AUSTRALIAN NETWORK OF STRUCTURAL HEALTH MONITORING

Newsletter

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Contents

President Message

Tommy Chan

Professor in Civil Engineering, Queensland University of Technology

Dear All,

First of all, let us join together to congratulate Prof Hong Hao that he was elected as a Foreign Member of the Chinese Academy of Engineering (CAE). That was officially announced on 23 November 2023. We were so excited about the news when informed by Prof YC Loo in the middle of our Advisory Board Meeting on the same day of the announcement. All those who attended the meeting were so excited about the news and were able to congratulate Prof Hong Hao, who was there in the meeting. Prof Hong Hao was surprised how the good news could be spread out so fast and we could congratulate him so timely.

Prof Hong Hao, being a member of ANSHM Advisory Board, has been devoting so much to ANSHM since its establishment and he has attended all the ANSHM Workshops and its associated ABMs and AGMs from the first one of the series, either in person or online.

Since its inception in 1996, the Chinese Academy of Engineering has been actively identifying and appointing exceptional foreign experts and scholars as esteemed foreign members. As outlined in the "Articles of the Chinese Academy of Engineering," the criteria for nomination and election as a foreign member are stringent. Prospective members must demonstrate a remarkable proficiency in engineering science and technology, possess an esteemed international reputation, and have made significant contributions to the advancement of China's engineering landscape or played a pivotal role in fostering global exchanges within the engineering science and technology community in China.

The title of Foreign Member in the Chinese Academy of Engineering is undoubtedly the pinnacle of academic honour. Bill Gates, elected in 2017, stands as a notable example of the calibre of individuals included in this prestigious group. Following the recent election, which welcomed 16 foreign members from 8 countries, the total count of foreign members within the Chinese Academy of Engineering is 124 individuals.

Congratulations, Prof. Hong Hao! Your achievement fills us with pride!

Another piece of good news is that Prof Tuan Ngo and his team secured a $2 million Federal Government International Clean Innovation Researcher Networks grant to build a Researcher Network for Decarbonising the Building Industry (DBI) and it was officially launched on 21 November 2023 with Prof Ngo as the Director of DBI. DBI is positioned to play a crucial role in meeting Australia's 2030 and 2050 emission reduction targets and climate goals by significantly reducing emissions in the building industry. Furthermore, it will enhance the supply chain and explore the application of cutting-edge technologies such as artificial intelligence, virtual reality, and the Internet of Things to enhance construction processes and design procedures. I believe with this new role in DBI, Prof Tuan will definitely engage ANSHM working more closely with DBI, as all these new technologies in decarbonisation can rely on SHM to monitor their performance as well as collect new information and develop new knowledge for the future design and construction.

Congratulations, Prof Tuan Ngo! We are proud to have you in our Executive Committee.

Below are the updates for the month.

ANSHM 15th Workshop

The 15th Workshop was a great success! It was held from 23rd to 24th November 2023, at Townsville and hosted by Rockfield Technologies and James Cook University (JCU). Many thanks for the organising committee led by Dr Govinda Pandey, CEO of Rockfield Technologies as the Chair and A/Prof Rabin Tuladhar as the Co-chair. We also thank DBI and EngAnalysis as the separate Gold Sponsors and Monash University as the Silver Sponsor of the Workshop.

The theme of the 15th ANSHM Workshop was Infrastructure Digitisation for Net Zero Transition with Day 1 as The Smart Infrastructure Summit 2023 and the 2nd Day as ANSHM Workshop. Dr Govinda Pandey, the Chair of the 15th ANSHM Workshop made the following statement which summarised well the success of these two days of event:

> *The summit successfully brought together Australia's leading thought leaders, researchers, service providers, and key users of infrastructure monitoring technologies. With over 120 delegates representing more than 30 organisations in attendance, including nearly 50 participants who travelled from various parts of the country to Townsville, the event's substantial turnout underscores its significance and relevance. The key highlight of the event is the resounding emphasis throughout the summit on the pivotal role that technology can and must play in ensuring a decarbonised future.*

Photo 1 Workshop Opening

On Day 1, the Workshop was opened with the Welcoming Speeches by Cr Jenny Hill, Mayor of Townsville City Council and Prof Jenny Seddon, Deputy CV Research of JCU. My speech served partly as a welcoming speech by introducing ANSHM and giving my visions and directions for SHM and ANSHM. Then we had speeches by different Keynote Speakers, in their presenting orders:

- Mr Michael Caltabiano, CEO - NTRO (ARRB)
- Mr Jason Hall, A/Chief Engineer - Energy Queensland
- Prof Ian Atkinson, eResearch Professor JCU and a Futurist
- Prof Brian Uy, Scientia Professor of Structural Engineering – UNSW
- Dr Torill Pape, A/Deputy Chief Engineer Structures, E&T - Dept of Transport and Main Roads
- Dr David Henderson, Chief Engineer - Cyclone Testing Station, JCU
- Dr Sam Mazaheri, Chair Northern Chapter PIANC ANZ and SI Specialist DBCT
- Mr John Vazey - Engineering Manager, EngAnalysis
- Prof Tuan Ngo - The University of Melbourne

All the presentations are very insightful covering SHM applications to roads, houses, buildings, ports and energy infrastructure and the views of the speakers on how SHM could help achieve Net Zero in 2050. We also had the presentations given by A/Prof Rabin on his research on Green Concrete and InfraVision shared their experiences on applying their developed technologies for monitoring powerlines.

We had two panel discussions on the first day with details as follows:

Panel Discussion 1:	Navigating Asset Management Challenges with Ageing Infrastructure: Opportunities and Barriers in Embracing Transformative Digital Technologies
Panellists:	Nigel Powers (ARRB) / Dr Torill Pape (TMR) / Peter Prasad (ARTC) / Kathy Noonan (Energy Queensland)
Facilitator:	Prof Jianchun Li (UTS)

Photo 2 Panel Discussion 1

Panel Discussion 2:	Collaboration Catalyst: Bridging Gaps and Overcoming Barriers Pitches on Industry by Dr Torill Pape (TMR) and Bill Weston (Queensland Rail) followed by a panel discussion on: Towards a Purposeful Industry-University-Government Collaboration
Panellists:	Prof Hong Guan (Griffith) / Mario Martini (CSIRO) / Dr Denise Hodge (JourneyTech) / Greg Bruce (Townsville City Council)
Facilitator:	Dr Ulrike Dackermann

Photo 3 Panel Discussion 2

The two panel discussions gave a lot of insights for those from the universities as well as from the industry to see how we could collaborate to deal with some practical issues on asset management using SHM technologies.

On Day 2, we had the welcoming speech by Prof Ron White, Dean – College of Science and Engineering. Then we had another Keynote Session, presented by the following Keynote Speakers:

- Dr Robert J Heywood, Department of Transport and Main Roads
- A/Prof. Colin Caprani, Monash University
- Dr David Lo Jacono, Jacobs
- Dr Desiree Nortje, Transurban

Followed by a panel discussion:

Panellists:	Dr Robert J Heywood (TMR), A/Prof. Colin Caprani (Monash), Dr David Lo Jacono (Jacobs), Dr Desiree Nortje (Transurban)
Facilitator:	Dr Govinda Pandey

After the Keynote Session, we had the traditional workshop presentations arranged into two parallel sessions, one in the morning and the other in the afternoon, with a total of 24 presentations.

Please click the link for the event booklet giving you more details on the 15th ANSHM Workshop, serving as a memento of the memorable summit for those who attended the Summit, and serving as an information booklet for those who had not attended. I received many kind words with positive comments about these two days events. Actually, all the commendations should be given to Dr Govinda Pandey and his organising committee, and the ANSHM Executive Committee members for their assistance. One important point is that,

Don't miss any of our ANSHM Workshops!

Govinda is working on sharing the recorded video, presentation pdfs, and photos and they will be uploaded to www.ANSHM.org.au as soon as they become available. I will let you know once it has been done.

The Advisory Board Meeting 2023

As our tradition, the Advisory Board Meeting (ABM) was held on the first day of the 15th ANSHM Workshop, at the Boardroom of James Cook University City Campus. The Boardroom is a moot court arranged purposedly to simulate a court environment.

Photo 4 The AGM was held at JCU Boardroom, a Moot Court with me a judge…

Photo 5 ...and the Board Members were like a jury 😉

Below show some outcomes of the ABM.

a) New Advisory Board Members

In the last Advisory Board meeting, we identified few key persons working in the field of SHM to be invited as our additional Advisory Board members. Two of them are Dr Desiree Nortje, Principal Asset Manager- Civil Structures, Transurban and Mr Isaac Scot, Manager Contracts and Structures, Brisbane City Council. Desiree attended the 15th ANSHM Workshop, so I could approach her quickly and she was so pleased to accept the invitation. I also contacted Isaac and he was also pleased to accept the invitation. I believe that both Desiree and Isaac could definitely help ANSHM to know better how SHM could meet the needs of the industry and strengthen our relationship with the industry. I will continue to approach the other person identified and invite her to serve on the ANSHM Advisory Board.

Desiree and Isaac, welcome on board!

b) Research Collaboration

In the meeting, we also discussed about how we could establish a more effective platform for research collaboration. Since ANSHM has been established for more than 14 years and we have devoted members from the universities, research organisations, government bodies and private sectors, we have developed an excellent atmosphere for academics collaborating with the industry as well as an exceptional team spirit within the Executive Committee, the Advisory Board and with other ANSHM members. It's about the time to go a step further, applying for the ARC Industrial Transformation Research Program grants to establish either an Industrial Transformation Training Centre or an Industrial Transformation Research Hub.

According to ARC,

Industrial Transformation Research Hubs (ITRH) Scheme funds Eligible Organisations to undertake cutting-edge research on new technologies and economic, commercial and social transformation to benefit industry partners in the Industrial Transformation Priority areas;

and,

Industrial Transformation Training Centres (ITTC) Scheme provides funding for partnerships between university-based researchers and those in industry. ITTCs provide Higher Degree by Research (HDR) and postdoctoral training for industries vital to Australia's future.

After a thorough discussion in the last AB meeting, we decided to go for an ITTC, as nearly all from the industry, especially those from the road authorities, considered it would help the industry to train more engineers, researchers and other SHM related personnels working for this expanding field of SHM and meeting the markets need, as well as conducting research to solve some of the SHM issues and make the SHM wish list of the industry come true. I am so pleased to see that it was so supportive within the board. I believe that our Advisory Board members from the industry will not only engage their organisations to be the Partner Organisations of this Centre and they will also work with the academics to approach potential Industry Partners (PIP) and prepare a strong proposal.

Our timeline for working on this ARC ITTC proposal submission is as follows:

i. February to April, 2024 – Plan for preparing the proposal
ii. April to July, 2024 – approach PIPs
iii. July, 2024
    i. Obtain some letters of support
    ii. Workshops to publicise the ITTC
iv. August – October, 2024
    i. ARC announces Rules and Calls for submissions
    ii. Proposal Preparation
    iii. Collection of Letter of Support
v. November, 2024
    i. Drafts for Review in early November
    ii. Submission in November

Your suggestions are welcome.

The 14th ANSHM Annual General Meeting

The 14th Annual General Meeting (AGM) of ANSHM was conducted on the 2nd Day of the 15th ANSHM Workshop. Because of the space, I could only report the two outcomes of the AGM.

a) Election of Executive Committee Officers

Prof Alex Ng, Dr Andy Nguyen, Aspro Colin Caprani, Aspro Jun Li, Aspro Lei Hou, Dr Mehrisadat Makki Alamdari, Prof Richard Yang, and Dr Ulrike Dackermann, whose term of service would be expired by end of 2023 and were all nominated to serve in the EC for another two years (2024-2025). All the 8 EC members were re-elected to serve in the committee for another 2 years. Hence the Executive Committee in 2024 will consist of the following officers:

- Tommy Chan (President)
- Jianchun Li (Deputy President)
- Alex Ng
- Andy Nguyen
- Colin Caprani
- Hong Guan
- Jun Li
- Lei Hou
- Mehrisadat Makki Alamdari
- Richard Yang
- Tuan Duc Ngo
- Ulrike Dackermann
- Xinqun Zhu

b) Subscription Fee

I am so pleased to inform you that we have decided the annual subscription fee for 2024 will continue to be null.

Because of the space, I need to stop here, and I will report the other outcomes of the ABM and AGM in the coming monthly updates. In the next sections, we will have two articles from our members. The first article is from RMIT University on Leveraging deep learning for condition assessment of stormwater Infrastructure assets. The other article is from Western Sydney University on the development of a risk ranking method for rail ultrasonic testing management. A/Prof Colin Caprani, our Guidelines and Specifications Task Force in-charge also gives his thoughts on what the Monitoring aims in the model specifications for Structural Health Monitoring should include. You are also welcome to give feedback and suggestions after reading Colin's statements.

With kind regards,
Tommy Chan
President, ANSHM
www.ANSHM.org.au

Leveraging Deep Learning Technique for Condition Assessment of Storm Water Infrastructure Assets

Abdulgani Yussuf[1], Haosen Chen[1], Nilmini Weerasinghe[1], Lei Hou[1] and Kevin Zhang[1]

[1]School of Engineering, RMIT University

Abstract

Urban infrastructure relies heavily on efficient stormwater pipe infrastructure to manage surface water runoff and prevent flooding. Condition assessment, regular maintenance and inspections are crucial to ensure these systems maintain acceptable levels of condition. The current manual approach is labour-intensive, time-consuming, and prone to errors. Smart condition assessment of these systems offers a multifaceted solution improving efficiency and environmental sustainability. In this regard, this research employed a deep learning application to automate the defects identification process. CCTV images of stormwater pipelines were incorporated to train the neural network model. The model was developed with a mean average precision score of 0.875. The model offers a cost-effective, time-efficient, and reliable approach to pipe inspection, providing immense value to asset managers and ensuring the safety and functionality of the stormwater infrastructure.

Introduction

In an era of rapidly adopting smart technologies, most traditional and manual practices are undergoing a transformation into smart approaches. Condition monitoring and inspections of urban infrastructure assets that are complex systems span over a large geographical area require careful management to ensure efficient maintenance while preserving their conditions. Current inspections are performed using closed-circuit Television (CCTV) technology with the support of skilled personnel. A huge amount of data (images and videos) is generated daily and the intervention of experts in this field is required for interpreting these datasets. Determining the condition of systems is important for predicting future conditions and efficiently maintaining the systems. However, conventional manual processes are time-consuming and labour-intensive. The recent advancements in computer vision and deep learning technologies enable it to transform into a smart condition monitoring system. As an initial step, this study develops an automated condition detection system for stormwater assets.

Recently, a few studies have utilised image processing and deep learning techniques to automate the condition assessment of civil infrastructures such as pipelines, bridges, roads, and tunnels [1-3]. Moselhi [4] employed image processing and neural networks for automated stormwater defect detection. Yang [5, 6] introduced a crack detection model incorporating a support vector machine. In addition to traditional machine learning algorithms, many recent studies have adopted deep learning techniques for condition detection. For example, Cha [7] developed a model for concrete crack detection and Hawari [8] created a model for identifying stormwater damages. Similarly, various studies have leveraged deep learning and computer vision techniques for condition assessments of infrastructure assets. Deep learning is particularly advantageous for building models with large and complex datasets, which results in enhanced performance [2].

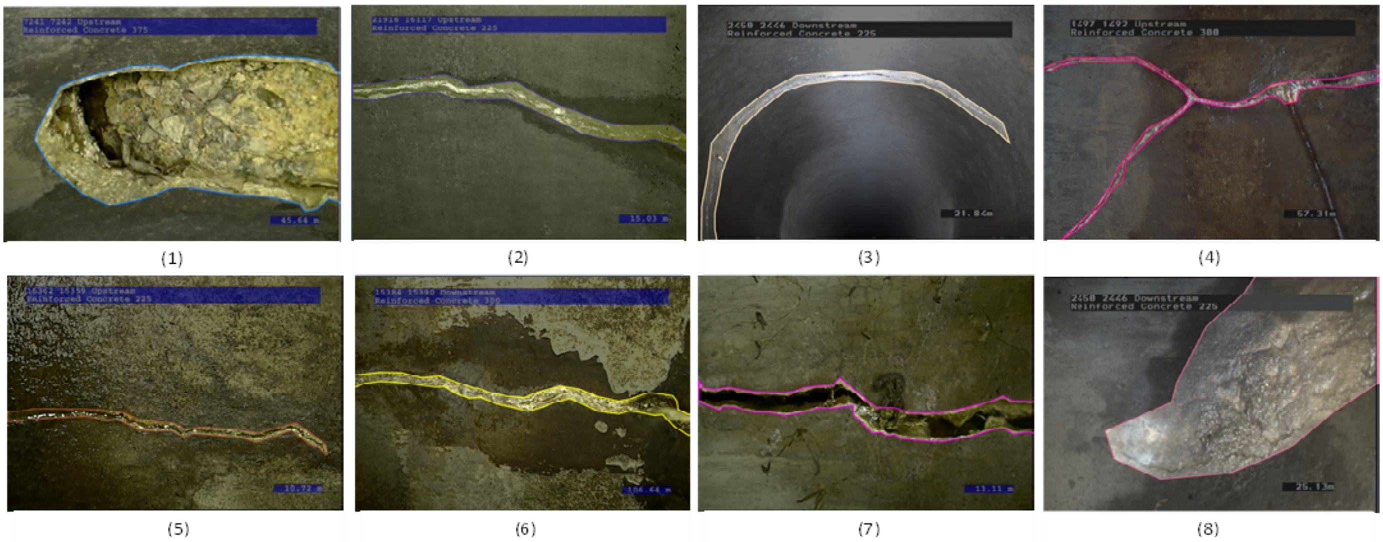
Developing an accurate and efficient detection system for condition assessments presents several challenges, mainly due to the influence of various factors. Some of these challenges include the dynamic nature of cracks (morphology, shape, magnitude), the scarcity of sufficient and real-world data for model execution and issues related to data acquisition systems (positions of cameras, etc.) [2]. The novelty of this study lies in the utilization of a new data set for implementing deep learning models. Also, the defect detection process is achieved by segmenting unknown images into 19 classes, allowing for the assessment of pipeline conditions to be identified by the width of cracks and spalling. Further, the high accuracy levels of the proposed model, with a large number of training data samples, contribute significantly to the knowledge in this field.

Model development

This research employed the convolutional neural network (CNN) technique, which is a state-of-the-art deep learning model used to detect images. CNN is highly regarded for its effectiveness in image detection and has been widely applied in various fields, including face recognition, object detection, medical research, and civil engineering applications. Deep learning-based methods for crack detection are typically categorised into image classification, object localization, and semantic segmentation. In this study, segmentation, a cutting-edge computer vision technique, was harnessed to enhance defect detection in various infrastructures resulting in improved performances [2, 9].

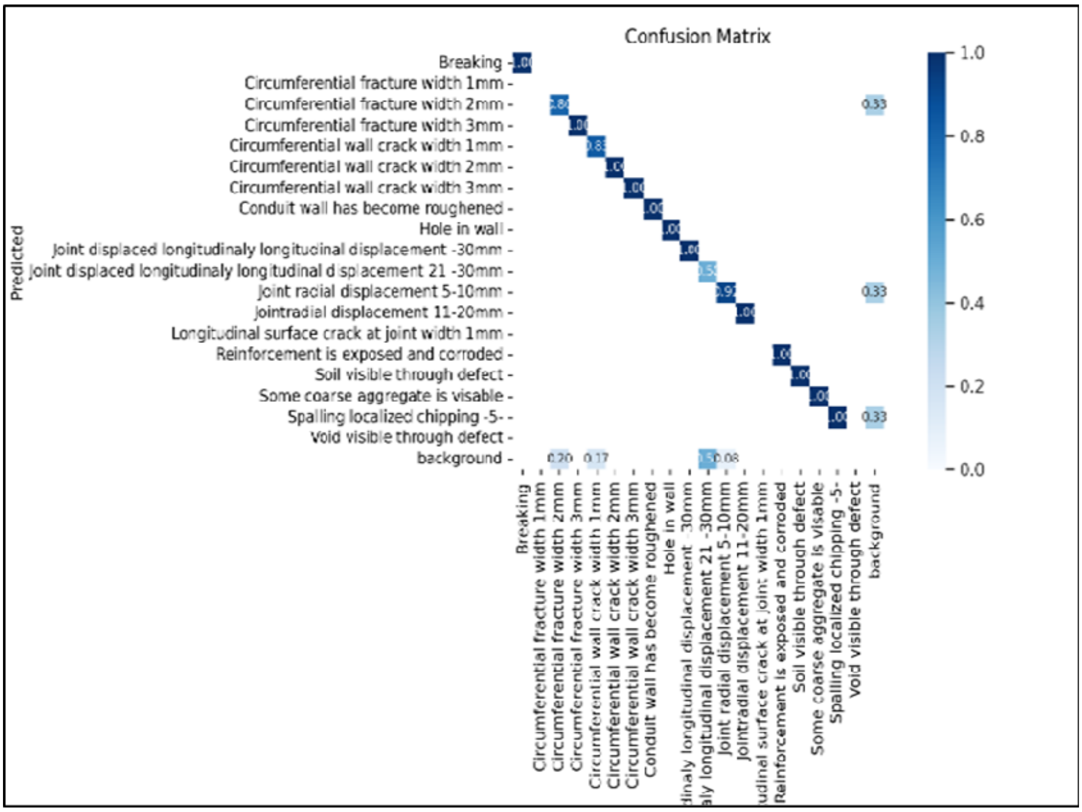
The model development process consisted of four steps: data preparation, data preprocessing, model training, and model evaluation. The first step: data preparation. This study collected the CCTV video recording of stormwater pipeline inspections from Banyule Council. The image frames were then extracted from those CCTV videos using FFmpeg [10] an open-source software. These images need to be labelled for input into the model. The images annotation was carried out through the Roboflow platform, which offers robust capabilities for managing and preparing datasets for machine learning applications. It was noticed that an expert person had been involved in defining defects of pipelines in some of the videos. These judgments adhere to the WSA code standards. These data were also considered in the annotation process, ensuring high accuracy. The identified defects were categorised into 19 classes representing different widths of fracture, wall roughness, joint radial displacement, spalling and more. To eliminate the data imbalances, a similar sample size of images was taken for each category. Some of the annotations can be seen in Figure 1. To further maintain the accuracy of the data set, an image augmentation technique was implemented. Augmentation method such as flipping, 90-degree rotation, and random cropping was applied when generating images. In total, 1073 non-augmented images and 2789 augmented images were prepared for the model training.

Fig. 1 Data classification



The next stage involved data preprocessing, which delivers the building of the model. YOLOv8 using Google Colab, a scalable and cloud-based platform for model training, was employed. YOLOv8 is an architecture designed for implementing CNN in large-scale image classification tasks [11]. It is particularly well suited for semantic segmentation tasks, making it ideal for defect detection within stormwater pipes. Subsequently, the model was trained with the prepared datasets. The distribution of data into training, validation, and testing subsets in this research was efficiently carried out within the Roboflow platform. It is notable to underscore the significance of the training data sample as the cornerstone of any machine learning undertaking. In this research, the non-augmented dataset was divided into an 80:10:10 ratio for training, validation, and testing samples, while the augmented data set was split into a 92:4:4 ratio. CNN possesses various hyperparameters. This study focuses on the hyperparameters of epochs. The epoch represents the number of times a machine learning model processes the entire training dataset. Within the scope of YOLOv8, this research strategically assesses the impact of epoch values on the model's accuracy and overall performance. A standard value is kept for other parameters. The base epoch value for YOLOv8 on the Google Colab environment was initially set at 25. In the pursuit of precision, this research systematically investigates the model's efficacy when subjected to 50 epochs. For instance, for epoch 25 with the YOLOv8s (small) framework, the training duration extended from approximately 25 to 35 minutes. In contrast, for epoch 50, the training time ranged between 1 hour and 15 to 20 minutes. These varying training times highlight a significant aspect of the research, capturing the trade-off between efficiency and computational demands.

By analysing the impact of epoch adjustments, the research unveils the temporal dimension of model evolution, drawing forth insights into the nuances of model training, accuracy, and computational requirements. Various well-recognized evaluation metrics were employed, including precision, recall, F1 score, Mean Average Precision (mAP) and confusion matrix as the next step of this research: performance evaluation of the model. In conclusion, while the 25-epoch models provide respectable results, the 50-epoch models, especially the one without augmentation, emerge as the most effective in detecting and localizing stormwater defects for the confusion matrix graph. The mAP50 at 0 epochs was 0.875. The results of the precision-recall curve and confusion matrix are illustrated in Figure 2. The condition assessment of the model was successfully built for the stormwater pipelines.



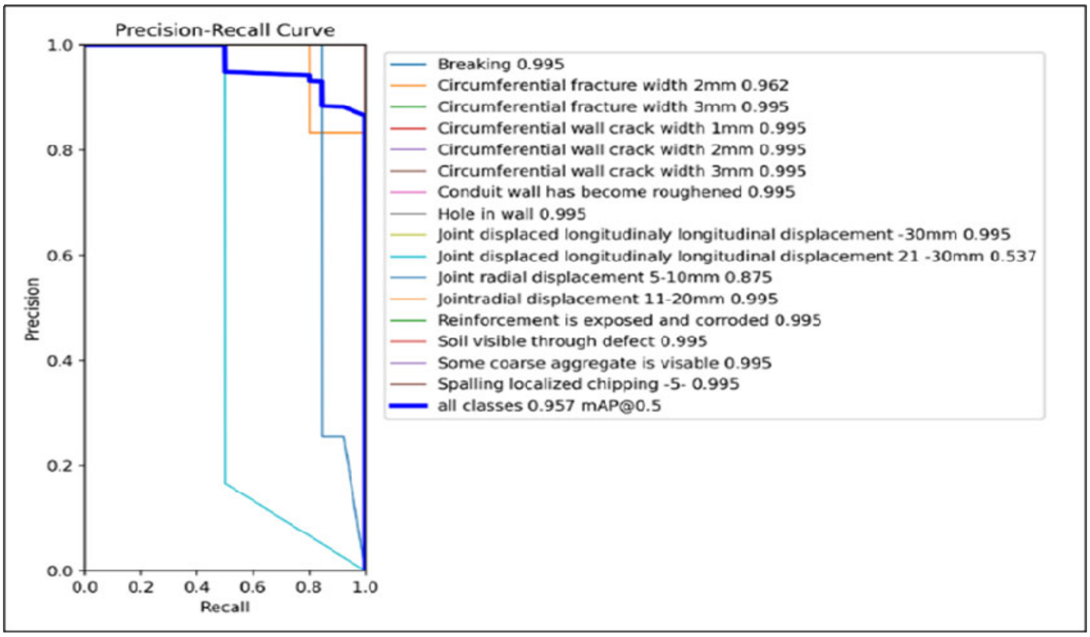


Fig. 2 Model evaluation using confusion matrix and precision-recall curve

Conclusion

The proposed model lays a robust foundation for assessing the condition of the stormwater infrastructure assets. However, it is important to note that this research is still in its early stages, and the model requires further improvements. Regular refinement of the hyperparameters, such as learning rate, is essential to even more precise detections. Extending the model capability to assess serviceability-related issues can further enhance its utility in infrastructure management. Additionally, developing real-time capabilities can lead to quicker response times and more proactive maintenance strategies. This research provides a promising starting point, and further developments hold the potential to make this model an even more valuable tool in the field of infrastructure asset management.

Acknowledgment

We acknowledge the Banyule City Council for providing the data on storm water pipe infrastructure assets to perform this research.

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AUSTRALIAN NETWORK OF STRUCTURAL HEALTH MONITORING
Newsletter

The Development of "Risk Ranking - Prioritization Matrix" Method and Its Application for the Rail Ultrasonic Testing Management

Ralph Zhang[1], Helen Wu[2] and Richard Yang[3]
[1, 2 ,3] *School of Engineering, Design and Built Environment, Western Sydney University*

Introduction

Rail internal failure related derailments are a major class of derailments costing, within Australia, efforts have been made to minimize service failures and risk of derailments, through more often and more effective ultrasonic testing. The major Australian railway authorities have issued explicit regulations of the schedules for a continuous search for internal rail defects. These regulations provide a minimum guideline for test frequency scheduling, and some railway corridors test more frequently to minimize the probability of service defects (broken rails) occurring, thus minimizing the risk and cost of derailment. However, due to the availability of the possessions or traffic planning reasons, as well as the capability and/or breakdown of the ultrasonic testing vehicles, the planned rail testing work cannot be finished within the schedules and overdue was happened. The non-compliance rail ultrasonic testing track sections have left high risk of rail broken and derailments, which is a critical issue and must be processed by additional rail testing works in a very short time frame.

Fig. 1 The ultrasonic testing vehicle

Concepts of the "Risk Ranking and Prioritization Matrix"

To minimize the potential risks caused by the non-compliance rail ultrasonic testing, a risk assessment-based prioritization and updated testing plan are developed. This technical solution is by using a so-called "Risk Ranking - Prioritization Matrix" model to undertake the data process of the non-compliance rail sections.

Regarding the risk ranking model, based on the standards of track maintenance and practices from all the major railway authorities in Australia, the potential risks of ultrasonic testing plans are mainly affected by two factors - the frequency and the condition of rail (e.g., the fatigue of rail materials, which is presented by the number of defects that has been found in per km of track in the history). In addition, considering the severe rail head wear distortion can alter the normal angle refraction of the ultrasonic probes, the impact of rail wear conditions has also been included within the risk ranking model.

To finalize the analysis by combing the final scores of risk-ranking of "frequency & overdue date", "rail defects & critical defects" and "condition of rail wear", a prioritization matrix is developed to "weight" the priorities for every non-compliance track section.

Raw Data and Pre-Processing for Analysis

The length of these individual non-compliance track sections can be varying from the minimum 0.010km to the maximum 50km, and, the involved tracks including main lines, loops, and yard crossover points, etc. Before the data process, all the non-compliance rail ultrasonic testing track sections and the locations of the defects are arranged by tabulating them in Microsoft Excel Spreadsheet with the information of "Description of the Track Section", "Start km", "End km", "reason missed", "frequency", "latitude", "overdue date", "overdue cycle represented by %", "number of defects" and "number of critical defects" within each specified track section which were found in the past, etc.

In addition, the re-railing program is provided as the reference to be utilized to confirm if the defective rails that were listed in the non-compliance rail sections have been replaced since they have been found by the ultrasonic testing vehicle that ran in last time. The raw data of non-compliance rail ultrasonic testing track sections were pre-processed by deleted all the rail defects that have been replaced by the previous re-railing works by means of cross-checking the mileage of the re-railing sections and the locations of the existing rail defects.

Finally, all the rail defects which exist in these non-compliance track sections and among them how many defects can be categorized into the level of "critical defects" need to be worked out. The critical defects are defined and included as showed in the Table 1.

Table 1: Definition of the types of critical defects

Types of Critical Defects			
Code	Location within Rail	Size	Description of Rail Defects
HSH	Head	S	Horizontal Split Head 25 to 100mm
HSH	Head	M	Horizontal Split Head 101 to 200mm

Types of Critical Defects			
Code	Location within Rail	Size	Description of Rail Defects
HSH	Head	L	Horizontal Split Head over 200mm
HSW	Web	S	Horizontal Split Web 20 to 40mm
HSW	Web	M	Horizontal Split Web 41 to 75mm
HSW	Web	L	Horizontal Split Web 75 to 150mm
HSW	Web	E	Horizontal Split Web over 150mm
TD	Head	M	Transverse defect 11 to 30%
TD	Head	L	Transverse defect over 30%
TDX	Head	S	Multiple Transverse Head Defects 5 to 10%
TDX	Head	M	Multiple Transverse Head Defects 11 to 30%
TDX	Head	L	Multiple Transverse Head Defects over 30%
VSH/IB	Head	N/A	Vertical Split Head < 50mm in length or up to 3mm in height
VSH	Head	S	Vertical Split Head 50 to 200mm
VSH	Head	M	Vertical Split Head 201mm to 400mm
VSH	Head	L	Vertical Split Head over 400mm
VSH	Head	E	Vertical Split Head Visible cracking or rail head collapse
VSW	Web	S	Vertical Split Web longitudinal Any registration in one rail length

Methodologies & Technical Details for the Modelling

Based on the standards of track maintenance and practices from all the major railway authorities in Australia, the potential risks of ultrasonic testing plans are mainly affected by two factors - the frequency and the condition of rail (e.g. the fatigue of rail materials, which is presented by the number of defects that has been found in per km of track in the history). Regarding to the risks from the frequency, both of the frequency itself and the overdue situation need to be considered and ranked.

Risk Ranking Based on Frequency

The frequency is dominated by the importance of the railway tracks in the whole network. The more important tracks have higher ultrasonic testing frequency. Focus on the railway networks of Australia, the risk ranking based on testing frequency is tabulated as following:

Table 2: Risk ranking based on frequency

Risk Rank (Score)*	Consequences	Frequency of Ultrasonic Testing Vehicle
3	Band 1	2
3	Band 1	4**
2	Band 2	6
1	Band 3	12

Note: * Highest number is highest priority.
** Standard ultrasonic testing schedule for the 1 class track

Risk Ranking Based on Overdue Date

Because of the availability of the testing (such as overdue) can significantly impact to the levels of risk that based on the scheduled test plan, hence, the risks from overdue time needs to be considered and ranked. The Overdue of the testing in the ultrasonic test management is represented as "Overdue %", and calculated as:

$$\text{Overdue Date in \%} = [(D_{Today} - D_{LT})/121] \times 100\%$$

Where:

D_{Today} - The Date of Today;

D_{LT} - The date of last test (for the testing frequency of 12 months and 6 months tracks, the D_{LT} value are modified by subtract 360 days and 180 days respectively);

The 121 days are used to represent the time interval of 4 months, which is the standard ultrasonic testing schedule for the 1 class track. The additional risks from overdue are ranked (can be seen as the "weight" of the risk ranking scores of the frequency) and tabulated as following:

Table 3: Risk ranking based on overdue date

Risk Rank (Weight of risk rank of frequency)	Consequences	Overdue days of Ultrasonic Testing Vehicle (Overdue days represented by %)
5	Band 1	≥ 200%
4	Band 2	< 200% and ≥100%
3	Band 3	< 100% and ≥50%
2	Band 4	< 50% and ≥0%
1	Band 5	< 0%

Updated Risk Ranking by the Combination of Frequency & Overdue Date

As pre discussed, because of the internal correlation of the risk of frequency and overdue date, risk ranking is further calculated by multiply them for each track section, i.e. calculate weighted scores for each track section as "score × weight".

Risk Ranking Based on Rail Defects

From the practices of routine maintenance of track, conclusions have been drawn for that the fatigue condition of rails (e.g. the fatigue of rail materials, usually is presented by the number of defects have been found in per km of track in the history) are directly related to the likelihood of rail broken/failure, hence, the risks from rail fatigue conditions must be included into the risk assessment.

Based on the available data of rail internal defects within a railway authority's network those have been found by ultrasonic test in the history, for each non-compliance track sections the average defects per km were calculated for further analysis. And, the risk ranking based on rail fatigue conditions is shown in Table 4.

Table 4: Risk ranking based on rail defects that found in the history (number of defects)

Risk Rank	Likelihood	Rail defects/km that found by the ultrasonic test vehicle (number)
5	Almost certain	Higher or equal to 10
4	Likely	≥7 & <10
3	Possible	≥4 & <7
2	Unlikely	>0 & <4
1	Rare	0

Risk Ranking Based on Critical Rail Defects

For the risk assessment that caused by the rail internal defects, there is no doubt for that the different types and size of the defects should have the different "analysis weight" for the risk assessment. So, the numbers of critical defects among the defects that have been found in the history by ultrasonic test are risk ranked as shown in Table 5.

Regarding to the threshold of the critical defects for this analysis, according to the risk based theory used for scheduling ultrasonic test frequencies which is developed by the US Department of Transportation (DOT), the number of "0.1 'Service' (i.e. 'Critical' in Australian railway) defects/mile" is acknowledged as the allowable baseline for US freight line. And, the risk value for "US Freight Average" and "Low Speed Passenger Service" are 0.1 and 0.03 respectively, i.e., the risk ranking weight of "Low Speed Passenger Service" is 3.33 times higher than the track which is predominated by freight traffic. Hence, the threshold value is set by: (0.1 / 1.6) / 3.33 = 0.0188 ≈ 0.02 critical defects/km.

Table 5: Risk ranking based on critical rail defects that found in the history (number of defects)

Risk Rank	Likelihood	Critical Rail Defects/km that Found by the Ultrasonic Test Vehicle (Number)
10*	Almost certain	Higher than 0.02
3	Likely	> 0 & ≤0.02
1	Possible	0

Note: The "step" of risk ranking for the situation of below and above the threshold value of critical defects is not linearly changed, which is used to represent the risk to rail broken/failure during the traffic revenue.

Risk Ranking by the Combination of Rail Defects and Critical Defects

Similarly, the risk ranking is updated by combine the number of rail defects and critical defects among them in each specified track sections. This is calculated by multiply the risk ranks for each track section.

Risk Ranking Based on the Condition of Rail Wear

Severe rail head wear distortion can alter the normal angle refraction of the ultrasonic probe from the transducer to such a critical level that the ultrasonic signals do not penetrate at the expected angle, or to the expected location, in the specimen. Especially, the 70° and 0° degrees probes of the Ultrasonic testing vehicle are to be experience difficulties when they fit with the rails with severe rail worn. This situation will impact the accuracy and productivity of the ultrasonic testing work. For this reason, the situation of the existing worn and condemned rails of each of the non-compliance rail sections needs to be included into the prioritization work by using of the logical and rational risk rankings.

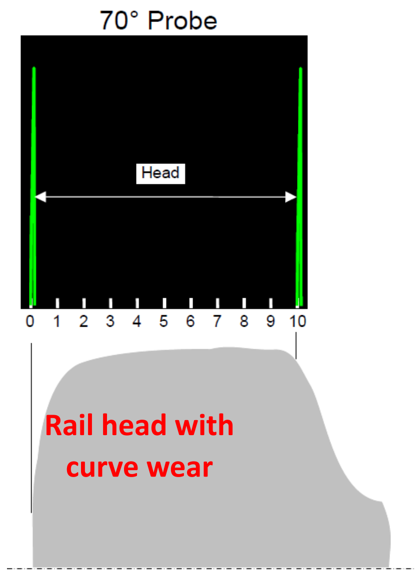

Fig. 2 Setting bottom of rail head.

For the risk ranking of the rail wear, both of the quantity (percentage of worn rail in each track sections) and severity are need to be considered.

Based on the available statistical methods of the raw data of worn rails, the locations and length of the worn rails are counted in two categories based on their conditions – reportable and condemned.

From the current available references, there is no information can be used to help to determine the thresholds of the risk ranking levels. For this analysis, the severe rail wear (reportable) and condemned rails are to be considered as two types of rail "defects" in two different classes. Based on this assumption, the concepts that have been used to risk-ranking the rail defects and critical defects can be transplanted and utilised for this work. In addition, the percentage of the length of worn rail is used rather than the number of locations as the unit for threshold.

Because of the reportable and condemned rails are counted separately, hence, the risk ranking for the combination of reportable and condemned rail wear can be calculated by simply add up the scores of reportable rail and condemned rail together.

Moreover, it is very clear that the risk of rail broken which is caused by the fatigue of rails is higher than the non-reliable which is caused by the ultrasonic probes work on the head worn rails. For this reason, the risk ranking scores is multiplied by a “weight of modification” which is 30%, i.e., the risk from non-reliable that caused by rail head wear is equal to 30% of the risk from the condition of rail fatigue.

Prioritization Matrix

To finalize the analysis by combing the final scores of risk ranking of “frequency & overdue date”, “rail defects & critical defects” and “condition of rail wear”, a prioritization matrix is developed to “weighting” the priorities for every non-compliance track section. It is used to represent that the reliability is a combination of the results of all factors of evaluations.

Within this prioritization matrix, the available “risk ranking scores of the combination of frequency & overdue date”, “risk ranking score of the combination of rail defects and critical defects” and “risk ranking score of the combination of reportable and condemned rail wear” are to be used as the “weight criteria”. The risk ranking scores of the combination of frequency & overdue date are input as the importance of “Consequences” in the order of from small to large in the longitudinal direction into the matrix. Then, the risk ranking score of the combination of rail defects and critical defects are input as the importance of “Likelihood” in the order of from large to small in the vertical direction into the matrix. The risk ranking scores of the combination of reportable and condemned rail wear are input as a “factored/modified” importance of “Likelihood” in the order of from large to small in the vertical direction into the matrix. The prioritization matrix is shown in Fig. 3.

Likelihood (Rail Defects & Critical Defects)	Consequences (Frequency & Overdue Date)					Situation of Rail Wear
	Band 5 (0-3)	Band 4 (4-7)	Band 3 (8-11)	Band 2 (12-15)	Band 1 (16-20)	
Almost Certain (≥20)	M (≥20, & within 20-23)	H (≥24, & 24-27)	VH (≥28, & 28-31+)	VH (≥32, & 32-35+)	VH (≥36, & 36-40+)	Almost Certain (1.8 – 4.5)
Likely (10-19)	L (≥10, & 10-22)	M (≥14, & 14-26)	H (≥18, & 18-30)	H (≥22, & 22-34)	VH (≥26, & 26-39+)	Likely (0.9 – 1.5)
Possible (5-9)	L (≥5, & 5-12)	L (≥9, & 9-16)	M (≥13, & 13-20)	M (≥17, & 17-24)	H (≥21, & 21-29+)	
Unlikely (2-4)	L (≥2, & 2-7)	L (≥6, & 6-11)	L (≥10, & 10-15)	L (≥14, & 14-19)	M (≥18, 18-24+)	Possible (0.6)
Rare (1)	L (≥1, & 1-4)	L (≥5, & 5-8)	L (≥9, & 9-12)	L (≥13, & 13-16)	L (≥17, & 17-21+)	

Fig. 3 Likelihood - severity risk ranking matrix (Prioritization Matrix)

By using this specified prioritization matrix, overall score of risks are obtained by simply add up the risks from the factors of "Consequences" and "Likelihood" together. The results of risk assessments are categorized into 4 risk levels based on the values of the risk scores after add up the values of consequences and likelihood. The areas (grids) of different risk levels are highlighted by "Red" colour for "very high", "Golden" colour for "High", "Yellow" colour for "Medium" and "Green" colour for "Low", as shown in Figure 3.

Remedial Actions

Adequate amount of samples have been used for determine the threshold value of different risk levels. The final results of the threshold value are shown in the grids of the prioritization matrix.

The remedial actions are suggested for each risk levels:

- Very high (VH) – Immediate action required / control obligatory;
- High (H) – Attention is needed and expected;
- Medium – Management responsibility must be clear and specified; and
- Low – Manage by routine procedures.

Results of Analysis and Recommendation

After the methodology of analysis has been developed, it has been fine turned by used it to undertake some preliminary analysis works against the different testing samples. The results have shown that it is a good and effective tool for undertaking the prioritization works. Both methodologies and analysis procedures will be keeping improved by the utilization and outcomes.

Reference

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Model Specifications for Structural Health Monitoring: Part 2 – Monitoring Aims

Colin Caprani, Monash University

Background

ANSHM is pursuing the development of Model Specifications for Structural Health Monitoring. In Part 1, an overview of what the specifications may address was introduced. In this part, we consider the type of guidance required on the aims of monitoring. As ever, feedback from the SHM community is actively sought and welcomed.

Goals of the Model Specifications

In Part 1 some potential goals of the Model Specifications were outlined and are repeated here:

1) Be created with expert and industry input, and published by a recognised neutral authority in the field, such as ANSHM.
2) Be published with an ISBN and other formal attributes, so that they can be referenced from legal instruments, and are generally available.
3) Be reasonably short, perhaps 10 to 15 pages in length, and understandable by structural engineers generally, without any specialist knowledge in SHM.
4) Provide a basis for the decision to utilise SHM, based on an informed appreciation of what can be gained from its use.
5) Be neutral in terms of any specific sensor or system technology, instead outlining performance expectations that suppliers' systems and sensors should meet.
6) Facilitate an informed conversation with a potential SHM supplier on the required data and its quality, as the basis for decision-making.
7) Not be a detailed technical document on installation or other matters pertaining to any specific sensor or system technology.
8) Not make bold claims about the possibility of damage detection.

Monitoring Aims

The Model Specifications should provide guidance on when to monitor, what to monitor, and any required actions during monitoring, and if or when monitoring should end.

When to Monitor

Monitoring may be considered when a load or sequence of loads are expected to cause effects in the structure that are anticipated to be close to its capability to resist them. This may be due to high loads, or a deteriorated state of the structure, or indeed, may simply be prognostic. Recognising that there are many uncertainties in both load and resistance, it is prudent to consider monitoring when the capacity-demand ratio (or rating factor) is expected to come somewhat close to RF = 1.0. Thus, as an example, we may consider monitoring when:

- RF < 1.20 for failure-critical limit states;
- RF < 1.10 for serviceability limit states.

These are merely guides, and due regard should be given to the importance of the structure, the consequences of a failure, and the ability to retrieve a situation should an allowable limit be exceeded.

What to Monitor

The need for structural monitoring is identified by the asset owner who has specific concerns. Typically, these concerns may be due to limitations of the structure with regards to one or more limit states. Once these concerns are identified, they should be clearly expressed. Quantifiable metrics for assessing the phenomenon should be identified. These metrics may be proxies for the issue of interest, but any potential error introduced by a surrogate measure should be understood, quantifiable, and accepted. Acceptable limits for the phenomenon and/or its proxy should be determined.

During Monitoring

The data coming from a monitoring system may be examined asynchronously or synchronously ("real-time"). Alerts on the data stream may also be enacted when certain thresholds are exceeded, and this may also be done asynchronously (i.e. anomaly detection), or synchronously ("alarm"). Early-warning thresholds should be set on the measurements for failure-critical limit states, such that there remains time to give an appropriate order to avoid the anticipated failure. However, due regard should be given to the avoidance of false alarms, which will limit the usefulness of real alarms.

As a specific example, in the case of a real-time monitoring situation for an exceptional load, measurements should be continually compared to their allowable limits. A plan should be in place and communicated to all parties in the event that a limit is exceeded. Due consideration should be given to circumstances in which the following orders should be given:

- proceed over the structure;
- stop and hold position;
- stop and reverse off the structure.

The monitoring of superloads is key to facilitating their safe movements
(photo: Colin Caprani, Monash University).

When to End Monitoring

Monitoring may terminate on a number of conditions:

- after a certain quantity of a particular kind of data is obtained (as required by the end-use of the data);
- after a certain duration of monitoring (days, weeks, etc);
- after a particular loading event has occurred (e.g. special transport);
- after some monitoring system resource has ended (e.g. battery power).

The specification should make clear which of these conditions apply, and what the order of priority is on these conditions such that both the client and supplier of the monitoring agree when the trigger occurs.

Feedback

Further articles on the topics in the Outline Contents (Part 1) will follow. However, noting the first goal of the Model Specifications given above, these articles are not be prescriptive, and have the simple aim of starting the consultation process. As such, your feedback on this and any article in the series is very welcome and sought to the author for possible incorporation in the Model Specifications.

Conference News

- **ANSHM minim-symposium "Emerging techniques for structural health monitoring of civil infrastructure" in the 18th East Asia-Pacific Conference on Structural Engineering & Construction (EASEC-18), 13-15 November 2024, Chiang Mai, Thailand. Organized by Aspro Jun Li, Prof Hong Guan and Prof Tommy Chan. https://easec18.org/**

- **11th European Workshop on Structural Health Monitoring , 10-13 June 2024, Potsdam, Germany. http://www.ewshm2024.com/**

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If you have any comments and suggestions, please contact

Acting Newsletter Editor: Andy Nguyen, University of Southern Queensland

Email: Andy.Nguyen@unisq.edu.au

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