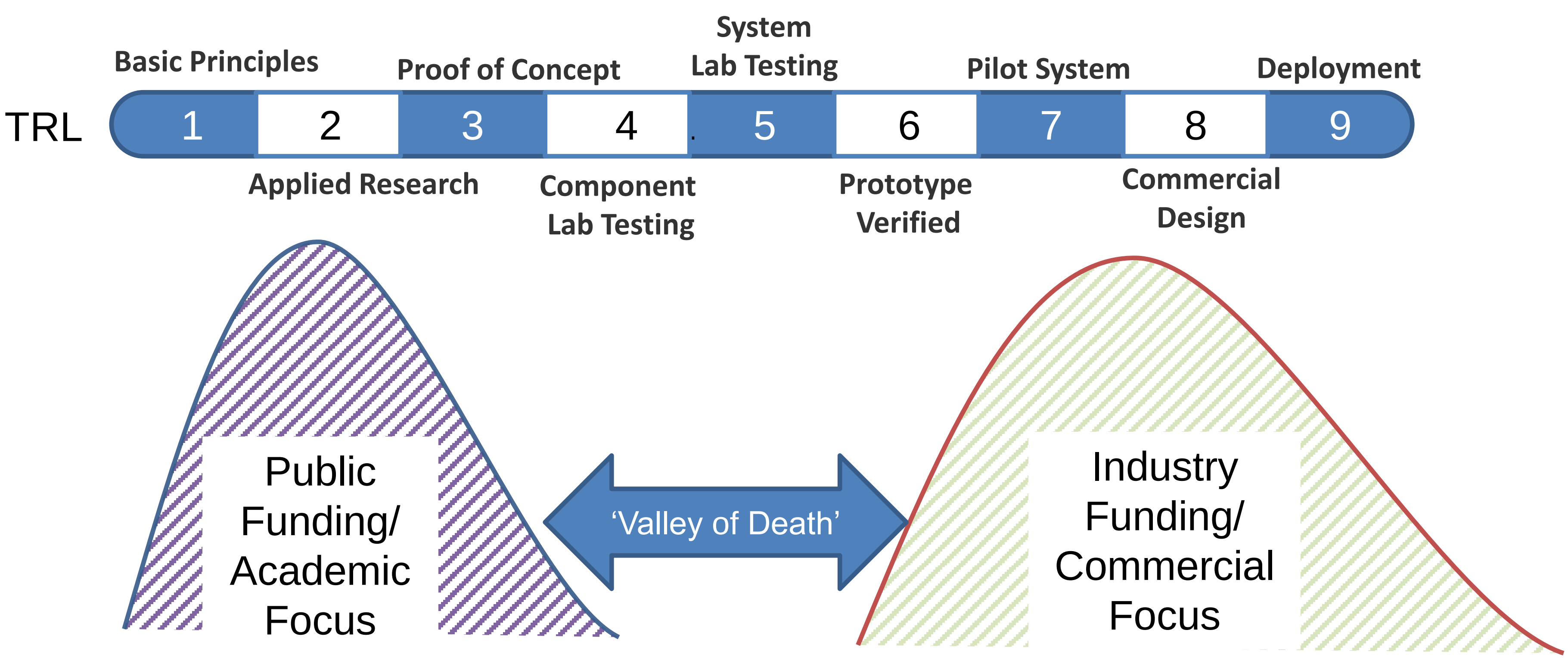
Intra-Plant Condition

Who is most similar → who will fail next?

Towards Business as Usual

TESTING AND DEMONSTRATION

Bridging the Innovation 'Valley of Death'



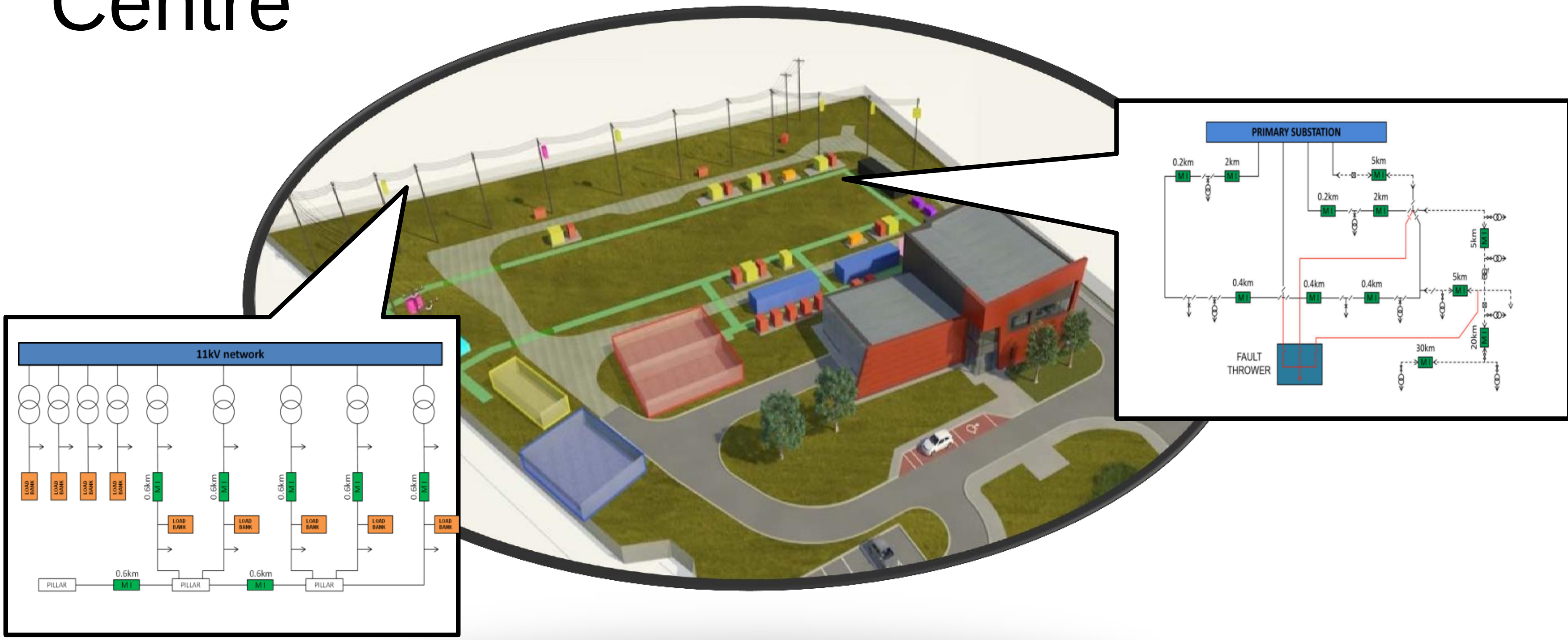
Before deployment

- Given the critical nature of some power assets, any new technology presents a risk
  - Will it work correctly?
    - Operational environments can be noisy…
  - Will it fit with existing processes/infrastructure?
- Usage of realistic lab test facilities to de-risk are essential in making the transition to an operational process

Power Networks Demonstration Centre

- Part of the University of Strathclyde operated in partnership with DNO members SPEN, SSE, UKPN
- Dedicated Power Systems R&D Facility
  - 11kV network with isolation
  - Fault throwing capability
  - Real Time HiL Simulation
  - Industry standard DMS
- Test in an operational environment before it goes onto public network

Power Networks Demonstration Centre



Going Forward…

- Developing prognostics and diagnostic tools for utilities is not just about large volumes of data
- Domain expertise is required to:
  - Inform sensor choice and placement
  - Constrain choice/design of analytical tools
  - Validate performance in the context of application
- Moving this to an operational environment requires an additional level of trust
  - Only realistic test environments can provide this

University of Strathclyde Glasgow