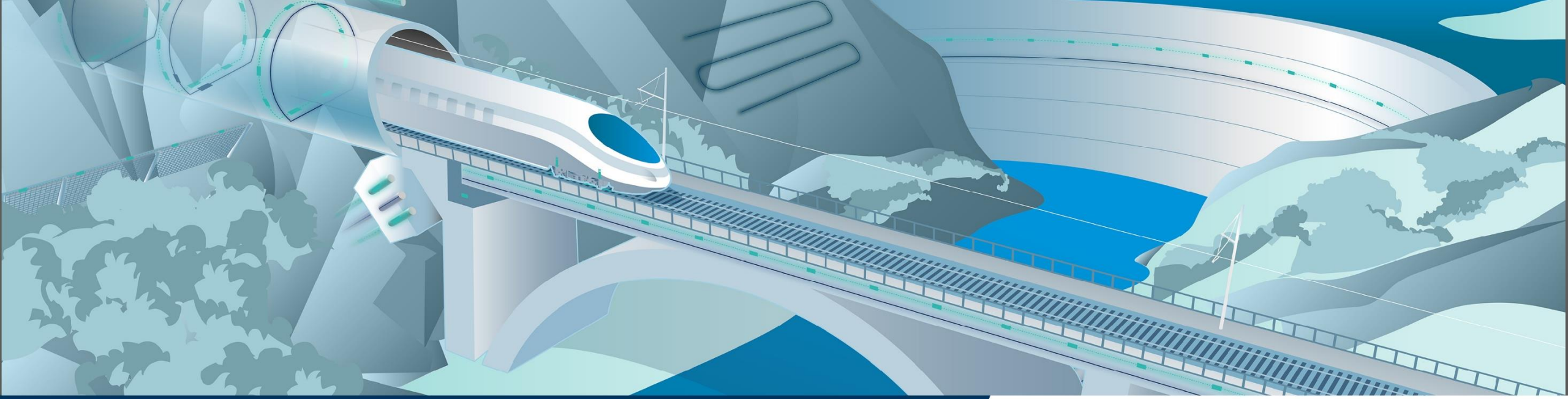


HBK Technology Days – Virtual Seminar Series

Tuesday, November 15, 2022

Machine Learning for Structural Health Monitoring, from Data-Driven to Physics-Informed

Presented by Prof. Elizabeth Cross,
Dynamics Research Group, University of Sheffield

Machine Learning for Structural Health Monitoring, from Data-Driven to Physics-Informed

Abstract

Structural health monitoring as a research field began by studying physical models for systems, comparing modelled and monitored response to understand observed behaviours. As sensing technology advanced and monitoring data became more readily available, many practitioners and researchers adopted a purely data-driven approach capitalising also on technology enhancement from the machine learning field. Today, where we would like to be able automatically assess the health of our structures across their operational envelope, we find that despite these advances, we often lack data that represent all behaviours of interest, thereby precluding an entirely data-driven approach. In this talk, we will discuss the development of a physics-informed approach to machine learning for structural health monitoring. This fast growing area of research attempts to build in our engineering knowledge of a system, alleviating some burden on data acquisition and increasing model interpretability.

About the presenter, Prof. Elizabeth Cross, Dynamics Research Group, University of Sheffield

Lizzy Cross is Head of the Department of Mechanical Engineering and a Professor in the Dynamics Research Group at the University of Sheffield with a research focus on advanced data analysis and machine learning for structural health monitoring (SHM) and nonlinear system identification. She has just completed an EPSRC Innovation Fellowship pioneering physics-informed machine learning for structural dynamics. Lizzy is a co-director of the Laboratory for Verification and Validation, a state-of-the-art dynamic testing facility (lvv.ac.uk). She has published over 140 articles, including 45 journal papers, 6 invited book chapters. She was recently awarded the Achenbach medal which recognises an individual (within 10 years of PhD) who has made an outstanding contribution to the advancement of the field of SHM.

HBK
HOTTINGER BRÜEL & KJÆR

The University Of Sheffield.

Machine learning for structural health monitoring, from data-driven to physics-informed

Lizzy Cross, Daniel Pitchforth, Matthew Jones,

Sam Gibson, Sikai Zhang, Tim Rogers

Dynamics Research Group

About us

Department of Mechanical Engineering

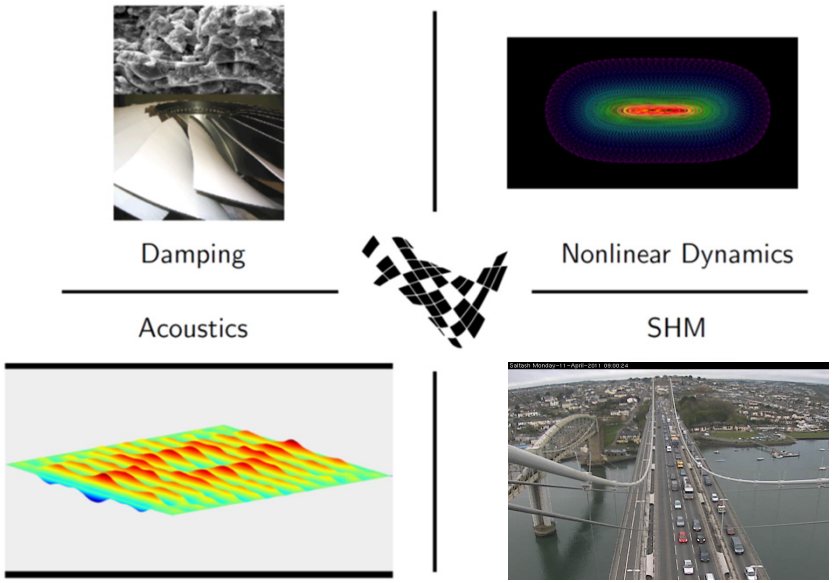
- Large department (60+ academics) covering a broad range of disciplines
- 5th in the UK for Mechanical Engineering in the Guardian University Guide 2023
- 6th in the Times Good University Guide Ranking
- National Student Survey: 1st in Russell Group for Overall Satisfaction

About us

The **Dynamics Research Group** has been hosted by the Department of Mechanical Engineering at the University of Sheffield since 1995.

We are an established group with leading researchers in SHM, nonlinear dynamics, acoustics and damping. Current work on digital twins bridges these themes.

The group currently has over 50 members, including 12 academics and >40 post-doctoral researchers and PhD students.



The path to validation

Lab for Verification and Validation (LVV)

Our latest facility enables controlled testing of components and full scale structures in a range of environments

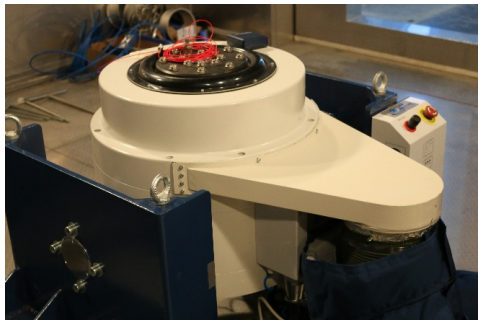
- 3 environmental chamber
- Wind and rain simulation
- 3 x 2 m shake table
- 12m wave tank

European Union
European Regional
Development Fund

EPSRC
Engineering and Physical Sciences
Research Council

The
University
Of
Sheffield.

Laboratory for Verification and Validation

European Union
European Regional Development Fund

EPSRC
Engineering and Physical Sciences Research Council

The University Of Sheffield.

The University Of Sheffield.

Machine learning for structural health monitoring, from data-driven to physics-informed

Lizzy Cross, Daniel Pitchforth, Matthew Jones,

Sam Gibson, Sikai Zhang, Tim Rogers

Dynamics Research Group

Structural Health Monitoring

Main Aim: the development of diagnostic systems capable of detecting structural degradation in an automated, online manner

- Damage detection, localisation, classification
- Prognosis: remaining useful life
- Understanding performance

Advantages: Increased safety and efficiency

Current Research in the DRG

Research Themes

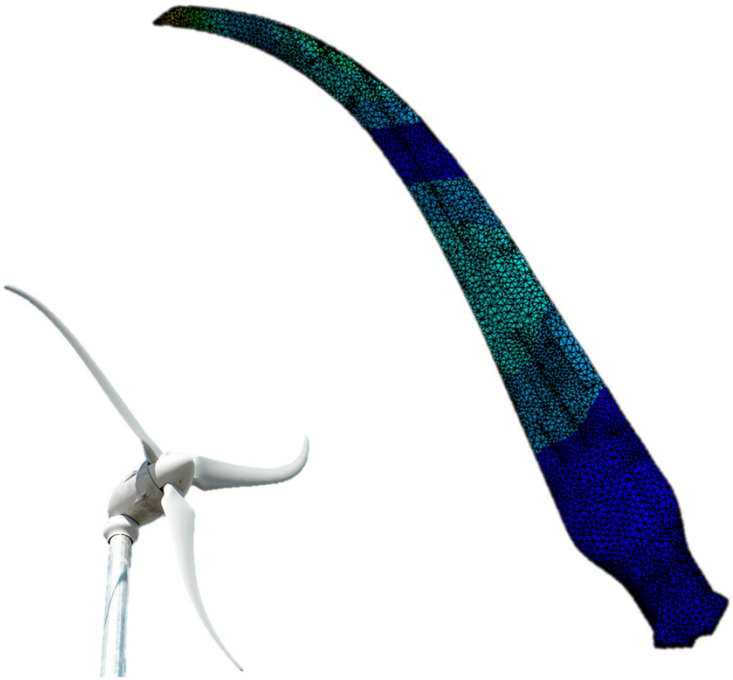
- Vibration-based SHM
- Guided Waves
- Acoustic Emission
- Vision-based SHM
- Machine Learning
- Statistical Methods
- Model-driven SHM

Application Areas

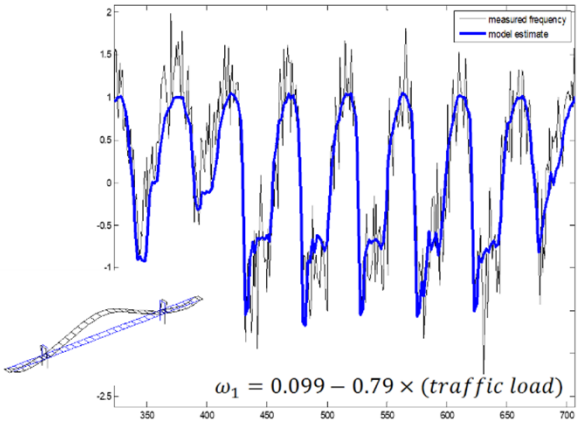
- Aerospace Structures
- Composite Materials
- Ground Vehicles
- Civil Infrastructure
- Wind Energy
- Machining
- Offshore Structures

How can we use our data?

Model-based approach

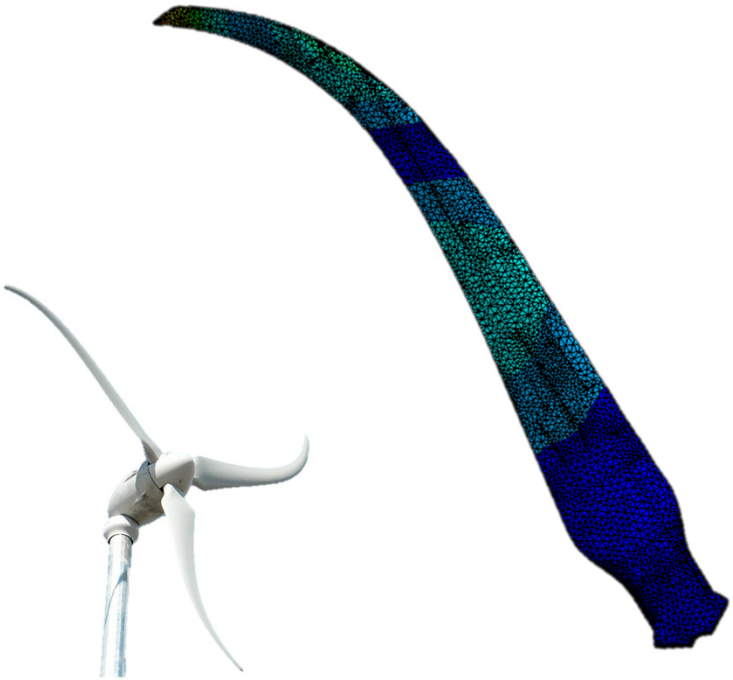


Data-based approach



How can we use our data?

Model-based approach



- Physics-based, interpretable/explainable
- Extrapolative

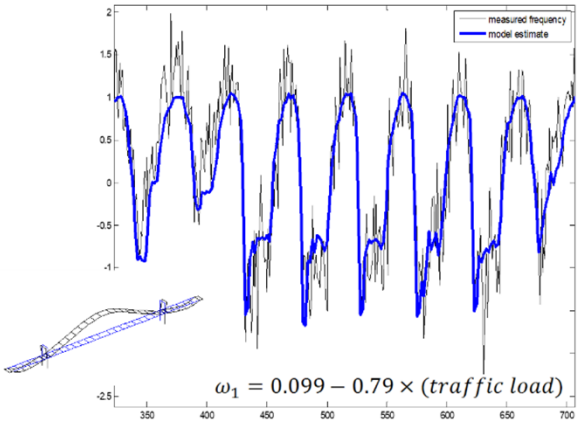
- Difficult to capture complex responses
- Can be wrong

How can we use our data?

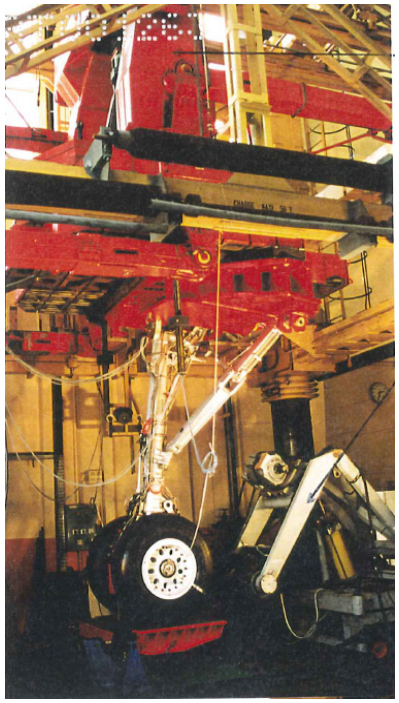
- Flexible with little need to prior knowledge
- Reflects in-operation response

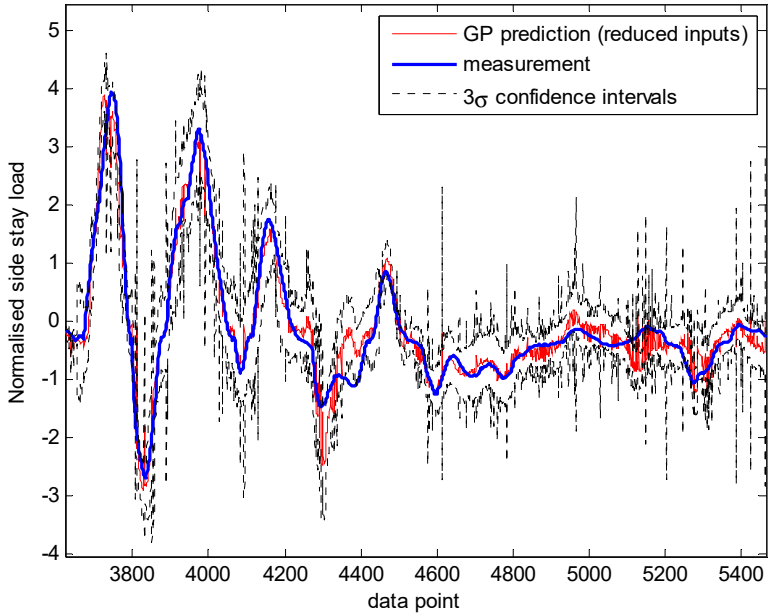
- Unable to extrapolate
- (Often) not interpretable

Data-based approach



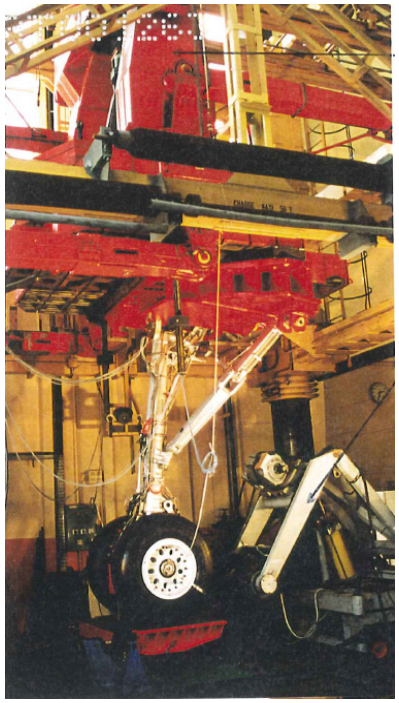
A closer look at data-driven models

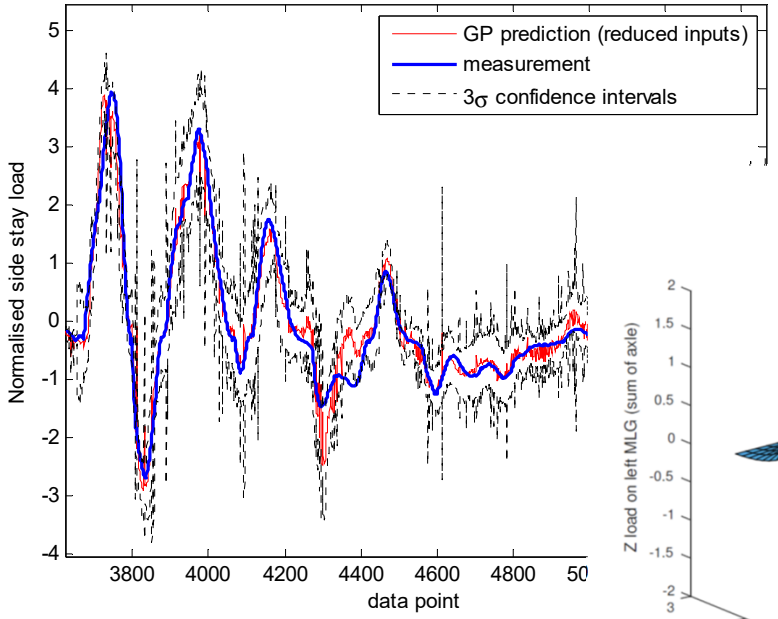


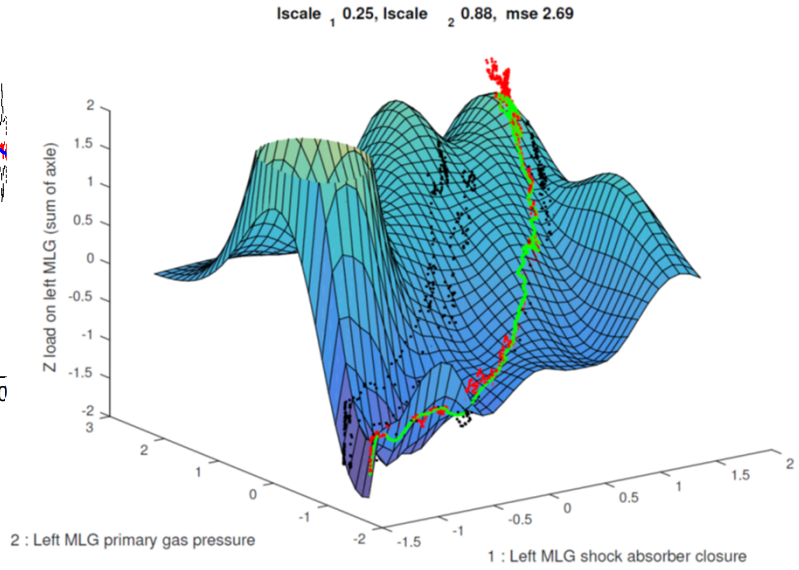


Holmes, G., Sartor, P., Reed, S., Southern, P., Worden, K., & Cross, E. (2016). Prediction of landing gear loads using machine learning techniques. *Structural Health Monitoring*, *15*(5), 568-582.

A closer look at data-driven models

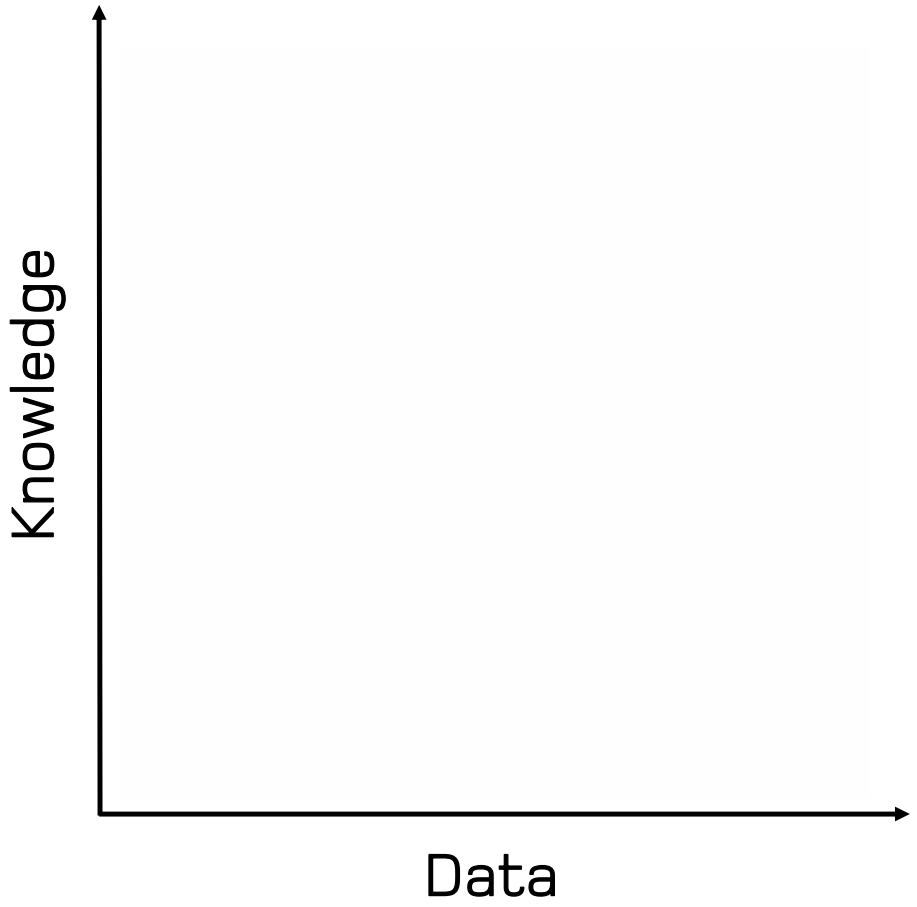




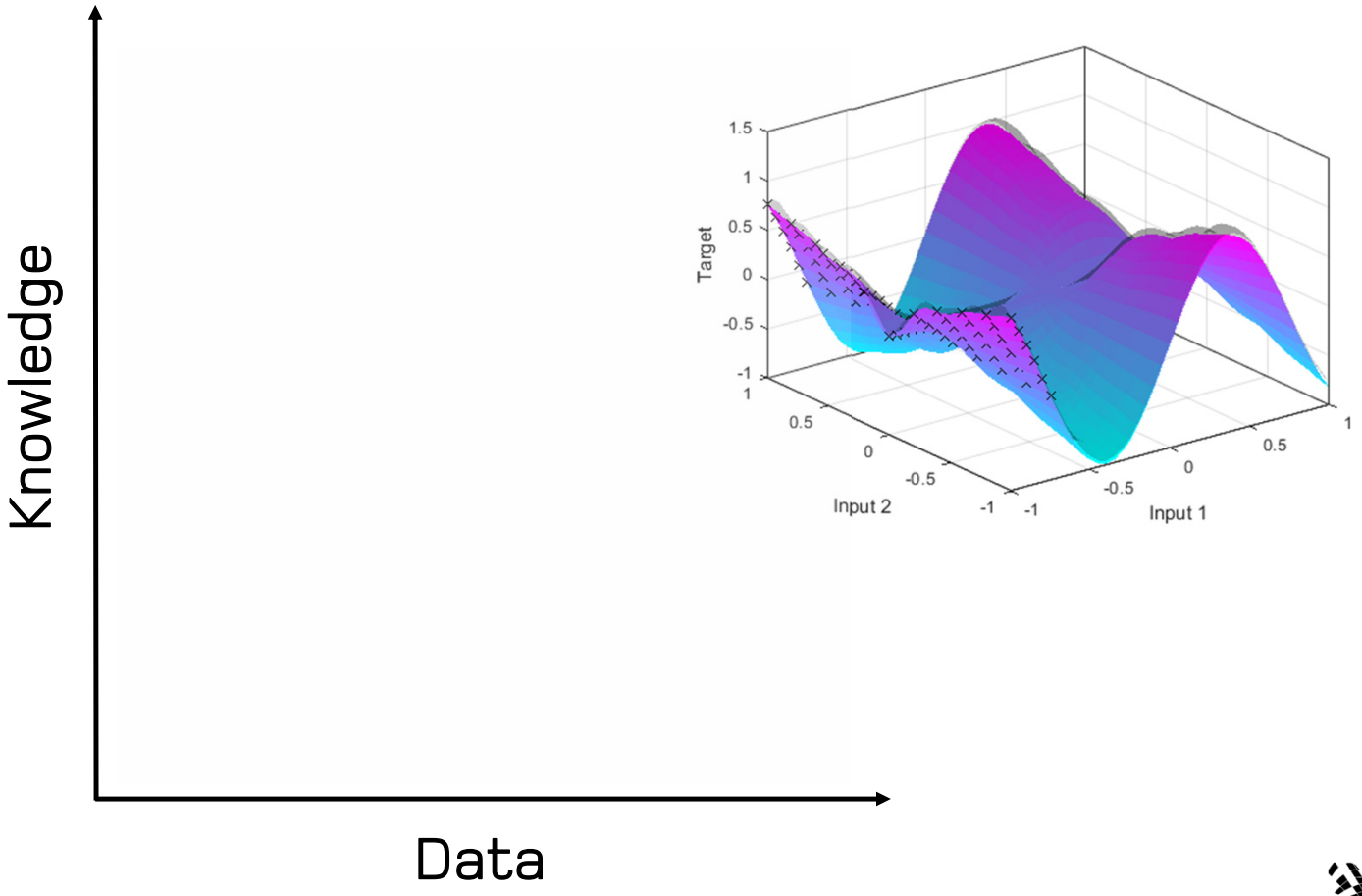


Holmes, G., Sartor, P., Reed, S., Southern, P., Worden, K., & Cross, E. (2016). Prediction of landing gear loads using machine learning techniques. *Structural Health Monitoring*, *15*(5), 568-582.

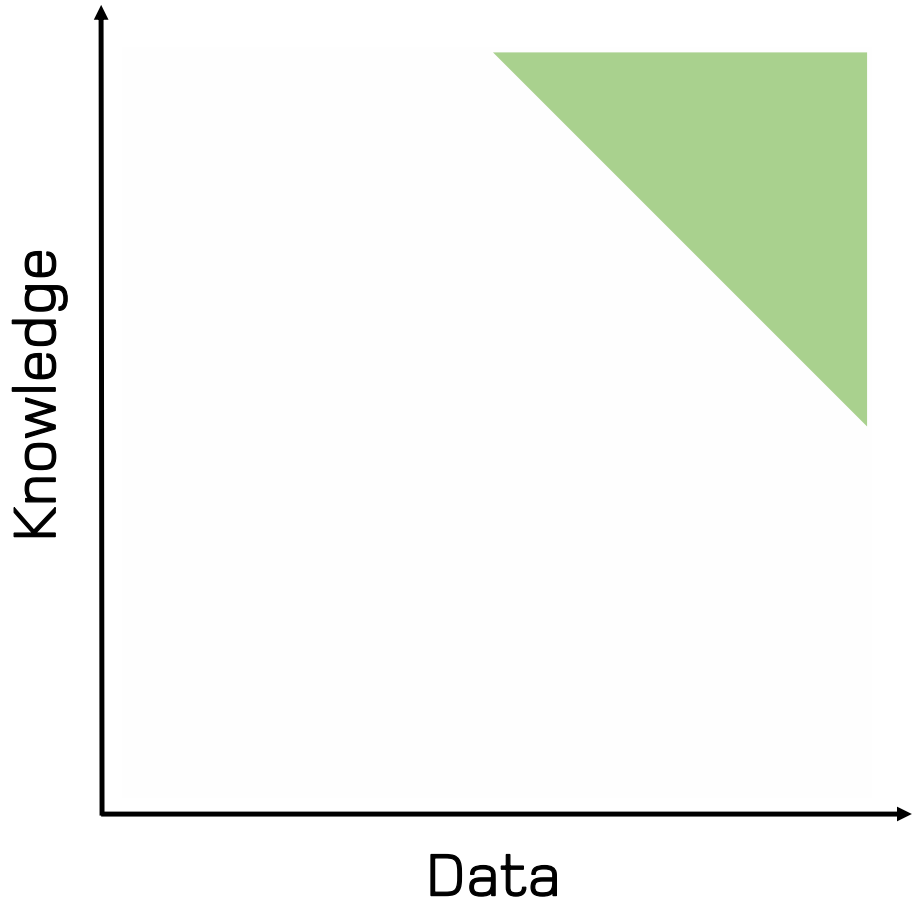
Where are you?



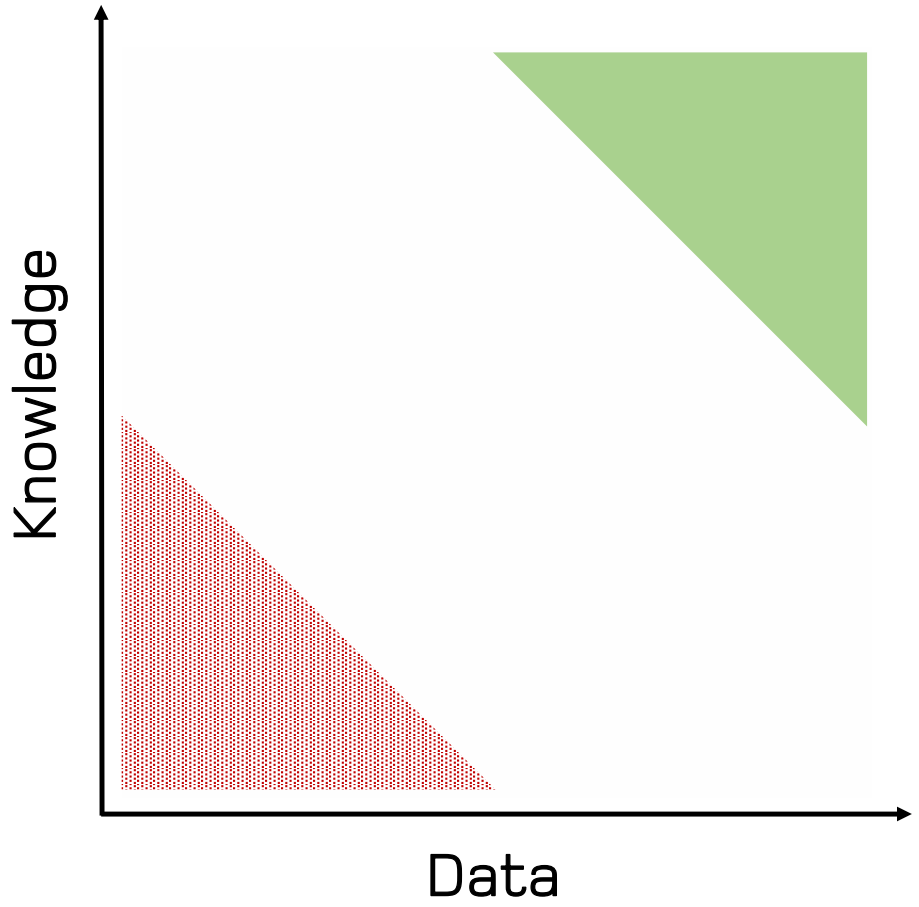
Where are you?



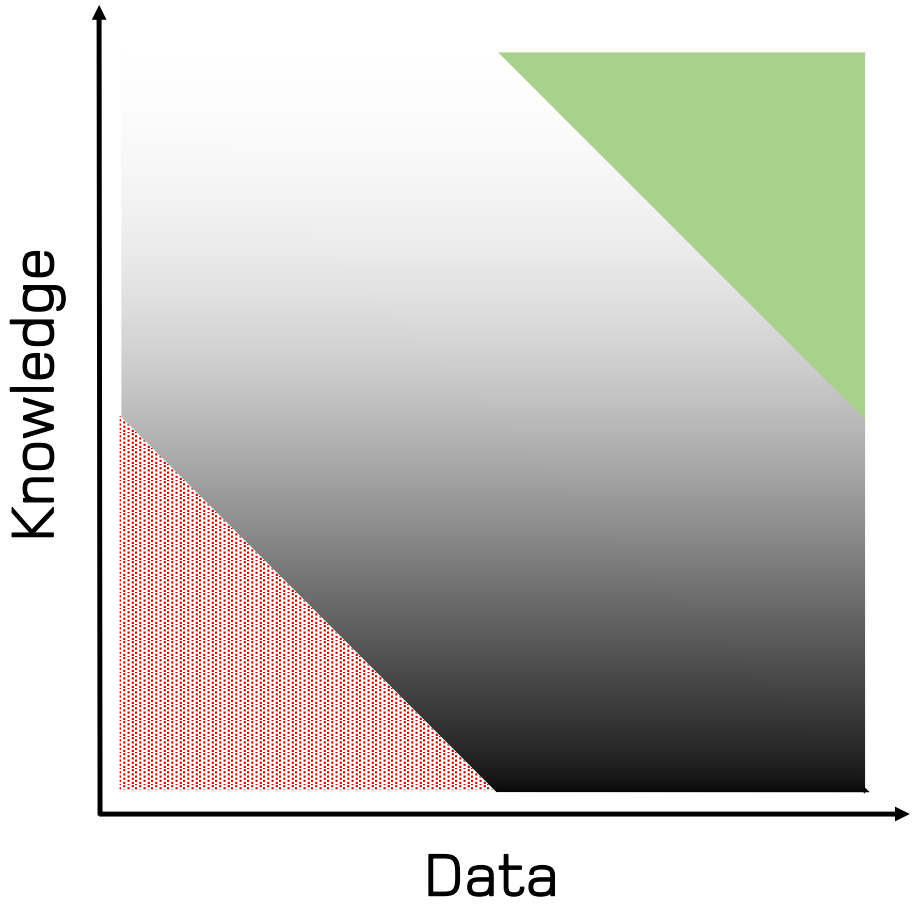
Optimising explanatory balance between data and physics



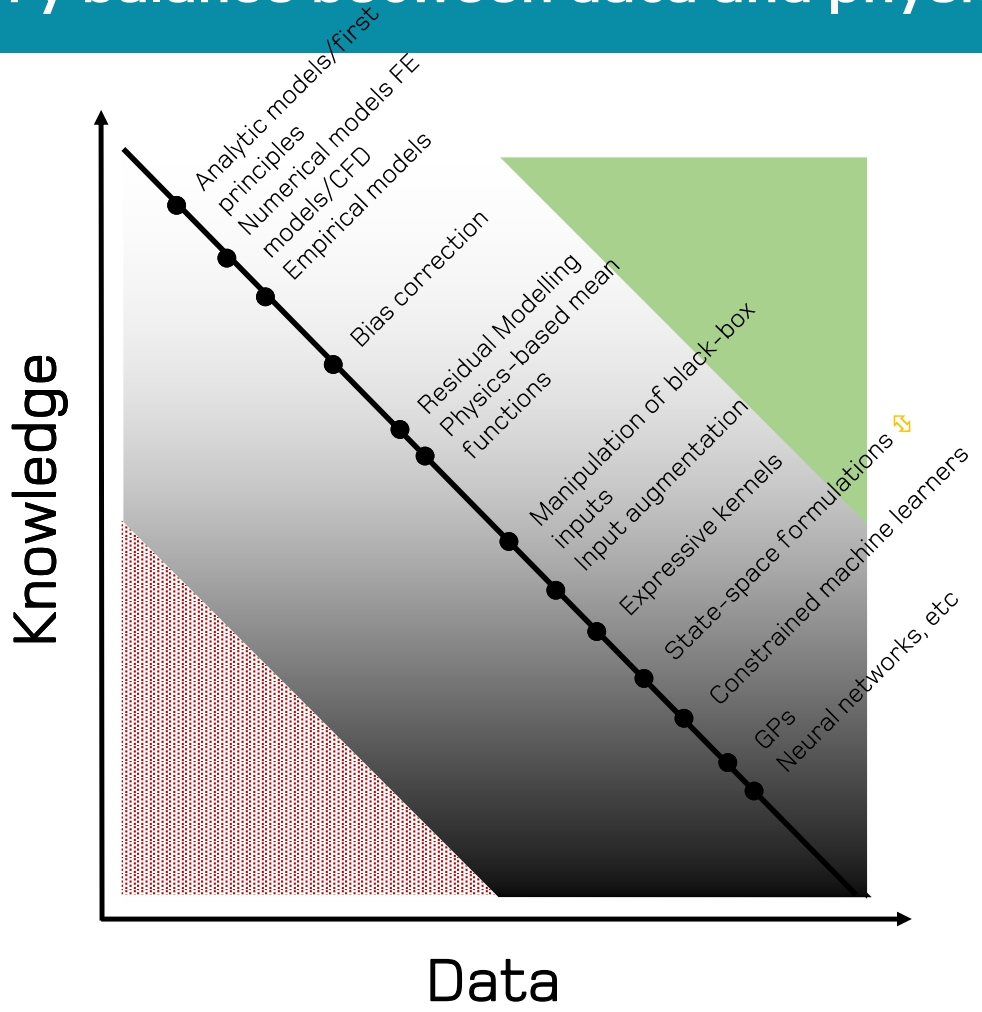
Optimising explanatory balance between data and physics



Optimising explanatory balance between data and physics

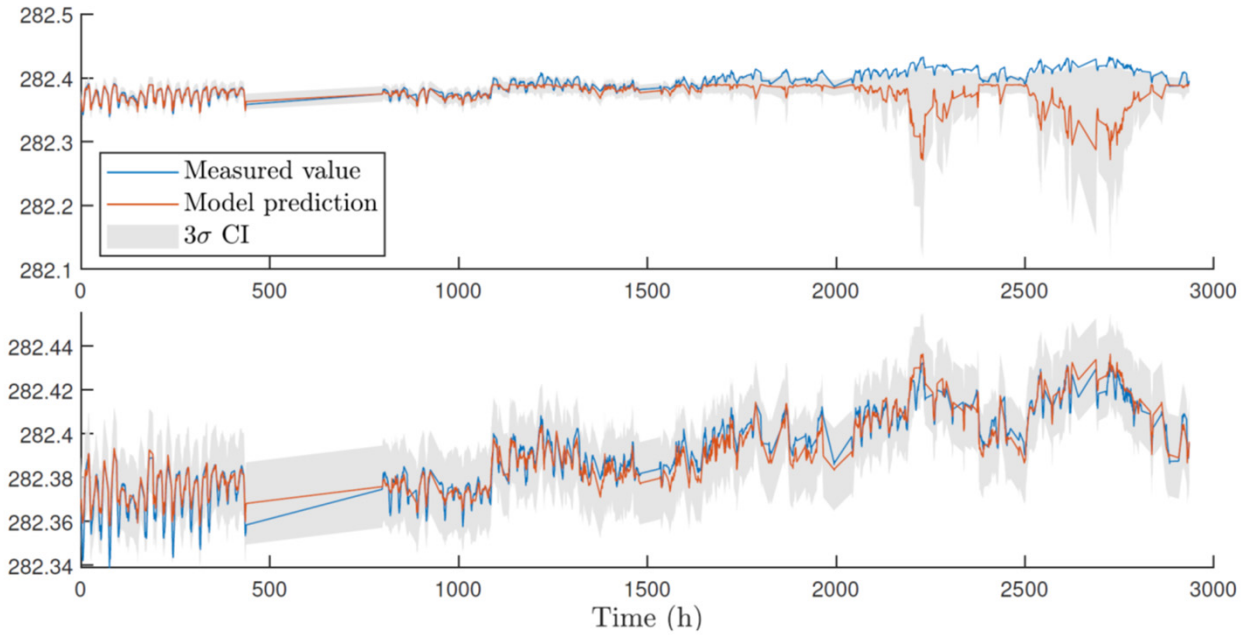


Optimising explanatory balance between data and physics



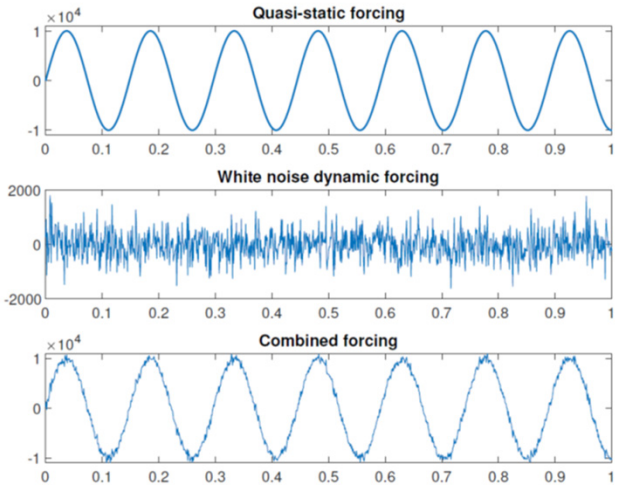
3 examples across the spectrum

Bridge monitoring example

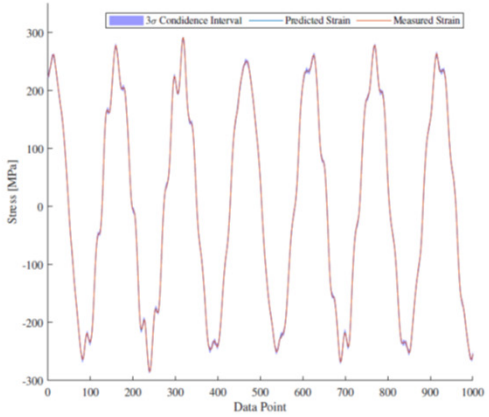


✎ *S. Zhang, T. J. Rogers, and E. J. Cross. Gaussian process based grey-box modelling for SHM of structures under fluctuating environmental conditions. EWSHM 2020.*

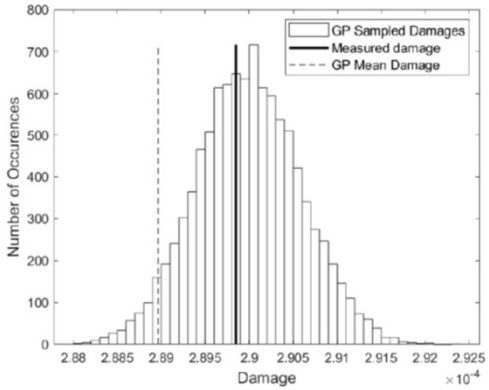
3 examples across the spectrum



$$f(\mathbf{x}) \sim \mathcal{GP}(\mu_P, g(k_P, k_{ML}))$$



(a) Posterior



(b) Damage distribution

✎ *S. Gibson, T. J. Rogers, and E.J. Cross "Data-driven strain prediction models and fatigue damage accumulation," in Proceedings of ISMA2020, 2020, pp. 3067–3075*

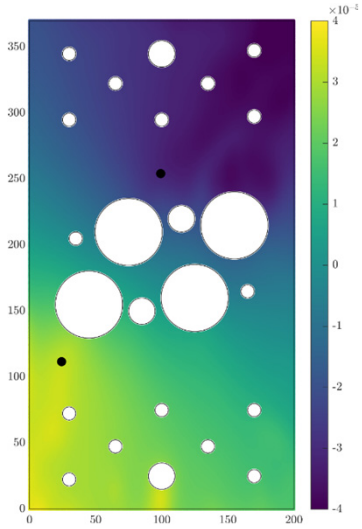
✎ *S. Gibson, T. J. Rogers, and E.J. Cross "Integrating physical knowledge into Gaussian process regression models for probabilistic fatigue assessment"*

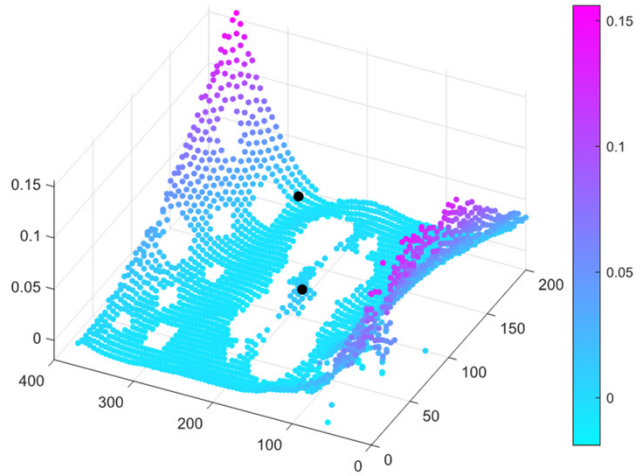
See also

✎ *M.R Jones, T. J. Rogers, and E.J. Cross "Physical covariance functions for dynamic systems with time dependent parameters" EWSHM 2022*

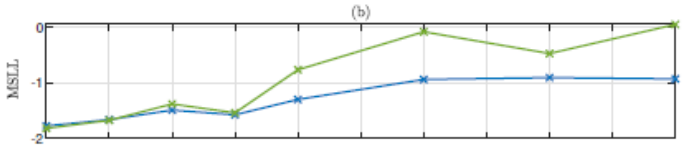
3 examples across the spectrum

Constrained machine learners for damage localisation with acoustic emission





$$f(\mathbf{x}) \sim \mathcal{GP}(0, g(k_{ML}))$$



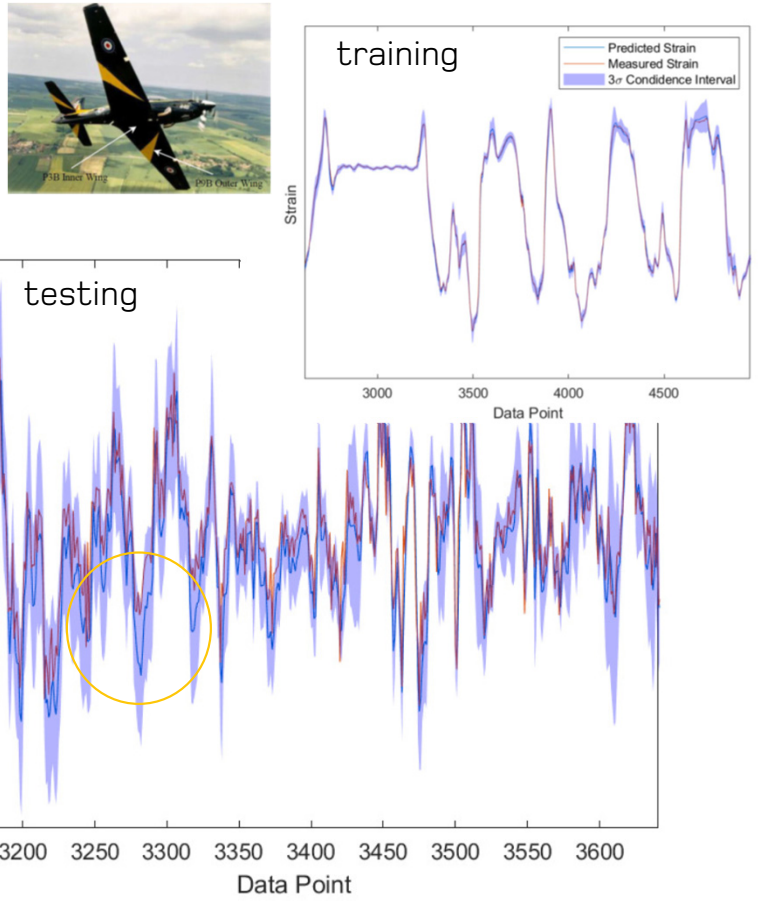
Interpolative model for crack localisation. Constrained learner allows accurate prediction with few training points.

- Matthew R Jones, Timothy J Rogers, Keith Worden, and Elizabeth J Cross. A Bayesian methodology for localising acoustic emission sources in complex structures. *Mechanical Systems and Signal Processing*, 163:108143, 2022.
- M. R. Jones, T. J. Rogers, and E. J. Cross. Constraining Gaussian processes for physics-informed acoustic emission mapping. *Submitted*, available on arXiv, 2022.
- M. R. Jones, T. J. Rogers, I. E. Martinez, and E. J. Cross. Bayesian localisation of acoustic emission sources for wind turbine bearings. In *In Proceedings of SPIE: Health Monitoring of Structural and Biological Systems XV*. 2020

Conclusions and final discussion

Why are we interested in physics-informed ML?

- We'd like to make inferences about our structures that are informed by (monitoring) data and our knowledge of the physics at work
- To address some of the challenges of using ML in an engineering setting..
    - A lack of training data that covers the operating envelope
    - Relationships that change depending on operational conditions
    - Sparse sensor networks with reliability problems



E. J. Cross, S. J. Gibson, M. R. Jones, D. J. Pitchforth, S. Zhang, and T. J. Rogers. "Physics-Informed Machine Learning for Structural Health Monitoring." In Structural Health Monitoring Based on Data Science Techniques, pp. 347-367. Springer, Cham, 2022.

Conclusions and final discussion

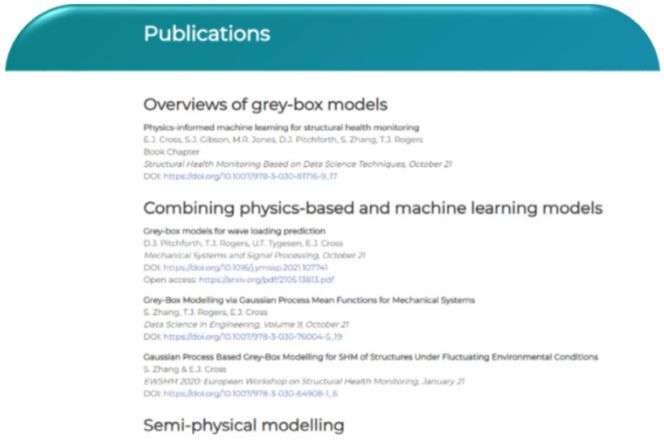
Fair warning

- Beware the hype train, these are not panaceas
- Assessing and expressing your prior knowledge in an appropriate form can be very challenging

When is it useful?

- When you can prescribe some behaviour not evident from your training data
- When you need a flexible but parsimonious model
- When you want interpretability
- When your knowledge simplifies the learning problem

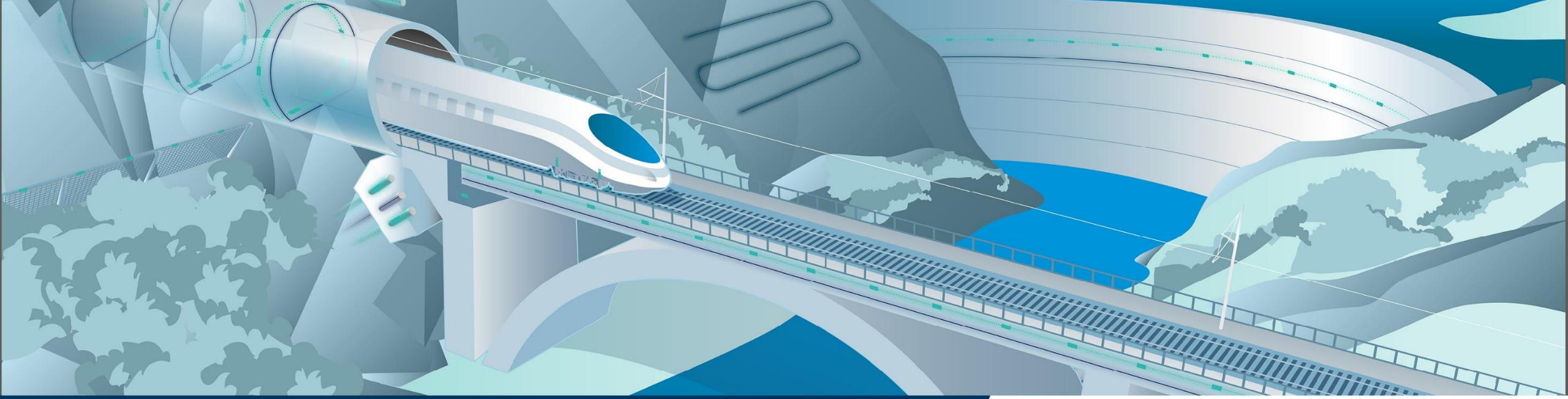
The University Of Sheffield.



Thanks for listening

drg-greybox.github.io/

Dynamics Research Group



HBK Technology Days – Virtual Seminar Series

Tuesday, November 15, 2022

Machine Learning for Structural Health Monitoring, from Data-Driven to Physics-Informed

Presented by Prof. Elizabeth Cross,
Dynamics Research Group, University of Sheffield