Uncertainty-Aware Modeling and Decision Support for Transport Infrastructure

(Focus on Bridges)

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Introduction and Motivation

- **Highway and rail bridges** are critical transport infrastructure
- But aging and under increasing loads/climate pressures.

- **Key challenges**:

    - Monitor and identify structural condition/deterioration

    - Uncertainties in loads (wind, traffic and earthquakes), model & material properties, environmental/operational conditions

    - Optimal maintenance & retrofit decisions under limited budgets

- Why uncertainty-aware modelling? Traditional deterministic approaches often fail in real-world conditions.

Goal: Develop models that explicitly quantify and propagate uncertainties to support better-informed, risk-based decisions.

Research Framework Overview

- **Physics-based modelling**
- Component test & **monitoring data**
- **Uncertainty quantification and propagation (UQ+P)**
- Decision support under uncertainty (e.g., **reliability analysis**, life-cycle cost optimization)

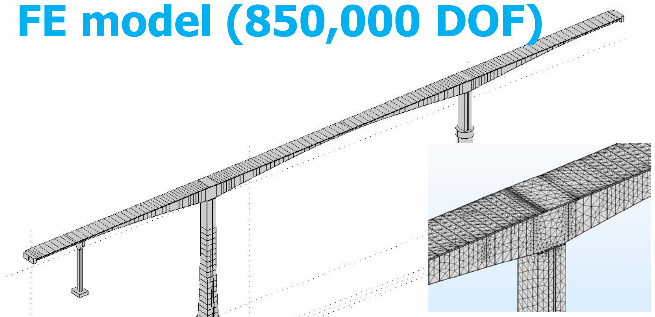
Uncertainty-Aware Modeling for Bridges

- **Sources of uncertainty:**
  - Modelling uncertainties (finite element model errors, material properties)
  - Environmental factors (temperature, humidity, scour)
  - Traffic loads (especially heavy vehicles & dynamic effects)
  - Extreme events (earthquakes, wind)
  - Degradation models & location
  - Long-term material degradation (corrosion, fatigue)

Methods for Uncertainty-Aware Modeling

- **Integrate:**
    - High fidelity finite element models and probabilistic methods
    - Sensor data/information
    - **Bayesian learning for Uncertainty Quantification & Propagation (UQ+P)**
    - Reduced models for efficient UQ+P: Physics-based (reduction at substructure level)
    - surrogate models for efficient UQ+P: GP, NN, etc

FE model (850,000 DOF)

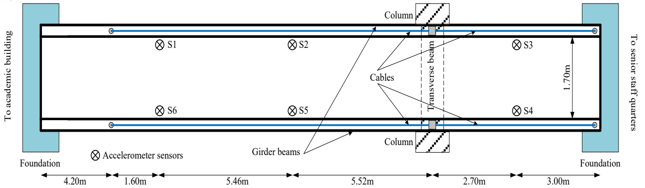


Tetrahedral Quadratic Lagrange Finite Elements

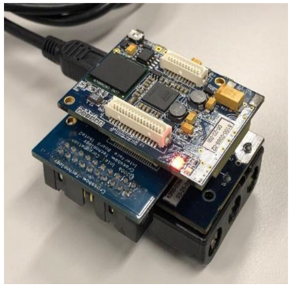
Sensor Data

Model Parameter Estimation

- **Bayesian learning** to account for uncertainty:
  - **Epistemic uncertainty; reducible** as number of data increases



Sensor Placement along deck



- Six set of Impote2© Accelerometers are placed along the bridge

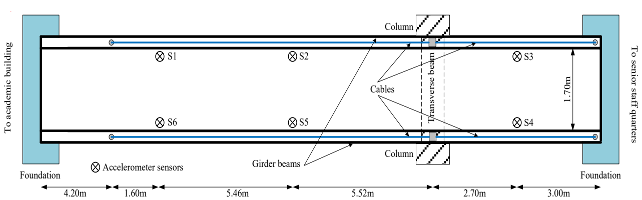
Au, Uncertainty law in ambient modal identification – Part I: Theory, MSSP, 2014

Model Parameter Estimation

- **Hierarchical Bayesian learning** to account for uncertainty:
  - Epistemic uncertainty; reducible as number of data increases
  - **Aleatoric uncertainty; irreducible**

- $N_D = 19$ **Data sets** each 5min long at 200 Hz sampling rate

- **Less than 1% uncertainty in modal frequencies**
- **4-7% uncertainty in mode shape components**
- **Greater than 100% uncertainty in modal damping ratios**



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Sedehi, Katafygiotis, Papadimitriou, Hierarchical Bayesian Operational Modal Analysis: Theory and computations, Mechanical Systems and Signal Processing, 2020

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Ballesteros, Angelikopoulos, Papadimitriou, Koumoutsakos, Bayesian Hierarchical Models for **Uncertainty Quantification in Structural Dynamics**, 2nd Int. Conf. Vulnerability & Risk Analysis (ICVRAM 2014), 2014

Behmanesh, Moaveni, Lombaert, Papadimitriou, Hierarchical Bayesian **Model Updating for Structural Identification**, MSSP, 2015

Song, Behmanesh, Moaveni, Papadimitriou. **Accounting for Modeling Errors and Inherent Structural Variability** through a Hierarchical Bayesian Model Updating Approach: An Overview, Sensors, 2020

Sedehi, Papadimitriou, Katafygiotis, Probabilistic Hierarchical Bayesian Framework for time-domain **Model Updating and Robust Predictions**, MSSP, 2019

Jia & Papadimitriou, Hierarchical Bayesian learning framework for **multi-level modeling using multi-level data**, MSSP, 2022.

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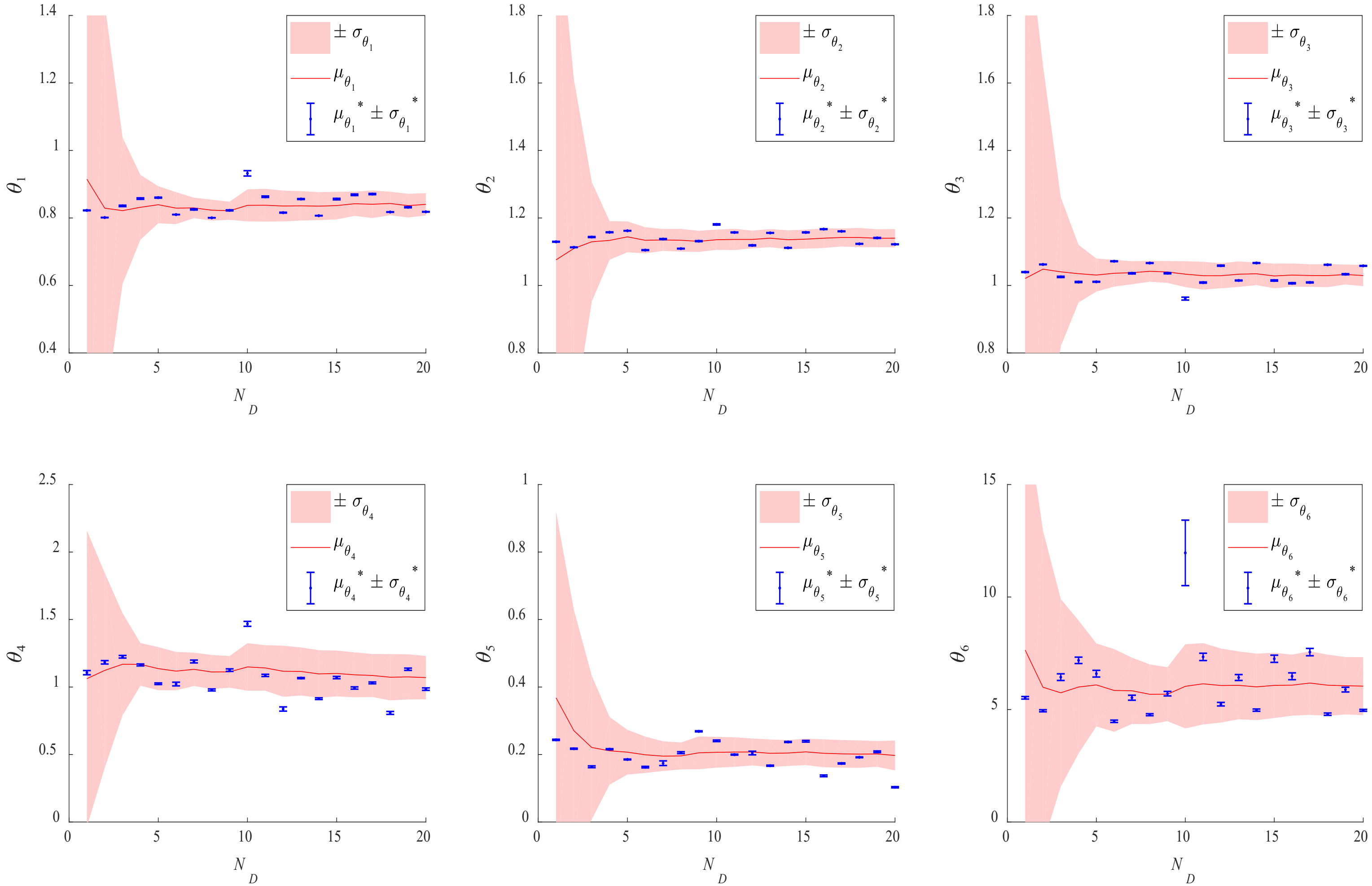

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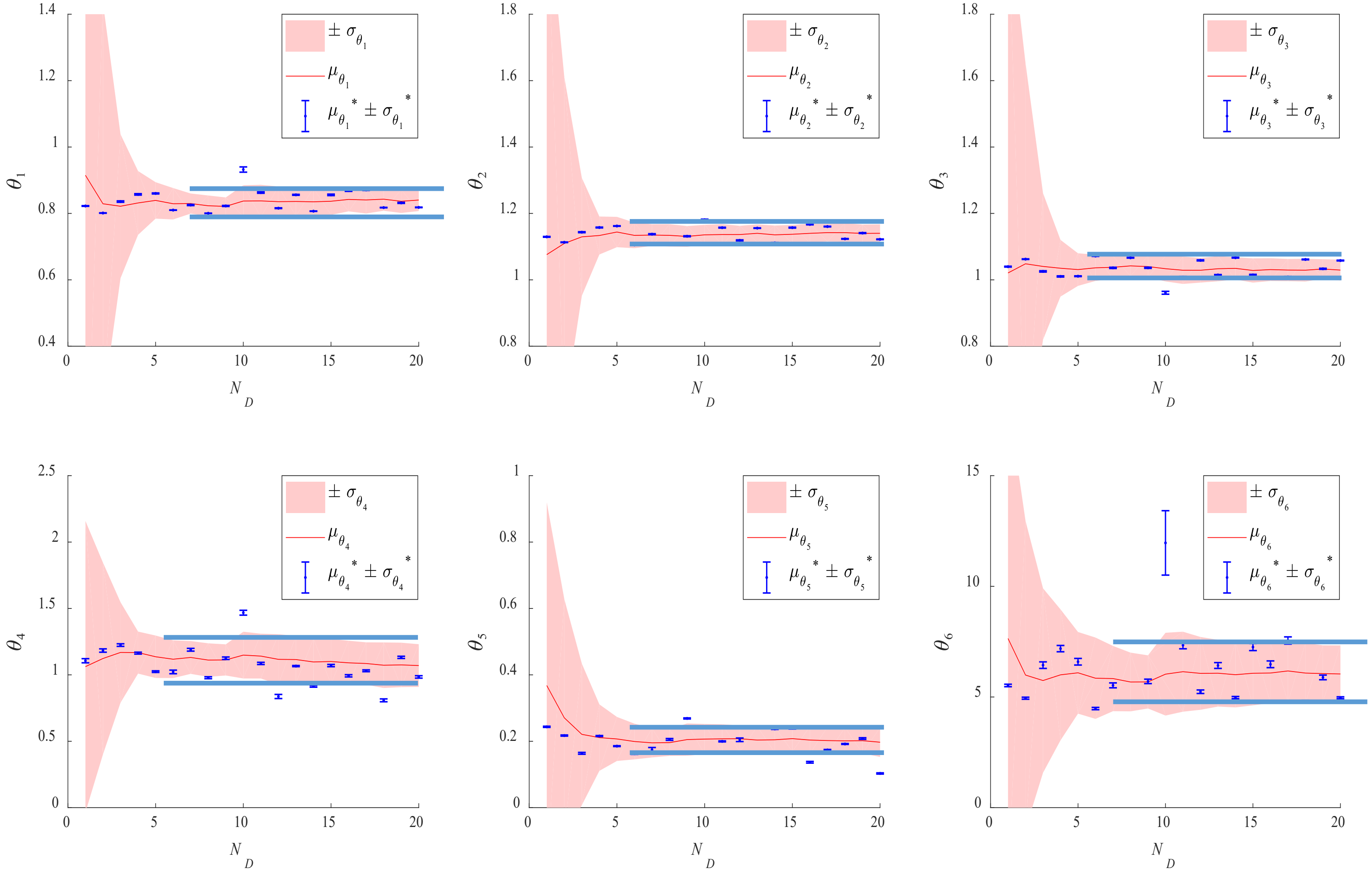

Virtual Sensing: Input and Response Reconstruction

Bayesian Sequential Filtering Techniques (input-state-parameter estimation)

Output only vibration measurements

- **Augmented Kalman Filter, 2012**
- **Dual Kalman Filter, 2015**

Lourens, Reynders, De Roeck, Degrande, G. Lombaert, An **augmented Kalman filter for force identification** in structural dynamics, MSSP, 2012.

Eftekhar Azam, Chatzi, Papadimitriou, A **dual Kalman filter** approach for **state estimation** via **output-only acceleration measurements**, MSSP, 2015.

Tatsis, Dertimanis, Papadimitriou, Lourens, Chatzi, A general **substructure-based framework for input-state estimation** using limited **output measurements**, MSSP, 2021.

Dertimanis, Chatzi, Azam, Papadimitriou, **Input-state-parameter estimation** of structural systems from **limited output information**, MSSP, 2019.

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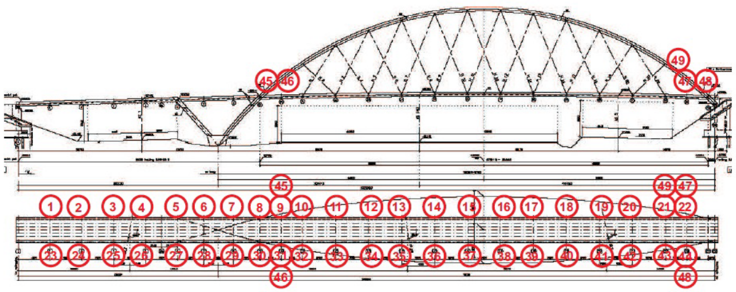

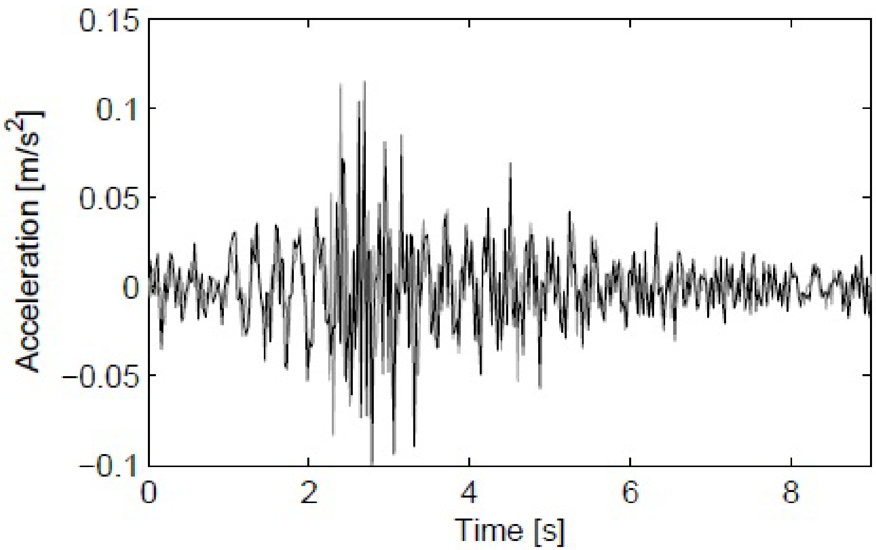

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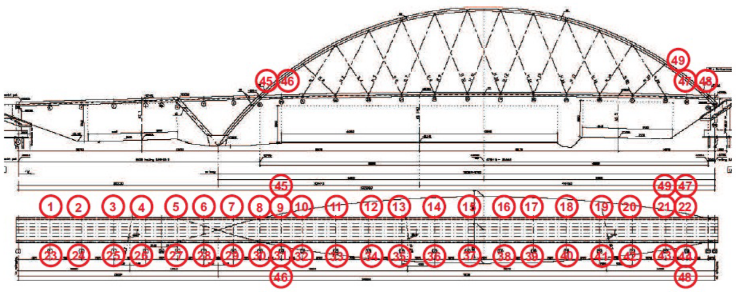

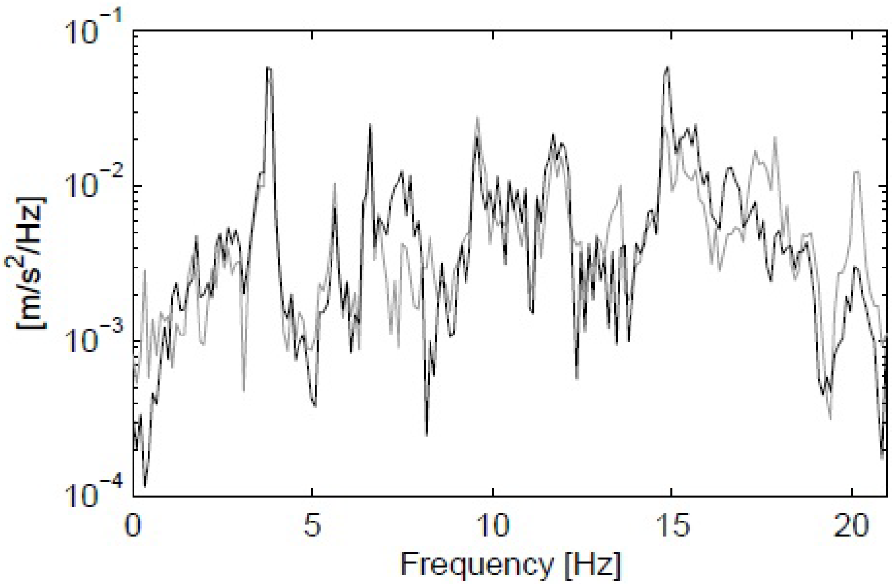

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Virtual Sensing: Input and Response Reconstruction

Bayesian Sequential Filtering Techniques

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- **Special Case:**
  - Strain/**stress reconstruction**
  - **Fatigue damage accumulation** (Palmgren-Miner Law, S-N Curves, rainflow stress cycle counting methods)

Papadimitriou, Fritzen, Kraemer, Ntotsios. **Fatigue Predictions in Entire Body of Metallic Structures from a Limited Number of Vibration Measurements using Kalman Filtering**. Structural Control and Health Monitoring, 2011.

Virtual Sensing: Input and Response Reconstruction

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- **Engineering Components**
  - Motorway/Railway Bridges
  - Offshore structures
  - Wind turbines (towers, blades)
  - Air and ground vehicles, Trucks
  - Steel towers
  - Mechanical systems/components
  - Rotating machinery
  - etc

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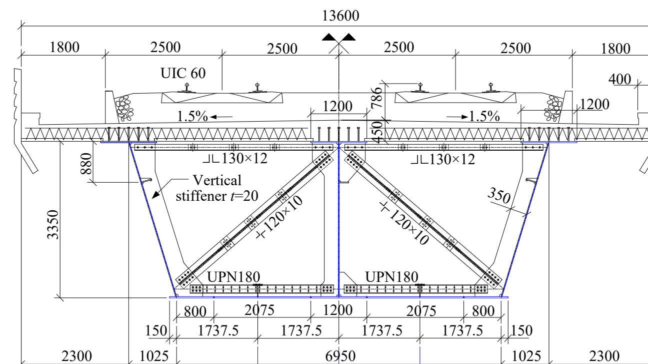
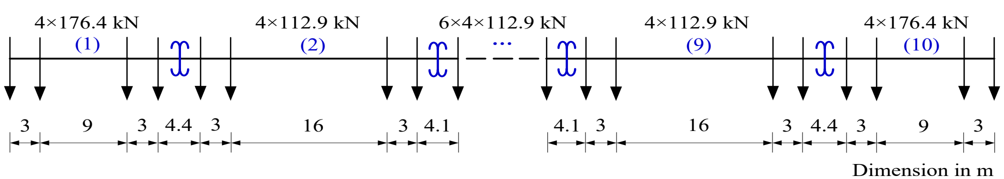
Bayesian Sequential Filtering Techniques

Output only vibration measurements

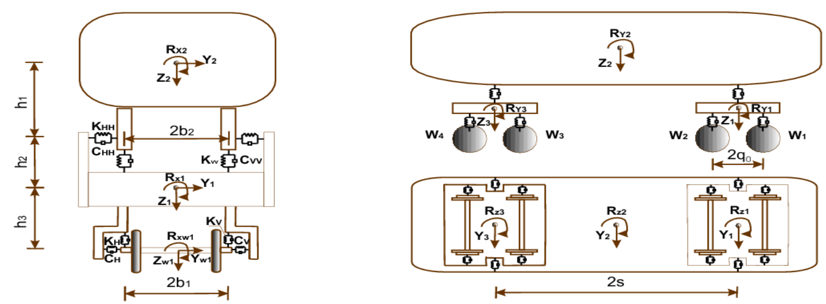
- **Fatigue Damage Accumulation** – Validation: Sesia Viaduct



Cross Section



Loading scheme of Italian high speed train



Liu, Reynders, De Roeck et al. Journal of Sound & Vibrations (2009)

15-DOF Vehicle Model

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Bayesian Sequential Filtering Techniques

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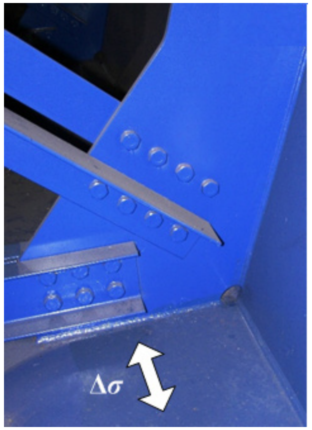
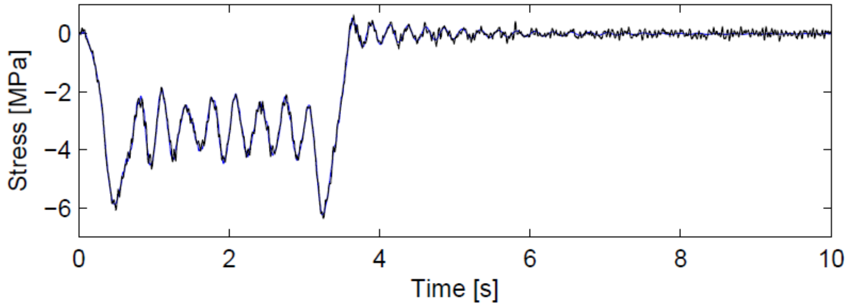


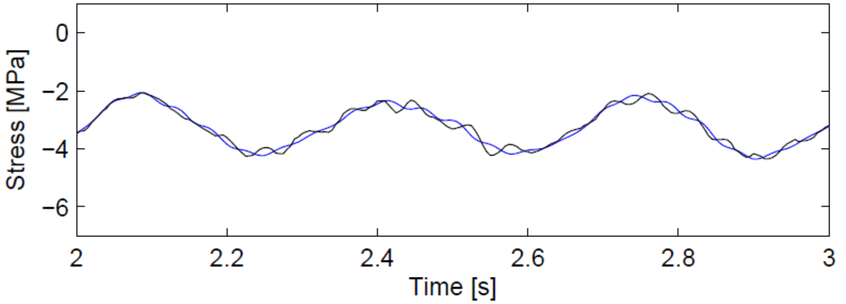
Structural Detail



(a)

Fatigue Damage Accumulation

	Train Passage
True D	**4.92 x 10e-12**
Identified D	**4.53 x 10e-12**



(b)

Papadimitriou, Lourens, Lombaert, De Roeck, Liu. Predictions of **Fatigue Damage Accumulation** in the **Entire Body of Metallic Bridges** by Analysing Operational Vibrations, 3rd Int. Symp. on Life-Cycle Civil Engineering, Vienna, 2012.

Input, State, Parameter Estimation

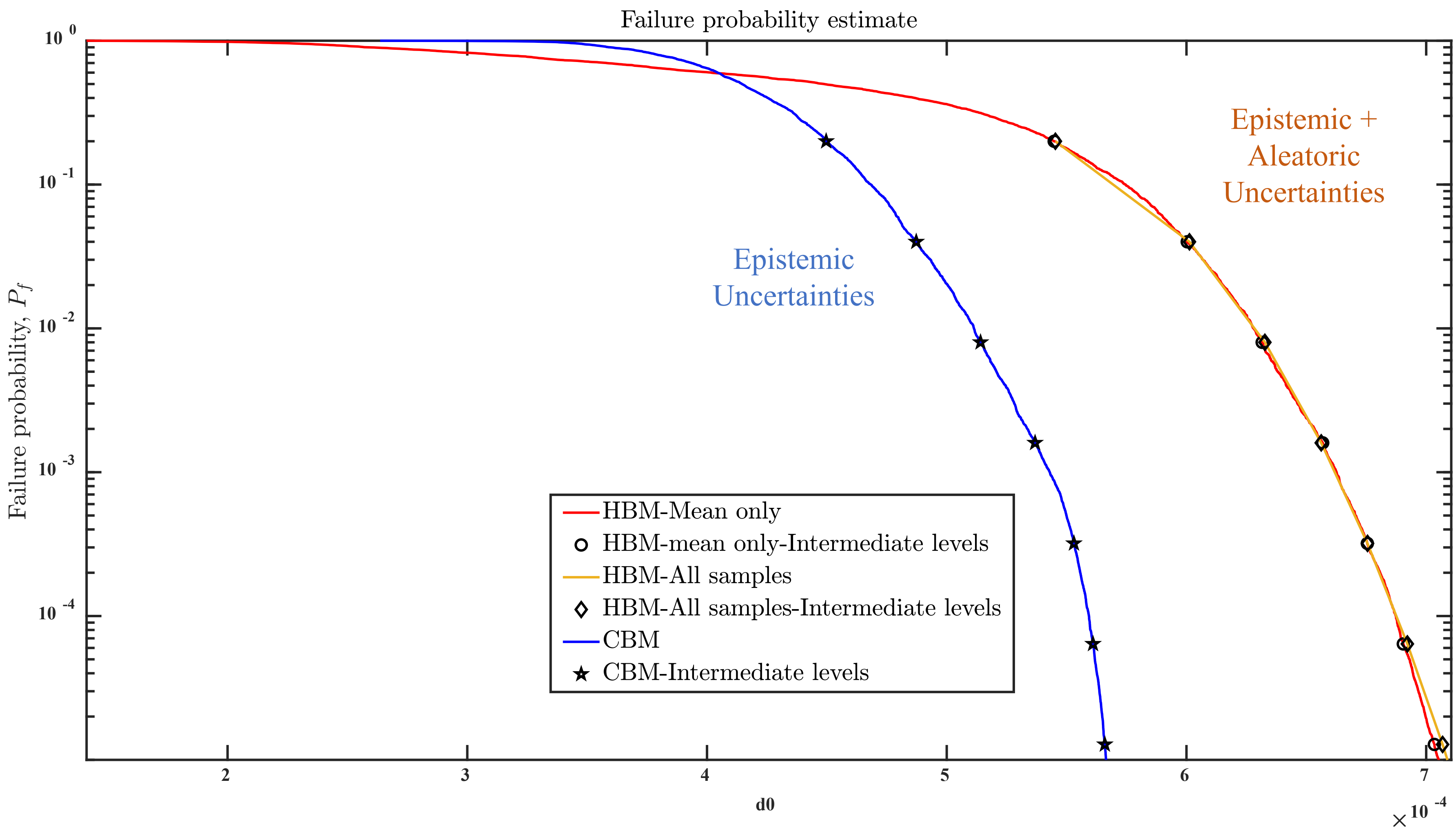
- **PINNs & Bayesian PINNs**

Lai, Mylonas, Nagarajaiah, Chatzi. **Structural Identification with physics-informed neural differential equations** Journal of Sound and Vibration, 2021.
Haywood-Alexander, Arcieri, Kamariotis, Chatzi, **Response estimation and system identification** of dynamical systems via **physics-informed neural networks**, Advanced Modeling and Simulation in Engineering Sciences, 2025
Mehrjoo, Tronci, Moaveni, A **physics-informed** framework for **input load estimation** in offshore wind turbines, Int Conf on Experimental Vibration Analysis for Civil Engineering Structures, 2025.

- **ODIL & Bayesian ODIL**

Karnakov, Litvinov, Koumoutsakos, Flow reconstruction by multi-resolution optimization of a discrete loss with automatic differentiation, Eur. Physics J. 2023
Karnakov, Litvinov, Koumoutsakos. Solving inverse problems in physics by optimizing a discrete loss: **Fast and accurate learning without neural networks**, PNAS nexus, 2024.
Amoudruz, Litvinov, Papadimitriou, Koumoutsakos, Bayesian inference for PDE-based inverse problems using the optimization of a discrete loss, CMAME, 2026.
Liang, Vogiatzoglou, Jia, Amoudruz, Koumoutsakos, Papadimitriou, **Bayesian Learning using Physics-Constrained Priors**, Computational Stochastic Mechanics (CSM9) Conf, 2026.

OUTPUT: Updating Reliability using Monitoring Data



Threshold Level Exceedance Probability

Xinyu, Papadimitriou. **Reliability updating using monitoring data**. CMAME, 2026.

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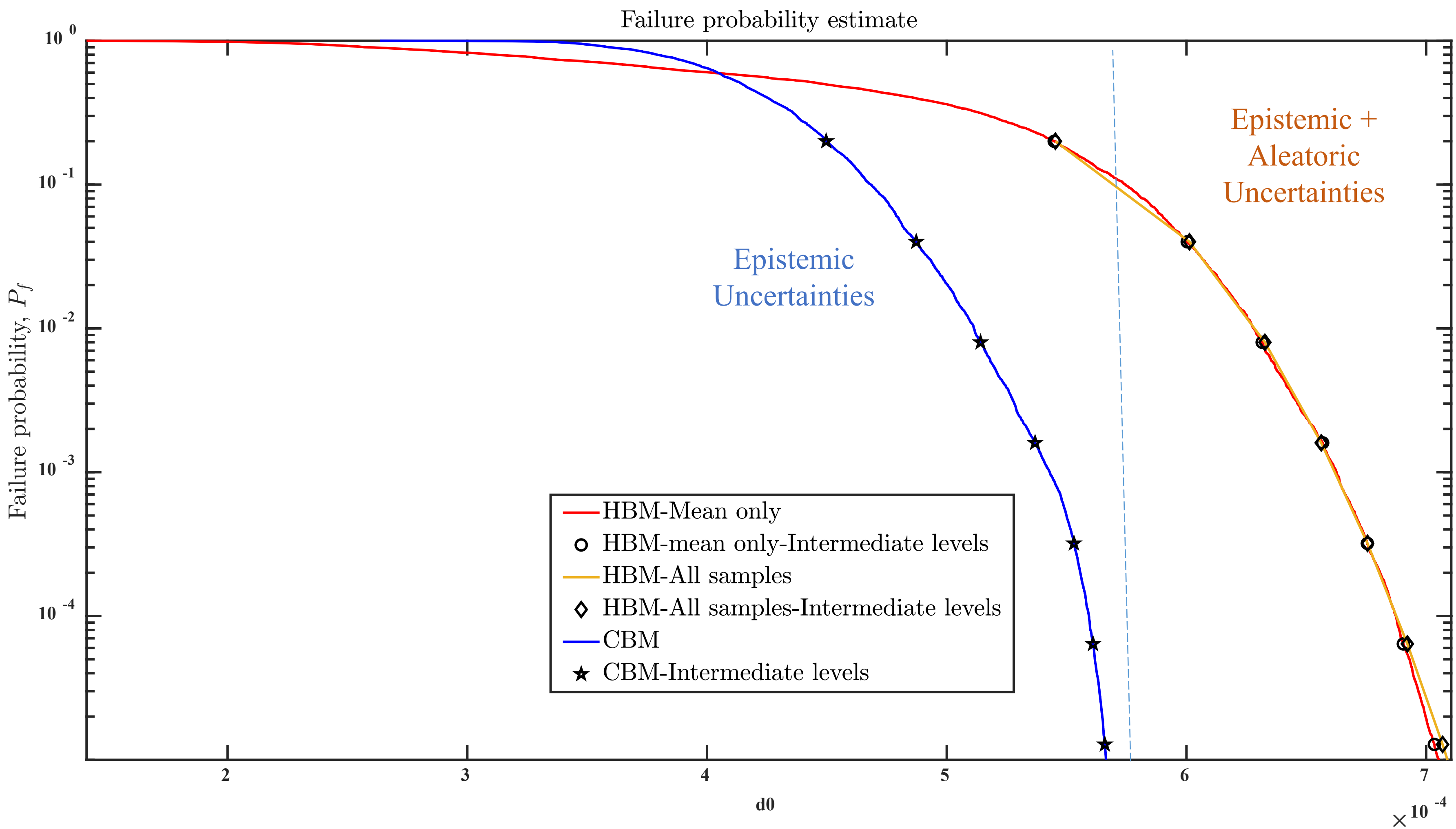

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Decision Support for Bridge Management

- From predictions to actions:
    - Risk-based inspection planning

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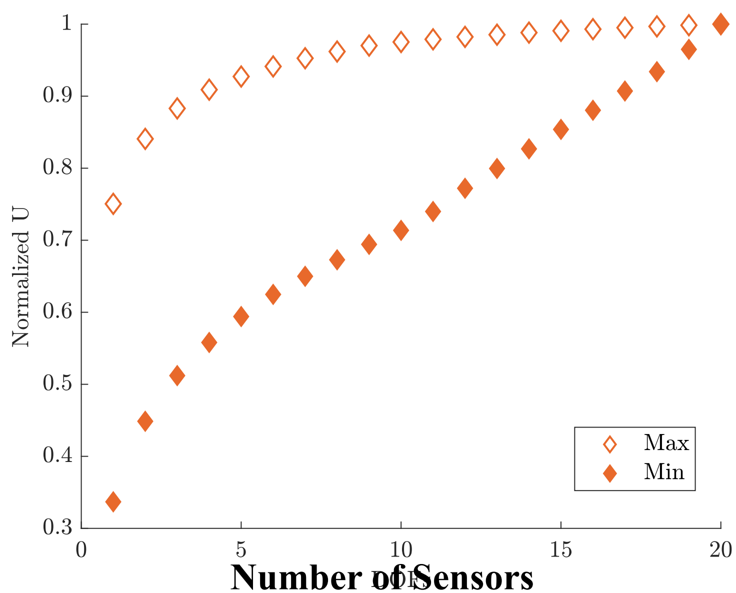
  - Optimal sensor placement (for maximum information gain under budget constraints)

$$\frac{U(\underline{\delta})}{U^{\max}}$$



Ercan, Papadimitriou. Bayesian optimal sensor placement for **parameter estimation under modeling and input uncertainties**, Journal of Sound and Vibration, 2023,
Ercan, Sedehi, Katafygiotis, Papadimitriou. Information theoretic-based optimal sensor placement for **virtual sensing using augmented Kalman filtering**, MSSP, 2023.

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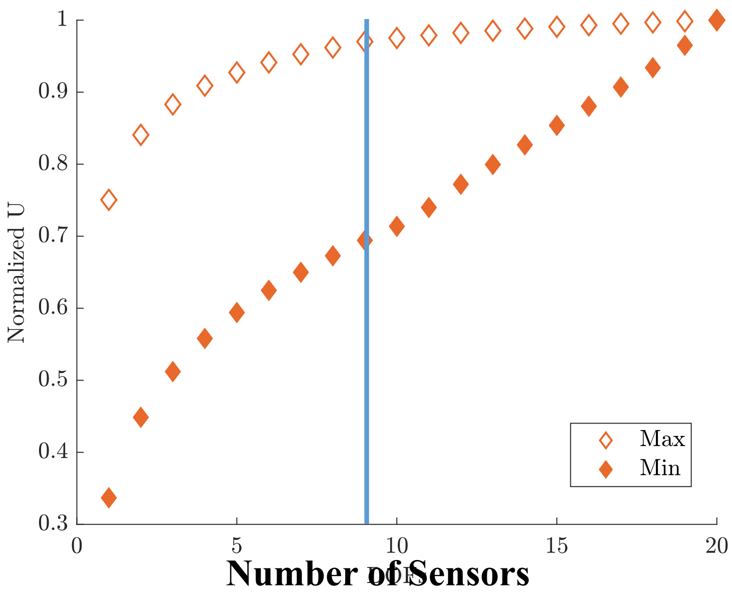

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Decision Support for Bridge Management

- From predictions to actions:
  - Risk-based inspection planning
  - Optimal sensor placement (for maximum information gain under budget constraints)
  - Maintenance/retrofit prioritization using life-cycle cost analysis under uncertainty
- Tools:
  - Value of Information (VoI) analysis
  - Multi-objective optimization (cost vs. reliability)

Kamariotis, Chatzi, Straub, **Value of information** from vibration-based structural health monitoring extracted via **Bayesian model updating**, MSSP, 2022.
Kamariotis, Chatzi, Straub, et al. Monitoring-supported value generation for managing structures and infrastructure systems. Data-Centric Engineering, 2024.

Conclusions

- **Uncertainty-aware modeling**

    - is essential for sustainable management of transport infrastructure

    - Leads to better (informed) decisions

- **Developments in Greece?**

  - **“Smart Bridges”**: Real time monitoring of 271 bridges using strain/acceleration sensors
  - Collected data can help build reliable **Digital Twins**
  - led by **OSMOS Hellas**