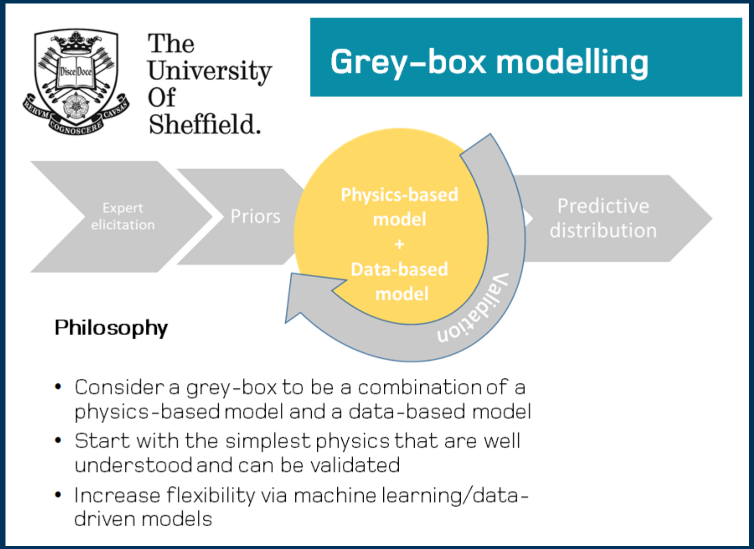
HBM Prenscia Technology Day

Virtual Seminar Series



Grey Box Modelling for Structural Health Monitoring

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

Session #6: Mathematical Modelling for
Data Analytics, Durability, and Reliability #2

Grey Box Modelling for Structural Health Monitoring

Abstract

The use of machine learning in Structural Health Monitoring is becoming more common, as many of the inherent tasks (such as regression and classification) in developing condition-based assessment fall naturally into its remit. This talk will introduce the concept of physics-informed machine learning, where one adapts ML algorithms to account for the physical insight an engineer will often have of the structure they are attempting to model or assess. We will look at how grey-box models, that combine simple physics-based models with data-driven ones, can improve predictive capability in an SHM setting. A particular strength of the approach demonstrated here is the capacity of the models to generalise with enhanced predictive capability in different regimes. This is a key issue when life-time assessment is a requirement, or when monitoring data do not span the operational conditions a structure will undergo.

About the presenter, Prof. Elizabeth Cross

Lizzy Cross is a Professor in the Dynamics Research Group at the University of Sheffield. Before starting her lectureship in 2012, she completed a Bachelors in Mathematics (1st class), and Masters and PhD in Mechanical Engineering.

She currently holds an EPRSC Innovation Fellowship on the development of grey-box models for assessing the health of structures in operation (grey-box models combine physics-based models with machine learning technology).

Lizzy is a co-director of the Laboratory for Verification and Validation, a state-of-the-art dynamic testing facility (lvv.ac.uk).

Grey-box modelling for Structural Health Monitoring

Lizzy Cross, Daniel Pitchforth, Samuel Gibson, Sikai Zhang, Tim Rogers

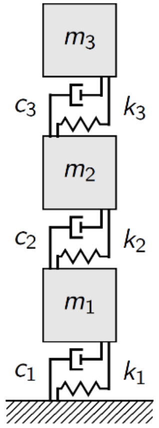
Department of Mechanical Engineering

Grey–box modelling

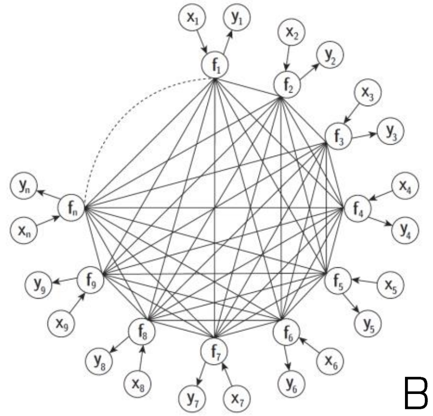
Grey-box modelling considers the incorporation of physical insight into machine learning algorithms. The hope is to gain the key strengths from both the physics-based and data-based modelling approaches.

White box / Physics based

- Structured
- Physically insightful



Grey-box



Black box / Machine learning

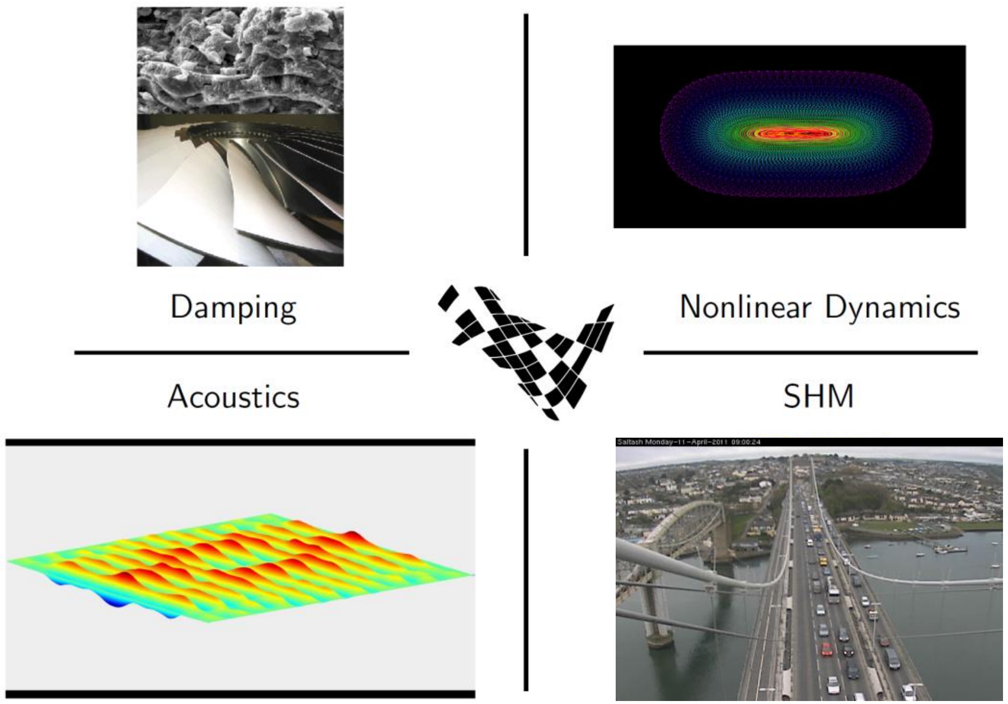
- Flexible
- Data driven

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.

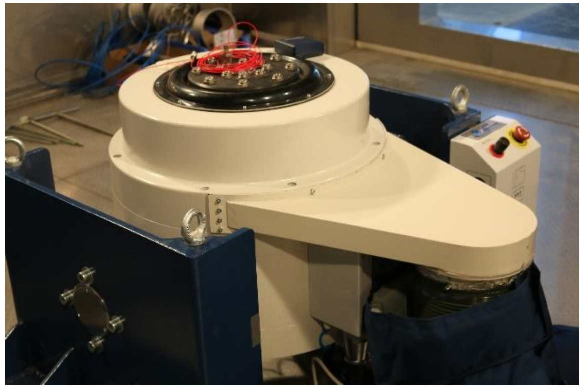
The group currently has over 50 members, including 12 academics and >40 post-doctoral researchers and PhD students.



About us

Our flagship laboratory is the LVV - the **Lab for Verification and Validation.** This facility enables controlled dynamic testing of components and full scale structures in a range of environments.

- 3 environmental chambers (largest 3x5x9m), temperature and humidity control
- Wind and rain simulation
- 3 x 2 m shake table in middle chamber
- 12m wave tank



European Union
European Regional Development Fund

EPSRC
Engineering and Physical Sciences Research Council

The University Of Sheffield.

Structural Health Monitoring – overview

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

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

Advantages: Increased safety and efficiency

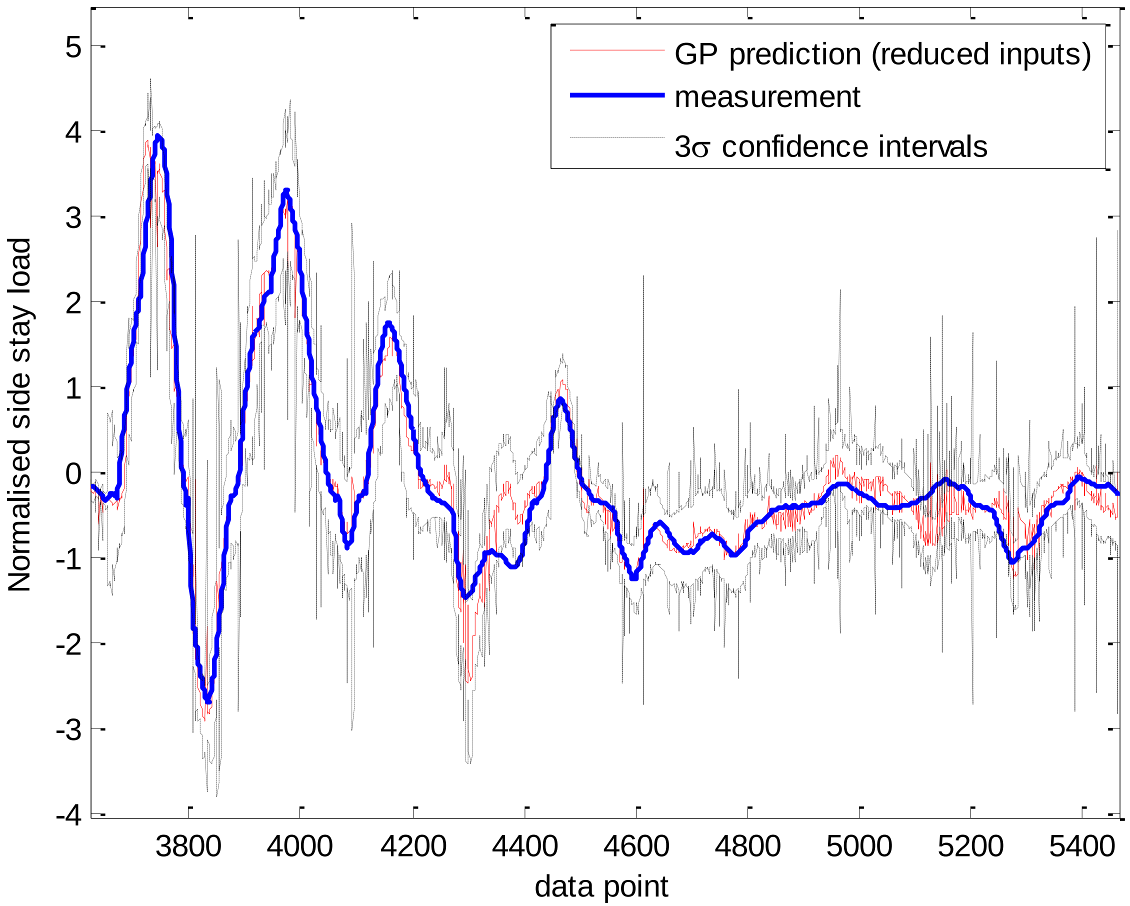
Current SHM Research in the DRG

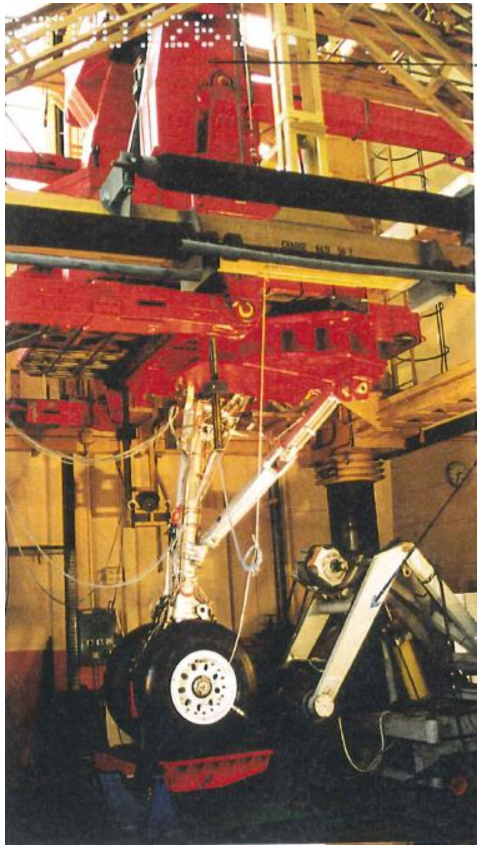
SHM is one of the primary foci of researchers in the DRG, we cover many research themes and application areas

Research Themes	Application Areas
Vibration-based SHM	Aerospace Structures
Guided Waves	Composite Materials
Acoustic Emission	Ground Vehicles
Vision-based SHM	Civil Infrastructure
Machine Learning	Wind Energy
Statistical Methods	Machining
Model-driven SHM	Offshore Structures

Black-box modelling for SHM

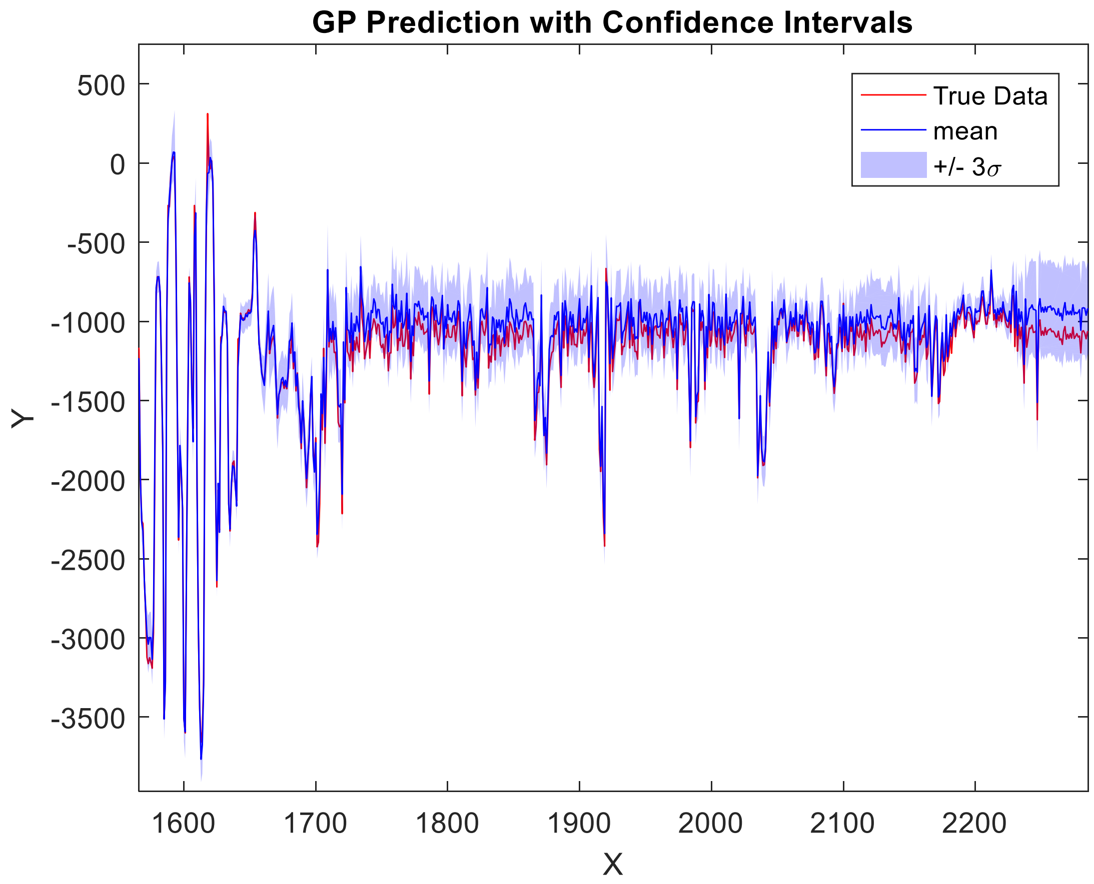
Using GPs for loads monitoring





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.

Using GPs for loads monitoring



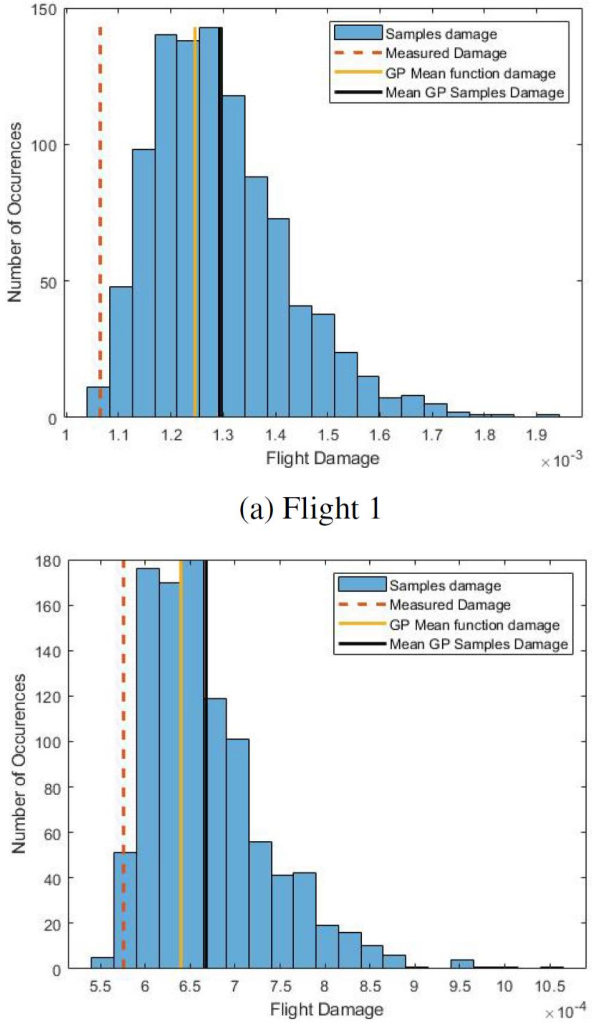
Holmes, G., Sartor, P., Reed, S., Southern, P., Worden, K., & Cross, E. (2016). Prediction of landing gear loads using machine learning techniques. *Structural Health Monitoring*, *15*(5), 568-582.

Fuentes, R., Cross, E., Halfpenny, A., Worden, K., & Barthorpe, R. J. (2014, July). Aircraft parametric structural load monitoring using Gaussian process regression. In *EWSHM-7th European workshop on structural health monitoring*.

Predictive distributions of fatigue damage

- How can we use, for example, strain predictions for a probabilistic fatigue assessment?
- A GP provides a predictive distribution
- Here we are using successive draws from a GP posterior distribution to provide an estimated distribution for fatigue damage

S. J. Gibson, T. J. Rogers, and E. J. Cross. Data-driven strain prediction models and fatigue damage accumulation. In *Proceedings of the 29th International Conference on Noise and Vibration Engineering (ISMA 2020)*, 2020.



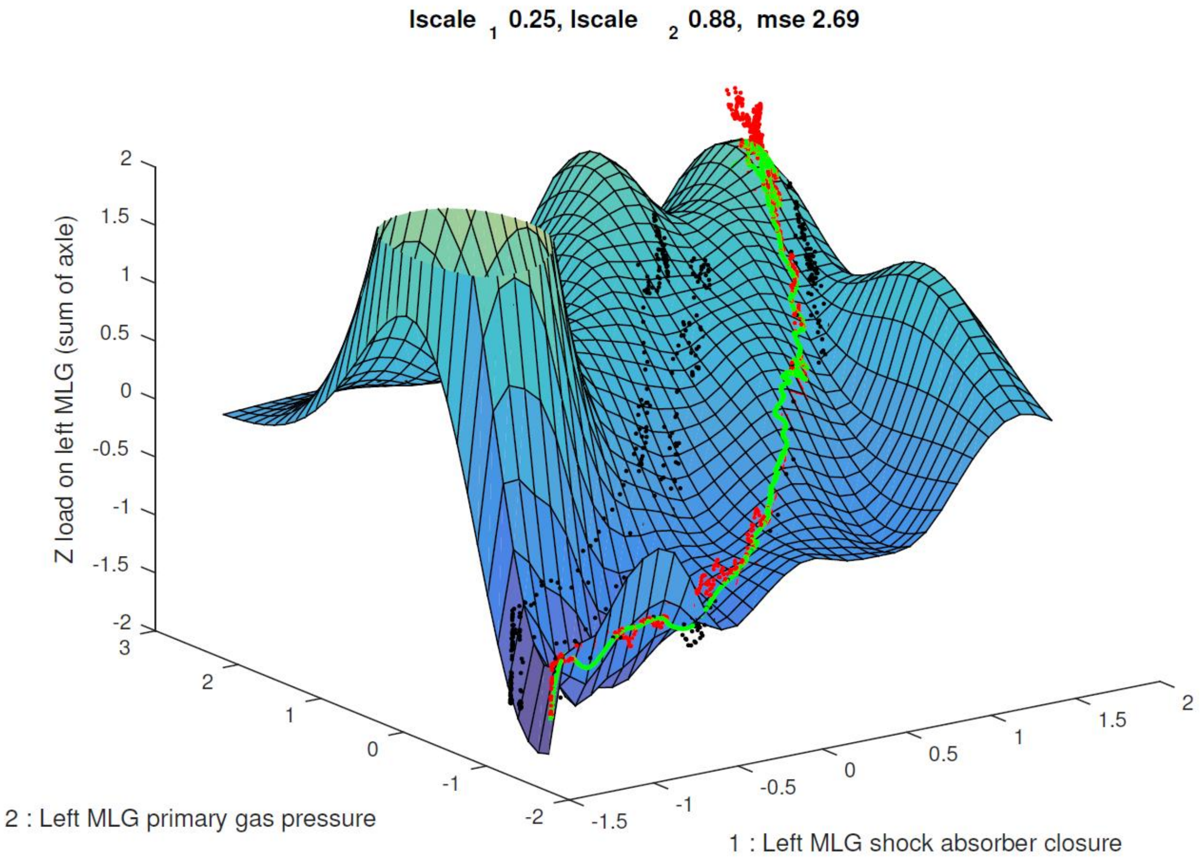
(a) Flight 1

(b) Flight 2

Challenges from the data-driven perspective

Common challenges arising from these problems

- A lack of training data that covers the operating envelope
- Relationships that change depending on operational conditions
- Sparse sensor networks with reliability problems

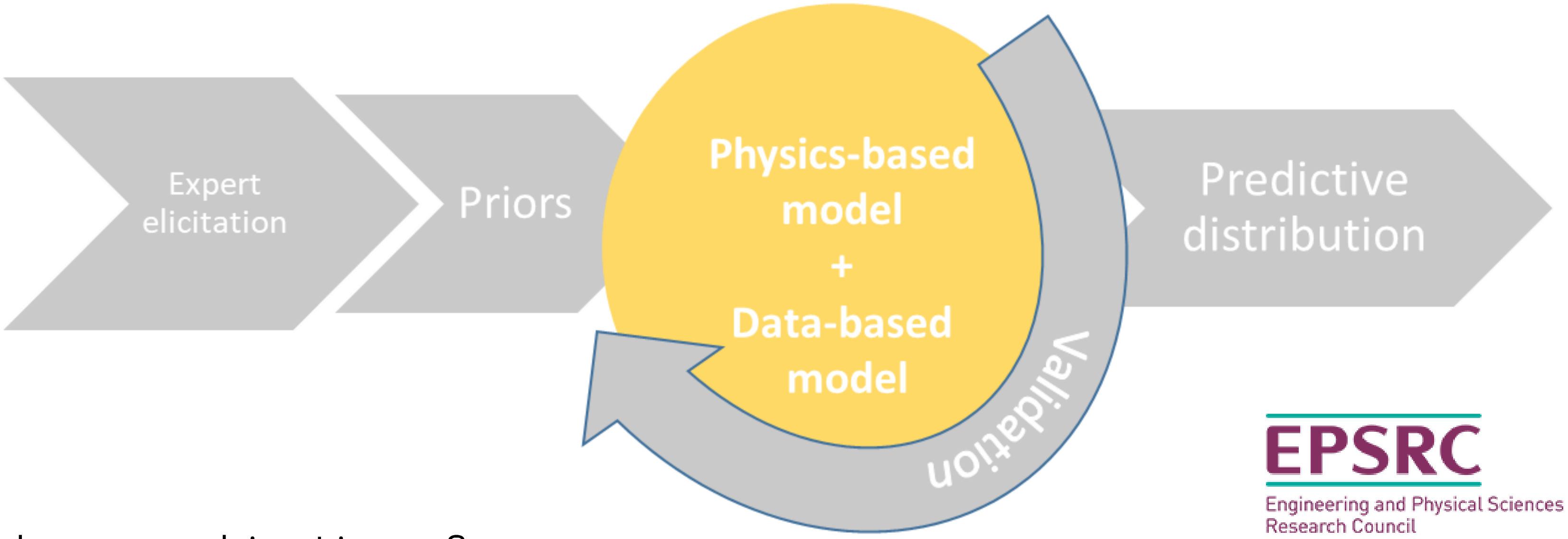


Challenges from the physics-based modelling perspective

Common challenges arising from these problems

- High fidelity models have a high level of complexity and are very expensive to run
- Validation of these models is a significant challenge
- Model updating strategies also a significant challenge
- Loading assumptions still necessary

Grey–box modelling



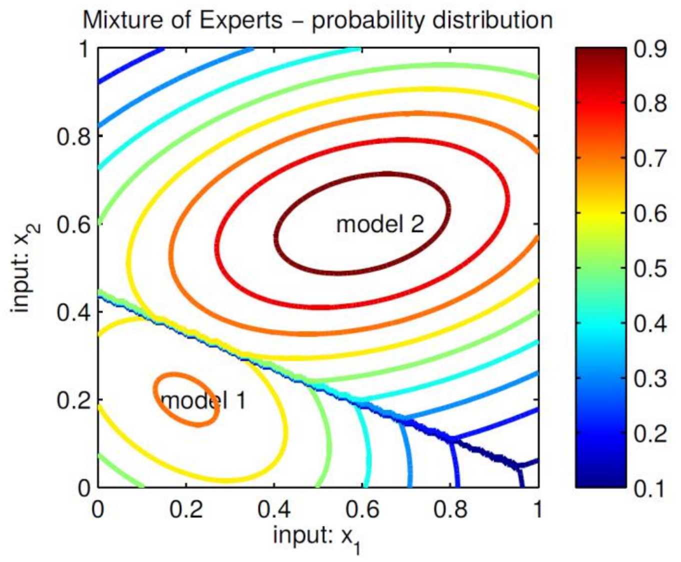
Philosophy

- Consider a grey-box to be a combination of a physics-based model and a data-based model
- Start with the simplest physics that are well understood and can be validated
- Increase flexibility via machine learning/data-driven models

Grey–box modelling

Key research questions to address

- Model formulation/architecture
- Optimal balance of exploratory power between the two components
- How to validate these models
- How to incorporate predictive distributions for use in a predictive maintenance strategy

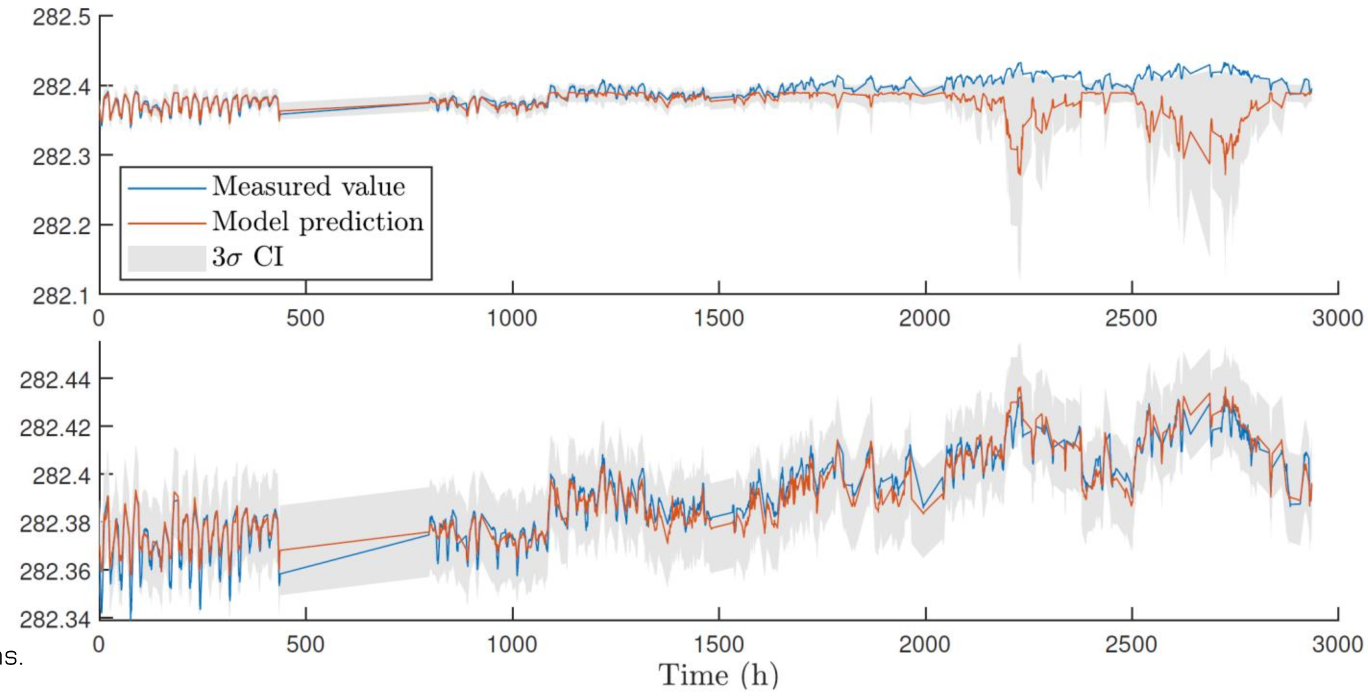


Grey-box modelling for SHM

Bridge performance monitoring

$$y \sim \mathcal{GP}(m(x), k(x, x'))$$

- Grey-box modelling achieved via physics-based mean function
- This is a simple yet effective approach to grey-box modelling



S. Zhang, T. J. Rogers, and E. J. Cross. Gaussian process based grey-box modelling for SHM of structures under fluctuating environmental conditions. In *Proceedings of 10th European Workshop on Structural Health Monitoring (EWSHM 2020)*, 2020.

Wave loading prediction

- Use particle velocity and acceleration to predict force on a structure
- White-box model is Morison's equation

$$F = \underbrace{\rho C_d A_p}_{\hat{C}_d} |U|U + \underbrace{\rho C_m V_0}_{\hat{C}_m} \dot{U}$$
$$= \hat{C}_d |U|U + \hat{C}_m \dot{U}$$

- Black-box is a Gaussian Process NARX
- Grey-box achieves 29.13% relative error reduction over white-box and 5.48% reduction over black-box

Residual model

$$\mathbf{y_p} = \overbrace{f(X)}^{\text{White Box}} + \overbrace{\epsilon(X)}^{\text{Black Box}}$$

Input augmentation

$$\mathbf{y_p} = \overbrace{g(X,\ \underbrace{f(X)}_{\text{White Box}}\ )}^{\text{Black Box}}$$

Model	Model type	NMSE (%)	MSLL
Morison's Equation	White-box	19.528	−0.813
Static GP	Black-box	16.433	−0.939
	Residual modelling	16.751	−0.914
	Input augmentation	15.627	−0.951
GP-NARX OSA	Black-box	2.702	−1.444
	Residual modelling	5.212	−1.012
	Input augmentation	2.947	−1.429
GP-NARX MPO	Black-box	14.773	−0.968
	Residual modelling	13.862	−0.872
	Input augmentation	14.072	−0.994
GP-NARX MC MPO	Black-box	14.643	−0.788
	Residual modelling	13.840	−0.835
	Input augmentation	14.088	−0.791

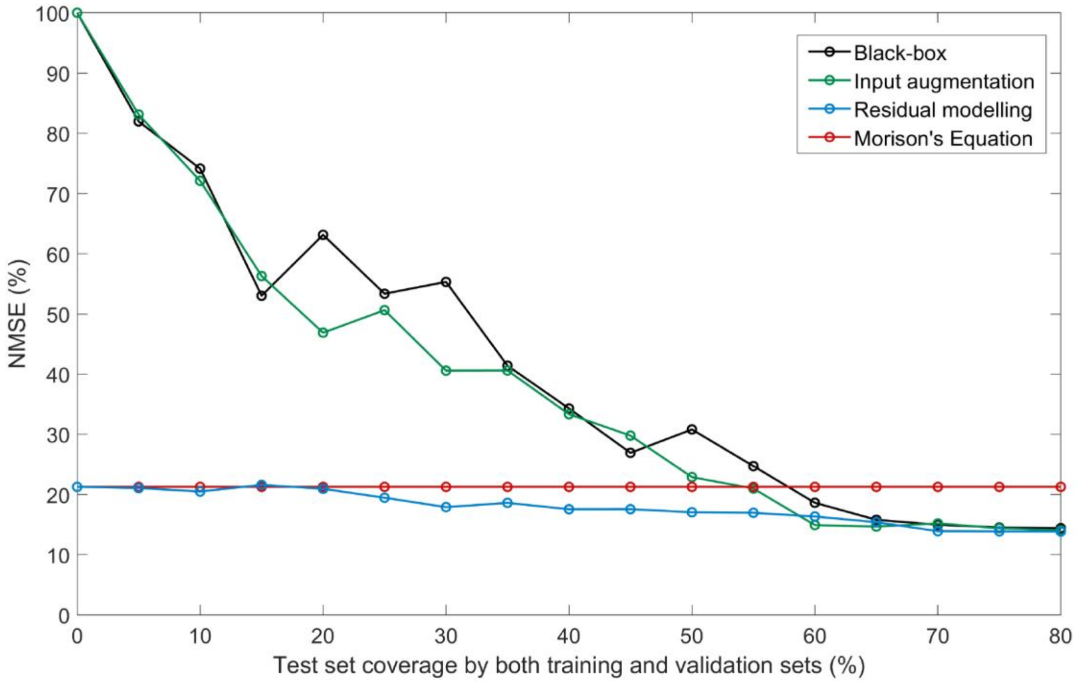
Wave loading prediction – extrapolation study

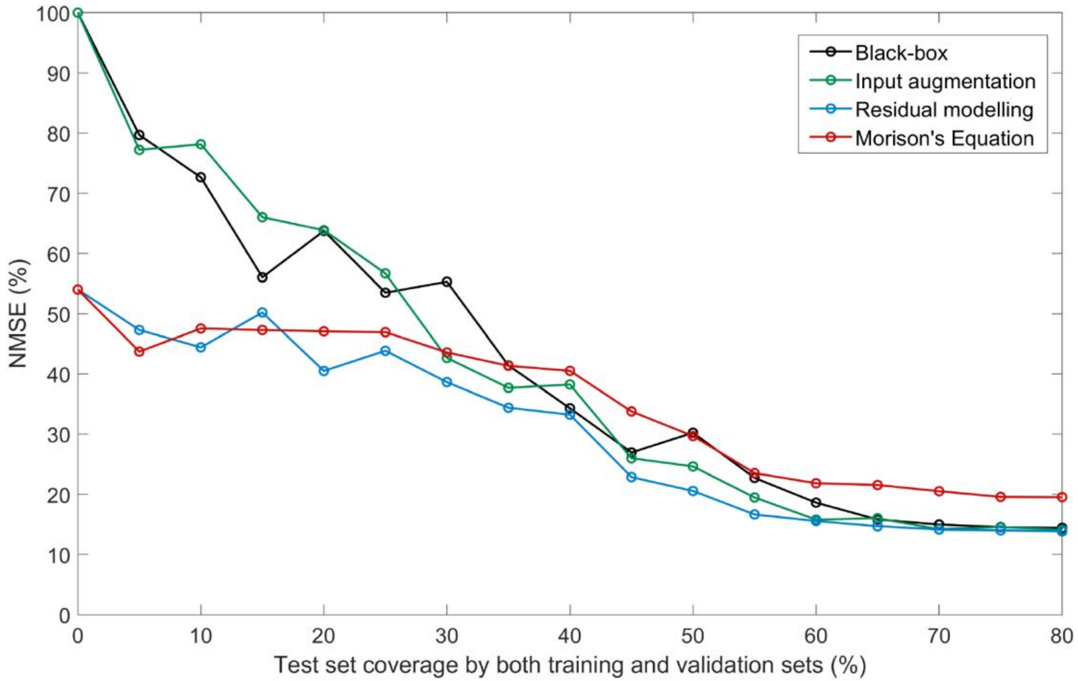
Residual model

$$\mathbf{y_p} = \overbrace{f(X)}^{\text{White Box}} + \overbrace{\epsilon(X)}^{\text{Black Box}}$$

Input augmentation

$$\mathbf{y_p} = \overbrace{g(X,\ \underbrace{f(X)}_{\text{White Box}}\ )}^{\text{Black Box}}$$





D. J. Pitchforth, T. J. Rogers, U. T. Tygesen, and E. J. Cross. A grey-box model for wave loading prediction with uncertainty propagation. In *Proceedings of the 29th International Conference on Noise and Vibration Engineering (ISMA 2020)*, 2020.

Summary

- Grey-box models – the best of both worlds?
- Examples of model architectures include residual modelling, input augmentation.
- Promising results so far in terms of predictive capability and extrapolation

The University Of Sheffield.

Thanks for listening

Dynamics Research Group

Q&A

- Muhammad Afzal (Omnicell, USA)
  - What's the commercial value of this kind of modelling?
    - *The commercial value depends on several factors, including; the application, the value/safety/criticality of the asset(s) being monitored, the potential cost savings of reduced instrumentation and sensor requirements for grey-box modelling compared with more direct measurements where the instrumentation and sensors may be intrusive and/or difficult to achieve directly.*
    - *For structures with limited public access, like offshore wind farms, the collective value of this modelling through the commercial operational life of the wind farm will be millions of $£€, and for structures with public access, like aircraft, bridges, buildings, etc. there is additional value to prevent loss-of-life.*

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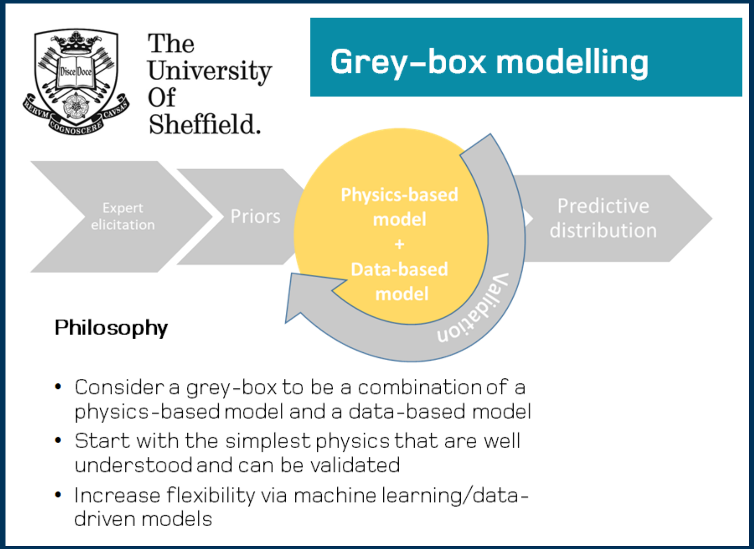

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