

# Short 15 Minute Break



STRETCH YOUR LEGS  
REST YOUR BRAIN





THEME 4

Infrastructure  
health monitoring  
and predictive  
maintenance

**Theme 4 Lead**

**Professor Tommy Chan**

**Saeed Khalaj**

**Bayesian Techniques for Rail Reliability  
Modelling and Maintenance Decision  
Support**



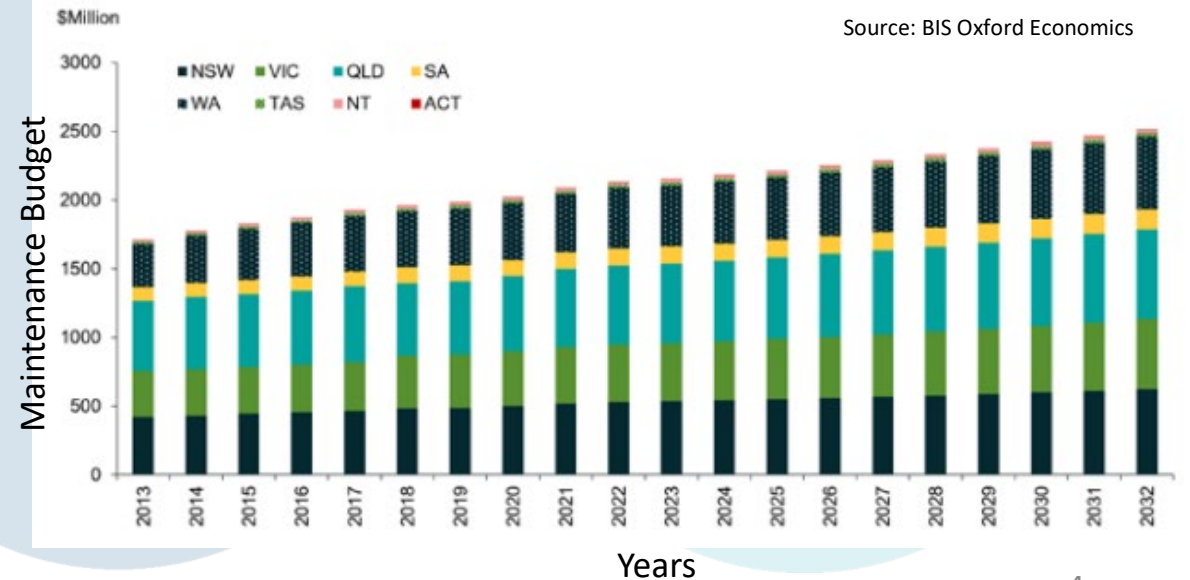
**Project 1 Title:** Prediction and Maintenance Strategies for Railway Surface Defects



**Industry involved/ CIs PIs involved:** Covaris, Queensland Rail (QR)

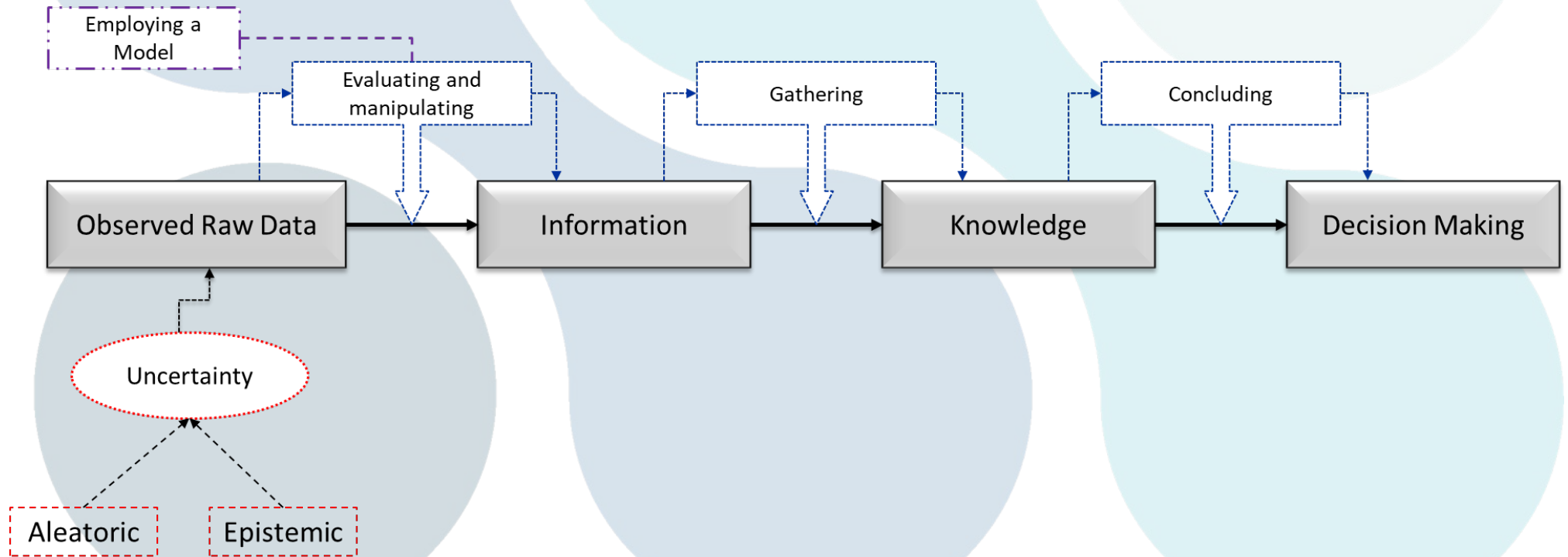


**Motivation:** Rail maintainers currently use time-based (scheduled) approaches to balance the costs and benefits of inspections and maintenance. Changing to condition-based inspection and maintenance planning has the potential to reduce costs and improve rail surface condition.

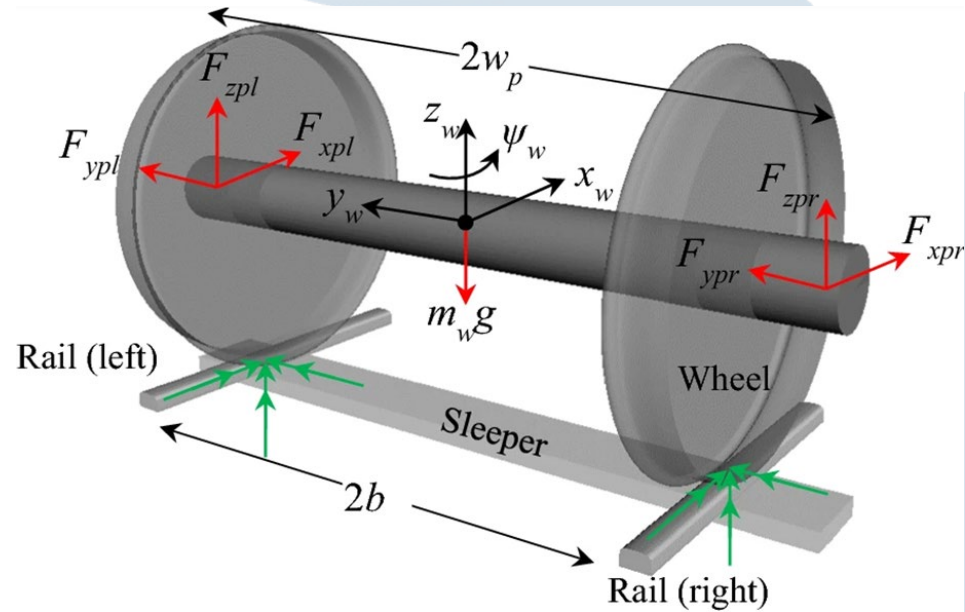




**Aims:** The current project aims at developing novel methodologies to overcome significant challenges corresponding to rail surface defect arrival prediction and developing inspection and maintenance strategies. To this end, advance mathematical-based techniques including Bayesian inference is employed addressing the epistemic and aleatoric uncertainties.



**Gaps in Knowledge:** developing a framework for Dealing with uncertainty of occurrence and evolution of rail surface defects and problems of scarce data for prediction of defects. Meanwhile, in the absence of surface defect severity criteria, inspection planning should be addressed.



**Expected outcome:**

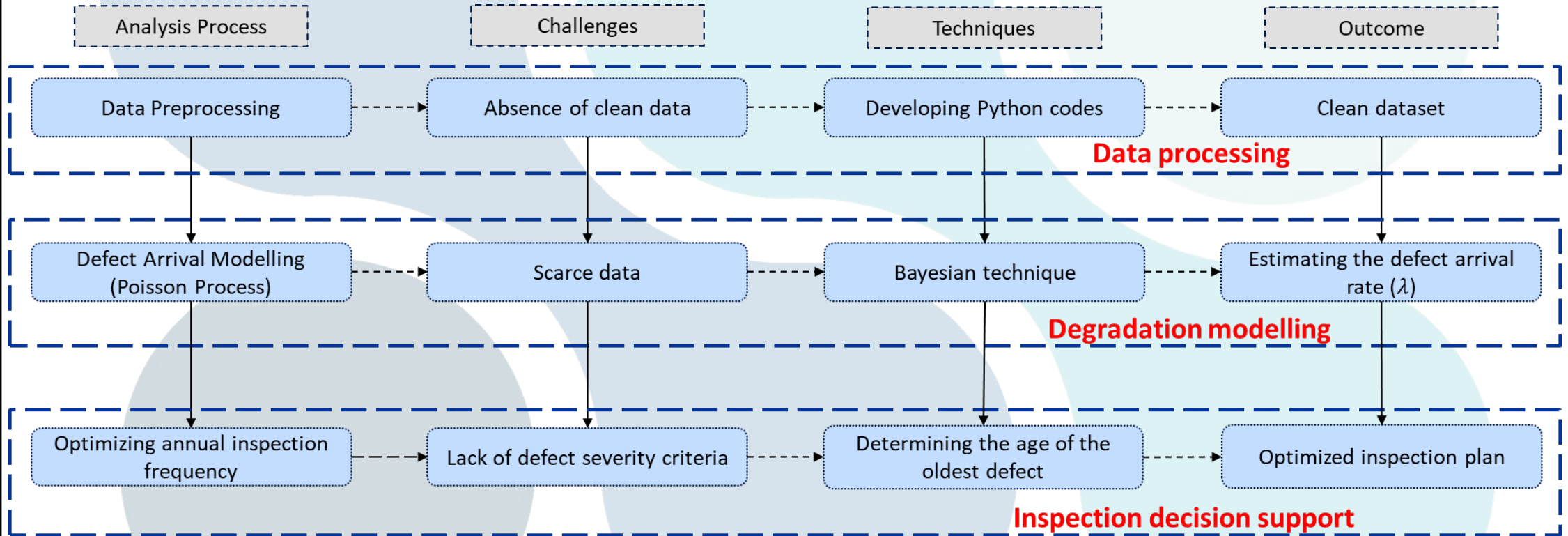
- 1) Developing a long-term prediction of defect arrivals on the surface under the data limitation and effective inspection planning (Phase I).
- 2) Developing a defect severity evolution model for predicting the propagation of surface defect, and maintenance planning according to defect severity (Phase II).
- 3) Developing a method to investigate the effect of major environmental and operational factors affect defect arrival and evolution and to incorporate them into the prediction model (Phase III).







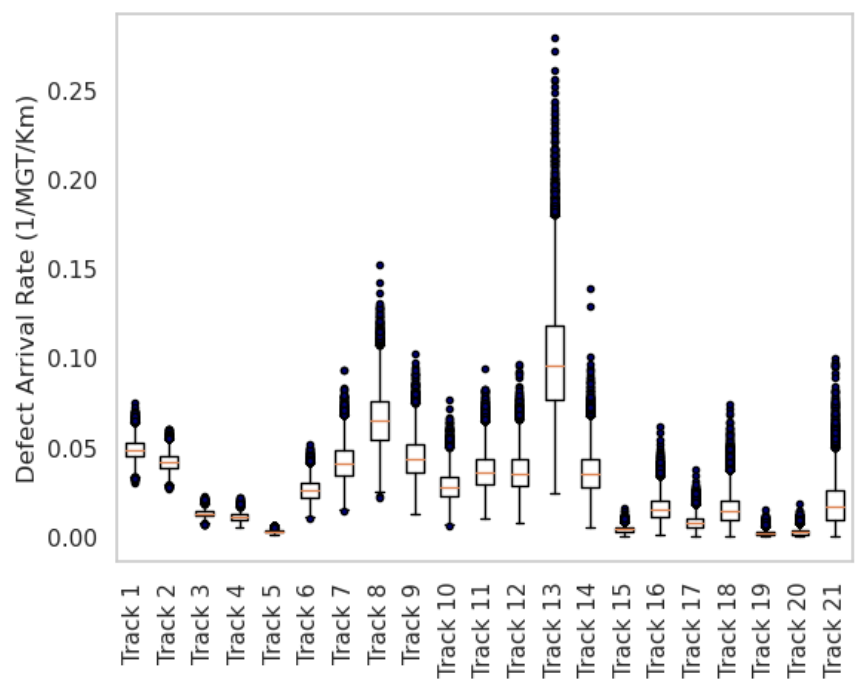
### Framework (Phase I):



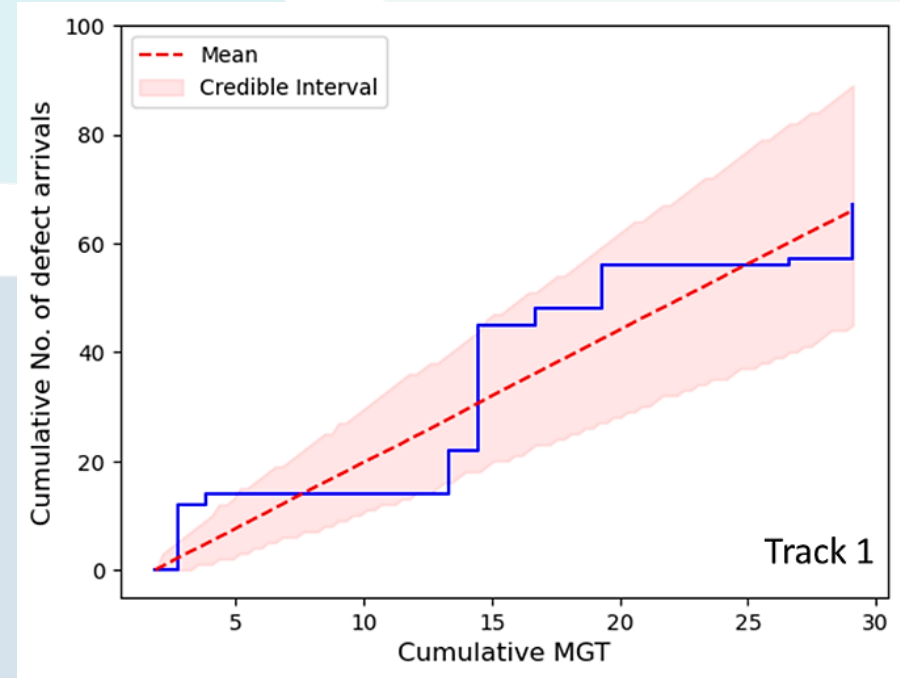


Progress to date:

Defect Arrival Rate



Posterior Fit

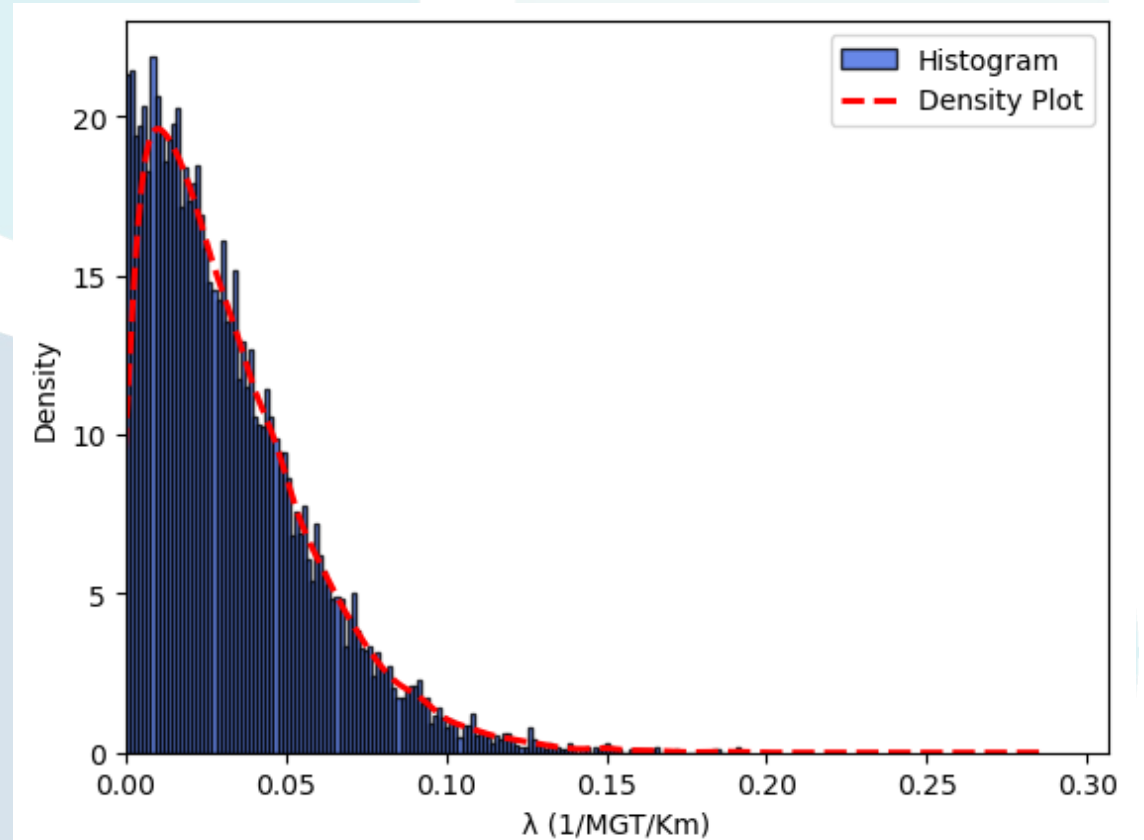


MGT = cumulative millions of gross tons transported over the rail



## Progress to date

- Initial predictive model for surface defect arrival on a track with same-built material.
- Helpful in planning future inspection and maintenance.



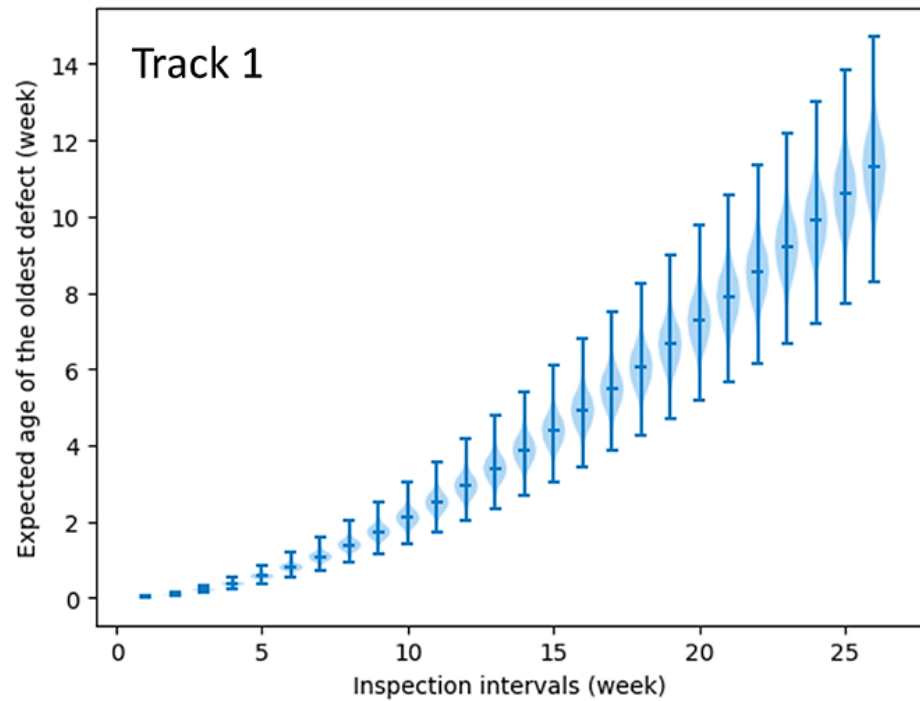
MGT = cumulative millions of gross tons transported over the rail



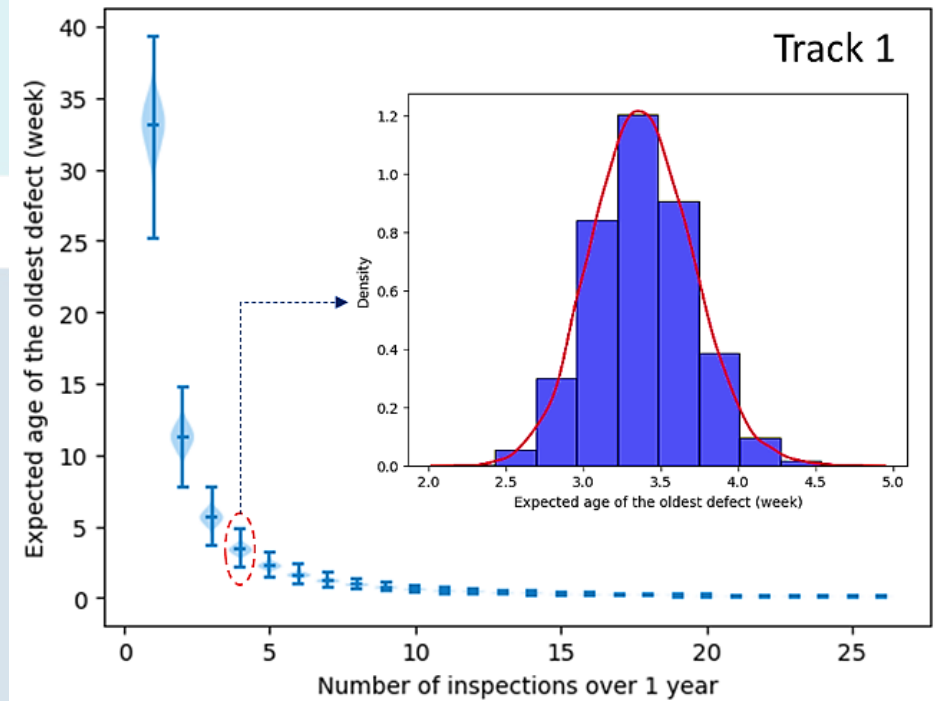


## Progress to date

### Oldest Defect Age



### Optimized Annual Inspection



**Saeed Khalaj**

# **Predictive Maintenance for Building Electrical Assets**

CI – A/Prof Michael E. Cholette  
& Prof Tommy Chan

Industry – Fredon via  
Asset Institute

Hub Theme 4

## **Project 2 Title:** Degradation Modelling & Maintenance Optimization for LED-based Lighting Systems

**Industry involved/ CIs PIs involved:** Fredon



**FREDON**

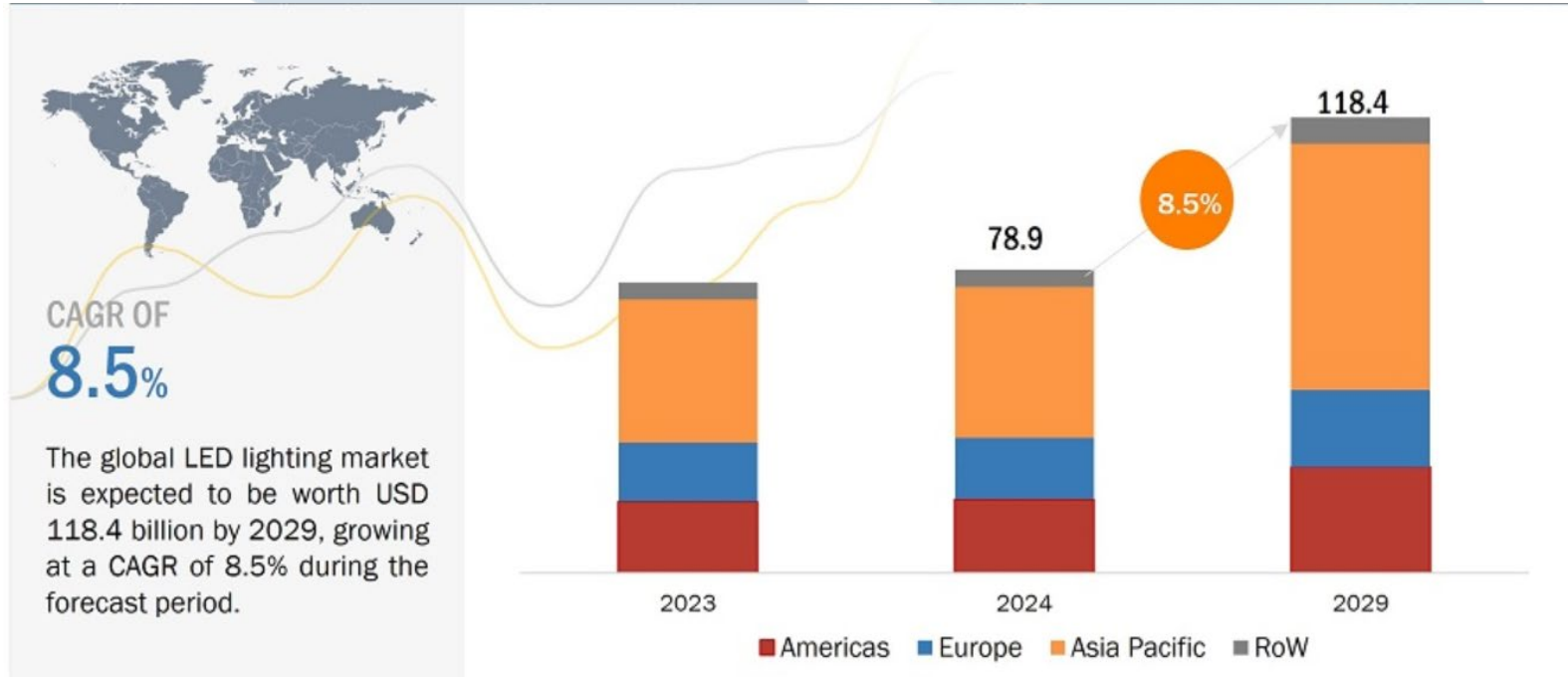




## Motivation

### The Advantages of Light Emitting Diodes (LEDs) Lighting

- **Long Lifespan:** Average 50, 000 hours (Energy Star)
- **Energy Efficiency:** 60% to 70% energy savings compared to traditional lighting sources
- **Environmentally friendly:** do not use mercury-like fluorescent lighting using
- **Dimming Capabilities:** perform well at almost any power percentage, from about 5% to 100%



Motivation:

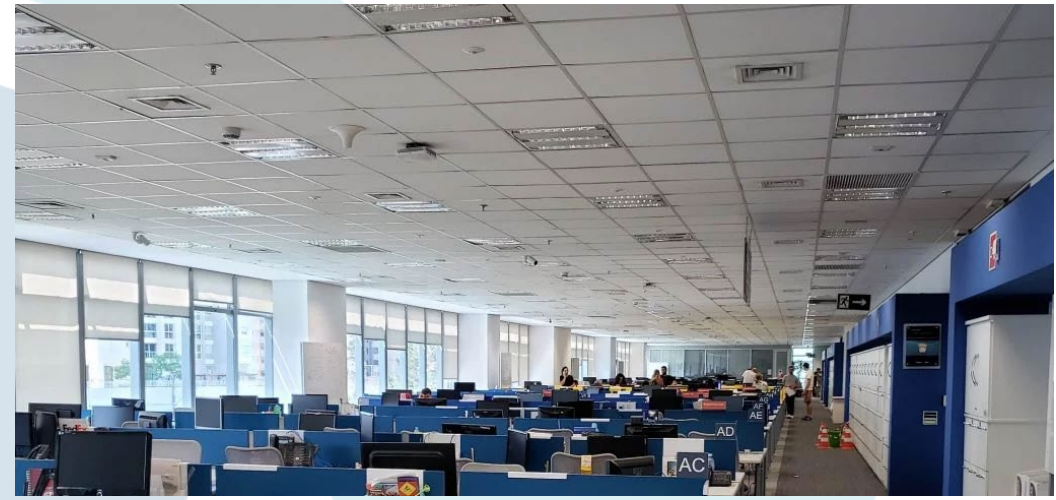
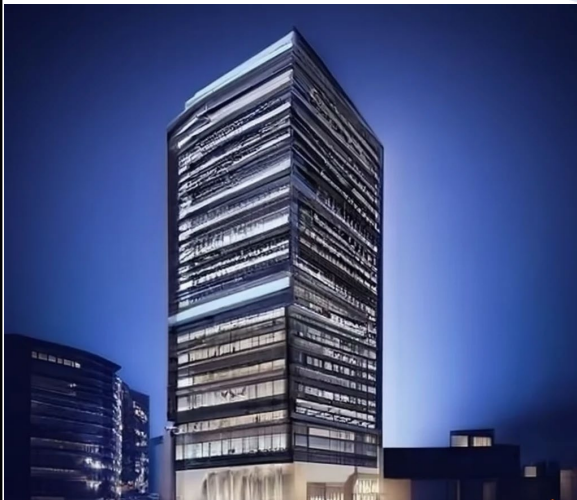
## Commercial Buildings Indoor LED lighting

### The Function of LED lighting system for offices

- Improved Productivity and Focus
- Health and Well-being Benefits
- Reduced Energy Consumption

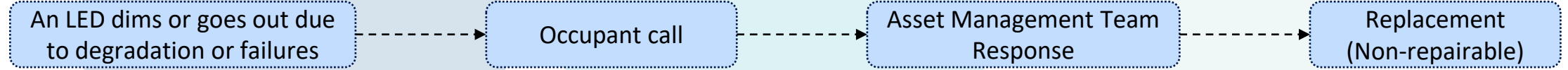
### Disadvantages of low lighting conditions

- Eye Strain
- Impaired Performance
- Increased Risk of Accidents
- Negative Impact on Mood



## Motivation

### Current Maintenance Plan



#### Respond immediately:

- High maintenance costs (mainly labour costs)

#### Delayed response:

- Occupants dissatisfaction
- Lighting system performance may fall below lighting standard requirements



#### Optimal maintenance plan

- Balance maintenance cost and lighting system performance





**AIMS:**

**A Novel Method for LED Luminaire Degradation and Remaining Useful Life Prediction**

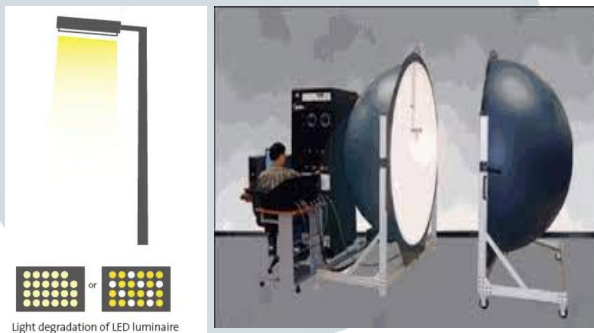
- Actual recorded failure data
- LED supplier test report
- Accelerated degradation experiment

**LED-based Lighting System Performance Degradation Simulation Model:**

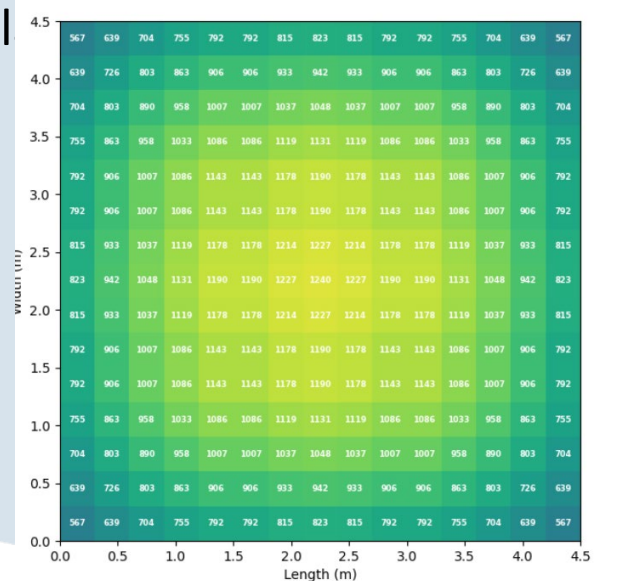
- Based on Python, developing a mode to simulate the LED lighting system change as the LED lamps degrade.

**Maintenance plan:**

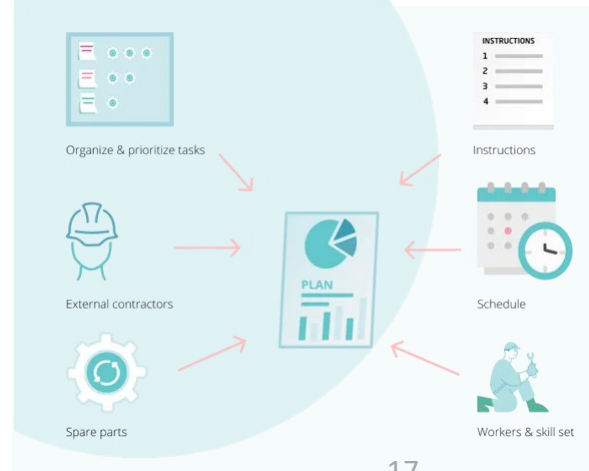
- Time-based preventive maintenance (PM) pl
- Opportunistic maintenance (OM) plan
- Condition-based maintenance (CBM) plan



Light degradation of LED luminaire



Min: 567 lux Max: 1240 lux Avg: 960 lux Illuminance Uniformity: 0.6



**GAPS:**

**Remaining useful life prediction**

- Long lifespan -- Scarce failure data
- Dimmable -- Unclear influence on the lifetime of LEDs
- Multicomponent system -- Complex degradation mechanism
- Uncertainties -- Operating conditions variations cause uncertainties in LEDs degradation



**Single LED: Failure criteria**

- L70: when the luminous intensity of an LED is decreased to 70% of the initial value, the LED is considered as failed. (Illuminating Engineering Society of North America)
- Color Rendering Index (CRI)
- Chromaticity Shift ...

**Lighting system: Lighting standards: AS NZS 1680.0-2018 Interior lighting**

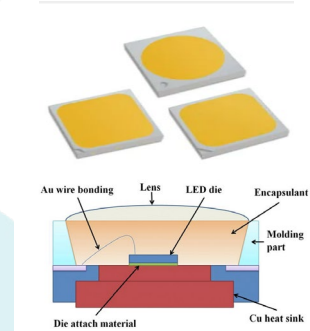
- Average Illumination
- Illumination Uniformity
- Unified Glare Rating...

**Maintenance optimization**

- A commercial building has a large number of LED lights: from hundreds to thousands



A LED Lamp structure

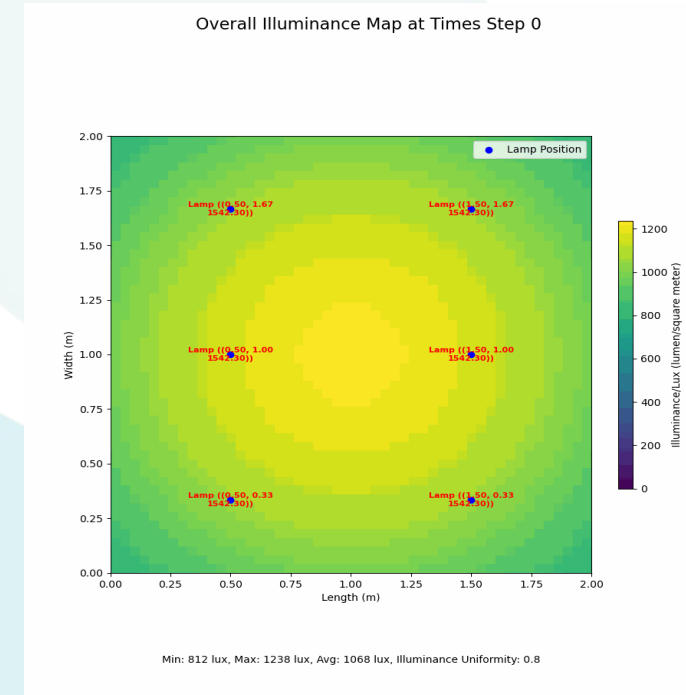


LED package



## EXPECTED OUTCOMES & PROGRESS TO DATE

- **Completed tasks:**
  - A simple room lighting system simulation model was built
  - The impact of different maintenance plans on lighting systems were tested
- **Future plan:**
  - Extend the established lighting system performance simulation model to the entire floor of a commercial building.
  - Establish LED remaining useful life prediction model based on available data
- **Possible industrial applications and extensions**
  - The proposed simulation model can be extended to different types of LEDs and different application scenarios (such as hospital, and retail places) for health monitoring
  - The proposed remaining life prediction model can be applied to the life prediction of other types of LED lamps



**Saeed Khalaj**

**Bayesian approaches for Performance  
Monitoring and Maintenance Planning  
in Facilities Management**



CI – A/Prof Michael E. Cholette  
& Prof Tommy Chan

Industry – Serco via  
Asset Institute

Hub Theme 4

**Defined – Yet to commence**

**Project 3 Title:** Bayesian approaches for Performance Monitoring and Maintenance Planning in Facilities Management

**Industry involved/ CIs PIs involved:** Serco

**Motivation:** Serco manages the structural, mechanical, and electrical assets of a number of facilities across Australia and the maintenance of these assets remains a significant challenge to the long lifetimes of these assets —which is the primary driver for the sparsity of useable degradation and/or failure data for predictive modelling. Moreover, Serco would greatly benefit from a structured process for utilizing reliability and maintenance data/experience from one site to aid in planning of a new site — even if the assets are not same.

**Aim:**

- Select key assets for study and collect data, interview experts.
- Develop reliability and degradation models based on existing data and expert opinion
- Develop asset decision optimisation models in close collaboration with Serco experts.
- Create approaches for translating reliability know-how to another site with data. Evaluate/validate predictive capability of this translation.
- Understand state-of-the-art monitoring for key assets and develop an optimisation model for new monitoring technologies.



**Gaps in Knowledge:** Data sparsity is a common challenge in reliability and prognostics, particularly for long-lived assets. This challenge is often overcome using detailed modelling (e.g. finite element analysis). However, this approach will not scale well since it is impossible for Serco to conduct detailed modelling for each key asset.

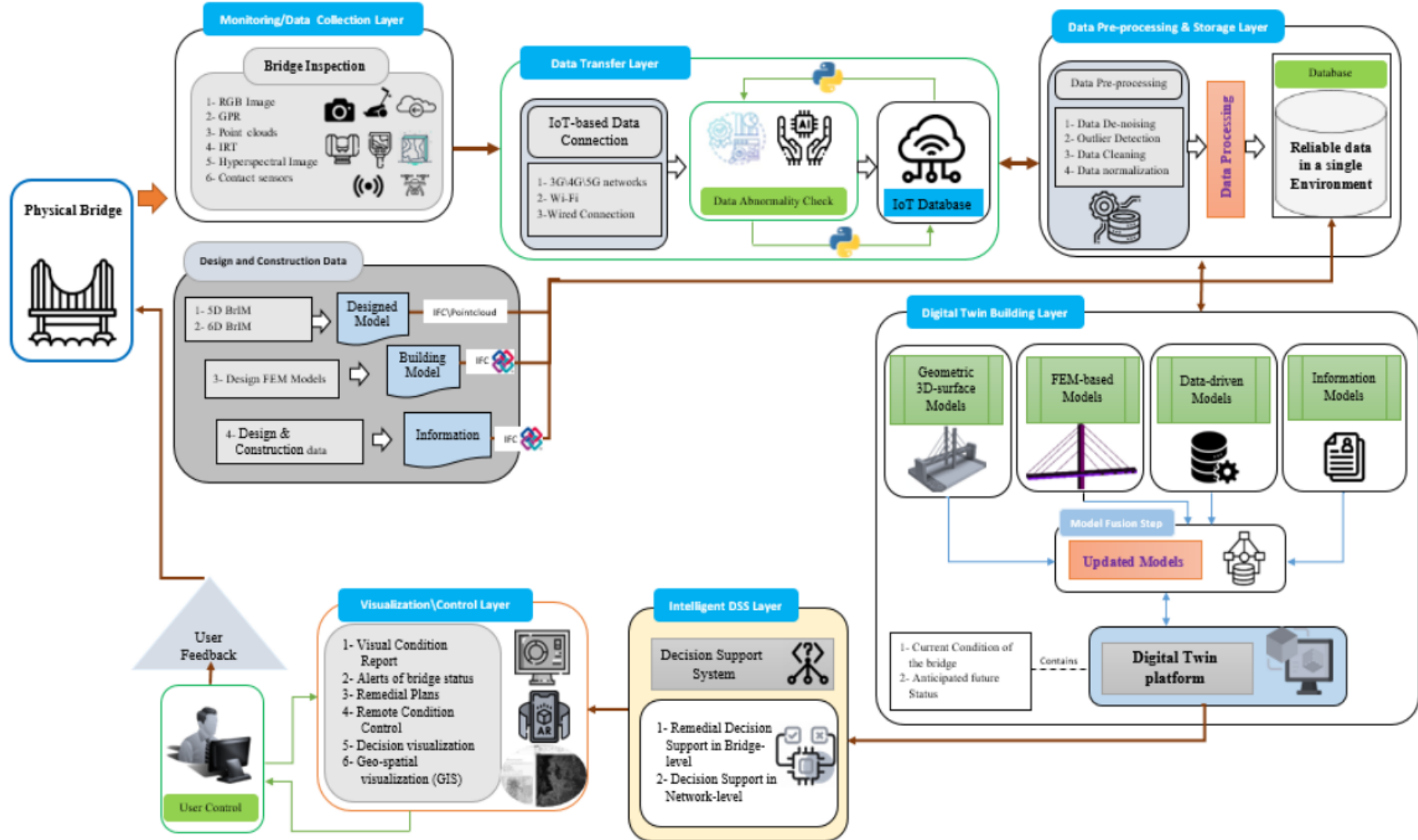
**Expected outcome:** This project will both leverage available data and suggest new data that could be economically obtained and have significant value for current and future management decision. The team will employ Bayesian approaches: eliciting expert opinion for informative priors and testing the predictive capacity of these priors before updating them with available data. Importantly, the team will also examine what type of data could be collected to aid in different asset management and evaluate its value not just on the current site, but on the information / learning that this data would provide for other (e.g. future) sites.

**Progress to date:** The Ph.D. has been recruited and is waiting for the visa approval.

**Dr Maria Rashidi**

**Development of Intelligent Bridge  
Management Systems (iBMS) Using  
Digital Twins and Decision Support  
Systems**

# Main Components of iBMS

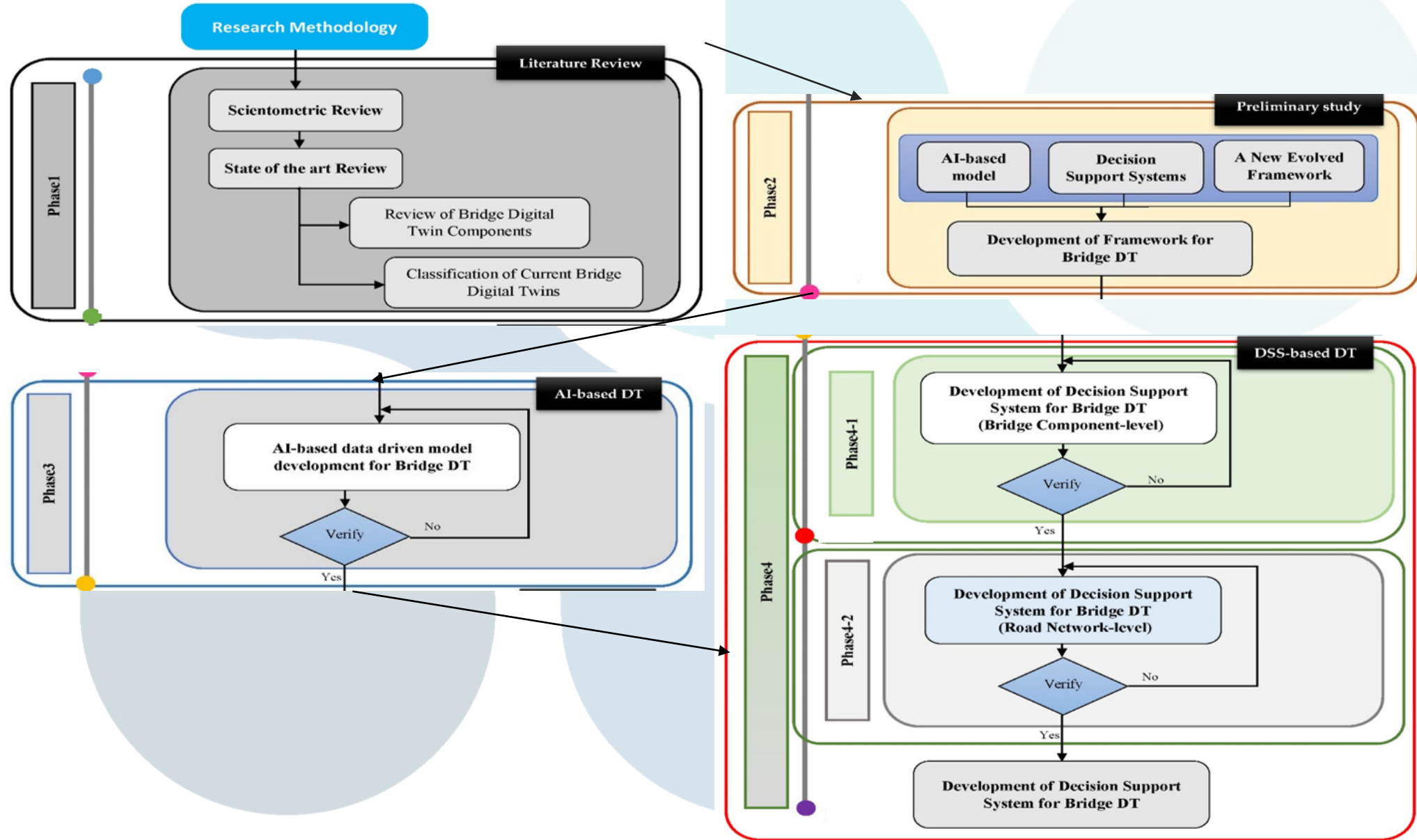


## Innovation

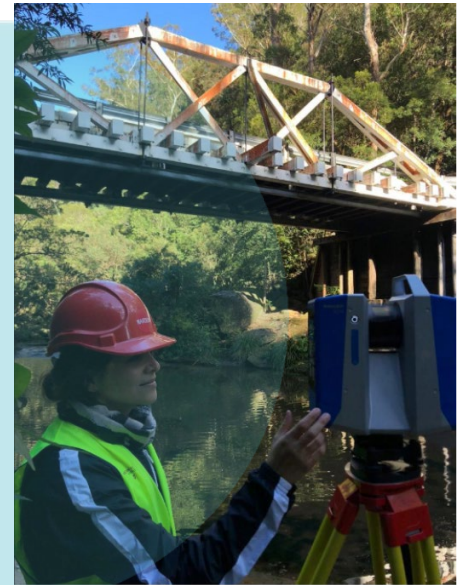
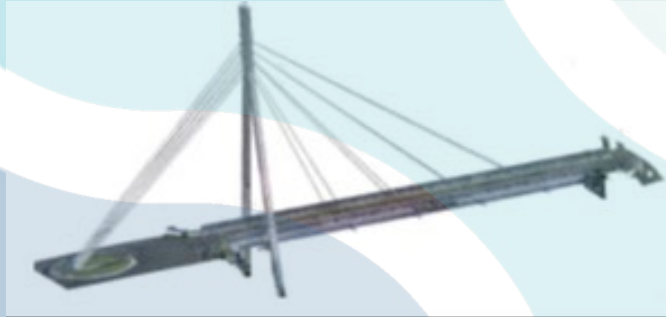
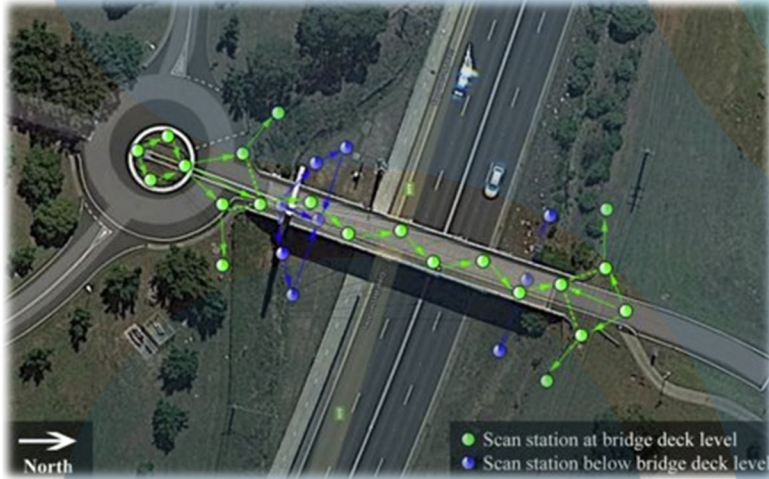
- Integration of Digital Twin Technology
- Advanced AI-based Decision Support System (DSS)
- Scenario Planning and Simulation
- Data Integration and Interoperability



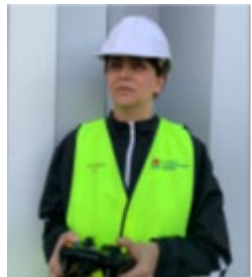
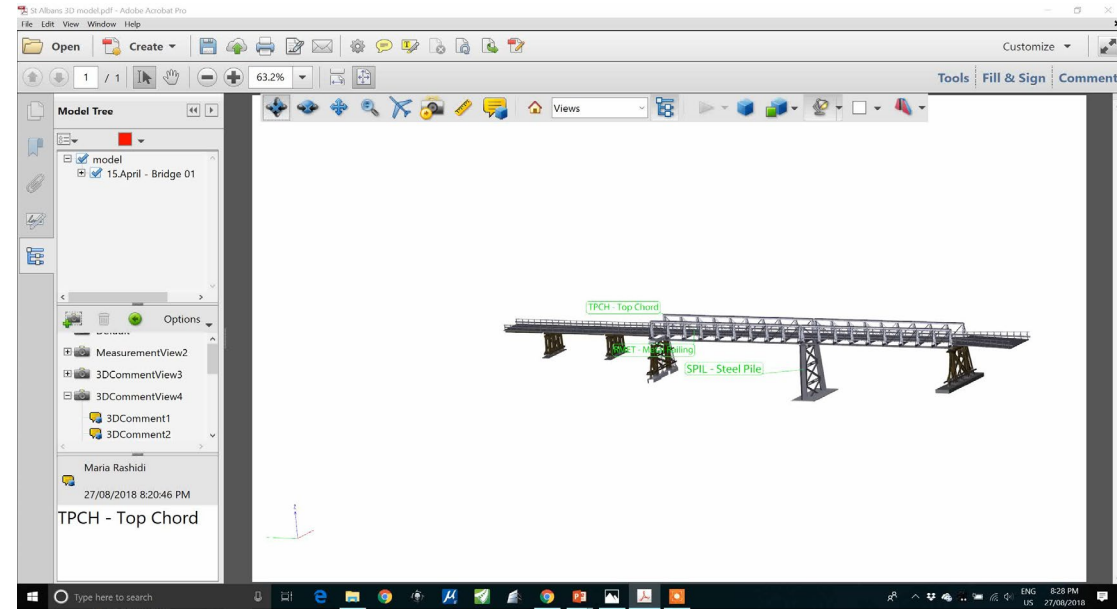
# Methodology



# Scan to BIM



# UAV Photogrammetry





THEME 5

Spatial data,  
Digital Twins and  
decision support

# Theme 5 Lead

# Professor Sisi Zlatanova



**Professor Sisi Zlatanova**

**Large Language Models for spatial  
concepts and asset definitions**



Defined – Yet to commence

**Project Title: Large Language Models for spatial concepts and asset definitions**

**Involved:**

UNSW: Prof Sisi Zlatanova, A/Prof Johnson Shen

Western Sydney University: Prof Srinath Perera

Frontier SI: Kate Williams

*PhD student is selected, start September 2024*

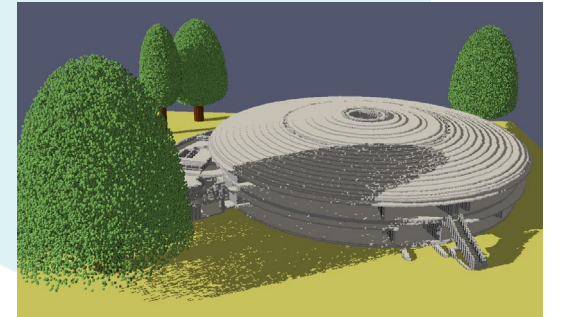
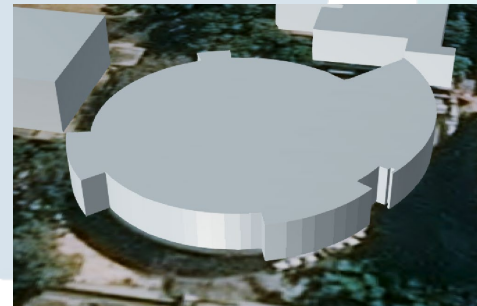
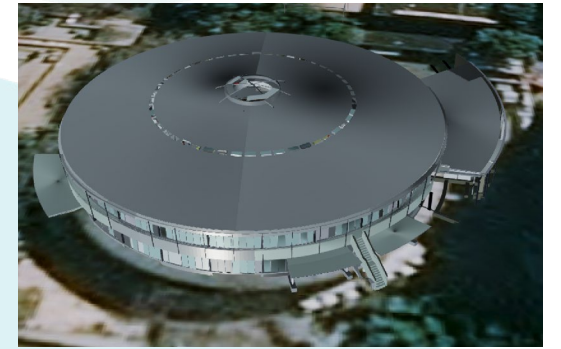
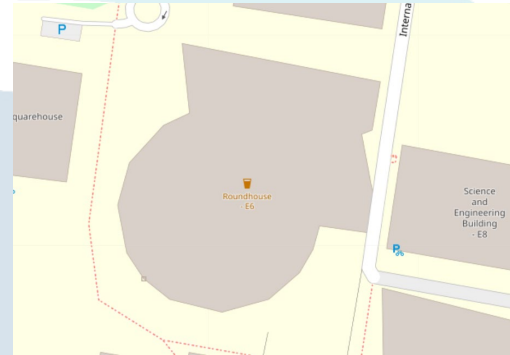
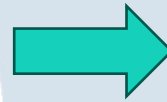
**Motivation:**

To address pressing 3D spatial data heterogeneity issues in building Digital Twins

## Problem definition:

**(3D) data heterogeneity:** application-dependent lexicons and descriptions for data, processes and systems

=> 3D data finding, sharing and exchange is **complicated and onerous**



Point clouds  
Reality Mesh  
...CAD model

**Aims:**

- Develop a framework to map and adapt current concepts in a multi-level library of shared symbolic abstractions and codes
- Develop a kind of ChatGPT search

=> To allow users to find (3D) data needed for a specific Digital Twin, process or prediction.





## Approach:

- Study International and National Standards from ISO, IEC, IEEE, ITU etc. => applicable for Australia and a sector or RIIS specific Digital Twin (urban, **tunnel**, etc.).
- Investigate approaches for linking Spatial Data (semantics and geometry)
- Re-using ontologies and knowledge graphs to establish links and enable reasoning
- Use AI to enrich the knowledge graphs.

*Rob Atkinson 'Approaches for simplifying 3D data exchange between system', 22-25 October, Fremantle, ISPRS TCIV symposium + UPINLBS + FOSS4G Perth, <https://www.isprs.org/tc4-symposium2024/>*



**Dr Johnson Shen/ Mr James Linke**

**Automated Scan-vs-BIM for Real-Time  
Construction Progress Management of  
Infrastructure Projects**

**Project Title:** Automated Scan-vs-BIM for Construction Progress Management of Infrastructure Projects

**Motivation:** Significant project delay and cost overrun for civil infrastructure construction. Increasing demands for automated reality capturing and intelligent decision support during infrastructure construction

**Aims:** A streamlined workflow and innovative approaches will be developed in this project in support of intelligent infrastructure construction

**Gaps in knowledge:**

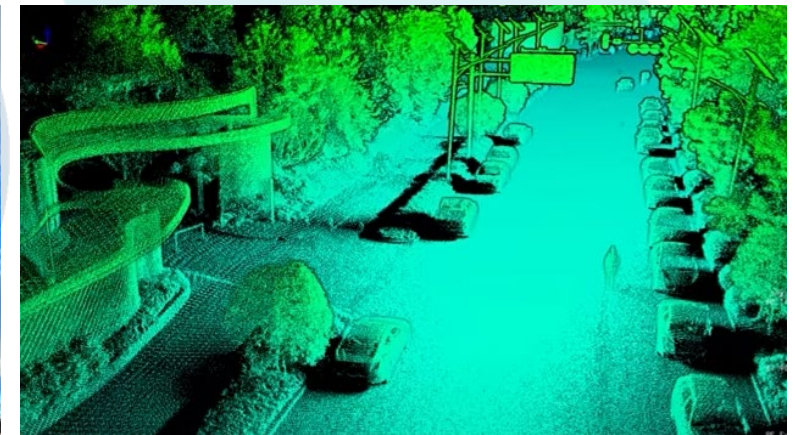
- Limited work on Scan-vs-BIM for automated progress monitoring and materials tracking in construction
- Lack of efficient solutions for processing big reality capturing data and converting raw data into as-built 3D modelling, and building digital twins of infrastructure construction projects



Sydney Light Rail 2019: 2-Year delay and \$1B Cost Overrun



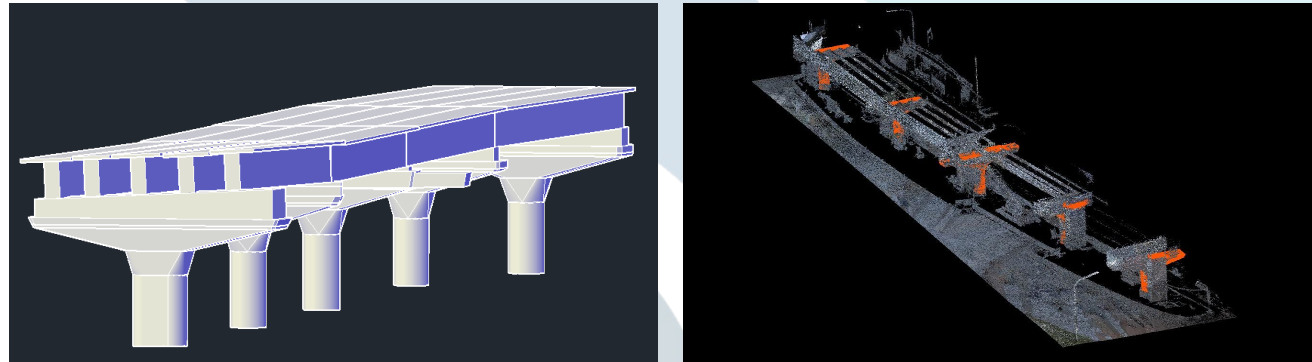
LiDAR-Camera Drone



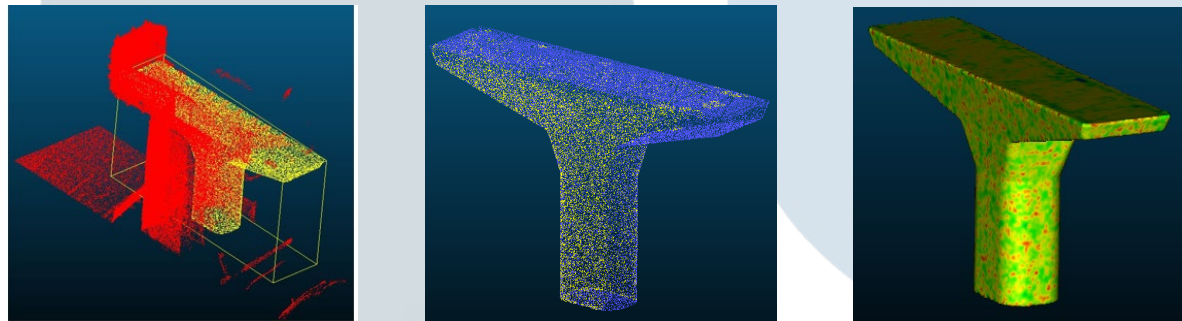
3D Point Clouds of Botany Road in Sydney 37

### Approach & Progress to date:

- RIIS PhD Student: Ziang Jiang
- Key technical Challenge: incompatible data between Scan & BIM
- Hausdorff Distance method is developed to filter out noises from SLAM point clouds data
- 3D reconstruction of bridge element after occlusion repairing



BIM Model and 3D SLAM Point Clouds of Case Project



Point Clouds Data Filtering and 3D Reconstruction of a Pier



Case Study of Overpass Construction at the Gateway Project in Sydney

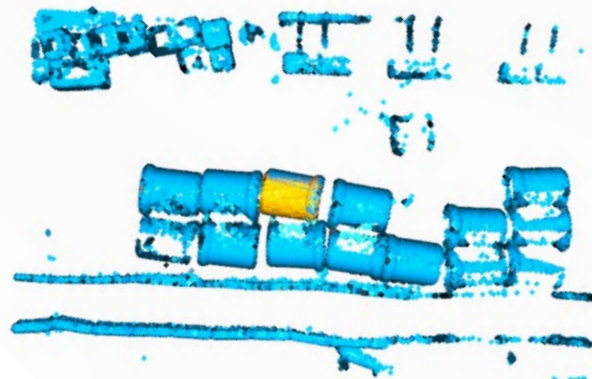


Backpack SLAM Mobile Mapper 38

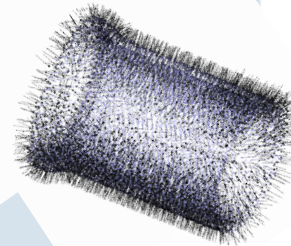
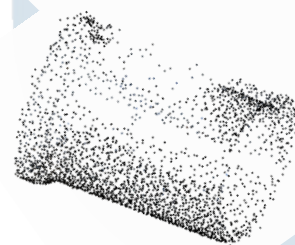
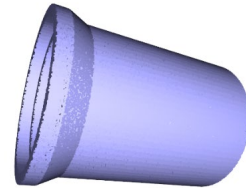
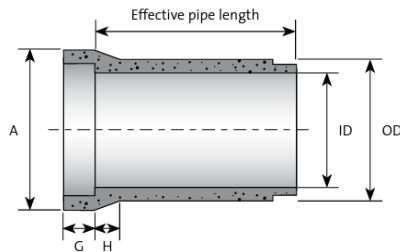


**Approach & Progress to date:**

- RIIS PhD Student: Kartika Nur Rahma Putri
- Key technical Challenge: Identifying and tracking construction materials from mobile LiDAR scan data
- Semantic information extraction of precast material from comparing point cloud data with 3D design



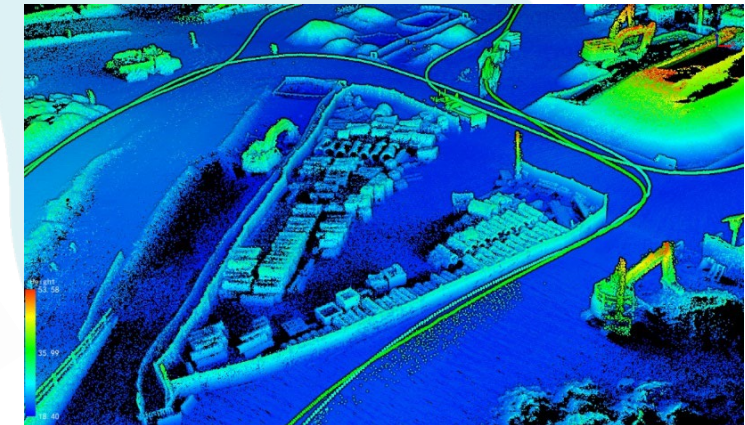
On-site Storage Yard of Precast Concrete Pipes and Raw Scan Data



Semantic information extraction and material tracking of precast concrete pipes



High precision LiDAR Mobile Mapper

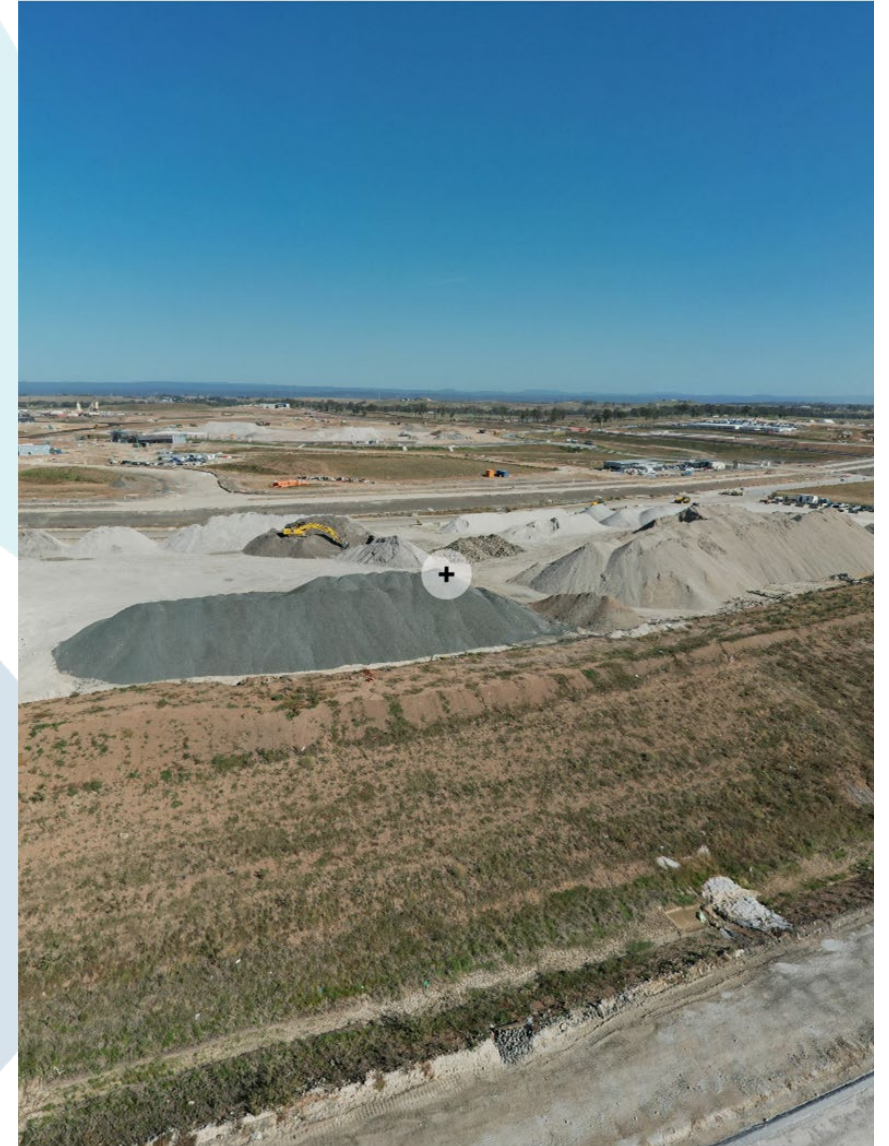


3D Point Clouds of Sydney Airport Gateway Project

## About GeoAI

- At GeoAI, we offer a Comprehensive Solution: From data collection to Digital Twin platforms, we provide end-to-end solutions
- Spatial Data Mastery: Our expertise allows us to recommend optimal solutions by starting with the desired end results
- Maximize Data Potential: Utilize our AI, analytics, and specialized skills to extract added value from collected data

GeoAI





## New Opportunity – Jervis Bay Intersection

- TfNSW Construction Project
- Smart construction POC
  - Weekly 360 camera drive
  - Weekly LiDAR drive
  - Weekly RPAS LiDAR
- Multiple time lapse camera
- Machine monitoring, hours of operation, off hire
- Feed into easy to digest dashboard
  - AI analytics automatically run on data
  - Input to program
  - CONTINUOUS REAL TIME REPORTING



# GeoAI



Transport  
for NSW



**Associate Professor Jagannath Aryal**

**Infrastructure protection utilising real time monitoring of affected catchments by developing predictive models during flash flooding events.**

CI – Jagannath Aryal

Industry – Spatial Vision / Woolpert  
/ Geoscape / Emerson / Rockfield/  
South East Water

Hub Theme 5 / Theme 1

**Project Title:** Infrastructure protection utilising real-time monitoring of affected catchments by developing predictive models during flash flooding events

**Motivation:**

Floods can inflict enormous hardships upon major infrastructures and local communities.

- The flood impacts can be social, environmental, economic, etc.
- Innovative solutions to address the challenges posed by flash-floods through infrastructure health monitoring are in demand.

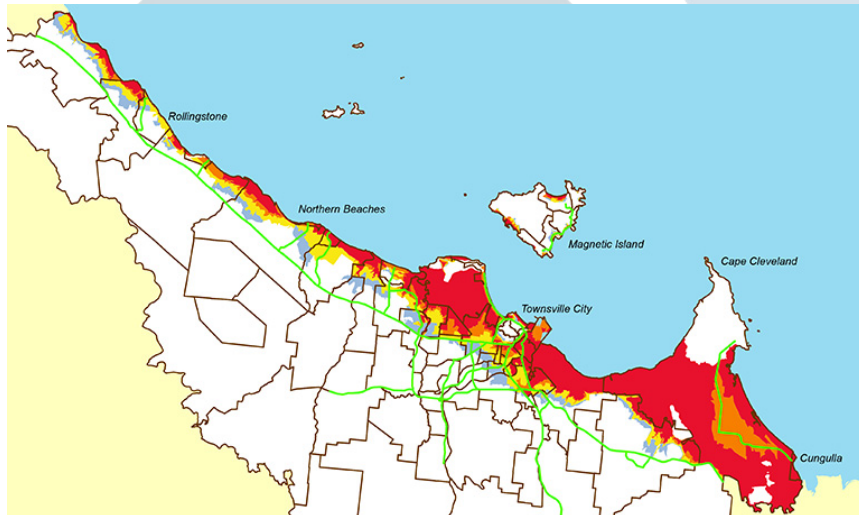


## Aims:

- To revolutionize **flood prediction and mapping**, enabling **spatial and temporal monitoring** through real-time cutting-edge technologies (e.g., **IoT, digital twins, and AI algorithms**).
- To empower communities with timely alerts and **informed decision-making** that ultimately can minimize the socio-economic impact of floods and enhancing overall resilience.

## Deliverables:

A digital twin of Townsville city, showcasing predicted flood maps for multiple time steps ahead, empowering stakeholders to make informed decisions regarding flood preparedness and response.



## Gaps in knowledge:

- Real-time data-driven flood forecasting techniques
- Seamless integration of model outputs with a digital twin platform to visualize and comprehend the predictive outcomes in real-time scenarios



## Approach:

- Leveraging a variety of **machine learning** and **AI-based techniques**, including **deep learning LSTM** algorithm to develop a **predictive model** capable of forecasting water levels at various monitoring stations.
- Generating flood maps using inter/extra-polation techniques for future time steps.
- Integration of model outputs into a **digital twin platform** for visual representations of the predicted flood scenarios, aiding in effective **decision-making** and **infrastructure planning**.

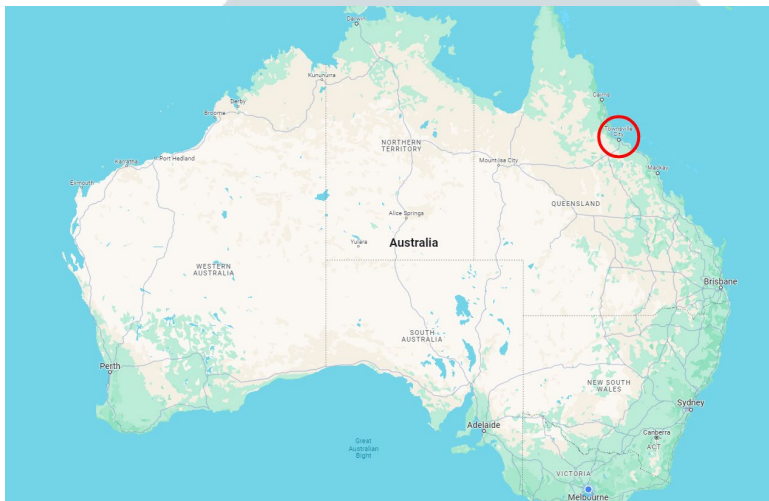


## Progress to date:

- Study site: Townsville City
  - 27 water level sensors
  - 55 rainfall sensors

Rainfall stations					
Aitkenvale	Alligator Creek	Annandale	Aplins Weir	Black River	Black Weir
Bluewater	Bohle River - Dalrymple Road	Bohle River - Hervey Range Road	Garbutt	Gordon Creek	Kirwan (Sandstone Drive)
Little Bohle River	Louisa Creek	Mount Bohle	Mysterton	Paluma Dam	Rollingstone
Rooneys Bridge	Ross River Dam	Saunders Creek	Stony Creek	Stuart Creek	The Lakes
Townsville Harbour	Upper Stuart Creek	Whites Creek			

Rainfall stations					
Aitkenvale	Alligator Creek	Annandale	Aplins Weir	Black River	Black Weir
Bluewater	Bohle River - Dalrymple Road	Bohle River - Hervey Range Road	Brabons	Bushland Beach	Calcium
Castle Hill	Cluden	Cormacks	Cungulla	Deeragun	Garbutt
Gleesons Mill	Gordon Creek	Kirwan	Kirwan (Sandstone Drive)	Little Bohle River	Louisa Creek
MacDonalds	Mount Bohle	Mount Margaret	Mysterton	Nelly Bay	Nettlefield
North Ward	Pallarenda	Paluma	Paluma Dam	Paradise Lagoon	Picnic Bay
Rollingstone	Rooneys Bridge	Ross River Dam	Saunders Creek	South Townsville	Stony Creek
Stuart	Stuart Creek	The Lakes	The Pinnacles	Toolakea	Toomulla
Townsville Airport	Upper Black River	Upper Bluewater	Upper Stuart Creek	Vincent	Whites Creek
Woodlands					



**Progress to date:**

- Methods employed:
  - Linear Regression

- Long Short-term Memory (LSTM) Neural network

Dependent Variable  
(Water Level at t+1)

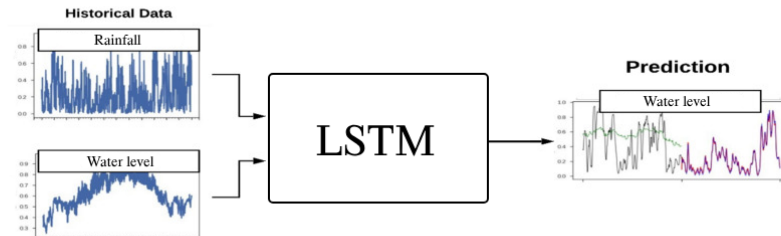
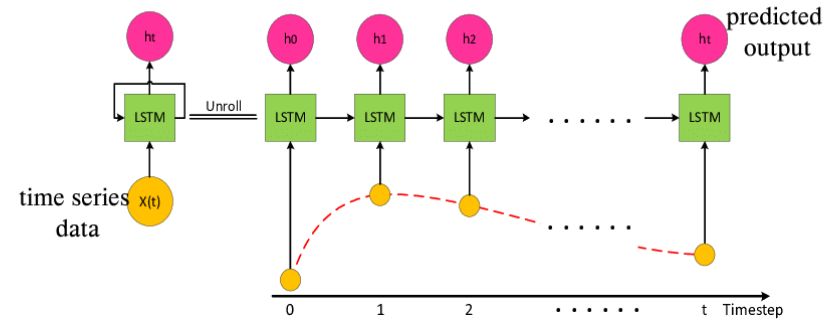
Independent Variable  
(Water Level & Rainfall)

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \epsilon$$

Y intercept

Slope Coefficient

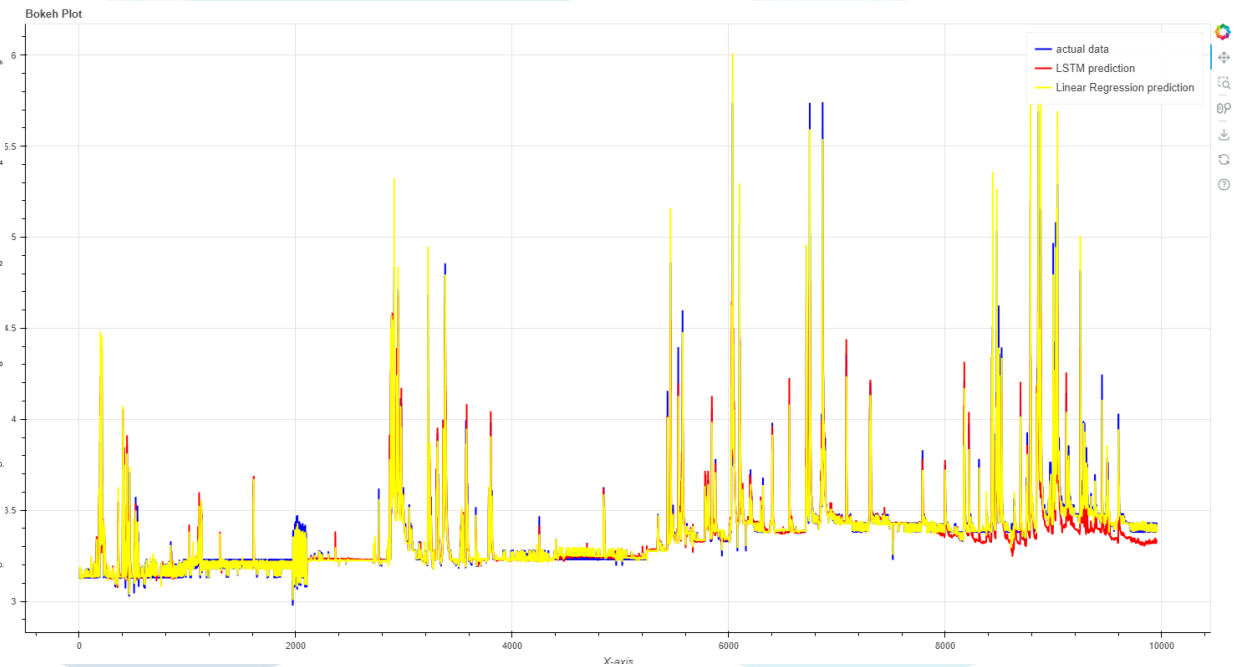
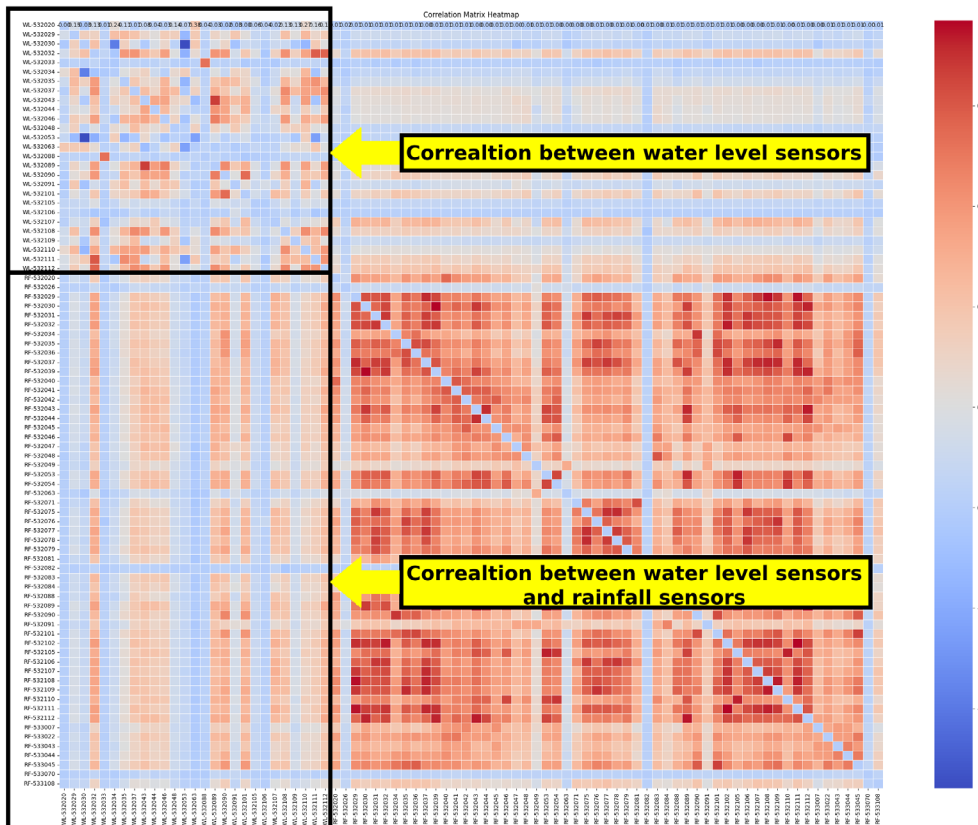
Error Term



### Progress to date (results):

- Identifying associations between rainfall and water level sensors through an in-depth correlation analysis.
- Development of two distinct models to predict water level at the Louisa Creek station using the inputs resulted from the correlation analysis.

Model	Test MSE	Test R <sup>2</sup>
Linear Regression	0.095	0.83
LSTM	0.037	0.67





## Progress to date and ongoing:

- Strong engagements with industries
- IoT data sets pipe-lined to Digital Twin
- Robustness of model performance and consideration of multiple timesteps ahead
- Validation of the model by accessing the records of historical flood events on the site and identifying flood-prone zones
- Development of Graphic User-interface in visualizing real-time flood maps
- Visualization of data and developed model in CSDILA Digital Twin
- Transferring the technology and knowledge developed from Queensland site in Victorian study site.

**Dr Benny Chan**

**Integrating Spatial Digital Twin with  
Automation System in Smart  
Infrastructure Asset Management**



**Project Title:** Integrating Spatial Digital Twin with Automation System in Smart Infrastructure Asset Management

**Event Presenter:** Dr Benny Chen

**Motivation:** A feasible solution for building a spatial digital twin (SDT) platform for key asset management in complex industrial plant environment and integrating with existing industry automation systems.

**Gaps in Knowledge:**

- Reconstruct 3D scene using multisource datasets for industrial environment.
- Key asset recognition and localisation from reconstructed 3D
- Integrate SDT with industrial Process Twin and Control Twin systems.

**Aims/ Objectives**

- MEP (Mechanical, Electrical, and Plumbing) asset recognition and localisation in industrial plant environment
- 3D reconstruction of industrial plant using multisource datasets
- Spatial Digital Twin (SDT) integration with industrial automation systems.
- Fault detection and classification for industrial conveyors using SDT and machine learning
- Improve O&M safety and efficiency by leveraging SDT capabilities

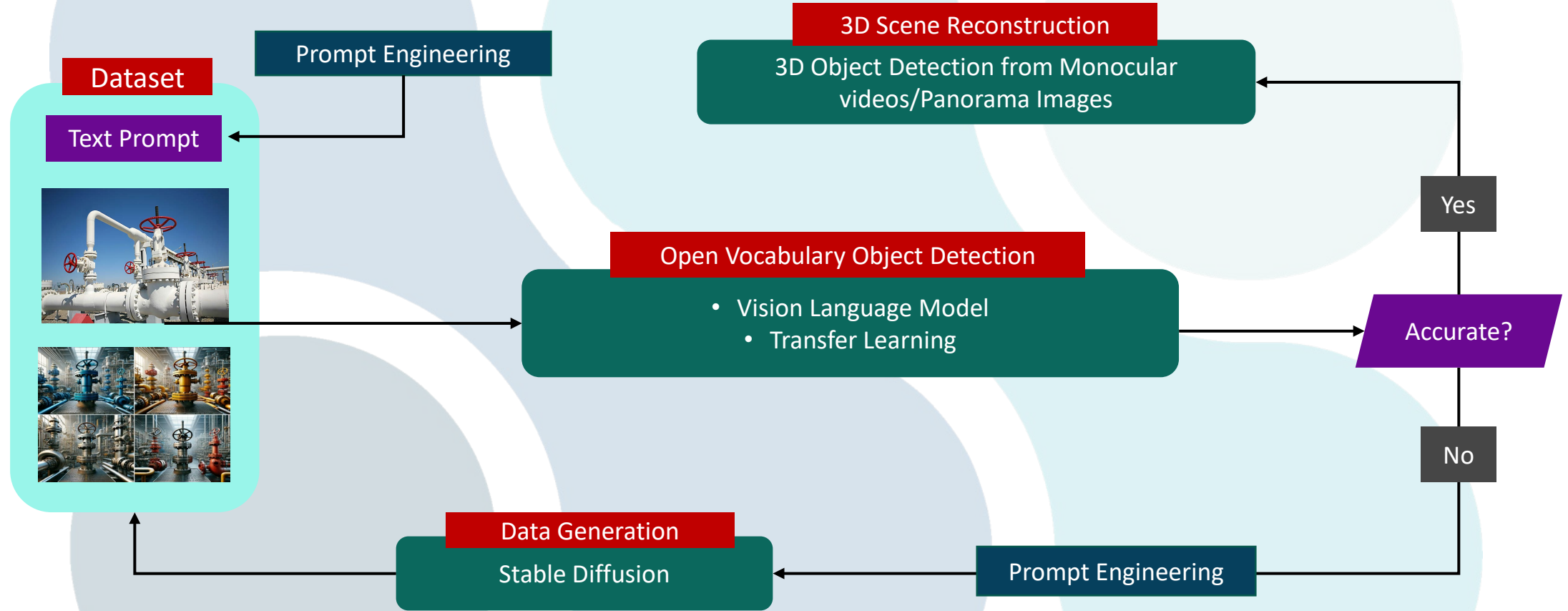


## Expected outcomes

- A semi-supervised object recognition solution for MEP components in industrial plant environment.
- Use vision language foundation models for complex industrial plant environment understanding.
- Use state-of-the-art AI technologies to streamline the 3D reconstruction process of industrial assets.
- Prototype a SDT architecture to integrate multi-dimensional data in industrial plant environment .
- Demonstrate and validate the usability and effectiveness of the conveyor fault detection prototype to improve O&M safety and efficiency.

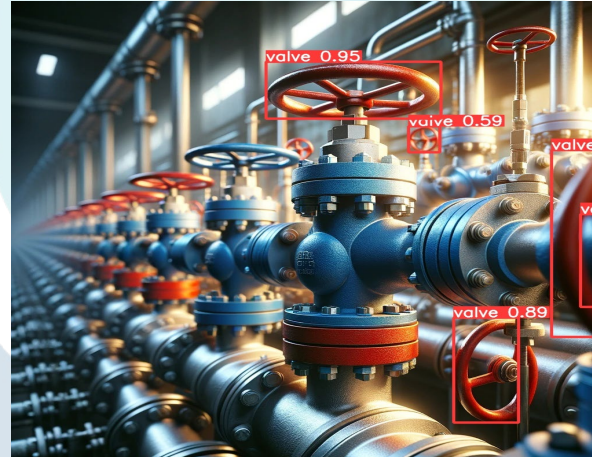


# Proposed Framework (SDT for Industrial Plant Environment )





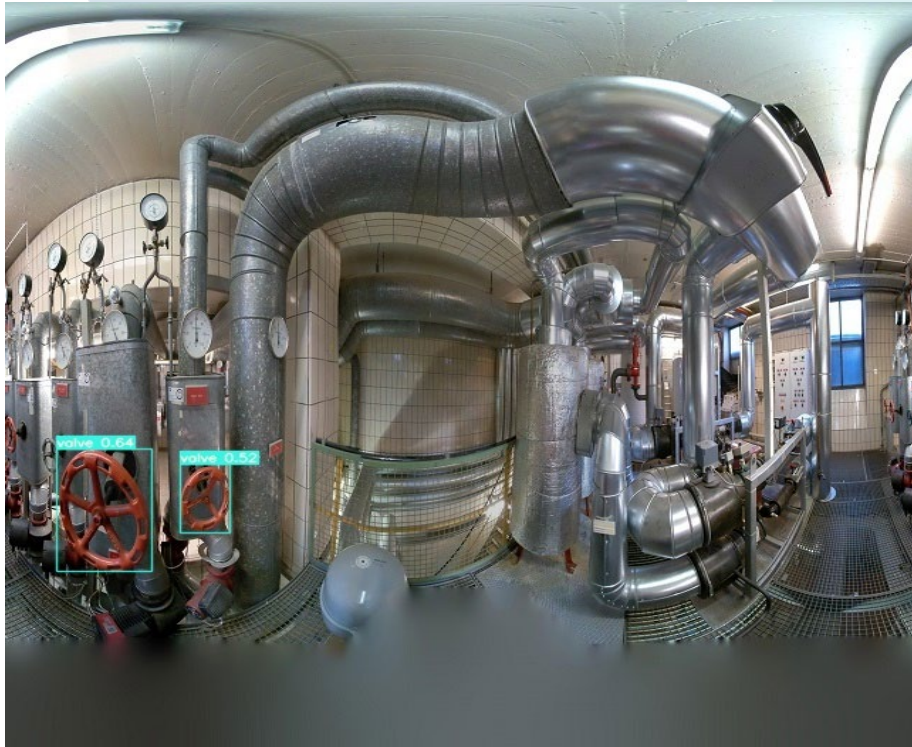
# Progress-to-Date (Results on Zero-shot Detection from Images)



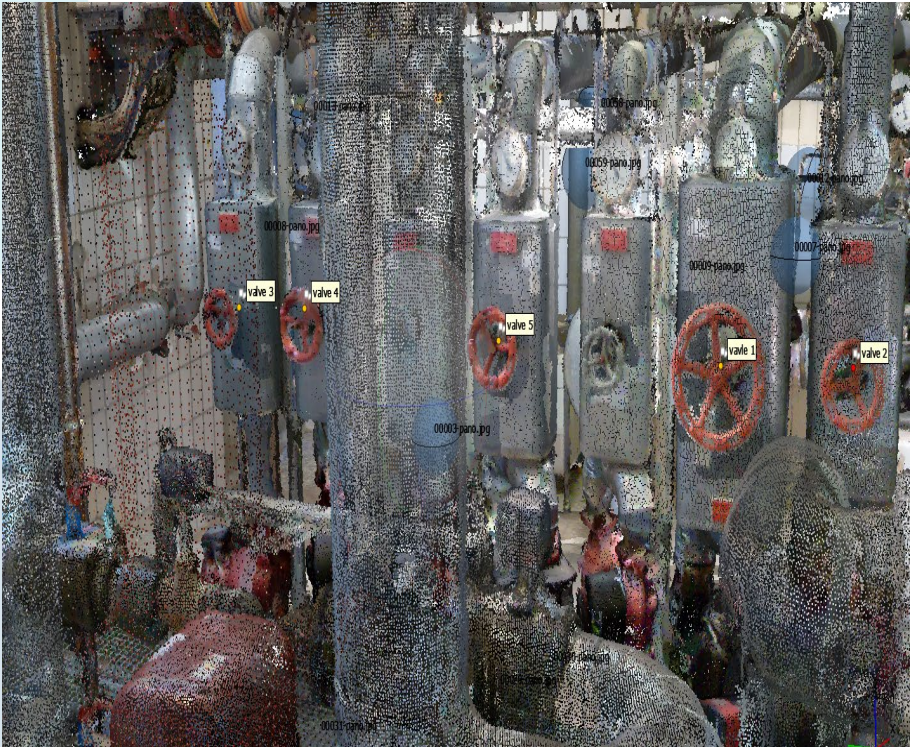


# Progress-to-Date (Results on 2D-to-3D Transformation)

Panorama Image



Point Cloud

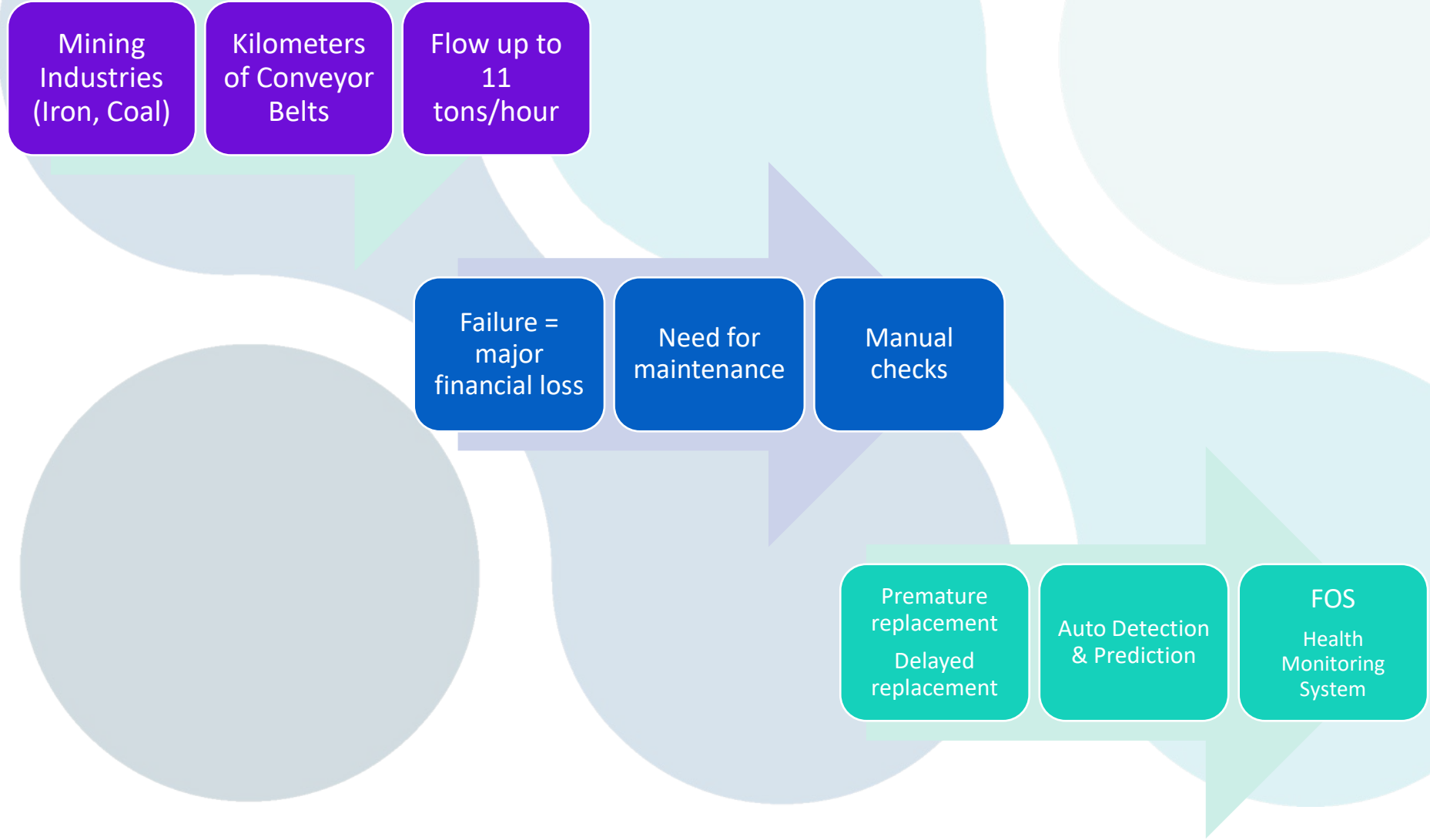


2D to 3D Trans.

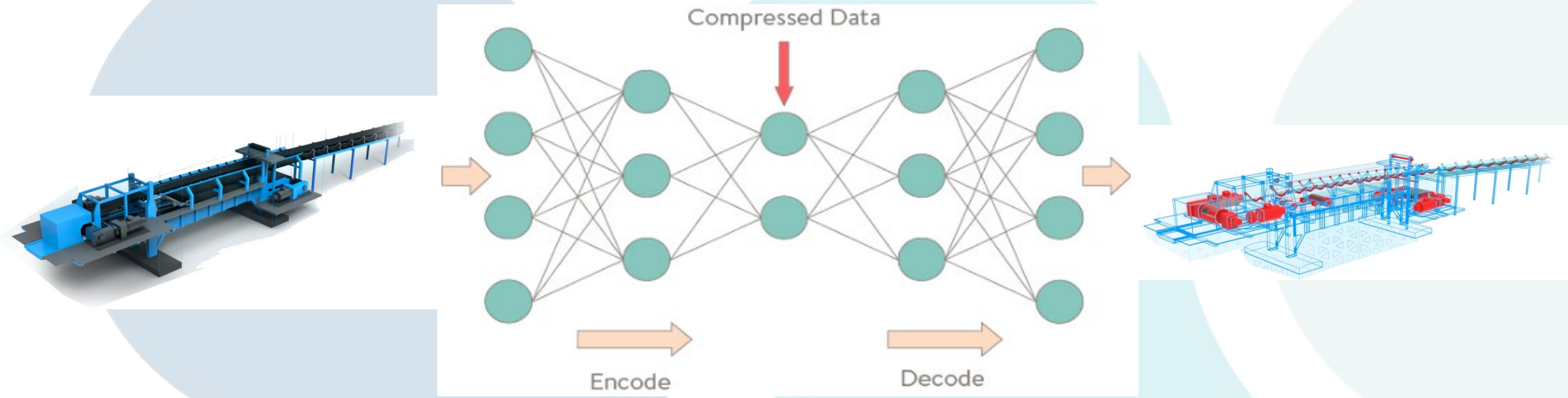




# Progress-to-Date (Conveyor Fault Detection)



# Progress-to-Date (Conveyor Fault Detection)



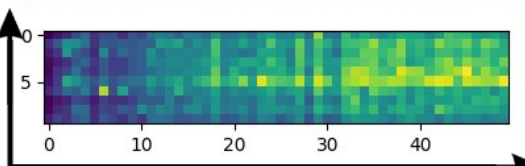
Train and deploy a convolutional autoencoder as a built-in module of SDT

Learn to reconstruct normal behavior of the system

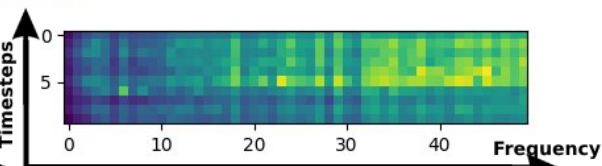
Anomaly detection based on reconstruction error

Performs predictive maintenance

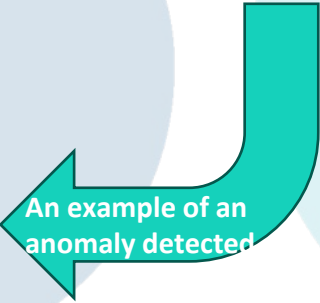
```
time now is: 373
abnormal behavior detected at time = 7 meaning now(9) minus 2 , 10 freuqncies are abnormal in one timestep! more than 13.
333333333333334 %
[16.59635971 13.9649387 15.43716676 22.34508821 13.52514293 17.47155598
13.36082353 17.35751788 15.79952127 14.56322217 17.72127408]
```



Real data for the last 10 timesteps



Reconstructed data for the last 10 timesteps



An example of an anomaly detected





Q & A

**Closing remarks**

**Professor Nasser Khalili**

**“TOWARDS PRODUCTIVE, CONNECTED, SUSTAINABLE AND SMART INFRASTRUCTURE”**



THANK YOU

