

RIIS Project Presentations

Thursday 14th March 2024

**RESILIENT AND INTELLIGENT
INFRASTRUCTURE SYSTEMS**

in urban resources and energy sectors.

Presentation Chair

Professor Sisi Zlatanova

Acknowledgment of Country

We acknowledge Aboriginal nations as first people of Australia, we thank them for their custodianship of the land and pay respects to Elders past and present



RIIS Director

Scientia Professor Nasser Khalili

“TOWARDS PRODUCTIVE, CONNECTED, SUSTAINABLE AND SMART INFRASTRUCTURE”

INDUSTRY TRANSFORMATION RESEARCH HUB

Resilient and Intelligent Infrastructure Systems

in urban resources and energy sectors



ARC Industry Transformation Research Hub



Nasser Khalili

Hub Director

n.khalili@unsw.edu.au



INDUSTRY PARTNERS

GeoAI



Azure Mining Technology



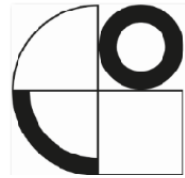
Asset Institute®
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IPWEA
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MINCKA

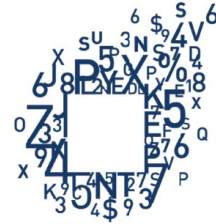


Geoscape

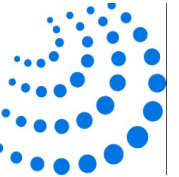
FRONTIER S I >



Spatial
Vision



South East
Water



ROOBUCK



Lindenbaum ∞



Research and Innovation Themes

The RIIS has the potential to transform advanced manufacturing, service and infrastructure engineering in Australia focusing on five main themes:

THEME 1 Sensing, intelligent and adaptive systems

- Robust, low energy sensors and actuators
- Ubiquitous positioning, sensing & communications
- Internet of Things (IoT) & sensing platforms
- Signal processing, network and sensing optimization

THEME 2 Data collection, security and integration

- Robotics, satellite, UAV, autonomous systems
- Big data management storage & transmission
- Data security, robustness and reliability

THEME 3 Modelling, simulations and prognostics

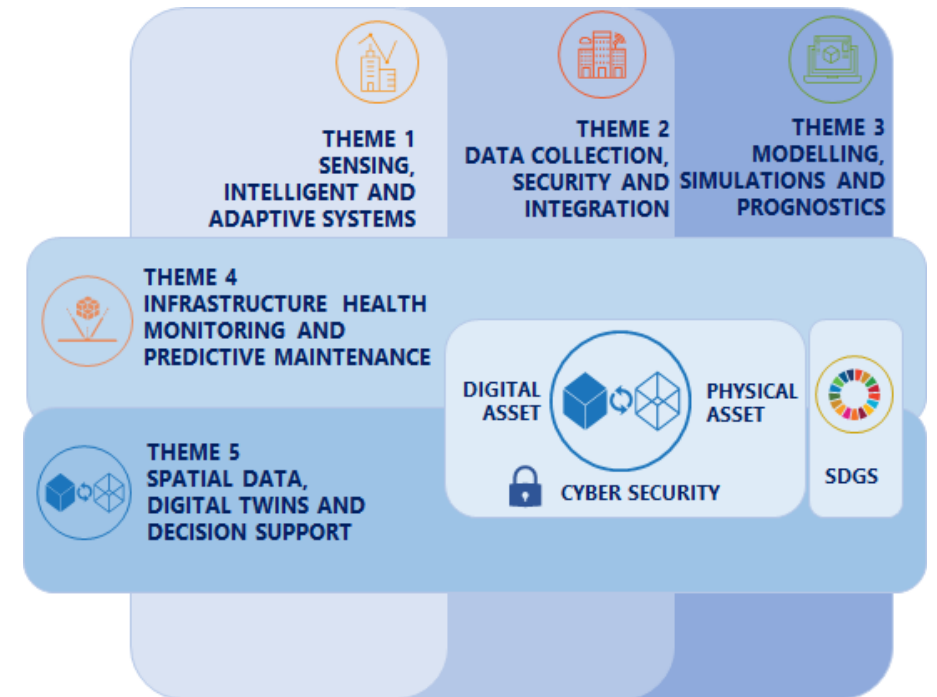
- Predictive modelling simulation & performance assessment
- Physics-informed artificial intelligence machine learning
- Real-time analytics – adaptive decisions

THEME 4 Infrastructure monitoring and predictive maintenance

- Degradation quantification & failure prediction Risk & safety
- Service life assessment
- Remedial & renewal technologies

THEME 5 Spatial data, Digital Twins and decision support

- Integration & structuring of data & prognosis
- Digital twins & decision support
- Visualisation, virtual reality & interactive guidance systems
- Adaptive, intelligent & resilient design





THEME 1

Ubiquitous sensing, intelligent and adaptive systems

Theme 1 Lead

Professor Ismet Canbulat

Dr Babak Shahbodagh

**A Computational Framework for
Structural Health Monitoring of
Geo-Infrastructures**

Project Title: A Computational Framework for Structural Health Monitoring of Geo-Infrastructures

Involved:

UNSW Cls: Prof Nasser Khalili, Dr Babak Shahbodagh, Dr Mohammad Vahab

Collaborator: Dr Ehsan Haghighat (Massachusetts Institute of Technology - MIT)

PhD Students: Sana Shahoveisi, Sina Akhyani

Introduction

Geo-structures - Dams, Roads, Rails, Levees, Embankments, Foundations, Tunnels, Slopes, etc.

- Significant Consequence of Failure



Failure of 50 levee banks along the River Murray, SA 2022.



Failure of Yallourn East Field Mine, VIC 2007.



Jamberoo Mountain Road Failure, NSW 2020.

Aim

**Develop a Computational Framework for
Structural Health Monitoring of Geo-Infrastructures**



Failure of 50 levee banks along the River Murray, SA 2022.



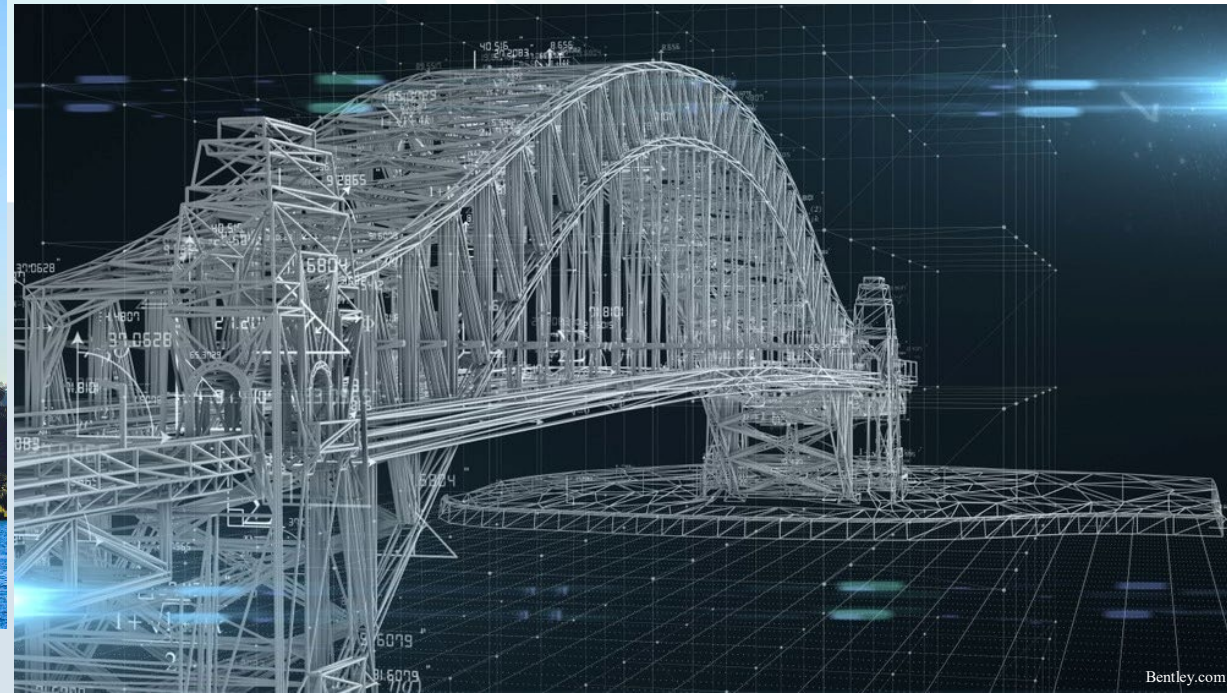
Failure of Yallourn East Field Mine, VIC 2007.



Jamberoo Mountain Road Failure, NSW 2020.

Aim

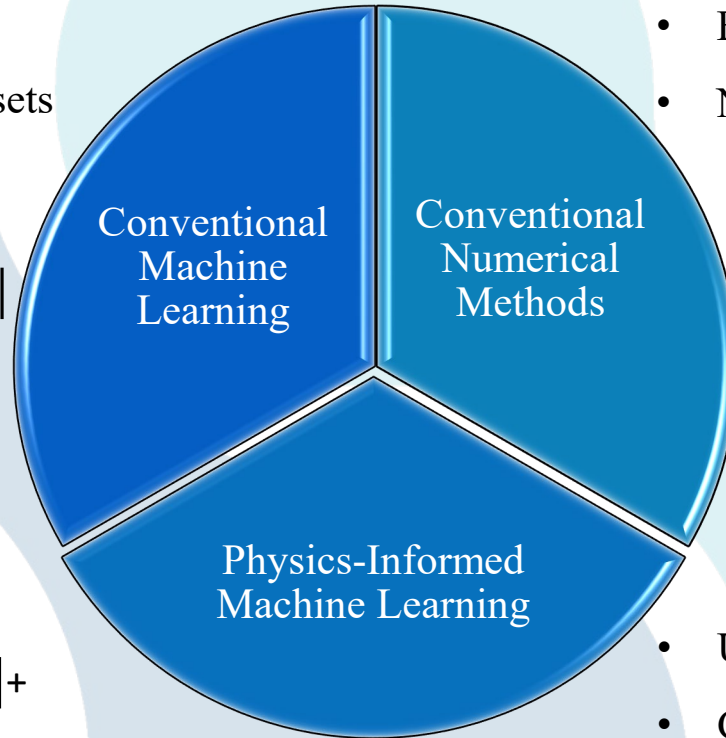
**Develop a Computational Framework for
Structural Health Monitoring of Geo-Infrastructures**



Physics-Informed AI Framework

- Black box AI models
- Requires extensive datasets
- Failure in extrapolation

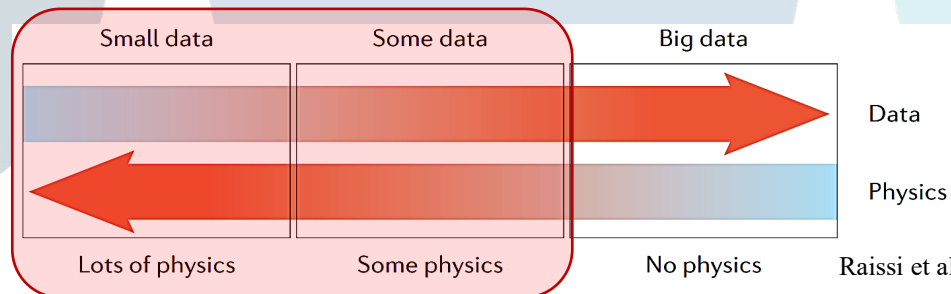
$$\arg \min L(\mathbf{x}^*) := \|f^* - \hat{f}(\mathbf{x}^*)\|$$



- Extensive computational cost
- Not suitable for inverse analysis

$$\arg \min L(\mathbf{x}^*) := \|f^* - \hat{f}(\mathbf{x}^*)\| + \|\mathcal{P}\mathbf{x} - 0\|_{\Omega} + \|\mathcal{C}\mathbf{x} - g\|_{\partial\Omega} + \dots$$

- Use of physics & field data
- Computationally efficient
- Excellent performance in inversion



Raissi et al. (2019); Karniadakis et al. (2021)

Physics-Informed AI Framework

Pile-Soil Interaction Problem

Governing Equations:

$$\frac{1}{r} \frac{\partial}{\partial r} (r\sigma_{rr}^\alpha) + \frac{1}{r} \frac{\partial \sigma_{r\theta}^\alpha}{\partial \theta} + \frac{\partial \sigma_{rz}^\alpha}{\partial z} - \frac{\sigma_{\theta\theta}^\alpha}{r} + f_r^\alpha = 0 ,$$

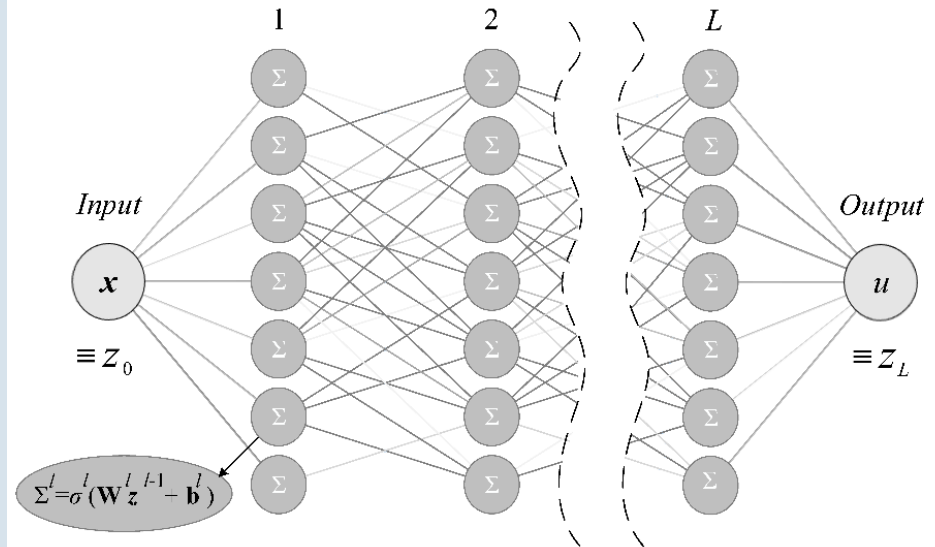
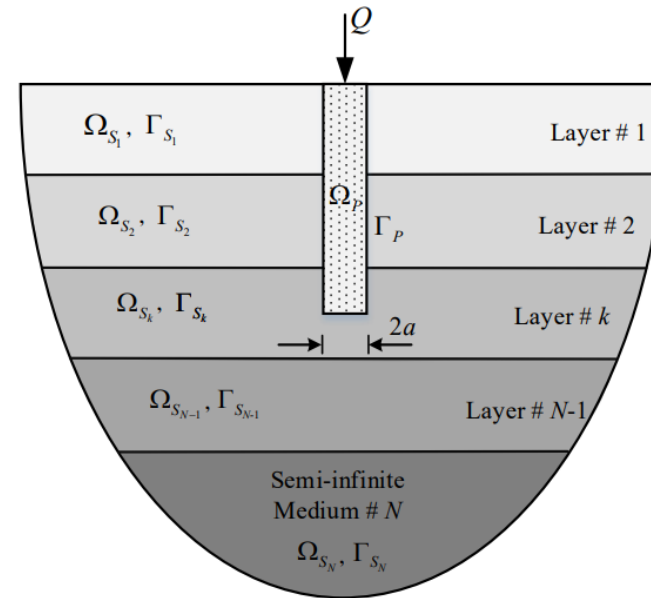
$$\frac{1}{r} \frac{\partial}{\partial r} (r\sigma_{r\theta}^\alpha) + \frac{1}{r} \frac{\partial \sigma_{\theta\theta}^\alpha}{\partial \theta} + \frac{\partial \sigma_{\theta z}^\alpha}{\partial z} + \frac{\sigma_{r\theta}^\alpha}{r} + f_\theta^\alpha = 0 , \quad \text{on } \Omega_\alpha \ (\alpha = P, S_k)$$

$$\frac{1}{r} \frac{\partial}{\partial r} (r\sigma_{rz}^\alpha) + \frac{1}{r} \frac{\partial \sigma_{\theta z}^\alpha}{\partial \theta} + \frac{\partial \sigma_{zz}^\alpha}{\partial z} + f_z^\alpha = 0 ,$$

$$\varepsilon_{ij}^\alpha = \frac{1}{2} (u_{i,j}^\alpha + u_{j,i}^\alpha)$$

Pile-Soil Interface:

$$\begin{aligned} (\sigma_{ji}^\alpha(\mathbf{x}) - \sigma_{ji}^\beta(\mathbf{x})) n_j^\alpha &= 0 , \\ u_i^\alpha(\mathbf{x}) - u_i^\beta(\mathbf{x}) &= 0 , \end{aligned} \quad \forall \mathbf{x} \in (\Gamma_\alpha \cap \Gamma_\beta), \text{ where } \alpha \neq \beta$$



Physics-Informed AI Framework (PINN)

Pile-Soil Interaction Problem

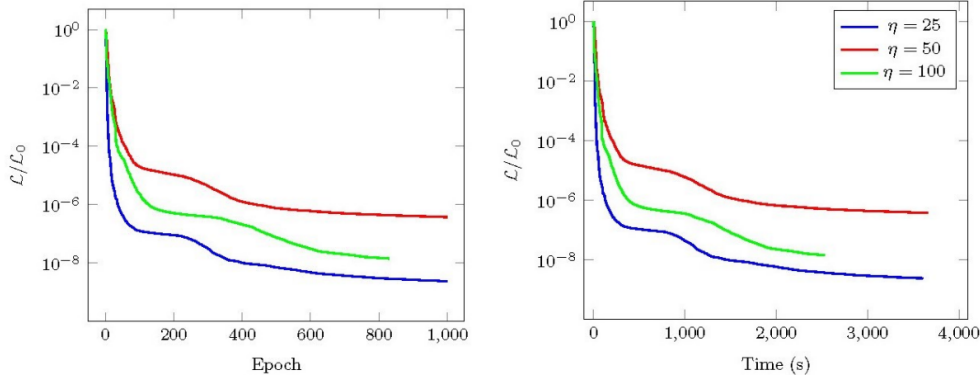
$$\mathcal{L}_T = \mathcal{L}_\Omega + \mathcal{L}_{\Gamma_{B.C.}} + \mathcal{L}_{\Gamma_{Cont}} ,$$

$$\mathcal{L}_\Omega = \lambda_1 \|\mathcal{P}_{rr}^P \mathbf{u}^P\|_{\text{on } \Omega_P} + \lambda_2 \|\mathcal{P}_{rr}^S \mathbf{u}^S\|_{\text{on } \Omega_S} + \lambda_3 \|\mathcal{P}_{zz}^P \mathbf{u}^P\|_{\text{on } \Omega_P} + \lambda_4 \|\mathcal{P}_{zz}^S \mathbf{u}^S\|_{\text{on } \Omega_S} ,$$

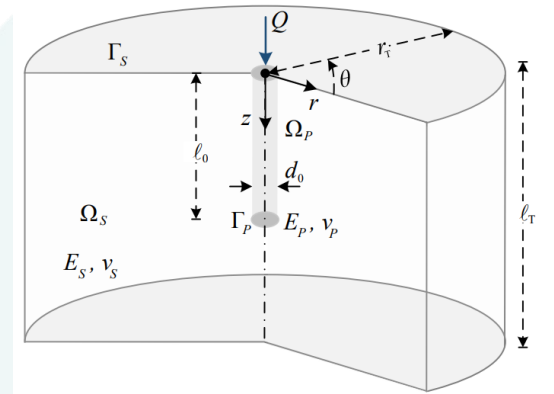
$$\mathcal{L}_{\Gamma_{B.C.}} = \lambda_5 \|\mathcal{B}_{rr}^P \mathbf{u}^P - g_{rr}^P\|_{\text{on } \Gamma_P \setminus \Gamma_S} + \lambda_6 \|\mathcal{B}_{rr}^S \mathbf{u}^S - g_{rr}^S\|_{\text{on } \Gamma_S \setminus \Gamma_P} + \lambda_7 \|\mathcal{B}_{zz}^P \mathbf{u}^P - g_{zz}^P\|_{\text{on } \Gamma_P \setminus \Gamma_S} + \lambda_8 \|\mathcal{B}_{zz}^S \mathbf{u}^S - g_{zz}^S\|_{\text{on } \Gamma_S \setminus \Gamma_P} ,$$

$$\mathcal{L}_{\Gamma_{Cont}} = \lambda_9 \|\mathbf{u}^P - \mathbf{u}^S\|_{\text{on } \Gamma_P \cap \Gamma_S} + \lambda_{10} \|\mathbf{t}^P - \mathbf{t}^S\|_{\text{on } \Gamma_P \cap \Gamma_S} ,$$

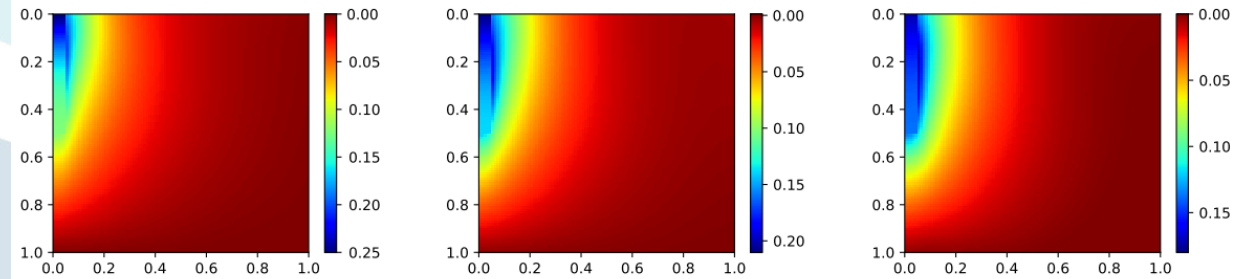
$$\eta = \frac{E_p}{E_s}$$



Networks training history



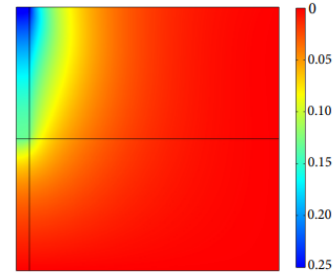
PINN



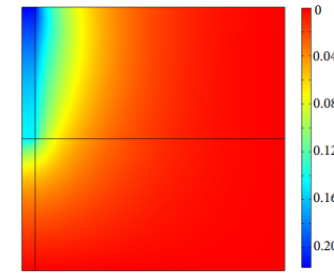
(a) PINN solution for $\eta = 25$

(b) PINN solution for $\eta = 50$

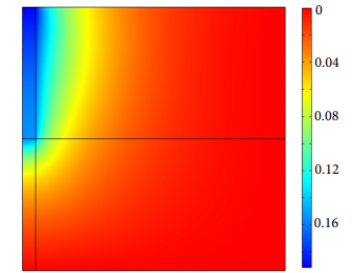
(c) PINN solution for $\eta = 100$



(d) Reference solution for $\eta = 25$



(e) Reference solution for $\eta = 50$



(f) Reference solution for $\eta = 100$

FEM

Normalised Vertical Displacement

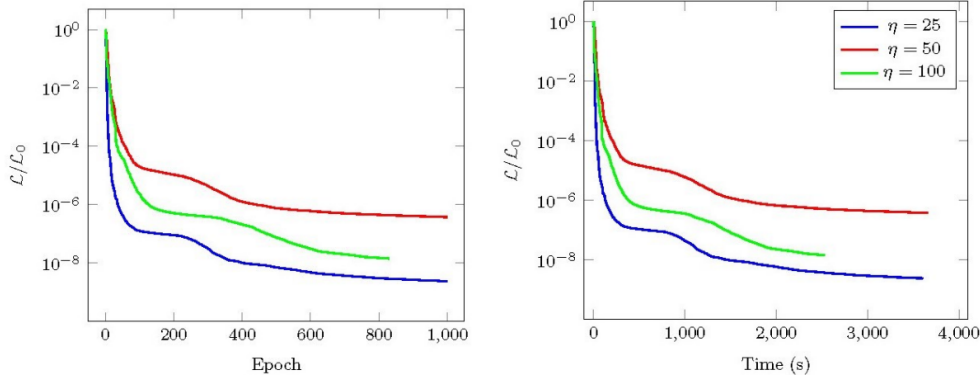
Physics-Informed AI Framework

Pile-Soil Interaction Problem

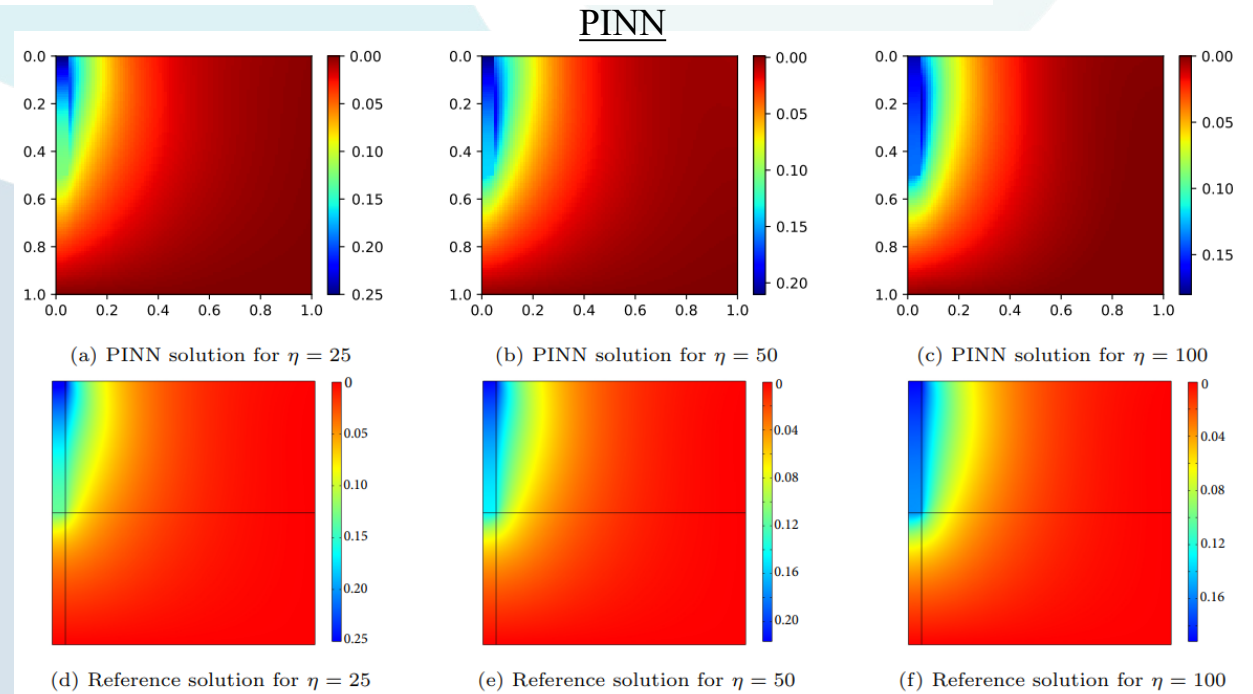
The computational complexity of the proposed PINNs solution vs the FEM analysis

DOFs	PINNs (4 × 20)	Iterative solvers (IS) ^a	$\mathcal{O}_{IS}/\mathcal{O}_{PINN}$	Direct solvers (DS) ^b	$\mathcal{O}_{DS}/\mathcal{O}_{PINN}$
1000	3.2E+5	1.0E+7	31.2	5.0E+8	1562.5
6000	1.9E+6	3.6E+8	187.5	1.1E+11	56250
10,000	3.2E+6	1.0E+9	312.5	5.0E+11	156250

$$\eta = \frac{E_p}{E_s}$$



Networks training history



PINN
FEM
Normalised Vertical Displacement

Next Steps

Extension of the Physics-Informed Artificial Intelligence Framework for modelling

- **Coupled Hydro-Mechanical Problems**
- **Wave Propagation in Multiphase Porous Media**
- **Material Nonlinearity**
- **Initiation and Progression of Flaws in Multiphasic Materials**



Dr Mahroo Bahador

**Nanosensor Integration and
Manufacturing Technology for Safe
Mining**



UNSW
SYDNEY



“TOWARDS PRODUCTIVE, CONNECTED, SUSTAINABLE AND SMART INFRASTRUCTURE”

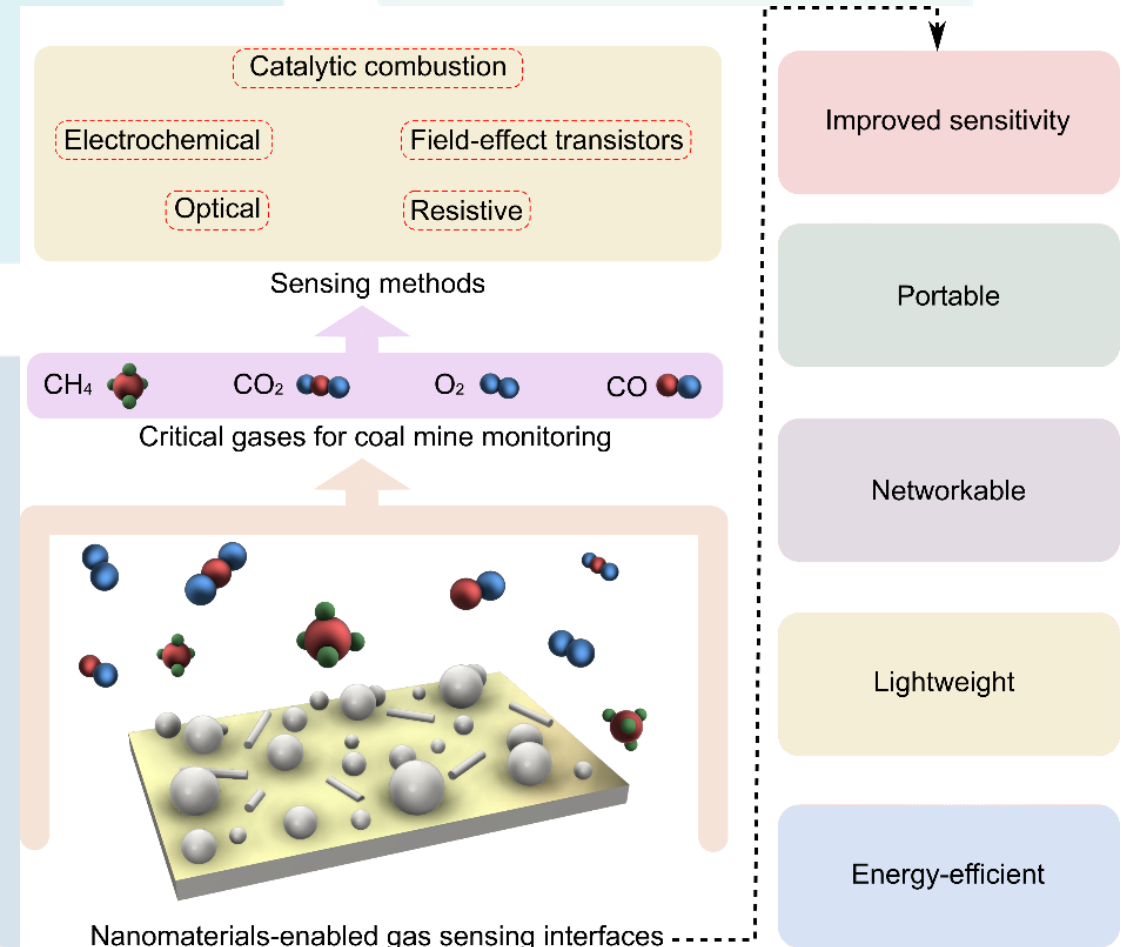
Project Title: Nanosensors Technology for Safe Mining

Motivation:

- ✓ Controlled crystallization of nanowires
- ✓ Enabling scalable manufacturing of miniaturized interconnected electronics suited for gas sensing.
- ✓ Addressing challenges of existing sensors such as limited sensitivity and low-selectivity.

Aims:

- ✓ Developing a scalable nanosensor manufacturing technique
- ✓ Tailoring selectivity by exploring different chemistries of NWs.
- ✓ Fabricating nanosensors with improved applicability and sensitivity.

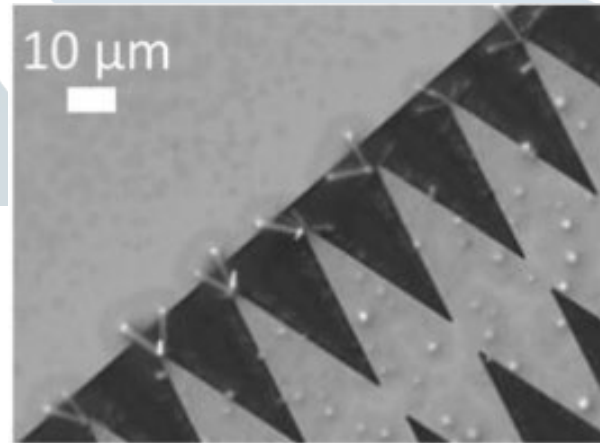
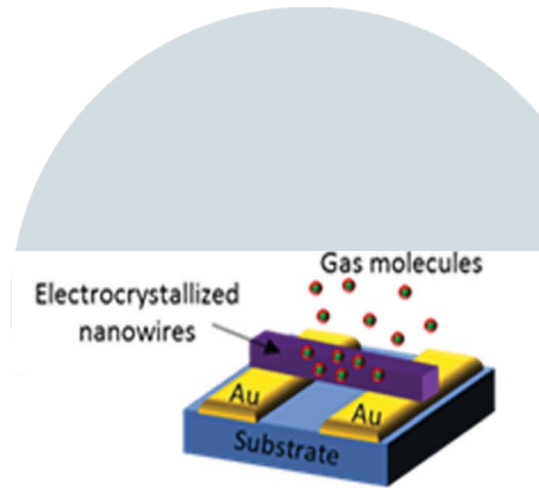
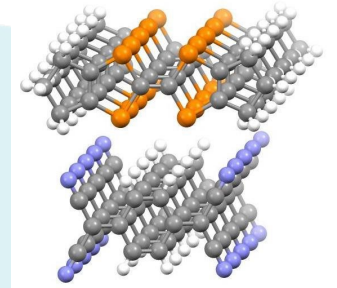


Gaps in knowledge:

- lack of a reliable and scalable manufacturing technique for nanosensing interfaces.
- Performance of existing gas sensors in the market is yet to be improved.

Approach:

- Introducing controlled crystallization of nanowires on microelectrodes, as a reliable technology for scalable nanosensor manufacturing.
- Nanoscale gas sensing interfaces offer higher sensitivity, energy-efficiency, and portability.

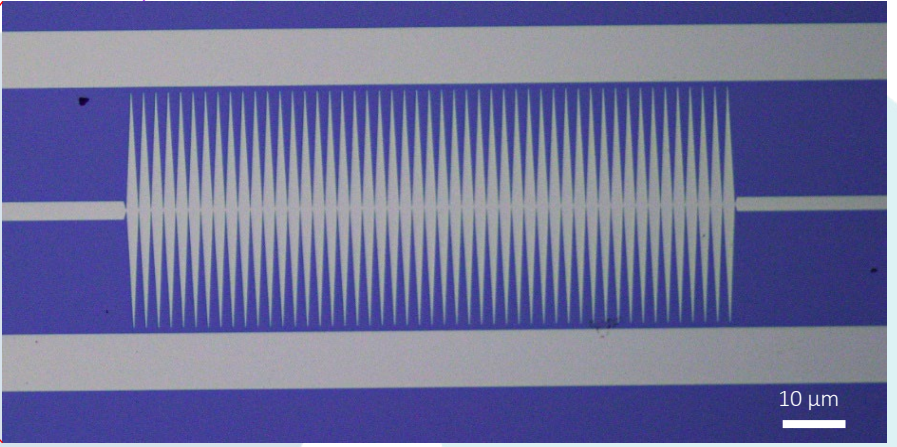
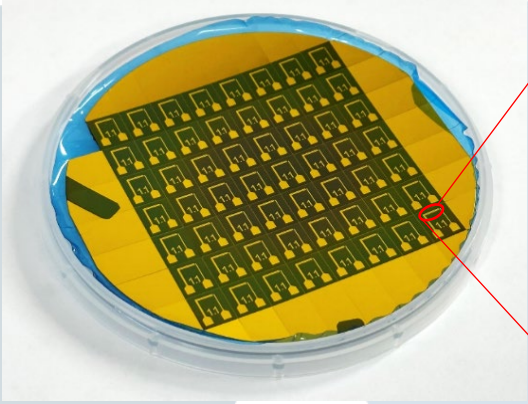
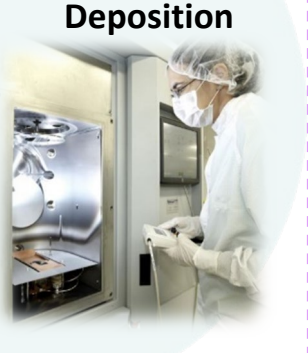
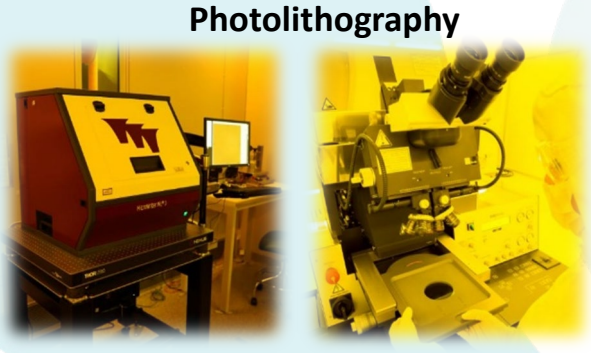
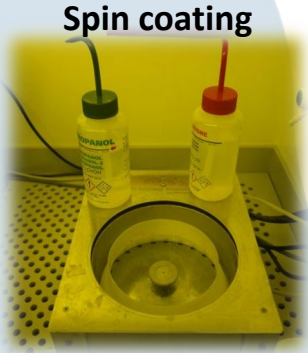
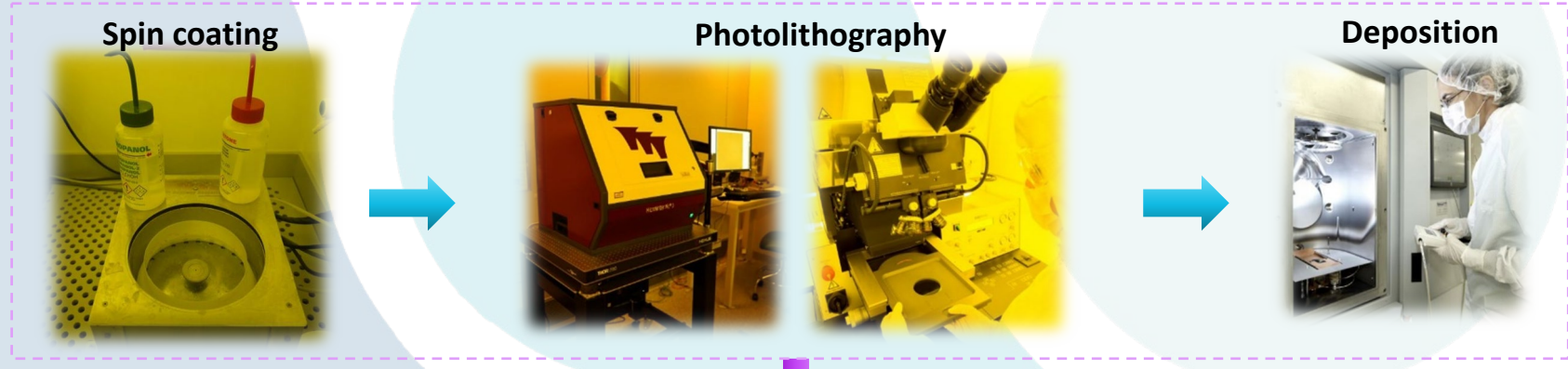


Milestone	Description	Progress
Phase 1		
1	Define technical parameters for nanosensor use for mining safety	Achieved
2	Demonstrate nanowire deposition reproducibility	Achieved
3	Demonstrate nanosensor performance for 4 hazardous scenarios in the mining field	Ongoing work
Phase 2		
4	One or more nanosensor prototypes completed on deployable platforms relevant to mining safety	Future work
5	Sensor device prototypes tested for reliability and stability in mining environments	Future work
6	Describe commercial production plan with our collaborators	Future work

Gas type	Standard No.	Detection range	Response time	Power consumption
Methane	AQ6203-2006	0-4%	<5s	2mW
Carbon monoxide	AQ6205-2006	0-1000ppm	<5s	2mW
Oxygen	MT981-2006	0-25%	<5s	2mW
Carbon dioxide	AQ1052-2008	0-5%	<5s	2mW



- Fabrication of substrate prototypes



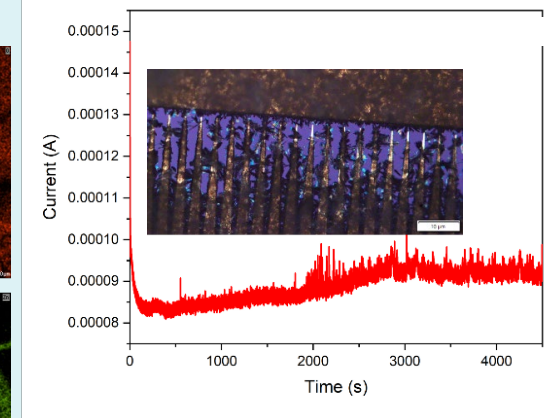
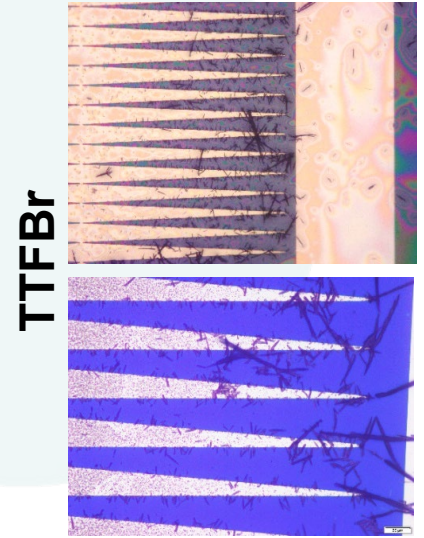
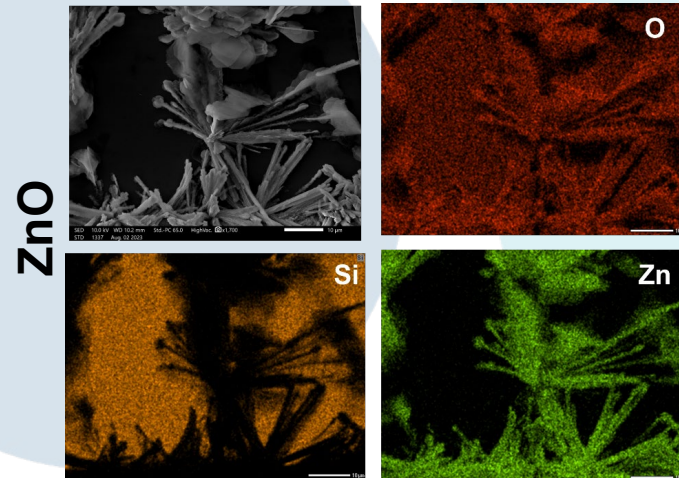
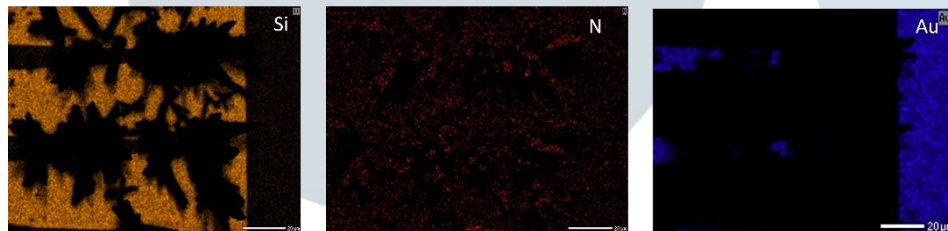
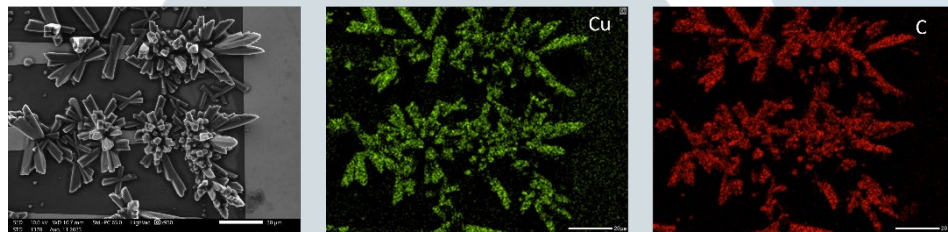
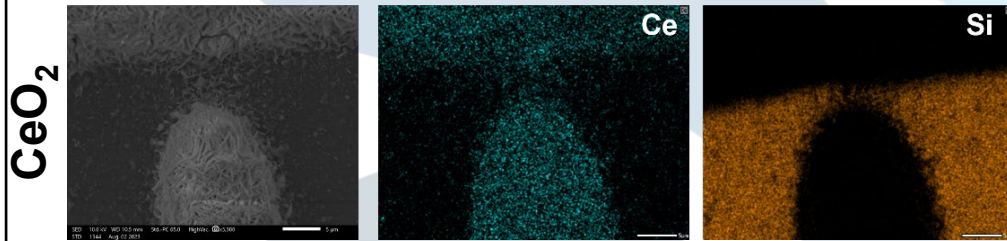
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- Developing gas sensing platforms

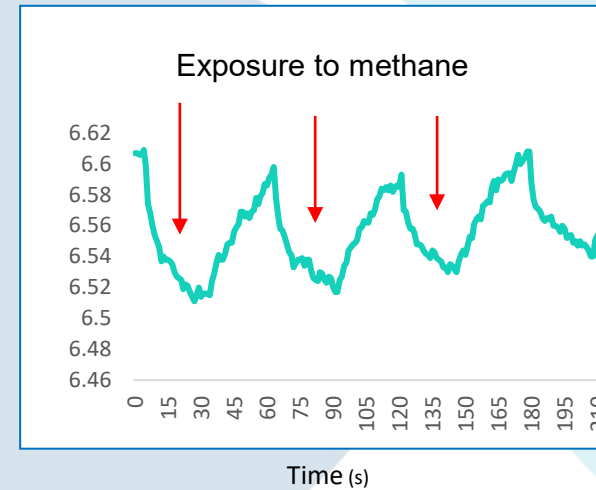
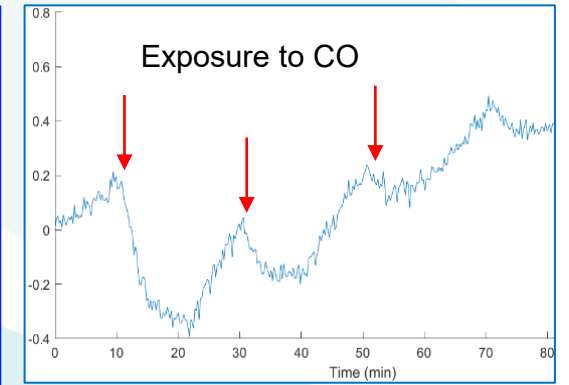
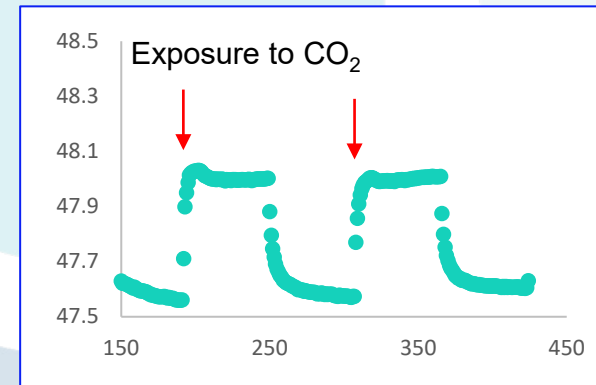
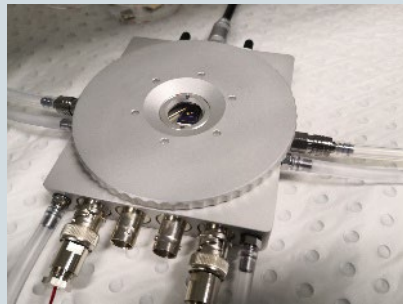
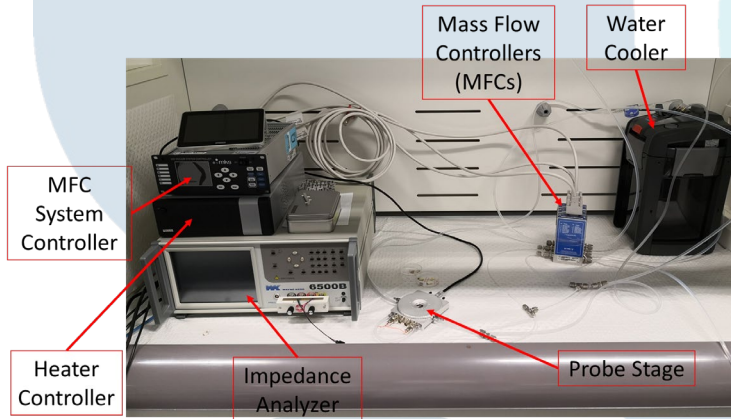
Structures explored so far:

- ✓ Charge transfer complexes (TTFBr, TTFCl, TTFI, CuTCNQ, and TTF-TCNQ)
- ✓ Metal oxides (ZnO, CeO₂, and SnO₂)



Ongoing Work

- Demonstrate nanosensor performance for 4 hazardous scenarios in the mining field



Summary and Future work

Progress:

- Defining technical parameters
- Fabricating substrate prototypes
- Exploring deposition of NWs

Ongoing work:

- Investigating the analytical figures for each gas

Future work:

- Nanosensor prototyping
- Reliability tests in mining fields



CCTEG



UNSW
SYDNEY



Dr Binghao Li & Dr Xu

**Text message broadcasting system for
underground mines and camera-based
tracking & obstacle avoidance**



UNSW
SYDNEY



“TOWARDS PRODUCTIVE, CONNECTED, SUSTAINABLE AND SMART INFRASTRUCTURE”

Project Title: Text message broadcasting system for underground mines and camera-based tracking

Background: In the challenging environments of underground mines, maintaining robust communication and ensuring the safety of personnel and equipment are paramount. This project leverages cutting-edge technologies to develop a solution that addresses these critical needs.

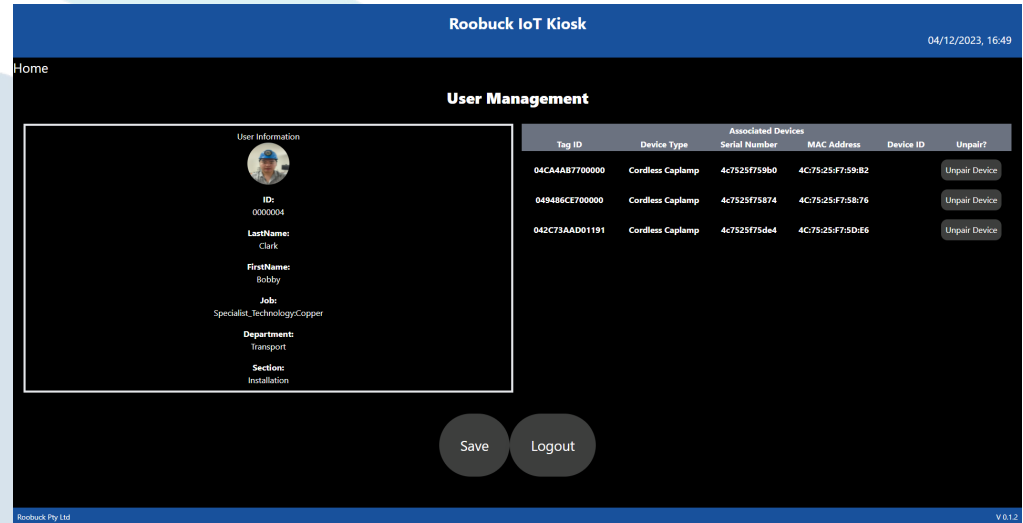
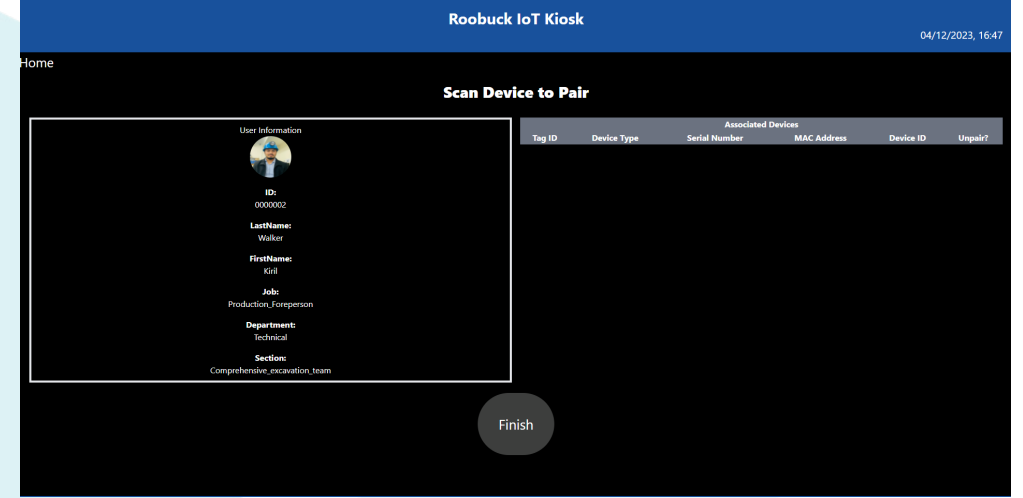
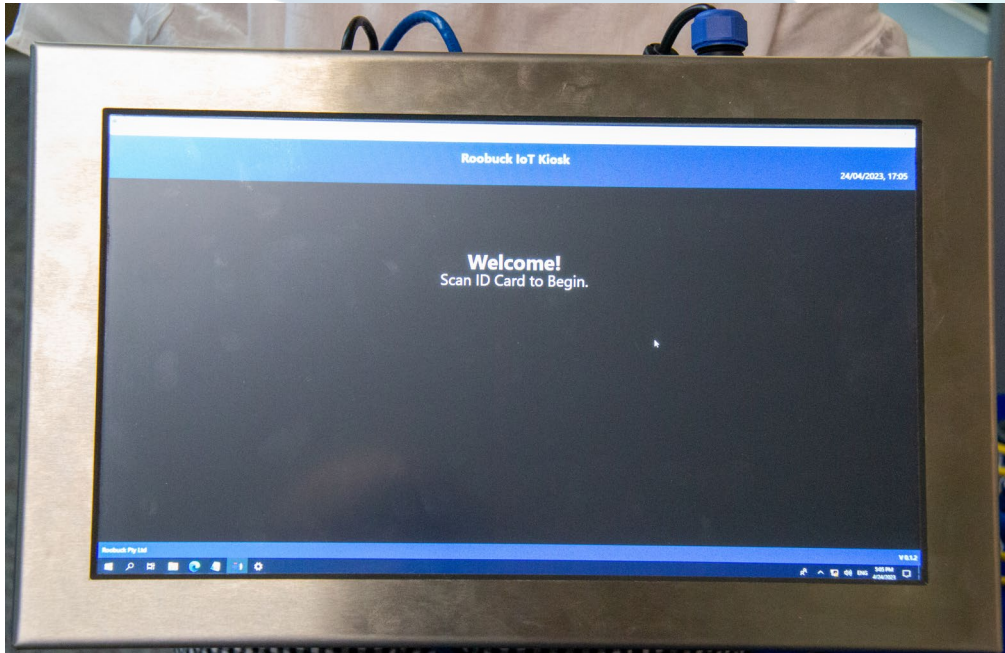
Objective: Develop a state-of-the-art text message broadcasting system coupled with a camera-based tracking and obstacle avoidance mechanism, designed specifically for the harsh conditions of underground mines. Fits seamlessly within the theme of resilient and intelligent infrastructure systems, focusing on improving the resilience of communication systems and the intelligence of safety mechanisms in extreme environments.

Technological Innovations:

- A broadcasting system designed for the extremely challenging underground environment.
- Deep learning-based low-light image enhancement technology and advanced object tracking solution.

Kiosk System

This system can pair user information and devices



Tag Board

After signing in by Kiosk System, users and devices information will be shown in tagboard. The personal will be tracked by RFID and WIFI. The location information will be shown in tagboard.

After click "Alert All" button, MQTT system will send emergency alert to each IOT devices.

The screenshot shows the Roobuck Tag Board interface. On the left is a floor plan map with several red location markers labeled 'Side_Bay_1A', 'EntryDecline_A', and 'Side_Bay_2A'. On the right is a list of users categorized by level:

Level: Level 1
Location Name: EntryDecline_A
Location Name: Side_Bay_2A
Martin Enoch
Anderson Tadeo
Thompson Mauro
Walker Kiril
Khalid Antonius
Level: Level 2
Location Name: Side_Bay_3A
Level: Level 3
Location Name: Side_Bay_3A

The screenshot shows the 'Department' user profile page in the Roobuck system. It displays the user's profile information:

- ID:** 000001
- LastName:** Anderson
- FirstName:** Tadeo
- Job:** Digital Systems, Technician
- Section:** Sparky
- Department:** General
- Login Time:** 23/10/2023, 16:51

The screenshot shows a 'Devices Information' dialog box overlaid on the user profile page. It displays the following information for a specific device:

- Asset Type:** IOT
- Device Type:** Cordless CapLamp
- LampSN:** 4-75259504
- LampMAC:** 4C792659A094
- Location(WiFi):** Level_1-Side_bay_2a
- Update time(WiFi):** 23/10/2023, 16:58
- Location(RFID):**
- Update time(RFID):**

The screenshot shows the 'Emergency Alert' interface in the Roobuck system. It displays a table of users and their device information:

ID	ID	ID	ID
20	20	20	20
LastName: Anderson	LastName: Clark	LastName: Clark	LastName: Clark
FirstName: Bobo	FirstName: Bobo	FirstName: Bobo	FirstName: Bobo
Device MAC: 4C792659A094	Device MAC: 4C792659A094	Device MAC: 4C792659A094	Device MAC: 4C792659A094
Device SN: 4-75259504	Device SN: 4-75259504	Device SN: 4-75259504	Device SN: 4-75259504
Last Update Time: 23/10/2023, 16:58	Last Update Time: 23/10/2023, 16:58	Last Update Time: 23/10/2023, 16:58	Last Update Time: 23/10/2023, 16:58
Location:	Location:	Location:	Location:

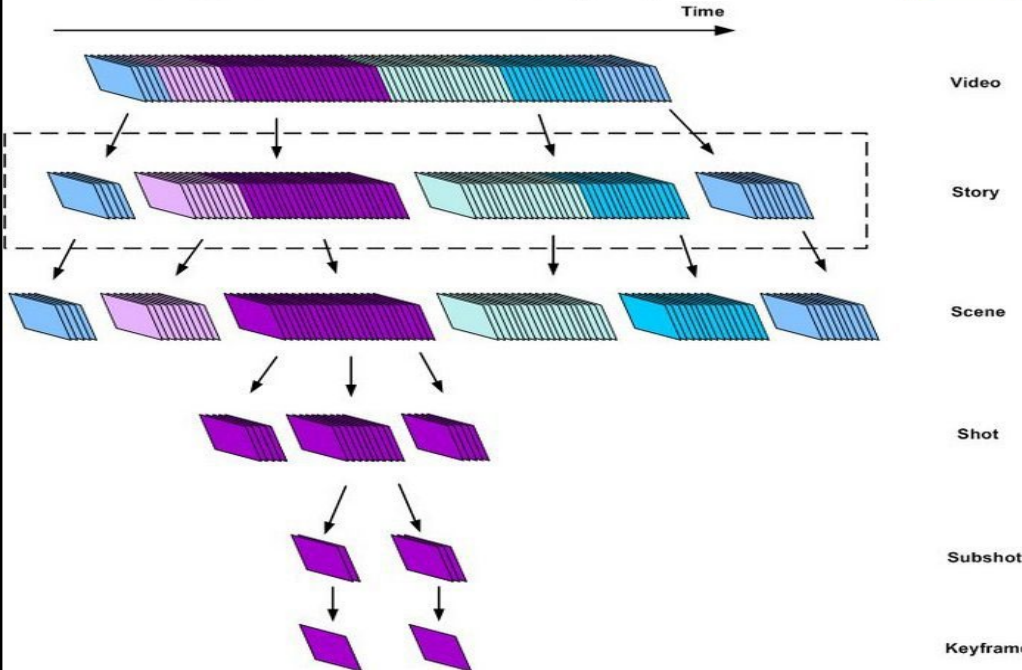
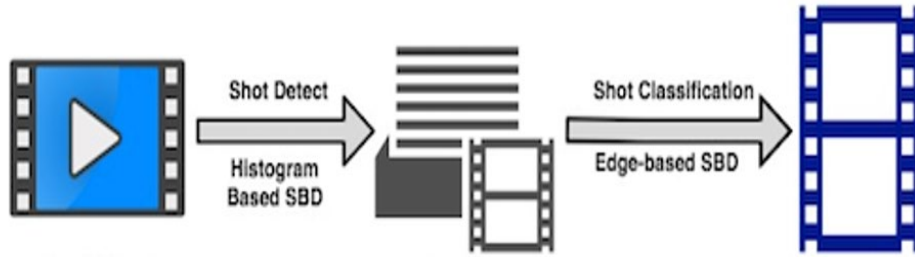
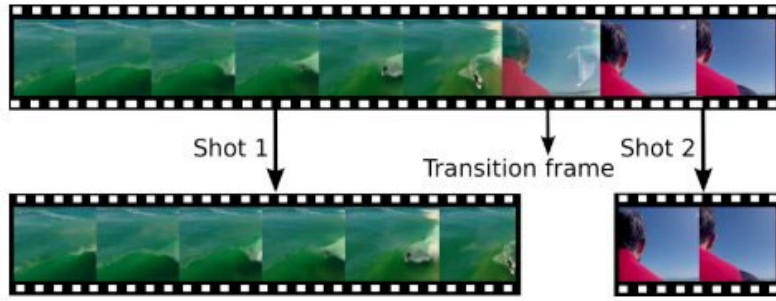
Below the table, the interface shows the status: 'Waiting for Network Connection', 'Alert Successfully Sent', and 'Alert Acknowledged by Personnel'.



Challenge 1: Low Light Mining Tunnel Environment

Objective: We need to utilize image enhancement algorithms for enhancing and brightening images captured by 2D cameras in low light environments. The purpose of this is to improve the accuracy of the tracking and collision avoidance components in downstream tasks. Brighter images mean higher and clearer contrast, which is a key upstream task for our subsequent tasks.

Zhou, Y., Wong, L.N.Y. Automatic, Point-Wise Rock Image Enhancement by Novel Unsupervised Deep Learning: Dataset Establishment and Model Development. *Rock Mech Rock Eng* **56**, 8503–8541 (2023). <https://doi.org/10.1007/s00603-023-03490-1>



Challenge 2: Tracking in the video

Key Frame Extraction: Identify and extract key frames from the video. These frames should represent significant or changing moments in the video.

Object Detection: Apply an object detection algorithm to identify vehicles within the key frames.

Feature Extraction: Extract features from detected vehicles for tracking.

Tracking Algorithm Implementation: Implement a tracking algorithm to follow the detected vehicles across frames. Use methods like optical flow or more complex association algorithms based on features or machine learning to track vehicles from one frame to the next.

Progress to date:

- Camera image enhancement– using low light enhancement method to brighten the tunnel image (done)
- Classifying and identifying vehicle within the camera footage by visual feature descriptor (done)
- Keyframes and intra-frame image identification from camera shots (undergoing)
- The third step involves designing a similarity image identification algorithm based on the keyframes (undergoing)

Dr Feng

Underground Navigation and Obstacle Avoidance for Unmanned Equipment



UNSW
SYDNEY



“TOWARDS PRODUCTIVE, CONNECTED, SUSTAINABLE AND SMART INFRASTRUCTURE”

Project Title: Underground Navigation and Obstacle Avoidance for Unmanned Equipment

Motivation: Automation and robotics are the future of the underground mine operation. The positioning, navigation, and control system that can be applied to underground mines is the key, however still in its early stage. There are clear market demands, but full of research challenges.

Aims: Integrate multiple sensors to achieve high accurate positioning, path planning, navigation, and obstacle avoidance for future autonomous operation in an underground mine.

Approach:

- Development of a multi-sensor integration system based on a mobile robot
- Development of underground navigation, route planning and obstacle avoidance algorithm
- Collaborate with industry partner for intensive testing

Progress to date:

- Vector Field based Strategy for Autonomous Subterranean Exploration
- Hardware development, multi-sensor integration including time synchronization



Highlights:

- Convert the task into collision-free path following within the constrained environment
- Plan the path from the structure of the underground
- Ensure collision-free in the movement phase
- Multi-sensor time synchronization from hardware aspect

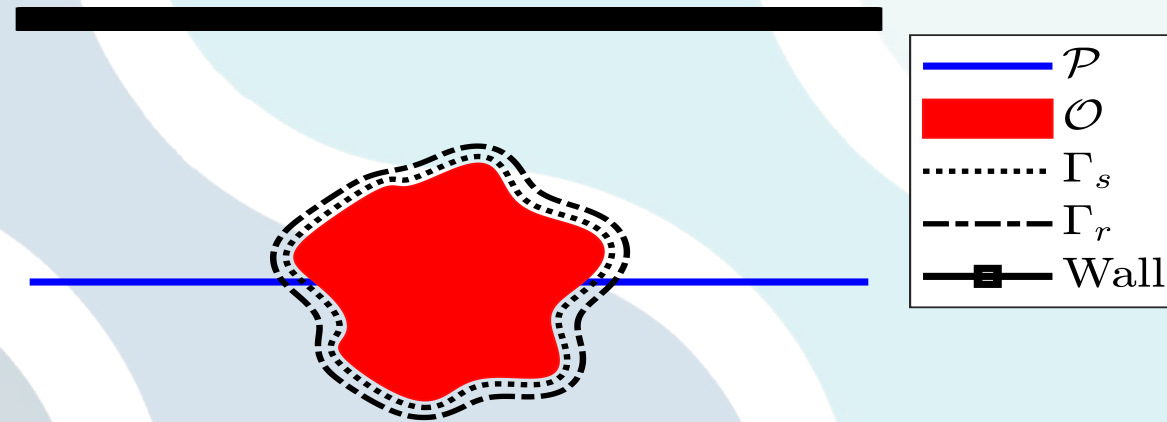
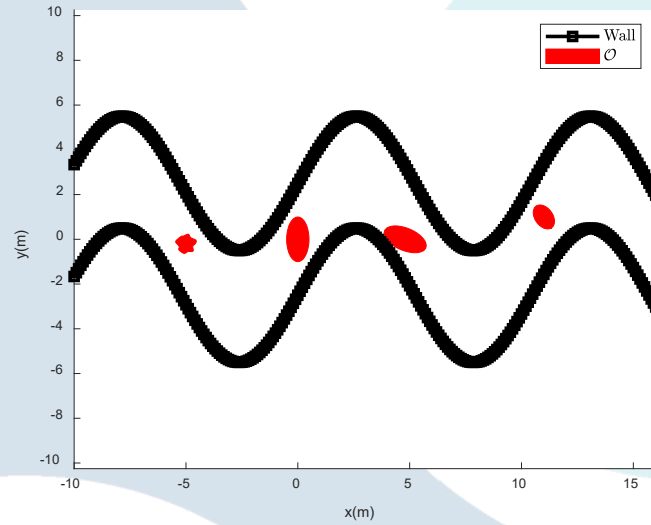


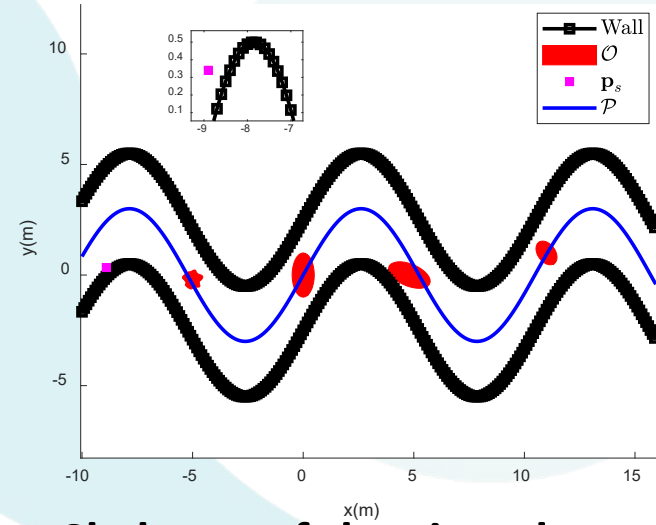
Illustration of the research problem

Technology & Completed design:

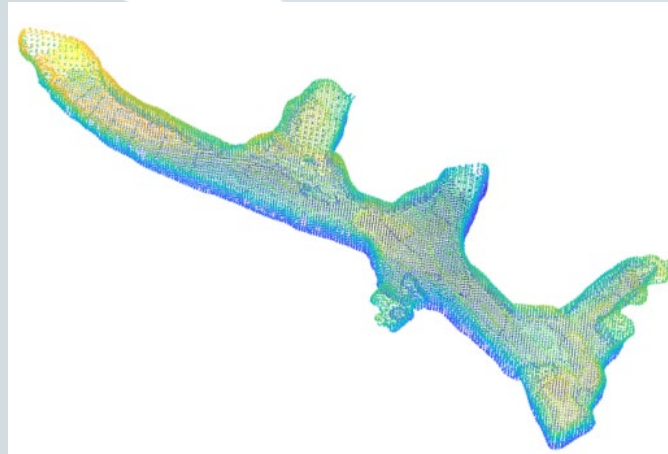
- Environmental skeleton-based reference path generation strategy



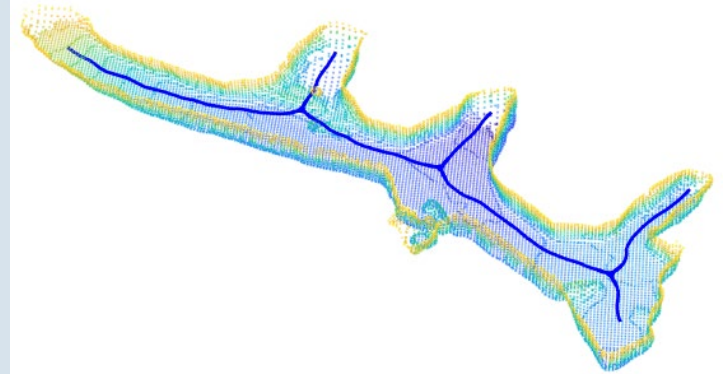
Sine-shaped tunnel



Skeleton of the sine-shaped



Cloud points of a real tunnel



Skeleton of a real tunnel



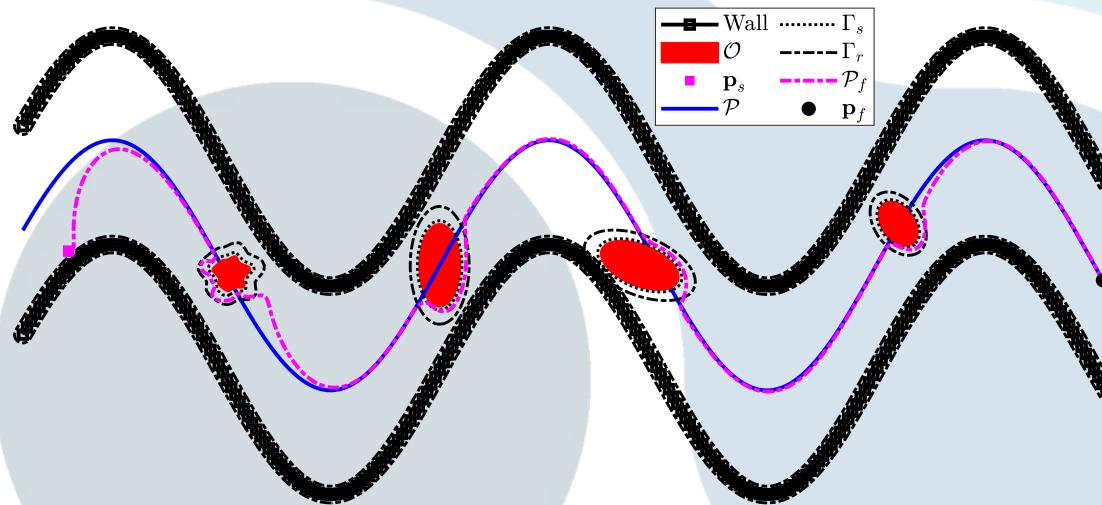
Technology & Completed design:

- Vector field-based collision-free path following strategy
 - ✓ Collision-free composite vector field design

$$\chi_c = \alpha\chi_a + \beta\chi_r$$

- Path following vector field χ_a
- Converge to the reference path
- Patrol along the reference path
- Collision avoidance vector field χ_r
- Move away from the reference path
- Patrol along the contour of the obstacle

✓ Simulation result



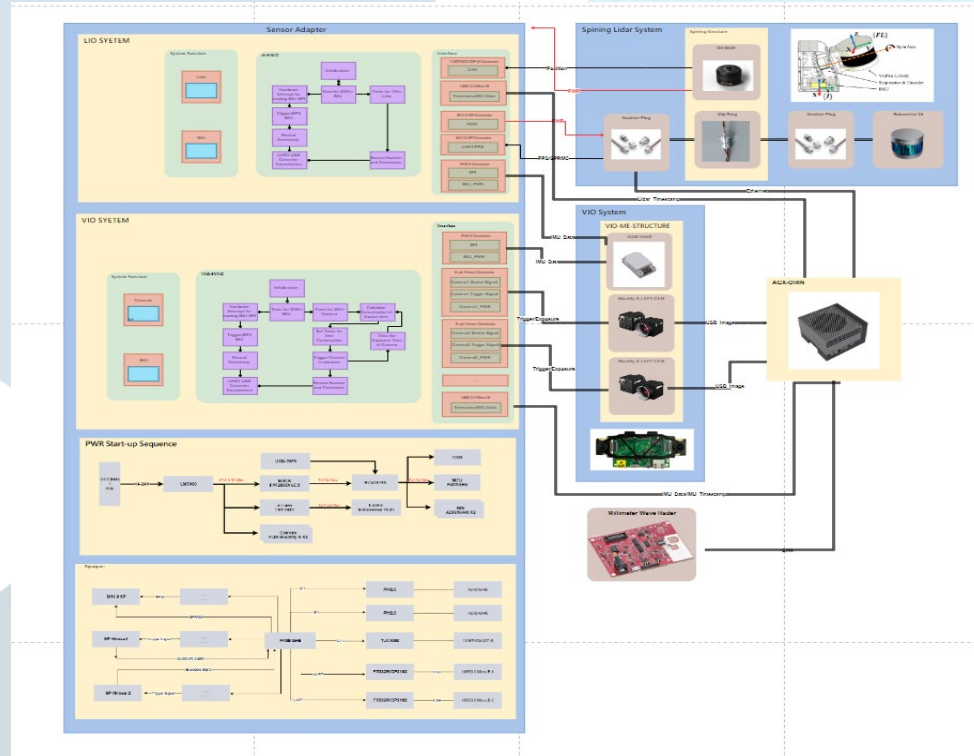
Exploration trajectory in a Sine-like tunnel



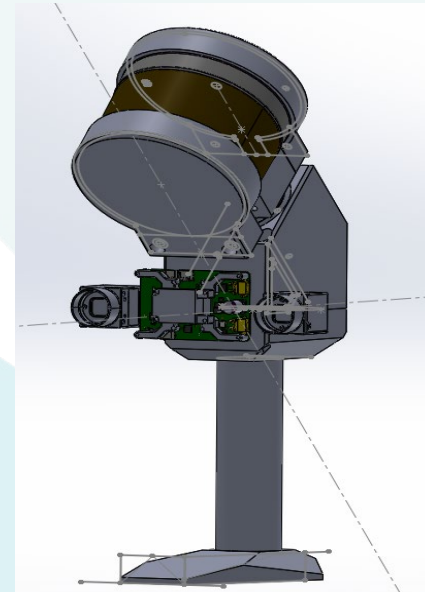
Exploration trajectory in a real tunnel

Technology & Completed design:

- Hardware development



Multi-sensor fusion platform schematic diagram



Structural design of rotating LiDAR with multi-sensors



Professor Chun Wang

**Self-powered sensor system for remote
condition monitoring**



UNSW
SYDNEY



“TOWARDS PRODUCTIVE, CONNECTED, SUSTAINABLE AND SMART INFRASTRUCTURE”

Project Title: Self-powered sensor system for remote condition monitoring

Participant: Chun Wang @ UNSW

Motivation:

Self-power sensor systems for condition monitoring infrastructure

- Piles, piers, transmission lines.

Strategies:

- Self-powered sensor coupled with an optical transducer for remote sensing.
- Self-powered IoT sensor with an energy harvester for wireless sensing.

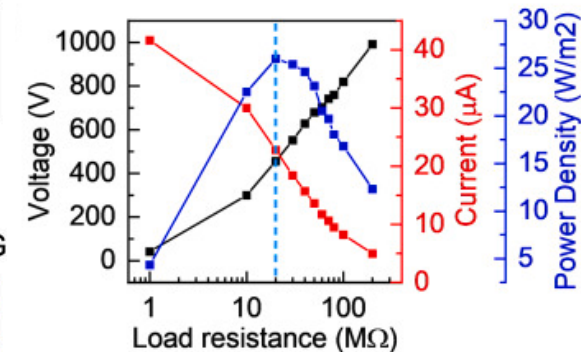
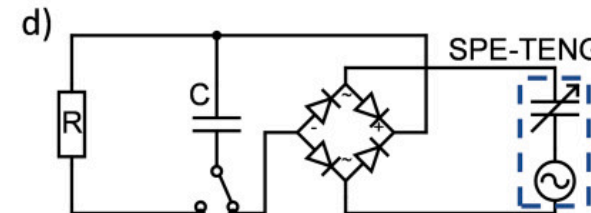
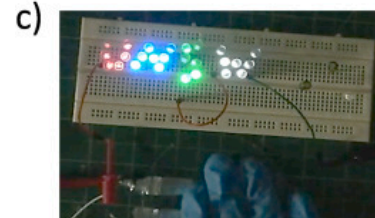
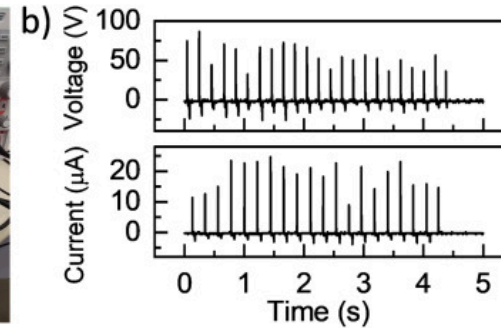
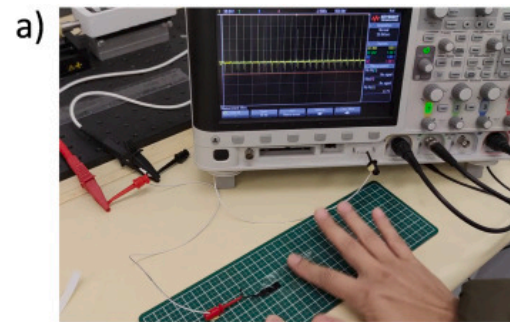
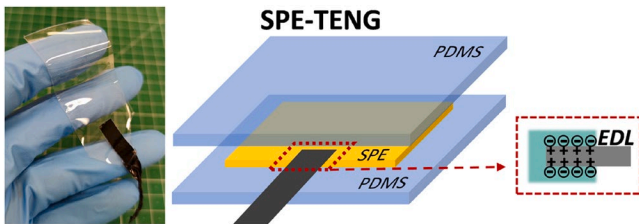
Self-powered or low-energy consumption sensors

- Low-energy consumption: μW to mW .
- Sensors: vibration, pressure using piezo- and tribo-electric effects.

Energy harvesters

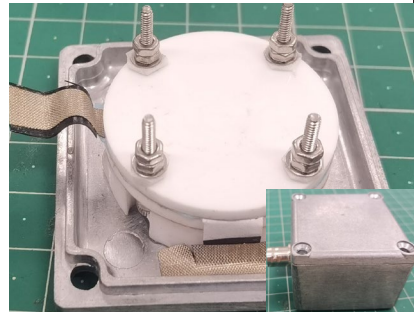
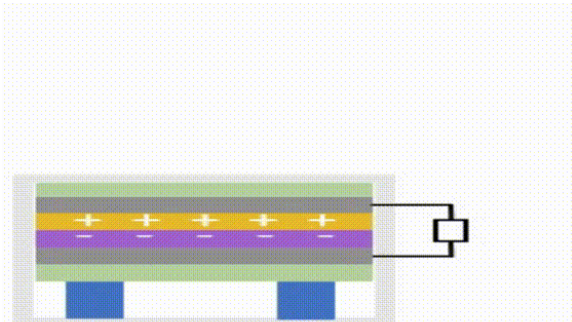
- Piezoelectric and triboelectric harvesters for vibration/waves (piles, piers)
- Electrical field, solar, wind (for transmission lines).

harvesting energy from dynamic pressure



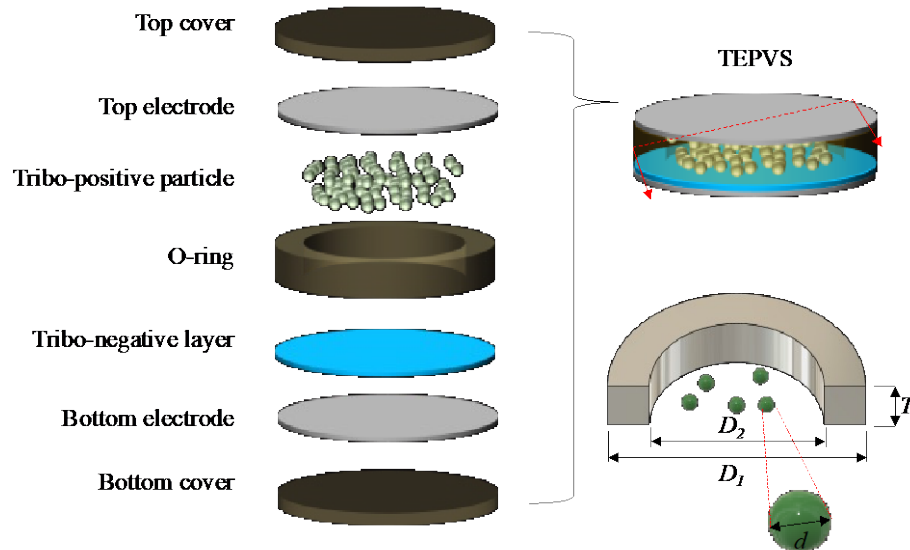
Self-powered Vibration Sensor

Clapping vibration sensor

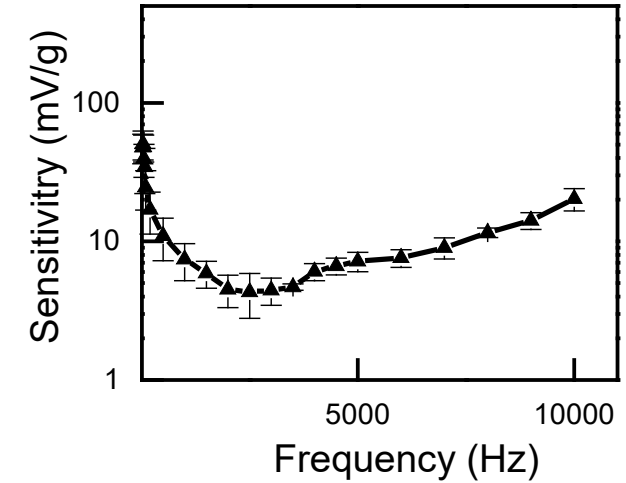
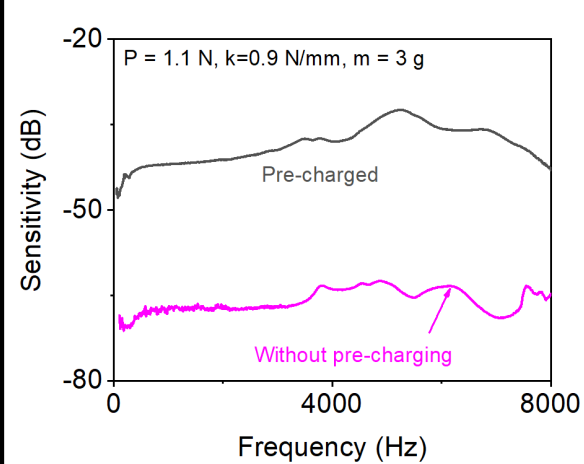
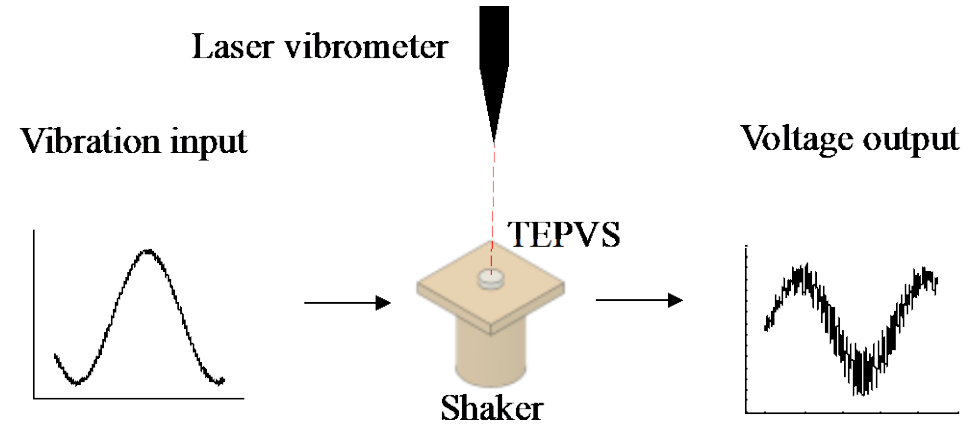


<https://www.sciencedirect.com/science/article/pii/S2211285523008583>

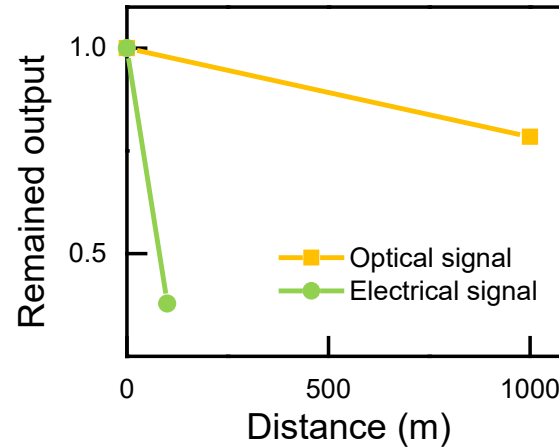
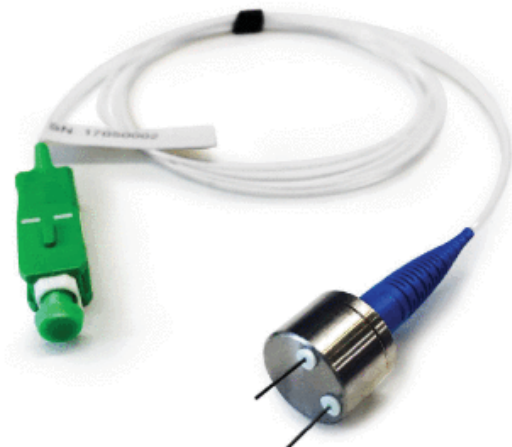
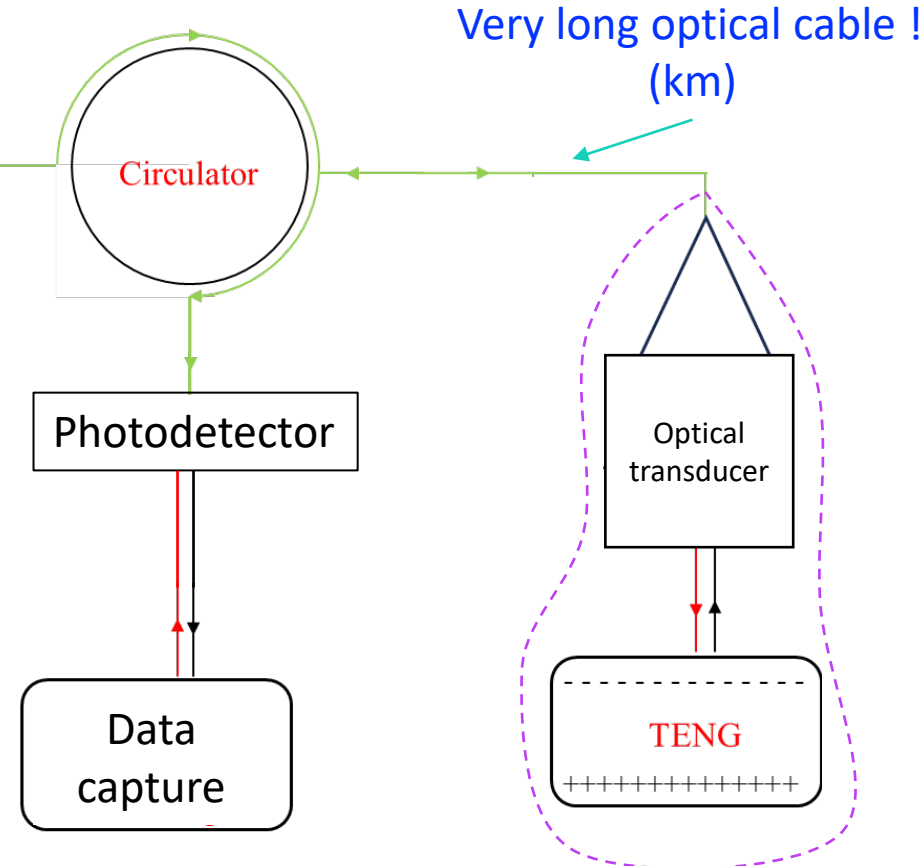
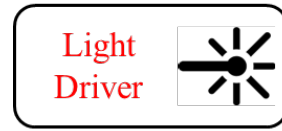
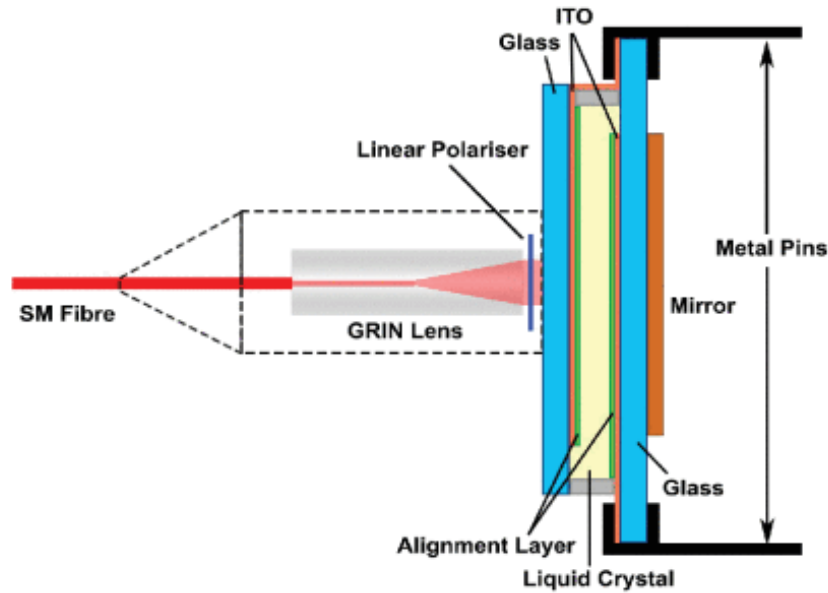
Bouncing particles vibration sensor



<https://www.sciencedirect.com/science/article/pii/S2211285523008972>



Long distance remote sensing using optical transducer



Remote location

Opportunities for Hub

1. Self-powered optical-electric sensor
 - Vibration and wave pressure
2. Wireless IoT sensors for transmission lines & tower
 - Vibration harvesters and sensors

Professor Khalili

**Real-time characterisation and 3D
reconstruction based on
photogrammetry, AI and edge
computing**



UNSW
SYDNEY



“TOWARDS PRODUCTIVE, CONNECTED, SUSTAINABLE AND SMART INFRASTRUCTURE”

Defined – about to commence

Project Title: Real-time characterisation and 3D reconstruction based on photogrammetry, AI and edge computing

Team: UNSW: A/Prof Stuart Clark, Prof Ryan Armstrong, Dr Mohsen Mousavi

Kumul Petroleum: Luke Liria

PhD student is selected, start September 2024

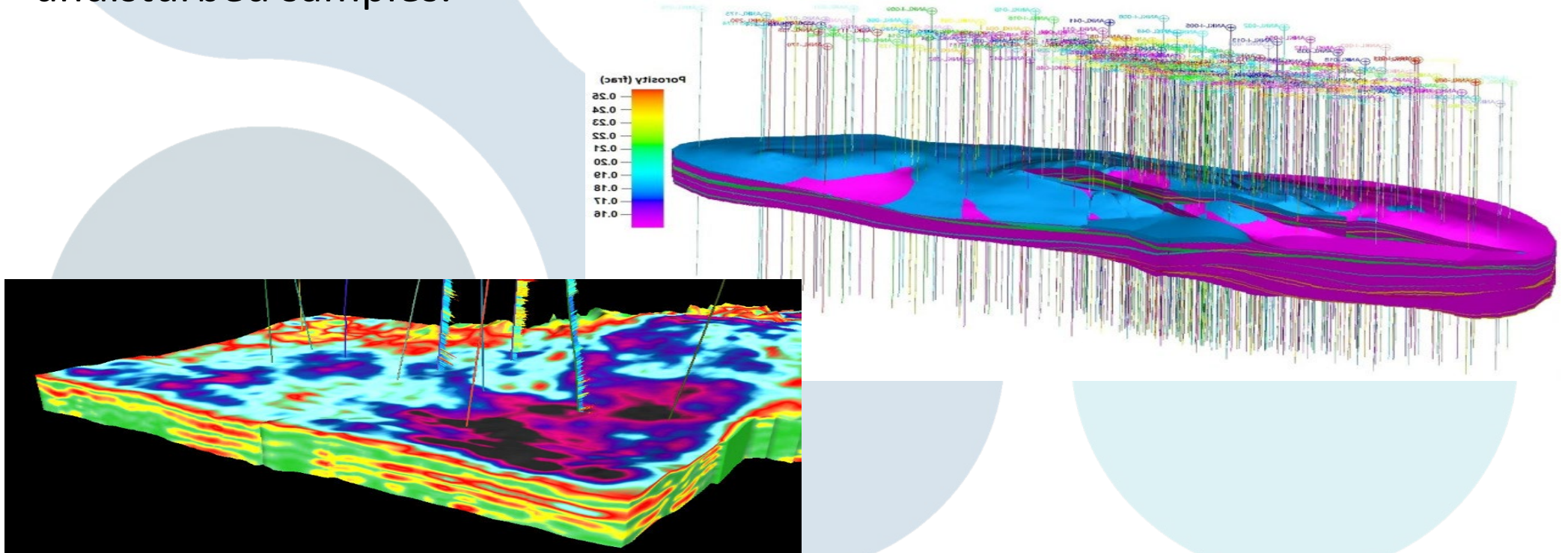
Motivation:

Develop an image-based automated methodology for borehole logging and characterisation including rock quality, fracture system and subsurface layering for reservoir development.



Statement of Problem:

Reservoir characterisation is one of the most elaborate and expensive elements in a reservoir development. It involves extensive borings, exhaustive manual examination of borehole logs, and numerous imprecise testing on disturbed and undisturbed samples.



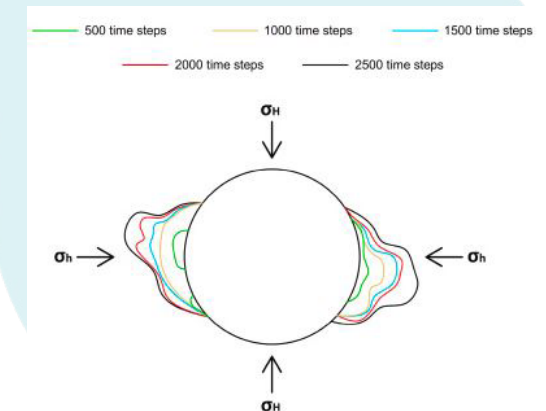
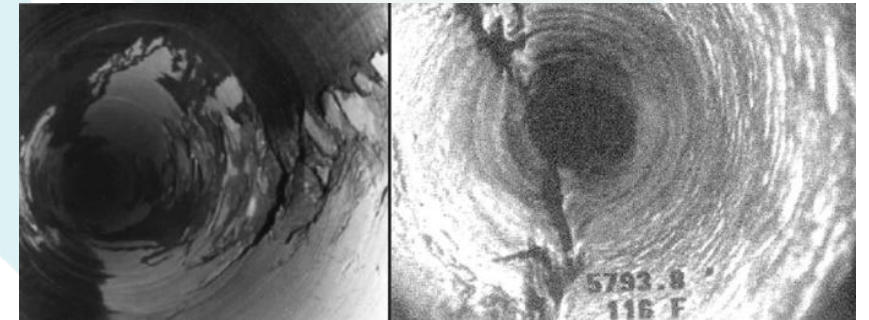
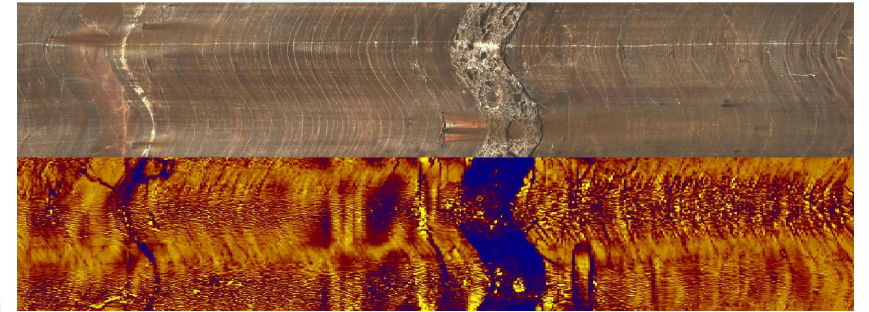
Aims:

- Provide a low-cost, cutting-edge technology for real-time in situ characterisation of subsurface.
- Enable access to information on lithology, structure and material characterisation in an undisturbed state.
- Identify flaws/structure/formation features and ascertain their properties/impact on the subsurface as well as quantification of their mechanical properties and fluid flow characteristics.



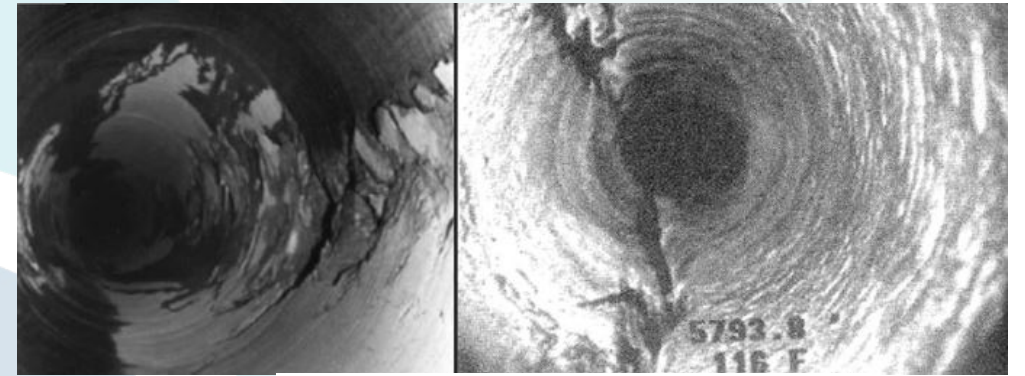
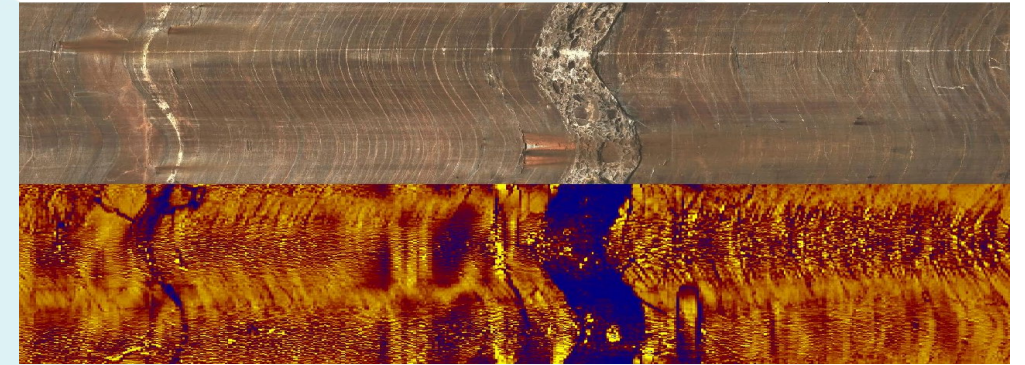
Approach:

- Analyse downhole optical, acoustic and electrical imaging, coupled with AI/ML to extract features, to identify rock/soil types and their properties and in situ stresses.
- Augment sparse data using physics informed neural network and utilize edge computing for real time analytics.
- Provide 3D digital twin of the subsurface.

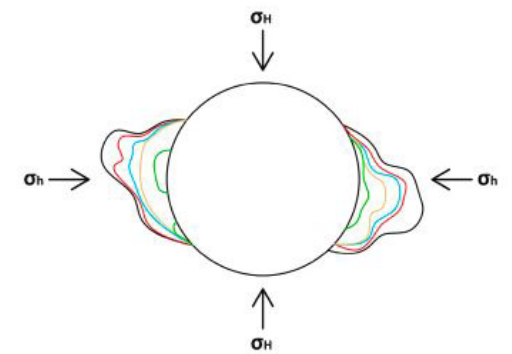


Deliverables:

- A fully validated platform for automated, real time well-log analysis for sparse data
- Subsurface digital twin



500 time steps 1000 time steps 1500 time steps
2000 time steps 2500 time steps





THEME 2

Data collection,
security and
integration

Theme 2 Lead

Professor Claude Sammut

Professor Claude Sammut

**Developing Remotely Operated
Submersibles for Pier Defect Detection
and Integrity Assessment**

Project defined – yet to commence

Project Title: An autonomous submersible for condition monitoring of piers and bridges

Involved:

UNSW: Will Midgley, Claude Sammut

UTS: Dikai Lu (collaboration under discussion)

Motivation:

To address the need for regular inspection and maintenance of piers in adverse conditions



Problem definition:

Autonomous inspection of submerged supporting structures to identify faults and assist in maintenance

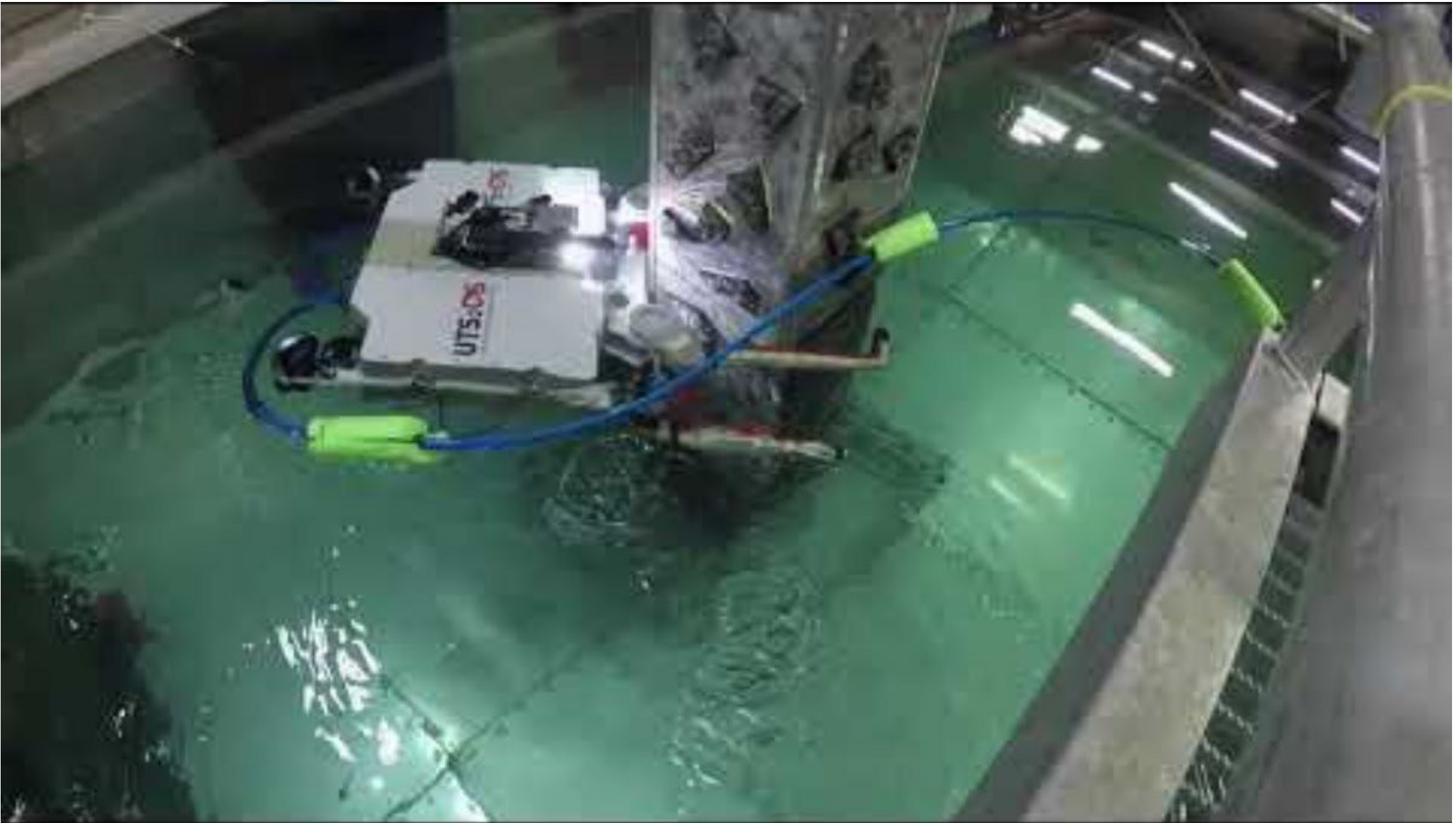
Currently done by divers – dangerous and error prone



Aims:

- Develop an autonomous underwater vehicle for inspection and maintenance (in collaboration with UTS Robotics Institute)
- Provide data for digital twins to model corrosion





PROJECT UPDATE CLAUDE SAMMUT



Approach:

- Underwater vehicle specification and design
- Sensor/actuator development and selection
- Control of underwater vehicle and inspector hardware
- Data collection and processing

Deliverables:

- Prototype underwater vehicle
- Scanning and data collection software



Professor Peyman Mostaghimi

**A Digital Technology for the
Characterisation of Oil/Ore Grade and
Distribution in a Rock Core**

Project defined – yet to commence

Project Title: 3D Digital Core Characterisation and Classification of Grains

UNSW: Professor Peyman Mostaghimi, Scientia Professor Nasser Khalili

PhD position advertised.

Motivation:

To address the issue of mineralogical heterogeneity required for high-fidelity core characterisation and porous media simulation



Problem definition:

The current digital core methods fail to capture the presence of various minerals within grains, despite their significant importance for mechanical and flow characterisation and simulation.

Sample Preparation

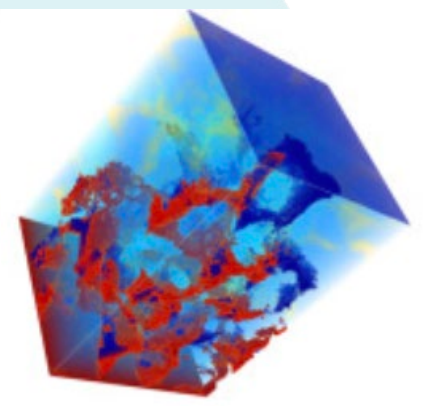
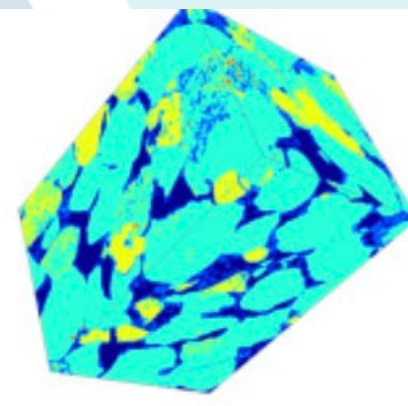
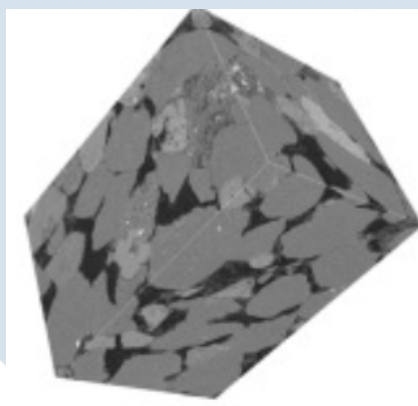
- Sample collection
- Diameter between 5 mm to 100 mm

X-ray Imaging and Analysis

- Generation of grey-scale image
- Multi-mineral segmentation

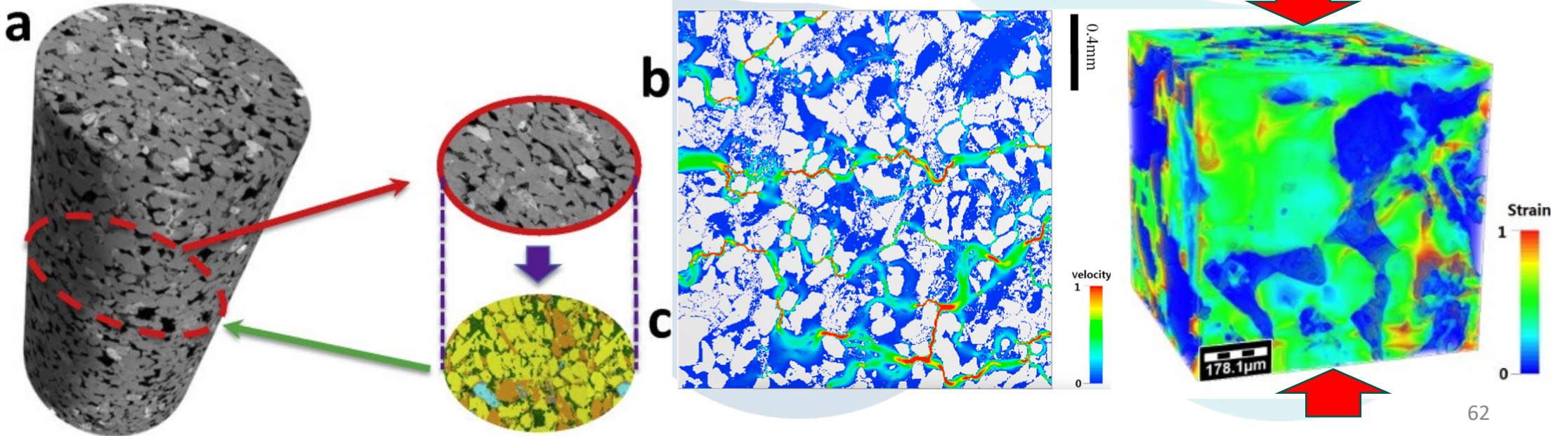
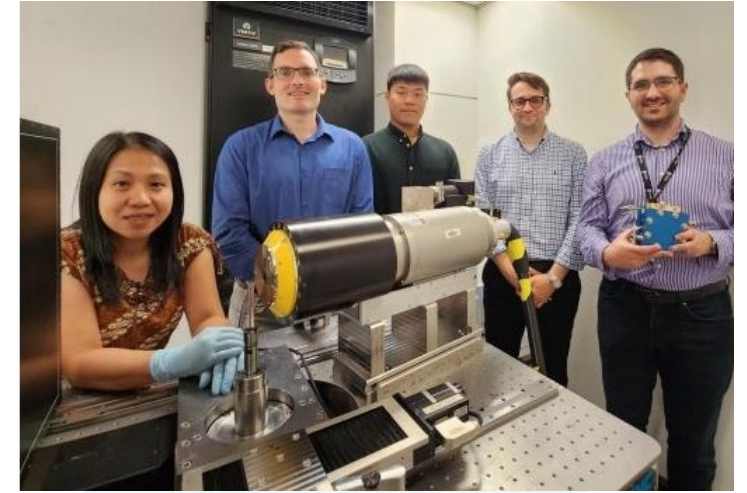
Upscale Core Characterisation

- Fluid flow
- Mechanical properties

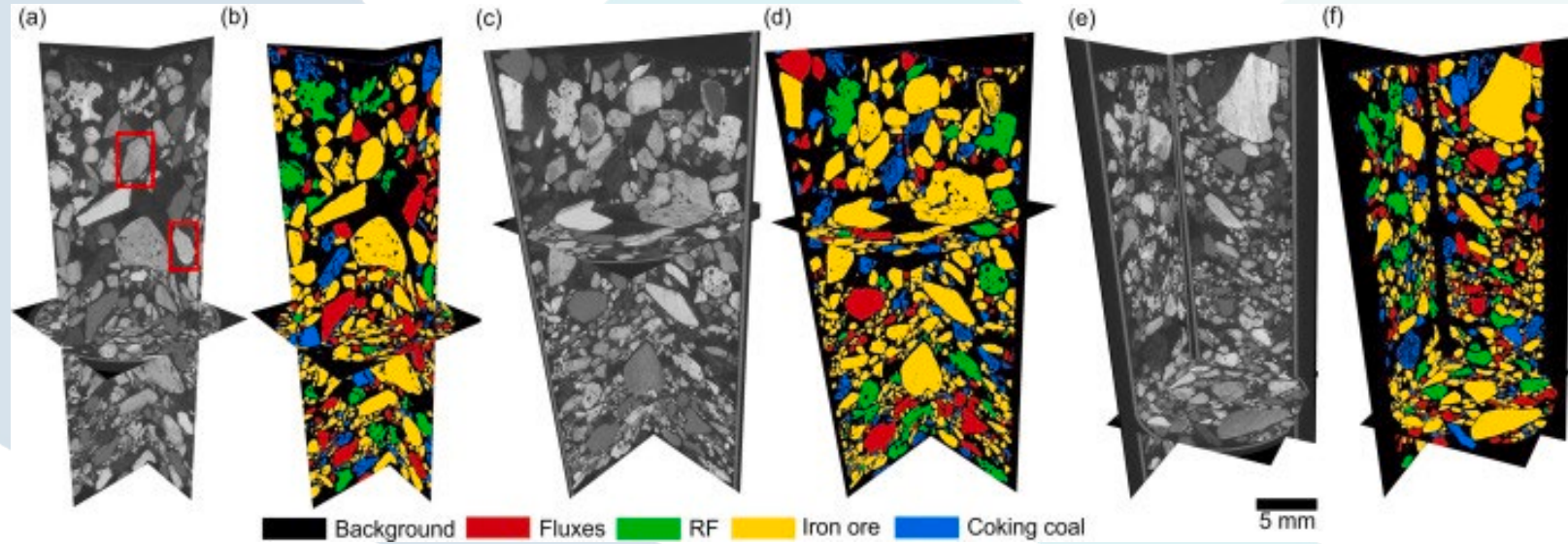


Aims:

- Identify minerals on X-ray images
- Coupled flow experiments
- Validation of results
- Reliable prediction of permeability, porosity and mechanical characteristics of porous sample



Grey-scale images: output of X-ray scanner | Coloured images: output of CNN method

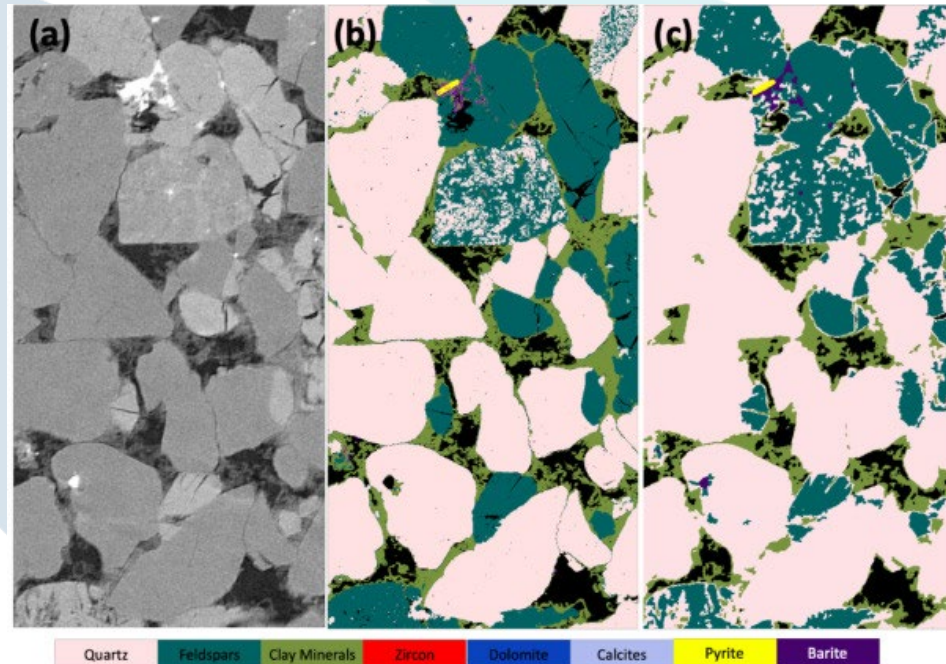


(a) Output of X-ray CT scanner

(b) Output CNN

(c) Output of QEMSCAN

≈95% accuracy



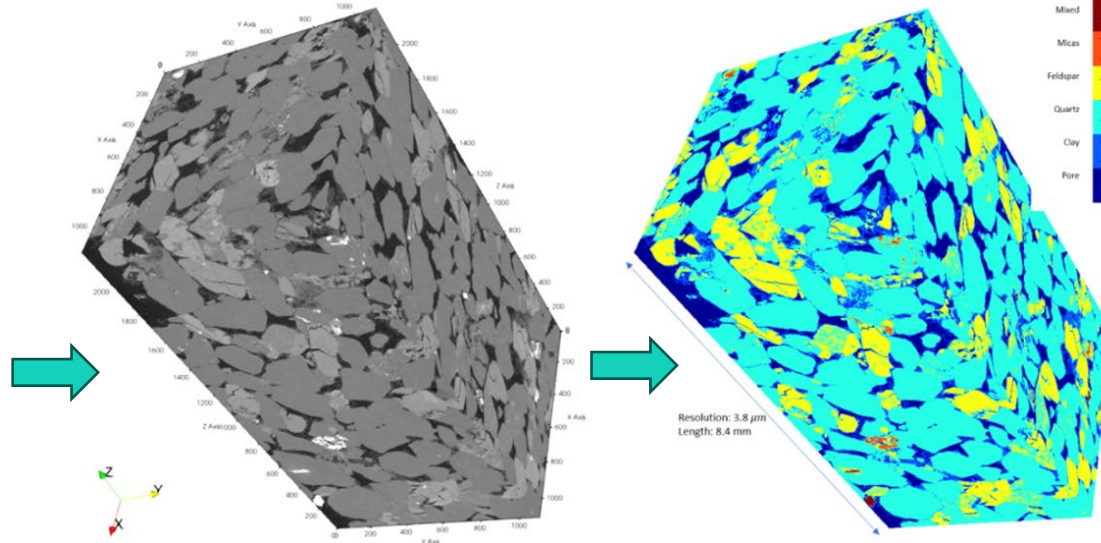
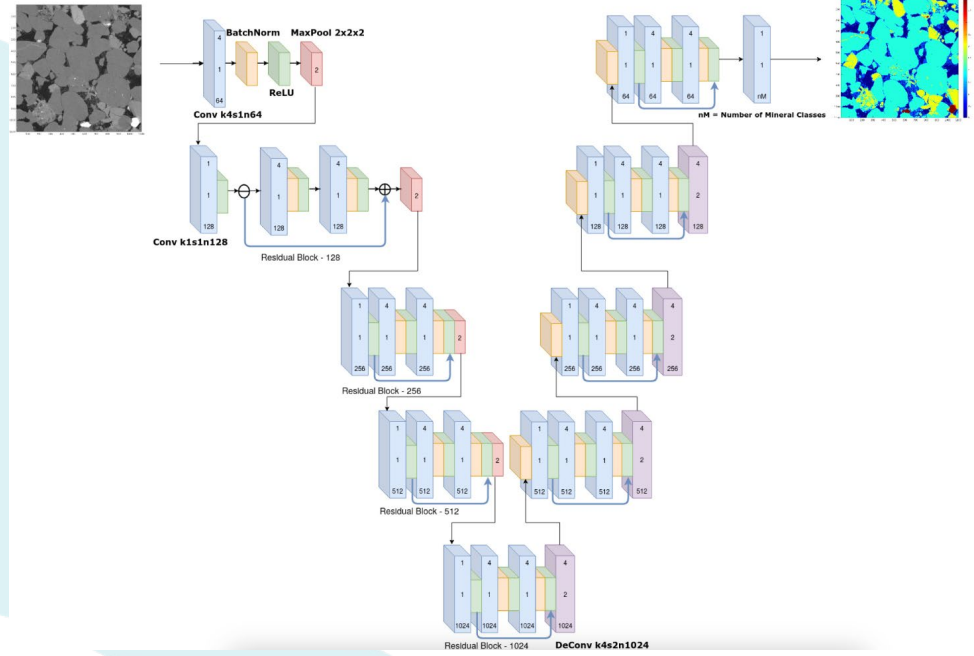
Our previous works:

application to iron ore sinter green bed | application to reservoir rock



Approach:

Data collection → AI training and testing → Identification of grains → Detailed numerical simulation → Validation → Prediction of flow and mechanical properties of core



- Wettability
- Young's modulus
- Porosity
- Permeability
- Capillary Pressure



THEME 3

Modelling,
simulations and
prognostics

Theme 3 Lead

Professor Nasser Khalili

Qihan Wang

**Development of computational tool
for data-driven structural safety
assessment and service life prediction**

Project Title: Development of computational tool for data-driven structural safety assessment and service life prediction

Motivation:







A wind turbine collapsed at the Alinta wind farm in Western Australia - causing the 89MW project to be temporarily shut down

<https://reneweconomy.com.au/wind-turbine-collapses-in-serious-event-at-wa-wind-farm/>

- Inherent uncertainty
- Higher frequency
- Serious consequence (human life, wealth, social impact, etc.)

Gaps in knowledge:

	Static / Dynamic	Nonlinear	Uncertainty	More Complicated
	✓	✓	✗	✗
	✓	✓	✗	✗
	✓	?	✗	✗
	✓	?	?	✗

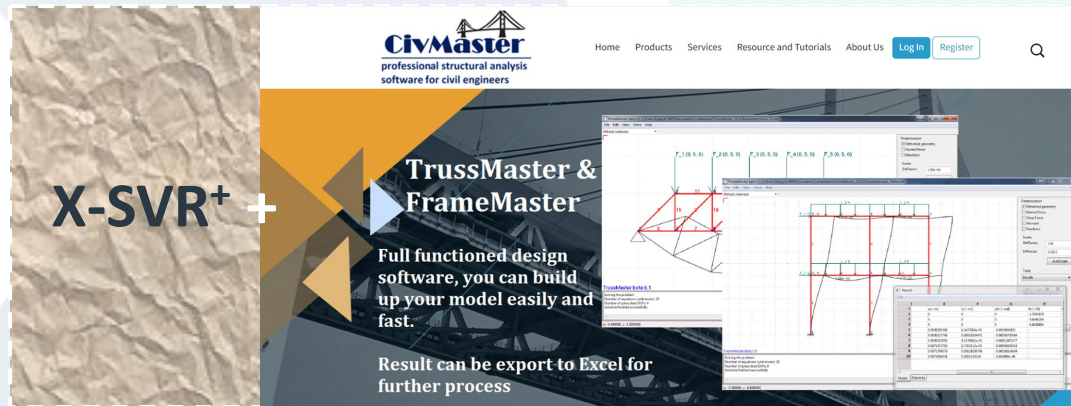
Challenging to Existing Tools

Aims:

- Develop an advanced tool underpinned by a *virtual reality modelling technique*
- Safety assessment and Service life prediction
- Contribute to build a more *Sustainable, Safe, and Efficient* Australia

Expected outcomes:

Virtual-Reality Interactive Analysis Framework



FEM Software CivMaster developed by Lindenbaum <https://www.civmaster.com.au/>

Alignment with RIIS:

- ★ **Theme 3:** Modelling, Simulations and Prognostics
- ✦ **Theme 4:** Infrastructure health monitoring and predictive maintenance
- ✦ **Theme 5:** Spatial data infrastructures, digital twin and decision support

Nonlinear / Static / Dynamic / Fracture

Multiphysics / Multi-scale Modelling

Material-Geometric Polymorphic Uncertainty

This complex block contains three main sections. The top section, titled 'Nonlinear / Static / Dynamic / Fracture', shows three heatmaps of a car body's interior, illustrating stress or temperature distributions. To the right is a 3D model of a mechanical assembly. The middle section, titled 'Multiphysics / Multi-scale Modelling', shows a molecular structure on the left and a multi-scale simulation of a material on the right, with a color scale for temperature in degrees Celsius ranging from 20.0 to 32.0. The bottom section, titled 'Material-Geometric Polymorphic Uncertainty', is partially visible.

Scientific Approach

Virtual-Reality Interactive Analysis Framework

- Multidisciplinary /Interdisciplinary applications
- Experiments
- Information and Communication Techniques (ICTs)

Virtual Space

Numerical Simulation

- Multiphysics /Multi-scale modelling
- Linear/Nonlinear/Static/Dynamic/Fracture

Geometric Model

Material Model

Physics

Environment



Analysis

- Displacement /Stress /Forces
- Safety /Reliability
- Risk/ Rest Life Assessment

Diagnosis

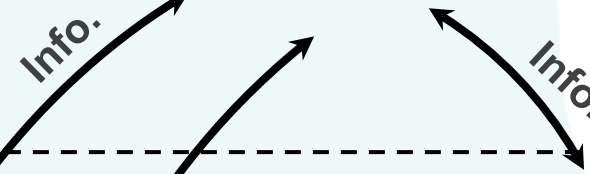
Prognosis

Optimization

Inverse Eng.

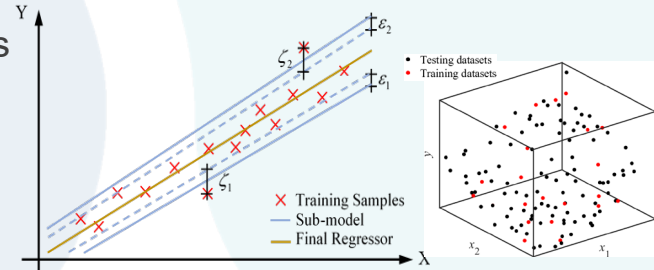


Reality



Virtual Modelling Technique

- Machine learning methods
- Cloud/Cluster computing
- Data processing
- Multi-fidelity modelling

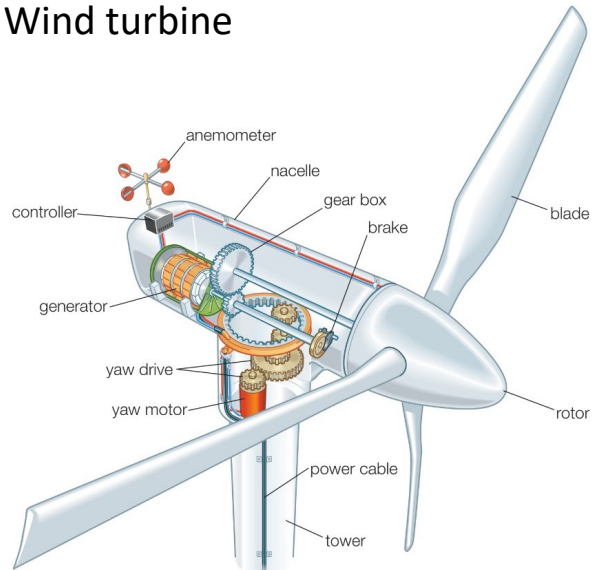


Progress to date: Efficient and powerful machine learning methods have been developed for structural analysis.

Structure

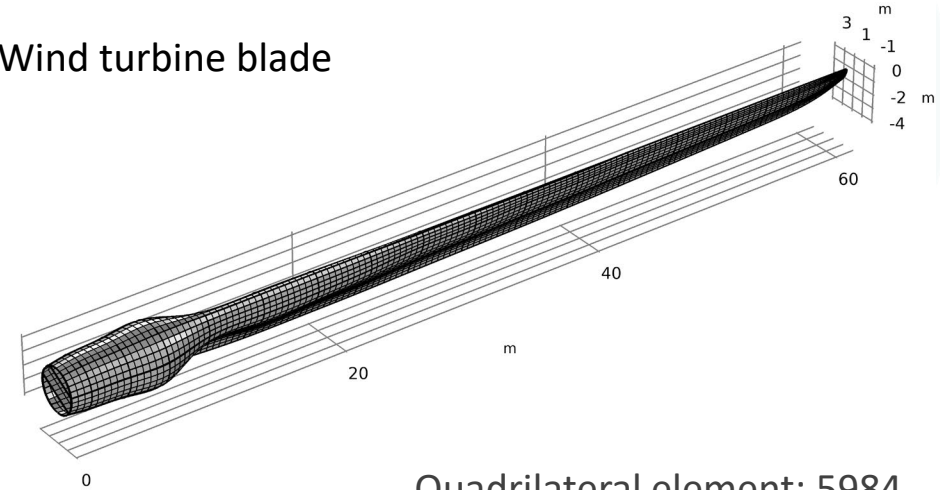


Wind turbine

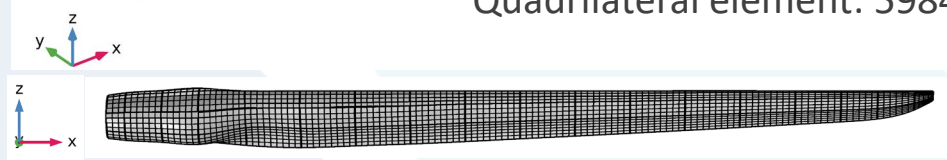


Analysis – Component

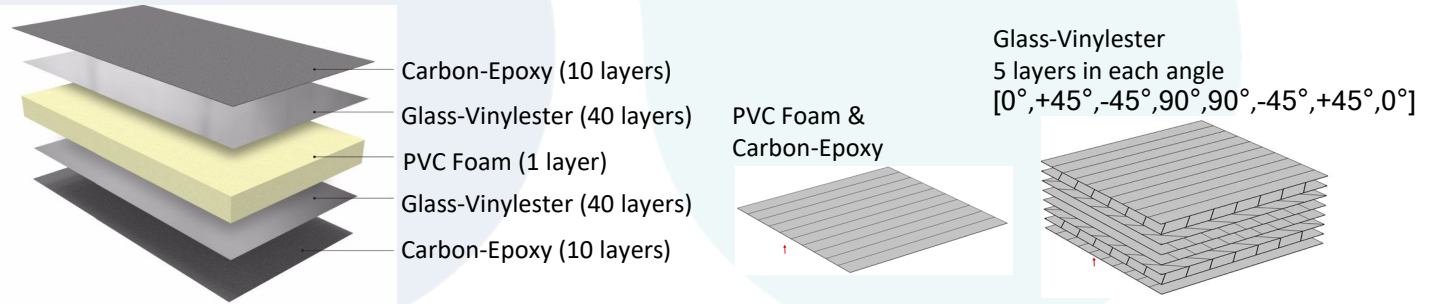
Wind turbine blade



Quadrilateral element: 5984



Composite Material

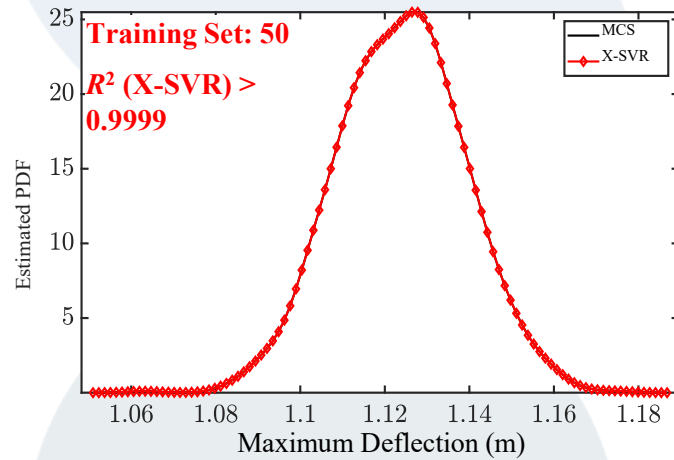


Progress to date: Efficient and powerful machine learning methods have been developed for structural analysis.

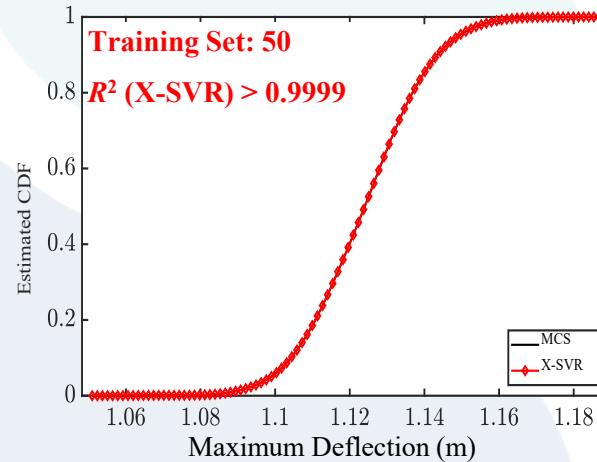
Computational Results on Virtual Model

10 System Uncertainties:

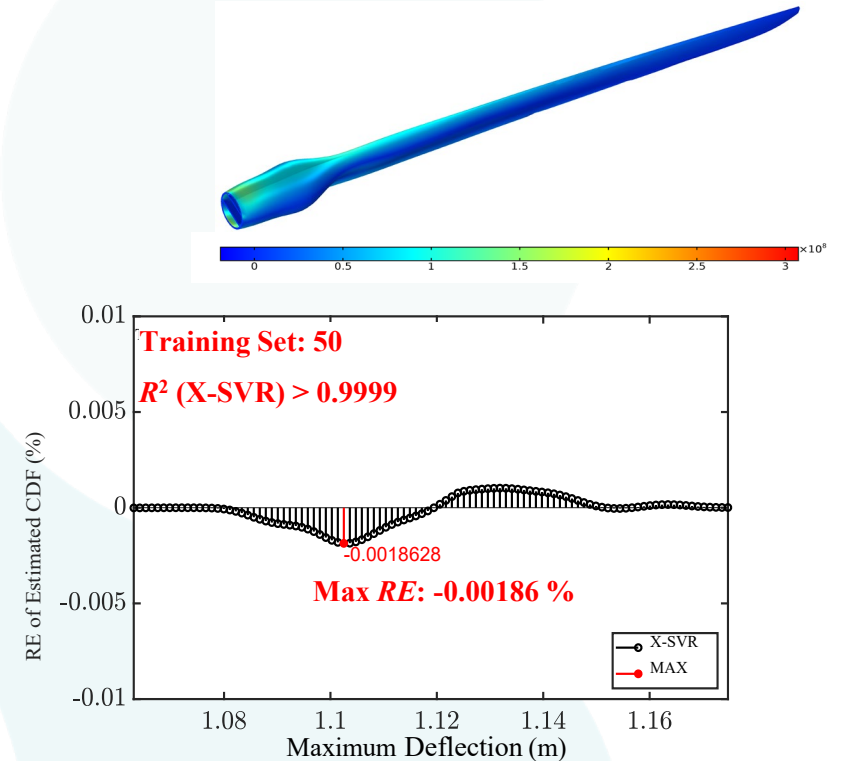
- Rotation speed (1)
- Material properties (9)



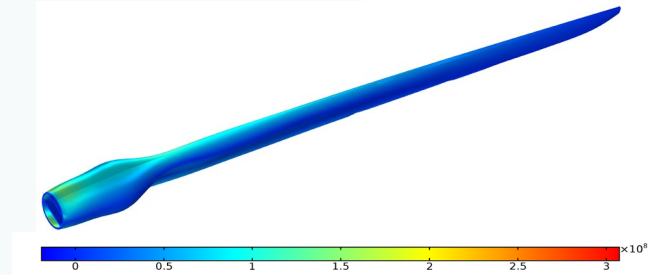
(a) Estimated PDF



(b) Estimated CDF



(c) RE of the estimated CDF



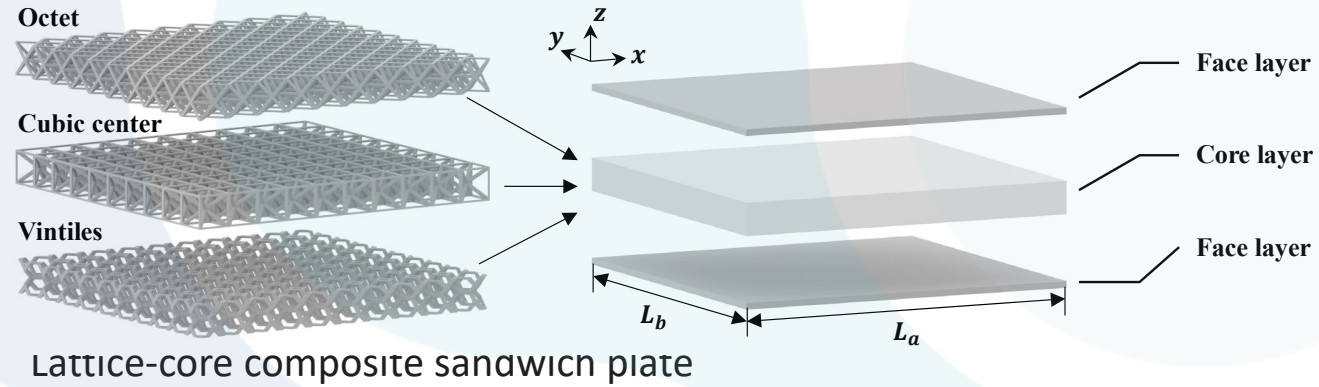
MCS – **10000** times FEA
X-SVR – **50** times FEA

Efficiency 200 times



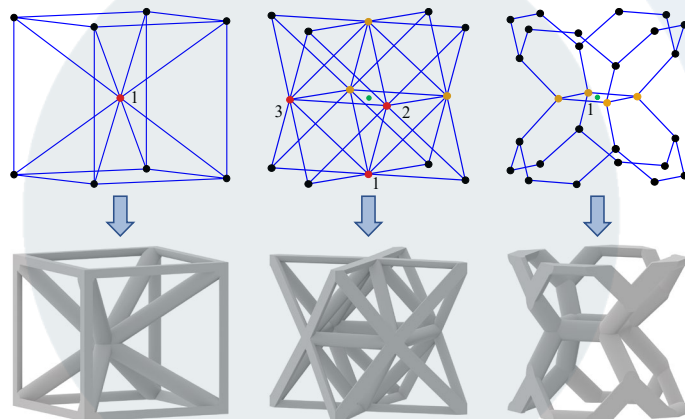
Progress to date: Efficient and powerful machine learning methods have been developed for structural analysis.

Analysis - Material (Microscale)

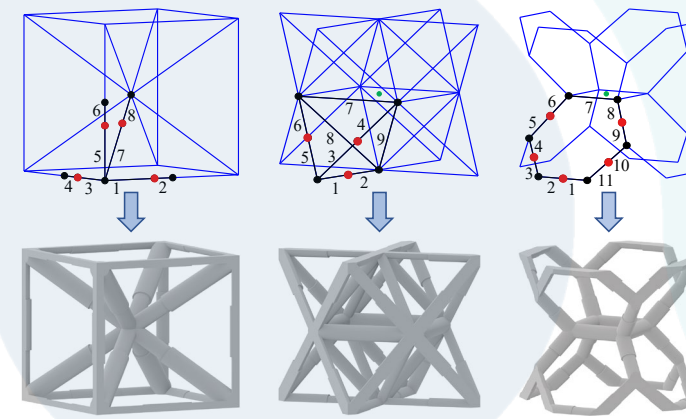


Imperfections

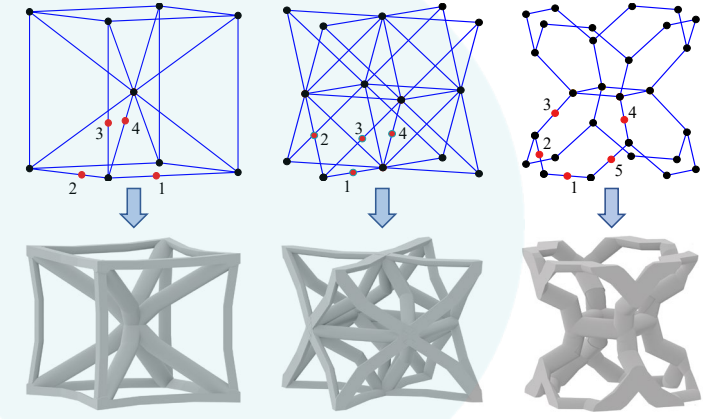
Node dislocation



Radius variations



Waviness

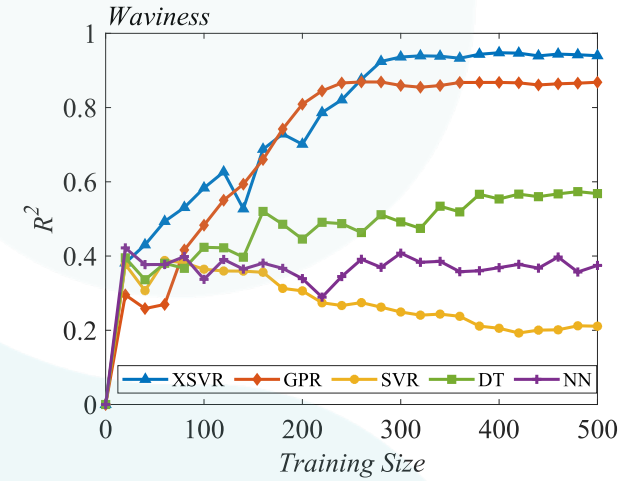
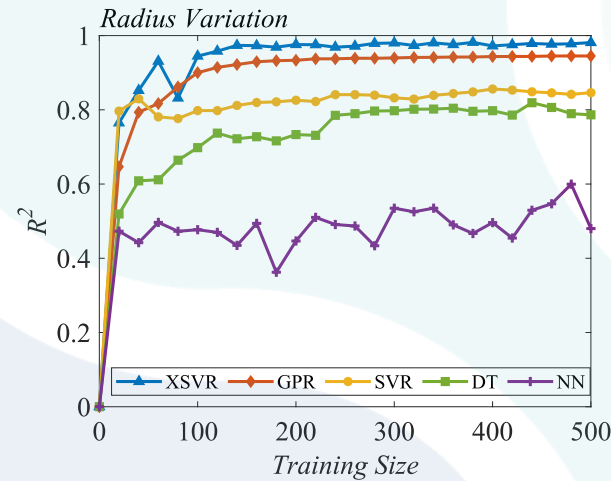
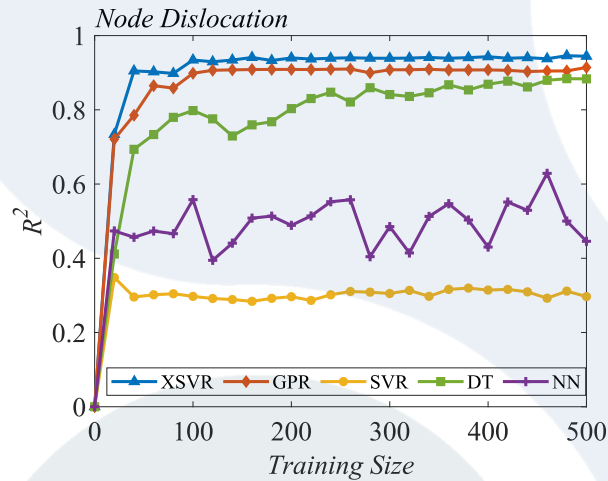


Tian, W., Li, Q., Wang, Q., Chen, D., & Gao, W. (2024). Additive manufacturing error quantification on stability of composite sandwich plates with lattice-cores through machine learning technique. *Composite Structures*, 327, 117645.

Progress to date: Efficient and powerful machine learning methods have been developed for structural analysis.

Analysis – Material

Virtual Model Construction



Fast Convergence & High Accuracy

Sensitivity Analysis

Radius variation > Waviness



Static buckling capacity of this product

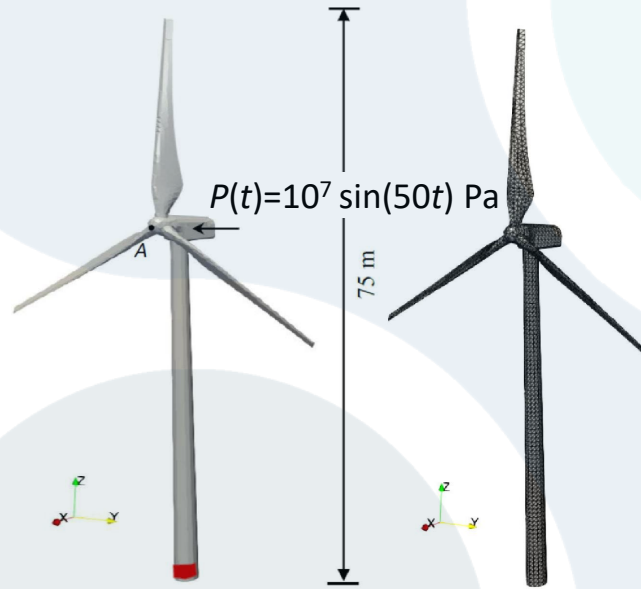
Contribute to the **Design Optimization, Manufacturing & Processing**

Tian, W., Li, Q., Wang, Q., Chen, D., & Gao, W. (2024). Additive manufacturing error quantification on stability of composite sandwich plates with lattice-cores through machine learning technique. Composite Structures, 327, 117645.

Progress to date: Efficient and powerful machine learning methods have been developed for structural analysis.

Analysis – Structure (Elastoplastic dynamic analysis)

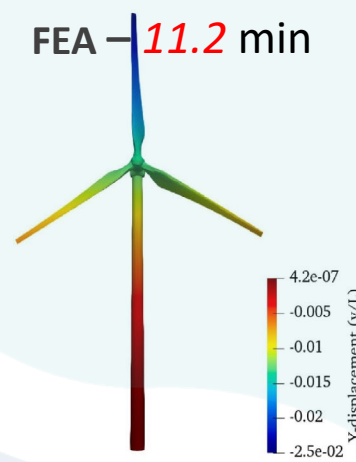
Numerical Model



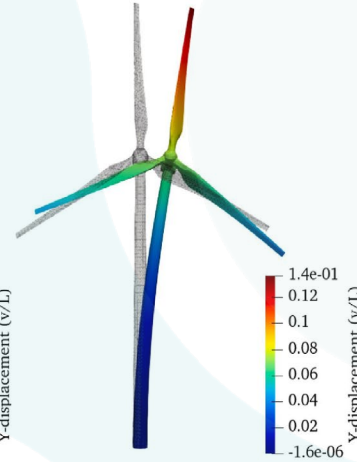
Tetrahedral element: 18072

Virtual model construction - 25 min

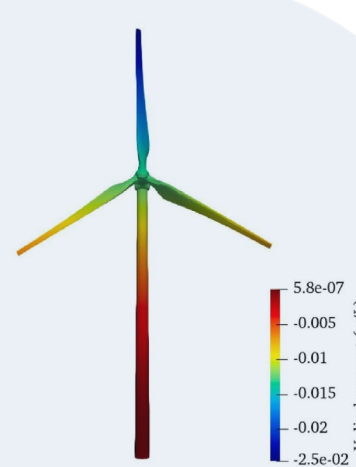
FEA – 11.2 min



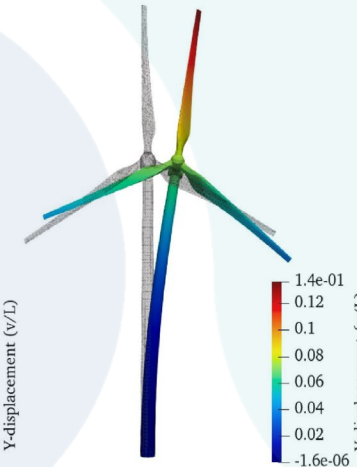
X-SVR (200 Samples) – 1.5 min



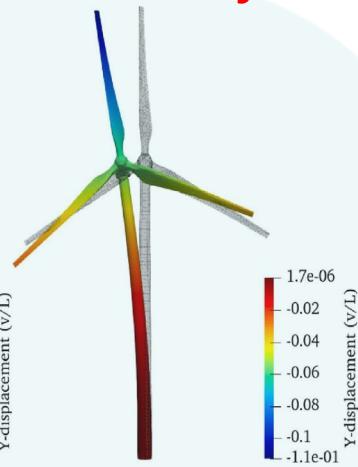
7 - 8 times faster interaction



Max RE: -0.797%



3.571%



-4.464%

Progress to date: Efficient and powerful machine learning methods have been developed for structural analysis.

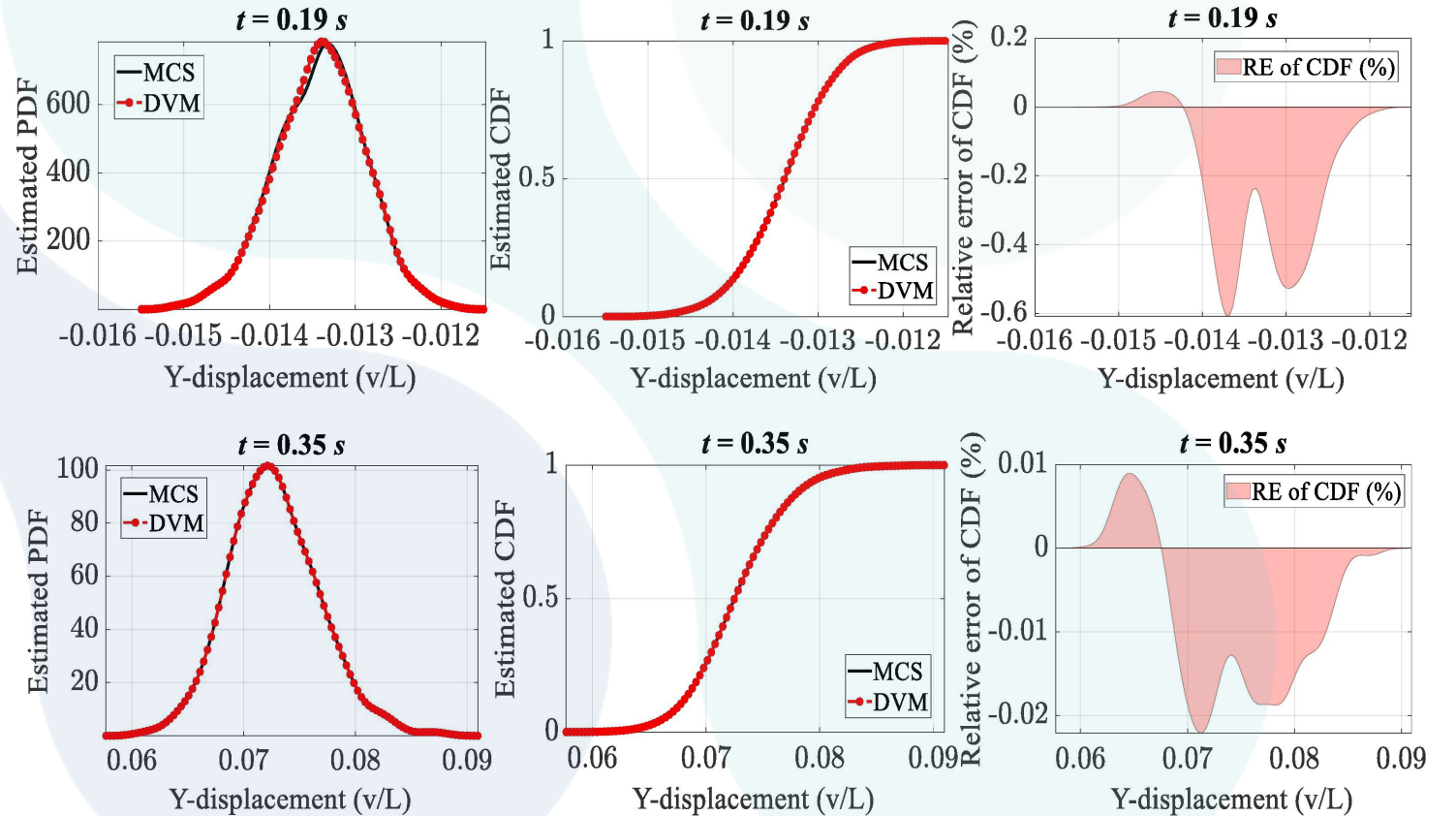
Analysis – Structure (Elastoplastic dynamic analysis)

Sufficient statistical information on arbitrary time spots and locations

System Uncertainty:

- Young’s modulus (GPa)
 - Normal (mean 206.9, std 10.3)
- Poisson’s ratio
 - Lognormal (mean 0.3, std 0.015)
- Density (kg/m³)
 - Uniform (Bounds [7315, 8085])
- Yielding stress (GPa)
 - Beta (mean 0.85, std 0.0425)

Various uncertainty models



Sana Shahoveisi

**Modelling of initiation and progression
of a flaw in multiphasic materials**

Project Title: Modelling of initiation and progression of a flaw in multiphasic materials

Involved:

UNSW: Sana Shahoveisi, Prof Nasser Khalili, Dr. Babak Shahbodagh

Motivation:

To Present a Framework for Modelling of Fracturing in Fluid Saturated Porous Media

Flaws and cracks resulting in failure



Benefiting from a network of artificial cracks

- Enhancing Gas/Oil recovery
- Enhancing Geothermal systems



Geothermal power project closes in SA

Knowledge gap:

- Lack a good representation of the fault's properties (opening) in Smeared methods.
- Lack a comprehensive framework with current approaches and methods.

Approach:

⇒ Propose a new formula and implement the methodology in a robust framework

$$\nabla \cdot \boldsymbol{\sigma}' - \rho \ddot{\mathbf{u}} + \rho \mathbf{b}^* = 0,$$

$$\left[\frac{2l_0}{G_c} (1 - k) \psi^{s+} + 1 \right] \phi - l_0^2 \nabla^2 \phi = \frac{2l_0}{G_c} (1 - k) \psi^{s+}$$

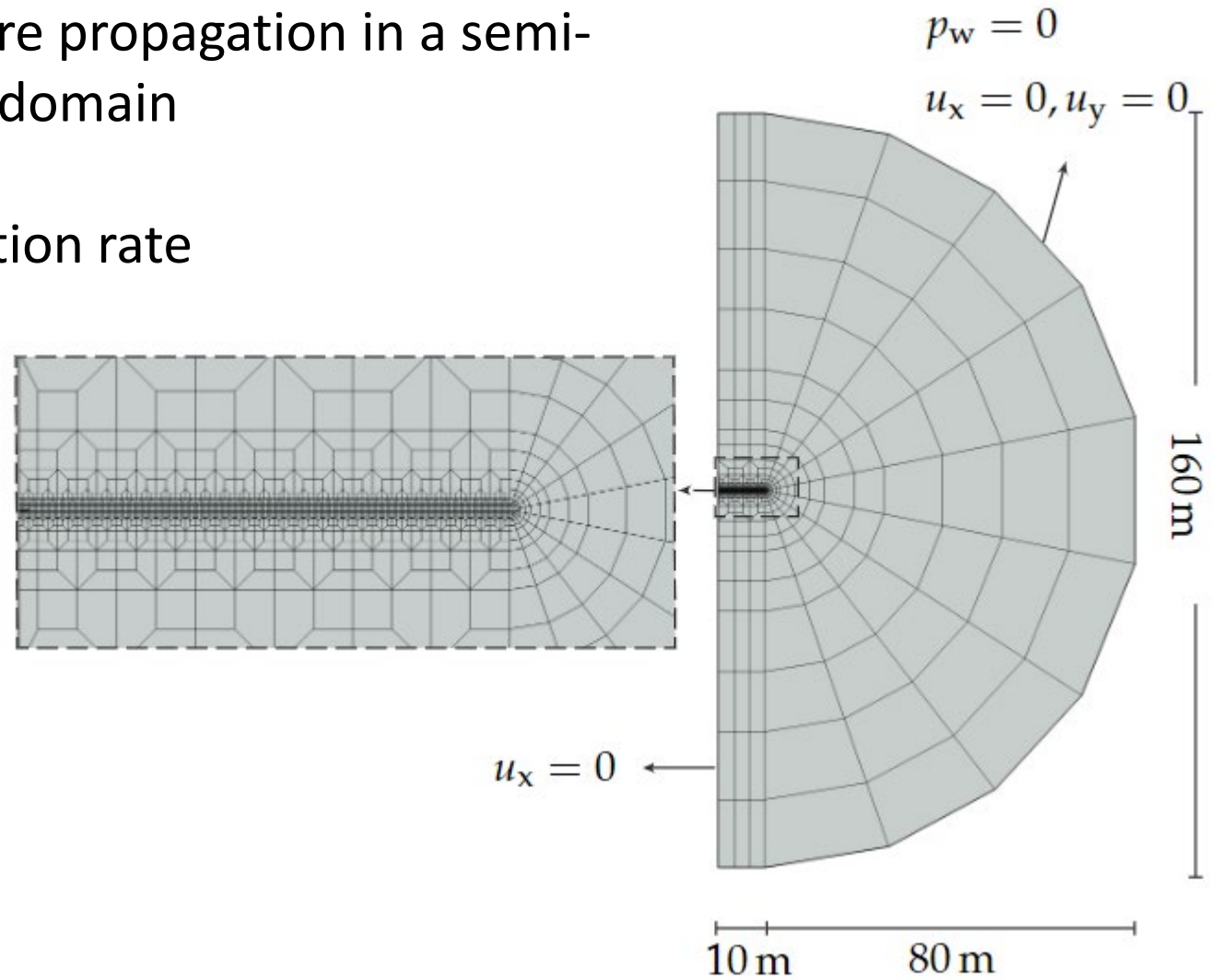
$$\dot{\mathbf{w}} = \frac{k_f}{\mu_f} (-\nabla p - \rho_f \ddot{\mathbf{u}} + \rho_f \mathbf{b}^*) \quad w_D := h_e \varepsilon_{vol}$$

⇒ Use AI (PINNs) to provide real-time results

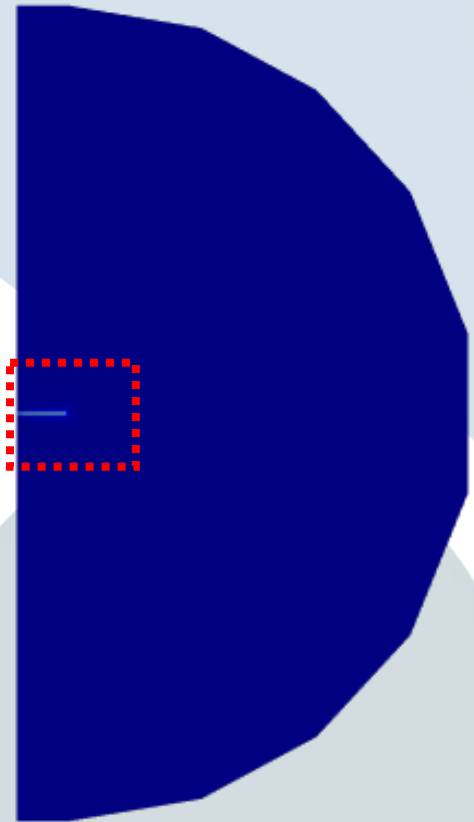
Verification example

- A fluid pressure driven fracture propagation in a semi-infinite impermeable porous domain
- Plane strain elastic domain
- Subjected to a constant injection rate

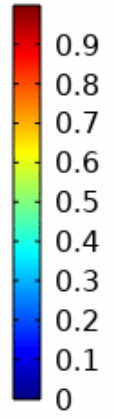
Parameters	Value	Unit
Shear Modulus	6	[GPa]
Poisson's ratio	0.2	N/A
Porosity	0.19	N/A
Bulk modulus	36	[GPa]
Flow rate	1e-4	[m ² /s]
Solid phase density	2000	[kg/m ³]



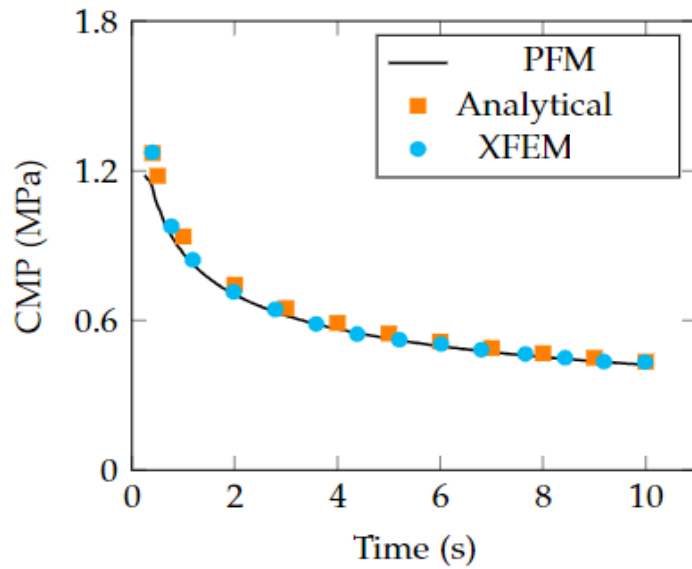
Crack Propagation over 10 seconds



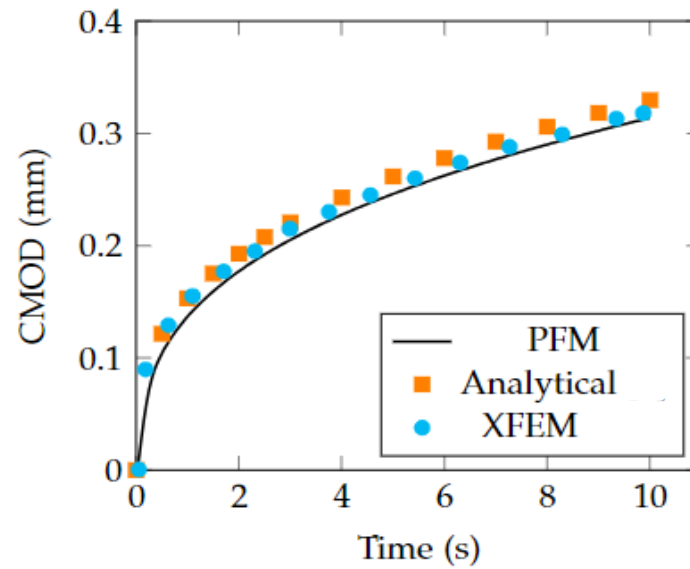
Phase Field
(φ)



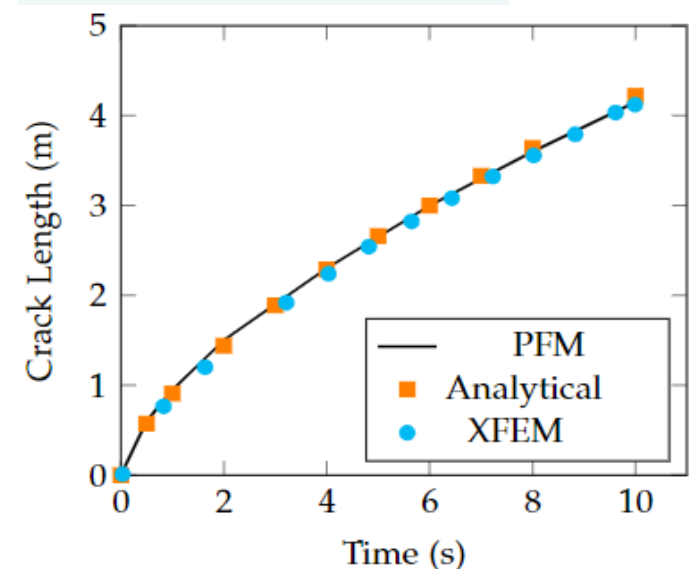
➤ Verifying the results with **analytical and numerical** studies



(a)



(b)

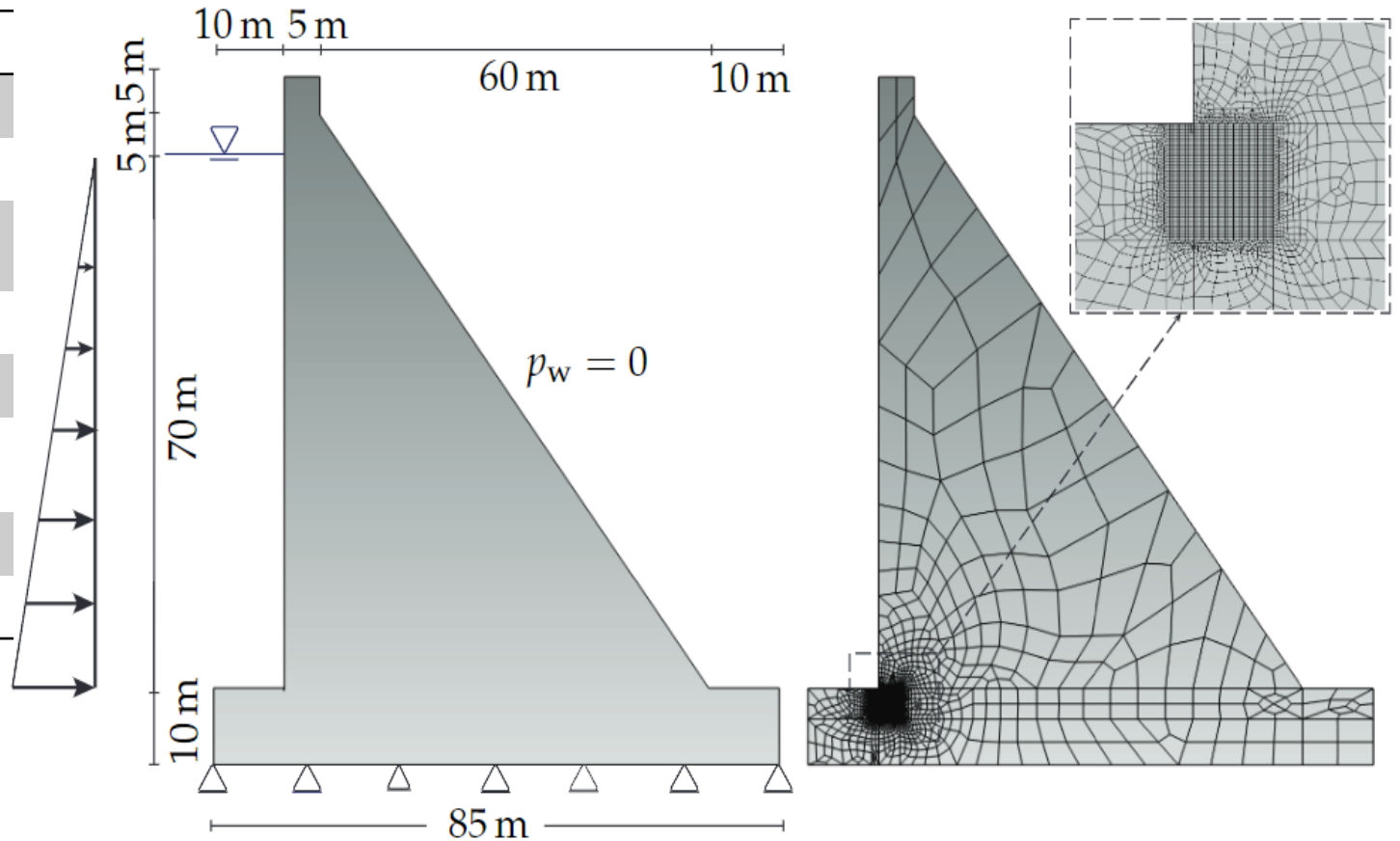


(c)

Gravity Dam

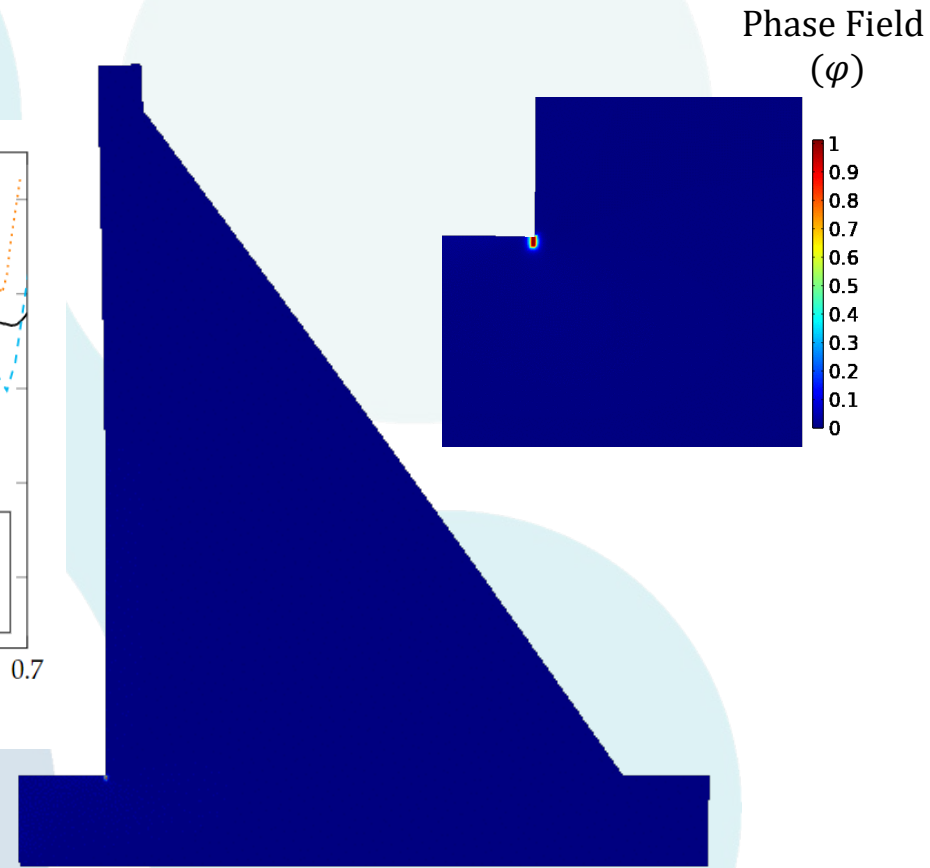
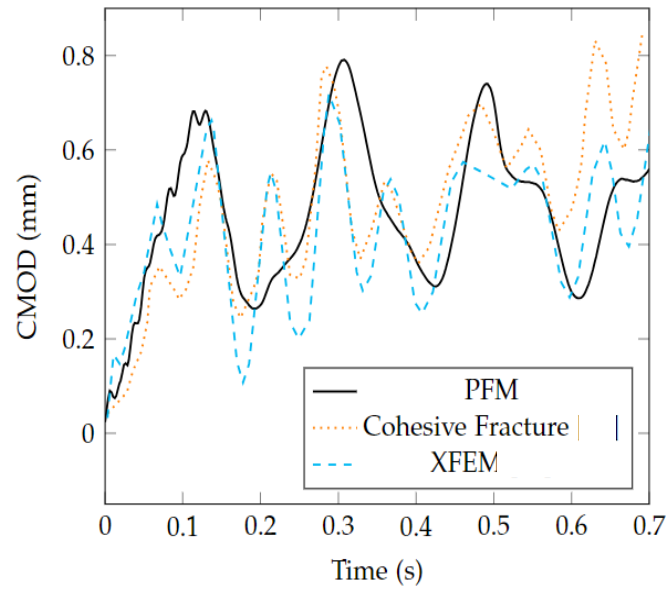
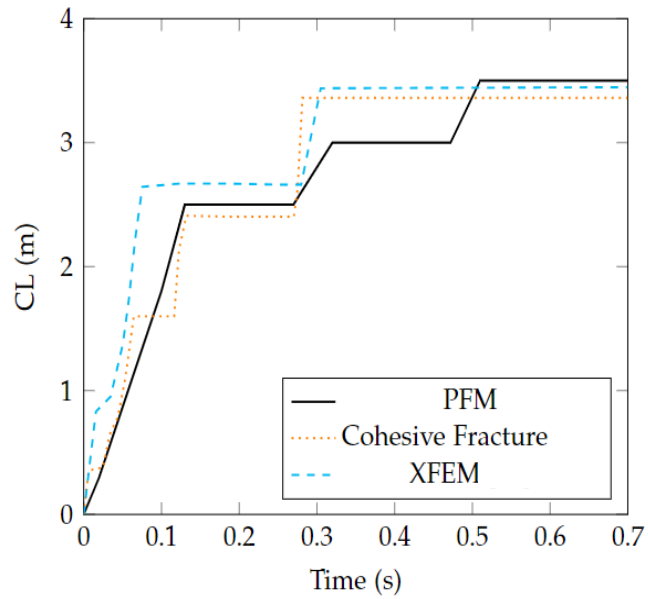
➤ Subjected to **hydrostatic pressure**

Problem parameters	Value	Unit
Poisson's ratio (ν)	0.15	
Elasticity modulus (E)	24	GPa
Solid phase density (ρ_s)	2400	Kg/m ³
Porosity (n)	0.19	
Permeability (k)	1 E-12	m ³ /Ns
Critical energy release rate (Gc)	150	N/m
Length scale (l_0)	5	cm
Minimum mesh size	2.5	cm



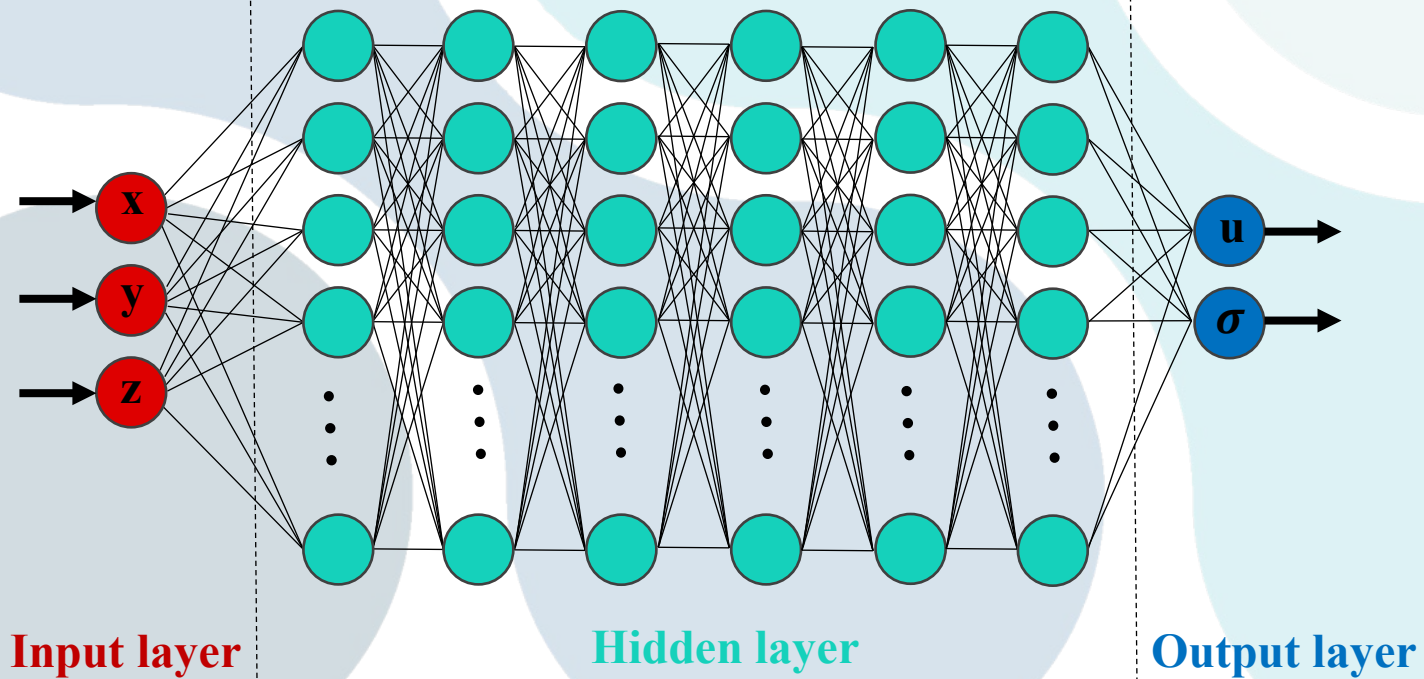
Gravity Dam

➤ Subjected to **hydrostatic pressure**



Physics Informed Neural Networks (PINNs)

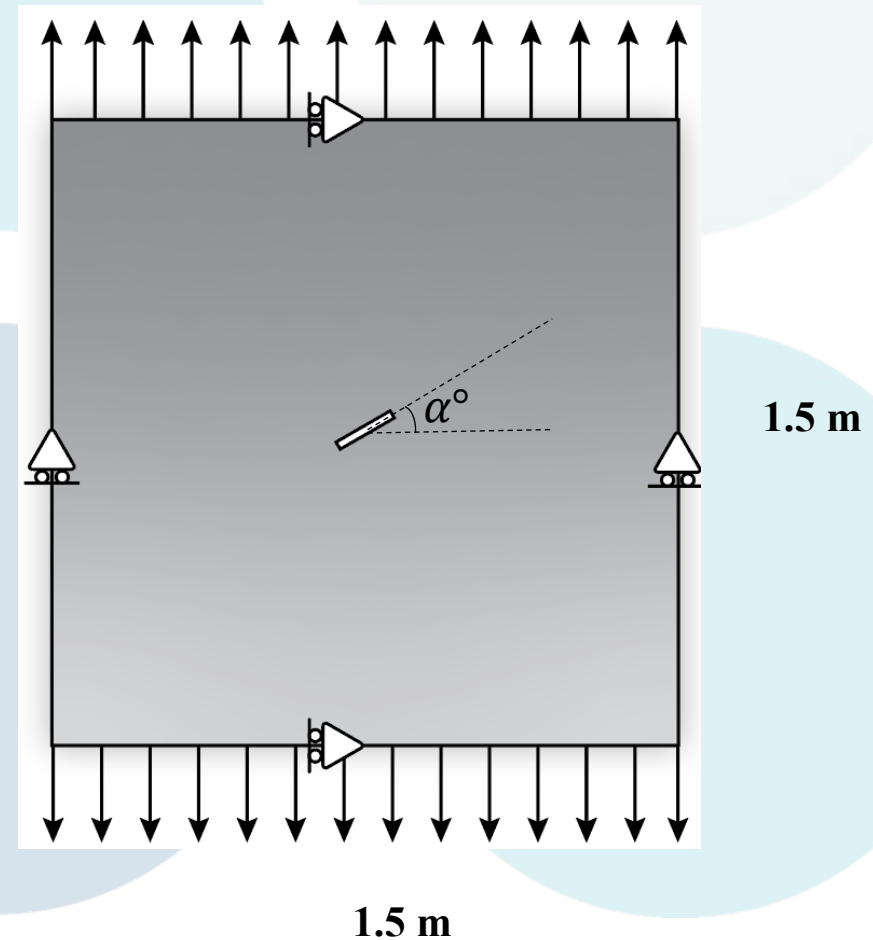
- Incorporate the governing equations (PDE) in the loss function of the NN
- Training : Minimising the residual of the PDE



Crack Modelling

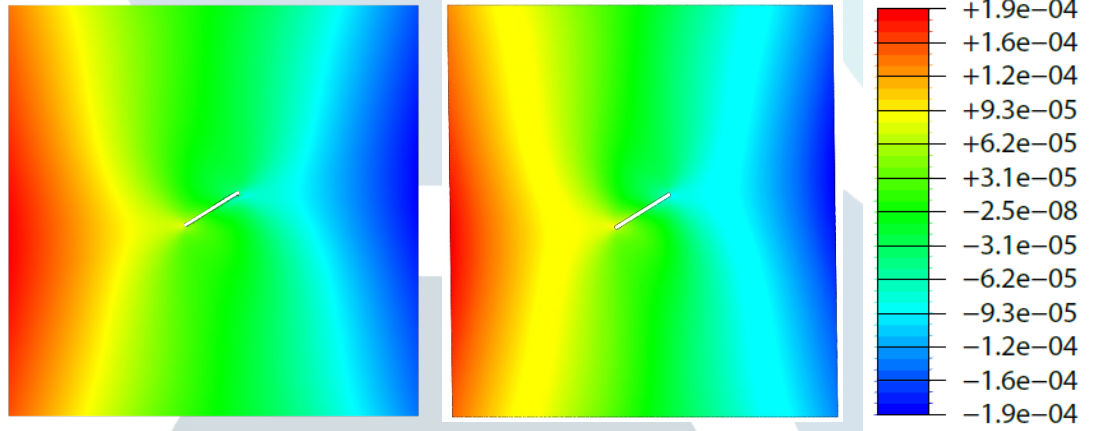
- Problem definition and boundary conditions for cracked plates
- Aluminum plate under tension
- Network 6x512

Problem parameters	Value	Unit
Poisson's ratio (ν)	0.33	
Elasticity modulus (E)	73	GPa
Tensile load (σ_0)	50	MPa
Network number of layers	6	
Network number of Neurons	512	
a'	0.25	m
Crack width	0.015	m



Crack Modelling

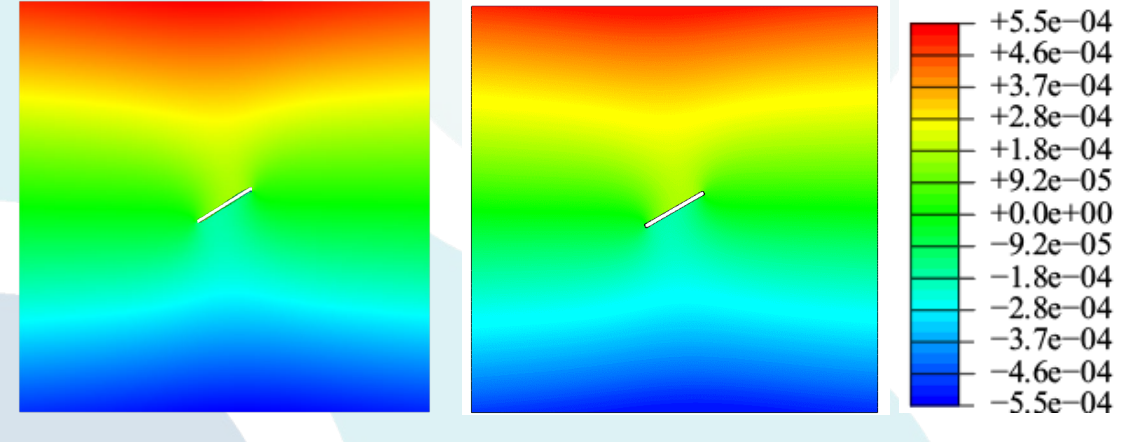
➤ Results for a crack inclined at 30°



(a) PINN

(b) ABAQUS

Horizontal Displacement (m)



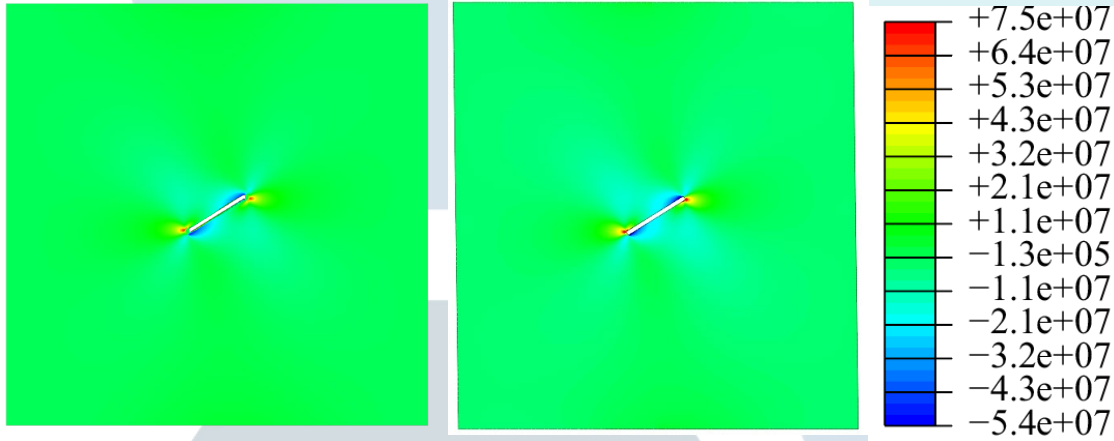
(a) PINN

(b) ABAQUS

Vertical Displacement (m)

Crack Modelling

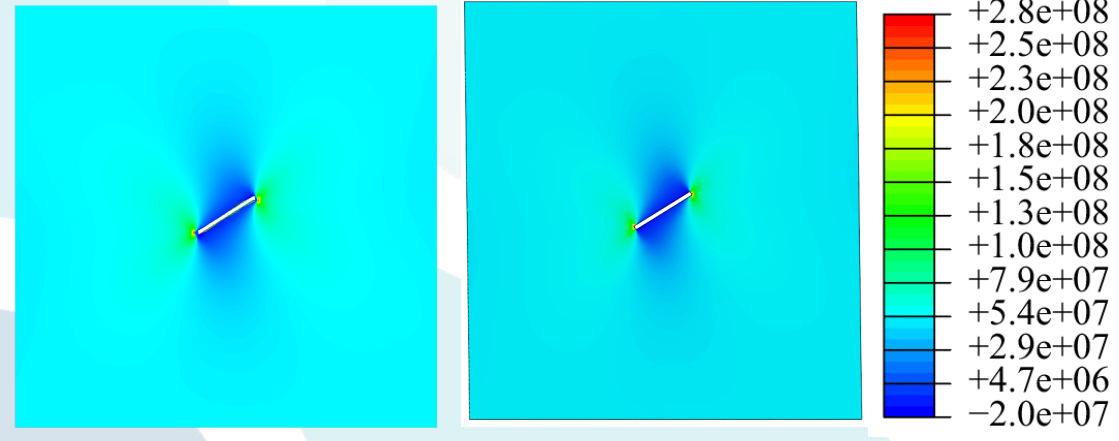
➤ Results for a crack inclined at 30°



(a) PINN

(b) ABAQUS

Stress xx (Pa)



(a) PINN

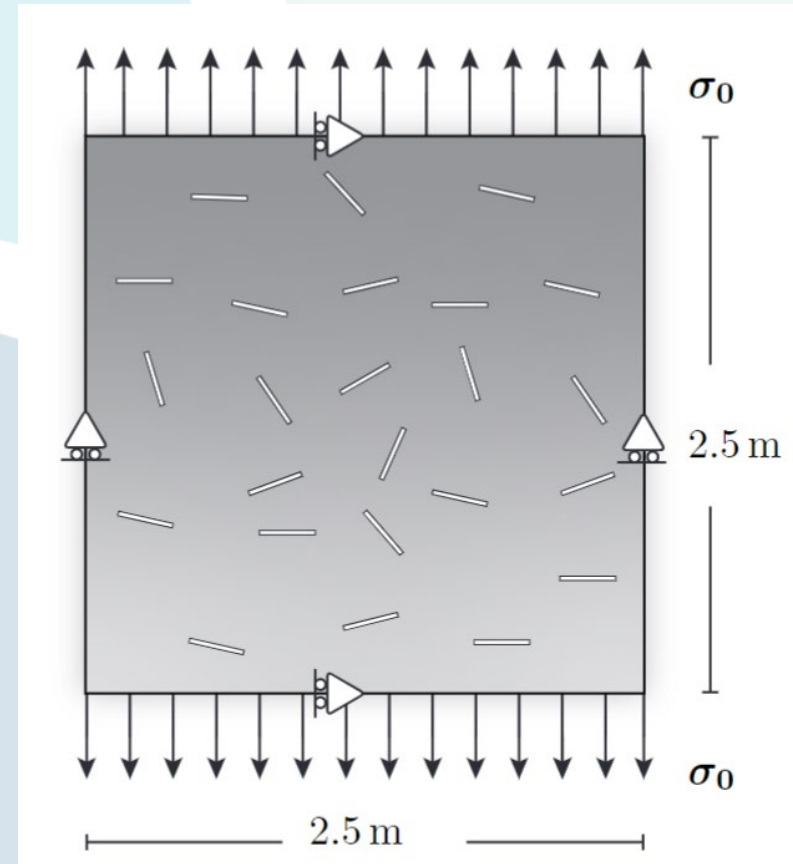
(b) ABAQUS

Stress yy (Pa)

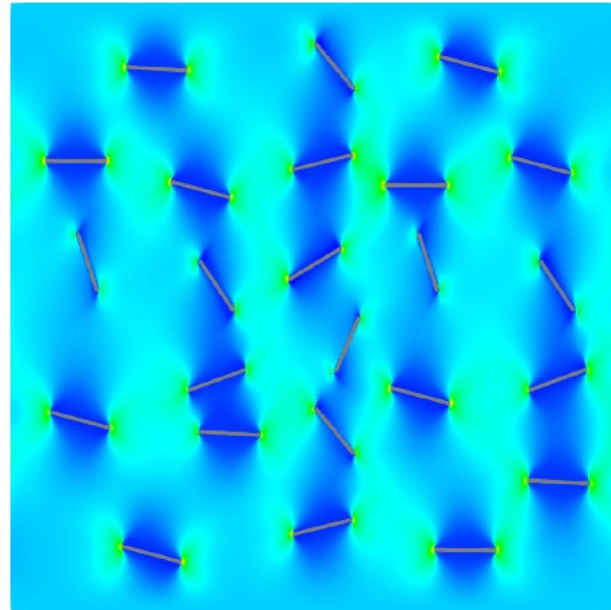
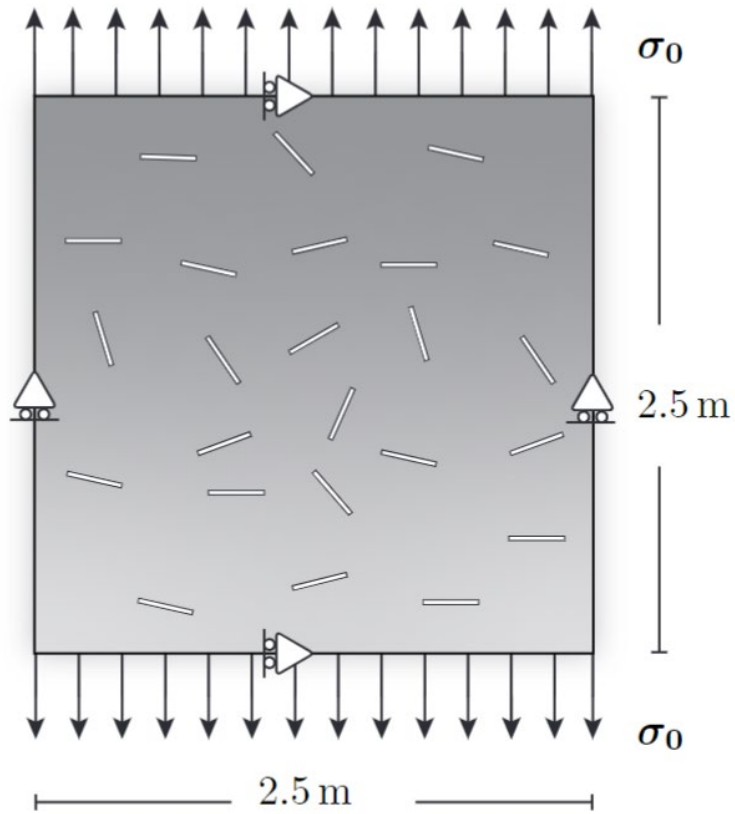
Heavily Fractured Domain

- Problem definition and boundary conditions for cracked plate

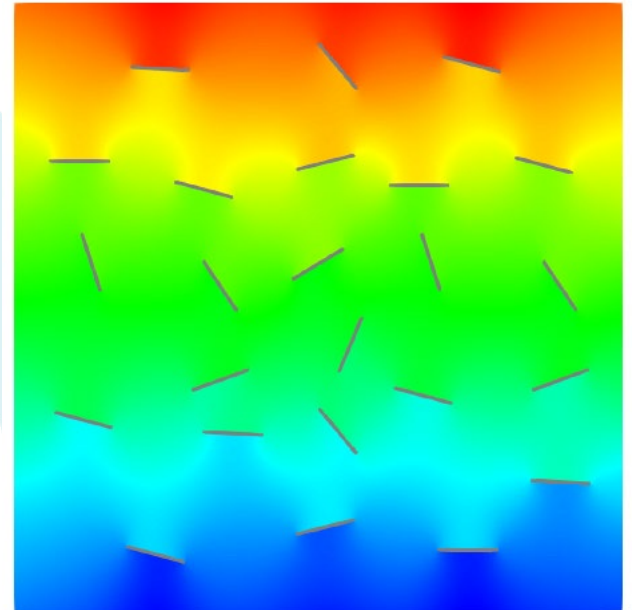
Problem parameters	Value	Unit
Poisson's ratio (ν)	0.33	
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Tensile load (σ_0)	50	MPa
Network number of layers	6	
Network number of Neurons	512	
a'	0.25	m
Crack width	0.015	m



Heavily Fractured Domain Results



Stress σ_{yy}



Vertical displacement

Dr Mohsen Mousavi

**Structural Integrity Assessment of Port
Systems through Anomaly Detection
Using Dynamic Signature Analytics and
Small Strain Vibration from Wave
Action**

Project Title: Structural Integrity Assessment of Port Systems through Anomaly Detection Using Dynamic Signature Analytics and Small Strain Vibration from Wave Action

UNSW: Dr Mohsen Mousavi, Dr Ulrike Dackermann, Professor Nasser Khalili

PhD student is selected, start December 2024

Motivation:

To provide a more accurate, efficient and continuous means of assessing structural integrity of port systems to improve their design and operation



Problem statement and practical gaps

Traditional human-operated
pile condition assessment

- ✓ Subjective
- ✓ Time-consuming
- ✓ Discrete
- ✓ Prone to human error



Existing Approaches & Gaps: A) Unbalanced classification

Challenges:

A1) Insufficient labelled data for the damage case

A2) Damage features are sensitive to environmental variations

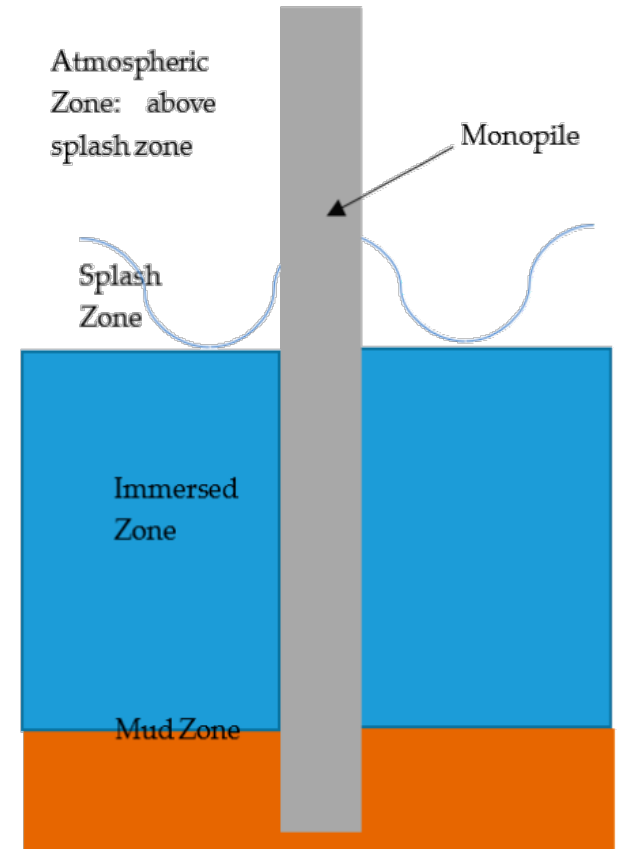
A1



Intact

A2

1. Wave Action
2. Currents
3. Tidal Variations
4. Wind
5. Seabed Conditions
6. Temperature
7. Biofouling
8. Storm Surges and Extreme Events



Existing Approaches and Gaps: B) Anomaly detection

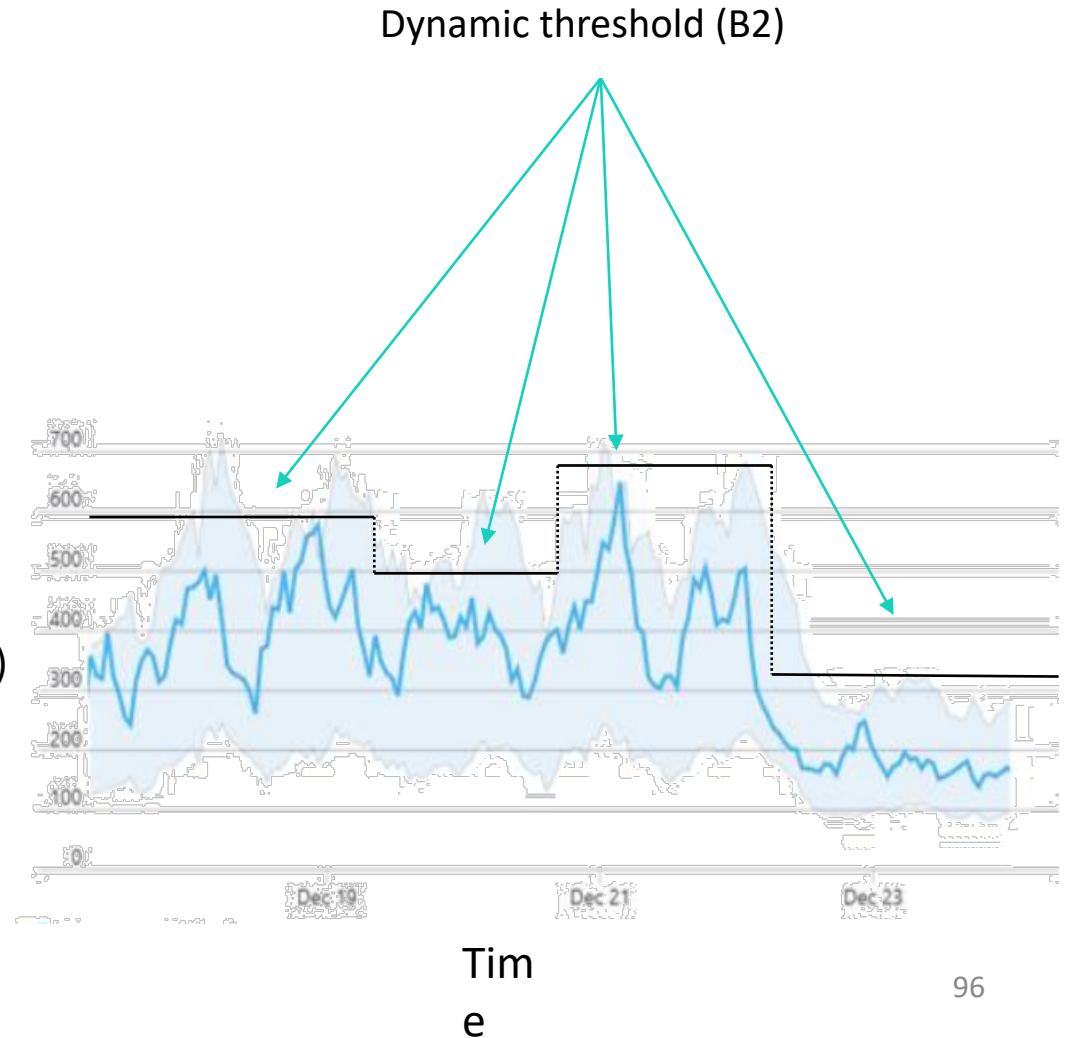
Challenges:

B1) Construct a robust damage sensitive feature (DSF)

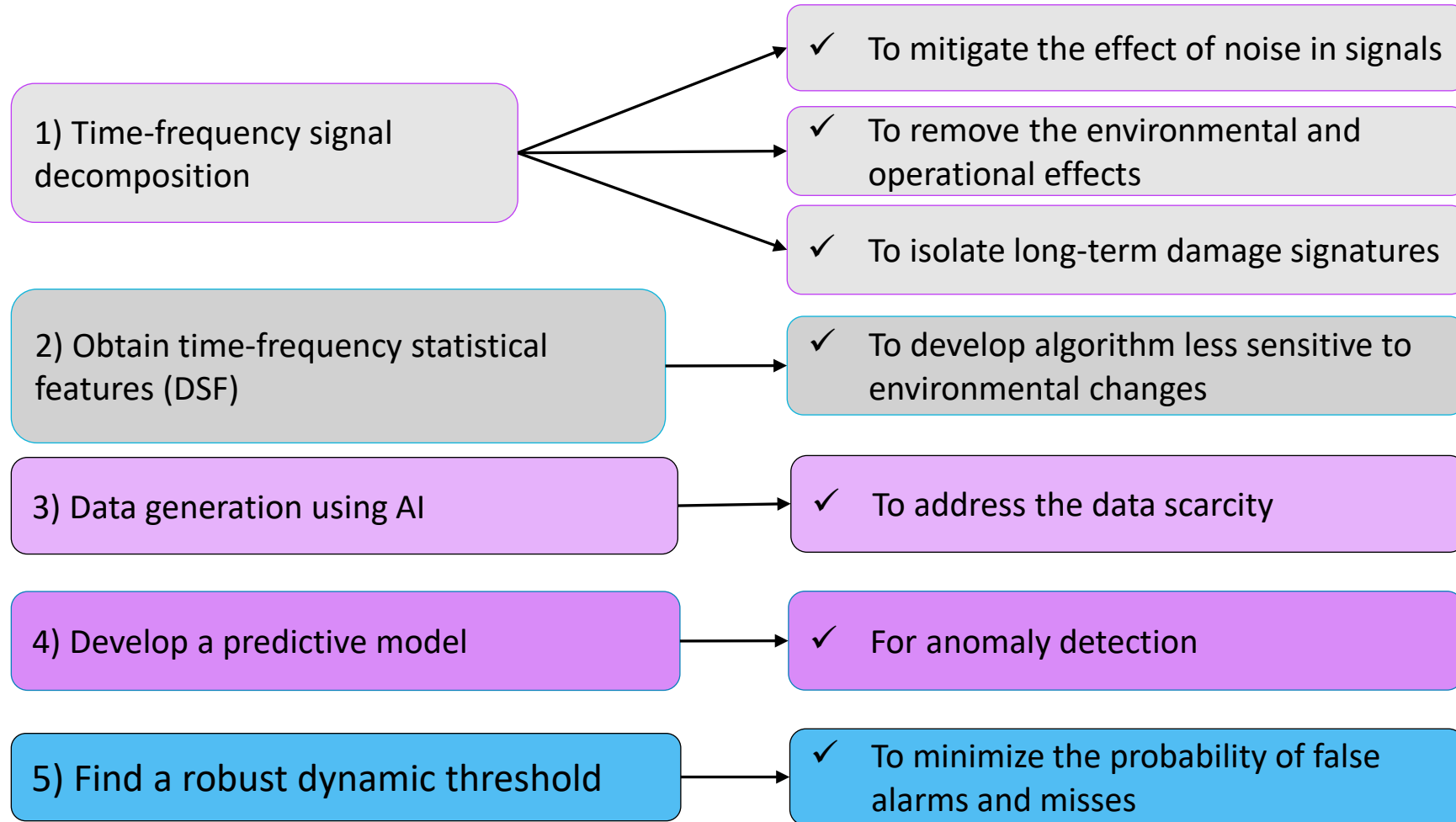
B2) Set a robust dynamic threshold in nonstationary conditions



DSF(B1)



Approach



✓ Development of an adaptable framework

✓ Development of a user-friendly GUI



✓ Dissemination of project findings

✓ Provision of technical support



Professor Bijan Samali

**Degradation modelling and remaining
service life assessment of piers in
aggressive sea-water environment**

Defined – Yet to commence

Project Title: Degradation modelling and remaining service life assessment of piers in aggressive sea-water environment.

Event presenter: Prof Bijan Samali

Industry involved: Kumul Petroleum, PNG

The Project scope is now defined but not yet started

Motivation:

To assist Kumul with its asset maintenance requirements and priority settings for their large stock of corroded piers.



Gap in Knowledge:

Lack of a reliable degradation model to predict the extent of pier corrosion leading to determining the remaining service life of the marine assets and the ability to estimate their remedial costs.



Aims:

- To develop an accurate and reliable corrosion degradation and progression model for steel structures in marine environments.
- To enable industry partner to make accurate predictions of remaining life of such structures and determining maintenance priorities.

Developing and testing a new model is the main objective of the project



Overview of Existing Corrosion Models

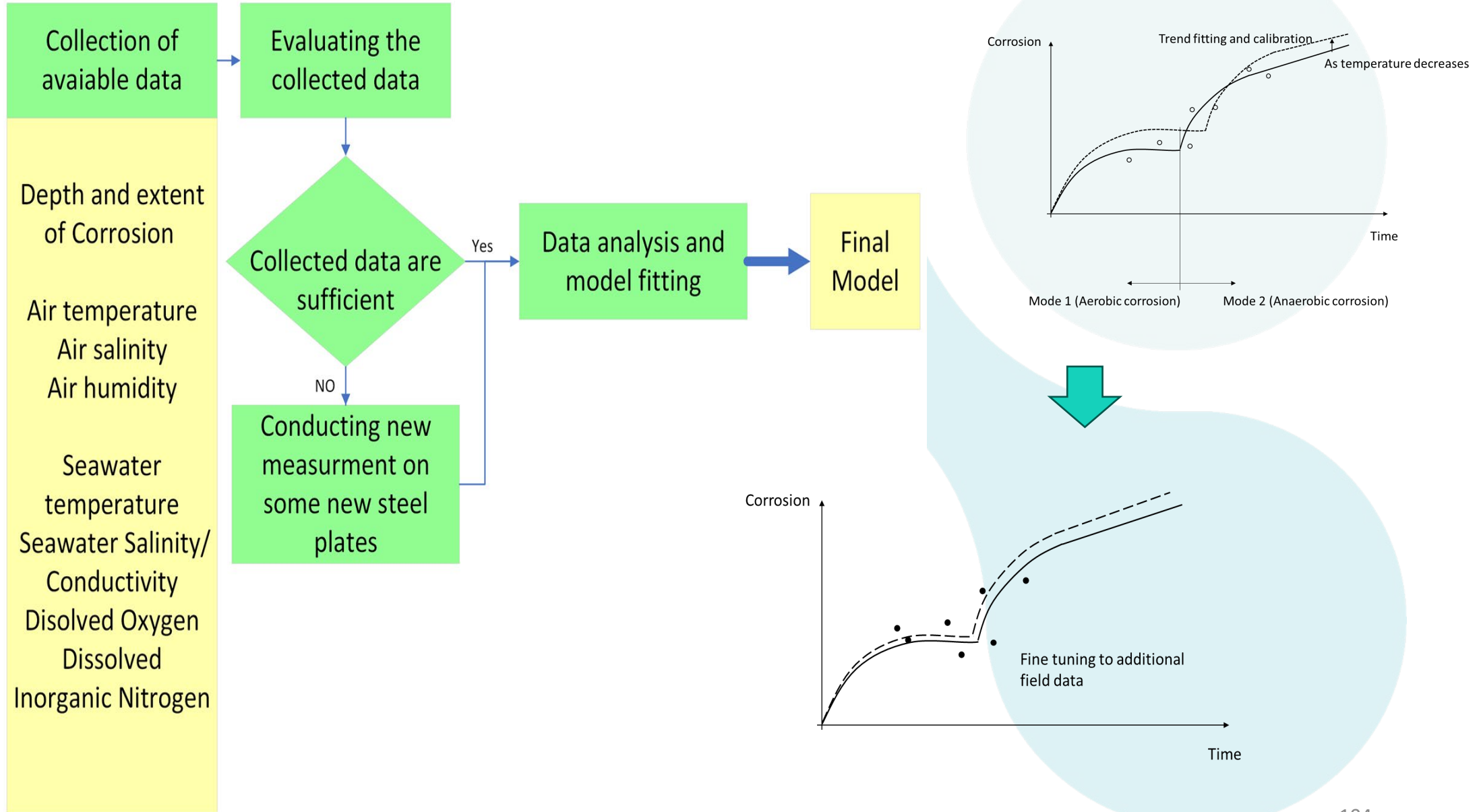
- Average Corrosion Rate Model
- Power-Law Model
- Bi-Modal Model

Limitations of Current Models

- Insufficient in addressing diverse corrosion patterns
- Lack of specific focus on specific sites
- Limited in the consideration of various parameters



The proposed research methodology



Short 15 Minute Break



STRETCH YOUR LEGS
REST YOUR BRAIN

