

National Rail Transit Electrification and Automation Engineering Technology Research Center (Hong Kong Branch)

國家軌道交通電氣化與自動化工程技術研究中心香港分中心

2025 ANNUAL REPORT

(English Version)



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Director's Foreword



As 2025 draws to a close, I am proud to reflect on a year of strong progress and impactful achievements at the Hong Kong Branch of the National Rail Transit Electrification and Automation Engineering Technology Research Center (CNERC-Rail (HK Branch)). Building on our mission to advance rail transit electrification, automation and resilient infrastructure, our center has delivered notable scientific breakthroughs, accelerated technology translation, expanded international collaborations, and deepened our commitment to talent cultivation. These accomplishments position us well to drive innovation that supports Hong Kong, the Greater Bay Area and national rail modernisation priorities.

On the technology front, we advanced multiple flagship directions. We delivered field validated engineering outcomes, notably the E1809 fastener clip replacement at the Diamond Hill–Kai Tak tight curve section, which resolved clip fatigue through resonance avoidance; city scale and vehicle mounted LiDAR deployments for real time wind and rainfall mapping and typhoon monitoring; and long term MiC lightweight concrete slab monitoring for construction quality assurance. We also progressed prototypes and pilots in flexible sensing, acoustic metamaterials for noise reduction, UAV enabled hazard detection, intelligent maglev control, and an LLM based tunnel defect analysis agent integrated with segmentation tools and RAG capability. Recognition of our team's efforts was further affirmed when we received PolyU's President's Award for Outstanding Achievement.

Operationally, we will strengthen collaboration with Hong Kong MTR Corporation Ltd., the Hong Kong Observatory and GBA partners to enable real time measurement, meteorological integration and coordinated pilot schedules. We will prioritise resilience of monitoring networks through edge hardening and standardised operation and maintenance procedures, and we will continue to front load laboratory validation to mitigate external constraints on field pilots.

In 2026 we will focus on three interlinked thrusts: industrialisation, intelligent operation and maintenance at scale, talent and standards. First, we will fast track GBA pilot deployments and industry partnerships to scale flexible sensors, acoustic energy harvesters and metamaterial

noise solutions toward commercial readiness. Second, we will complete and deploy AI driven predictive maintenance modules and digital twin frameworks for automated diagnostics and prognostics, with measurable targets for fault prediction accuracy and inspection time reduction. Third, we will expand strategic recruitment under PolyU's hiring plan, train compound experts in climate compound hazards and AI, and implement our succession plan to develop future Center leadership. We will also engage regulators and standards bodies to convert validated solutions into technical guidelines and standards.

CNERC Rail enters 2026 with a clear strategic pathway: convert prototypes into repeatable engineering solutions, accelerate technology transfer and commercialisation, and codify best practices into standards that benefit Hong Kong, the Greater Bay Area and beyond. I thank our researchers, technical staff, students, industry collaborators and funding partners for their commitment. Together, we will build on 2025's breakthroughs and deliver robust, low carbon, and AI enabled rail solutions that serve society.

Yi-Qing Ni

Chair Professor

Yim, Mak, Kwok & Chung Endowed Professorship in Smart Structures

Director of National Rail Transit Electrification and Automation

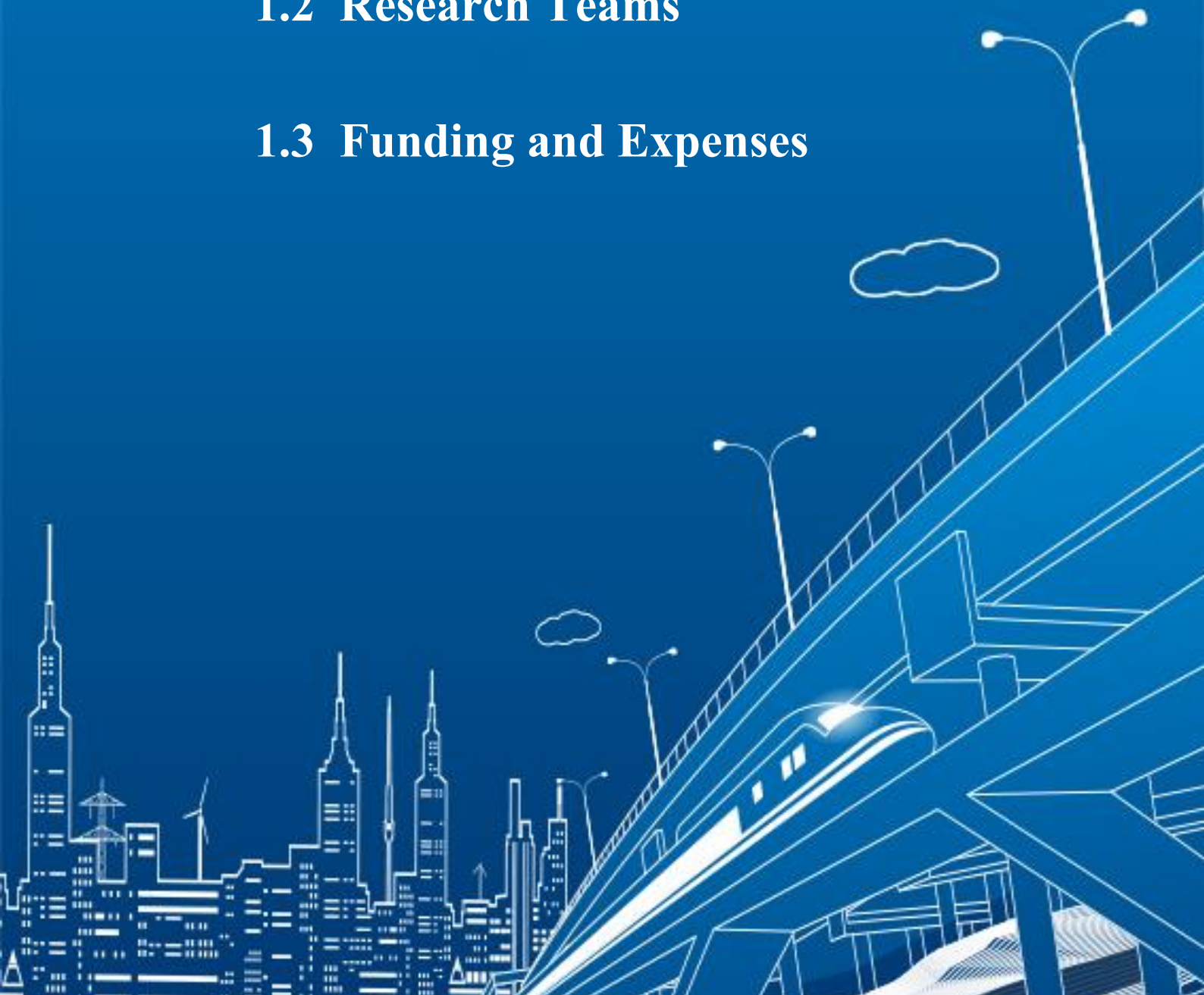
Engineering Technology Research Center (Hong Kong Branch)

1. Overview of CNERC-Rail (HK Branch) in 2025

1.1 Introduction

1.2 Research Teams

1.3 Funding and Expenses



1. Overview of CNERC-Rail (HK Branch) in 2025

1.1 Introduction

The National Rail Transit Electrification and Automation Engineering Technology Research Center Hong Kong Branch, CNERC-Rail (HK Branch), was established in 2015 upon approval by the Ministry of Science and Technology of the People's Republic of China. It affiliates to the Hong Kong Polytechnic University (PolyU) and operates under the management of the university. It receives financial support regarding research and daily operations from the Innovation and Technology Commission (ITC) of the Hong Kong SAR Government and the PolyU. CNERC-Rail (HK Branch) has built up an interdisciplinary research team taking advantage of research resources in advanced sensing, smart materials, and data-driven analysing techniques available in the university.



Mission: To develop state-of-the-art monitoring technologies embracing smart materials and advanced big data analysis methods for the rail transit system.

Vision: To accelerate the process of constructing intelligent rail transit including high-speed rail, metro, and maglev systems concerning safety and reliability, promoting innovative monitoring technologies for rail transit from Hong Kong to Asia and worldwide.

CNERC-Rail (HK Branch) has achieved fruitful outcomes in terms of academic research, and engineering application in 2025 through undertaking scientific research projects, performing engineering and consultancy services, and strengthening partnership with other research institutes and enterprises.

Major items of work of CNERC-Rail (HK Branch) in 2025 are presented in detail in the following sections.

1.2 Research Teams

CNERC-Rail (HK Branch) consists of 9 Founding members (see Table 1.1) and 12 collaborative members (see Table 1.2) from different departments who lead R&D projects. To strength its research capability and to enable efficient execution of research tasks, CNERC-Rail (HK Branch) also actively recruits research talents from worldwide (see Table 1.3) to participate in R&D projects.

Table 1.1 Founding members of CNERC-Rail (HK Branch)

No.	Name and Position	Department	Remark
1	Yi-Qing NI Chair Professor	Department of Civil and Environmental Engineering	Director
2	Kang-Kuen LEE Professor of Practice	Department of Electrical and Electronic Engineering	Deputy Director
3	Songye ZHU Professor	Department of Civil and Environmental Engineering	Secretary
4	Jian-Nong CAO Chair Professor	Department of Computing	Project Leader
5	Hwa-Yaw TAM Chair Professor	Department of Electrical and Electronic Engineering	Project Leader
6	Siu-Wing OR Professor	Department of Electrical and Electronic Engineering	Project Leader
7	Xiao-Li DING Chair Professor	Department of Land Surveying and Geo-informatics	Project Leader
8	Li CHENG Chair Professor	Department of Mechanical Engineering	Project Leader
9	Zhongqing SU Chair Professor	Department of Mechanical Engineering	Project Leader

Table 1.2 Collaborative members of CNERC-Rail (HK Branch)

No.	Name and Position	Department	Remark
1	Siu-Kai LAI, Associate Professor	Department of Civil and Environmental Engineering	Project Leader
2	You DONG, Associate Professor	Department of Civil and Environmental Engineering	Project Leader
3	Prof. Zhi-Zhao LIU Professor	Department of Land Surveying and Geo-Informatics	Project Leader
4	Hai GUO Professor	Department of Civil and Environmental Engineering	Project Leader
5	Zhen LENG Professor	Department of Civil and Environmental Engineering	Project Leader
6	Catherine C. LIU Associate Professor	Department of Data Science & Artificial Intelligence	Project Leader
7	Kai ZHOU Assistant Professor	Department of Civil and Environmental Engineering	Project Leader
8	Xin-Yu ZHOU Research Assistant Professor	Department of Electrical and Electronic Engineering	Project Leader
9	Shu-Chien HSU Associate Professor	Department of Civil and Environmental Engineering	Project Leader
10	Si-Qi DING Research Assistant Professor	Department of Civil and Environmental Engineering	Project Leader
11	Shun-Yee Michael LIU Senior Scientific Officer	Department of Electrical and Electronic Engineering	Project Leader
12	Zheng-Wei CHEN Research Assistant Professor	Department of Civil and Environmental Engineering	Project Leader

Table 1.3 Recruited staff of CNERC-Rail (HK Branch)

No.	Name	Position	Period of Employment	
1	Su-Mei WANG	Research Assistant Professor	2021-09-01	2025-06-30
2	You-Wu WANG	Senior Research Fellow, Research Assistant Professor	2021-01-04	2025-06-20
3	Si-Qi DING	Research Assistant Professor	2024-02-19	2026-06-30
4	Jian-Guo CAI	Senior Research Fellow	2025-01-27	2025-02-24
5	Wai Kei AO	Research Fellow	2025-07-01	2026-06-30

6	Hong-Wei LI	Research Fellow	2025-07-01	2026-06-30
7	Wen-Qiang LIU	Research Fellow	2024-10-05	2026-10-04
8	Lok Hin CHO	Research Fellow	2025-04-01	2026-03-31
9	Chi-Ming TANG	(PT) Research Fellow	2025-08-01	2026-07-31
10	Kai Yuen WONG	(PT) Principal Research Fellow	2024-11-27	2026-11-26
11	Weng Hong CHUNG	(PT) Research Fellow	2025-04-01	2026-03-31
12	Xiao WANG	(PT) Research Fellow	2025-08-01	2026-01-21
13	Wen-Bo HU	Postdoctoral Fellow	2023-08-28	2025-08-27
14	Yun-Fan YANG	Postdoctoral Fellow	2024-05-06	2025-05-06
15	Xiu-Yu CHEN	Postdoctoral Fellow	2025-02-13	2026-03-13
16	Shuo HAO	Postdoctoral Fellow	2025-08-01	2025-09-18
17	Zi-Jian GUO	Postdoctoral Fellow	2023-11-13	2025-11-12
18	Si-Yi CHEN	Postdoctoral Fellow	2025-08-01	2026-07-31
19	Yue DONG	Postdoctoral Fellow	2024-02-27	2025-02-26
20	Qi-Wu ZHU	Postdoctoral Fellow	2024-06-18	2025-06-17
21	Chao YANG	Postdoctoral Fellow	2024-05-15	2025-05-24
22	Zhi LI	Postdoctoral Fellow	2024-08-29	2025-08-28
23	Xiao-Ming TAN	Postdoctoral Fellow	2024-03-19	2025-03-18
24	Yao HU	Postdoctoral Fellow	2025-02-13	2027-02-12
25	Jia-Sheng HUANG	Postdoctoral Fellow	2025-12-19	2026-06-18
26	Shuai ZHAO	Postdoctoral Fellow	2025-02-28	2025-08-30

27	Guanghao ZHAI	Postdoctoral Fellow	2025-07-21	2026-07-20
28	Imran GHAFOR	Postdoctoral Fellow	2025-08-04	2026-02-28
29	Jun PENG	Postdoctoral Fellow	2025-08-28	2026-03-27
30	Numan MALIK	Postdoctoral Fellow	2025-09-01	2026-08-31
31	Xiao-Ming WANG	Postdoctoral Fellow	2025-09-18	2026-03-17
32	Hong-Min ZHU	Postdoctoral Fellow	2025-09-19	2026-03-18
33	Fei-Fei REN	Postdoctoral Fellow	2025-10-22	2026-04-21
34	Hafiz Khurram SHAHZAD	Postdoctoral Fellow	2025-12-08	2026-06-07
35	Jamal-deen MUSAH	Postdoctoral Fellow, Research Associate	2025-01-01	2025-12-31
36	Lei YUAN	Research Associate	2025-07-22	2026-01-21
37	Yang LU	Research Associate	2024-10-01	2025-09-30
38	Wei-Jia ZHANG	Research Associate, Research Assistant	2025-05-02	2026-03-09
39	Hei Shek Anson TAM	Research Associate	2025-04-01	2026-03-31
40	Jia-Yu WANG	Research Associate	2025-09-22	2026-08-07
41	Yi-Ying WANG	Research Associate	2025-10-02	2026-04-01
42	Xian-Hua YAO	Research Associate	2025-11-19	2026-11-18
43	Jun-Ping ZHONG	Research Associate	2024-07-15	2025-07-15
44	Zhen-Dong LI	Research Associate	2024-08-07	2025-02-07
45	Da-Zhi DANG	Research Associate	2025-06-01	2025-12-08
46	Di-Feng HU	Research Associate	2025-05-14	2025-11-13

47	En-Ze RUI	(PT) Research Associate	2025-01-20	2025-07-01
48	Kong-Yang ZHAO	Research Associate	2025-04-03	2025-10-02
49	Chong ZHONG	Research Associate	2025-04-13	2025-07-31
50	Qi ZHU	(PT) Research Associate	2025-06-09	2025-08-31
51	Le CHANG	(PT) Research Assistant	2025-09-01	2026-05-31
52	Hang-Xing LI	(PT) Research Assistant	2025-09-01	2026-02-28
53	Jin-Ze LI	(PT) Research Assistant	2025-09-01	2026-04-30
54	Fu-Zhen WEN	(PT) Research Assistant	2024-11-15	2025-05-14
55	Zhen-Xing YE	(PT) Research Assistant	2025-09-15	2025-11-30
56	Yuan-Man ZHANG	(PT) Research Assistant	2025-02-03	2025-12-31
57	Zi-Rui ZUO	(PT) Research Assistant	2025-09-15	2026-08-31
58	Yu-Hang LU	Research Assistant	2025-09-11	2026-03-10
59	De-Hui OUYANG	Research Assistant	2025-07-10	2025-08-31
60	Zu-Yu XIE	Research Assistant	2025-01-10	2025-12-28
61	Sheng-Jie NI	Research Assistant	2025-03-24	2026-03-24
62	Jia-Xin HUANG	Research Assistant	2025-03-12	2026-03-11
63	Yi-Ting XIANG	Research Assistant	2025-04-01	2026-09-30
64	Yi-Ming NI	Research Assistant	2025-08-15	2026-02-14
65	Wei-Kai KONG	Research Assistant	2025-01-03	2026-01-01
66	Yan-Hui PENG	Research Assistant	2025-01-03	2026-01-01
67	Huan-Zi LIU	Research Assistant	2024-09-02	2025-08-31

68	Yu-Hao LIU	Research Assistant	2025-04-02	2026-04-01
69	Xin-Rui LI	Research Assistant	2025-04-02	2026-04-01
70	Peng-Cheng WANG	Research Assistant	2025-07-08	2026-01-06
71	Hang ZHANG	Research Assistant	2025-09-05	2026-03-04
72	Ao ZHENG	Research Assistant	2024-06-03	2025-06-02
73	Cong-Guang ZHANG	Research Assistant	2024-02-20	2025-02-19
74	Huan YUE	Research Assistant	2023-07-13	2026-01-10
75	Qi-Fan ZHOU	Research Assistant	2021-03-08	2025-08-20
76	Tsz Ying LEUNG	Research Assistant	2024-02-01	2025-06-30
77	Xin-Yuan LIU	Research Assistant	2023-07-13	2026-01-10
78	Yu-Chen LIU	Research Assistant	2024-11-22	2025-05-21
79	Yu-Duo ZHAO	Research Assistant	2024-07-02	2025-01-01
80	Zhen LIN	Research Assistant	2024-09-02	2025-03-31
81	Liang-Sheng QIU	Research Assistant	2025-12-17	2026-08-19
82	Chen GONG	(PT) Research Assistant	2025-12-15	2026-03-31
83	Si-Hui LI	(PT) Research Assistant	2025-12-15	2025-08-31
84	Xiao-Cheng ZHANG	(PT) Research Assistant	2025-12-15	2025-01-31
85	Ji-Wei YE	(PT) Student Assistant	2025-12-15	2025-06-30
86	Wing-Laam YAU	(PT) Student Assistant	2024-09-02	2025-02-28
87	Tai-Tung WAI	Research Technical Assistant	2024-01-23	2027-01-22
88	Wing-Hong KWAN	Research Assistant	2025-04-01	2027-03-31

1.3 Funding and Expenses

General breakdown for 2025:

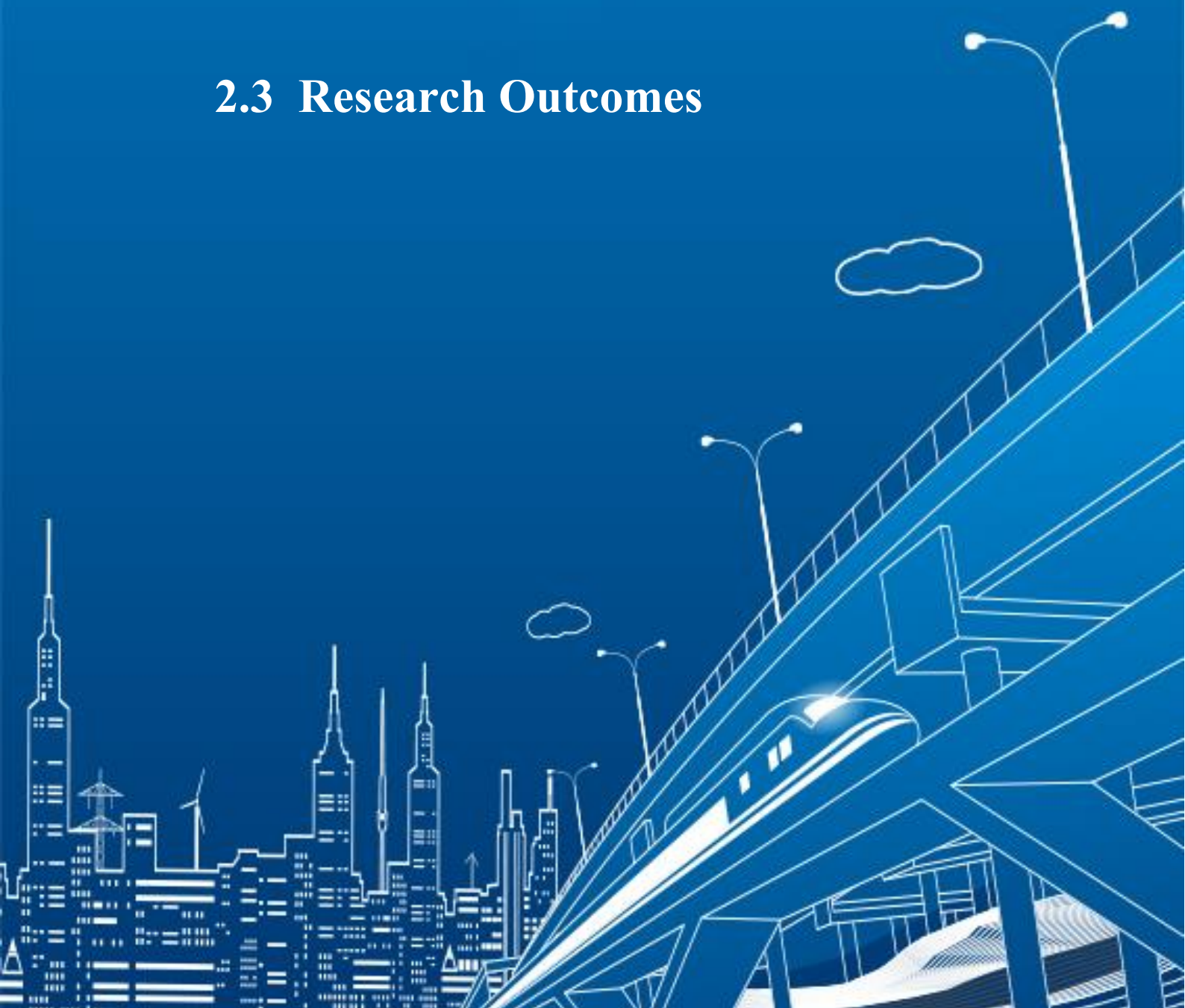
1. Income: HKD 24,000,000	
ITC Funding	20,000,000 HKD
PolyU Funding	4,000,000 HKD
2. Expenses: HKD 24,000,000	
Research Projects	3, 557,800 HKD
Human Resource	10,131,994 HKD
Equipment Purchase	4,357,994 HKD
General Expenses	5,952,212 HKD

2. R&D Activities of CNERC-Rail (HK Branch) in 2025

2.1 Research Projects

2.2 Research Progress

2.3 Research Outcomes



2. R&D Activities of CNERC-Rail (HK Branch) in 2025

2.1 Research Projects

2.1.1 Research Grants Applications

In 2025, the CNERC-Rail (HK Branch) led or collaborated in the submission of research project proposals. Of these, have successfully secured funding, with a total grant amount of approximately HK\$ 20,089,215, while the remaining HK\$ \$12,150,000 are currently under review. The projects are funded by various sources, including a theme-based research scheme under the Research Grants Council (RGC) of the Hong Kong SAR Government, Innovation and Technology Commission (ITC) of the Hong Kong SAR Government, Hong Kong Research Grants Council, Hong Kong Highways Department, and The Hong Kong Polytechnic University. A list of concerned projects is given in Table 2.1.1.

Table 2.1.1 Projects seeking research grants in 2025

No.	Title	Funding Source	Amount	Status
1	Low-Cost Plastic Waste-Derived Flash Graphene-Modified Highly Durable and Self-Sensing Concrete for Sustainable Marine Infrastructure	Hong Kong Research Grants Council General Research Fund	1,169,801 HKD	Approved
2	Novel Latched Tuned Mass Dampers for Vibration Control of Flexible Structures With Ultra-Low Frequencies	Hong Kong Research Grants Council General Research Fund	1,134,931 HKD	Approved
3	Metapowered Iot System: A Metamaterial-Powered Internet of Things System for Structural Health Monitoring	Hong Kong Research Grants Council Junior Research Fellow Scheme	850,200 HKD	Approved
4	Flow evolution characteristics, dynamic instability mechanism, and aerodynamic load rebalancing method for high-speed maglev train operational safety in time-varying wind environments	Hong Kong Research Grants Council General Research Fund	1,134,931 HKD	Approved

5	Intelligent Detection Technology of Concealed Defects in Asphalt Pavement Using Ground-Penetrating Radar	Innovation and Technology Fund-Partnership Research Programme	2,201,400.00 HKD	Approved
6	AI-Driven Monolithic Microwave Integrated Circuit Design Based on Wide Bandgap Semiconductors	Innovation and Technology Fund-Partnership Research Programme	2,432,951.50 HKD	Approved
7	High-Fidelity Monitoring and Prediction of Extreme Climate Events in Hong Kong and Surrounding Regions	Otto Poon Charitable Foundation	2,080,000.00 HKD	Approved
8	Sustainable Train Operation Control Platform Based on The Wind-Vehicle-Track Coupled Model for Reduced Energy Consumption and Enhanced Riding Comfort	MTR Research Funding Scheme	1,245,000 HKD	Approved
9	Towards Life-Cycle Intelligent Predictive Maintenance for Railway Tracks: Advancing with Deep Learning Algorithmstechnology	Hong Kong Research Grants Council Research Impact Fund	7,840,000 HKD	Approved
10	Research on UAV BDS/GNSS Positioning, Navigation, and Rapid Identification/Warning Technology for Aviation Hazardous Weather in Complex Urban Environments	Mainland-Hong Kong Technology Cooperation Funding Scheme (MHKTCFS)	4,000,000 HKD	Pending
11	Optimisation And Regulation of Lithium-Sulfide Cathodes for Lithium-Ion Sulfur Batteries of High Energy Density And High Safety	2025 年深港澳科技计划项目（C 类项目）	3,000,000 RMB	Pending
12	Improve GPS/Beidou/GNSS Large-Scale Precise Positioning Applications Through Correction Data Augmentation from AI and	CAS-Croucher Funding Scheme for Joint Laboratories (PI)	3,750,000 HKD	Pending

	Numerical Weather Prediction Models			
13	Research Proposal of Real-Time Vessel Collision Assessment on Kap Shui Mun Bridge by Artificial Intelligence (AI) and Digital Twin (DT)	Bridges & Structures Division of Highways Department	\$1,400,000 HKD	Pending

2.1.2 Research Projects Supported by CNERC-Rail (HK Branch)

In 2025, CNERC-Rail (HK Branch) has funded a total of 9 research projects, as listed in Table 2.1.2.

Table 2.1.2 Research projects supported by CNERC-Rail (HK Branch) in 2025

No.	Title	Principal Investigator	Department	Start-End Data
1	Structural Health Monitoring with Meta-Materials for Engineering Structures Pertinent to Railway Applications	Prof. Li CHENG	Department of Mechanical Engineering	2024-06-01 ~ 2026-05-30
2	Towards Greener and Artificial Intelligence Renewable Energy Devices and Management Systems for Smart Electrified Urban Transportation	Prof Siu-Wing OR	Department of Electrical and Electronic Engineering	2024-03-15 ~ 2027-03-14
3	Photovoltaic-Powered Laser-Based Multi-Parameter Sensor System for Continuous Railway Catenary Monitoring	Prof. Hwa-Yaw TAM	Department of Electrical and Electronic Engineering	2025-03-01 ~ 2027-02-28
4	Development of Integrated Vibration Mitigation and Sound Absorption Devices	Prof. Song-Ye ZHU	Department of Civil and Environmental Engineering	2021-5-1 ~ 2026-04-30
5	“Totally-Additive-Manufacturing” Driven in Situ Health Monitoring of Cfrps Used in High-Speed Train Structures	Prof. Zhong-Qing SU	Department of Mechanical Engineering	2024-07-11 ~ 2026-06-10
6	Development Of Mobile Surveying Technology for Detection of Sinkholes	Prof. Xiao-Li DING	Department of Land Surveying and Geo-Informatics	2025-02-04 ~ 2027-01-31
7	In-Service Diagnostics and Intelligent Maintenance of Rail Networks	Prof. You DONG	Department of Civil and Environmental Engineering	2025-01-1 ~ 2026-12-31
8	AI-Driven Monolithic Microwave Integrated Circuit Design Based on Wide Bandgap Semiconductors	Dr. Xin-Yu ZHOU	Department of Electrical and Electronic Engineering	2025-11-20 ~ 2027-11-19
9	Intelligent Detection Technology of Concealed Defects in Asphalt Pavement Using Ground-Penetrating Radar	Prof. Zhen LENG	Department of Civil and Environmental Engineering	2025-11-1 ~ 2027-10-31

2.1.3 Postdoctoral Research Supported by CNERC-Rail (HK Branch)

In 2025, CNERC-Rail (HK Branch) co-funded research works of 8 postdoctoral fellows in collaboration with The Hong Kong Polytechnic University through Postdoctoral Matching Fund Scheme. Project details are listed in Table 2.1.3.

Table 2.1.3 Postdoctoral research funded in 2025 by CNERC-Rail (HK Branch)

No.	PDF Name	Fund Scheme	Grant No.	Amount
1	Dr. Xiao-Ming TAN	Postdoctoral Matching Fund Scheme	K-BBY1/1-W32Z	HKD 365,400
2	Dr. Chao YANG	Postdoctoral Matching Fund Scheme	K-BBY1/1-W35L	HKD 365,400
3	Dr. Yun-Fan YANG	Postdoctoral Matching Fund Scheme	K-BBY1/1-W330	HKD 365,400
4	Dr. Qi-Wu ZHU	Postdoctoral Matching Fund Scheme	K-BBY1/1-W35Q	HKD 365,400
5	Dr. Zhi LI	Postdoctoral Matching Fund Scheme	K-BBY1/1-W35N	HKD 365,400
6	Dr. Xiu-Yu CHEN	Postdoctoral Matching Fund Scheme	K-BBY1/1-W40B	HKD 365,400
7	Dr. Zi-Jian GUO	Postdoctoral Matching Fund Scheme	K-BBY1/1-W311	HKD 365,400
8	Dr. Yao HU	Postdoctoral Matching Fund Scheme	K-BBY1/1-W39W	HKD 365,400

2.2 Research Progress

2.2.1 Machine learning-assisted design of bio-inspired acoustic metamaterials for railway noise control

In addressing the critical challenge of railway noise control within the dominant 400-2500 Hz frequency range, this project examined the evolving landscape of bio-inspired acoustic metamaterials (AMMs) enhanced by machine learning techniques to overcome the limitations of conventional noise control materials. Recent bio-inspired AMM developments use natural structures to achieve superior broadband sound absorption performance through cavity resonance mechanisms, photonic crystal bandgap control, and topological wave manipulation. The integration of machine learning techniques has also revolutionised AMM optimisation processes, achieving significant speed-up ratios compared to traditional finite element simulations while enabling exploration of complex parameter spaces (see Fig 2.1 Machine learning assisted design of bio-inspired acoustic metamaterials for railway noise control.).

In further advancing the bio-inspired acoustic metamaterial framework for railway noise mitigation, a novel multi-layer honeycomb structure combined with micro-perforated plates was developed, integrating Kolmogorov-Arnold Networks (KAN) with Bayesian Optimisation to overcome computational complexity limitations in traditional design approaches. The bio-inspired four-layer configuration achieved exceptional broadband sound absorption with $\alpha > 0.8$ across the critical 500-2000 Hz frequency range while maintaining a compact thickness of 69 mm and practical minimum perforation diameter of 0.30 mm. The KAN-based surrogate modeling demonstrated superior performance with the lowest mean absolute error (MAE = 0.0084) and highest R^2 (0.9057) compared to conventional neural networks, while providing interpretability through learnable B-spline activation functions that revealed the hierarchical importance of cavity diameters and layer heights in governing acoustic performance (see Fig 2.2 Kolmogorov-Arnold Networks-optimised honeycomb acoustic metamaterials for railway noise control.).

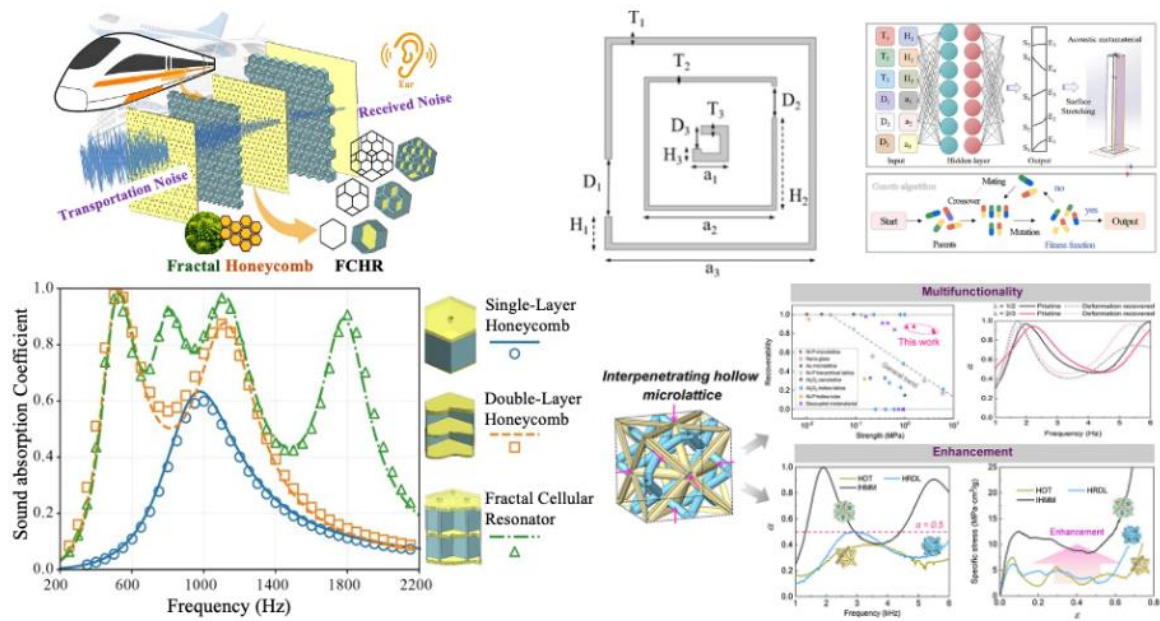


Fig 2.1 Machine learning assisted design of bio-inspired acoustic metamaterials for railway noise control.

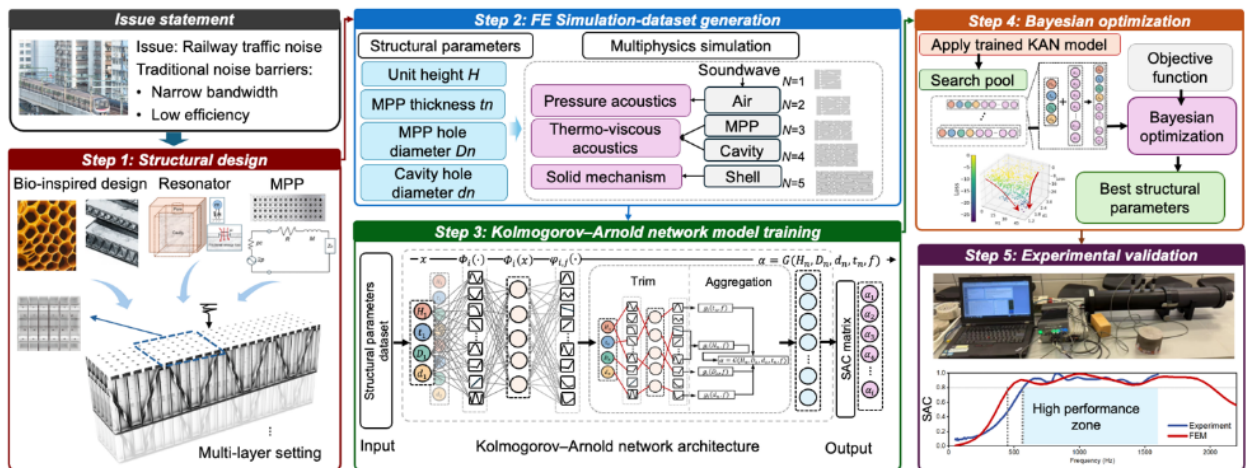


Fig 2.2 Kolmogorov-Arnold Networks-optimised honeycomb acoustic metamaterials for railway noise control.

2.2.2 Development of green foam concrete metamaterials near-rail noise barrier and plan for application on Shenzhen metro

Systematic research was conducted to develop a high-performance, sound-absorbing foam concrete. This foundational work involved designing and preparing 65 groups of foam concrete with varying proportions, totally over 200 samples. The study encompassed multi-dimensional variables, including density, water-solid ratio, foaming agent dilution, and admixture dosage. To reduce costs and carbon emissions, industrial by-products such as slag, fly ash, and tailings sand were evaluated as cement replacements. After multiple rounds of formulation and testing, a dual-admixture scheme incorporating slag was selected for its superior performance in sound absorption, mechanical strength, and water resistance. This optimised material achieved an ideal balance between acoustic performance, stability, and cost, establishing an engineering-oriented design (see Fig 2.3).

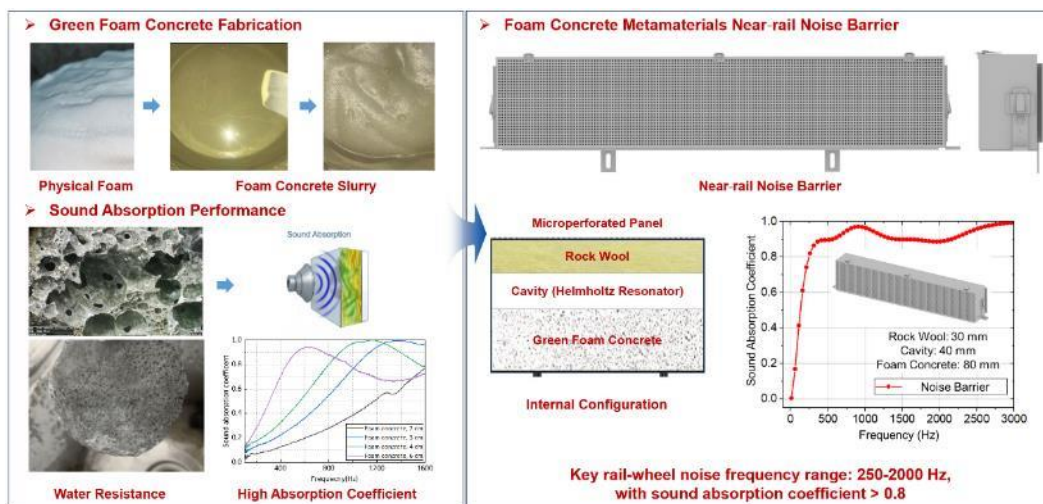


Fig 2.3 Preparation and performance optimisation of foam concrete metamaterials near-rail noise barrier

Based on this material, a foam concrete near-rail noise barrier was developed using a metamaterial design concept. This approach aimed to create acoustic performance beyond that of traditional materials by refining both the internal material properties and the external multi-layered structure. The core principle was the efficient conversion of acoustic energy into thermal energy through the synergistic effect of the layers, enabling effective broadband noise absorption. The overall structure and layer parameters were optimised using machine learning models to maximise synergy in sound absorption efficiency across all frequency bands.

The barrier was encapsulated in a lightweight, corrosion-resistant stainless steel shell to ensure long-term stability and low maintenance in near-rail environments. The modular design featured a detachable microperforated front cover, integral side and back plates, and standardised fasteners for convenient installation and maintenance. The layered system, from front to back, consisted of a microperforated panel, a 30 mm rock wool layer, a 40 mm air cavity, and an 80 mm foam concrete layer. This composite structure integrated micro-perforated panel absorption, porous material absorption, and cavity resonance tuning to effectively target mid- to high-frequency wheel-rail noise while enhancing low- to mid-frequency absorption. The standard unit dimensions were 1200 mm in length, 250 mm in width, and 150 mm in thickness.

The acoustic performance was first simulated using the pressure acoustics module in COMSOL Multiphysics, which confirmed the effectiveness of the optimal configuration. To experimentally validate these findings, a comparative analysis was conducted using impedance tube and semi-anechoic chamber tests on three configurations: rock wool alone (Case 1), foam concrete alone (Case 2), and the composite structure (Case 3) (see Fig 2.4).

Impedance Tube Test: The results showed that rock wool (Case 1) was effective at high frequencies, while foam concrete (Case 2) excelled at low frequencies. The composite structure (Case 3) successfully integrated these strengths, demonstrating a significantly higher average sound absorption coefficient across the entire frequency range and achieving a coefficient above 0.9 at mid-to-high frequencies. This confirmed superior broadband sound absorption under normal incidence.

Semi-Anechoic Chamber Test: In a simulated semi-free sound field, the composite structure (Case 3) again surpassed the single-material configurations. It achieved an average noise reduction exceeding 10 dB at low frequencies (50-250 Hz) and over 20 dB at high frequencies (2000-8000 Hz). These results verified the barrier's high-efficiency noise reduction capabilities in practical scenarios involving oblique sound incidence.

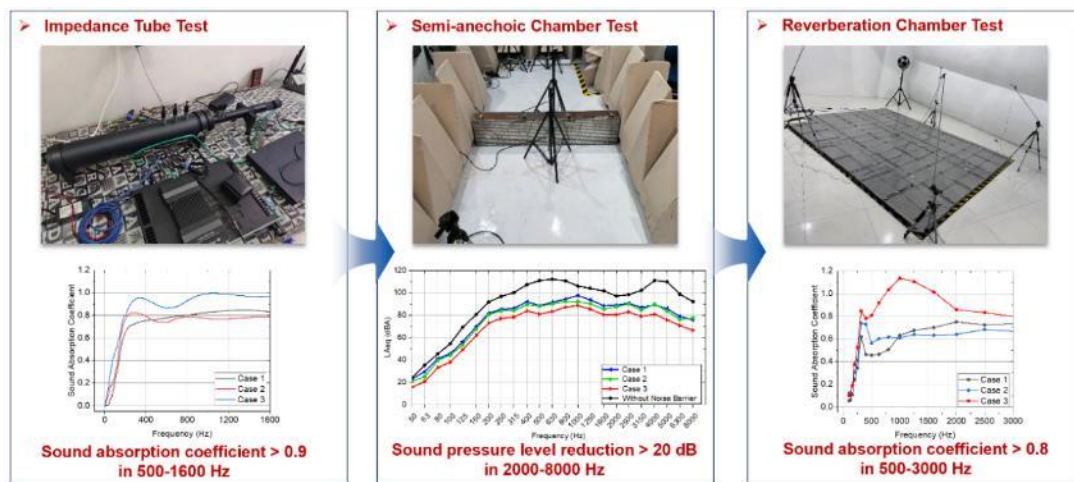


Fig 2.4 Performance evaluation of foam concrete metamaterials near-rail noise barrier.

Next, a field application will be conducted at the Shiyuecheng Section near Shajing Station of Shenzhen Metro Line 11. An installation scheme has been designed based on the existing environment, where the back of the noise barrier is aligned with a drainage channel and secured to the track slab with expansion bolts. To evaluate the on-site noise reduction performance, both far-field and near-field tests will be conducted before and after the barrier's installation. Far-field noise will be monitored at a distance of 25m from the outer rail centerline using free-field microphones to assess the overall noise intensity and structural secondary radiation. Near-field trackside noise will be measured using three microphones fixed to the barrier's facade to specifically analyse the wheel-rail noise components and quantify the barrier's direct noise reduction effect. These on-site tests will be designed to provide a comprehensive evaluation of the foam concrete near-rail noise barrier's performance in a real-world operational environment.

2.2.3 Study on a novel dual-layer graded honeycomb metamaterial and its advanced design for bridge anti-collision systems

In response to the growing risk of ship-bridge impacts and the limitations of conventional protective systems, a dual-layer graded honeycomb (DLGH) mechanical metamaterial is proposed and investigated (see Fig 2.5). The upper layer is a high-porosity, large-cell honeycomb tailored for progressive collapse and energy absorption (EA), while the lower layer adopts a denser, small-cell geometry to provide stiffness and stability. Together they

form a porosity-graded architecture that enables the dual functions of EA and load-bearing support. Through finite-element simulations and experimental validation, the DLGH exhibits strong EA capacity and buffering capability. To further enhance performance, an advanced CSP-DLGH is studied by integrating a corrugated-core sandwich panel (CSP) into the EA layer, which strengthens bending stiffness and the buckling resistance of local buckling units, yielding force-deformation characteristics consistent with efficient energy dissipation during collapse. Furthermore, a multilayer perceptron (MLP) surrogate coupled with genetic algorithm (GA) to perform multi-objective optimisation centred on EA performance, aims to achieve optimised designs. Collectively, these results demonstrate a practical pathway to high-efficiency, lightweight anti-collision components for both ships and bridges.

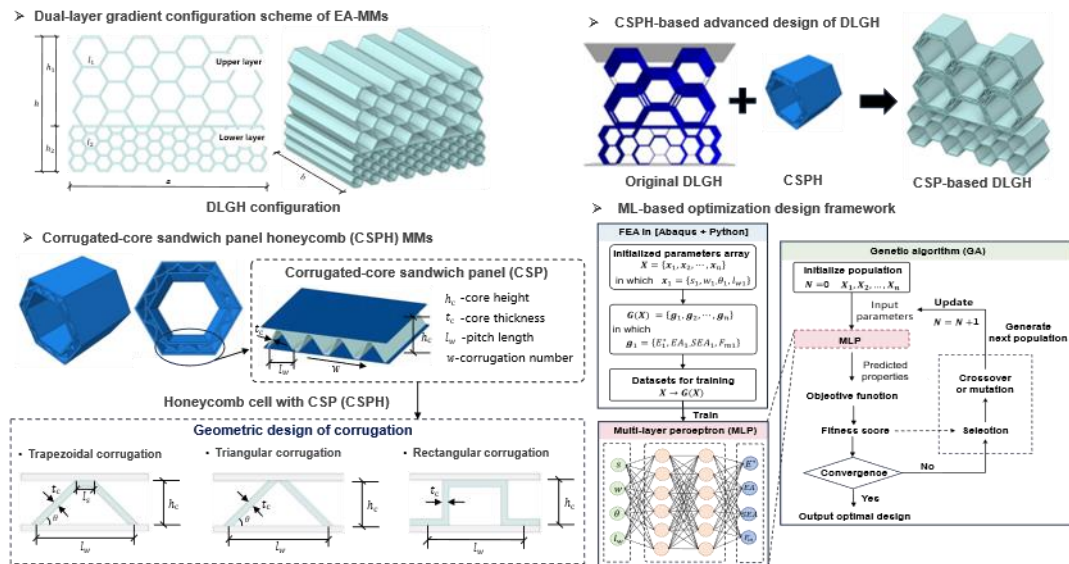


Fig 2.5 Dual-layer gradient honeycomb (DLGH) metamaterials and its ML-optimised advanced design.

2.2.4 Long-term performance monitoring of lightweight concrete slabs in modular integrated construction (MiC)

On April 7, 2025, Dr. Chao Yang, Mr. Liangsheng Qiu, and Mr. Guang Zhou from the research center visited the site leveling and infrastructure project on Tsing Yi West Road, Kwai Tsing District, Hong Kong. Sensors were installed in both the lightweight concrete slab (LCS) and the common concrete slab (CCS) of the modular integrated construction (MiC) to monitor and compare the long-term shrinkage behavior of lightweight and common concrete slabs. As shown in Fig 2.6, a total of four vibrating wire strain gauges and four self-sensing concrete strain sensors were installed in the CCS and LCS, respectively. The long side of the rectangular box indicates the monitoring direction of stress and strain for the sensors.

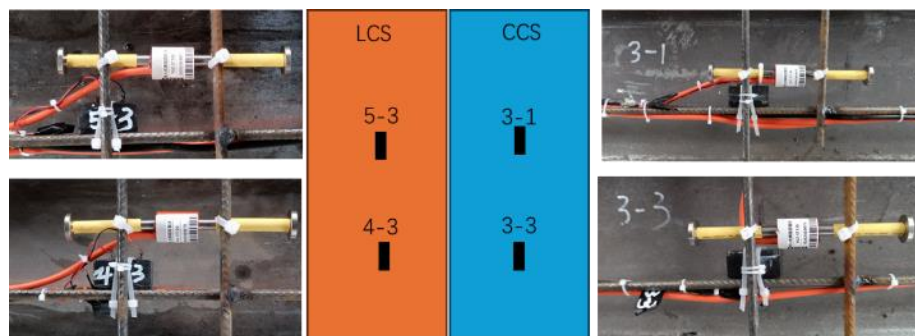


Fig 2.6 Arrangement of sensors

As shown in Fig 2.7, the research team connected the sensors to the corresponding data acquisition devices, debugged the equipment, and verified that the data collection was functioning properly. Subsequently, the two slabs were cast with different types of concrete, and after the MiC units were completed, they were transported to the site for installation and use, together with the monitoring system. The sensors installed in this project will provide long-term monitoring of slab performance, offering a data foundation for the application of lightweight concrete in MiC floor slabs.



Fig 2.7 Installation of the monitoring system

2.2.5 Full-process performance monitoring of joints in modular integrated construction (MiC) during experimental testing

As shown in Fig 2.8, modular buildings are constructed by transporting factory-fabricated room functional module units to the site and assembling them into a structure through reliable joints. Joints are key components of modular structures. During long-term service, due to wind loads, seismic actions, and long-term creep and shrinkage, the grouted joints between modules may sustain damage, which can adversely affect the structural performance. To monitor and evaluate the damage of these joints, piezoelectric (PZT) sensor-based electromechanical impedance (EMI) technology and guided wave technology are used for non-destructive testing of the joints. Combined with the monitoring results throughout the experimental process, relevant damage evaluation indices could be obtained.

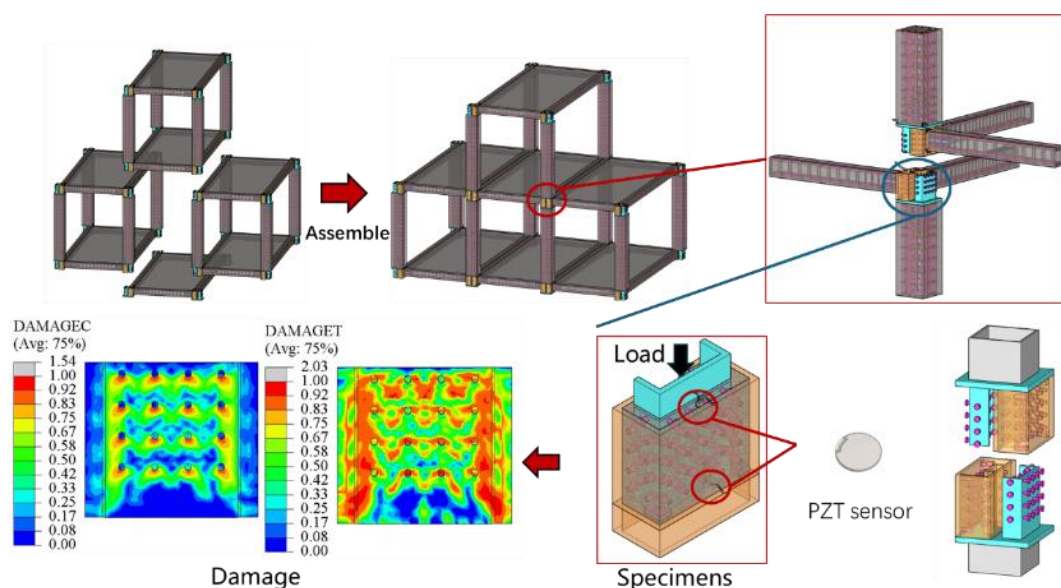


Fig 2.8 Joint of modular structures

The EMI method is a real-time health monitoring technique that evaluates the damage state of a structure by measuring changes in the electromechanical coupling characteristics between a piezoelectric material and the monitored host structure. As shown in Fig 2.9, PZT sensors were attached to the outer surface of the specimens to monitor the impedance changes throughout the entire loading process. The monitoring results throughout the entire experiment indicated that as the loading slip increases, the damage evaluation index (*RMSD*) gradually rose, demonstrating that the EMI technique can effectively detect the full-process damage of grouted joints. Furthermore, a quantitative relationship between a newly developed damage index and slip was established using the EMI method, providing a reliable method for assessing the health and damage state of the MiC connection during real-time service.

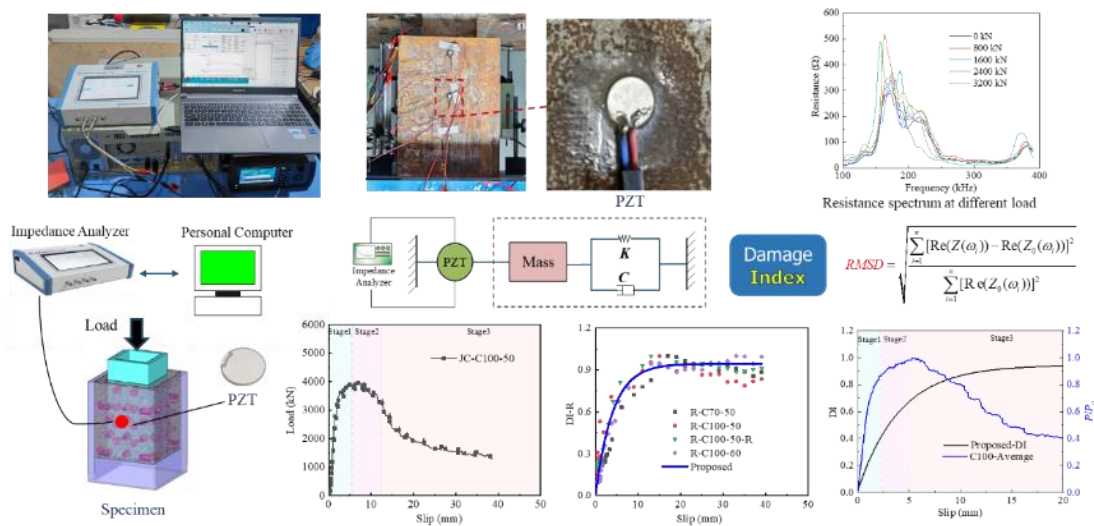


Fig 2.9 Damage detection technology of grouted connection based on EMI technology

As shown in Fig 2.10, by placing piezoelectric sensors on the surface or inside the grouted joint to excite and receive stress waves, the degree of damage in the grouted joint can be determined based on changes in the amplitude of the received stress waves. Experimental results showed that as the axial load increased, the amplitude of the signal received by the sensor gradually decreased, indicating that damage occurred in the grouted joint along the detection path during the loading process. Since the degree of damage plays a crucial role in evaluating the performance of grouted joints in modular structures, the relationship between the damage index (DI) and interface slip was established through further analysis. The damage state of the joint was divided into three ranges to characterise the degree of damage. This study

demonstrates that the guided wave method can successfully quantify the severity of damage in joints of modular structures, highlighting its potential of the guided wave method for damage monitoring and assessment of grouted joints. Based on the full-process damage monitoring conducted during the axial pull-out tests of grouted joints, subsequent studies will focus on monitoring damage related to flexural and seismic performance. In addition to using PZT sensors, self-sensing concrete, electrical impedance tomography (EIT), and digital image correlation (DIC) technologies will also be employed. Furthermore, defects in grouting have a significant impact on the mechanical performance of the joints. Future work will include the detection of varying degrees of grouting defects in the joints and the development of appropriate evaluation indices for the rapid detection of grouting defects in practical engineering applications.

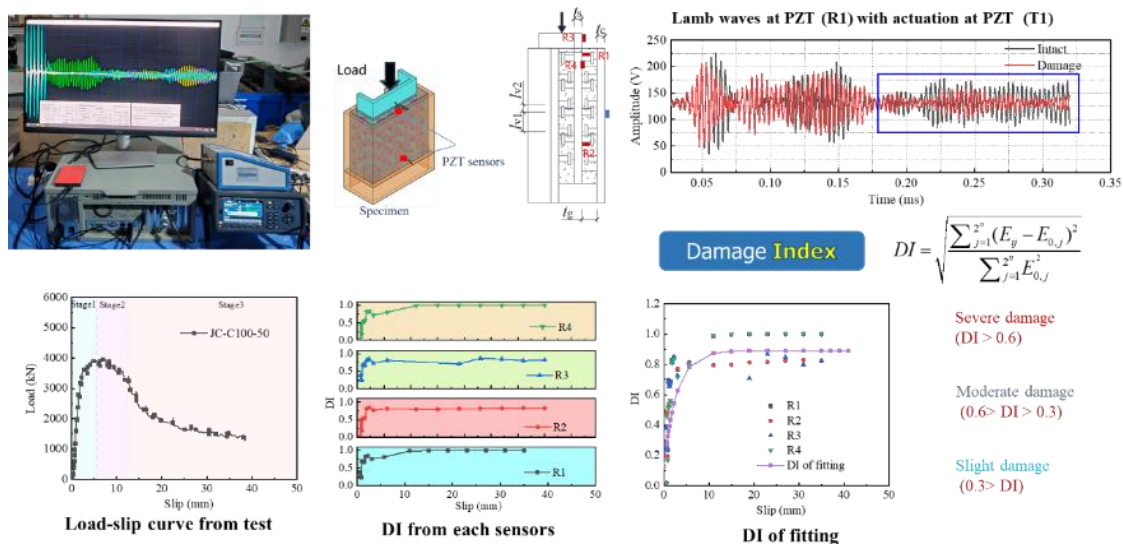


Fig 2.10 Damage detection of grouted joints based on guided wave technology

2.2.6 Weather database of Hong Kong

Fig 2.11 illustrates the workflow of weather research and forecasting (WRF) model data assimilation (WRFDA). WRFDA is capable of seamlessly merging satellite radiance data from Himawari-8, wind profile from The Hong Kong Polytechnic University's LiDAR network, and meteorological data from the Hong Kong Observatory's surface stations and aircraft within a unified framework. This integration enables the generation of a high-resolution and high-

precision reanalysis dataset, establishing a weather database of Hong Kong for high-resolution weather forecasting and climate research in the Hong Kong region.

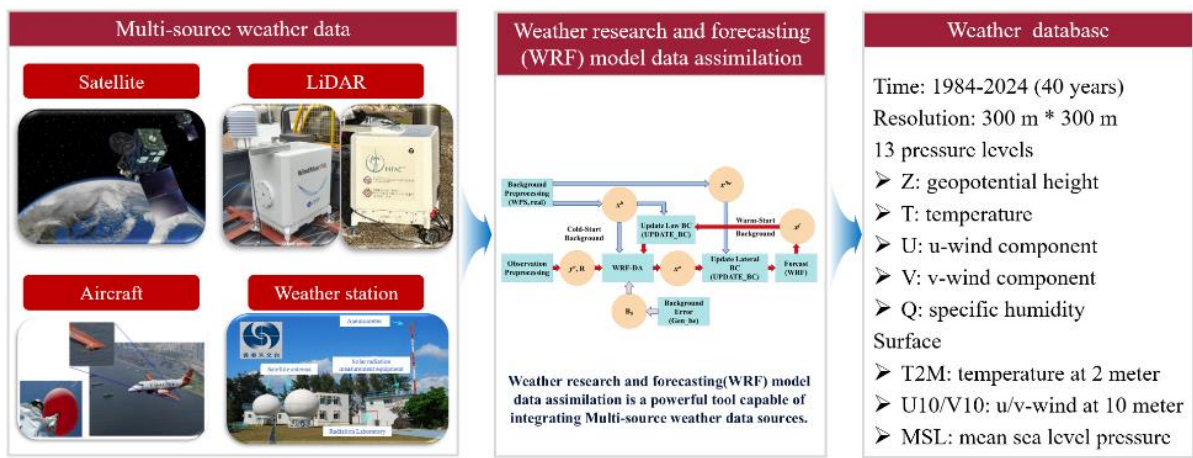


Fig 2.11 The workflow of weather research and forecasting model data assimilation (WRFDA)

2.2.7 Real-Time Monitoring, Numerical Simulation, and Experimental Study of Wind Effects

(1) Real-time structural health monitoring system

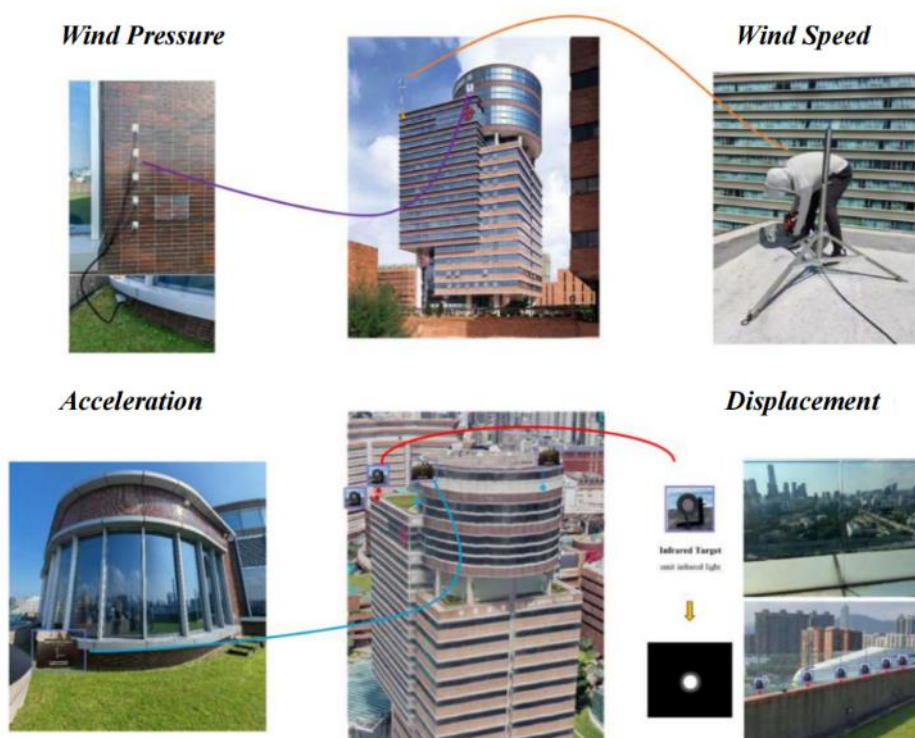
To mitigate typhoon risks and enhance structural safety and resilience in Hong Kong’s urban buildings, The research team from the CNERC-Rail (HK Branch) has deployed real-time monitoring systems. The system has been fully deployed at the Galaxy Twin Towers (Shenzhen) and the Li Ka Shing Tower (PolyU) and has been operational since June 2025. It integrates four categories of sensors (Fig 2.12) to monitor key parameters in real time, including wind speed, wind pressure, structural acceleration, and displacement.

Throughout 2025, the SHM system captured comprehensive dynamic response data from both towers during multiple extreme events. These included Qingyuan earthquake (23 June) in Guangdong and six typhoons: Wutip (14 June), Wipha (20 July), Podul (14 August), Tapah (8 September), Mitag (19 September), and Ragasa (24 September). Notably, Typhoons Wipha and Ragasa prompted the issuance of No. 10 Hurricane Signals. For these specific hazards, the multi-source monitored quantities enable immediate assessment of seismic and wind impacts on structural performance, which provide reliable input for maintenance and risk-management decisions, earning strong support from building owners. Additionally, to further evaluate the dynamic behavior of high-rise buildings under typhoon conditions, portable accelerometers

were used to assess three tall buildings in Hong Kong during Typhoon Ragasa. Fig 2.13 shows the locations of these buildings and their recorded acceleration responses.



(a)



(b)

Fig 2.12 Real-time structural health monitoring system in Hong Kong and Shenzhen: (a) The Galaxy twin towers and (b) Li Ka Shing Tower.

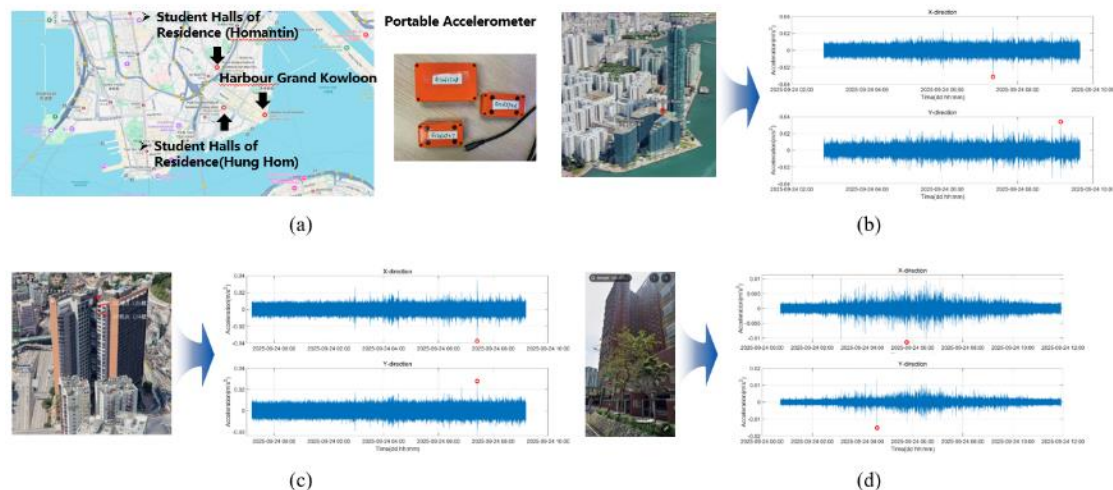


Fig 2.13 Portable accelerometer for monitoring building performance during Typhoon Ragasa. (a) Location of the three buildings and schematic of the portable Accelerometer. (b) Acceleration time history recorded at Harbour Grand Kowloon. (c) Acceleration time history recorded at the Homantin Student Halls of Residence. (d) Acceleration time history recorded at the Hung Hom Student Halls of Residence.

(2) Numerical simulation of wind loads

This study employs the LES model to explore the scale effect on the aerodynamic behavior of high-rise structures and their interactions with surrounding urban environments. The Federal Advisory Aeronautical Research Council (CAARC) building, a widely recognised benchmark for wind tunnel testing and numerical model calibration, is selected for this analysis. Wind tunnel test data of the CAARC building are utilised to validate the LES model. Additionally, the window damage caused by Typhoon Mangkhut in September 2018 at the Harbourfront building in Hong Kong highlights the critical and urgent need to understand the influence of scaling on the aerodynamic behavior of high-rise building clusters. Therefore, the study examines the influence of scaling on wind pressure distribution and flow field dynamics, using both the CAARC building (Fig 2.14) and the Harbourfront building clusters (Fig 2.15) in Hong Kong as case studies. Through comparative analysis across different geometric scales, this research aims to provide valuable insight into the reliability of model-scale simulations and their implications for wind-resistant design in real-world applications.

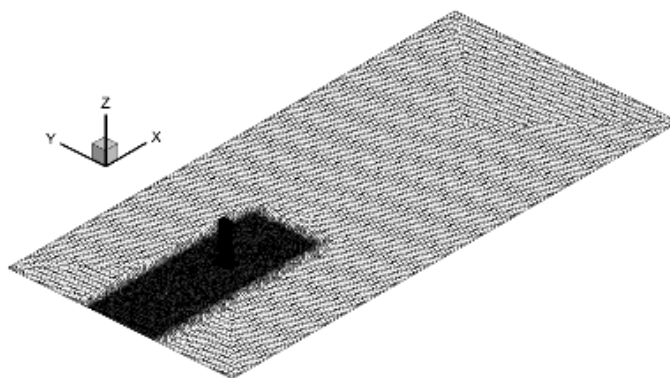


Fig 2.14 Schematic diagram of CAARC standard building

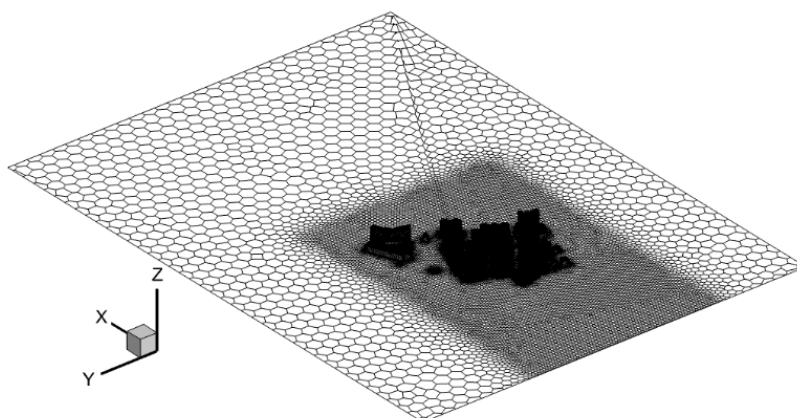


Fig 2.15 Schematic diagram of Harbourfront building clusters

The CAARC standard high-rise building and the Harbourfront building clusters were numerically simulated, and the results were validated through comparison with experimental data from three independent wind tunnel experiments. For the CAARC standard high-rise building, the Harbourfront building, and the Harbourfront Tower, compared to the windward face, the influence of scaling on wind pressure is more pronounced on the crosswind faces, where fluid separation, reattachments, and wake regions occur. This highlights the importance of considering scale effects in wind tunnel testing, especially when evaluating pressures on the crosswind face, where smaller negative pressure values are more sensitive to scaling discrepancies.

(3) Experimental study of debris impact damage mechanism

Experiments are conducted to investigate the impact of wind-borne debris on glass façades. Using a compressed air cannon (Fig 2.16), three types of typical debris were launched, a 16g steel ball, multiple 1.2g glass balls, and irregular sand particles weighing 0.6–0.8g from a fixed

distance of 0.4 meters. Impact velocity was precisely controlled by adjusting pressure (0.01–0.75 MPa), and two high-speed cameras simultaneously captured the debris trajectory and glass fracture process. The tests covered 6mm, 8mm, and 10mm single-layer tempered glass, systematically studying their critical impact resistance and failure mechanisms under typhoon conditions.

All tested glass thicknesses exhibited clear critical thresholds with sudden failure and minimal safety margins. While thicker glass improved resistance to multiple impacts, it offered limited protection against high-energy single impacts. Thus, in typhoon-prone areas, increasing glass thickness alone is insufficient, and additional reinforcement is essential. Cross-shaped tape reinforcement is a low-cost and effective emergency measure recommended upon typhoon warnings. This study provides a scientific basis for the design of impact-resistant curtain walls and household safety preparedness.

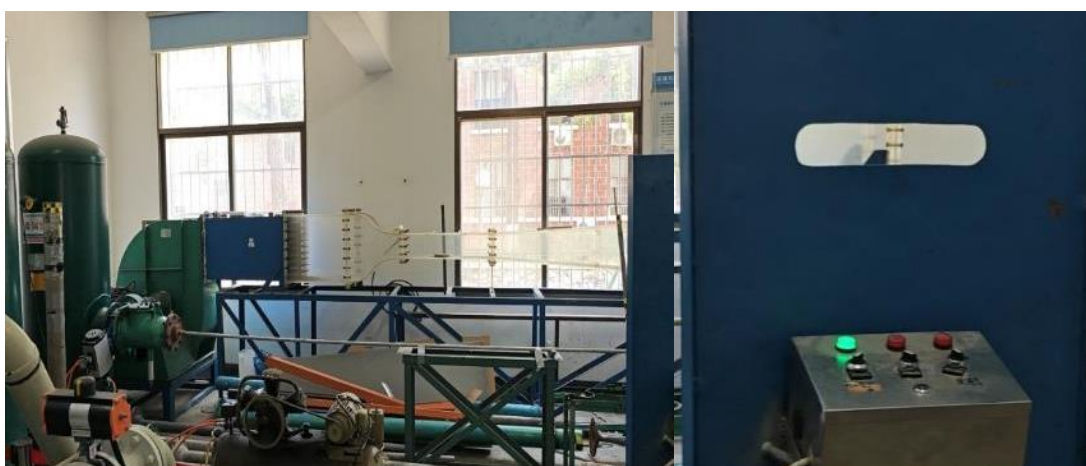


Fig 2.16 Schematic diagram of air cannon and launcher.

2.2.8 Multi-Platform LiDAR Monitoring Network in Hong Kong

(1) LiDAR network for monitoring wind environments cross the entire territory of Hong Kong

Members of the CNERC-Rail (HK Branch) deployed a city-scale boundary-layer LiDAR network covering about 36×36 km across Hong Kong. Installation and calibration were completed in July 2024, after which the system has remained in continuous operation (Fig 2.17). The six PBL LiDARs provide real-time vertical wind profiles with an effective radius of about 15 km per station. In 2025, the network continues long-term observations, supplying real-time

data to HKO for typhoon assessment and supporting the development of a 1-km urban meteorological model that captures spatial and temporal variations of boundary-layer winds.



Fig 2.17 LiDAR network over Hong Kong (2025).

Wipha (2025) originated east of the Philippines in mid-July; on 20 July it passed just south of Hong Kong, made landfalls at Taishan (17:50; 33 m/s, 975 hPa) and Hailing Island (20:15), weakened to a severe tropical storm, moved WSW into the Beibu Gulf on 21 July, made landfall in northern Vietnam on 22 July, and degenerated on 23 July. LiDAR observations captured urban boundary-layer winds, revealing marked spatial and temporal variability across Hong Kong.

(2) Vehicle-mounted LiDAR mobile monitoring system: Monitoring during Typhoon Ragasa

A vehicle-mounted LiDAR monitoring system, established by Prof. Yi-Qing Ni, Dr. E Deng, and other researchers from the CNERC-Rail (HK Branch), mainly consists of LiDAR, an inertial navigation system, and antennas (Fig 2.18). Compared with fixed stations in LiDAR monitoring networks, the vehicle-mounted LiDAR monitoring system offers greater mobility and flexibility. It can dynamically adjust monitoring locations according to the real-time movement path of a typhoon, thereby capturing extreme wind environment cross the entire territory of Hong Kong during typhoons. During September 23–24, 2025, the “Chasing Storm

Team” led by Prof. Yi-Qing Ni conducted field observations of the wind environment of Hong Kong under Typhoon Ragasa, successfully obtaining spatial distribution data of wind speeds across different regions of Hong Kong (Fig 2.19)



Fig 2.18 Vehicle-mounted LiDAR.

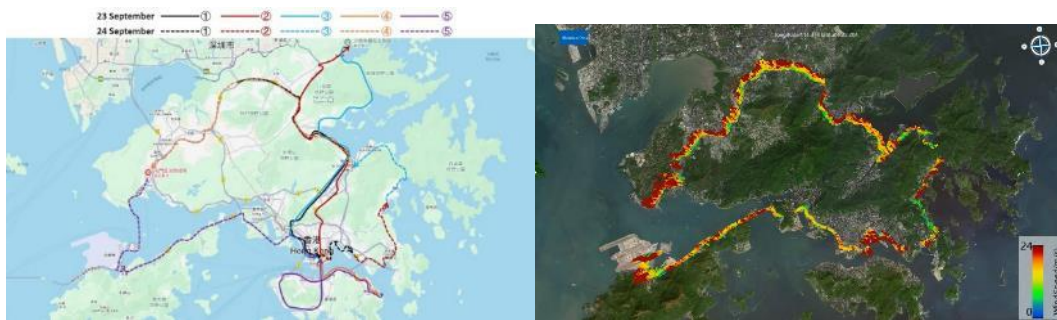


Fig 2.19 Monitoring route and result during Typhoon Ragasa based on vehicle-mounted LiDAR.

2.2.9 Tunnel Specific AI Agent for Automatic Defect Detection

For the maintenance of tunnels, systematic detection of tunnel lining defects in time and evaluation of the impact of tunnel defect severity on tunnel structure through artificial intelligence (AI) is crucial for economic maintenance of tunnel. Existing digital twin models face significant challenges in synchronising with their physical tunnel twin on a regular basis to advise the operator about maintenance schedules. One natural contender for a suitable AI technology to achieve such an ambition is LLMs which have shown themselves to be surprisingly versatile in civil engineering and able to integrate information from multiple sources including images to give meaningful responses to human questions.

(1) LLM-Based Agent for Tunnel Defects Detection

This work developed a tunnel LLM-based agent that integrates large language models (LLMs) with self-developed defect segmentation models for the segmentation, quantification, and evaluation of tunnel lining defects. As shown in Fig 2.22 the tunnel LLM-based agent consists of LLM core, planner agent, tool selection agent, and coder agent. The LLM-based agent can segment and quantify defects in images according to the user input (i.e. prompting words). The LLM core understands the prompting words; the planner agent divides the objective task into some subtasks to implement according to prompting words; the tool selection agent then selects suitable deep learning (DL) or machine learning models to complete the subtasks; the coder agent generates the Python codes to complete the whole tasks.

The aforementioned DL-based model, designed on the MMS egmentation platform using the Deeplab v3+ baseline with attention modules for segmenting tunnel lining defects (such as leakage and cracks), is registered/embedded in the tunnel LLM-based agent. In the LLM-based agent, this self-developed DL model is described as “a tool that can segment and quantify tunnel lining defects given a text prompt such as category names or referring expressions”. When words of “segment and quantify tunnel lining defects” appears in prompting words, the tool selection agent can select this model to complete segmentation and quantification tasks.

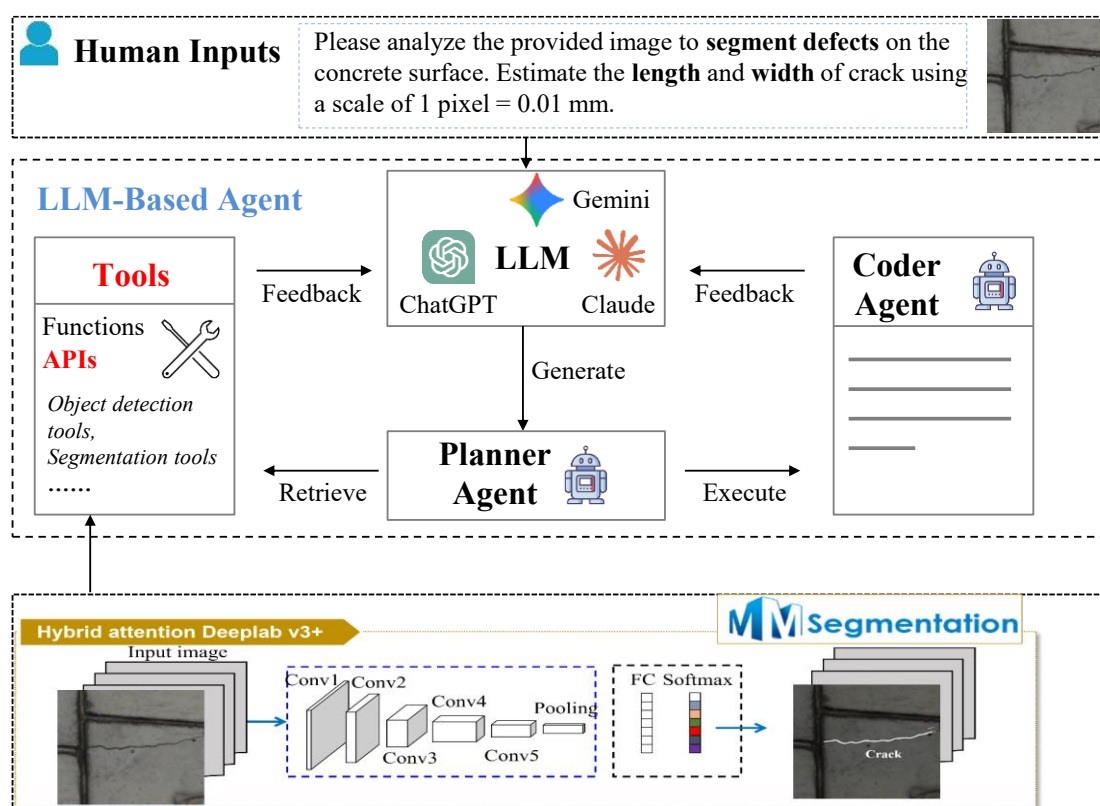


Fig 2.20 Framework of tunnel LLM-based agent

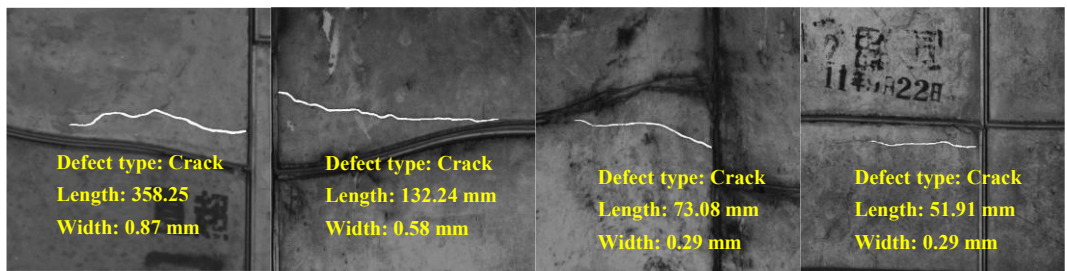


Fig 2.21 Detection results based on tunnel LLM-based agent

As shown in Fig 2.23, the detection results demonstrate that the agent achieves accurate crack segmentation, and the integrated LLM component can generate detailed defect inspection reports automatically, thus facilitating intelligent tunnel condition assessment.

The retrieval-augmented generation (RAG) is introduced into the tunnel LLM-based agent. Through RAG, LLM-based agent is able to query external knowledge bases such as professional databases and norms or standards in the tunnel industry when needed, thereby evaluating the tunnel defect severity and the impact of tunnel defect on tunnel structure according to the norms or standards of tunnel engineering.

Additionally, based on the Cursor platform, a Human-in-the-Loop Feedback module is being designed for the LLM-based agent to provide an intuitive user interface for tunnel engineers (Fig 2.24). This module allows users to upload tunnel lining images and input textual instructions, upon which the agent automatically performs defect detection and evaluation. As illustrated in Fig 2.25, the system is capable of handling various types of defects, such as cracks, leakage, and surface deterioration, and provides corresponding recognition results. Once the detection results are generated, the interface enables engineers to manually review, verify, and, if necessary, revise the defect assessment and recommended maintenance measures. This interactive process allows for the flexible integration of human expertise at key decision points, ensuring both reliability and interpretability of the automated inspection workflow.

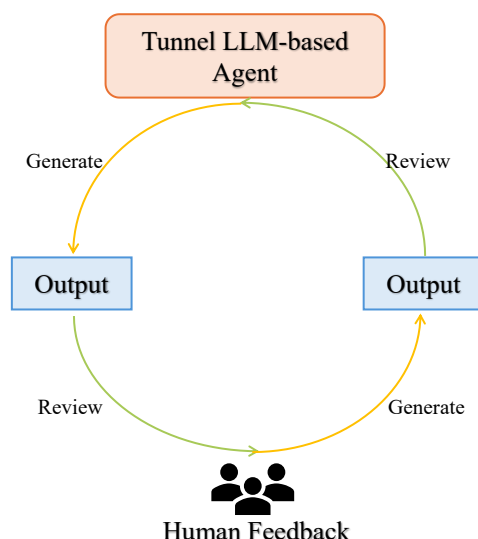


Fig 2.22 Illustration of human-in-the-loop mechanism for Tunnel LLM-based agent



Fig 2.23 Demonstration of the user interface and detection results for various tunnel lining defects

(2) Development of AI-Driven Ground Penetrating Radar Tools under a Customised Agent Framework

The customised LLM-based agent is built on the Qwen-VL-Max-Based Agent System and operates as a multimodal coordination layer that integrates vision-oriented tools for image segmentation, object detection, video understanding, and other task-specific deep learning models. While these capabilities address general perception tasks, a tunnel-specific AI agent also requires domain tools for ground penetrating radar (GPR) analysis and the capacity to generate metro tunnel inspection reports that conform to relevant standards. Accordingly, this research extends the framework with agentic retrieval-augmented generation (RAG) and a series of GPR-focused analytical tools, enabling automated interpretation of multi-frequency

radar data and structured reporting. In addition, a set of auxiliary report-generation tools has been incorporated to enable the automated summarisation and interpretation of on-site measurements data, including laser-scanning point clouds, crack and seepage mapping, and tunnel deformation monitoring data.

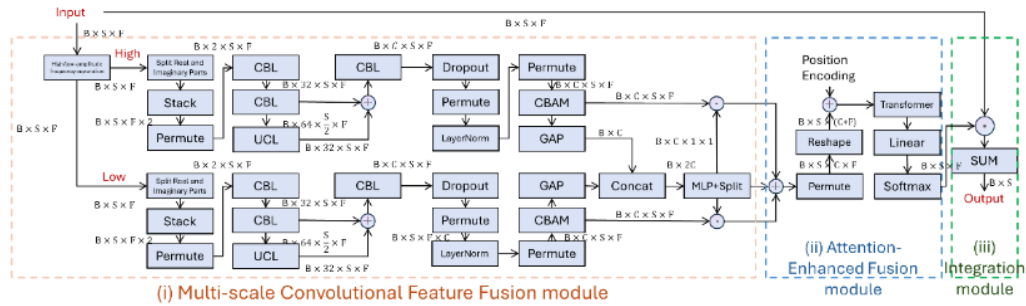


Fig 2.24 Architecture of DFNet.

The first tool developed under the customised agent framework is an unsupervised deep learning method for multi-frequency GPR data fusion in tunnel lining inspection. The trade-off between resolution and penetration across different frequency bands inherently limits GPR performance. It becomes critical in tunnel linings composed of heterogeneous and layered materials. To address this limitation, this study proposes DFNet, an unsupervised deep learning framework for dual-frequency GPR fusion. Fig 2.26 illustrates the general architecture of the proposed fusion network. DFNet decomposes high- and low-amplitude components into parallel branches, applies multi-scale convolutional encoding with attention mechanisms, and integrates a Transformer encoder to capture both local and global dependencies. The fused time-domain representations are adaptively weighted through an information-aware loss function that combines entropy-based and statistical frequency constraints, preserving fine structural details while ensuring smooth transitions across tunnel layers.



(a) GPR data acquisition system (b) Water tanks behind lining (c) Interior View

Fig 2.25 Illustration of the experimental design and data acquisition system.

To validate the proposed dual-frequency fusion framework (DFNet) under real tunnel conditions, ground penetrating radar (GPR) experiments are conducted at the Wuchang Vehicle Base of Hangzhou Metro Line 5. As part of the experimental design, water tanks are positioned behind the tunnel lining to simulate water-filled cavities, as shown in Fig 2.27(b).

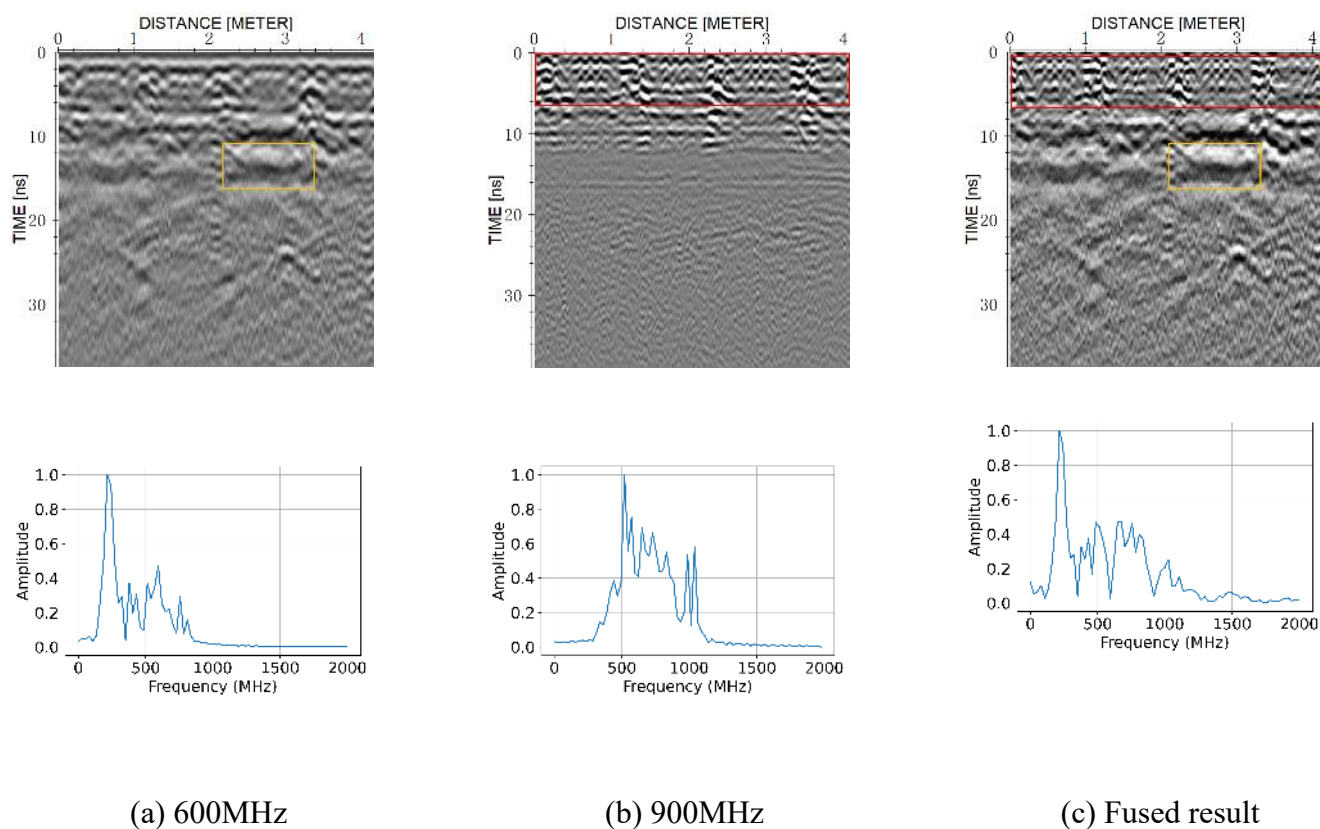


Fig 2.26 Simulated radargrams before and after fusion and the Spectrum of radargrams at No.280 trace.

The datasets acquired at the two central frequencies are processed by the proposed fusion network. As shown in Fig 2.28(a), the 600 MHz radargram provides clear reflections of the water tank but insufficient resolution for shallow reinforcement identification. In contrast, the 900 MHz radargram (Fig 2.28(b)) reveals dense hyperbolic signatures of rebars yet fails to capture deeper anomalies. The fused result (Fig 2.28(c)) effectively integrates both advantages, retaining high-frequency structural details while enhancing the low-frequency response from deeper regions. The spectrum at the 2.8 m trace exhibits a broadened frequency band that combines dominant low-frequency and preserved high-frequency components, confirming improved detectability and characterisation of subsurface defects such as water-filled cavities.

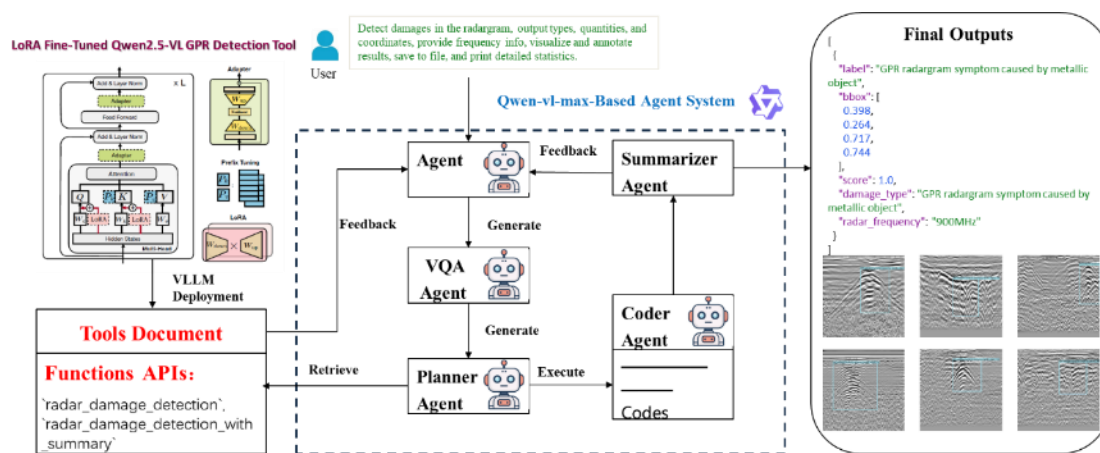


Fig 2.27 LoRA-fine-tuned Qwen2.5-VL GPR defect detection tool integrated into the agent framework.

The second component developed within the customised agent framework is a vision-language model for GPR defect detection, fine-tuned from Qwen2.5-VL through Low-Rank Adaptation (LoRA). In this implementation, LoRA matrices are inserted into the attention and multilayer perceptron (MLP) linear projections of both the visual and textual branches, enabling parameter-efficient domain adaptation to GPR imagery. The training corpus consists of GPR radargrams acquired from Guangzhou Metro tunnels. The fine-tuned model is subsequently deployed via VLLM inference architecture and integrated into the agent’s tool library through two dedicated APIs, which operate jointly with the unsupervised fusion network developed earlier. Within the Qwen-VL-Max-based orchestration, multiple specialised agents—including the planner, visual question-answering (VQA), coder, and summariser agents—coordinate to accomplish radar-specific analytical tasks, tool selection, and automated reporting. Empirical evaluation indicates that the tool invocation accuracy

exceeds 95%, and the task completion rate remains above 90%, demonstrating the robustness and operational reliability of the enhanced agent framework in tunnel-specific GPR inspection scenarios.

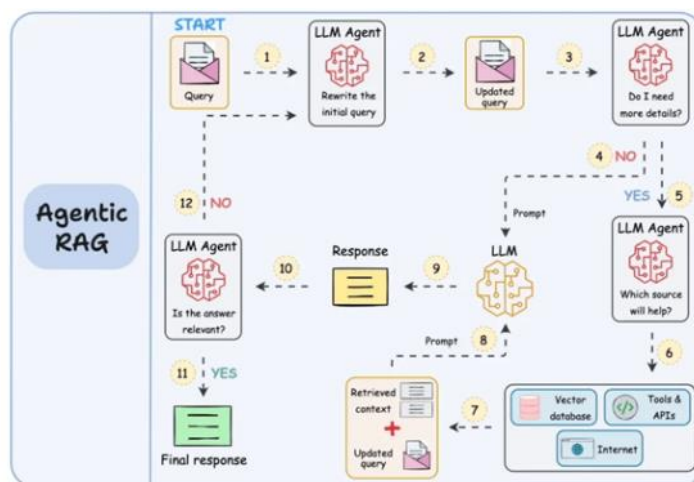


Fig 2.28 Architecture and reasoning loop of Agentic RAG.

This work next develops a Standards-RAG Agent, i.e., an agentic RAG module that performs iterative retrieval, clause-level grounding, and self-verification against urban rail tunnel standards (e.g., T/CECS 788-2020 and related codes). This Standards-RAG Agent will extract and interpret textual clauses, tabular data, graphical diagrams, and mathematical formulas, and link multi-source measurements to normative thresholds, integrating them into the knowledge base accessible by other agents. Deliverables include a regulation-aware knowledge index, compliance tables, and auto-generated assessment paragraphs, enabling reliable, auditable tunnel-inspection reporting within the customised agent framework.

(3) LLM-Based Agent for Tunnel Stability Assessment

Accurate prediction of tunnel face stability is critical in underground construction, as it directly affects construction safety and project quality. Once the surrounding rock becomes unstable, construction schedules are disrupted and severe safety incidents may occur. Consequently, achieving accurate and rapid assessment of tunnel face stability remains a core challenge in engineering practice. Traditional prediction methods, such as acoustic testing, drilling and sampling, and on-site observation based on engineering experience, can reflect the state of the surrounding rock to some extent. However, they generally suffer from complex operation, reliance on expert knowledge, delayed data feedback, and safety risks during testing, making them insufficient to meet current demands for efficiency, intelligence, and unmanned

operations in tunnelling. With the rapid development of artificial intelligence, exploring new intelligent prediction approaches has become an inevitable trend to advance stability assessment.

During construction, abundant multimodal data is provided by the tunnel face, including face images, videos, GPR (Ground Penetrating Radar) inspection reports, horizontal advanced drilling data, and geological sketches. These sources capture different dimensions of the rock mass, from surface appearance to internal attributes, thereby offering valuable potential evidence for stability prediction. Nevertheless, directly fusing such heterogeneous data presents multiple challenges: data schemas vary markedly across modalities, semantic associations are weak, and samples are imbalanced, all of which hinder the accuracy and robustness of conventional deep learning methods. In this context, LLMs, with their capabilities in cross-modal representation learning and knowledge transfer, offer distinct advantages. They can capture latent relationships among complex features in multimodal settings, providing new technical pathways for tunnel face stability prediction.

Based on tunnel face stability monitoring, with reference to the BQ classification system, images were evenly partitioned into five stability classes. The initial baseline dataset included 9,000 tunnel-face frames; analysis showed Class III accounted for over 60%, whereas Class V comprised less than 5%, which severely constrained the ability of LLMs and CV models to learn discriminative features for the tunnel face. Prolonged on-site waiting to capture rare rock-mass classes is time-consuming and disrupts construction. To this end, an intelligent augmentation paradigm based on generative adversarial mechanisms was proposed, and the rock image synthesis capabilities of five mainstream methods, including GPT-4o, Ali-Qwen, Keling, Yuanbao, and Doubao, were systematically evaluated (Fig 2.31).



Fig 2.29 Comparison of different generated images based on Different LLMs

For tunnel videos, the Vision Agent was adopted to recognise and segment dynamic rock-mass features, showing strong engineering applicability and analytical efficiency. Driven by natural language prompts like “identify leakage areas, segment their contours, and compute real-time area.” Vision Agent automatically parses user intent, composes the processing pipeline, and outputs visual overlays with quantitative results. Fig 2.32 demonstrates strong information extraction capabilities of Vision Agent for leakage area and weak interlayer characterisation in tunnel-face videos.

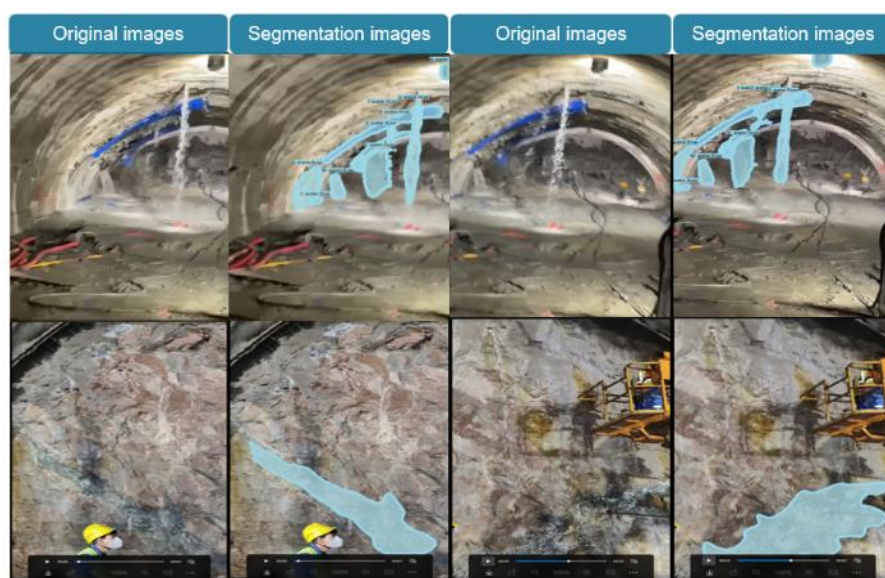


Fig 2.30 Video processing results of tunnel working face based on Vision Agent.

To achieve the prediction of rock hardness based on multi-modal data, several advanced LLMs capable of processing multi-modal datasets were selected as the foundational architecture, including GPT, DeepSeek, Qwen, and Yuanbao-T1. These interactive LLMs possess deep reasoning capabilities, enabling them to handle complex problems and multi-modal data more effectively, thereby facilitating the prediction of rock hardness using the designed multi-modal dataset in this study. To enhance the efficiency of secondary development for multiple LLMs in rock hardness prediction, the Dify platform was employed. This platform offers fully visualised end-to-end development and supports hybrid deployment of multiple models and multi-modal data, allowing for better performance comparison among fine-tuned LLMs. The secondary development process based on the Dify platform is illustrated in Fig 2.33, demonstrating the prediction of tunnel stability under multi-modal data conditions. The fine-tuned predictive models were designated as follows: (a) TunnelRHP-GPT, (b) TunnelRHP-DeepSeek, (c) TunnelRHP-Qwen, and (d) TunnelRHP-Yuanbao (Fig 2.34).

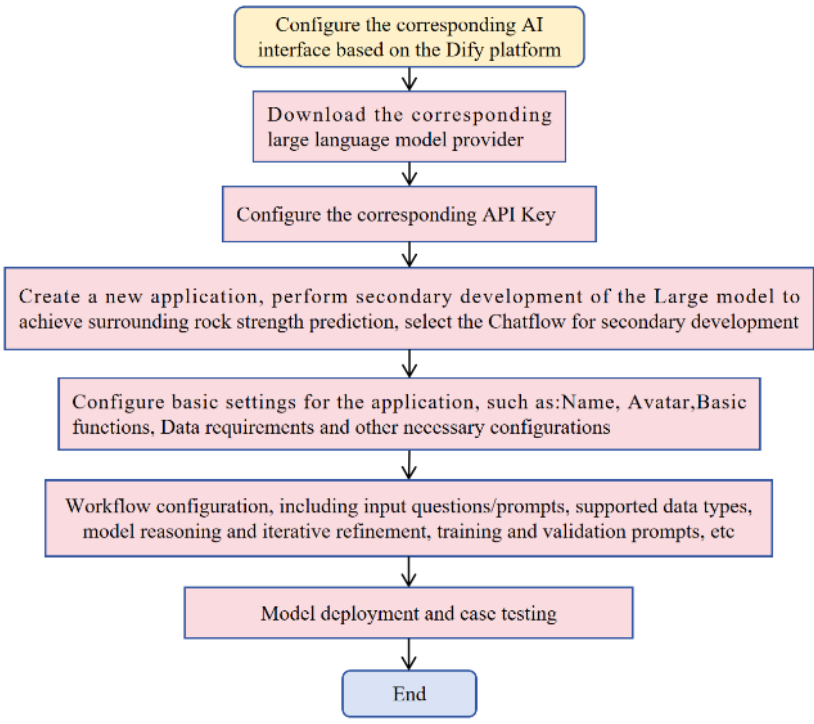


Fig 2.31 Workflow example for fine-tuning LLMs

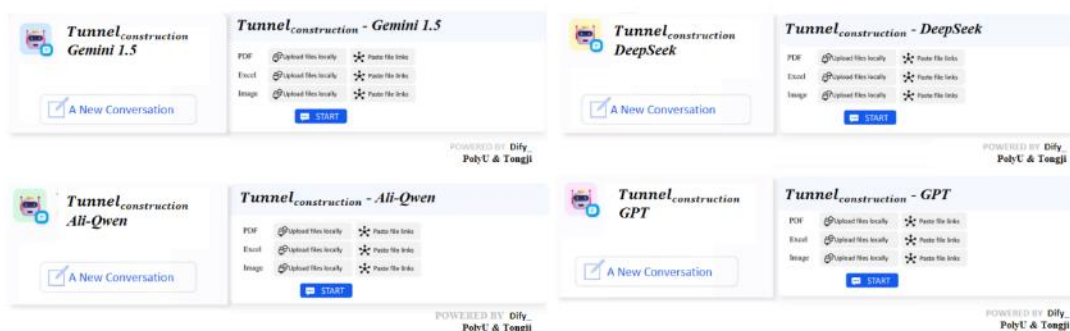


Fig 2.34 Multiple prediction models for secondary development:
 (a) Tunnel construction-Gemini1.5 (b) Tunnel construction-DeepSeek,
 (c) Tunnel construction-Ali-Qwen and (d) Tunnel construction-GPT

2.2.10 The Active Early Warning System of Bridge Anti-Vessel Collision

With the increasing busyness of modern waterway traffic, bridges, as critical transportation infrastructure, face potential risks of vessel collisions. Incidents such as the vessel collision at the Guangzhou Lixinsha Bridge have resulted in severe casualties and property losses. Research on an active anti-collision warning system for bridges, aimed at identifying potential collision risks, is of great significance for enhancing bridge safety. To overcome the bottlenecks in existing technologies, the CNERC-Rail, in collaboration with the Shenzhen Academy of Disaster Prevention and Reduction, has initiated the project "Key Technologies for Active Warning and Emergency Response of Bridge Anti-Vessel Collision Based on Multi-Source Sensing and Artificial Intelligence Algorithms." During the project, Dr. Wenqiang Liu, Dr. Junping Zhong, and Dr. Sumei Wang proposed a series of research solutions and methods to address practical engineering challenges.

(1) Site Selection For Demonstration Bridge And Hardware Platform Setup of The Active Early Warning System of Bridge Anti-Vessel Collision

As shown in Fig 2.42 and Fig 2.43, to install, test, and demonstrate the developed warning system at an actual bridge site, members of the CNERC-Rail, staffs from the Shenzhen Academy of Disaster Prevention and Reduction, personnel from the Guangzhou Bridge Management Unit, and hardware equipment manufacturers conducted on-site surveys and equipment tests at the Guangzhou Shawan Bridge on March 31, 2025, and the Guangzhou

Beidou Bridge on October 31, 2025. Ultimately, the Guangzhou Beidou Bridge was selected as the demonstration bridge for installation.

As illustrated in Fig 2.44, the developed warning system includes visual cameras, marine radars, 3D LiDAR, spot LiDAR, AIS, integrated structural safety detectors, and acoustic-optic-electrical warning devices. The system primarily integrates data from visual cameras, marine radars, and AIS to actively identify, track, locate, and predict the trajectories of vessel objects. LiDAR devices are used to detect the ultra-high status of vessels. By synthesising various monitoring information, the system can proactively assess the risk of bridge-vessel collisions and utilise acoustic-optic-electrical warning devices to actively alert vessels, thereby preventing disasters.



Fig 2.32 On-site survey of Guangzhou Shawan Bridge.



Fig 2.33 On-site survey of the Guangzhou Beidou Bridge.

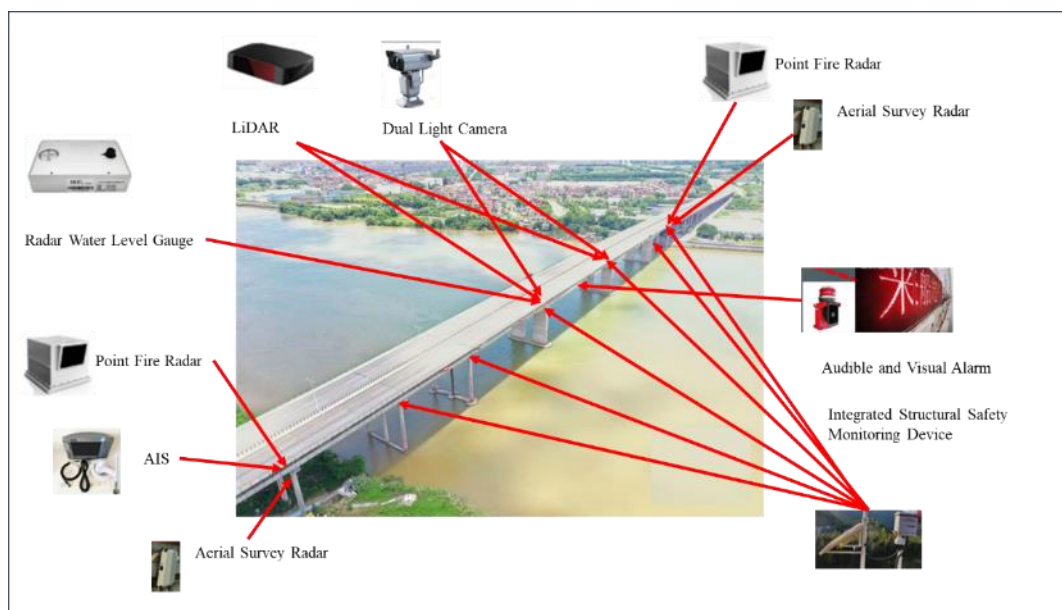


Fig 2.34 Schematic diagram of the installation and deployment of the active early warning system of bridge anti-vessel collision.

(2) Research on Active Tracking Algorithm for the Active Early Warning System of Bridge Anti-vessel Collision

As shown in Fig 2.45 and Fig 2.46, the research proposes a fast prompt-based learning vessel object tracking method. First, a bridge monitoring system—comprising surveillance cameras, illuminometers, and visibility detectors—is installed on bridges in navigable waters to collect vessel images and ambient environmental data, thereby constructing a multimodal vessel monitoring dataset. Second, a prompt-based learning model for vessel image restoration in complex environments is developed to achieve precise recovery of vessel images. Finally, an anti-occlusion vessel object tracking method is constructed to enable effective tracking of vessel objects. Compared with traditional object tracking methods, the proposed prompt-based learning model for vessel image restoration in complex environments improves the quality of vessel images and effectively addresses the difficulty of vessel recognition caused by image degradation. Meanwhile, the developed anti-occlusion vessel object tracking method overcomes the issue of missed detections caused by mutual occlusion when two vessels encounter each other, significantly enhancing vessel tracking performance. Specific tracking results are illustrated in Fig 2.47.

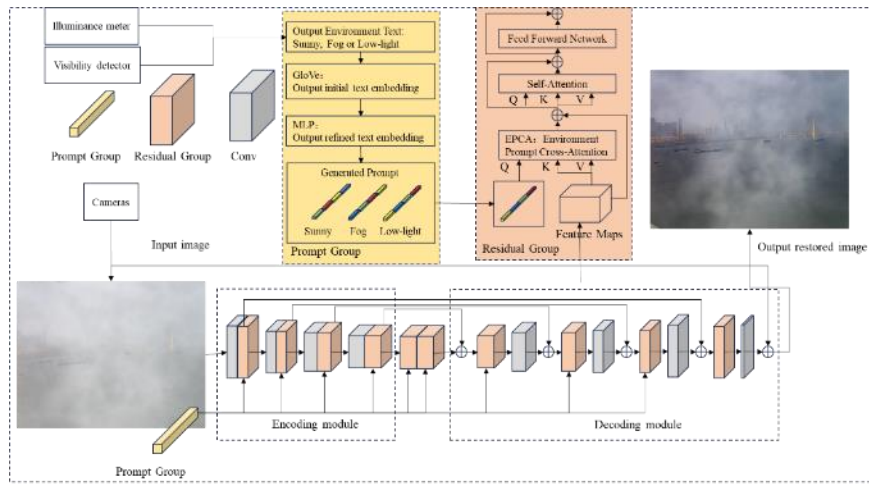


Fig 2.35 Schematic diagram of the network structure of the proposed vessel image restoration method.

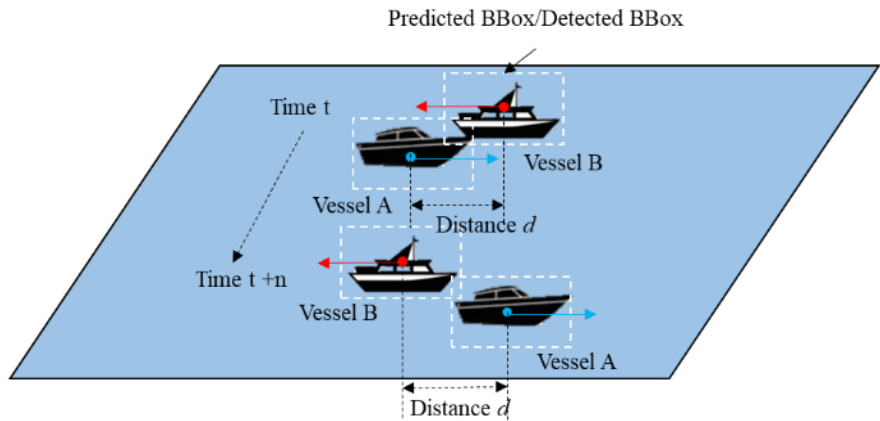


Fig 2.36 Schematic diagram of the proposed vessel object occlusion tracking method.

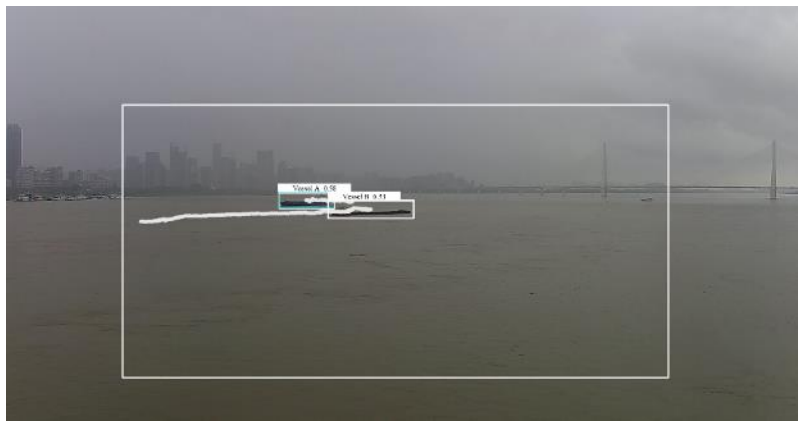


Fig 2.37 Schematic diagram of the vessel encounter tracking effect.

2.2.11 Multi-scenario experiments at MTR Diamond Hill Station: dynamic test, noise monitoring, corrugation measurement, DAS-based dispersion curve extraction, and obstacle intrusion detection.

Project objectives

1. The primary objective of the dynamic test was to clarify the underlying failure mechanism of the original PR401A clips and assess the impact of clip replacement. An impact hammer test was performed to determine the modal frequencies of clips in their assembled configuration. The vibration frequencies of the wheel-rail system were identified by measuring rail acceleration during metro operation. Comparisons were made between the vibration characteristics of the clip and the wheel-rail system.

2. The aim of noise monitoring was to evaluate the noise level at the small-radius curve section with abnormal corrugation. A sound pressure sensor was mounted on the tunnel wall at a track section with severe rail corrugation to monitor the wheel-rail noise during a whole-day operation period.

3. The objective of rail corrugation measurement was to acquire the corrugation characteristics and wear distribution of the track before and after the clip replacement.

4. High-performance DAS interrogator integrated with a 400-meter-long distributed optical fibre was employed to capture ambient noise inside an MTR tunnel. A passive multi-channel surface wave analysis (MASW) algorithm was employed to extract dispersion curves.

5. The obstacle intrusion detection using intelligent Obstacle Intrusion Detection System (OIDS) at key monitoring locations aimed to provide real-time intrusion alerts to the dispatch centre so that potential accidents could be prevented.

Research progress

Track vibration measurement:

Clip failure frequently happens in the small-radius curve segment of the Tuen Ma Line connecting Diamond Hill Station and the Kai Tak Station (as shown in Fig 2.48), posing significant risks to train safety and stability. To solve this problem, the Hong Kong Branch of the National Rail Transit Electrification and Automation Engineering Technology Research Center (CNERC-Rail) at The Hong Kong Polytechnic University (PolyU) was invited to conduct relevant tests and analyses.

A typical section of the small-radius curve track was selected as the test site. At this section, structural vibration and noise of the track were collected. The vertical and lateral rail

vibration was measured via triaxial accelerometers mounted on webs of the inner and outer rails. The vertical vibration of the track slab was measured using single axis accelerometers, which were mounted on the middle of the track slab. A sound pressure sensor was mounted on the tunnel wall to measure the wheel-rail noise. Fig 2.49 illustrates the sensor layout on the tunnel cross-section view. The sensors were connected to the data acquisition device Dewesoft and stored in a laptop through cables, Fig 2.51 illustrates the on-site setup of the rail acceleration measurement. Four test crews were participating in the initialisation of the track vibration measurement.

Clip modal test

Test grid of the clip modal test is shown in Fig 2.52. The acceleration of the clip was tested using triaxial accelerometers. Three test points were set on the clip, and a reference point was set on the rail head near the hammer hit location. These four test points were defined as A1, A2, A3, and A4. The coordinate orientation of the accelerometers is also presented in Fig 2.52. It is noted that the excitation force was near A4. The accelerometers were connected to the Dewesoft data acquisition and the data was stored in a laptop. Each test was repeated five times, and the frequency response function (FRF) would be calculated as the average result.

Two members were participating in this test. Fig 2.53 shows the field processing situation of the test.

Corrugation measurement

The rail corrugation was measured using a Bilateral Corrugation Analysis Trolley (Bi-CAT). This device enables precise measurement of rail corrugation on both the inner and outer rails in a single pass. A laptop was placed on the Bi-CAT to monitor the real-time measured data. The on-site usage of the Bi-CAT is illustrated in Fig 2.54. The sampling interval was set to 2 mm, and the walking speed was 0.8-1.2 m/s.

Two members were participating in this measurement with one person pushing the Bi-CAT and the other monitoring the real time measured data and watching for the track discontinuity. The measurement was performed simultaneously with the clip modal test.

DAS-based dispersion curve extraction

An optical fibre with 2 mm diameter is placed right at the centre of the track slab to measure the Rayleigh waves on the rail surface, as shown in Fig 2.55. The optical fibre has a sampling frequency of 210 Hz and a spatial resolution of 1.63 m.

Fig 2.56 shows how the optical fibre and the DAS interrogator are fixed in the test site. In the middle of the track slab, there is a steel cable bracket. The optical fibre is secured at the bottom of the bracket using cable ties, with the fixing interval matching the spacing between two brackets. The connecting optical cable between the track slab monitoring points and the interrogator is affixed to the ground with fibre-reinforced adhesive tape to prevent it from being lifted during train operation, which could interfere with the train's movement. The interrogator is housed in a custom-designed signal acquisition box for protection. The bottom of this box is bolted to the ground and is further secured to a nearby pipeline by aviation cable ties.

Railway Obstacle Intrusion Detection

Fig 2.57 illustrates the 24-hour OIDS monitoring test conducted at Diamond Hill Station. The camera-LiDAR integrated sensor box and the PC were installed on and inside a custom-made equipment cabinet, respectively. The devices were powered by a 220V AC supply. The deployment work was completed before 03:00 a.m. on August 11, 2025.

The system utilises a time-synchronised camera and LiDAR sensor for data acquisition, ensuring temporal alignment and consistency across multiple data sources. The collected data are primarily stored on local storage devices, with the local server equipped with an NVIDIA RTX 4090 GPU. To enable remote access and centralised management, the system also supports synchronously uploading the acquired data to a cloud platform. Representative samples of the captured images and point clouds are shown in Fig 2.58 and Fig 2.59 respectively.

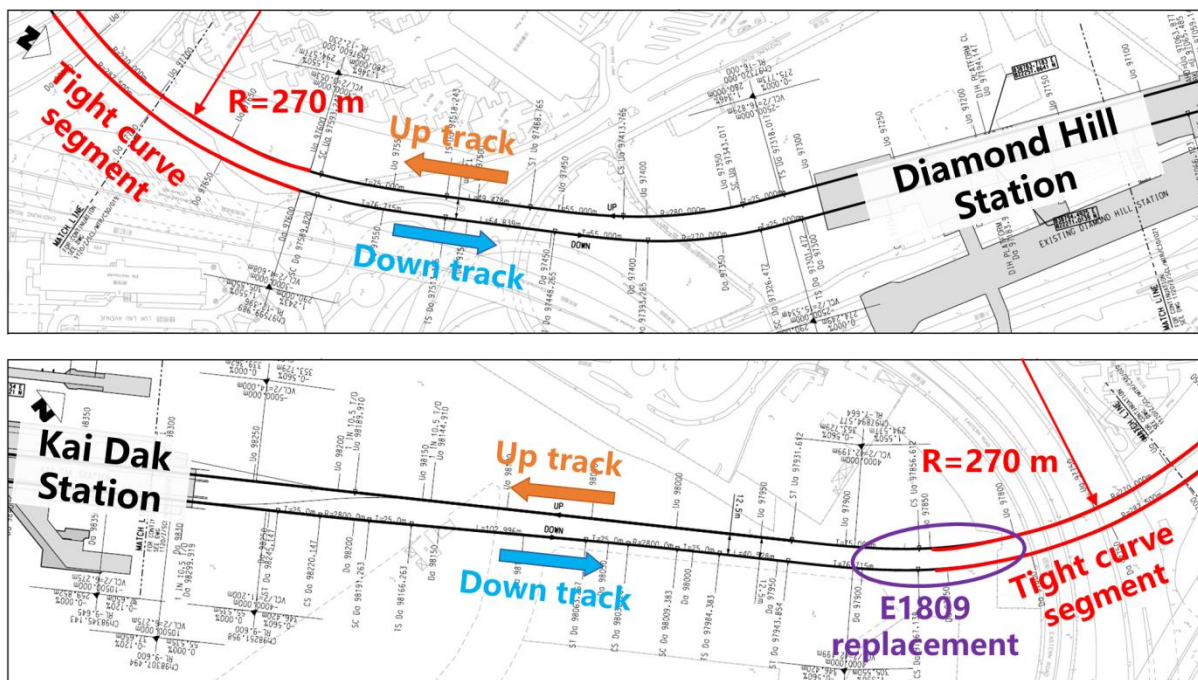


Fig 2.48 Track layout of the Tuen Ma Line connecting the MTR Diamond Hill Station and Kai Tak Station.

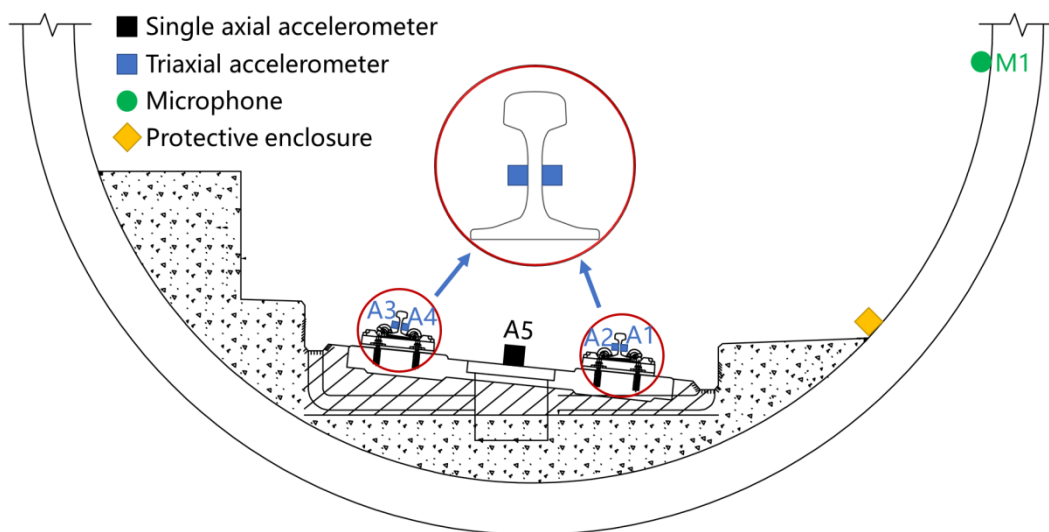


Fig 2.49 Sensor layout of track vibration measurement.

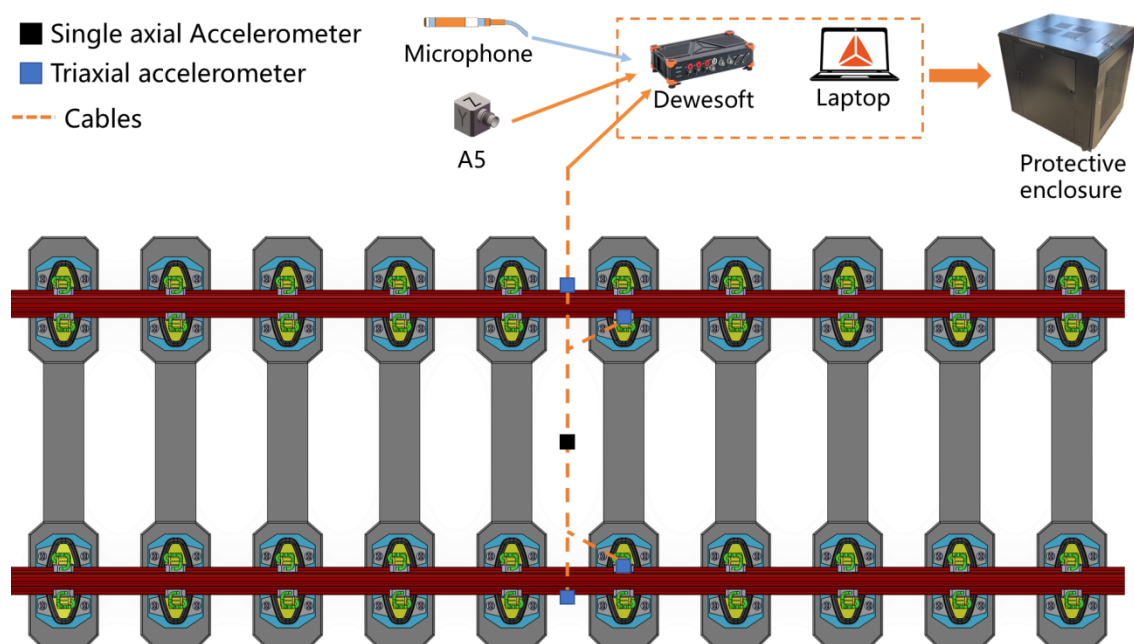


Fig 2.50 Sensor layout of the track vibration measurement on the top view.

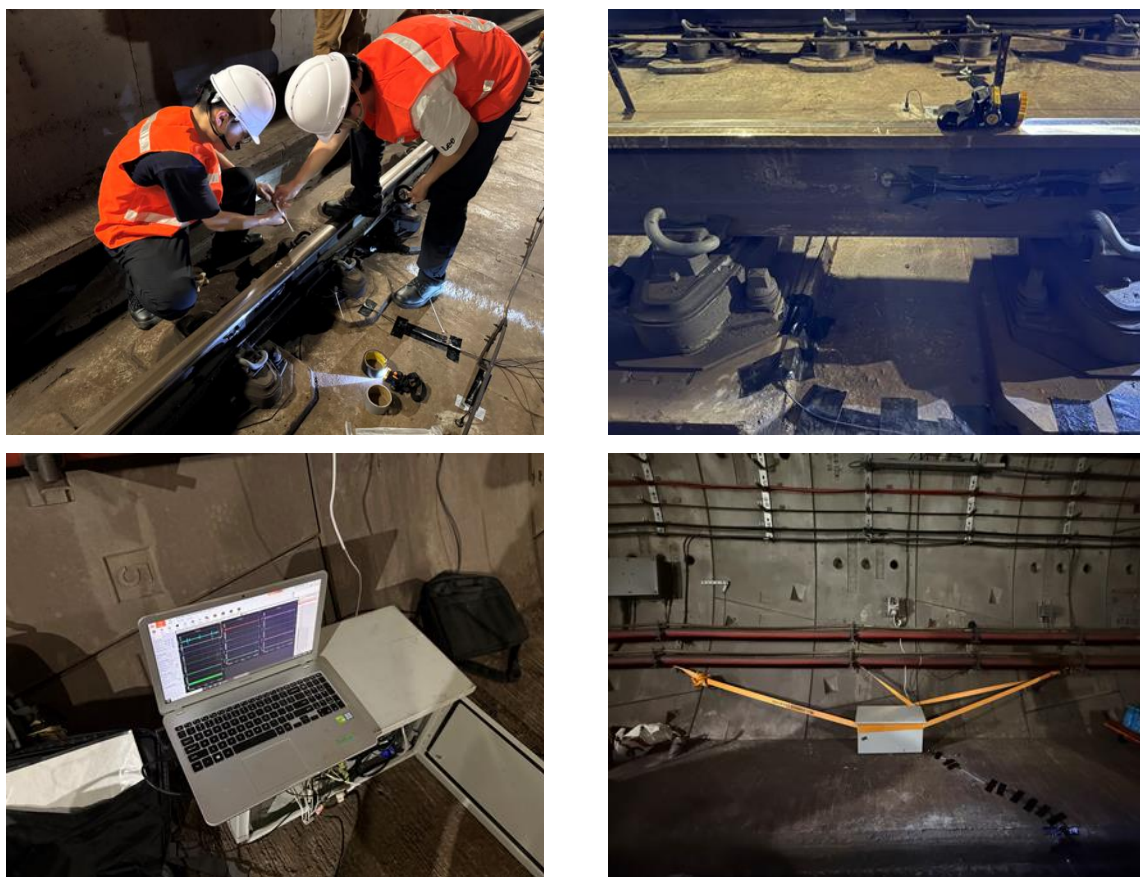


Fig 2.51 On-site setup of the rail acceleration measurement.

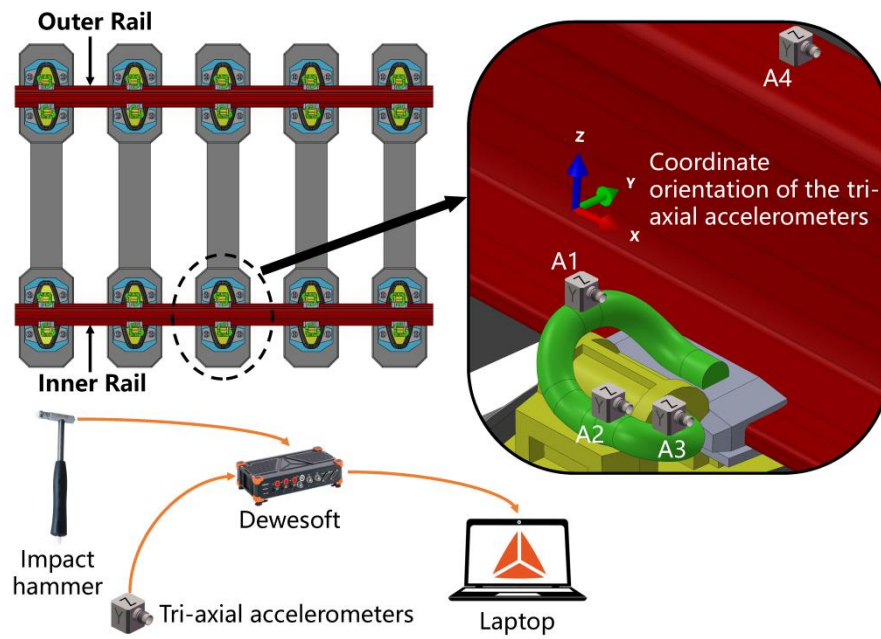


Fig 2.52 Test grid of the clip modal test.



Fig 2.53 Field processing situation of the impact hammer test.

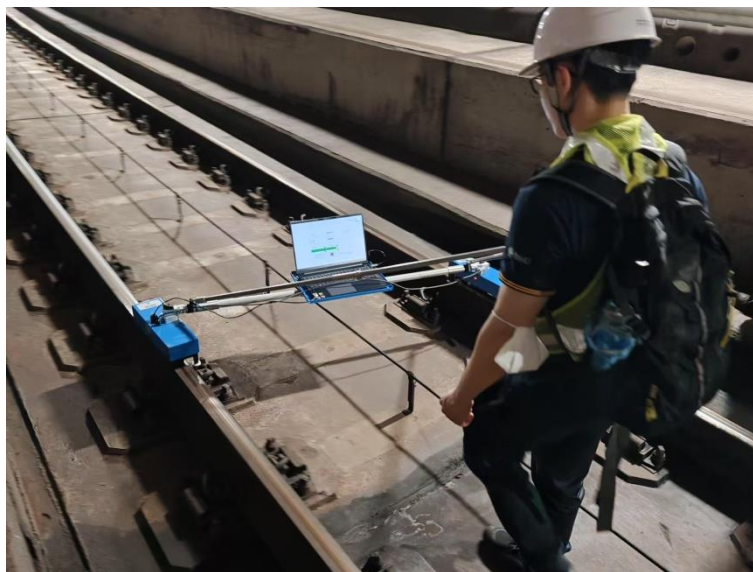


Fig 2.54 On-site usage of the Bi-CAT.

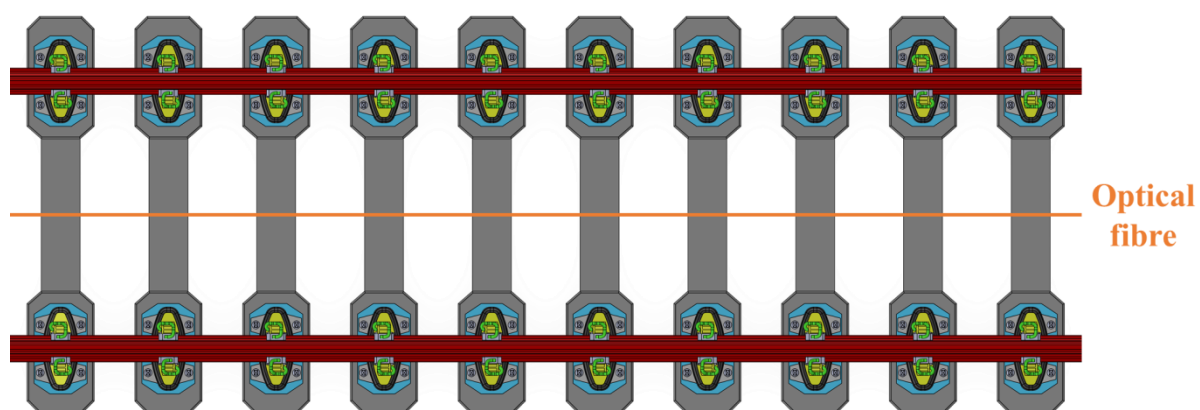


Fig 2.55 Sensor layout of the track vibration measurement on the top view.

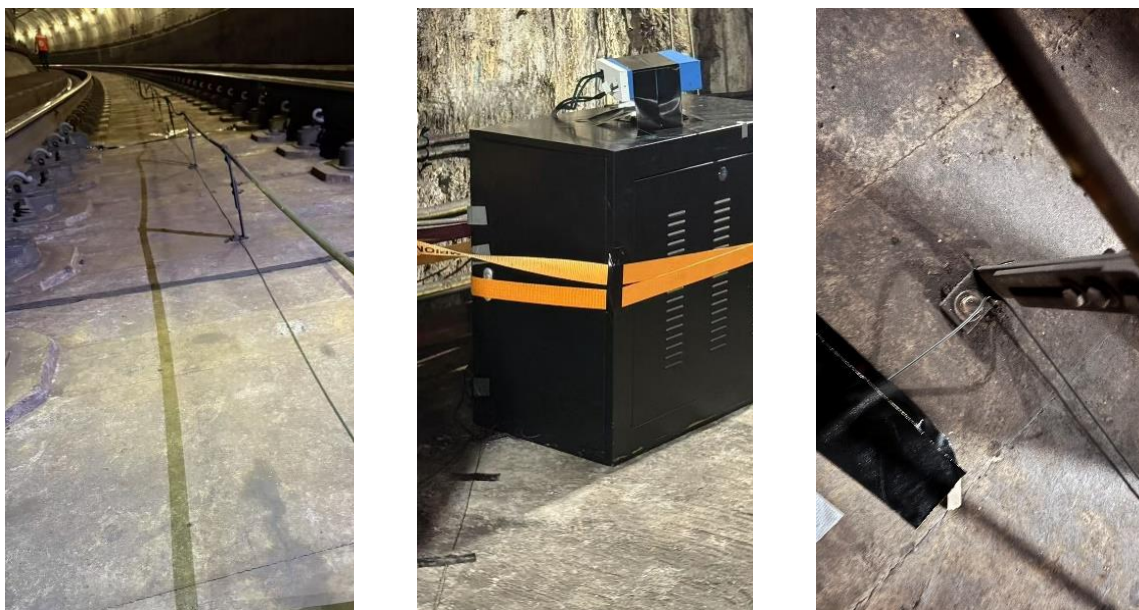


Fig 2.56 On-site setup of the optical fibre and interrogator.

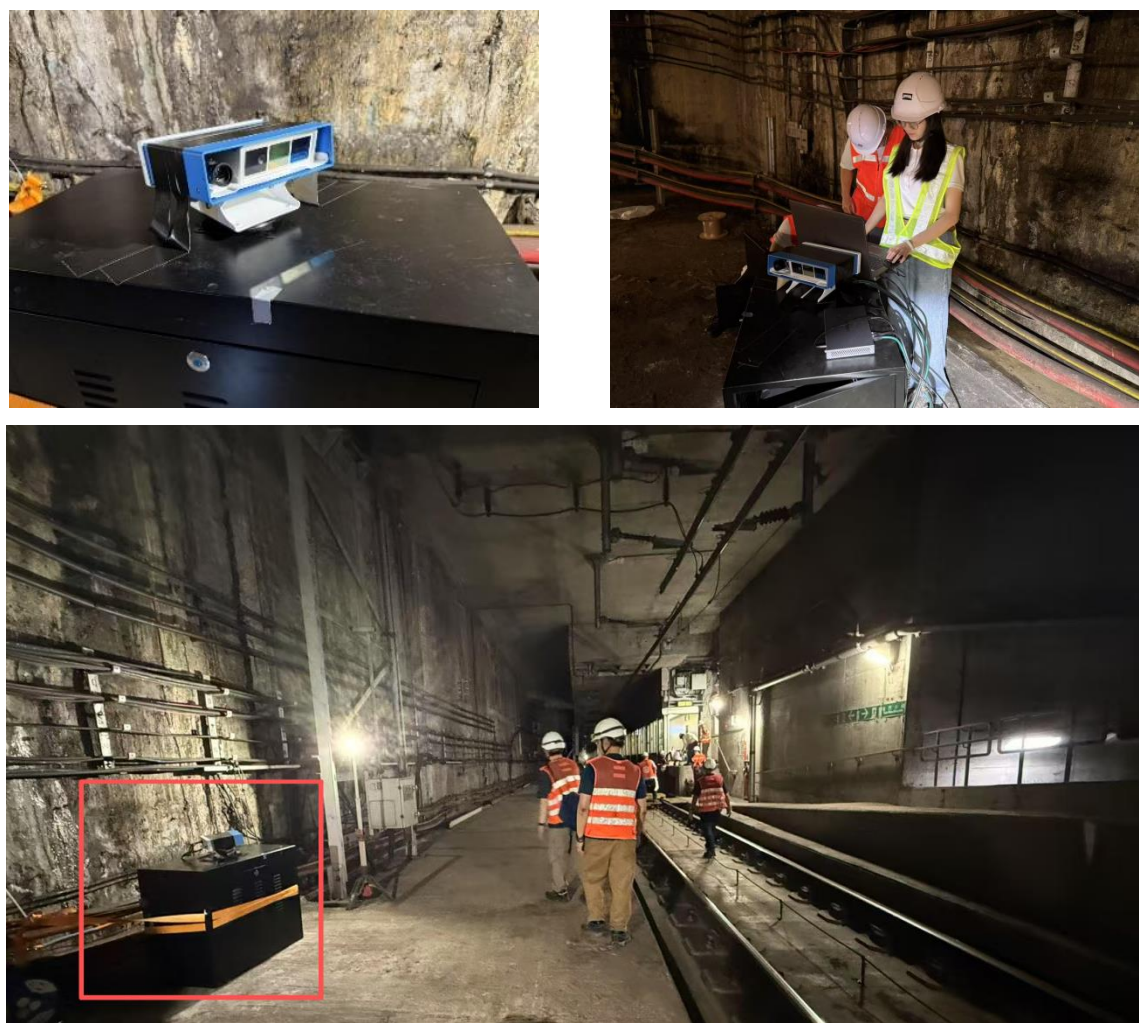


Fig 2.57 On-site setup of the OIDS.

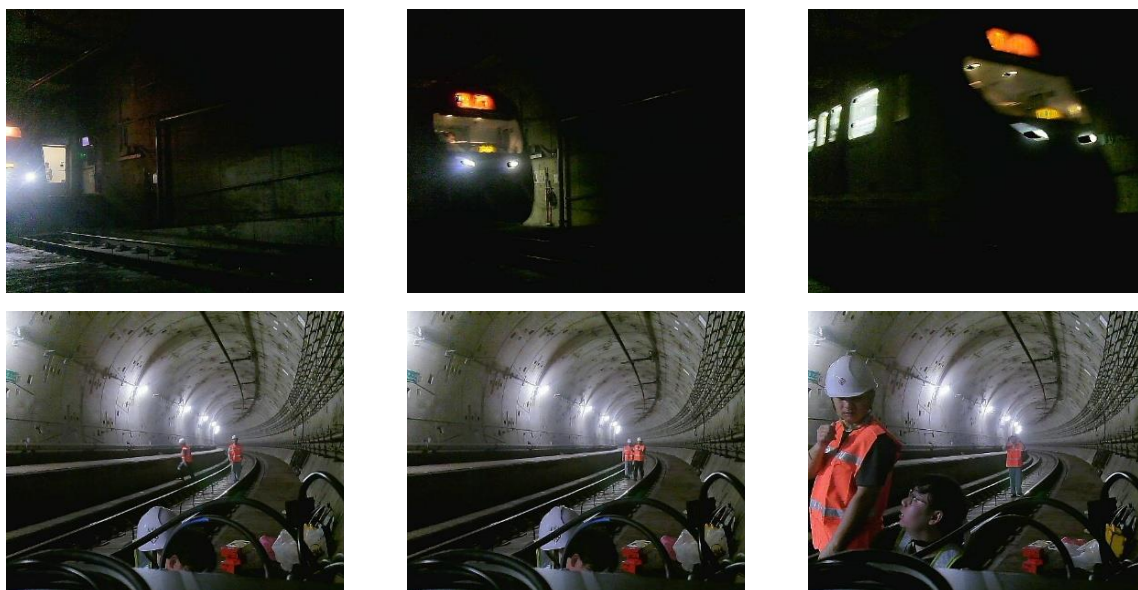


Fig 2.58 Sample images captured by the OID.

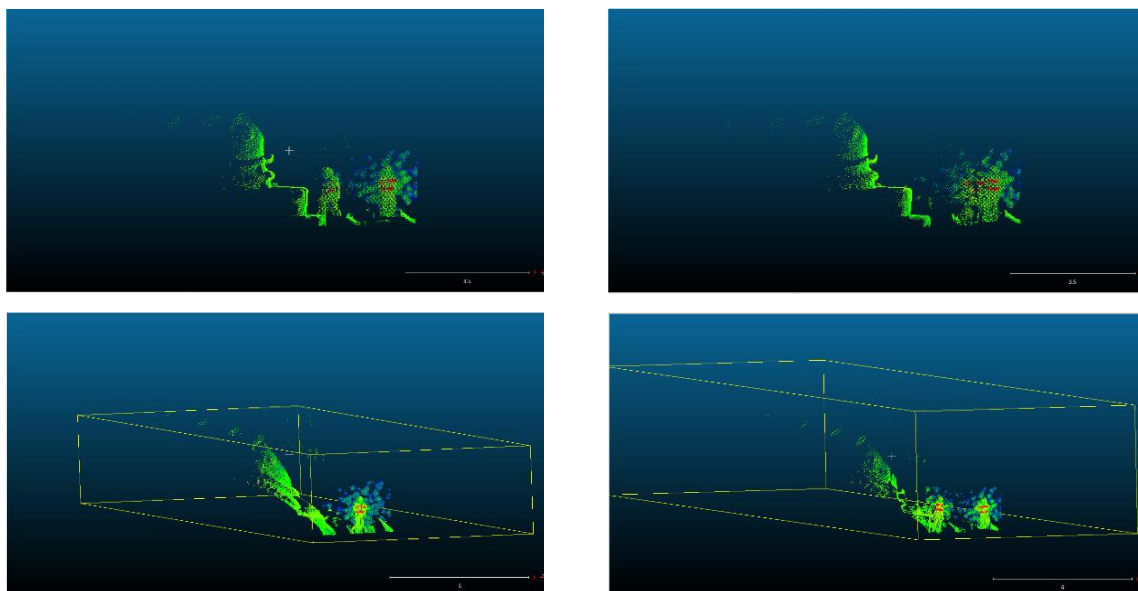


Fig 2.59 Sample point clouds captured by the OID.

2.2.12 Railroad Condition Monitoring using Distributed Acoustic Sensing (DAS)

Increasing railway traffic growth, train speed and heavier axles and vehicles load make the railway infrastructures highly susceptible to degradation and failure. Conventional railway monitoring techniques are regarded as expensive. For example, track circuits (TC) technique

consume very large amount of electricity. On the other hand, in case of communication-based train control (CBTC), sensors like Accelerometers or speed sensors are required in large number to cover the monitoring of both the vehicles and infrastructure.

In recent years Distributed Acoustic Sensing (DAS) which is a new type of fibre-optic sensing technology has been rapidly developed. Like ordinary fibre-optic sensing technologies DAS has advantages like anti-electromagnetic interference, corrosion resistance, slenderness, and flexibility. Additionally, DAS can also measure dynamic strains (e.g., vibrations and sound waves) in real-time manner along fibre paths in a long-distance. In railway applications, various acoustic sources can reach the sensor fibre, allowing the detection of events like third party interference (TPI), including walking, digging and theft activities, vehicles, rock fall and many more. Therefore, DAS technology can enhance railway safety by providing real-time monitoring and early detection of potential hazards.

This study aims to investigate the capabilities of DAS system in determining real-time train tracking (train position and speed monitoring, railway traffic monitoring), structural health monitoring (e.g. broken rails, flat spots, cracks, corrugation, fastener/bolts looseness) and ensuring railroad safety (by sensing human footsteps, discriminate between rattle, kick, and climb, and detect approaching vehicles and their types). Currently this research is in initial stage and as a first step an experimental setup was developed in a laboratory at PolyU Hangzhou Technology and Innovation Research Institute, Hangzhou, China. The experimental apparatus consisted of DAS interrogator, railway tracks placed on concrete blocks, optical fibre and a hammer. The optical fibre was installed on one side of 5 m long railway track and hammer was used to create vibrations in this track. The total length of the fibre used was around 90 meters, and its diameter was around one meter. The fibre was laid along the rail track using duct tape as shown in Fig 2.60.

(a)



(b)



(c)



(d)

Fig 2.60 Experimental setup for railway track monitoring, (a) the DAS interrogator, (b) the rail tracks, (c) the optical fiber installed on the track and (d) the hammer to generate vibrations in the track

Fig 2.61 presents the waterfall, time and corresponding frequency plots of the signal captured by the DAS along the optical fibre. The waterfall diagram and time domain signals in Fig 2.61(a) and Fig 2.61(b), indicates that the DAS precisely detected and located the impact of hammer on the five-meter-long rail track in real time. Further, frequency domain signal in Fig 2.61(c) reveals a broad spectrum of the acoustic signals as expected from a high energy hammer impulse and structural resonances of the rail track. These results confirm that DAS can effectively detect not only train position, intrusions or threats, and structure related anomalies but also can classify the nature of the events. Future, research will be focused on fields tests to investigate the DAS capabilities in determining train position and tracks related

anomalies. Since DAS generates large amount of data consisting of unstructured patterns and noise which is difficult to analyse with traditional signal processing methods. Therefore, future research will also be focused on developing deep learning-based analysis methods to pinpoint and classify event related signals.

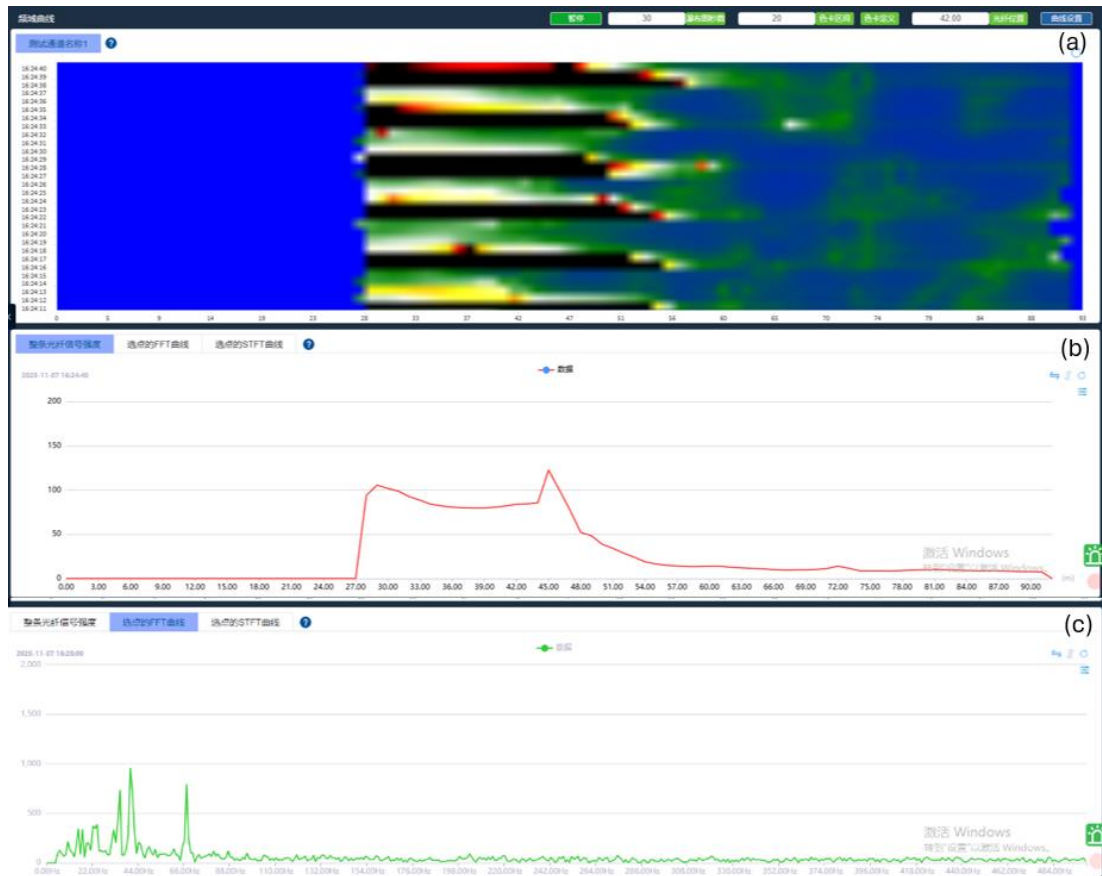


Fig 2.61 Results-data analysis Interface of the DAS, (a) the waterfall diagram, (b) time domain signal and (c) its corresponding frequency plot

2.2.13 Generalisation Study on Detection Model of Catenary Support Device Components for Different High-Speed Railway Lines

By the end of 2025, China's high-speed railway operating mileage had exceeded 50,000 kilometers, bringing with it a massive workload for the operation and maintenance of railway catenary facilities. However, current research on the generalisation of high-speed railway catenary support device component detection models has many shortcomings. To address these issues, the project conducted a series of theoretical studies and proposed a set of theoretical methods for strong generalisation of catenary component detection models. For the problem of accurate positioning of small sample components under imbalanced samples, three theoretical

methods were proposed, including: a) a catenary component detection model with few shot based on meta-learning; b) a catenary component fault detection method based on a structure-guided denoising diffusion model; and c) a novel self-supervised pre-trained model for catenary support component detection model. To address the problem of efficient localisation of abnormal catenary components in complex imaging environments, this project proposed five theoretical methods: a) a low-illumination catenary component image detection method based on a physical information model; b) a low-illumination catenary component detection model based on semi-supervised and adversarial domain adaptation; c) a catenary component detection model based on attention mechanism and confidence-guided non-maximum suppression; d) a novel improved YOLOv8 catenary component detection model; and e) a novel graph-guided Mamba-DETR detection model. For the effective localisation of multiple types of catenary components across different lines, this project proposed a universal detection network model for catenary components of different systems guided by multi-dimensional prior information. These theoretical methods can overcome interference from different imaging environments, achieving efficient localisation of abnormal catenary support device components; they can solve the problem of sample imbalance, achieving accurate localisation of small samples of catenary support device components; and they can eliminate the problem of diverse catenary types across different lines, achieving effective localisation of multiple types of catenary support device components across different lines. Ultimately, this comprehensively improves the generalisation ability of the catenary support device component localisation model. After long-term field verification, this theory can improve the operation and maintenance efficiency of railway catenary infrastructure. While improving detection results, it can also reduce equipment hardware costs, demonstrating significant engineering application value. Furthermore, this theory can be applied to other engineering fields with similar situations (such as vision-based pavement damage and tunnel defects), exhibiting versatility and universality.

According to the project's research plan, the research mainly focused on the following four aspects:

a) Establishment of a sample image database of catenary support device components. To address this, the project team reviewed relevant field survey reports, collected information on problems encountered during daily catenary inspections, and constructed various types of databases using images acquired on-site by the catenary inspection vehicle's image acquisition

system. These databases were used for research on different types of detection model algorithms and for performance evaluation and verification, as shown in Fig 2.63.



Fig 2.62 Image acquisition system of the catenary inspection vehicle

b) Precise localisation of small sample components under imbalanced sampling. To address this, the project proposes a series of theoretical methods. First, for the detection of novel components in special sections, a meta-learning-based model is proposed for detecting small sample components in the catenary system. As shown in Fig 2.63, this model is based on the DETR object detection framework and introduces the concept of meta-learning. By performing feature matching and task matching on query features and support features, the correlation between small sample components and other components is effectively learned, thereby achieving precise detection of small sample components.

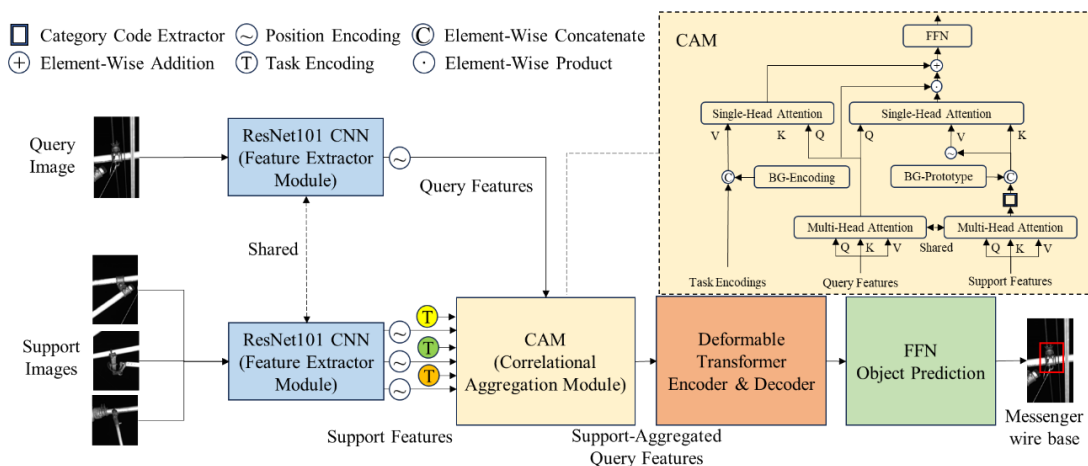


Fig 2.63 Schematic diagram of the network structure of the catenary small sample component detection model based on meta-learning.

To address the problem of insufficient defect detection samples, this project proposes a fault detection method for catenary components based on a structure-guided denoising diffusion model, as shown in Fig 2.64. This model consists of three key steps: First, it introduces a state-of-the-art generative artificial intelligence (AI) denoising diffusion probabilistic model (DDPM) to progressively transform arbitrary component images into realistic and clear images of normal components. Second, to address the structural variation problem, it guides the component generation process by constraining the reconstructed component images to share the same low-frequency features as the input component images, thus ensuring that the reconstructed components have similar structures to the input components. Finally, a Twin-CNN neural network is proposed to locate defect regions by comparing the differences in CNN features between test samples and reconstructed samples.

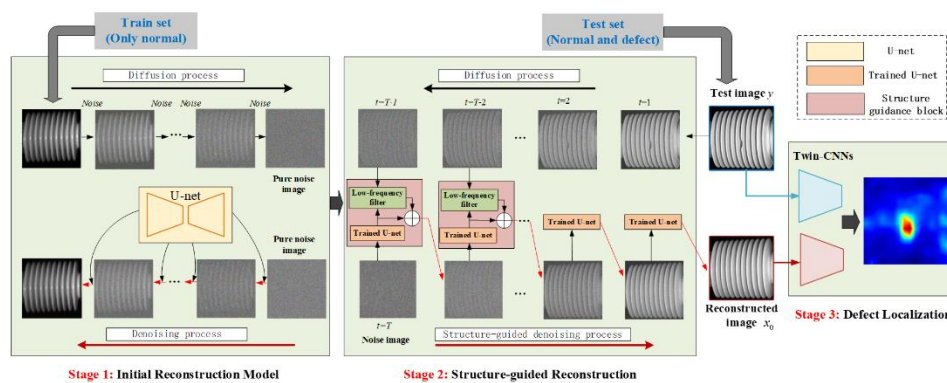


Fig 2.64 Schematic diagram of the fault detection method for catenary components based on the structure-guided denoising diffusion model.

To address the issue of large amounts of existing catenary data but limited labeled data, this project proposes a novel self-supervised pre-training model for detecting catenary support components. As shown in Fig 2.65, the model comprises three modules. First, a novel semantic masking strategy based on the features of the catenary support rod area (CSRA Masking) is proposed to guide the model in learning meaningful catenary semantic information during pre-training. Furthermore, a novel foreground-background dual-path interactive reconstruction network (DIR) is designed for dual-path reconstruction of the semantic mask. This framework integrates an information interaction enhancement module (IIEEM) to extract global features of the catenary domain and a cross-layer fusion decoding (CLFD) module to fuse multi-scale feature layer information. Finally, a multi-scale knowledge distillation (MSKD) strategy is introduced to assist the self-supervised model in acquiring specific and general feature

representations of the catenary field and transferring multi-scale information, thereby benefiting subsequent detection tasks.

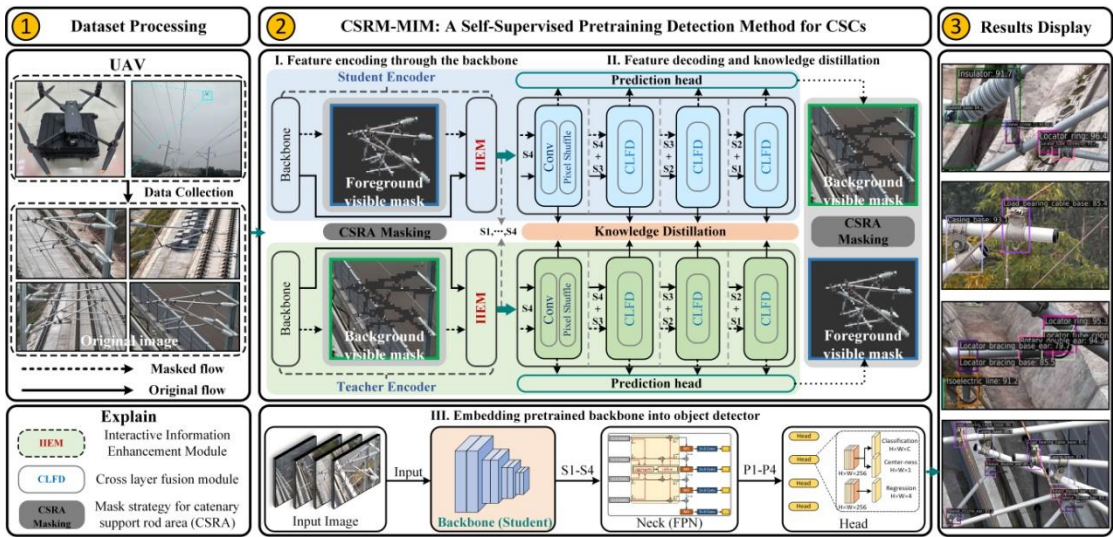
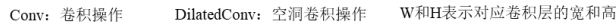


Fig 2.65 Network structure diagram of a novel self-supervised pre-trained model for the detection model of catenary support components.

c) Efficient localisation of abnormal sample components in complex imaging environments. To address this, the project proposes the following series of theoretical methods. First, considering the low illuminance in night images acquired by the system, a low-illuminance catenary component image detection method based on a physical information model is proposed. As shown in Fig 2.66, this method first constructs a natural image reconstruction model of the catenary using an atmospheric scattering model and dark channel theory, enabling rapid transfer of low-illuminance and normal-illuminance images to an intermediate domain. Second, based on a guided filtering model, a generative model is constructed, and generative adversarial thinking is used to further align the two image domains. Once the two image domains are aligned, the model trained using a normal-illuminance image (the normal-illuminance image after intermediate domain transfer) can be used to accurately detect components in the low-illuminance image (the low-illuminance image after intermediate domain transfer).



model.

focus of model weights.

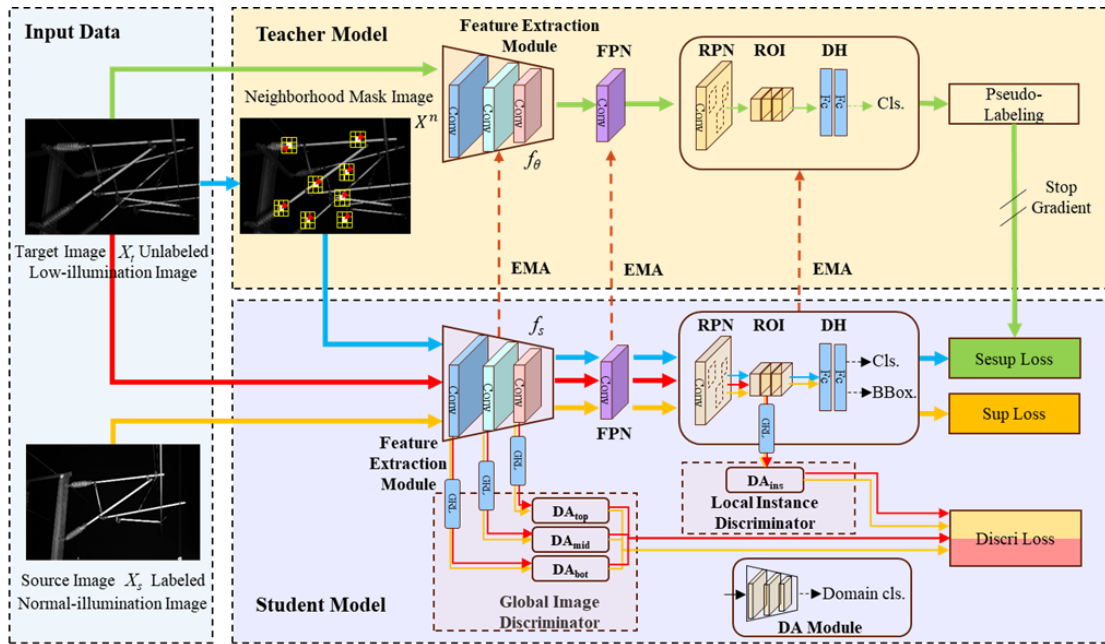


Fig 2.67 Schematic diagram of the network structure of the low-light catenary component detection model based on semi-supervised and adversarial domain adaptation.

Secondly, considering the complex image detection background of catenaries, a detection model for catenary components based on attention mechanism and confidence-guided non-maximum suppression (CNMS) is proposed. As shown in Fig 2.68, this detection model is improved in three main aspects. First, given the standard installation structure of catenary components, a spatial attention module is incorporated into the component detection network to reduce the false detection rate (A2CDM) of components in non-overhead contact areas. Second, during the training process of the catenary component detection network, the varifocal loss (VFL) function is used to increase the weight of positive samples, further improving the detection accuracy of components. Finally, to address the low-score and overlapping detection problems caused by the scale differences of catenary components, an improved CNMS method is proposed. Based on the overlap degree of overlapping detection boxes, a confidence update equation is constructed, effectively improving the confidence of components and avoiding the problem of missed detection of components.

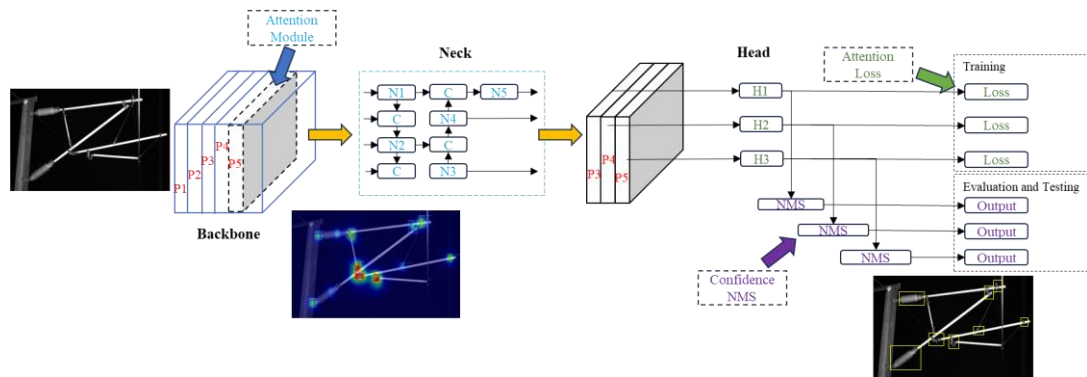


Fig 2.68 Schematic diagram of the proposed A2CDM-CNMS detection model structure.

Furthermore, to address the multi-scale problem of catenary components, a novel improved YOLOv8 catenary component detection model is proposed from the perspectives of temporal sequence and attention. As shown in Fig 2.69, firstly, a long short-term memory (LSTM) module is added to the backbone intermediate layer of the model to effectively capture the long-range dependencies of objects, thereby improving the ability to extract long-range features from sequential data. Secondly, a large separable kernel attention (LSKA) module is introduced into the spatial pyramid pooling feature (SPPF) layer to further enhance the model's ability to capture long-range image dependencies, thus effectively improving the detection accuracy of catenary components.

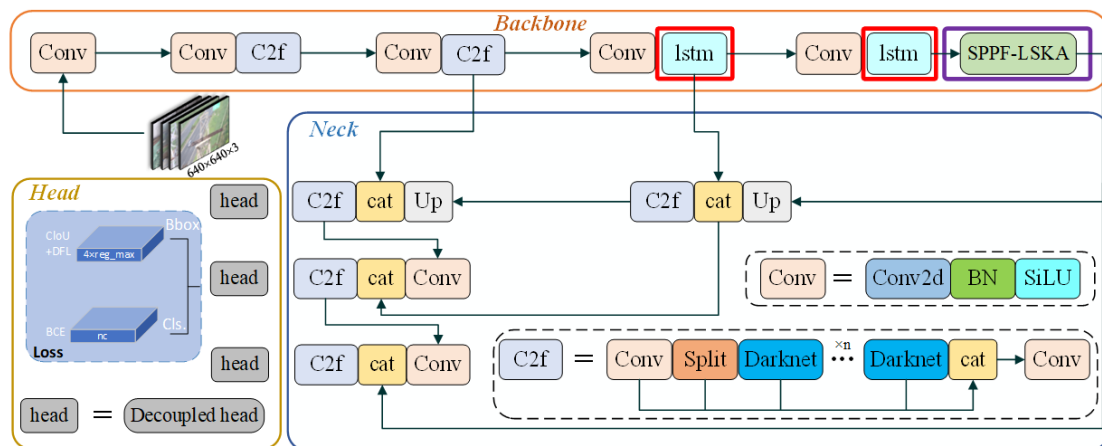


Fig 2.69 Schematic diagram of the improved YOLOv8 network structure.

Finally, to address the problem of multi-scale and localised occlusion in catenary components, this project proposes a novel graph-guided Mamba-DETR detection model. As shown in Fig 2.70, this method first proposes a novel backbone network (DAMamba-Adapter) to enhance the model's ability to correlate features between long-interval regions, and employs

multi-scale training (MST) to solve the multi-scale problem. Secondly, a semantic graph-guided module (SGM) and a positional graph-guided module (PGM) are designed to alleviate the occlusion and multi-class component detection problems by extracting prior class relationships with global semantic features and component geometric information.

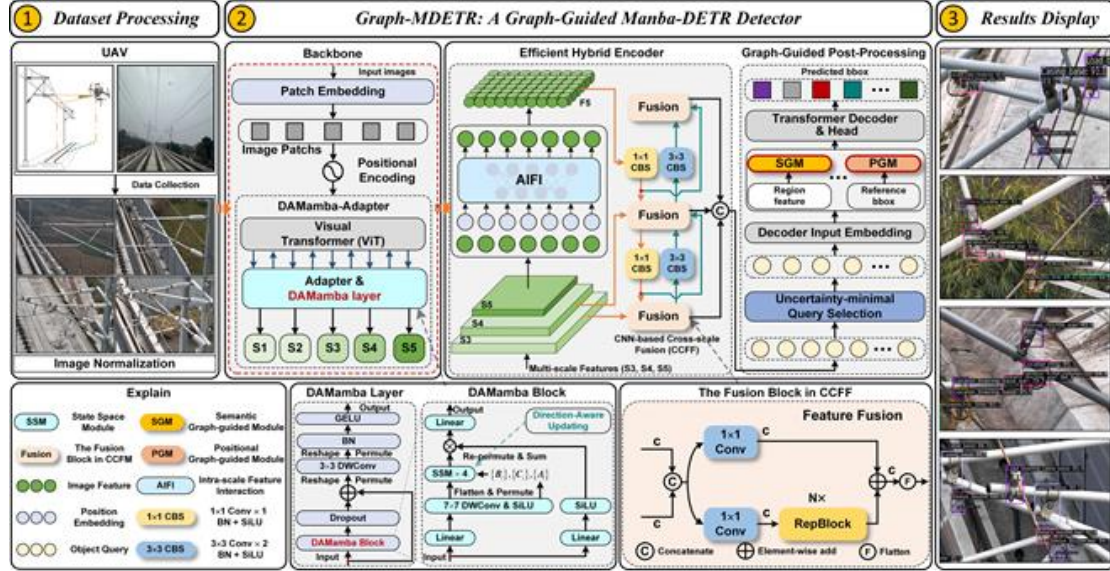


Fig 2.70 Schematic diagram of the proposed Graph-MDETR detection network structure.

Effective localisation of various types of catenary components across different lines. To address this, the project proposes a multi-dimensional prior information-guided universal detection network model (MDPI-UDN) for catenary components of different standards. As shown in Fig 2.71, this model first obtains prior spatial information of the target based on the DINOv2 universal feature extraction model. Then, it constructs a multi-scale general feature spatial guided fusion module (MSGFSGF) to spatially guide the fusion of features in the model's backbone feature extraction network. Next, the model establishes a visual catenary image type embedded feature channel guided fusion model (VGTEFCGF) to obtain prior information on the catenary type. Finally, it constructs a catenary type embedded feature channel guided fusion model to channel-guide the fusion of the input features of the model's feature encoding network. This incorporates catenary type information into the model, improving the universality and generalisation of the detection model.

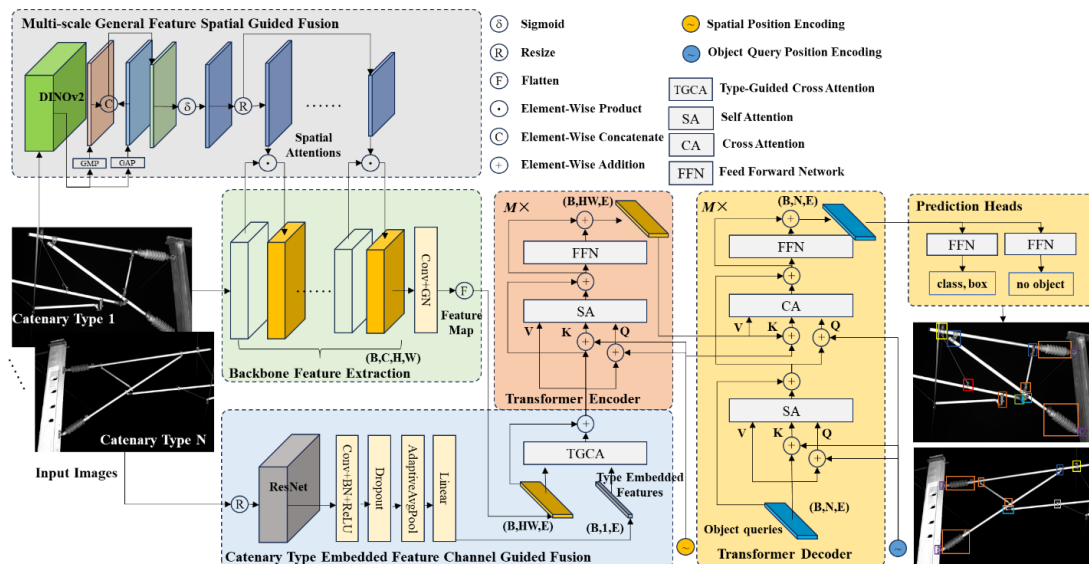


Fig 2.71 Schematic diagram of the proposed MDPI-UDN network structure.

2.2.14 Development of a Novel Physical Model System for Landslide and Rockfall Monitoring using DAS and FBG sensing technologies

Dr. Numan Malik and PhD candidate Mr. Liang Lyu from CNERC-Rail (HK Branch), has developed a novel physical model system at the PolyU Hangzhou Technology and Innovation Research Institute. This system is engineered for physical simulation and testing of geohazards specifically landslides and rockfalls, affecting highway and rail infrastructure. The primary monitoring technology is Distributed Acoustic Sensing (DAS) for event detection and localisation. Furthermore, Fiber Bragg Grating (FBG) sensor arrays will be deployed to provide benchmark validation for the DAS system and to quantitatively monitor landslide displacement dynamics. Fig 2.72 shows the schematic illustration of the physical model system and Fig 2.73 shows the progress of preparation work for establishing the experimental setup.

A DAS fibre optic cable will be installed in a dense grid pattern within the soil mass of the slope model. The DAS system will be the primary tool for monitoring the geohazard. It functions as a continuous, thousands-of-points acoustic sensor array, capable of:

- Detecting and locating micro-acoustic emissions generated by soil particle movement and micro-cracking within the slope, serving as an early warning indicator.
- Tracking the propagation of the shear surface and the dynamics of the failing soil mass in real-time with high spatial and temporal resolution.

- Sensing the vibrations and impacts of falling rocks on the slope surface, allowing for the analysis of their trajectory and energy.

In addition, an array of multiplexed FBG sensors will be installed alongside the DAS cable. The FBG arrays serve two critical functions:

- Providing high-accuracy, discrete strain and temperature measurements at specific points to validate and calibrate the quantitative strain data derived from the DAS system.
- Measuring localised strain build-up at critical points (e.g., potential slip surfaces), offering complementary data to the broad-area acoustic sensing of the DAS.

This hybrid sensing technology approach ensures data validation and provides a comprehensive dataset encompassing both distributed acoustic activity (DAS) and localised strain (FBG), offering an unprecedented view into the complete failure process.

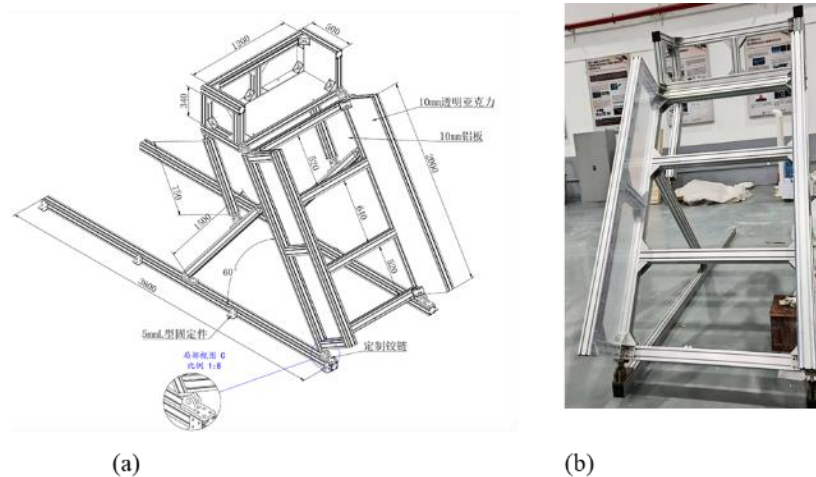


Fig 2.72 Schematic illustration and photo of the physical model system; (a) Schematic illustration and (b) Photo.



Fig 2.73 Photos of the preparation work for establishing the experimental setup

2.2.15 Mechanics-feature Informed Autoencoder for Structural Health Monitoring of Tsing Ma Bridge

A mechanics-feature informed autoencoder (MF-AE) framework that integrates data-driven learning with mechanics-based prior knowledge to enable robust and interpretable structural health monitoring is proposed as shown in Fig 2.74. To train the model, time-series data from the sensors are first measured, segmented, and compressed. The compressed representation includes the mean (μ) and standard deviation (σ) for each sensor. The MF-AE is then trained to reconstruct this compressed sensor data. After training, the network computes a reference for reconstruction errors, calculated as the mean squared error (MSE) between the input and reconstructed output for each sensor. This reference represents the baseline of the intact structure, corresponding to the initial structural state. Subsequently, data from subsequent years are processed by the trained model to obtain reconstruction errors. These errors are compared against the baseline reference to assess the structure's work state. The distribution of reconstruction errors reveals how closely the structural response resembles the original system.

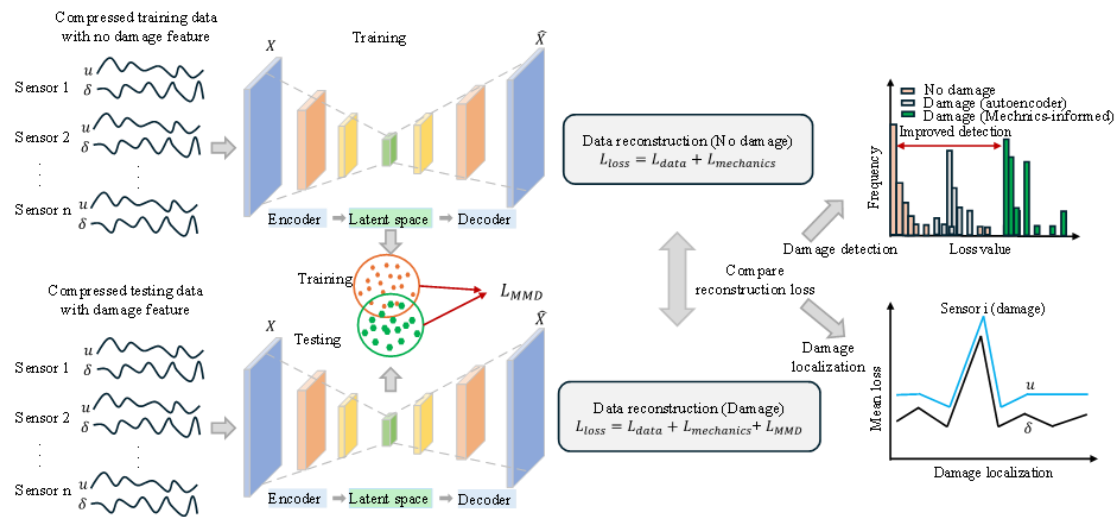


Fig 2.74 A mechanics-feature informed autoencoder (MF-AE) framework for structural health monitoring

The MF-AE framework is applied to assess the main girder's work state of the Tsing Ma Bridge from 2015 to 2019, as shown in Fig 2.75. Using 2015 as the baseline, low loss values indicate intact structural behaviour. From 2016–2017, slight changes are observed, while cumulative strain from 2017–2019 leads to increasing deviations from the baseline, reflecting evolving structural conditions. These results demonstrate that the model effectively captures potential patterns under varying environmental and operational conditions. Moreover, embedding mechanics-informed features enhances explainability and generalisation across diverse scenarios.

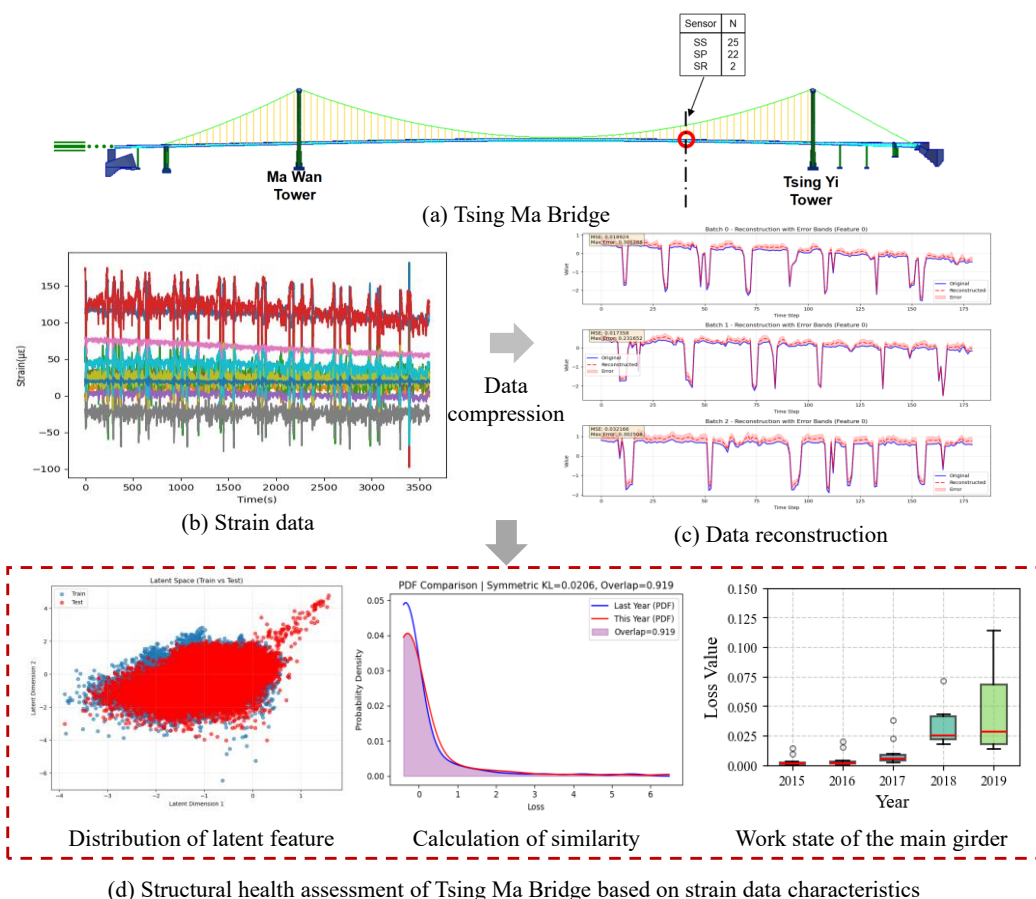


Fig 2.75 Assessment of the evolution of structural conditions of the Tsing Ma Bridge

2.2.16 Comparative Study of Near-field Aerodynamic Noise on Open Tracks and in Tunnels for Subway Trains

As the operational speeds of subway trains in China incrementally increase to 160 km/h, the enclosed nature of tunnel environments poses significant challenges by restricting free airflow. This limitation leads to intense airflow disturbances and turbulence phenomena within tunnels, consequently exacerbating aerodynamic noise issues. This study delineates a refined simulation model of the pulsating flow field within an infinitely long tunnel using the large eddy simulation framework, combined with acoustical non-reflective boundaries. Furthermore, an acoustic computation model for the near-field noise of the subway train is constructed employing finite element methods, the perfectly matched layer technique, and adaptive acoustic mesh technologies.

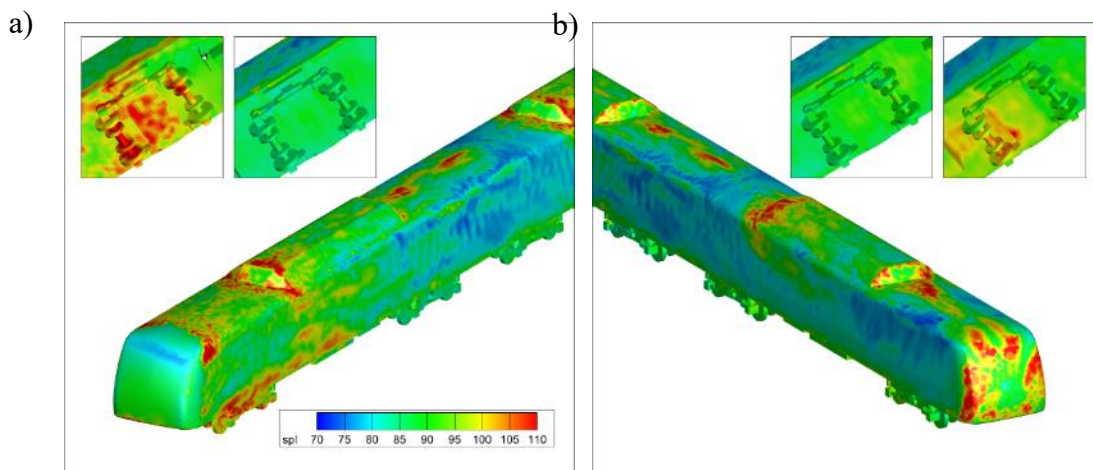


Fig 2.76 SPL contours on the train surface on an open track: a) leading car; b) tailing car

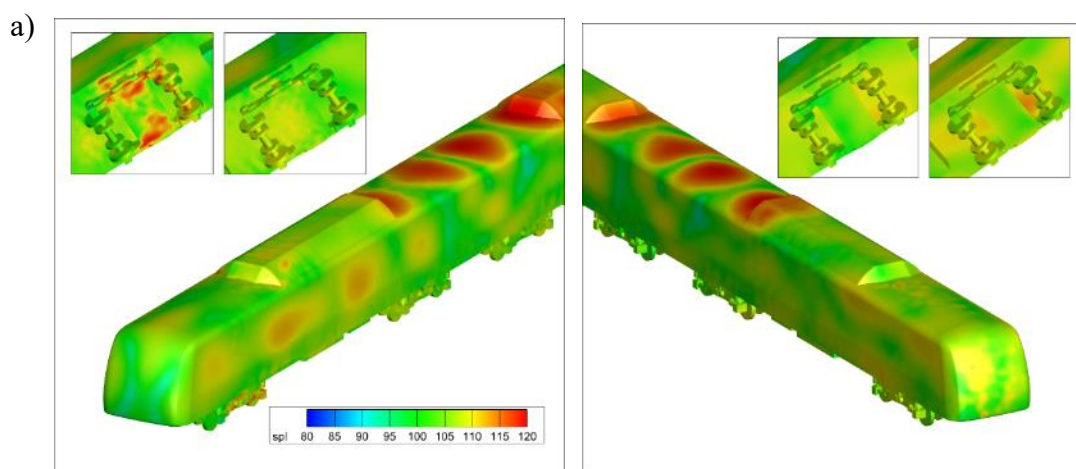


Fig 2.77 SPL contours on the train surface inside a tunnel: a) leading car; b) trailing car

This study conducts a comparative analysis of the near-field noise characteristics of subway trains traveling at 120 km/h on open tracks versus within an infinitely long tunnel, yielding the following conclusions:

(1) The flow field structures around the trains on open tracks and within the tunnel exhibit similarities. However, there are significant differences in their intensities and scales. Notably, the cavity flow formed between two air conditioning units in the tunnel shows approximately a doubling in the intensity of the vortex structures.

(2) There are substantial differences in the distribution of sound pressure levels on the surfaces of trains on open tracks. Specifically, the sound pressure levels are notably higher around the heads and tails of the intermediate cars, bogies 1 and 4, and near the shoulders of the air conditioning units. Conversely, the distribution of sound pressure levels on the surfaces of trains within the tunnel is more uniform, overall being 15 dB higher than on open tracks, with the highest levels occurring between the two air conditioners.

(3) The frequency distribution of surface sound pressure levels on open track trains exhibits significant variability. The leading car area shows a marked decrease in sound pressure with increasing frequency, while the trailing car and its wake show a slight decrease in sound pressure below 400 Hz and a minor increase between 400 and 1000 Hz.

(4) The spectral distribution of surface sound pressure levels within the tunnel is more homogenous. Low-frequency sound pressure levels are notably enhanced compared to those on open tracks, while high-frequency levels attenuate more rapidly.

(5) In tunnels with a high blockage ratio, the positioning of subway train air conditioning units either too high, concentrated, submerged, or outfitted with sound-absorbing materials can effectively lower the sound pressure levels in these areas, thereby enhancing the acoustic performance of the train within the tunnel.

Based on the comparative analysis of near-field noise characteristics in open tracks versus confined tunnel environments, this study provides critical insights for optimising acoustic design in underground transportation systems. The revealed intensified low-frequency noise propagation patterns and localised vortex-driven sound pressure amplification in high-blockage-ratio tunnels highlight the necessity of strategic noise control measures, such as aerodynamic component repositioning and targeted sound-absorbing material applications. These findings advance the development of comprehensive noise reduction strategies for underground infrastructure, offering actionable solutions to improve acoustic comfort while maintaining functional compactness in subway system design – a crucial advancement for sustainable urban underground mobility.

2.2.17 Bridge rating system integrates monitoring data and manual inspections

Currently, the assessment of bridge conditions faces three major challenges: Firstly, traditional methods predominantly rely on single data sources and fail to adequately integrate monitoring data with routine inspection results, leading to incomplete evaluation dimensions. Secondly, inspection outcomes based on manual observations are highly dependent on experiential judgment, resulting in strong subjectivity and low efficiency. Additionally, existing assessment results often lack interpretability, making it difficult to provide effective decision-making feedback for bridge management authorities.

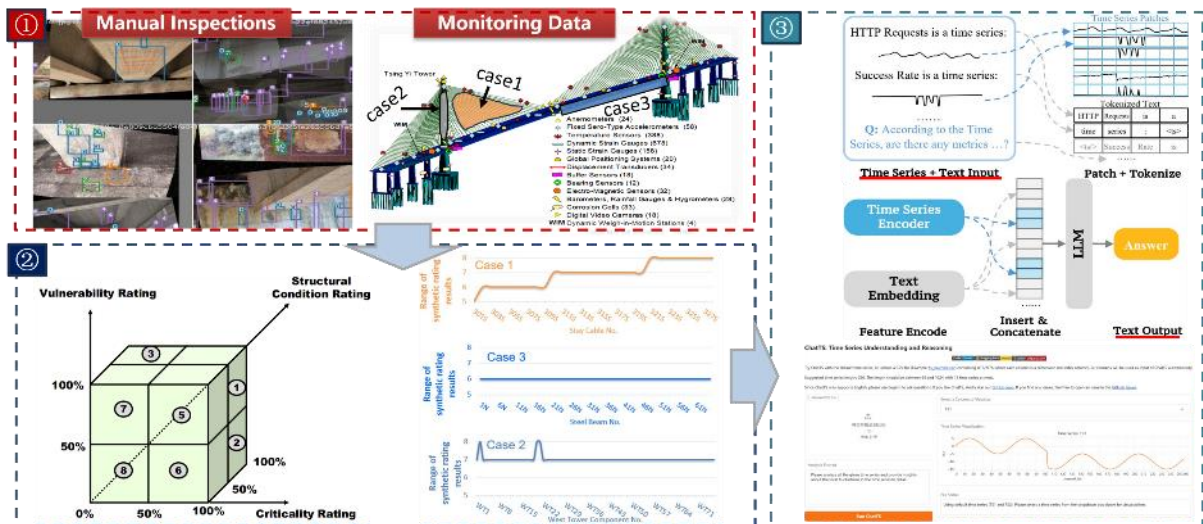


Fig 2.78

To address these issues, the CNERC-Rail (HK Branch) members (including Dr. Zhi Li, Dr. Yao Hu, Dr. Qiwu Zhu, and Mr. Yiting Xiang) has developed an intelligent bridge rating system that integrates monitoring data with routine inspections. This system utilises the YOLO-v7 proxy model to automatically process inspection images, accurately identifying the location and type of structural defects while quantifying scores based on established standards. Concurrently, a time-domain prediction model is employed to analyse long-term stress time-history data from the health monitoring system. By inputting both types of processed results—defect scores and preprocessed stress time-history data—into the rating system, the system can accurately trace the historical evolution of bridge conditions. Finally, through the proprietary temporal large model ChatTS, the evolutionary patterns are translated into readable text summaries, significantly enhancing the interpretability of evaluation results and providing robust intelligent support for bridge maintenance decisions.

2.2.18 Bridge maintenance data platform with intelligent Q&A

Bridge health assessment is a highly specialised and interdisciplinary engineering task. While conventional large language models possess broad general knowledge, they lack sufficient training on domain-specific data, making it difficult for them to accurately comprehend professional terminology and logical frameworks in bridge engineering. Moreover, the knowledge system within the bridge industry is highly fragmented, encompassing tens of thousands of regulatory provisions, millions of design drawings, and massive volumes of monitoring data. Relying solely on limited human resources makes systematic integration and

efficient interpretation challenging. Therefore, leveraging artificial intelligence to synthesise and internalise this vast knowledge has become an essential pathway to improving the efficiency and accuracy of assessments.

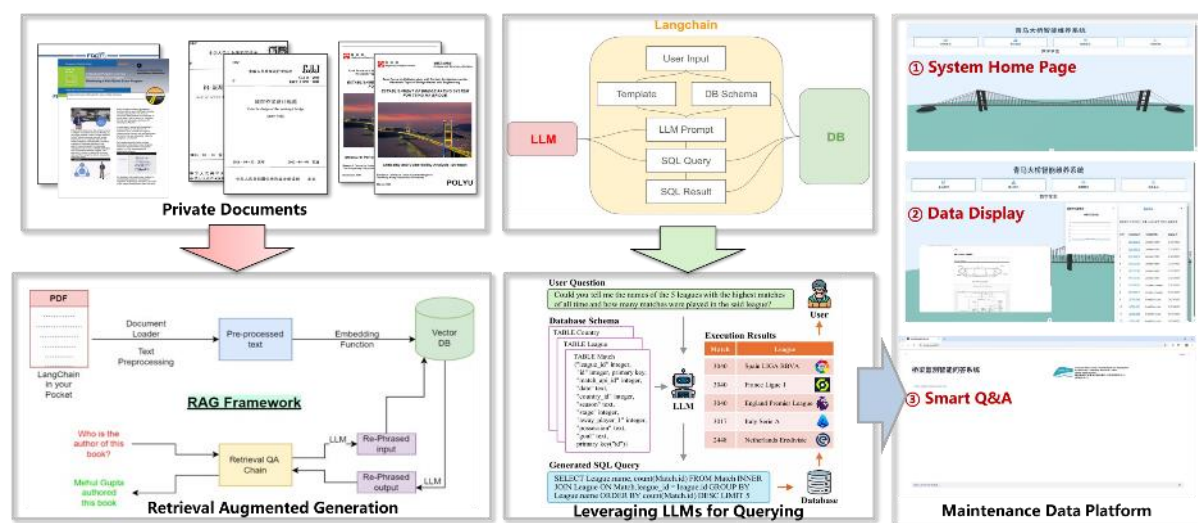


Fig 2.79 Bridge maintenance data platform with intelligent Q&A

In response to these challenges, the CNERC-Rail (HK Branch) members (including Dr. Zhi Li, Dr. Qiwu Zhu, Dr. Yao Hu, and Mr. Yiting Xiang) has developed a domain-specific large model system based on the RAG (Retrieval-Augmented Generation) architecture. This model incorporates long-term accumulated textual materials and time-series monitoring data from multiple cross-sea bridges in Hong Kong, combined with the team's professional expertise in bridge condition monitoring. As a result, the system achieves precise language comprehension and generation capabilities within the field of bridge health monitoring. By establishing a systematic application platform and continuously refining the knowledge base, the model now supports various functions, including accurate Q&A on bridge maintenance knowledge and technical summarisation. It demonstrates broad application potential in academic research, professional training, and engineering decision-making support.

2.2.19 Drafting of potential cooperation projects with the Highways Department

On the evening of October 23, 2015, a local tugboat collided with the Kap Shui Mun Bridge while towing a barge from Sha Lo Wan towards the Yau Ma Tei Typhoon Shelter in the New Territories. The crane arm on the barge struck the bridge, damaging six tracks on the maintenance platform beneath the mid-span and causing bolt loosening in partial track areas on the deck, which triggered the bridge collision alarm system. The incident led to the nearly two-hour closure of the Kap Shui Mun Bridge for structural inspection, disrupting services on the North Lantau Highway (Tsing Ma Control Area) and the Airport Express for approximately two hours. This event underscored the urgent need for rapid assessment of bridge and track structural integrity following vessel collisions, to avoid prolonged traffic disruptions due to uncertainties in structural safety.

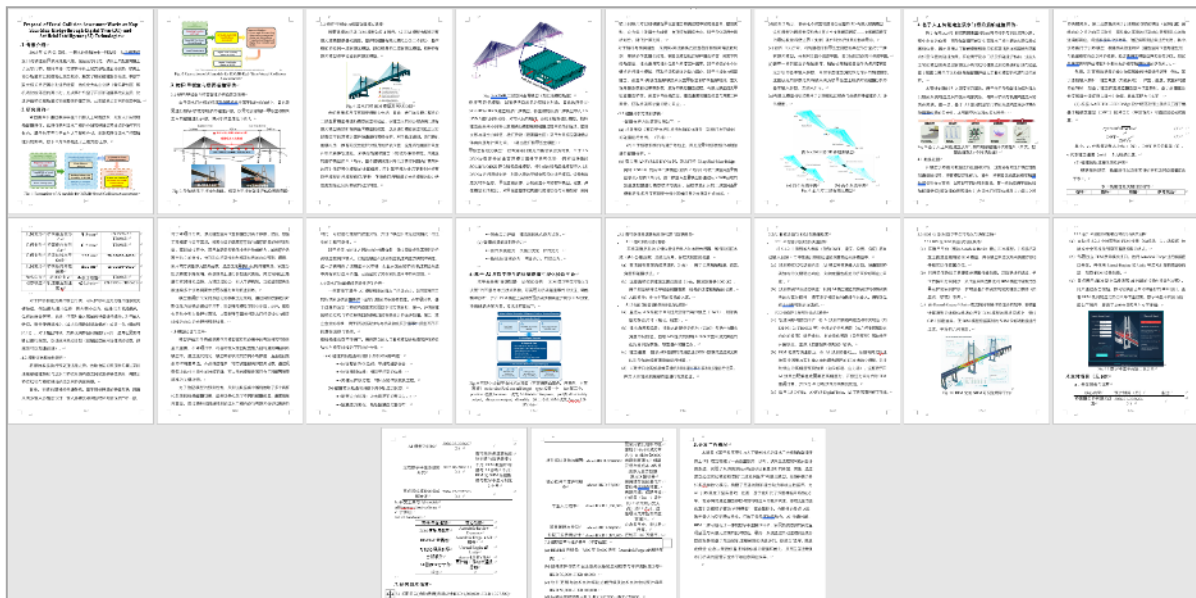


Fig 2.80 Drafting of potential cooperation projects with the Highways Department

In response, commissioned by the Highways Department, team members from CNERC-Rail (HK Branch) (including Dr. Kai-Yuen Wong, Dr. Zhi Li, Dr. Qiwu Zhu, Dr. Yao Hu, Mr. Jiaxin Huang, and Mr. Yiting Xiang) proposed a project titled "Proposal of Vessel Collision Assessment Works on Kap Shui Mun Bridge through Digital Twin (DT) and Artificial Intelligence (AI) Technologies". This project established an intelligent safety assessment system covering the entire process of perception, diagnosis, and decision-making, achieving a leap from traditional lagging analysis to second-level intelligent diagnosis. The system first developed an experimentally mode-calibrated "3D spatial fishbone" finite element model to conduct multi-condition parametric simulations, constructing a comprehensive database of

dynamic responses to vessel impacts as a data foundation for AI training. On this basis, a deep neural network core engine was developed, capable of instantaneously mapping the complex relationship between impact parameters and structural responses, forming an efficient surrogate model that overcomes the timeliness limitations of traditional simulations. Furthermore, the system innovatively integrated AIS, LiDAR, and visual perception devices to build a digital twin operational platform that combines multi-source data fusion, AI rapid diagnosis, and BIM 3D visualisation, enabling real-time representation of damage conditions and comparative validation with finite element results. Finally, the system automatically generates four-color coded damage alert reports and rapidly evaluates track service performance based on specifications, forming a closed-loop assessment capability. This provides a scientific basis for emergency decisions such as "resuming traffic, imposing speed restrictions, or suspending operations," thereby significantly enhancing the operational safety and emergency response efficiency of the Kap Shui Mun Bridge.

2.2.20 A novel data-enhanced CFD-based time-averaged flow field simulation strategy and its application to train aerodynamics

(A)3D flow field reconstruction around a building model in wind tunnel using a physics-informed neural network with dynamic self-adaptive loss balancing

1) Structure of PINN

The basic structure and principle of the PINN model adopted in this study will be described in detail here. By directly embedding physical equations, initial and boundary conditions, and measurement data into the total loss function for training a neural network, PINN is proven to be a charming physics-informed data-driven approach for solving forward and inverse physical problems involving differential equations. The residuals of the physical constraints tend to converge toward zero during PINN's training process with the aid of an optimiser. In this way, the PINN is configured to achieve its function to approximate solutions to PDEs. The schematic diagram of the PINN targeting to achieve the RANS simulation of the three-dimensional fluid flow is depicted in Fig 2.83. The left part of the PINN is an FCNN which maps the relationship between the spatial coordinates (x, y, z) and flow characteristics of the wind field (u, v, w, p). Here, u, v , and w represent the velocity components in the x, y ,

and z directions, respectively, and p represents the pressure. In the middle part of the PINN, AD is applied to calculate the gradients of the outputs with respect to the inputs, which also plays a key role in training the neural network. The right part of the PINN is the total loss, which takes the following form

$$L = w_f L_f + w_b L_b + w_d L_d \quad (1)$$

where

$$L_f = \frac{1}{N_f} \sum_{n=1}^{N_f} \sum_{i=1}^4 |f_i^n|^2 \quad (2)$$

$$L_b = \frac{1}{N_{nb}} \sum_{i=1}^{N_{nb}} |r_{nb}^i|^2 + \frac{1}{N_{db}} \sum_{i=1}^{N_{db}} |r_{db}^i|^2 \quad (3)$$

$$L_d = \frac{1}{N_d} \sum_{i=1}^{N_d} |r_d^i|^2 \quad (4)$$

In the above expressions, L_f , L_b , and L_d denote the loss components associated with the residuals of the governing equations, boundary conditions, and data constraints, respectively; w_f , w_b , and w_d denote the weighting coefficients of the corresponding loss terms; f_i^n is the residual of the i th governing equation in Fig 2.83; r_{nb}^i , r_{db}^i , and r_d^i are the residuals for the Neumann boundary, Dirichlet boundary, and data constraints, respectively. N_f is the number of collocation points used to calculate the residual of the governing functions, while N_{nb} , N_{db} , and N_d are the numbers of points used to calculate the residuals for the Neumann and Dirichlet boundaries, and for the data constraints, respectively. Once the total loss is formed, the error backpropagation algorithm is then employed for calculating the gradients of the parameters to be optimised and updating their values.

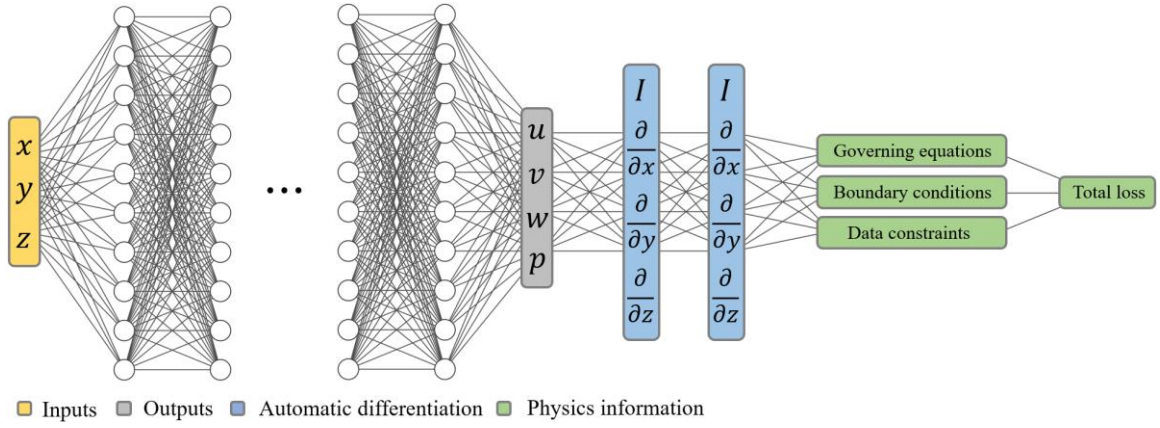


Fig 2.83. Schematic diagram of PINN for the RANS simulation of the three-dimensional fluid flow.

2) Dynamic prioritisation loss balance strategy

How to balance the loss terms in the total loss function during the training process of PINN has become a challenging issue. The imbalance between different loss terms may significantly diminish the convergence rate and computational efficiency in the training of a PINN. To alleviate this problem, we rewrite the total loss in the following form:

$$L = L_f + w_u L_u + w_v L_v + w_w L_w + w_p L_p \quad (5)$$

where

$$L_u = \sum_{n \in \mathbf{U}_r} \frac{1}{N_n} \sum_{i=1}^{N_n} |r_n^i|^2 \quad (6)$$

$$L_v = \sum_{n \in \mathbf{V}_r} \frac{1}{N_n} \sum_{i=1}^{N_n} |r_n^i|^2 \quad (7)$$

$$L_w = \sum_{n \in \mathbf{W}_r} \frac{1}{N_n} \sum_{i=1}^{N_n} |r_n^i|^2 \quad (8)$$

$$L_p = \sum_{n \in \mathbf{P}_r} \frac{1}{N_n} \sum_{i=1}^{N_n} |r_n^i|^2 \quad (9)$$

Unlike the original expression in Eq. (1), the total loss function is now reshaped to consist of five separate components, i.e., L_f , L_u , L_v , L_w , and L_p . L_f has the same meaning as given before; L_u , L_v , and L_w denote the loss terms directly related to the velocity components u , v ,

and w , respectively; L_p denotes the loss term related to the pressure p ; w_u , w_v , w_w , and w_p denote the weighting coefficients of the corresponding loss terms. $\mathbf{U}_r$, $\mathbf{V}_r$, $\mathbf{W}_r$, and $\mathbf{P}_r$ represent the sets which are composed of formula numbers related to u , v , w , and p . The details will be further explained in the following validation case. r_n^i is the residual of Eq. (n) on the i th collocation point, and N_n is the number of collocation points used to calculate the residual of Eq. (n). It can be seen that the residuals of various boundary conditions and data constraints form the loss terms L_b and L_d in Eq. (1) in the default PINN. However, they are reorganised in the proposed dpPINN to form the u , v , w , and p -related loss terms. Such a reconfiguration enables us to balance each loss term in the following way:

$$w_i = \left[\frac{k_i}{\min_j(k_j)} \right]^\gamma, i, j = u, v, w, p \quad (10)$$

$$k_i = \frac{\|\mathbf{U}_{T_i} - \tilde{\mathbf{U}}_{T_i}\|_2}{\|\mathbf{U}_{T_i}\|_2}, \quad i = u, v, w, p \quad (11)$$

where γ is a newly introduced hyperparameter that affects the weight balance between different loss terms; $\|\cdot\|_2$ denotes the ℓ_2 -norm; $\mathbf{U}_{T_i}$ denotes the vector of the labelled data on the training points; and $\tilde{\mathbf{U}}_{T_i}$ denotes the vector of PINN predictions on the training points. Such a setting means that the relative errors of u , v , w , and p between the PINN predictions and the reference data are calculated at the training points after certain iterations. A flowchart is depicted to further illustrate the updating mechanism of the dpPINN's weighting coefficients, as shown in Fig 2.84. In the first step, current weights will be assigned to the loss function of a dpPINN and the dpPINN will make its prediction as a normal neural network model. What follows is an evaluation process, where the errors between the dpPINN predictions and the reference data on the training points, i.e., Eq. (11), are calculated. For example, in Fig 2.84, the velocity component w is found to possess the highest relative error during the evaluation process. Then it will be given the highest weight using Eq. (10) in the following training process, as a punishment for the low prediction accuracy in the past training process. The assigned weight will be used to form the total loss to update the neural network parameters.

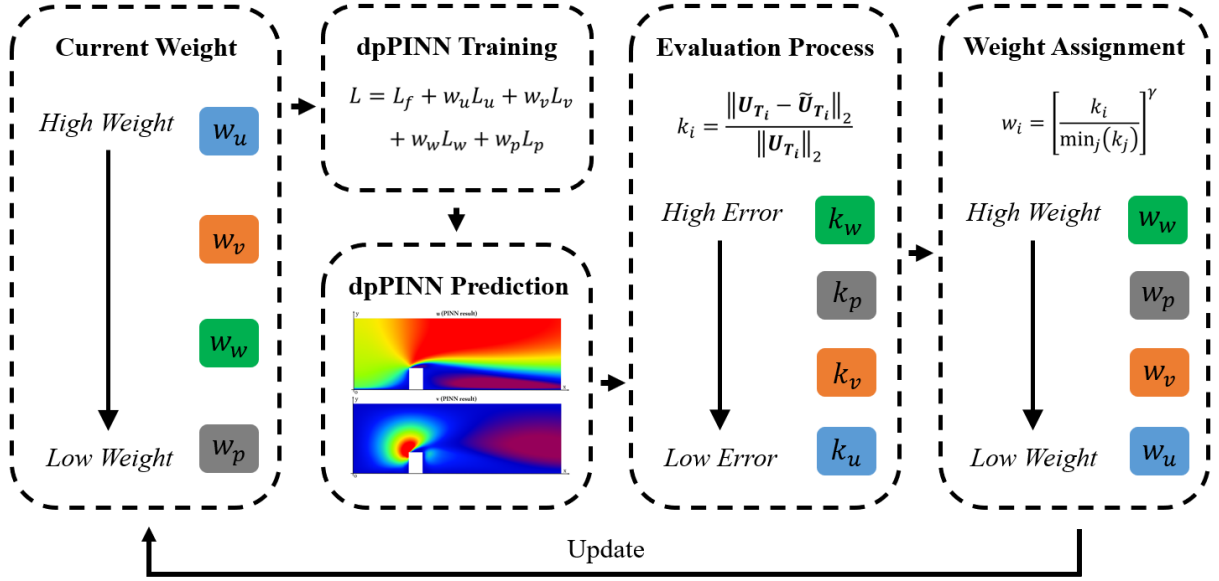


Fig 2.84 Updating mechanism of the dpPINN weighting coefficients.

3) Results compared with experimental data

As mentioned before, this study simulates the flow field around the scale model of a building in a wind tunnel by using sparse near-wall velocity data under the dpPINN framework. In this section, the dpPINN predictions are validated with the measured wind velocity components at the measurement points from which the data were not used in dpPINN training. All simulations are conducted on the platform equipped with PyTorch v1.9.0 and NVIDIA A100 graphics processing units.

The value of the coefficient γ is preliminarily set as 2. Because no pressure data is embedded in the dpPINN training, the weighting coefficient w_p is set to 1 in this case. A dpPINN with six hidden layers, each containing 40 neurons, is formulated for outdoor airflow simulation. The hyperbolic tangent function (Tanh) is adopted as the activation function in the neural network. The Adam optimiser with 1×10^5 iterations is used to train the dpPINN. The learning rate is set as 3×10^{-4} , and 26944 collocation points are uniformly distributed within the cubic computational domain. These collocation points are used to compute the residuals of the governing equations. Additionally, 9900 collocation points distributed on the domain boundaries are used to compute the residuals of the boundary conditions.

In this case study, one training iteration takes roughly about 0.318 second. It takes about 53.6% of the duration for AD to calculate the physical residuals and form the components of the total loss, and the remaining 46.4% is for error backpropagation to update the neural network parameters.

As indicated previously, among the total 186 measurement points, 93 near-wall points are selected for training the dpPINN (21 in the cross-section $y = 0.35$ m, 60 in the cross-section $z = 0.01$ m, and 12 in the cross-section $z = 0.10$ m). The velocity data at the 93 training points are used for supervised learning and updating of the weighting coefficients. Excluding the training points, the remaining measurement points (the data from which are referred to as reference data) are used to verify the proposed approach for outdoor airflow simulation.

After training the dpPINN model, its prediction results are obtained as shown in Fig 2.85 and Fig 2.86, which are compared with the reference data from wind tunnel measurements. The black solid lines, red dotted lines, and blue dash-dot lines represent the dpPINN predictions of the velocity components u , v , and w , respectively. The black dots, red squares, and blue diamonds denote the experimental mean values of the velocity components u , v , and w , respectively, at the measurement points.

From the results, it can be found that the dpPINN predictions show a good agreement with the experimental data even when the experimental data used for verification were not included in training the dpPINN.

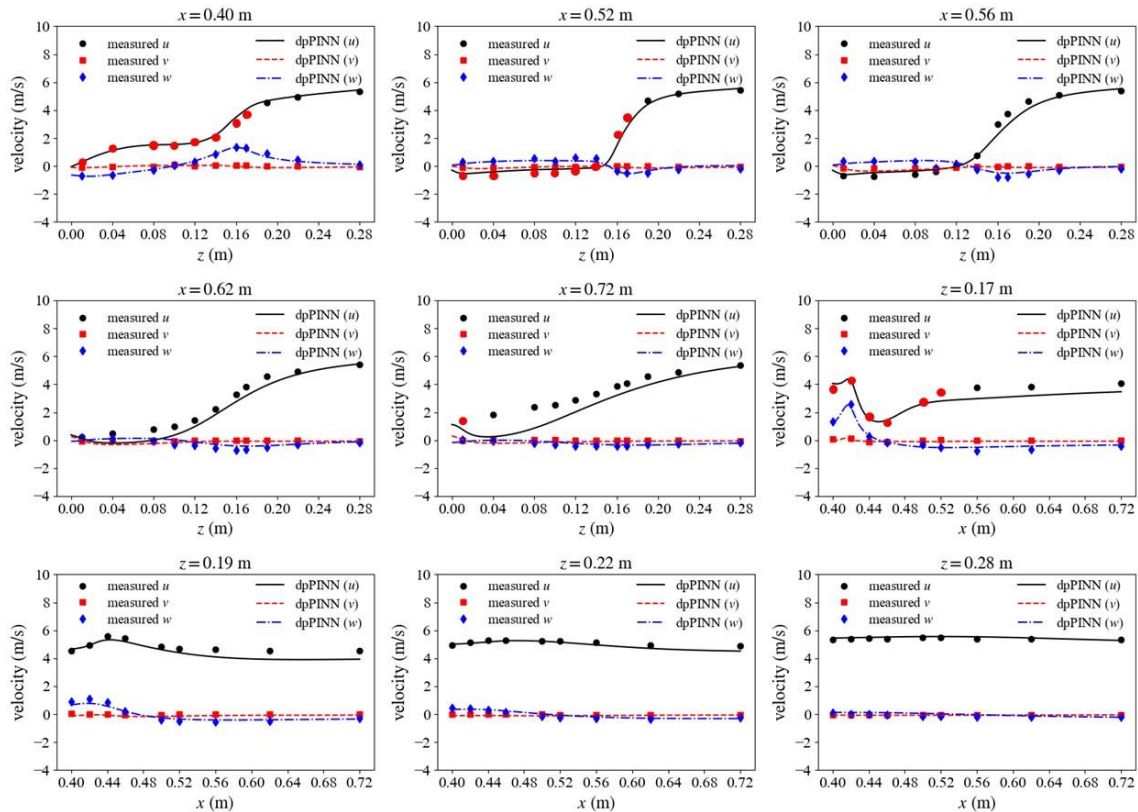


Fig 2.85 Comparison of results between dpPINN predictions and wind tunnel measurements in the cross-section $y = 0.35$ m.

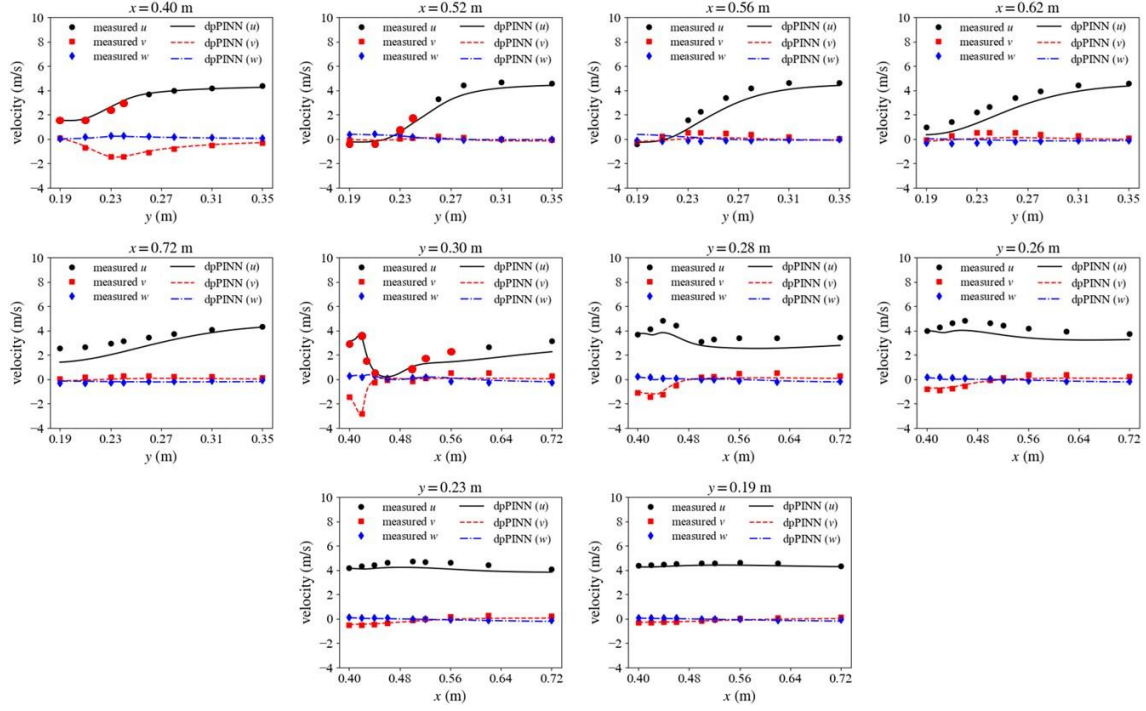


Fig 2.86 Comparison of results between dpPINN predictions and wind tunnel measurements in the cross-section $z = 0.10$ m.

(B) Time-averaged flowfield reconstruction using a multi-fidelity physics-informed neural network and nonlinear information fusion

1) NIF algorithm

In the NIF algorithm, multifidelity modeling is based on the GP algorithm and is achieved by combining low-fidelity models with a small number of high-fidelity observations. Now, the GPs f_h and f_l represent high-fidelity and low-fidelity models, respectively. The NIF algorithm expresses f_h as follows:

$$f_h(\mathbf{x}) = g_h(\mathbf{x}, f_{*l}(\mathbf{x})) \quad (12)$$

where $g_h \sim \mathcal{GP}(f_h | \mathbf{0}, k_h((\mathbf{x}, f_{*l}(\mathbf{x})), (\mathbf{x}', f_{*l}(\mathbf{x}'))); \theta_h))$. A GP posterior at the low-fidelity level is given by $f_{*l}(\mathbf{x})$. θ_h is the hyperparameter. As a covariance kernel, k_h can be decomposed into:

$$k_h = k_{h_\rho}(\mathbf{x}, \mathbf{x}'; \theta_{h_\rho}) \times k_{h_f}(f_{*l}(\mathbf{x}), f_{*l}(\mathbf{x}'); \theta_{h_f}) + k_{h_\delta}(\mathbf{x}, \mathbf{x}'; \theta_{h_\delta}) \quad (13)$$

A squared exponential form covariance function is used here, with ARD weights applied to k_{h_ρ} , k_{h_f} , and k_{h_δ} (Rasmussen 2003). θ_{h_ρ} , θ_{h_f} , and θ_{h_δ} are hyperparameters. Based on the NIF algorithm, the high-fidelity model may be derived from the input coordinates $\mathbf{x}$ and the

output of the low-fidelity model $f_{*l}(\mathbf{x})$. Therefore, it is a joint representation of the low-fidelity model's input space and its posterior prediction. Eq. 12 also incorporates both $\mathbf{x}$ and $f_{*l}(\mathbf{x})$ into its covariance kernel, which captures nonlinear nonfunctional cross-correlations of space-dependent nonlinearity. Optimisation of the hyperparameters of the GP model is based on minimising the negative log marginal likelihood (NLML), which can be described as:

$$NLML = \frac{1}{2} \log |\mathbf{K}| + \frac{1}{2} \mathbf{y}^T \mathbf{K}^{-1} \mathbf{y} + \frac{n_d}{2} \log 2\pi \quad (14)$$

where $\mathbf{K}$ represents the kernel function, $\mathbf{y}$ represents the training target, and n_d represents the dimension of the input space. Based on the optimised hyperparameters, the posterior distribution of the high-fidelity GP model at a test point $(\mathbf{x}_*, f_{*l}(\mathbf{x}_*))$ can be calculated as follows:

$$p(f_{*h}(\mathbf{x}_*)) = \int p(f_h(\mathbf{x}_*, f_{*l}(\mathbf{x}_*)) | \mathbf{y}_h, \mathbf{x}_h, \mathbf{x}_*) p(f_{*l}(\mathbf{x}_*)) d\mathbf{x}_* \quad (15)$$

To simulate the posterior distribution of the high-fidelity model, Monte Carlo simulation is used. In the low-fidelity model, the posterior prediction follows a Gaussian distribution because it is a standard GP regression with parametric input data points. High-fidelity models, however, are GP regression models with the input of the posterior prediction from the low-fidelity model. This results in a non-Gaussian posterior distribution for the high-fidelity model. Therefore, Monte Carlo integration of Eq. 15 is applied here to calculate the high-fidelity model's posterior mean and variance.

2) Workflow of the multifidelity strategy

As a summary of the multifidelity flow field reconstruction strategy, which is proposed in this study, the following workflow is given (also shown in Fig 2.87):

Step 1: A PINN model is used to generate massive quantities of low-fidelity continuous data. In the training process of neural networks, residuals of governing equations and boundary conditions are incorporated.

Step 2: A sample of training data is obtained from the PINN results in the computational domain for the low-fidelity GP modeling. Then minimise the NLML of Eq. 14 to optimise the hyperparameters of the low-fidelity GP model. Calculate the posterior mean and variance of the low-fidelity standard GP regression model.

Step 4: Using the posterior prediction of the low-fidelity model and a small number of high-fidelity observations, the high-fidelity GP regression model of Eq. 12 is constructed. In

the high-fidelity GP model, the hyperparameters are optimised by minimising the NLML of Eq. 14, using the kernel function from Eq. 13.

Step 5: According to the Monte Carlo integration of Eq. 15, the posterior mean and variance for the high-fidelity GP model can be outputted. In this step, the posterior mean and variance of the low-fidelity standard GP regression model in *Step 2* will be used.

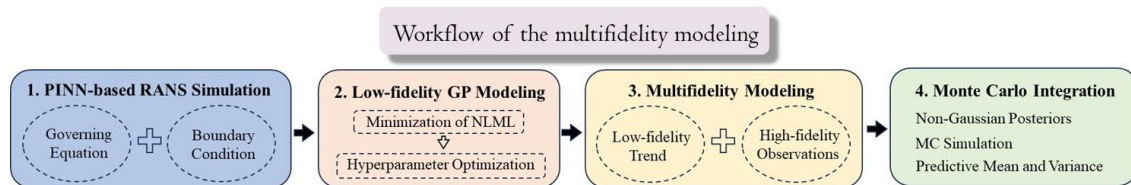


Fig 2.87 Workflow of the multifidelity strategy.

3) Results of square cylinder flow

This case study describes a turbulent flow around a two-dimensional square cylinder, as shown in Fig 2.88. In the middle of the computational domain, which measures 0.44 m in length and 0.32 m in width., a 0.04 m $\times$ 0.04 m square cylinder is located at the left center.

According to Fig 2.88, point A is located at the bottom left corner of the square cylinder at a coordinate of (0.10, 0.14). There is an initial speed boundary on the left boundary of the computational domain, where the fluid velocity stabilises at 0.535 m/s. The right boundary of the computational domain is a zero-pressure outlet, while upper and lower boundaries are defined as symmetry wall boundaries. As the fluid velocity equals zero at the surfaces of the square cylinder, they are considered to be wall boundaries. In the experiment, there were 517 experimental measurement points capturing the time-averaged flow velocity components u and v inside the flow field.

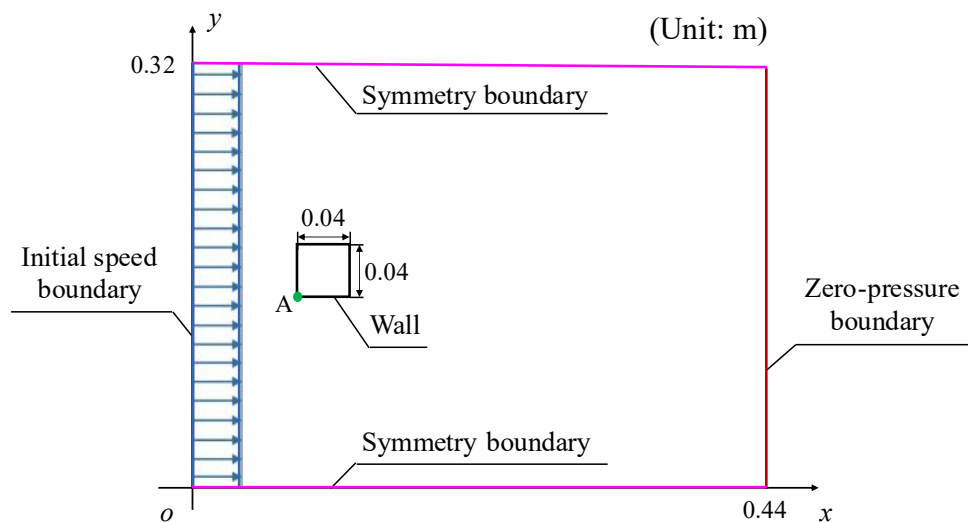


Fig 2.88 Computational domain for the flow past a two-dimensional square cylinder.

Generally, Case 2 and Case 1 differ significantly in two aspects. First, the most intuitive aspect is the different geometric appearances. Second, the velocity component v , in addition to u , is assumed to be known on the high-fidelity points that are utilised to establish the multifidelity model. From the 517 high-fidelity measurement points, 36 points scattered along nine vertical lines are selected for training the multifidelity model. **Table 1** tabulates their spatial coordinates. In selecting training points, the principle of distributing the training points over the whole computational domain as evenly as possible is still abided by.

Table 1. Spatial coordinates of the high-fidelity points used for multifidelity modeling.

x coordinate (m)	0.000	0.100	0.155	0.200	0.250	0.300	0.350	0.392	0.400
y coordinate (m)	0.200	0.200	0.160	0.160	0.160	0.160	0.160	0.160	0.160
	0.240	0.240	0.180	0.200	0.200	0.200	0.200	0.200	0.200
	0.280	0.280	0.200	0.240	0.240	0.240	0.240	0.240	0.240
	0.320	0.320	0.220	-	-	0.280	-	0.280	0.280
	-	-	-	-	-	0.320	-	0.320	0.320

The objective of Case 2 remains to apply all available physical restrictions and sparse measurement information to reconstruct the high-fidelity mainstream velocity u within the entire computational domain. As the data of v is also included in the training process (considered known), the number of schemes has increased from three to five. In Case 2, the performances of five distinct schemes are horizontally compared to achieve this objective.

For the first three schemes, the NIF algorithm and sparse u measurements are utilised for establishing the multifidelity model. The only difference between these three schemes is the low-fidelity data source. A PINN without training data (purely physics-based), a PINN with v embedded in its training process, and CFD are used as the low-fidelity data sources, respectively. The fourth scheme is a data-driven PINN which both u and v are embedded in to train the neural network parameters, and the NIF algorithm is not engaged in Scheme 4. The fifth scheme is an FCNN which is similar to that mentioned in Case 1. For the sake of explanation, the five strategies are now clarified in **Table 2** as follows.

Table 2. Five flow field simulation strategies in Case 2.

Scheme 1	Scheme 2	Scheme 3	Scheme 4	Scheme 5
PINN+NIF	v -embedded PINN+NIF	CFD+NIF	u v -embedded PINN	FCNN

It is meaningful to go into further detail on the PINN and CFD frameworks separately due to the multiple sources of the low-fidelity data in this case study. For the PINN framework, its configuration remains the same as that in the previous case except that there are only 108 collocation points to be excluded inside the two-dimensional square cylinder, which ultimately leads to a total of 9892 internal collocation points. In addition, there are 50 boundary equally-spaced collocation points on the initial speed boundary, zero-pressure outlet, upper symmetry boundary, lower symmetry boundary, and each of the four side surfaces of the two-dimensional square cylinder, respectively. Thus, a total of 400 boundary collocation points is used to calculate the physical residuals in this case. For the CFD framework, the simulation of the time-averaged flow field is performed based on the commercial software *Star CCM+* in this study, and the mesh inside the computational domain consists of more than 36484 cells. For both the PINN and CFD frameworks, the standard k - ε model is adopted in RANS turbulence modeling.

The prediction results of the mainstream velocity u from different schemes are depicted in Fig 2.89, which are also compared with the experiment results. These velocity contours show that Scheme 2, notably in the upstream region of the square cylinder, reconstructs the fluid features most accurately and efficiently. This may be due to the fusion of measured fluid features from upstream regions in Scheme 2 in low-fidelity modeling. Again, ℓ_2 error is used to quantitatively evaluate the accuracy of predictions from different models. As tabulated in **Table 3**, the ℓ_2 error of Scheme 2 is the lowest among those of all schemes, which is only 8.8% compared with the experimental results.

In particular, when v -embedded PINN, instead of CFD, is used as the low-fidelity data source, the ℓ_2 error has decreased by 6.6%. This is because measurement information has been included, and compared to CFD, the simulation results from v -embedded PINN are more accurate. However, when field information is unavailable, the precision of the PINN's prediction drops dramatically. This resulted in the ℓ_2 error of Scheme 1 being 18.1%, which is the worst among those of the multifidelity models.

The significance of physical information fusion in neural network modeling should be emphasised, nevertheless, as it is clear that Scheme 1 has an improved accuracy of 10.2% over

Scheme 5. By the way, it can be observed that all strategies involving PINN, i.e., Scheme 1, 2, and 4, are time-consuming, compared to CFD. Undeniably, this is one of the main drawbacks of PINN, which urgently needs to be addressed by further research. Fig 2.89 also illustrates the verification results. Across the entire computational domain, the multifidelity model predictions (Scheme 2) show good agreement with high-fidelity data (experiment measurements). The accuracy of the multifidelity model is still evaluated quantitatively by the ℓ_2 error.

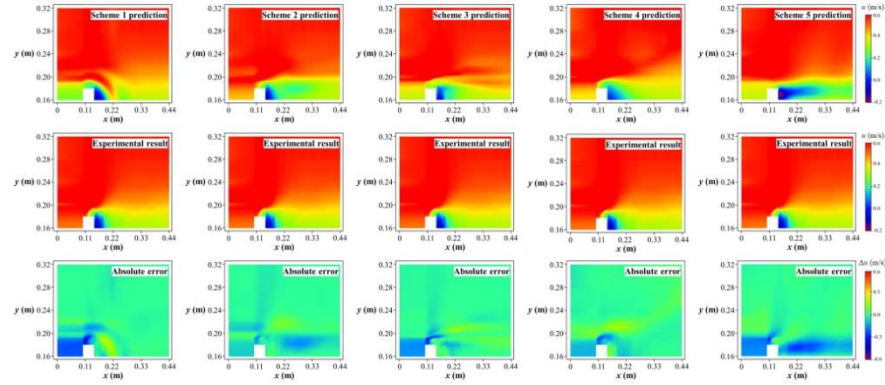


Fig 2.89 Prediction of u using five distinct schemes: (top) prediction; (middle) experimental result; (bottom) absolute error.

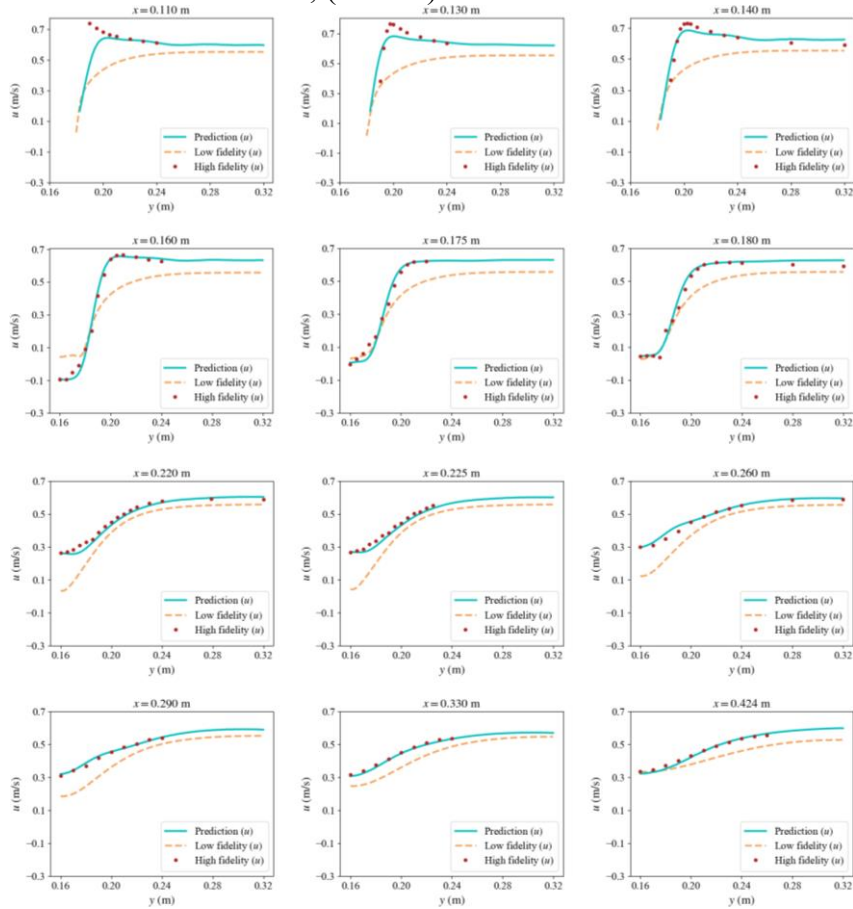


Fig 2.89(b) Comparison of the results between the multifidelity model prediction (Scheme 2) and the high/low-fidelity data on twelve vertical lines.

Table 3. Performance of different flow field reconstruction strategies.

	Scheme 1	Scheme 2	Scheme 3	Scheme 4	Scheme 5
ℓ_2 error	18.10%	8.80%	15.40%	15.50%	29.10%
Computing time (s)	2.8×10^4	2.8×10^4	5.4×10^2	2.8×10^4	2.1×10^1

(C) Impact of embedded data distribution on flow field reconstruction accuracy around crosswind-affected trains using physics-informed neural networks

1) Numerical simulation

Obtaining large amounts of measured data from the full-scale test and wind tunnel test would be a challenge, due to the complexities associated with conducting experiments in real scenarios and the expenses involved in testing diverse experimental subjects. In light of this, numerical simulations are employed to access datasets in the flow field in this work. Numerical simulations are a reliable approach to assessing the flow field around trains in crosswinds, provided their trustworthiness has been substantiated. To furnish the requisite foundational data for the formulation of expeditious predictive models, datasets obtained from numerical simulations have been widely harnessed. In this work, an equal cross-section high-speed train is adopted, with a width of $0.91h$, where h denotes the train's height measuring 3.5 m. The train model omits the bogies and pantograph structures, in order to enhance the computational efficiency and concentrate on the physics laws of predominant flow. Due to the significant characteristics of the train slenderness ratio, local area simplification of the model will not affect the dominant flow physics around the train, which thereby is widely used in the previous research of train aerodynamics. As shown in Fig 2.90, the computational domain is established as a 1/8 scale model to form finer meshes in the structure's vicinity and to capture detailed flow, while the cross-section of the computational domain is $10.28h \times 3.40h$. To ensure the complete development of the flow field, the distance from the upstream boundary to the train's center is $1.71h$, while the distance from the train's center to the downstream boundary is $8.57h$. Meanwhile, the length of the computational domain is $5.99h$. Furthermore, the blockage ratio in the numerical wind tunnel stands at 0.35%, falling below the EN standard requirement of 1%.

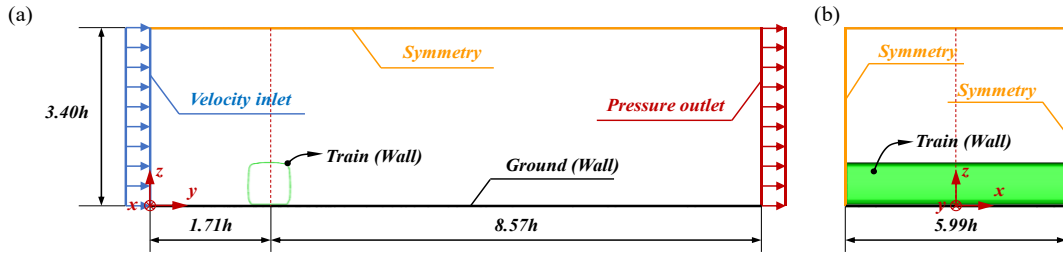


Fig 2.90 Computational domain and boundary conditions: (a) side view; (b) front view.

The incoming flow is initiated with a consistent and steady velocity of $U = 1$ m/s at the velocity-inlet boundary. In contrast to the velocity-inlet, the downstream boundary is set with a zero-pressure-outlet condition ($P = 0$ Pa). A symmetry boundary condition is utilised at the top of the calculational domain. Meanwhile, the train and ground are set with the stationary wall boundary conditions. Due to the numerical results would be the reference dataset to evaluate the capability of PINN, to facilitate subsequent comparative analysis, the flow field around the train in crosswinds therefore is simulated based on the steady Shear Stress Transport (SST) $k - \omega$ turbulence model, and a pressure-based incompressible solver is adopted in the current work. The pressure-velocity coupling equation is solved using the semi-implicit method for the pressure-linked equation consistent (SIMPLEC) algorithm in a numerical simulation. For the convection and diffusion terms, the second-order upwind scheme is utilised, and the gradients in the control volumes are computed based on the Green-Gauss cell-based method.

The structured hexahedral mesh is generated for spatial discretisation of the computational domain. Additionally, the concerned object is equipped with prism meshes consisting of ten layers to evaluate the gradual change in the velocity gradient near the train surface caused by the wall effect. Fig 2.91(a) presents enlarged views of the train in both longitudinal and cross-section. The non-dimensional wall distance y^+ for the first layer falls between 30 – 40. To better capture the details of occurring flows close to the structure, the grid refinement strategy is used around the train model, especially the flow around the train, as shown in Fig 2.91(b).

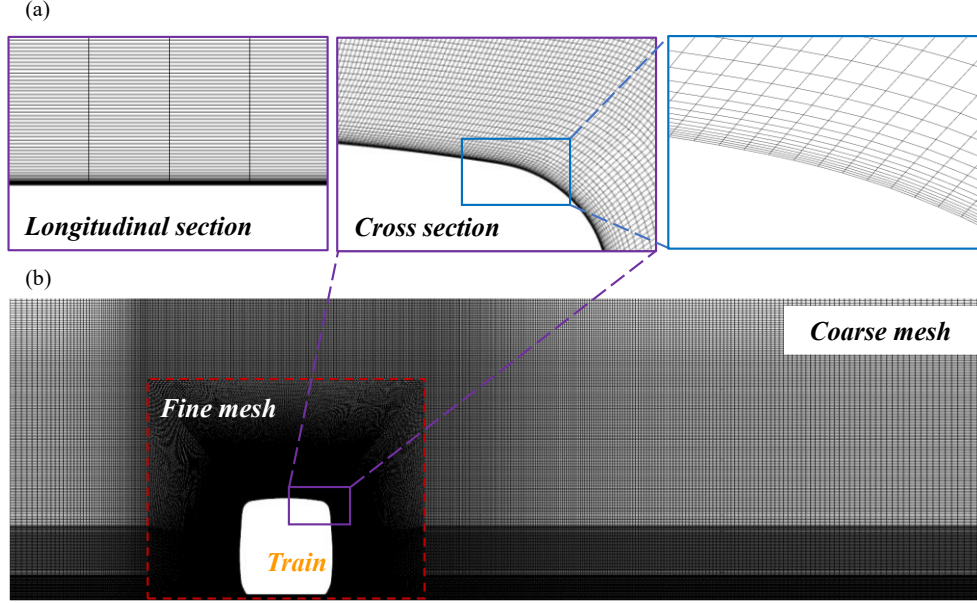


Fig 2.91 The computational mesh: (a) enlarged view of the local grid near the train surface; (b) mesh slicing.

2) Physics-informed neural network (PINN)

PINN, a kind of deep neural network, incorporates physical equations and measurement data into the overall loss function to train the parameters of the neural network, thereby improving its ability to address various PDE problems. In this work, a two-dimensional time-averaged flow field regarding a train under crosswind scenario is reconstructed via the PINN method with the aid of sparse flow field data. The RANS equation used to describe two-dimensional turbulent flow can be expressed as follows:

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x_i} (\rho u_i) = 0 \quad (16)$$

$$\frac{\partial}{\partial t} (\rho u_i) + \frac{\partial}{\partial x_j} (\rho u_i u_j) = -\frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j} [\mu_{\text{eff}} (\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i})] \quad (17)$$

where ρ , u_i , p , and μ_{eff} represent the density of the medium, velocity component in the x_i direction, pressure, and effective viscosity of the medium, respectively. The total viscosity is the combination of the turbulent viscosity μ_t and the laminar viscosity μ , which can be represented as:

$$\mu_{\text{eff}} = \mu_t + \mu \quad (18)$$

In addition, the Chen model is used to solve the RANS equations by assuming that the turbulent viscosity is equal to the local velocity v multiplied by the distance from the nearest wall l . In Chen's model, turbulent viscosity is described as:

$$\mu_t = 0.03874\rho vl \quad (19)$$

Then, PINN is applied to address the RANS equations based on the Chen model. During the computation process, the allocation points are evenly arranged within the computing region or on its boundaries and controlled by the physical constraint, including the governing equations and boundary conditions, to perform a pivotal function in evaluating the residuals linked to the physical equations. Subsequently, through the utilisation of optimisers, these integrated residuals within the PINN loss function gradually converge toward zero during the training. Fig 2.92 demonstrates the PINN framework employed for flow field reconstruction. The diagram depicts a fully connected neural network where the left side consists of spatial coordinate parameters as inputs and generates flow field information, encompassing pressure and velocity components, as outputs.

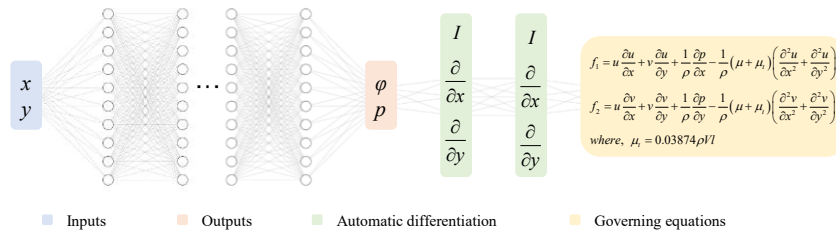


Fig 2.92 PINN framework.

3) Effects results of embedded points distribution

In this section, the effect of the distribution interval of embedded points in the far wall area is investigated. To ensure result comparability, the distribution of embedded points remains consistent in the near wall area and the near train surface area, despite variations in the embedded points distribution in the far wall area. The embedded points are spaced at intervals of D_{near} in the incoming direction n and H in the vertical direction within the near wall area. Additionally, an even distribution of 24 data points is observed on the near train surface area. To investigate the effect of embedded points distribution of far wall area, there are 5 different intervals in the incoming direction under consideration, namely, D_{far} , $2D_{far}$, $4D_{far}$, $8D_{far}$, and $16D_{far}$.

For the aerodynamic performance of the train in crosswinds, the airflow velocity in the incoming direction is the dominant factor in its influence, namely u , and the velocity in the vertical direction, namely v , is relatively weak by comparison. Fig 2.93 shows the ℓ_2 error of the predicted velocity components u and v in these two directions, respectively, against the

values calculated by numerical simulations. As portrayed in Fig 2.93(a), for u , the sparse distribution of embedded points in the vertical direction leads to an increase in the predicted value errors, compared with the reference data. Specifically, with the spacing in the vertical direction of embedded points from H to $2H$, the ℓ_2 error of the predicted velocity components u demonstrates a tendency to expand in all presented cases. Compared with the case of embedded points with the interval of H in the vertical direction, the maximum error is obtained in the interval of $8D_{far}$ in the incoming direction as the distance of embedded points expands to $2H$ in the vertical direction, with a difference of 1.80%. This ℓ_2 error also demonstrates an obvious discrepancy in the case of the embedded points with an interval of D_{far} in the incoming direction, which exhibits a discrepancy of 1.46%. However, an insignificant discrepancy occurred in the case of the embedded point interval with a spacing of $4D_{far}$. In addition, for the cases listed in Fig 2.93(a), with the increasing spacing between embedded points in the incoming direction, a downward and then upward trend of ℓ_2 error is observed at various vertical spacing intervals of H and $2H$. When the vertical spacing of the embedded points is H , the ℓ_2 error declines in the cases of D_{far} , $2D_{far}$, and $4D_{far}$ from 9.36% to 8.87%, which upon increase to 9.14% and 9.94%, respectively, as the interval of the embedded points rising to $8D_{far}$ and $16D_{far}$ in the incoming direction, respectively.

In the aspect of the predicted velocity component v , owing to its small value in the flow field, the ℓ_2 error appears relatively obvious. In addition, compared with the reference data, the ℓ_2 error of the predicted vertical velocity component v in the flow field is portrayed in Fig 2.93(b). With the increasing of embedded points vertical spacing from H to $2H$, the ℓ_2 error of the embedded points with the spacing of D_{far} and $16D_{far}$ in the incoming direction show a reduction in value by 1.56% and 4.20%, respectively. However, a reverse is obtained in the cases of embedded points with the spacing of $2D_{far}$, $4D_{far}$, and $8D_{far}$ in the incoming direction. The scheme of embedded points with the spacing of $2D_{far}$ and $4D_{far}$ in the incoming direction shows a slight difference of less than 1% in the ℓ_2 error, and the case of $8D_{far}$ exhibits the largest discrepancy of 2.18% in the ℓ_2 error. In two different embedded point schemes in the vertical direction, the lowest ℓ_2 error of the velocity component v occurred in the case of embedded points with the interval of $4D_{far}$ in the incoming direction, which portrays a discrepancy of 17.13% and 18.00%, respectively.

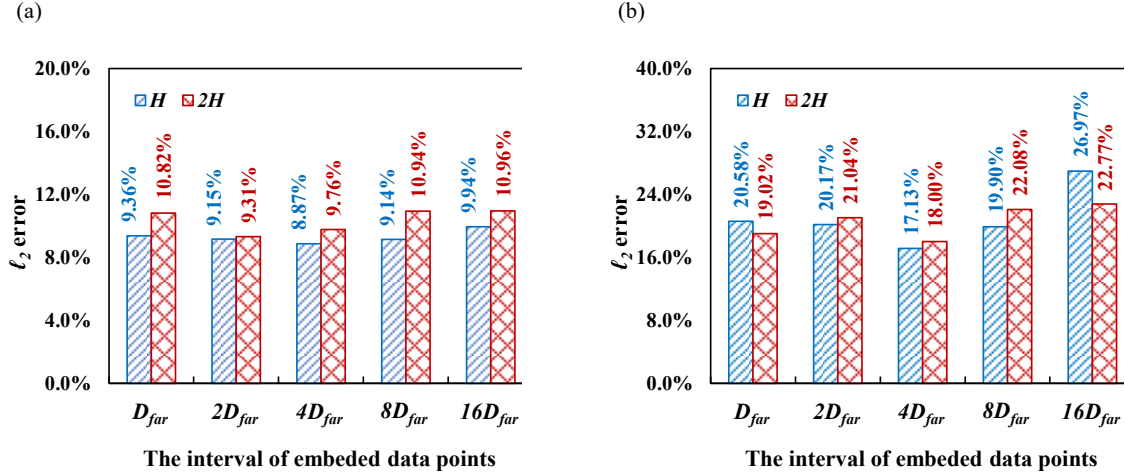


Fig 2.93 Compared results of ℓ_2 error on embedded points distribution of far wall area: (a) u ; and (b) v .

As far as the analysis of the flow field predicted results of PINN in the previous section is concerned since the best predicted results are obtained as the vertical embedded points are spaced at H , this section will mainly focus on the results of flow field reconstruction on it. The distribution of different velocity components, namely u and v , in the flow field is shown in Fig 2.94 and Fig 2.95. To facilitate the comparison and further analysis, the numerical results are presented in Fig 2.94(a) and Fig 2.95(a). The results presented in Figs. 2.95(b-d) are the PINN predicted results for embedded points with the interval of D_{far} , $4D_{far}$, and $16D_{far}$ in the incoming direction, respectively, and the number is about 1.32%, 0.49%, and 0.28% of the validation points, respectively. The variation between the flow field velocity u predicted by PINN and the CFD results for different intervals of embedded points in the incoming direction is less different, but it still has some influence on the reconstruction accuracy of the flow field. For instance, the distribution of embedded points in the far wall area not only affects the velocity distribution characteristics on the leeward side of the train but also affects the flow field distribution near the windward side of the train, as shown in Region I of Fig 2.94 Compared with the spacing of D_{far} , and $16D_{far}$ in the incoming direction, as the interval of the embedded points is $4D_{far}$, the velocity distribution at the near ground position on the windward side of the train is most similar to the CFD simulation results. Since there is a gap between the bottom of the train and the ground, the airflow along the bottom of the train will be accelerated due to the slit effect and affect the velocity distribution on the leeward side of the train. It can be seen in the cases listed in this section, such as Region II, that the reconstruction of the flow field on the leeward side of the train, especially for the flow across the bottom of the train, is better when the spacing

of the embedded points are D_{far} and $4D_{far}$ in the incoming direction. However, for the interval of $16D_{far}$ between embedded points in the incoming direction, the prediction performance of PINN in Region II was less than satisfactory. In addition, for the areas away from the train, compared with the results of CFD, the interval of the embedded points of D_{far} and $4D_{far}$ in the incoming direction exhibits a better-predicted result, especially for low-speed flows on the leeward side of the train (the area lower than the dividing line in Fig 2.94). Using an interval of $16D_{far}$ between embedded points in the incoming direction yields predicted results that exhibit significant fluctuations, which also indicates an excessively wide distribution of embedded points in the incoming direction is not conducive to the formation of time-averaged turbulent vortices on the leeward side of the train.

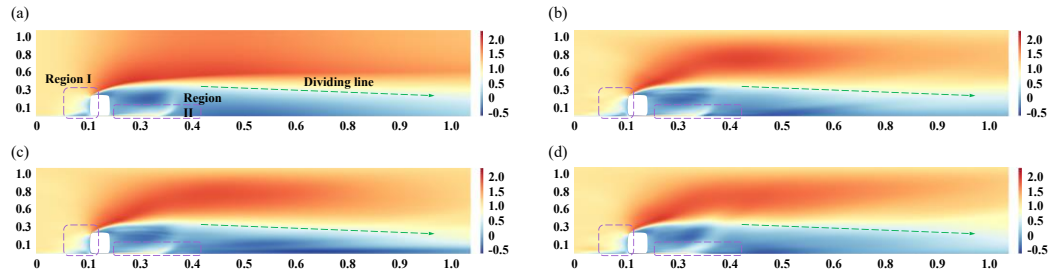


Fig 2.94 Compared results on embedded points distribution of far wall area between numerical results and PINN predictions in the velocity component u : (a) CFD; (b) D_{far} ; (c) $4D_{far}$; and (d) $16D_{far}$.

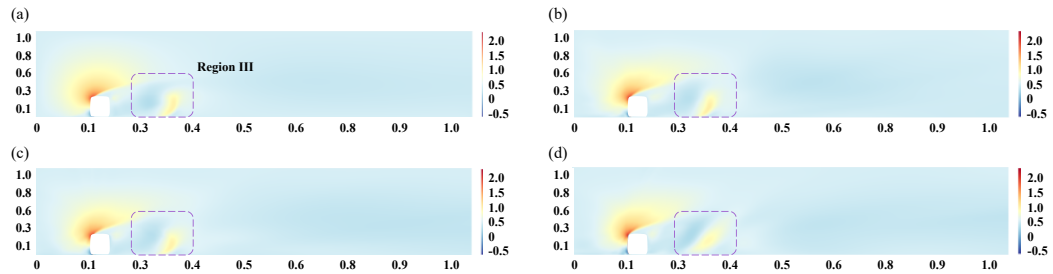


Fig 2.95 Compared results on embedded points distribution of far wall area between numerical results and PINN predictions in the velocity component v : (a) CFD; (b) D_{far} ; (c) $4D_{far}$; and (d) $16D_{far}$.

Similarly, the results presented in Figs. 2.94(b-d) are the PINN predicted results for the interval of D_{far} , $4D_{far}$, and $16D_{far}$ between embedded points in the incoming direction, respectively. As shown in Fig 2.94, although a relatively large error is obtained between CFD results and PINN predicted results, the variation between the flow field velocity v predicted by PINN and the CFD results for the different intervals of embedded points in the incoming direction is compared, which indicates that the PINN has a high capacity in flow field reconstruction. Compared to the case with the interval of D_{far} , and $16D_{far}$ in the incoming

direction, namely Fig 2.94(b) and Fig 2.94(d), as the spacing of embedded points is $4D_{far}$, namely Fig 2.94(c), Region III on the leeward side of the train is relatively well reconstructed. However, as the spacing of embedded points is $16D_{far}$ in the incoming direction, the distribution of velocity v in Region III is relatively poor. For other areas of the velocity distribution of the flow field, none of them presents significant differences.

2.2.21 Theoretical Study of High-Speed Train Aerodynamic Noise Calculation

Dr. Xiao-Ming Tan from the CNERC-Rail (HK Branch) established the near-field aerodynamic noise calculation theory for trains below 350 km/h based on the acoustic potential fluctuation equation and sponge layer sound-absorbing boundary, as shown in Fig 2.98, 98 Schematic diagram of near-field aerodynamic noise calculation for trains under 350 km/h, and successfully debugged the coefficients applicable to the theory with engineering application value, e.g., the largest aerodynamic noise source in the bogie region was found as shown in Fig 2.98, and the focus is to manage the aerodynamic noise of bogie crossbeam and cylinder region.

In addition, Dr. Tan constructed a theoretical system of radiated noise correction for aerodynamic acoustic principal mode correlation in bow-cavity coupled systems: due to the limitations of acoustic wind tunnel size and computational scale/precision, the aerodynamic noise of high-speed trains is usually investigated by using a reduced-ratio vehicle body model. However, due to the complexity and diversity of aerodynamic sound bodies, it is difficult to give a consistent scale similarity law. Based on the aeroacoustic similarity parameters in the self-modelling region (including the Mach number Ma , the Strahl number St , and the dimensionless sound source parameters), combined with the theory of sound power computation for unipolar, dipolar, and quadrupolar sound sources, the aerodynamic noise conversion relations for different scale models can be simply established. This is the current general practice for solving such problems. However, they do not take into account the flow field morphology migration effect caused by the change of Reynolds number, the field coupling effect caused by the change of spatial distance of different components, and the change of incoming boundary layer parameters. To address the above scientific issues, a fine aeroacoustic simulation technique for a full-size bow-cavity coupled system is developed and improved, and

the dominant flow modes and their scale evolution mechanisms in the region are obtained by a data-driven approach, and the acoustic similarity law of the dominant aeroacoustic modes is obtained by combining the aeroacoustic theory of cavities/rods. Then, a radiated noise correction model associated with the dominant aerosound modes is constructed, which can be used to correct the scaled model test or numerical simulation results.

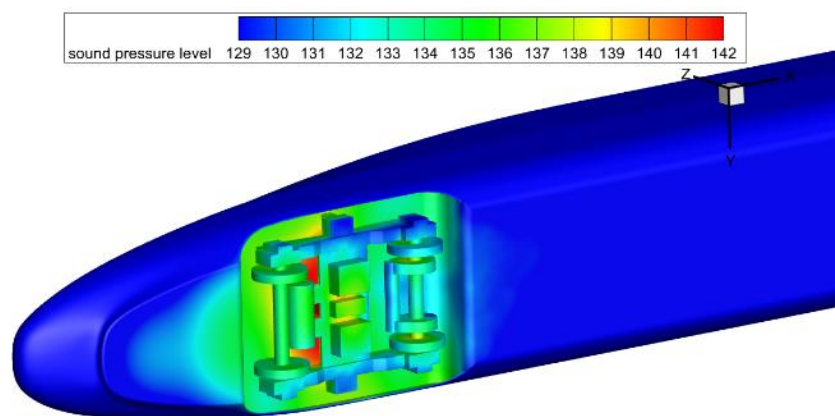


Fig 2.98 Schematic diagram of near-field aerodynamic noise calculation for trains under 350 km/h

2.2.22 AI Vision-Based Intelligent Safety Supervision and Interaction System for Electric Power Operations

In high-risk operation fields such as electric power and energy, achieving intelligent, refined, and real-time safety production supervision is a key industry demand. Currently, traditional safety supervision models face issues such as insufficient real-time capability, supervision blind spots, and passive post-event traceability. To address these challenges, the project team initiated the R&D of the "AI Vision-Based Intelligent Safety Supervision and Interaction System for Electric Power Operations" this year. It aims to integrate advanced multimodal sensing, edge computing, and artificial intelligence technologies to establish a new paradigm of proactive safety supervision capable of pre-event warning and in-process intervention.



Fig 2.99 Proof-of-Concept Prototype

The core of this project is the development of an intelligent supervision system featuring "Device-Edge-Cloud" collaboration. The system front-end relies on industrial-grade intelligent perception terminals to collect on-site operation audio and video data in real time. The edge side performs preliminary data processing and real-time analysis. The cloud is responsible for complex AI model computation and global decision-making. The ultimate goal is to build an intelligent supervision platform covering the entire operation process, enabling automatic identification of typical violations, risk warnings, and voice prompts, thereby significantly enhancing the safety and standardisation of on-site operations.

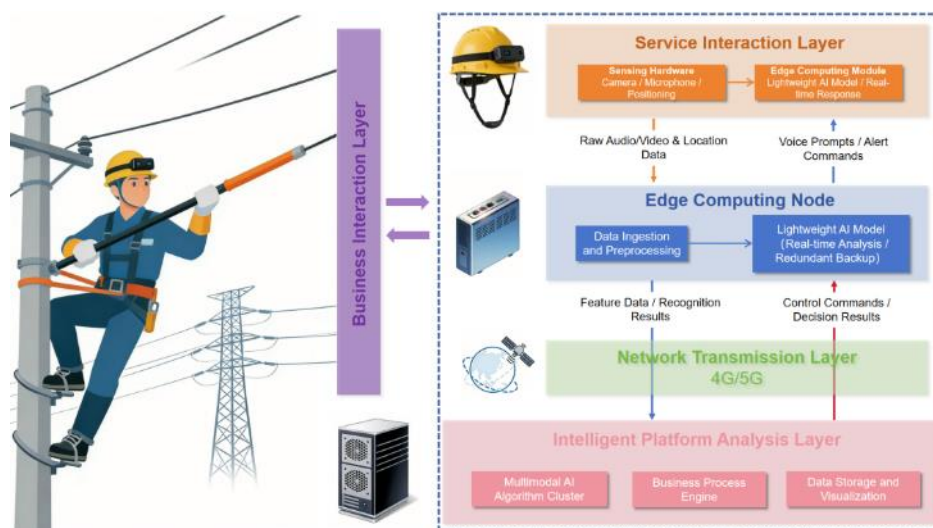


Fig 2.100 Smart Terminal Operation Workflow

To date, the project has successfully completed the prototype system development and integration testing phases, achieving the following key milestones in field application groundwork and physical prototype verification:

On-site Application Foundation: The project team has completed preliminary environmental assessments and data collection at typical electric power operation sites. Approximately 5,000 on-site operation image samples covering different seasons, weather, and lighting conditions have been systematically collected, laying a high-quality data foundation for AI algorithm training and optimisation.

Functional Prototype: The project has successfully developed the first-generation head-mounted smart terminal prototype integrated with AI visual analysis capabilities. This prototype integrates a high-definition camera, noise-canceling microphone, and an edge computing module, possessing basic environmental perception and AI analysis capabilities. In laboratory simulation environments, it has successfully validated core functions such as safety helmet wearing detection and insulated glove detection, with the system linkage response time meeting design expectations.

Technical Feasibility: Test results based on the physical prototype indicate that the adopted "Device-Edge-Cloud" technical architecture is reasonable and feasible. The core algorithms have achieved the expected accuracy indicators in typical scenarios, providing strong technical support for the next phase of on-site pilot application and productisation.

In the next stage, based on the validated prototype, the project will focus on promoting engineering implementation: firstly, conducting industrial-grade deep customisation of

terminal hardware to enhance its reliability in complex outdoor environments; secondly, continuously optimising and expanding AI algorithms to improve their recognition accuracy and coverage in scenarios like extreme weather; thirdly, completing full system integration and conducting pilot verification in real operation environments to comprehensively evaluate its stability and business value.

2.2.23 Acoustic metamaterial and seismic metamaterial design

We have developed a hierarchical seismic metamaterial to improve multidirectional earthquake wave mitigation. The design has been validated with the existing benchmarks.

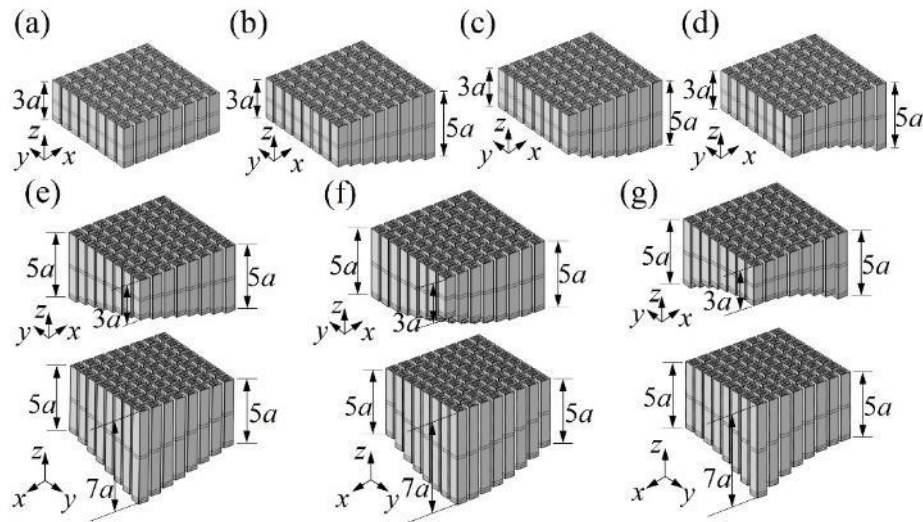


Fig 2.101

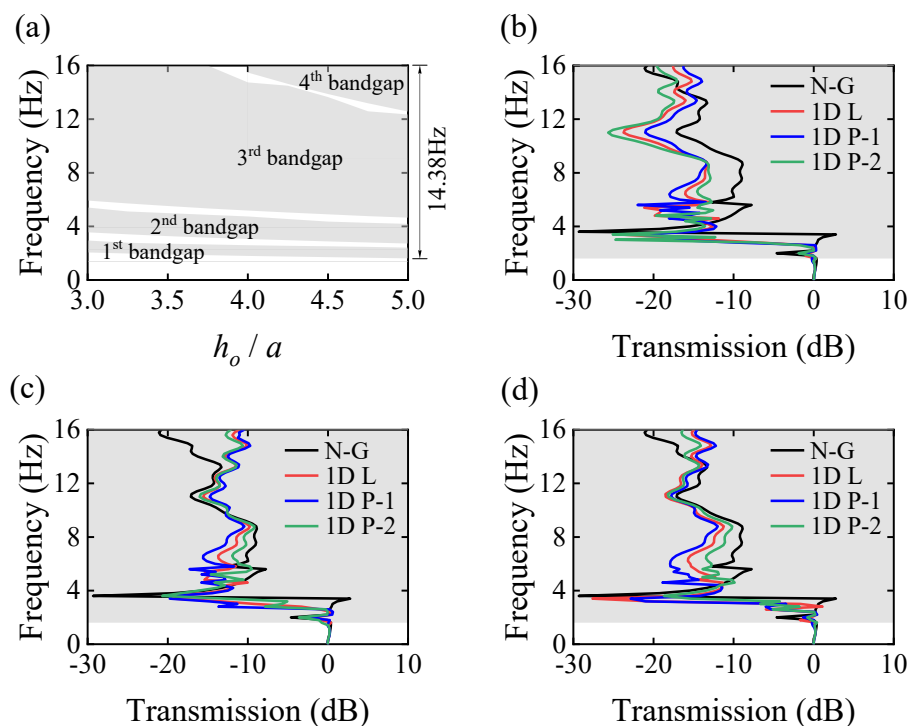


Fig 2.102

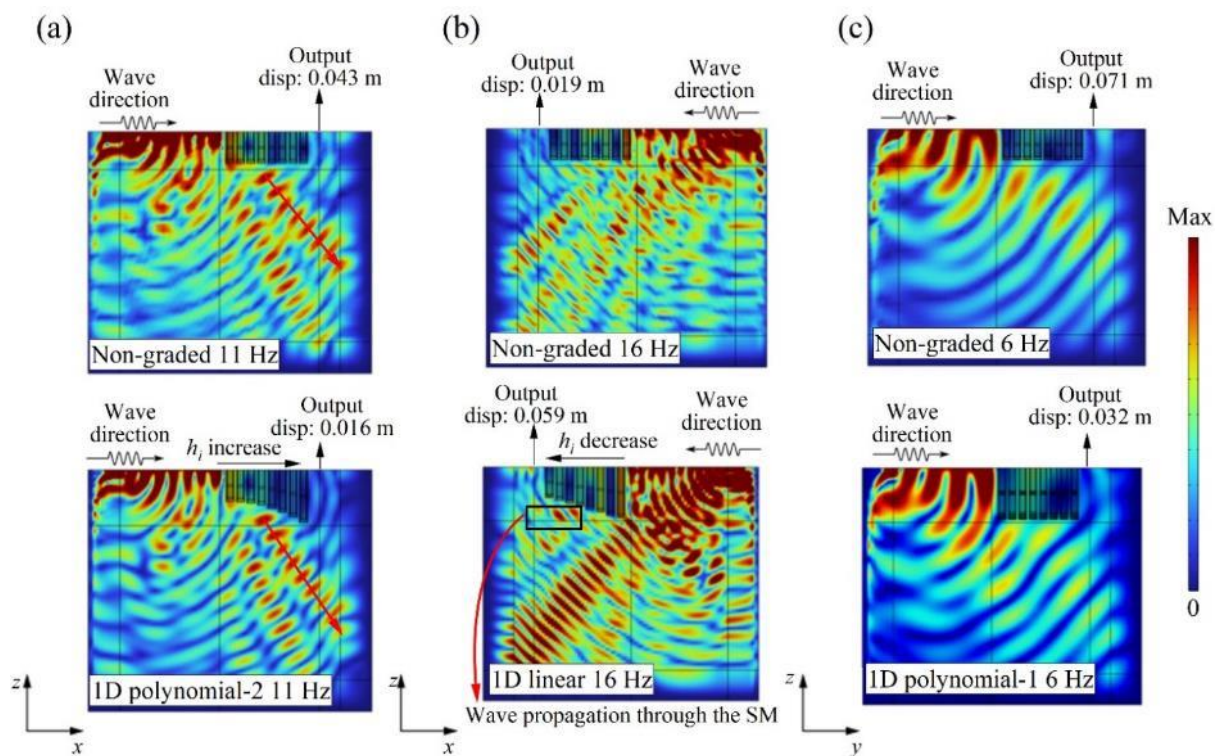


Fig 2.103

We have developed several tunable membrane-type acoustic metamaterials for both the sound insulation and absorption. In the meantime, we have developed the new structural-

acoustic coupled numerical model to capture how the large deformation of the membrane affects the sound manipulation performance.

Design 1:

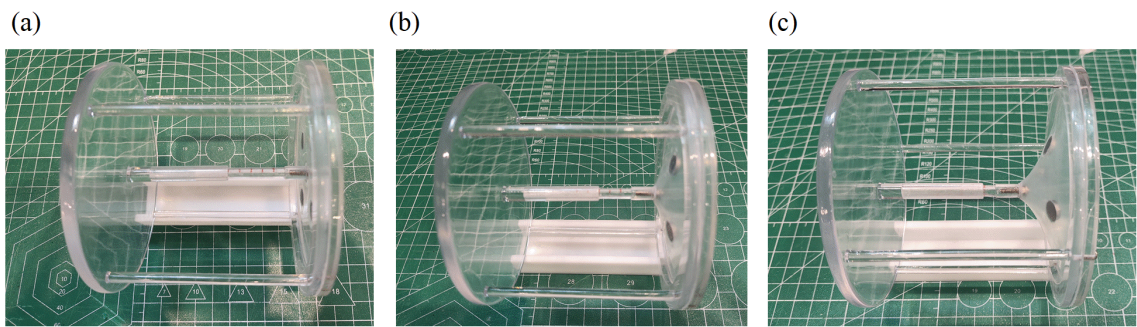


Fig 2.104

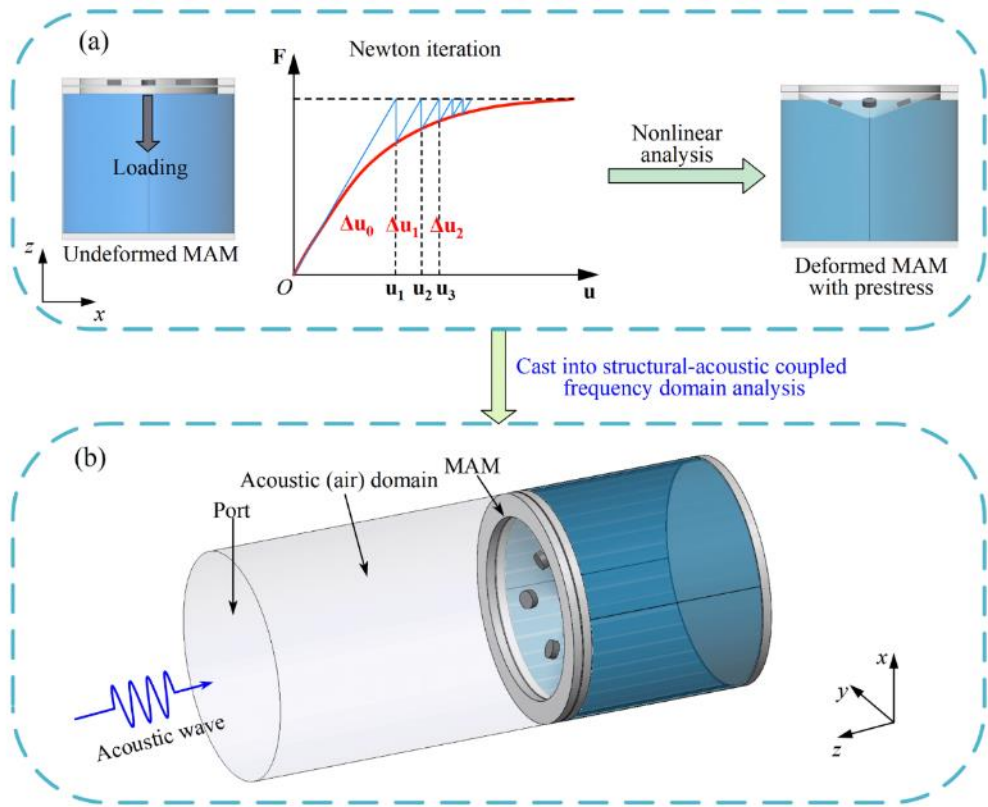


Fig 2.105

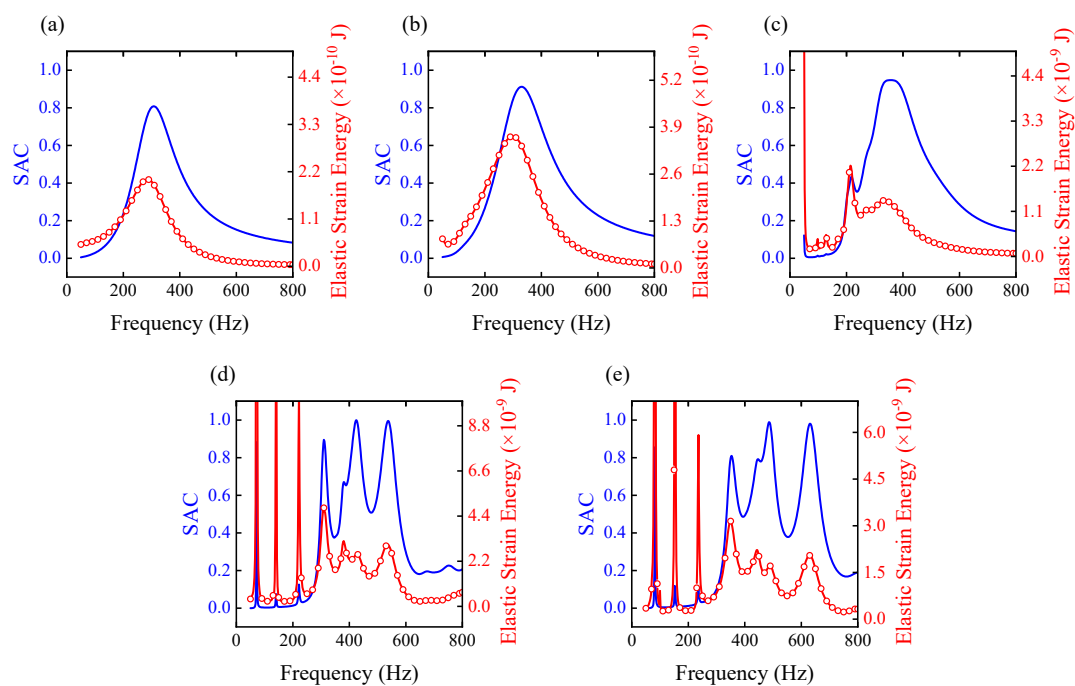


Fig 2.106

Design 2:

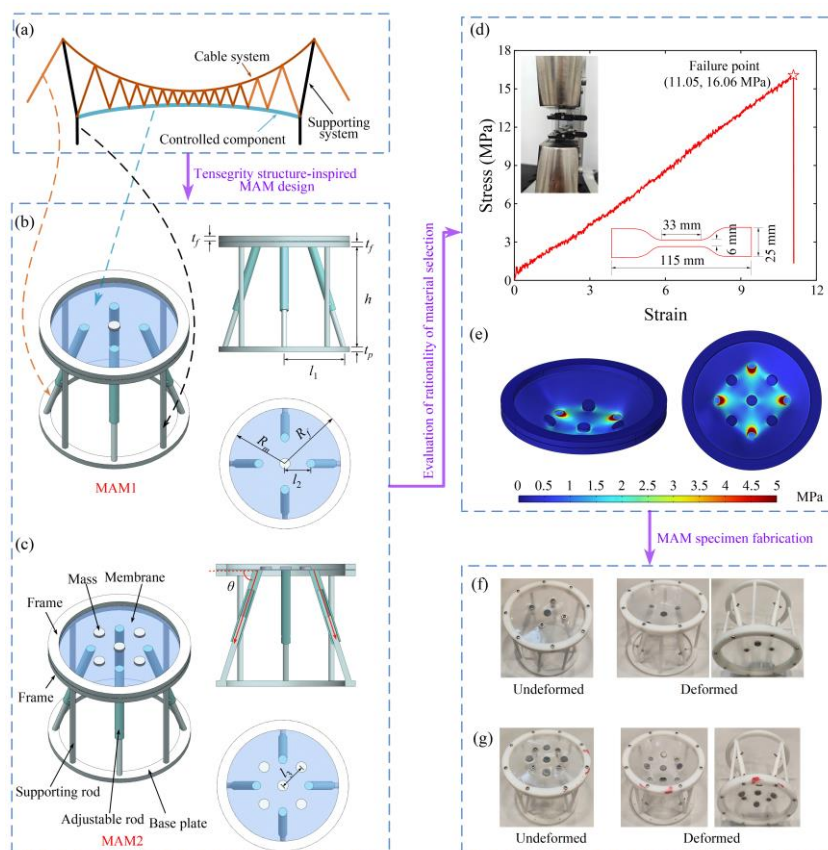


Fig 2.107

2.2.24 Structural health monitoring of the offshore infrastructure

We have developed the novel integrated deep learning methods to conduct the mooring line damage identification, and the feasibility has been fully validated by the full-scale water tank test in USA.

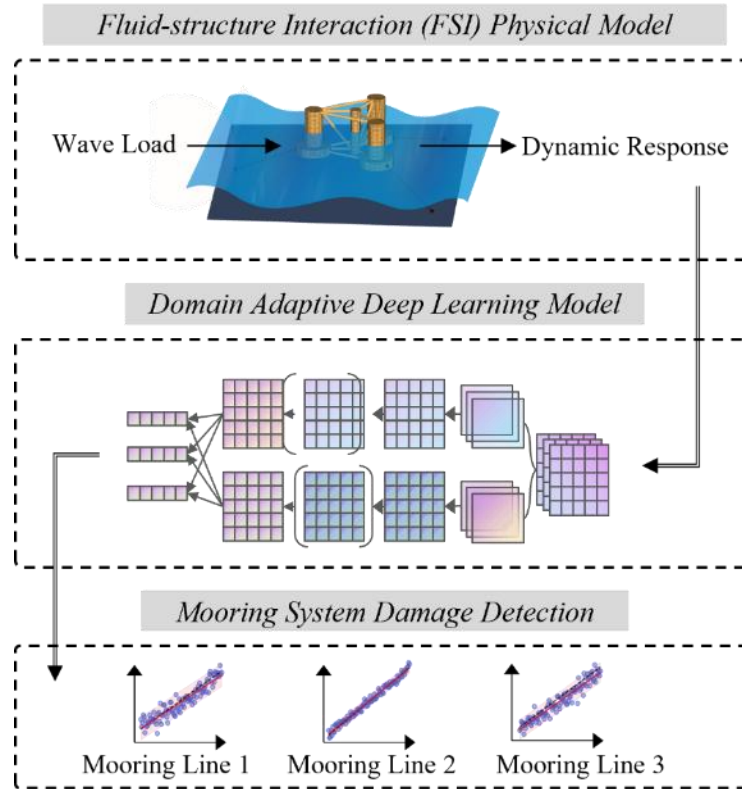


Fig 2.108

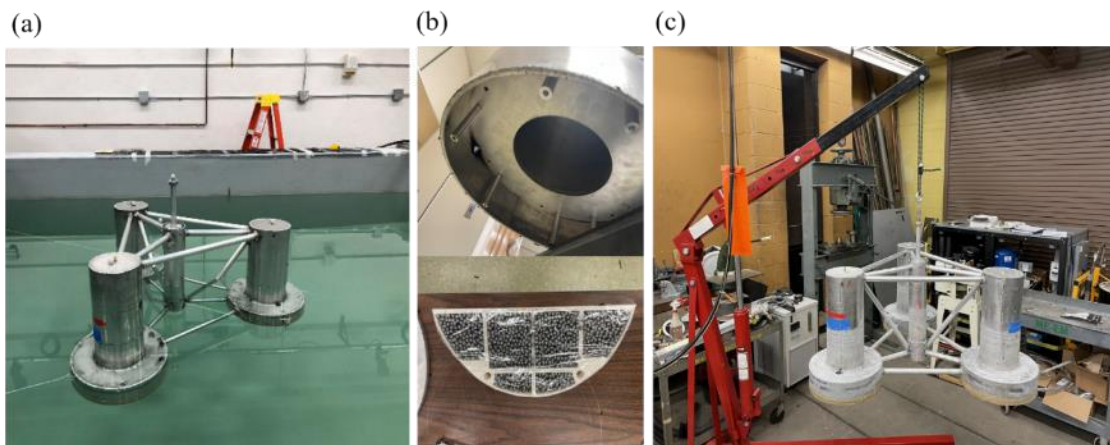


Fig 2.109

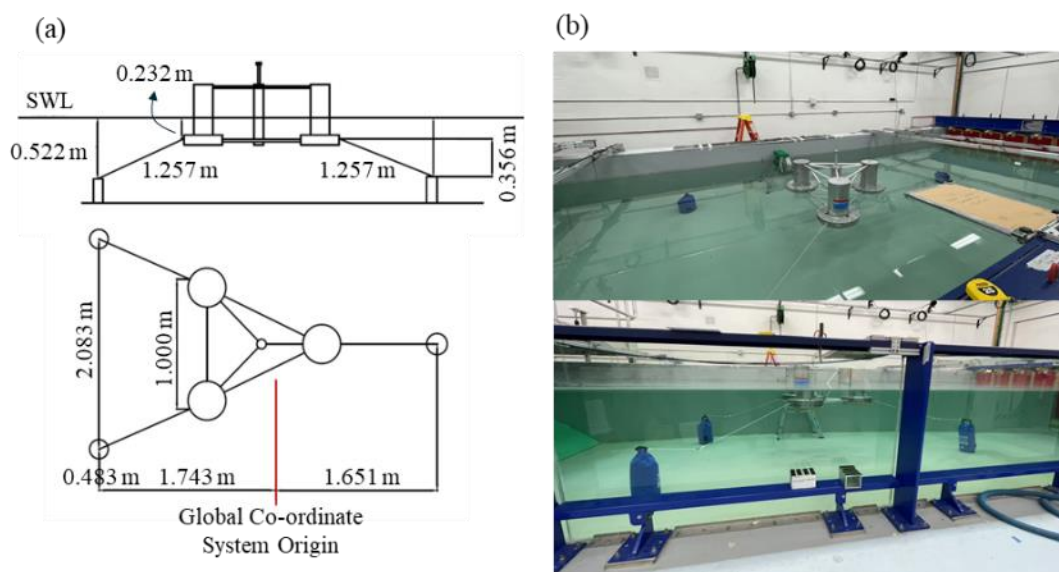


Fig 2.110

2.2.25 Development of High-Reliability, Multifunctional Intelligent Sensors

Driven by the urgent demand of the rail transit industry for high reliability, high integration, and intelligent operation and maintenance, the project team addressed critical challenges faced by sensors used in structural health monitoring under extreme environments—such as extreme-cold and high-altitude conditions and strong electromagnetic interference—including insufficient stability, low integration levels, and limited intelligence. The team systematically carried out research on next-generation rail transit sensor technologies and their engineering applications, ultimately forming a high-performance, multifunctional, highly integrated sensor system solution.

The developed sensor system is designed for extreme-cold and high-altitude railway lines, complex climatic regions, and scenarios with strong electromagnetic interference. It is mainly applied to structural safety monitoring of various infrastructures, including railways, bridges, tunnels, and buildings, enabling dynamic multi-parameter data acquisition as well as board-level edge computing. By introducing low-temperature-drift sensing materials, wide-temperature-range electronic components, and multi-layer anti-interference designs, the system significantly improves sensor stability and consistency under conditions such as temperatures below $-40\text{ }^{\circ}\text{C}$ and large day–night temperature variations. In addition, the system integrates multiple sensing functions to enable coordinated acquisition of key structural parameters,

including vibration, inclination, acceleration, and temperature, thereby reducing the installation complexity and high maintenance costs associated with the distributed deployment of multiple standalone sensors in traditional solutions. At the system architecture level, the project further enhances sensor integration and intelligence. By embedding edge computing and self-diagnostic capabilities into sensor nodes, the system achieves signal preprocessing, abnormal feature extraction, and self-monitoring of operational status. This effectively reduces data redundancy and significantly improves the safety and reliability of critical rail transit structures operating under extreme environmental conditions.



Fig 2.111 High-reliability multifunctional integrated all-in-one sensor

2.2.26 Flexible Sensor R&D Project

To address the difficulty of accurately acquiring the distribution of wind loads on structural surfaces under high-speed train operation and typhoon conditions, the project team developed flexible array pressure sensors for distributed wind pressure monitoring. These sensors can be attached over large areas to complex curved surfaces such as train bodies, tunnel walls, and glass curtain walls of high-rise buildings, enabling high-spatial-resolution measurement of wind pressure distributions. Compared with traditional rigid single-point sensors, this solution allows continuous acquisition of the spatiotemporal variations of wind pressure, providing more comprehensive data support for aerodynamic analysis and structural safety assessment.

By optimising the structural design of the flexible sensing units, material systems, and signal acquisition methods, the flexible array pressure sensors achieve a balance between high

sensitivity and a wide measurement range, while also exhibiting excellent fatigue resistance and environmental adaptability. The sensors can withstand long-term vibration, temperature fluctuations, and outdoor service conditions typical of rail transit applications. These research outcomes provide critical technical support for wind-induced vibration analysis, extreme weather risk assessment, and structural safety early warning systems.



Fig 2.112 Flexible Sensor

2.2.27 Dynamic Evaluation Tests on the Performance of Noise Reduction Damping Rings for Rail Transit Wheels

With the acceleration of urbanisation in China, noise pollution caused by the operation of subways and intercity trains has become a bottleneck for the sustainable development of rail transit. To meet the limit of 70 dB(A) during daytime as stipulated in the Environmental Quality Standard for Noise (GB 3096-2008), research on vehicle-based noise control technologies has been spearheaded by the CNERC-Rail (Hong Kong Branch).

This field experiment was conducted under the guidance of Chair Professor Yi-Qing Ni. The research team, comprising Dr. Wai Kei Ao, Mr. Yu-Ling Wang, and Mr. Yu-Hang Lu, successfully completed the data collection in November 2024 at the circular test track of the China Academy of Railway Sciences in Beijing. Utilising non-destructive monitoring techniques, the study focused on evaluating the suppression efficiency of damping rings with various materials and structures against wheel-rail howling and interior structure-borne noise during the stepped variable-speed operation (40 km/h to 140 km/h) of a CRRC-TS intercity EMU.



Fig 2.114 Circular test track at test base

The study was implemented on a closed-loop track. By configuring different testing schemes across five bogies of a single train, a parallel comparative analysis of multiple operational conditions was achieved.



Fig 2.115 Layout of microphone sensors in the wheel-rail near-field



Fig 2.116 Layout of microphone sensors inside the train cabin

Sensor Layout: A total of 8 key measurement points were arranged longitudinally along the train. TP1-TP5 were designated as wheel-rail near-field points (positioned 0.5 m vertically above the rail surface) to capture source radiation. TP6-TP8 were located inside the passenger compartment (1.2 m above the floor) to monitor noise from the perspective of passenger perception.

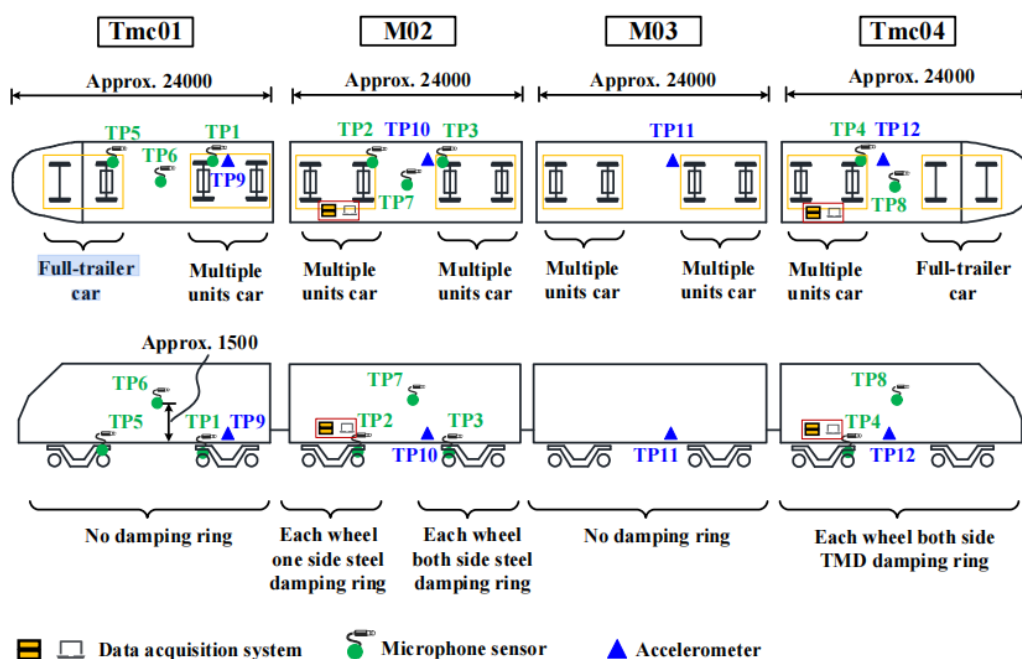


Fig 2.117 Layout of sensors

Hardware Configuration: B&K 4939 free-field microphones (measurement range: 16-143 dB) were used in conjunction with a Dewesoft SIRIUS multi-channel system. A high sampling frequency of 50 kHz was employed to ensure the complete capture of high-frequency transient signals.



Fig 2.118 Data acquisition system

Testing Procedure: The train maintained a constant speed for at least 500 meters at each target velocity (40, 80, 100, 120, and 140 km/h). Data acquisition was triggered once the speed stabilised within a fluctuation range of ± 1 km/h, with each valid data segment lasting no less than 120 seconds.

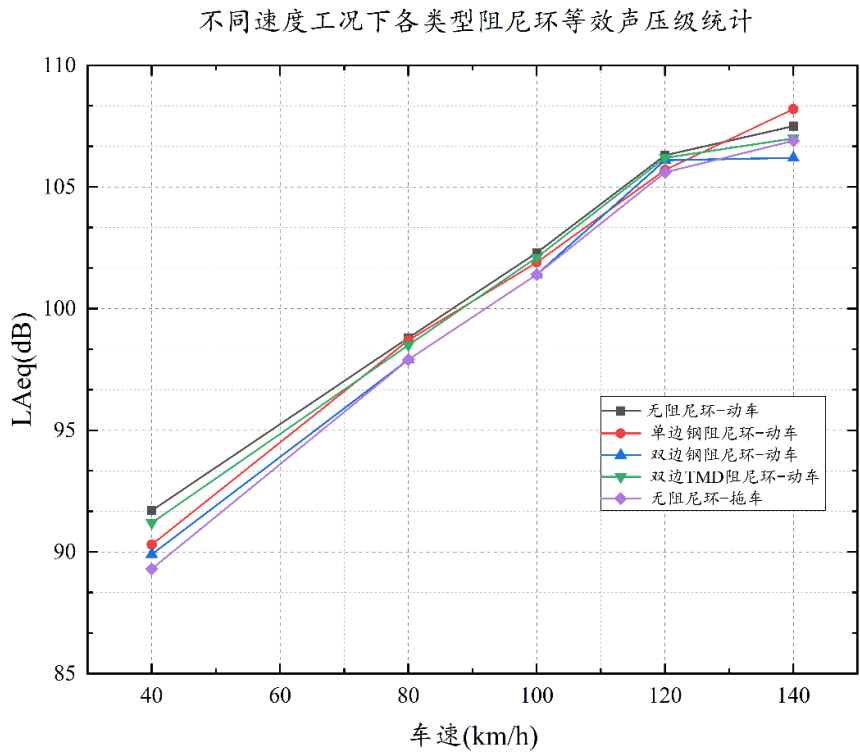


Fig 2.119 LAeq statistics for various damping ring types across different speed conditions in the wheel-rail near-field

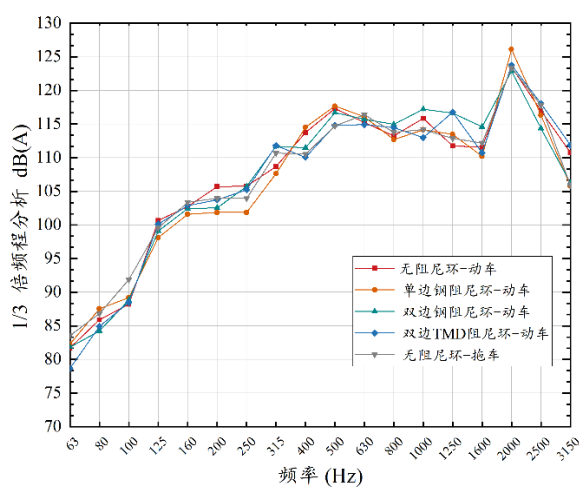
The experiment focused on evaluating three configuration schemes, revealing a significant correlation between noise reduction efficiency and operational speed:

Double-sided Steel Damping Rings (TP3): Demonstrated the best broadband suppression characteristics. Under the low-speed condition of 40 km/h, the noise reduction reached 1.8 dB. It showed continuous suppression of medium-to-low frequency vibrations (63-315 Hz), with an interior structure-borne noise suppression efficiency ratio as high as 89%.

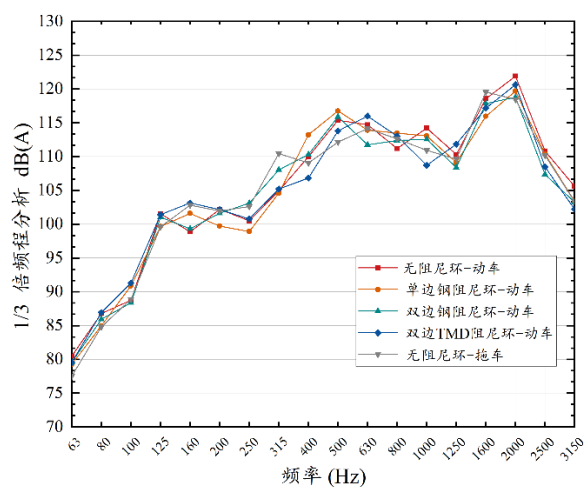
TMD-type Damping Rings (TP4): Exhibited excellent high-speed adaptability. At 140 km/h, although the external noise reduction was only 0.5 dB, it achieved a significant 4.9 dB reduction inside the cabin (9.8 times the external effect), accurately blocking the vibration transmission path from the bogie to the passenger compartment.

Single-sided Steel Damping Rings (TP2): Exposed a risk of noise reduction failure at high speeds (≥ 100 km/h). Asymmetrical installation triggered modal coupling, which even led to the deterioration of noise in certain frequency bands.

Velocity Model Validation: The growth trend of measured noise with increasing speed highly coincided with the classic theoretical model, verifying the scientific validity of the data.



140km/h



120km/h

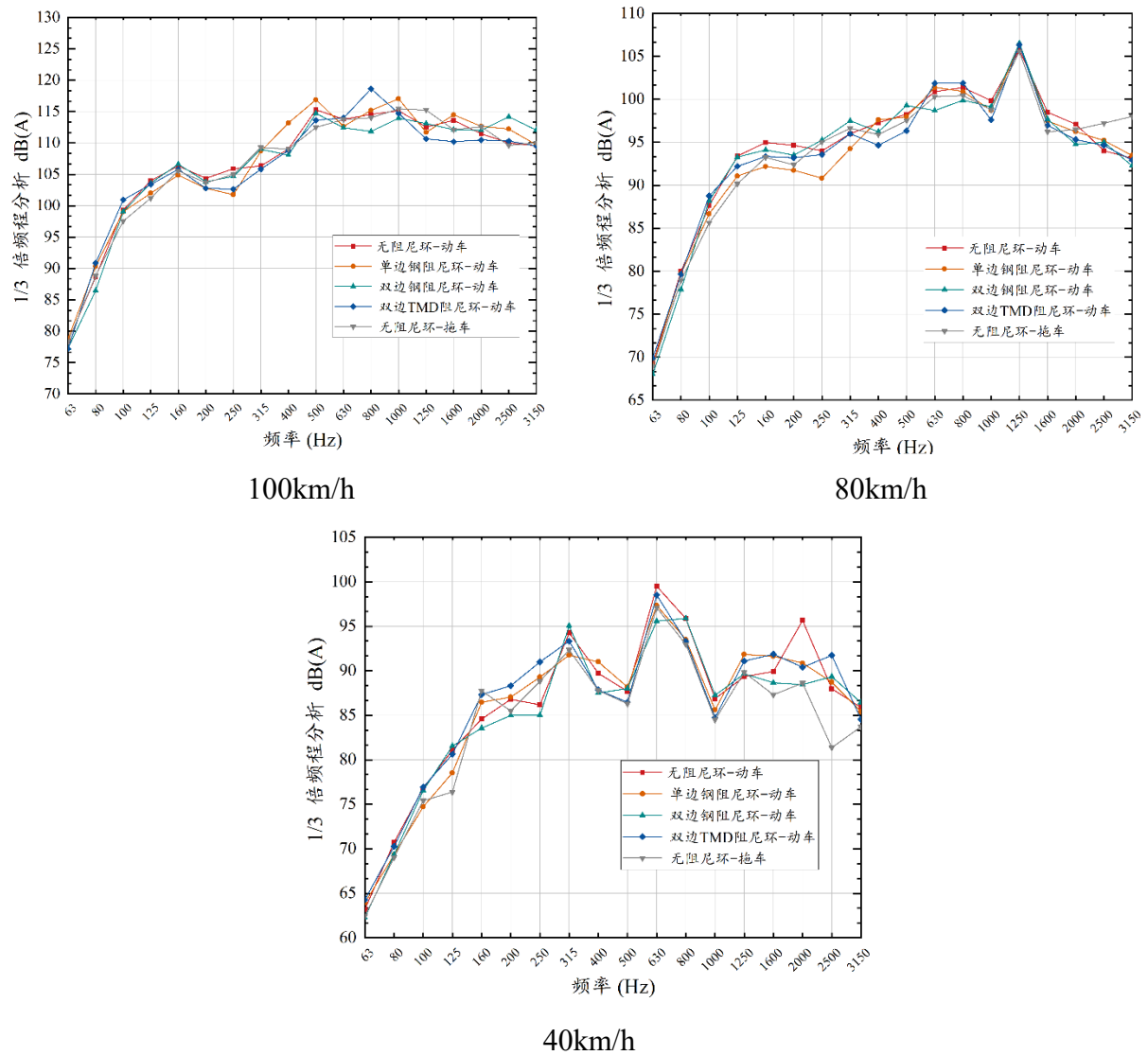


Fig 2.120 1/3 octave band statistics of wheel-rail near-field noise at different speeds (a. 140km/h; b. 120km/h; c. 100km/h; d. 80km/h; e. 40km/h)

Based on the spectral evolution patterns observed in this 1/3 octave band analysis, the research team proposed the following collaborative control strategies:

- Intercity and High-Speed Rail: Priority should be given to deploying TMD-type damping rings on the bogies of the leading and trailing cars. This leverages their targeted suppression of high-speed howling to ensure cabin noise remains below 62.2 dB(A).
- Subway Systems: The use of double-sided steel damping rings is recommended to address the low-frequency wheel-rail impact noise caused by frequent starting and stopping.
- Composite Solutions: For long-consist trains, a hybrid "Steel + TMD" configuration is suggested to achieve full frequency coverage from 500 Hz to 2500 Hz.

2.2.28 “Totally-additive-manufacturing” driven in situ Health Monitoring of CFRPs Used in High-speed Train Structures

Prof. Su and his team have conducted systematic and in-depth research on multiphysics topological metamaterials and intelligent functional structures, aiming to achieve robust wave manipulation and integrated self-sensing capabilities. By leveraging topology optimisation and inverse design methodologies, novel acoustic, elastic, and photonic topological insulators featuring Landau levels and higher-order corner states are developed to overcome conventional propagation losses and realise flexible, large-area energy transport. Meanwhile, advanced additive manufacturing and ultrafast optoacoustic technologies are introduced to functionalise carbon fiber-reinforced polymers (CFRP) and structural batteries, effectively embedding real-time health monitoring networks into load-bearing structures without compromising mechanical integrity. On this basis, robotic semantic perception and global localisation algorithms are further integrated, enabling a holistic framework for next-generation intelligent systems that possess both superior physical wave-steering properties and autonomous environmental awareness.

Robust Wave Manipulation via Landau Levels

To realise flexible acoustic energy conveying, the team first established a continuum model based on the $k \cdot p$ perturbation theory to visualise acoustic Landau bulk modes. By designing a gradient-varying lattice that mimics a strong pseudomagnetic field, they successfully guided acoustic energy along a specific Z-shaped conductive channel. As shown in Fig 2.121(a), this design effectively suppresses backscattering even at sharp corners, providing a new paradigm for constructing arbitrary wave paths. Addressing the bandwidth limitations of traditional topological insulators, the team further developed broadband ultrasonic Fig 2.121 chiral Landau levels in elastic systems. By introducing rotation-symmetric substructures into the unit cell, they broke the spatial symmetry to induce chiral modes, significantly expanding the operational frequency range for robust ultrasonic transport. Moreover, to prove the universality of these topological protections, spin-locked acoustic helical Landau levels were constructed. The researchers demonstrated that by manipulating the pseudospin-momentum locking mechanism, robust unidirectional transport can be achieved in both hexagonal and square lattices. As illustrated in Fig 2.121(b), this finding confirms that the

topological protection is intrinsic to the Hamiltonian and remains effective regardless of the specific lattice symmetry.

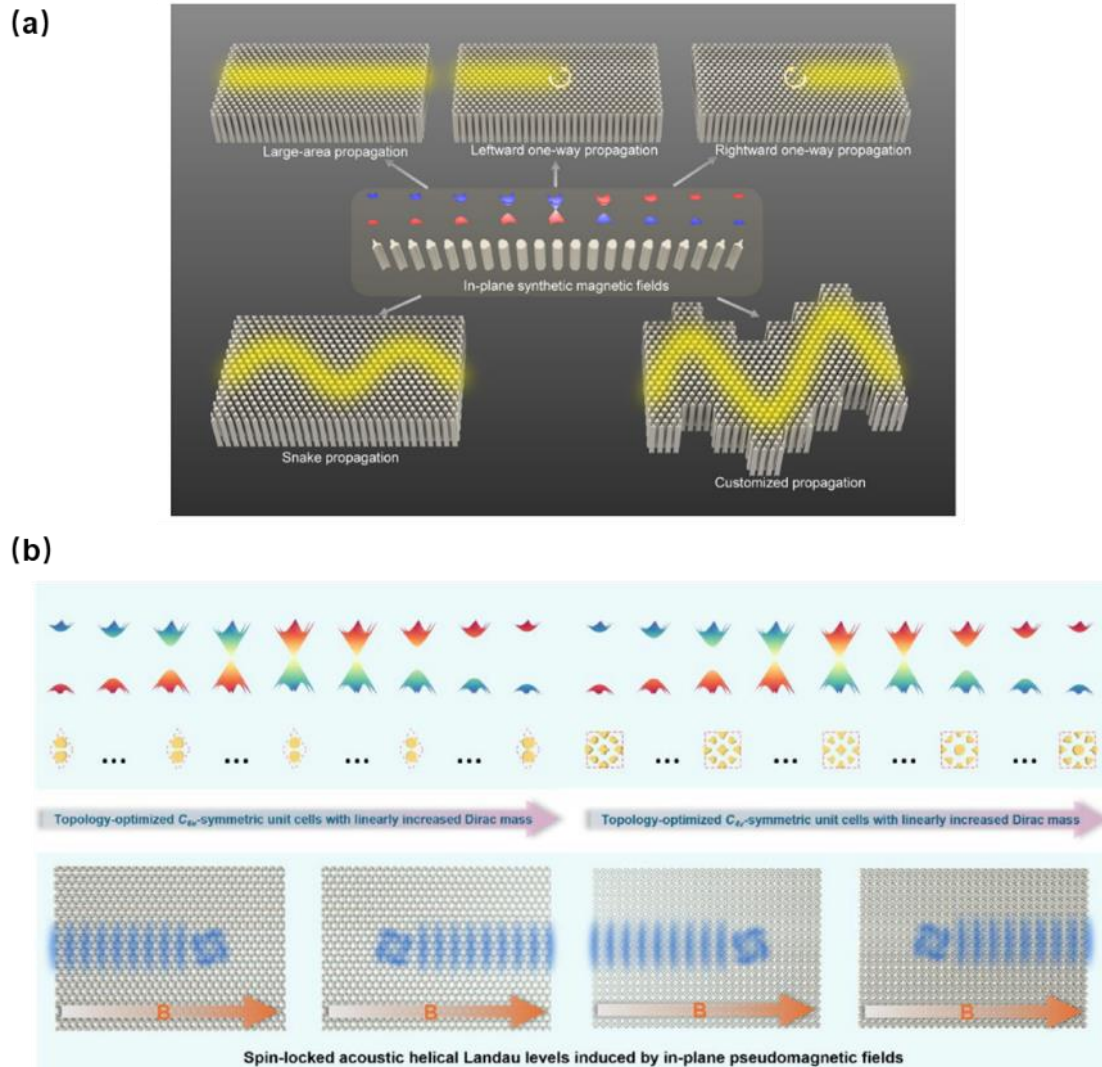


Fig 2.121 Topological Landau Levels. (a) Visualisation of the Z-shaped acoustic energy path enabled by Landau bulk modes, showing immunity to backscattering. (b) Dispersion relations and mode shapes of spin-locked helical Landau levels realised in metamaterials with different lattice symmetries.

Higher-Order Topology and Inverse Design Optimisation

To enable high-density signal processing on micro-scale devices, an on-chip second-order elastic topological insulator (SETI) was designed and fabricated using MEMS technology. This work aimed to manipulate corner states precisely; by controlling the inter-cell and intra-cell couplings, the device successfully demultiplexes out-of-plane and in-plane corner modes. As

depicted in Fig 2.122(a), this allows for the separation of different elastic wave modes within a single chip, paving the way for integrated acoustic logic devices. To further enhance the performance of such devices, a topology-optimisation-empowered dual-band SETI was proposed. Unlike traditional forward design methods which are often limited to single-frequency functionality, this approach utilises inverse design algorithms to mathematically optimise the material distribution. As demonstrated in Fig 2.122(b), the resulting structure strictly confines acoustic energy at corner states across two distinct frequency bands simultaneously, maximising the localisation efficiency and spectral utility.

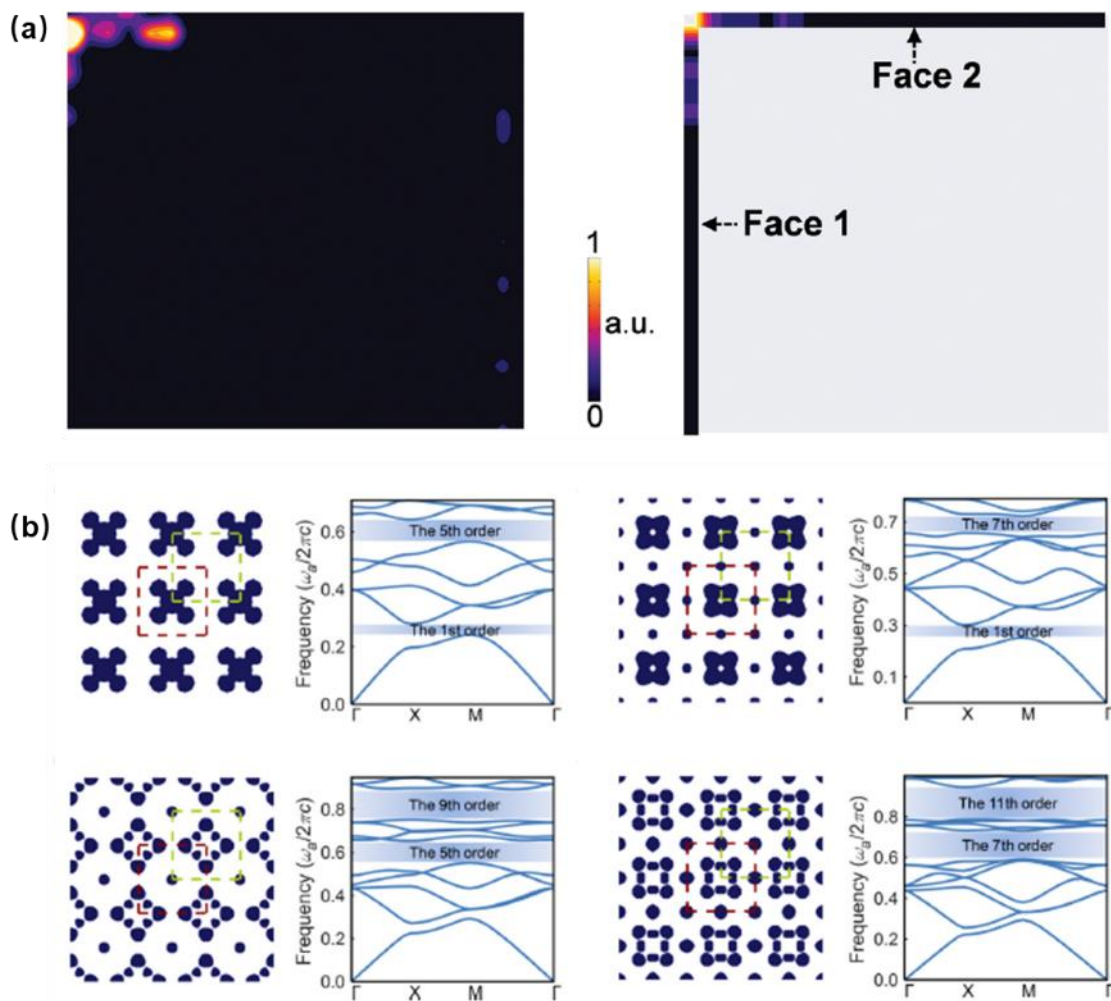


Fig 2.122 Higher-Order Topological Devices. (a) Experimental measurement of the on-chip SETI for mode demultiplexing. (b) Topology-optimised structure showing strict corner state confinement at two different frequencies.

To achieve simultaneous control over sound and light, photonic topological insulators were experimentally realised. The challenge lay in creating a structure that possesses bandgaps for both acoustic and photonic waves; the team solved this by designing a dual-scale periodic structure. As presented in Fig 2.123(a), this unified platform supports robust edge states for both physical fields within overlapping bandgaps, offering a foundation for novel acousto-optic interaction devices. In the field of wavefront manipulation, the team addressed the difficulty of focusing energy through obstacles by demonstrating a reconfigurable ultrasound focusing effect. Through the inverse design of acoustic barriers, they created a meta-lens capable of reshaping the wavefront to penetrate scattering media. As visualised in Fig 2.123(b), the acoustic field is successfully focused through a barrier with high transmission enhancement, and the focal point can be dynamically adjusted, which is critical for medical ultrasound and non-destructive testing.

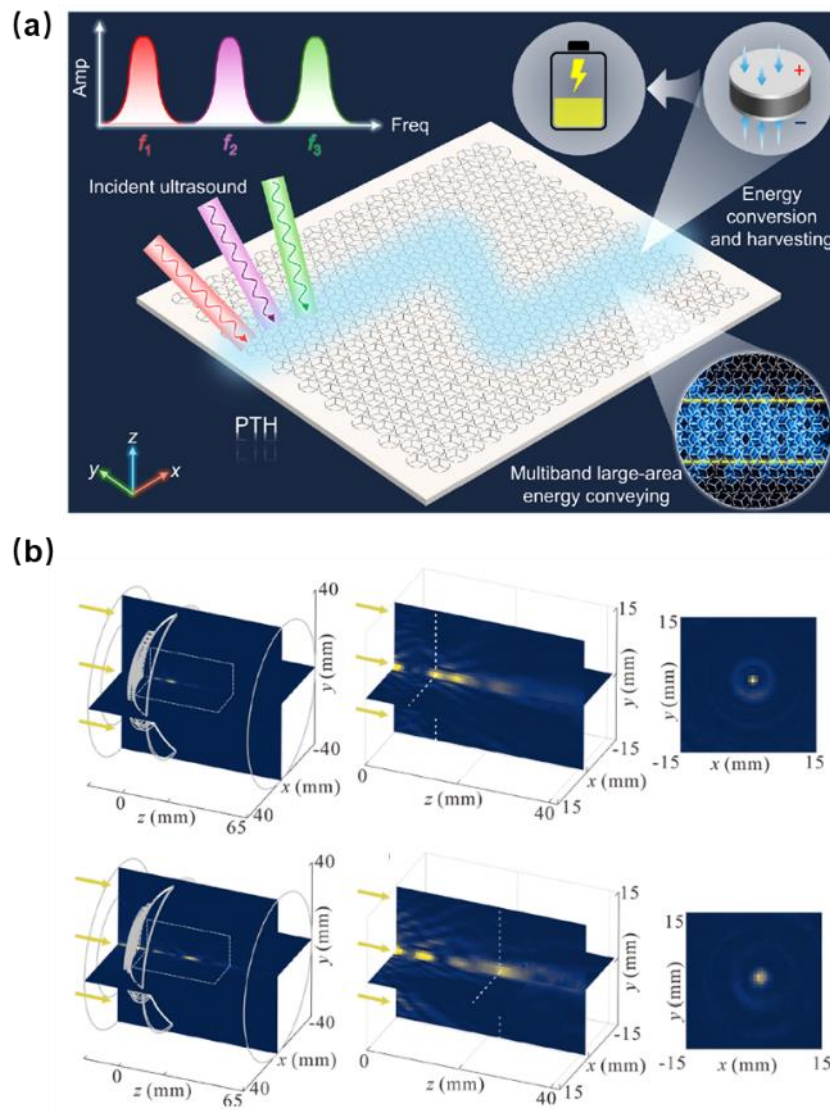


Fig 2.123 Multiphysics and Wavefront Control. (a) Band structures and field distributions of the photonic crystal for simultaneous acoustic and photonic control. (b) Simulation and measurement of ultrasound focusing penetrating through an obstacle via an inverse-designed meta-lens.

Intelligent Functional Structures and Additive Manufacturing

To solve the longstanding issue of sensor detachment in composite materials, a "totally-additive-manufacturing" strategy was introduced for carbon fiber-reinforced polymer (CFRP). The team utilised continuous fiber 3D printing to integrate an ultrasensitive self-sensing network directly into the load-bearing structure. As shown in Fig 2.124(a), this integrated "nervous system" allows the composite to monitor strain and detect structural damage in real-time, ensuring long-term reliability without external instrumentation. Furthermore, addressing the safety concerns of emerging energy storage systems, implantable graphene/PVA-coated

glass fibers were developed for structural batteries. These functionalised fibers serve a dual purpose: reinforcing the mechanical structure and acting as internal sensors. As displayed in Fig 2.124(b), they enable in-situ strain monitoring during complex electrochemical cycling and external loading, providing critical health data to prevent battery failure.

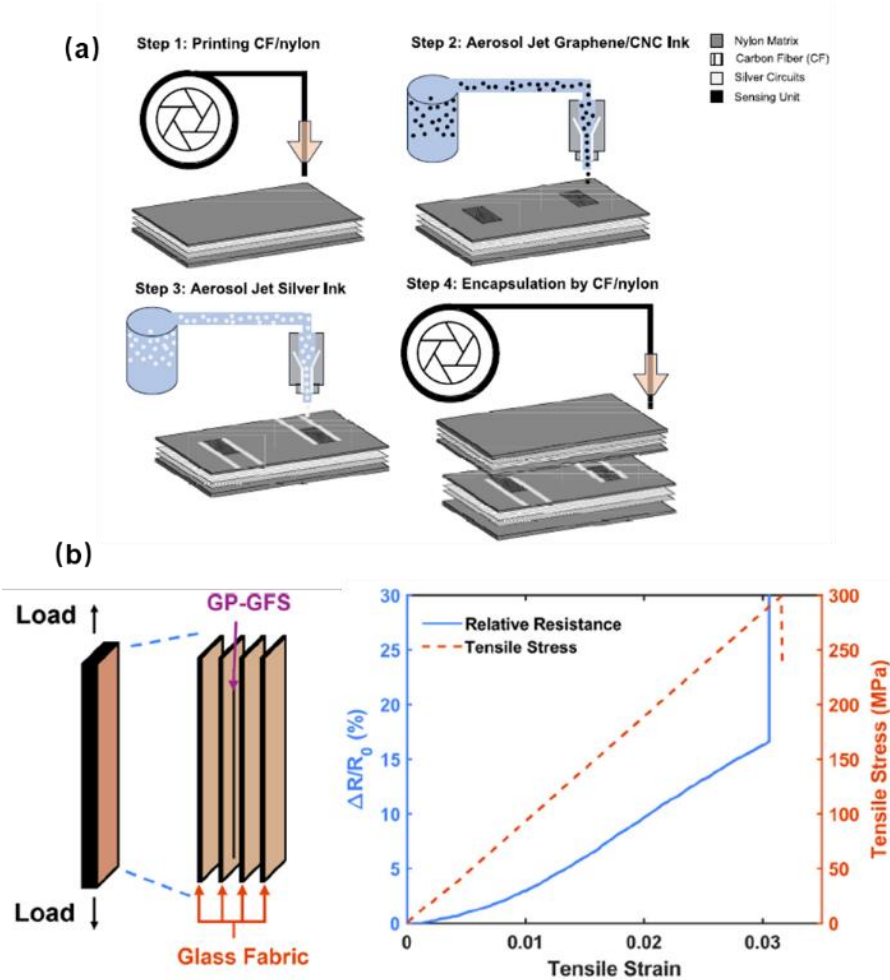


Fig 2.124 Smart Functional Structures. (a) Schematic of the "totally-additive-manufacturing" process and the printed CFRP specimen with embedded sensors. (b) Configuration of the structural battery with implantable graphene-coated fibers for in-situ monitoring.

Optoacoustic Technologies and Robotic Semantic Perception

For the non-destructive inspection of semiconductor devices, an ultrafast laser-enabled optoacoustic characterisation system was developed. Traditional optical methods often fail to see below the surface, so this system utilises the optoacoustic effect to generate high-frequency acoustic waves that penetrate the material. As schematically shown in Fig 2.125(a), it successfully images three-dimensional nanoscopic interior features of microchips with sub-

optical wavelength resolution, revealing defects that were previously invisible. On the macroscopic scale, to solve the “wake-up” problem in autonomous driving, TripletLoc, a semantic-aided one-shot global localisation system, was proposed. Instead of relying on raw point clouds which are computationally heavy, this method extracts semantic triplets (objects and their spatial relationships) from LiDAR scans. As outlined in Fig 2.125(b), by constructing and matching lightweight topological graphs, the system achieves fast and robust registration of a single scan to a large-scale map, significantly outperforming traditional methods in dynamic urban environments.

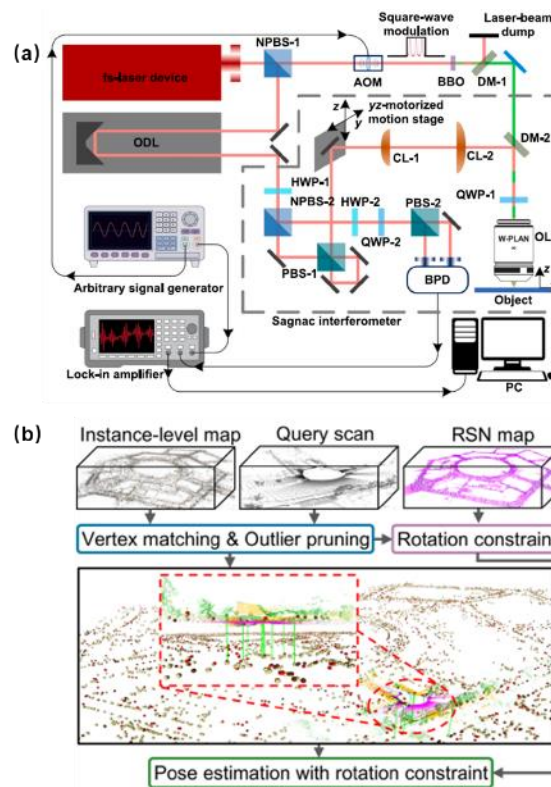


Fig 2.125 Advanced Perception Systems. (a) Setup of the ultrafast laser-enabled optoacoustic imaging system for microchip inspection. (b) Workflow of Triplet Loc showing semantic triplet generation and graph matching for global robotic localisation.

2.2.29 R&D of DAS-based Ground Collapse Monitoring System

The core achievement of this project is the integration of Distributed Acoustic Sensing (DAS) data with Multichannel Analysis of Surface Waves (MASW). This combination allows for the analysis of short-duration, short-distance data, achieving a detection spatial resolution of approximately 3 meters.

- **High-Resolution Imaging with Short-Distance DAS Data:** We processed two sets of ground collapse monitoring data from Shenzhen (spanning only 50m). This validated that short-distance DAS data can achieve high-precision (3m resolution) continuous shear wave velocity imaging.
- **Advanced DAS Data Denoising:** We developed a self-supervised learning model (Noise2Noise/N2N) specifically designed to remove instrument floor noise, particularly coherent fading noise, from DAS data. After denoising, the Signal-to-Noise Ratio (SNR) of the Noise Cross-correlation Functions (NCFs) improved by 68%. Furthermore, the resulting dispersion energy spectra exhibited more concentrated energy and superior high-frequency response.
- **Validation of Multi-Stacking Schemes:** We evaluated five different stacking schemes. The Coherent Stacking Approach (CSA) demonstrated a faster convergence rate compared to Phase-Weighted Stacking (PWS) and Time-Frequency Phase-Weighted Stacking (tf-PWS) methods (obtaining stable dispersion within just 5 minutes) and provided more stable high-frequency information.

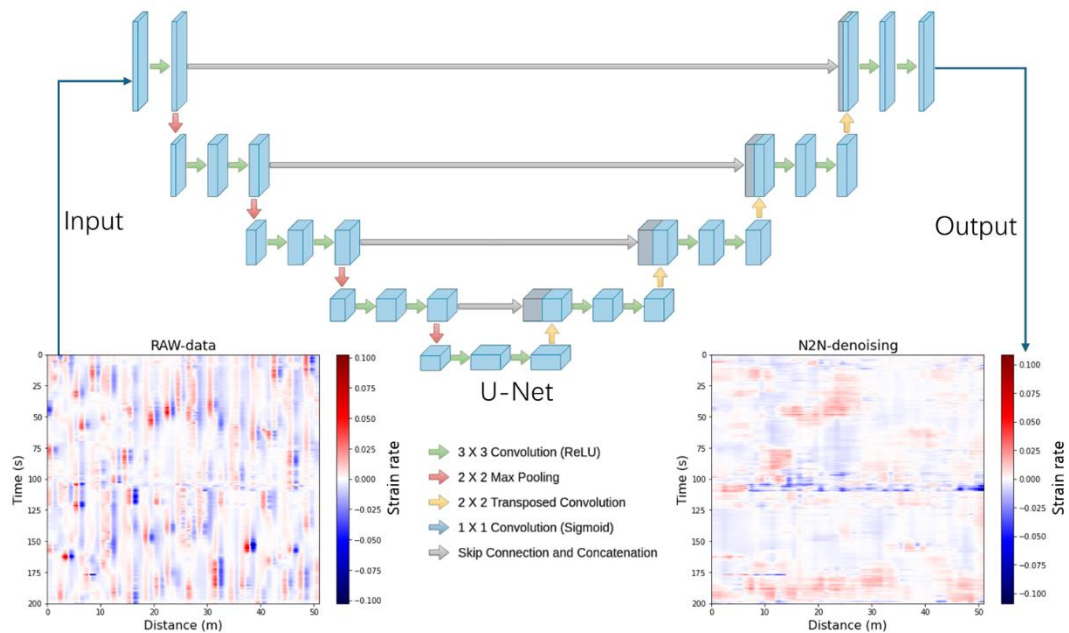


Fig 2.126 N2N model and comparison of denoising DAS data

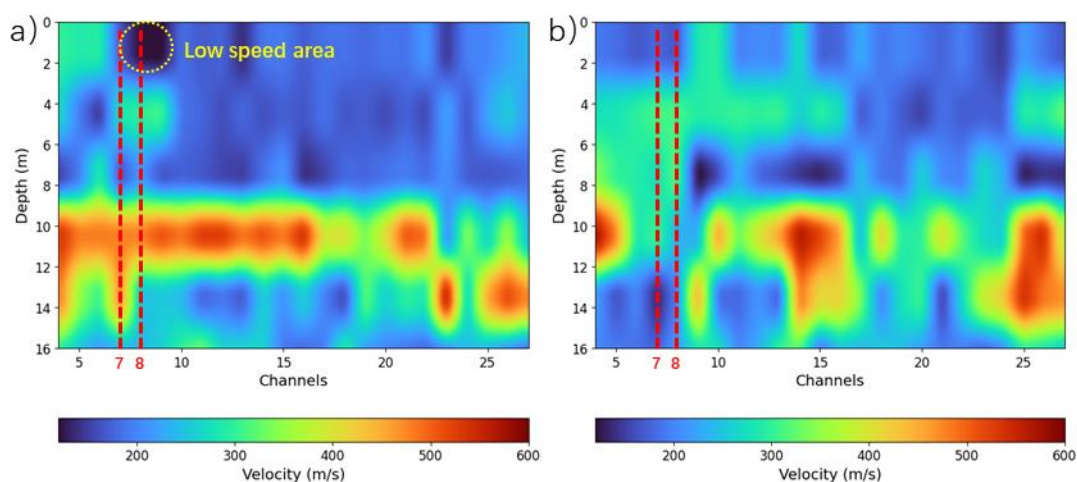


Fig 2.127 2D VS profile obtained by one-dimensional inversion results

By combining the unsupervised denoising model with the CSA stacking method, a shear wave velocity profile with a spatial resolution of 3m and a depth of up to 20m can be obtained using only 2 hours of DAS ambient noise data. This provides a flexible and cost-effective solution for collapse monitoring and subsurface geophysical exploration.

- Direct Enhancement of Extreme Precipitation Forecasts

We conducted long-term DAS data acquisition along a 17km stretch of highway in Zhejiang Province. Rockfall events were simulated by dropping wooden stakes of varying masses freely at different locations along the section. By fusing multiple deep learning models, we achieved high-precision identification and monitoring of rockfall signals.

- Recognition Algorithm Based on Multi-Model Fusion: Taking into account both the time-frequency domain and spatial distribution of the signals, we integrated PANNs (Pre-trained Audio Neural Networks) with the ACMIX model. This fusion achieved a recognition accuracy of over 90% while maintaining an extremely low false alarm rate of 0.06%.
- Combination of Field Rockfall and Laboratory Landslide Tests: To investigate the characteristics of rockfall signals, we not only performed field simulations but also set up a specialised landslide and rockfall test bench in a laboratory in Hangzhou. This allowed us to analyse the time-frequency domain and spatial distribution characteristics of rockfalls from different heights and on slopes with varying inclinations.

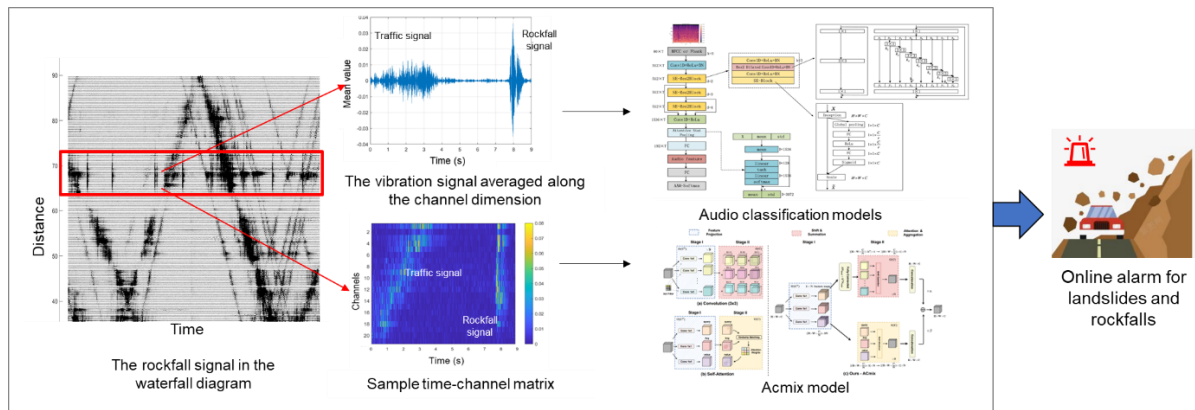


Fig 2.128 DAS-Based Online Rockfall Monitoring System Using Multi-Model Fusion

Conclusion :

This study successfully constructed an online monitoring system for transportation infrastructure based on Distributed Acoustic Sensing (DAS), providing a solid scientific basis and technical support for enhancing the operational safety of railway infrastructure.

2.2.30 Development of a Novel Physics-Informed Neural Network Framework for Unknown Structural Parameter Identification

A novel physics-informed neural network (PINN) framework was proposed and validated to identify unknown structural parameters from sparse measurement data, enabling practical structural evaluation and health monitoring. Two methodological upgrades were introduced. First, analytically derived modulating functions were concatenated with neural network outputs to hard-embed boundary conditions, eliminating penalty terms associated with boundary conditions and improving convergence while guaranteeing exact satisfaction of constraints. Second, auxiliary outputs were introduced as lower-order derivatives of neural network outputs to downscale high-order governing equations into coupled first- or second-order forms, reducing automatic differentiation overhead and alleviating gradient exploding or vanishing issues.

The proposed framework is applied to identify unknown rotational stiffness of semi-rigid joints of structures. Numerical studies on a non-prismatic cantilever beam with a semi-rigid end joint and a single-bay frame with two semi-rigid joints showed that accurate stiffness identification is achievable using only a small number of measured deflections. The approach

remained robust under measurement noise and outperformed conventional PINN with soft constraints in both efficiency and accuracy. Finally, laboratory experiments confirmed practicality, with PINN-identified joint rotations matching measured values within 5% across all test scenarios. Overall, the work provides a mesh-free, data-efficient pathway for on-board structural parameter identification and full-field response reconstruction. The resulting surrogate can also predict deflection, rotation, and internal forces at arbitrary locations without meshing.

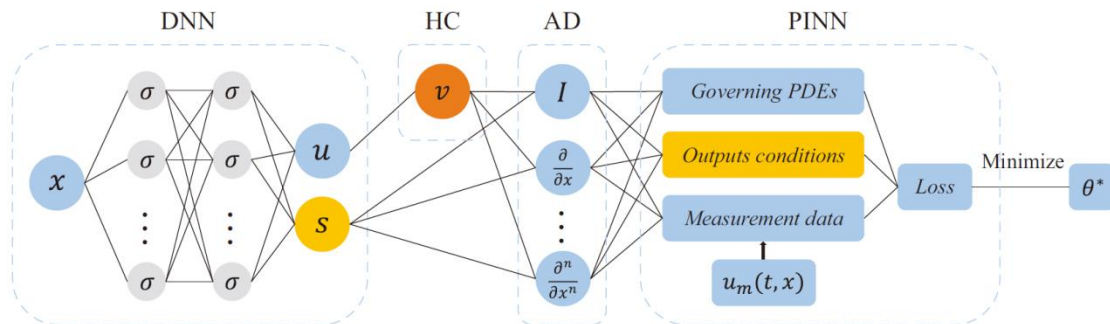


Fig 2.129 The proposed novel physics-informed neural network for unknown structural parameter identification

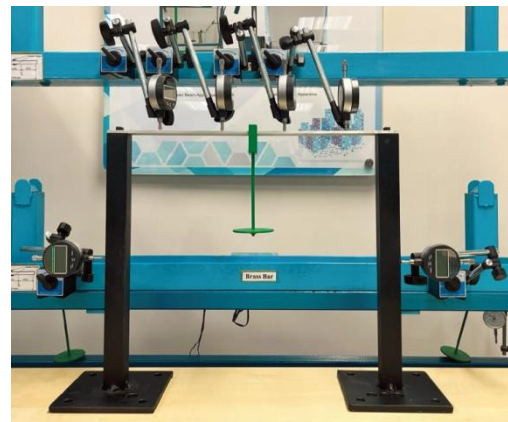
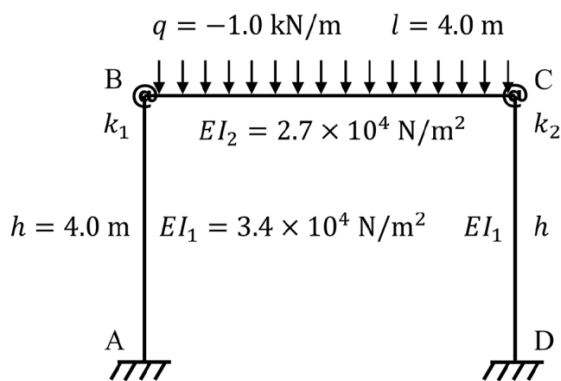


Fig 2.130 Numerical and experimental validation of the proposed framework

2.2.31 Deep learning-empowered tropical cyclone track and intensity predictions

As one of the most devastating natural disasters, tropical cyclones (TCs) bring grave risks to human life, property, and critical infrastructure—including railway networks. Consequently, accurate and fast predictions of TC track and intensity hold immense value for early warnings and disaster risk reduction. This study investigate the application of deep learning to advance the predictions of TC track and intensity, with key findings summarised as follows:

- This study introduces a novel deep learning-based multimodal sequence-to-sequence model (MSSTC) for predicting TC intensity. In contrast to conventional deep learning-based methods that directly extract and fuse features across multiple data sources, the MSSTC model utilises an encoder-decoder architecture to initially produce pseudo-predictive sequences from each input channel. Feature extraction and fusion are then executed on these predicted sequences, allowing a more efficient integration of multimodal information. Additionally, this framework integrates temporal encoding and Transformer-based architecture to improve its ability to capture temporal features and correlations in TC evolution. Experimental findings indicate that the proposed model attains an average enhancement over 20% compared to operational forecasts from meteorological agencies and surpasses current mainstream DL-based models by over 15% in predictive accuracy.

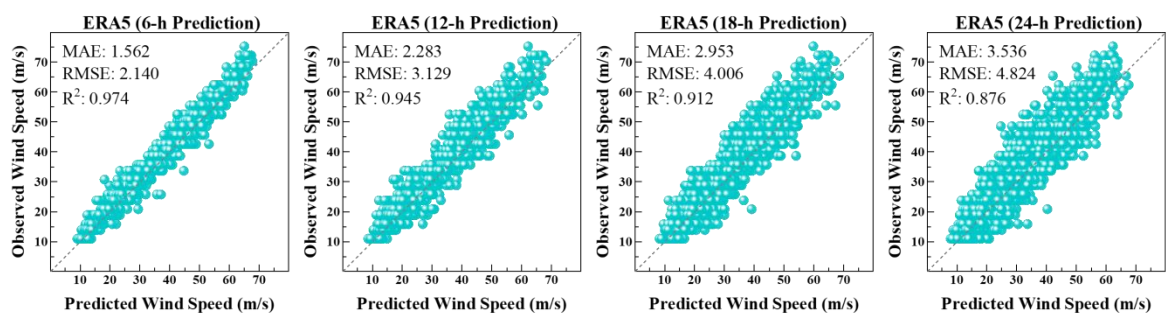


Fig 2.131 TC intensity prediction performance of MSSTC.

- This study evaluates TC track and intensity prediction skill in the western North Pacific during 2018 by comparing physics-based Weather Research and Forecasting (WRF) simulations initialised with boundary conditions from five deep learning-based global models. These hybrid configurations—WRF-FengWu, WRF-FourCastNetV2, WRF-FuXi, WRF-GraphCast, and WRF-Pangu (collectively DLWRF)—are compared with

WRF setups initialised with the Integrated Forecast System (WRF-IFS) and the Global Forecast System (WRF-GFS). DLWRF models on average surpass the baselines in track predictions, attaining reductions in positional errors of 5.8%, 17.9%, and 41.9% compared to WRF-IFS at 72-, 120-, and 168-hour lead times, respectively, and 41.7%, 36.8%, and 55.5% compared to WRF-GFS. Furthermore, DLWRF models on average show comparable maximum wind speed prediction performance relative to WRF-IFS and WRF-GFS across these lead times, while exhibiting 7.4% and 16.9% lower minimum central pressure prediction errors than WRF-IFS, and 17.1% and 10.0% lower than WRF-GFS, at 120-hour and 168-hour lead times, respectively.

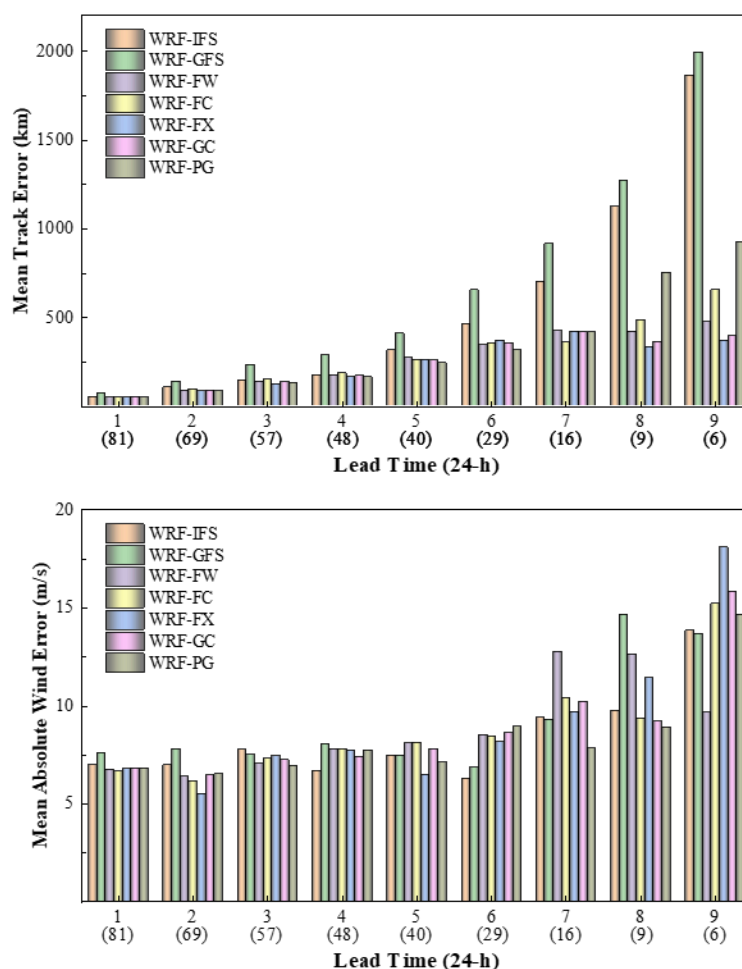


Fig 2.132 Comparison of TC track and intensity prediction performance.

2.2.32 Movable sensor-based baseline-free electromechanical impedance technique for detecting delamination of concrete cover

Prof. Zhu's team developed a non-destructive testing (NDT) method to detect concrete cover delamination using movable sensors based on the baseline-free electromechanical impedance (BF-EMI) technique. A PZT cuboid coupled with a double-sided tape was employed as the movable sensing system, as illustrated in Fig 2.133(a) and (b). By extracting the resonant frequencies associated with defects through the BF-EMI technique, the location of delamination could be identified and its area estimated. Experimental validations were performed on a reinforced concrete slab, as shown in Fig 2.133(c). The slab contained two steel rebars that were subjected to an electric current to induce accelerated corrosion. After 180 hours of corrosion, the measured results were plotted in Fig 2.133(d). The first resonant frequencies obtained from each testing point revealed that the left rebar experienced significantly more damage than the right. Based on the first resonant frequencies, the width of the delamination layer was estimated to range from 97 mm to 112 mm.

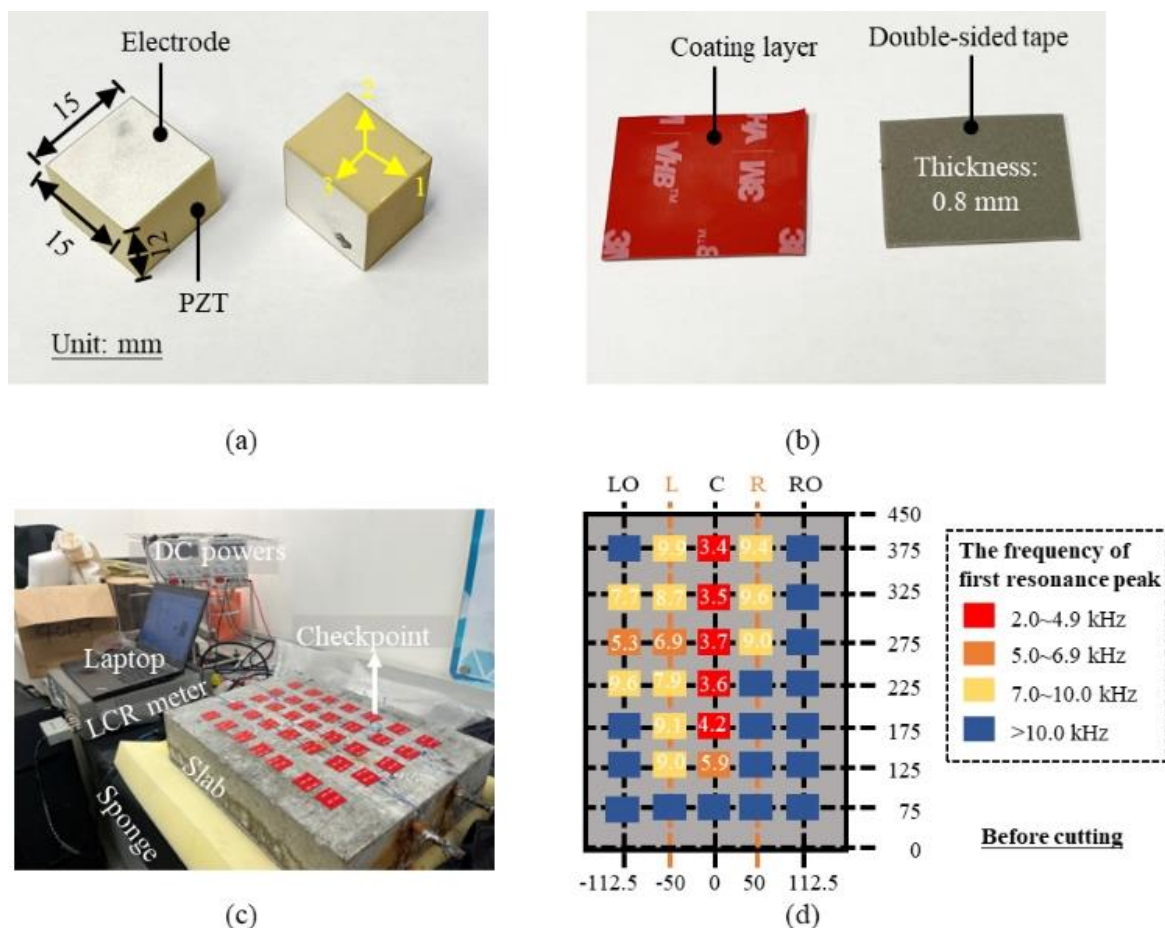


Fig 2.133 Details of developed movable sensor and experimental setup and results: (a) details of the PZT sensor; (b) details of the double-sided tape; (c) experimental setup when testing; and (d) map of the first resonant frequencies

On-site testing was carried out in Hong Kong to assess the applicability of the proposed technique beyond laboratory conditions and to validate its effectiveness in real-world scenarios. The method was applied to an old building, where the concrete slab of a selected room was tested. The suspected area was then exposed for verification. Successful detection was achieved, as illustrated in Fig 2.134(a), where a corroded rebar with a diameter of 7 mm was identified, as shown in Fig 2.134(b).

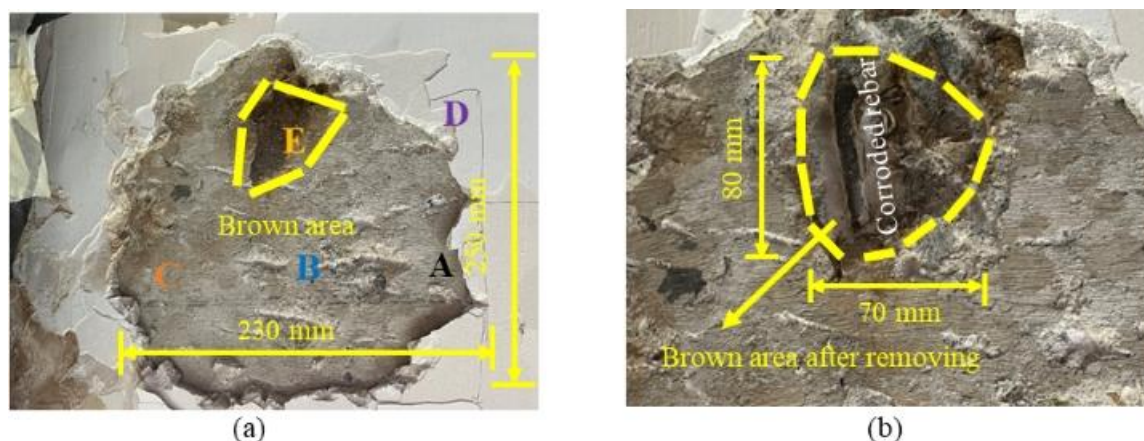


Fig 2.134 Opening results for field verification in Hong Kong: (a) Opening up results, and (b) corroded rebar

Overall, a rapid and reliable NDT method integrating a single movable sensor with the BF-EMI technique has been developed for detecting delamination in concrete, opening new avenues for future research and practical applications.

2.2.33 Extreme resonant absorption of surface elastic waves by two coupled resonators

Prof. Songye Zhu and Dr. Yifei Xu have developed a novel approach for extreme surface wave conversion using only two tailored resonators placed on a semi-infinite substrate. By leveraging near-field coupling between two resonators, the coupled resonance properties can be modified to tune the far-field scattering pattern, offering new degrees of freedom in metamaterial design.

Conventional metamaterials typically depend on numerous subwavelength scattering units to formulate bandgap, enabling advanced control over acoustic or elastic waves. Although such designs offer significant wave manipulation potential, this large number of scattering elements is an important limitation in the efficiency of metamaterials and metasurfaces, since in practice the number of different scattering elements are usually limited.

To overcome this difficulty, Prof. Songye Zhu and Dr. Yifei Xu propose a new design principle for engineering wave-based devices, which paves the way for innovative applications in vibration control and energy harvesting. This work demonstrates how a minimal set of scatterers, specifically, a pair of passive resonators that operate without external power, can be

tuned to direct wave energy along desired paths and achieve targeted control for a given incident wave. As shown in Fig 2.135, we particularly focus on a pair of passive resonators operating without external energy input. By harnessing their near-field evanescent coupling, both reflected and transmitted far-field surface waves can be simultaneously suppressed, resulting in exceptional surface wave conversion efficiency.

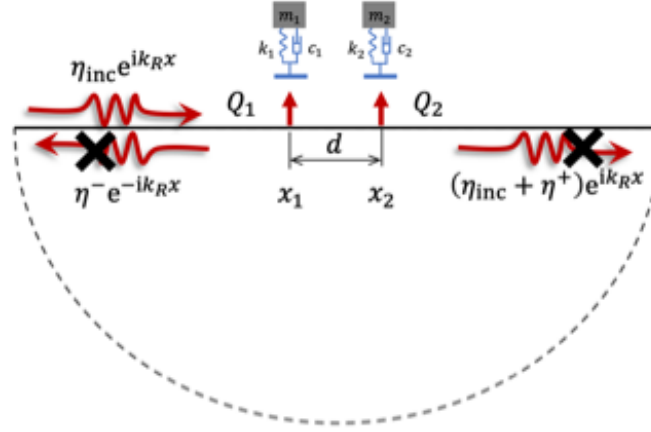


Fig 2.135 Perfect absorption of incident surface waves by two resonators on an elastic half-space, where reflected and transmitted surface waves are simultaneously cancelled

A multiple scattering formulation is developed to characterise the mutual interactions between the two resonators, quantifying the forces applied to the substrate through their admittance operators. By targeting a specific asymmetric scattering pattern (see Fig 2.136), the required resonator properties are analytically determined. As shown in Fig 2.136, the total field illustrates nearly complete cancellation of both the reflected and transmitted surface waves, leading to the near-total wave conversion.

Overall, the proposed design framework is based on multiple scattering theory, and the general principle is applicable to any kind of classical wave.

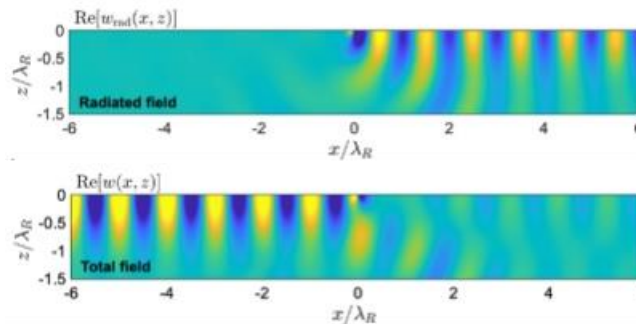


Fig 2.136 Near-total Rayleigh wave conversion: the radiated wave field and the total field.

2.2.34 Experimental Investigation on Dynamic Behaviour of Thick Rubber Bearings

Prof. Songye Zhu and Dr. Zengde Zhang are conducting an experimental study on the dynamic behaviour of rubber bearings with a low first shape factor, hereafter referred to as thick rubber bearings. The primary objective of this study is to investigate the frequency-dependent variation of the dynamic stiffness of such bearings.

Impact tests have been performed on thick rubber bearings subjected to different levels of compressive load. In addition, the test specimens were designed with varying geometric parameters to examine their influence on dynamic response. Fig 2.137 illustrates the schematic layout of the experimental setup used for the dynamic characterisation of thick rubber bearings. An impact hammer was employed to excite the specimens, while accelerometers were mounted on both the top and bottom plates to measure the dynamic responses.

Based on experimental measurements, the dynamic stiffness of thick rubber bearings was evaluated, and the acceleration transmissibility of the bearings was obtained. These results provide valuable insights into the vibration isolation performance of thick rubber bearings over a broad frequency range. The findings also offer a basis for the targeted design of rubber bearings for vibration mitigation in specific frequency bands through the optimisation of their geometric parameters.

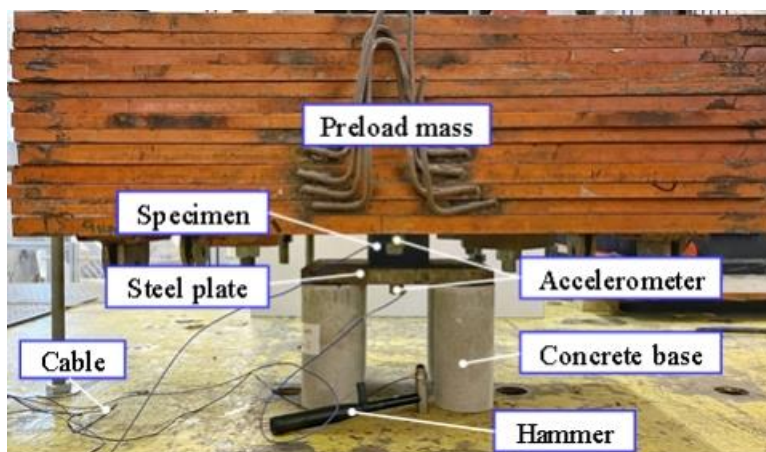


Fig 2.137 Schematic diagram of impact tests to a elastomeric bearing

2.2.35 Development and Experimental Validation of A Novel Variable Inerter Damper

Prof. Songye Zhu and Mr. Jubin Lu successfully developed and validated a novel variable inerter damper (VID), representing a completed milestone in this research program. The proposed VID was designed to enable continuous and independent tuning of both inertance and damping coefficients, addressing key limitations of existing inerter-based devices. The finalised design incorporated three major functional modules. First, a ball screw mechanism constrained by linear motion guides was implemented to convert linear motion into rotational motion with high transmission efficiency and mechanical stability. Second, a continuously variable transmission (CVT) integrated with a flywheel was adopted to generate adjustable inertance by varying the transmission ratio, allowing smooth and uninterrupted tuning over a wide range. Third, a rotary electromagnetic (EM) DC motor was integrated into the system to provide controllable damping through electromagnetic resistance. The coordinated operation of these modules resulted in a compact and highly adaptable VID configuration, capable of meeting diverse performance requirements for structural vibration control applications.

Following the completion of the design phase, a prototype of the novel VID was fabricated and subjected to comprehensive experimental testing. The experimental setup, as shown in Fig 2.138, was established to evaluate the mechanical behaviour, tuning capability, and overall performance of the prototype under controlled loading conditions. The completed experiments confirmed that both inertance and damping coefficients could be adjusted continuously and independently, which aligned well with the needs of optimisation-based inerter damper design. Compared with existing VID devices, the developed prototype demonstrated notable advantages in terms of tuning flexibility and achievable parameter ranges. Specifically, the inertance of the VID was successfully varied from 1.18 to 7.37 tons, while the electromagnetic damping coefficient was adjusted from 0 to 41.46 kN·s/m. These results verified that the developed VID provided substantial and practical tuning ranges suitable for a wide variety of structural control scenarios, including seismic and wind-induced vibration mitigation. Overall, the successful design, fabrication, and experimental validation of the VID marked the completion of a key research objective for the year and laid a solid foundation for subsequent application-oriented and system-level studies.

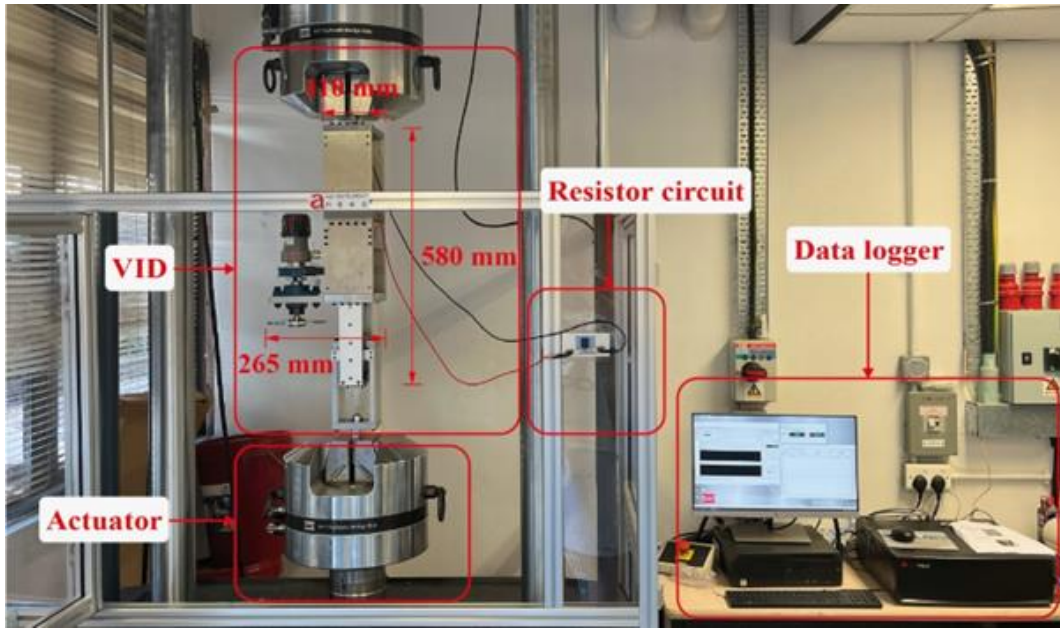


Fig 2.138 Experimental setup for the developed variable inerter damper.

2.2.36 Active Nonlinear Vibration Control of Buckled Beam Using DRL

Yi-Ang Zhang and Songye Zhu from Hong Kong Polytechnic University developed a model-free active vibration control strategy (Fig 2.139) for nonlinear structures using deep reinforcement learning (DRL), validated on a shallow simply supported buckled beam with up to third-order geometric nonlinearity (Fig 2.139). The approach formulates structural control as a Markov decision process, training a neural network controller via the Twins delayed deterministic policy gradient (TD3) algorithm through direct interaction, eliminating the need for precise mathematical models.

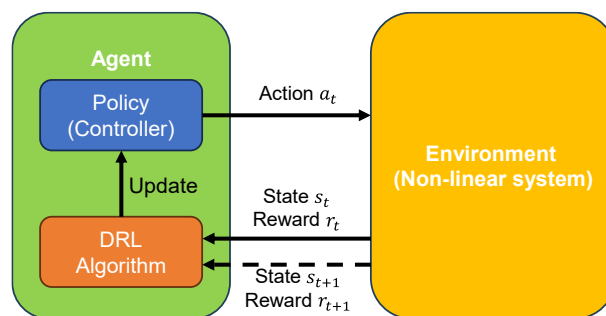


Fig 2.139 DRL structure

Numerical studies systematically compared the DRL controller against first-order LQR and up to third-order polynomial controllers under free vibration, escape load conditions, step loads, and random excitations. Near the buckling escape point in free vibration, the TD3

controller stabilises the system to the zero-equilibrium position, achieving optimal trade-off between vibration suppression and control energy.

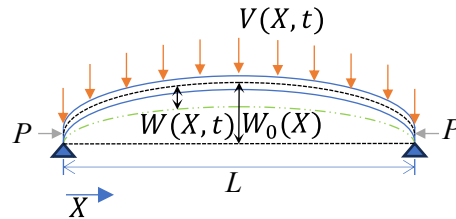


Fig 2.140 Buckled beam setup

Under step loads related to static and dynamic buckling, DRL significantly expanded safety margins over third-order control by over 20%, effectively suppressing snap-through buckling while demonstrating superior energy efficiency (Fig 2.140). Under long-duration random white-noise excitation, lower-order controls failed to prevent snap-through buckling, while third-order and TD3 both maintained the beam in the safe potential well, with DRL showing superior performance in displacement and force metrics (Fig 2.141).

Despite training on specific step loads, the controller generalised well across load levels and random excitations, affirming DRL's potential for nonlinear structural vibration control.

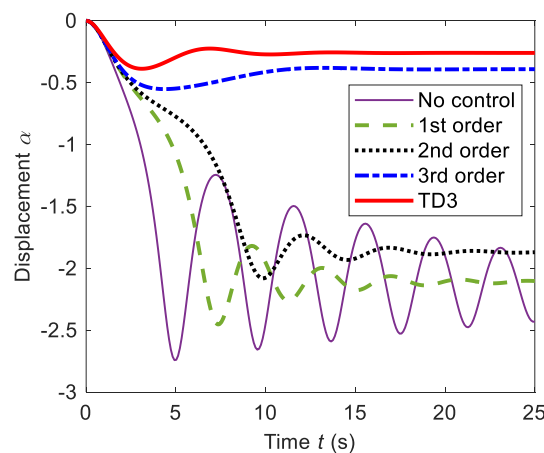


Fig 2.141 Step load time histories comparison across controllers

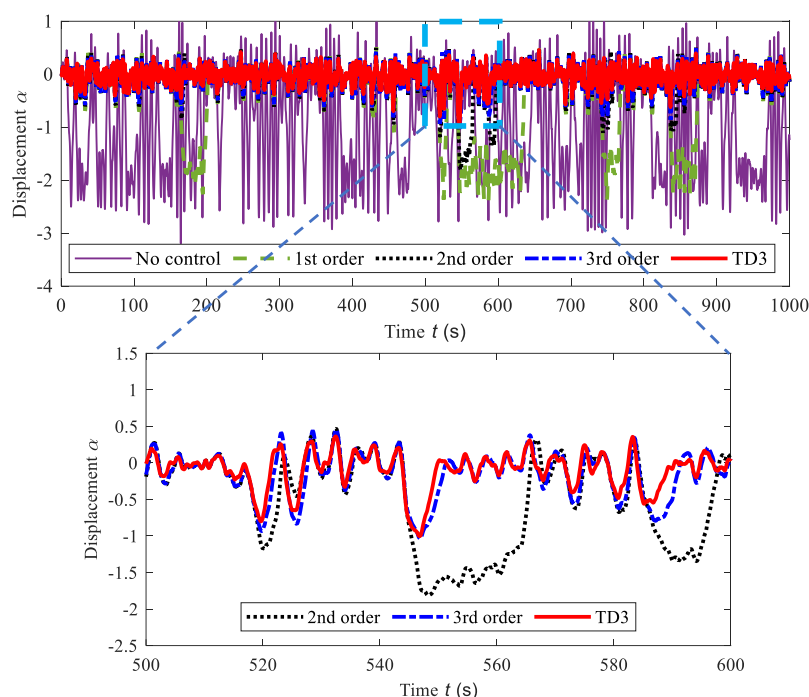


Fig 2.142 Random excitation response demonstrating DRL robustness

2.2.37 Towards Greener and Artificial Intelligence Renewable Energy Devices and Management Systems for Smart Electrified Urban Transportation

Prof. Siu Wing Or, Dr. Guannan Li, Dr. Jamal-Deen Musah, Mr. Yuxuan Wang, Mr. Yuduo Zhao, and others from CNERC-Rail (HK Branch) have developed critical technologies to advance the research towards greener and more sustainable renewable energy devices and green artificial intelligence (green-AI) energy management systems for promoting sustainability and efficiency in the smart electrified urban transportation (SEUT) networks in general and in the smart electrified railway (SER) networks in specific.

For greener and more sustainable renewable energy devices, the research efforts have focused on thermoelectric generators, including: (1) the development of bioinspired 3D black phosphorus (BP)-doped Bi₂Te₃/hydrogel hybrid films and their ultra-efficient, flexible thermoelectric generators for wearable energy harvesting (Fig 2.147); and (Fig 2.148) the introduction of an active strain engineering approach to prepare rare-earth cerium (Ce) and

antimony (Sb) co-doped Bi_2Te_3 as a novel thermoelectric generator material with ultrahigh thermoelectric performance (Fig 2.147).

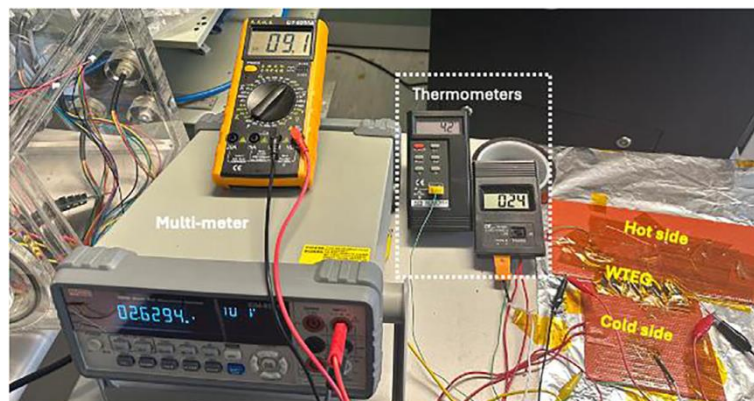


Fig 2.147 Schematic illustration of the ultra-efficient, flexible thermoelectric generator prototype.

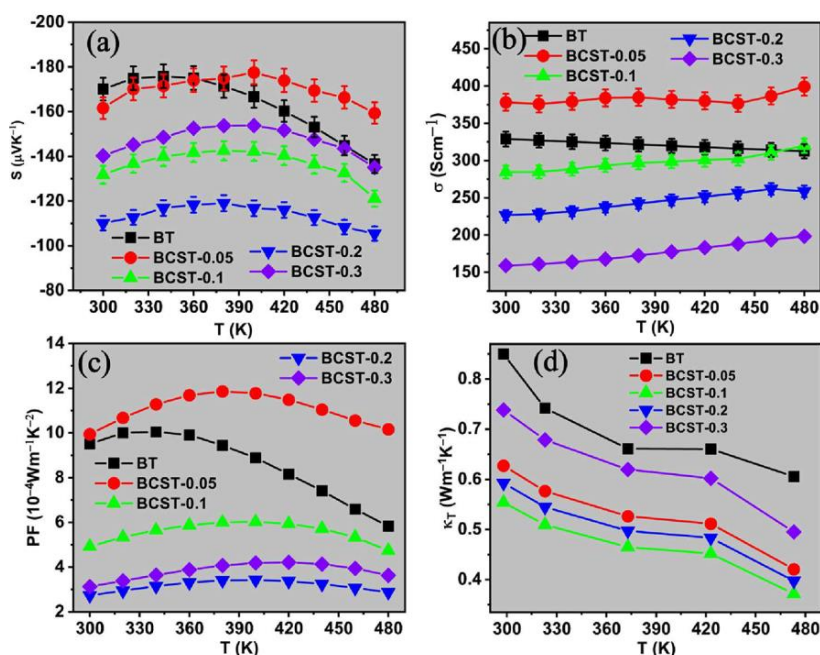


Fig 2.148 Temperature dependence of (a) Seebeck coefficient, (b) electrical conductivity, (c) calculated power factor, and (d) total thermal conductivity for various Ce–Sb co-doped Bi_2Te_3 thermoelectric generator materials.

For green-AI energy management systems, the research has been directed to using green-AI techniques and models to develop and implement: (1) a hybrid knowledge-based and data-driven electrical safety risk prediction method considering spatio-temporal characteristics of extreme rainfalls for identifying distributed photovoltaic systems with high risks of waterlogging-induced shutdowns (Fig 2.148); (2) a multi-task reinforcement learning approach

for synergistic sizing and energy management optimisation of hybrid electric storage systems under spatio-temporal urban rail traffic (Fig 2.149); and (Fig 2.150) a bi-level robust coordinated restoration strategy for enhancing the operational resilience of multi-energy networked microgrids with high shares of renewables (Fig 2.151).

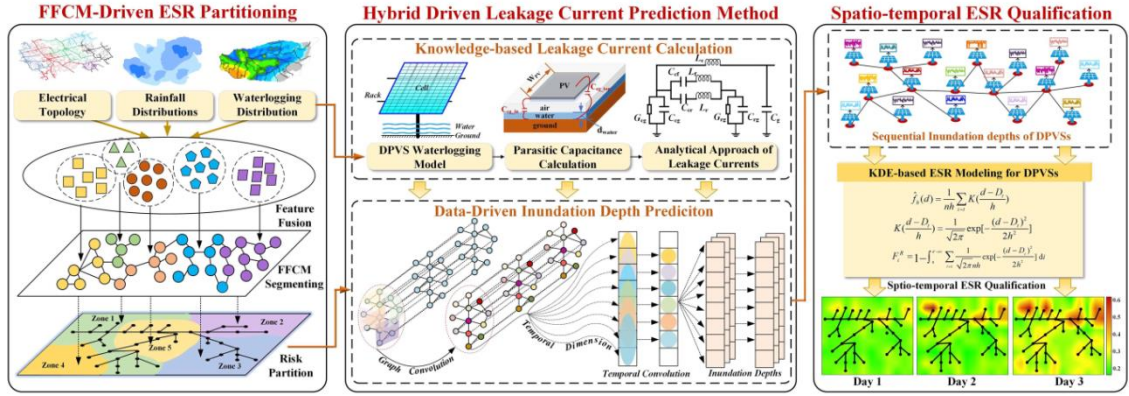


Fig 2.149 Proposed hybrid knowledge-based and data-driven electrical safety risk prediction methodology for distributed photovoltaic systems under extreme rainfalls.

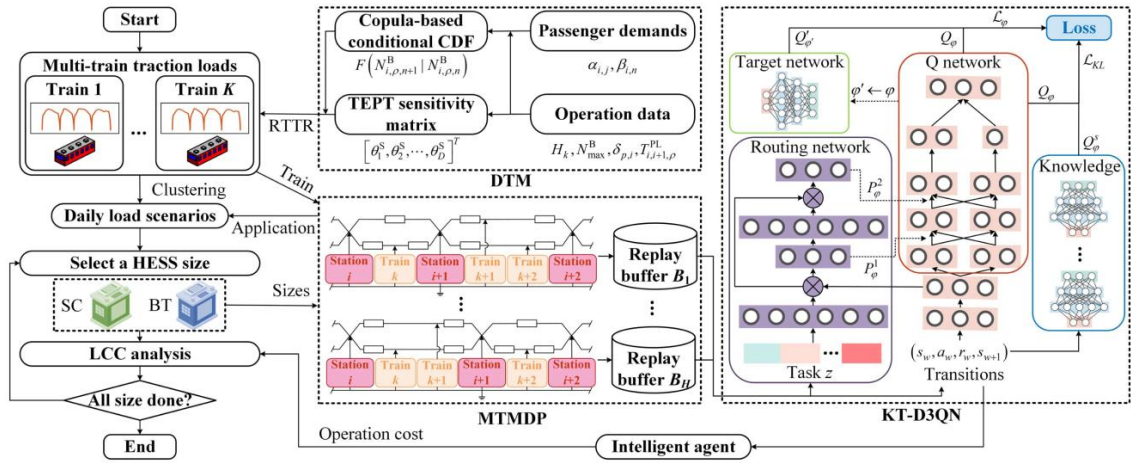


Fig 2.150 Proposed framework of multi-task reinforcement learning-based synergistic hybrid electric storage system sizing and energy management optimisation.

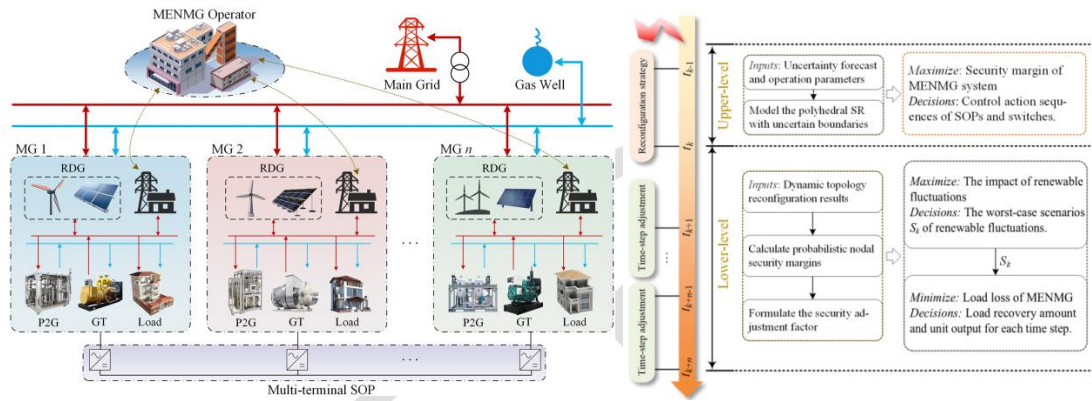


Fig 2.151 Structural diagram of multi-energy networked microgrids (left) and flowchart of proposed bi-level robust coordinated restoration strategy (right).

2.2.38 Self-powered actively controlled lateral suspensions of high-speed trains using energy-regenerative electromagnetic damper and model predictive control

To overcome the deficiency of the conventional active control with high energy consumption, Prof. Zhu's team proposes the model predictive control (MPC) to operate the active device that can fulfill the dual objective of active control and self-powering. Given that active power analysis is usually carried out for single-DOF or two-DOF systems under harmonic excitation, this study uses a 17-DOF high-speed train under stochastic German track irregularities to study the feasibility of self-powering active control. The previously established electromagnetic damper with H-bridge circuit (HB-EMD) is employed as the active device since it allows bidirectional power flow between the HST and the EMD. As shown in Fig 2.143, the two independent HB-EMD are implemented in the front and rear lateral suspensions, respectively.

As demonstrated in Fig 2.144(a), the MPC (N=30) achieves vibration reduction in the car lateral acceleration comparable to the active LQG controller. Although the LQG and the proposed MPC achieve close control performance, the LQG consumes power, while the MPC is capable of harvesting power, as illustrated in Fig 2.144(b). It is because the MPC adjusts its control strategy at each time step to fulfill the self-powering objective. In contrast, the conventional LQG can't involve circuit dynamics, and its control objective only uses quadratic force terms to represent the power requirement without considering the circuit dynamics and resistor dissipation. Whether the system is able to harvest power is determined preliminarily

by the LQG gain and the EMD parameters including the EM constants and the internal resistance.

Generally, this study, for the first time, validates the feasibility of designing a self-powered, actively controlled secondary lateral HST suspension system without relying on an external power source, which will potentially pave the way for a new active vibration control paradigm for other generic structures. By adjusting the weight in objective of MPC, the controller can transition from vibration reduction-oriented to power maximisation-oriented control.

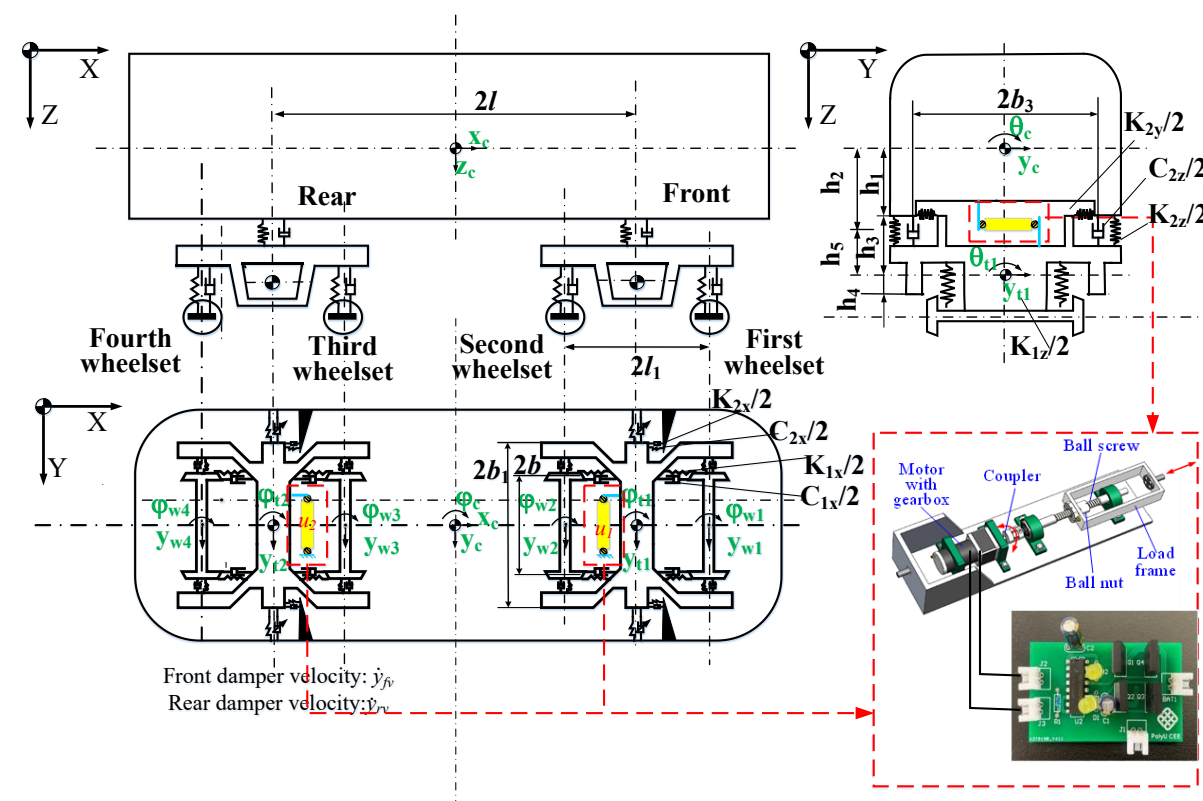


Fig 2.143 The 17-DOF HST model with the proposed damper (displayed in yellow color) in the secondary lateral suspension

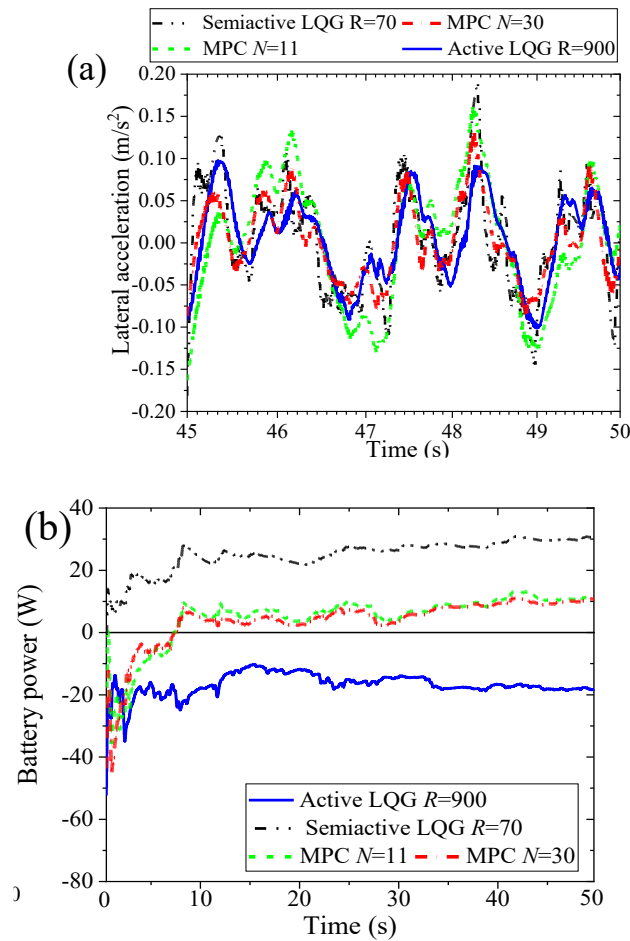


Fig 2.144 Control and energy harvesting performances compared among four controllers: (a) the time history of the car lateral acceleration; (b) the accumulative battery charging power of the front damper for the four controllers

2.2.39 AI-driven Monolithic Microwave Integrated Circuit Design Based on Wide Bandgap Semiconductors

Dr. Zhou and his team have conducted systematic and in-depth research on artificial intelligence (AI) driven monolithic microwave integrated circuit design methodologies, aiming to achieve automated circuit design. By developing high-accuracy AI-based electromagnetic (EM) surrogate models to replace conventional computationally intensive full-wave EM simulations, the design efficiency is significantly improved. Meanwhile, pixelated microstrip structure representations are introduced to enhance circuit compactness and effectively reduce circuit size. On this basis, intelligent optimisation algorithms are employed for iterative optimisation, enabling performance-driven inverse design according to specified targets, such

as bandwidth, gain, efficiency. This research framework has been successfully applied to various microwave circuit structures, including filters and power amplifies (PAs), as shown in Fig 2.145 and Fig 2.146.

In terms of EM surrogate model, a Transformer-based framework is developed to globally capture the interactions between EM structural elements, overcoming the local dependency constraints of convolutional neural networks. The EM structures are reformulated as context information and frequency points are reformulated as query sequences.

In terms of filter design, a triangular-like edge anti-aliasing connection method is introduced in the pixelated configuration. This approach incorporates triangular transition structures between diagonally adjacent pixel, converting 90° bends or discontinuous diagonal connections into continuous 135° transmission lines. Furthermore, the methodology expands explorable design space by introducing GND-via elements (encoded as 2) into the traditional 0-1 void-mental encoding design space.

In terms of PA design, a fixed-size pixelated design space is reserved at the layout level. By integrating ideal microstrip topology exploration, automatic generation of impedance-clustering-based constraints, a Transformer-based EM surrogate model, and genetic algorithm optimisation, the proposed method enables the coordinated and fully automated design of both the input matching network (IMN) and the output matching network (OMN).

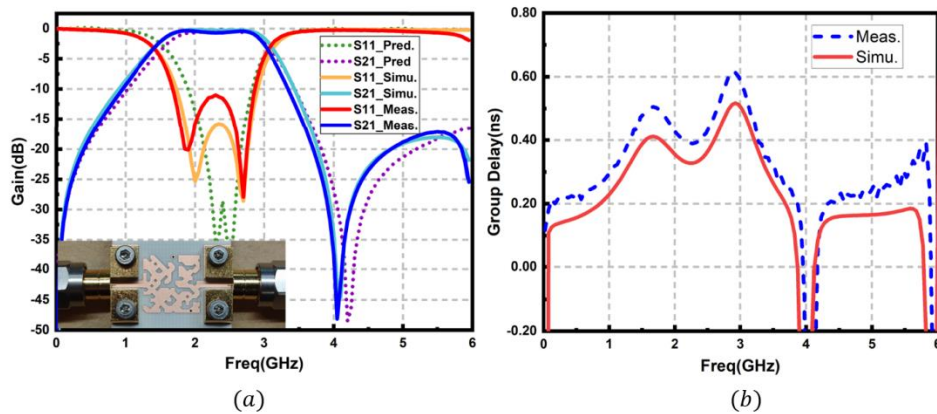


Fig 2.145 AI-driven filter design (a) Fabricated prototype photo with S-parameters prediction-simulation-measurement result. (b) Group delay simulation and measurement result

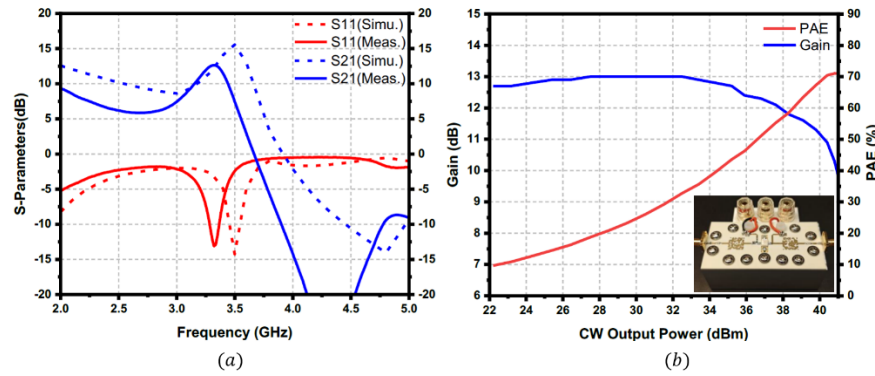


Fig 2.146 AI-driven PA design (a) Measurement and simulation of S-parameter (b) HB performance of PA

In summary, this AI-driven inverse circuit design approach is applicable both passive circuits and active circuits. It can significantly improve design efficiency, optimise circuit structures, reduce overall size. Moreover, through intelligent modelling and optimisation, this method has potential to advance complex circuit design toward high performance, low power consumption and high integration, providing a more flexible and efficient technological solution for modern electronic system design.

2.2.40 Structural health monitoring with meta-materials for engineering structures pertinent to railway

Over the past year, Prof. Cheng and his team have conducted systematic investigations centered on the project research objectives, meta-material-assisted elastic wave-based structural health monitoring (SHM) for railway structure applications. Stable progress has been made in enhancing the capability of elastic-wave-based SHM, particularly for potential applications in both thin- and thick-walled engineering structures.

To solve the ineffective excitation of shear horizontal (SH) waves in thin-walled structures due to the inefficiency of shear-type PZT transducers or the installation inconvenience of electromagnetic transducers (e.g., EMAT), we propose an SH wave generation scheme based on the mode conversion from Lamb waves activated by PZT transducers, as sketched in Fig 2.152 (a). By embracing the concept of meta-materials, a meta-material-mediated converter (referred to as a meta-converter), mounted on the surface of a host structure, is designed topologically to achieve high-efficiency energy conversion from Lamb waves to SH waves.

Analyses of band structures and mode shapes elucidate the mechanisms of the mode conversion within the targeted frequency band. The meta-converters are finally 3D-printed using the selective laser melting technique, as presented in Fig 2.152 (b). Experimental tests validate the effective enhancement of SH waves achieved by the designed meta-converters. Specifically, the amplitude of SH waves is increased significantly from 15 mV to 155 mV with the aid of the meta-converter, as shown in Fig 2.152(c), evidencing its efficacy for SH wave generation. The proposed method offers an alternative and feasible route for SH wave generation and paves a novel way for further SH-wave-based SHM applications.

For thick-walled hollow cylinder (TWHC) structures, which are widely used in railway engineering (e.g., train axles), methods based on nonlinear elastic waves have exhibited high sensitivity in detecting incipient damage in this type of structures. Our previous investigations have revealed that the interaction between quasi-surface waves and incipient damage in a TWHC produces strongly directional nonlinear wave scattering. Building on this physical insight, we further establish a strategy for damage localisation in TWHC. The proposed method starts with the definition of an effective detection zone (EDZ) for each sensor placed along the inner the surface of a TWHC (as shown in Fig 2.153(a)), followed by the construction of a network-level detection zone through the merging of multiple EDZs. Numerical analyses and experiments confirm the effectiveness of the proposed method, as illustrated by Fig 2.153(b), pointing out its great potential in applications such as early damage localisation of train axles.

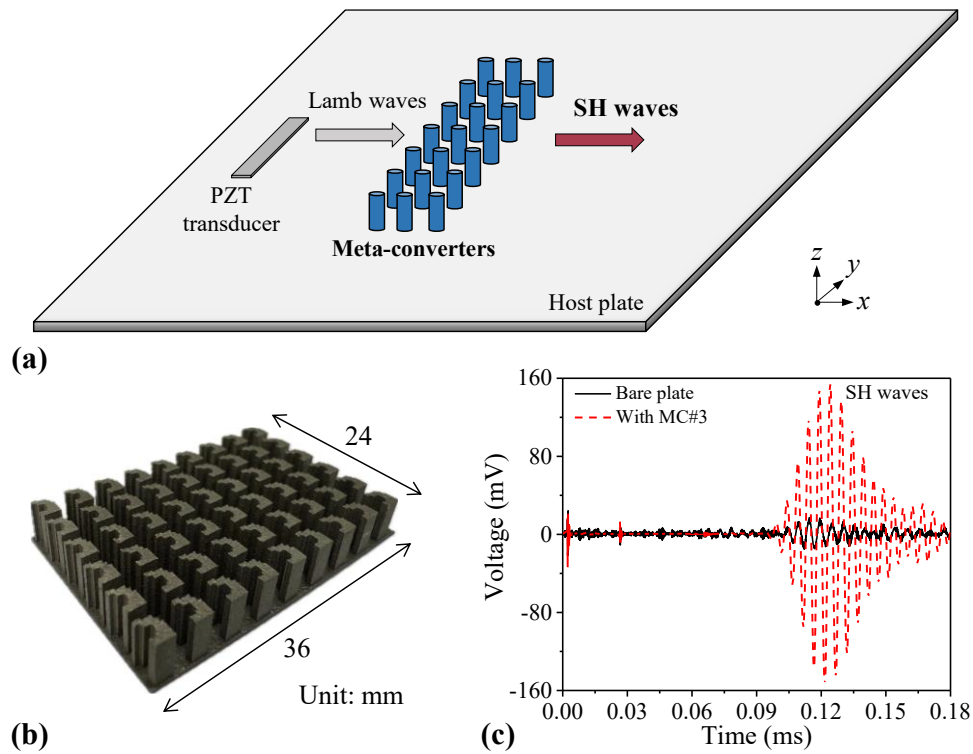


Fig 2.152 Meta-converter-enabled SH wave generation converted from Lamb waves: (a) schematic of the proposed method, (b) sample of the topology-optimised meta-converter, and (c) experimental time-domain signals with/without the meta-converter.

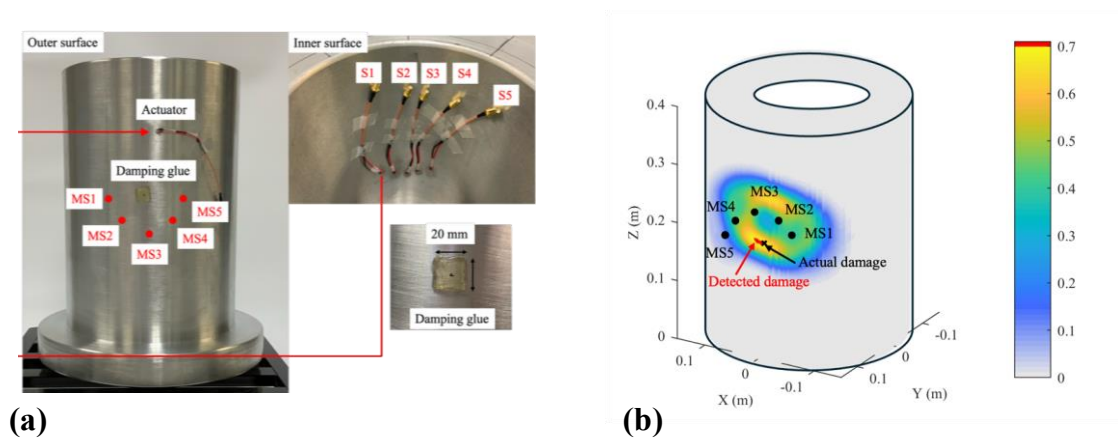


Fig 2.153 (a) Experimental setup and sensor arrangement on the hollow cylinder, and (b) incipient damage localisation results using the proposed damage localisation strategy.

In summary, the proposed method or strategy significantly enhances the elastic wave-based SHM methods, including both linear and nonlinear ones, for high-accuracy damage detection/localisation. For linear methods, the topologically designed meta-converters dedicated to SHM applications is expected to contribute to the development of SH-wave-based

SHM technology. For nonlinear methods, the presented strategy offers a new avenue for incipient damage localisation in a TWHC through the exploration of the nonlinear bulk wave scattering, potentially offering useful guidance for engineering applications such as the early detection and localisation of damage in train axles, as a typical example of the TWHC.

2.2.41 Dynamic Response Analysis of High-Speed Train Tunnel-Portal Passage Under Coupled Wind–Rain Conditions Considering Dry–Wet Transition of Wheel–Rail Contact State

To investigate the complex coupling between aerodynamic load fluctuations during tunnel-portal passage and rainfall-induced transient changes in wheel – rail adhesion, this study developed a refined coupled dynamics model integrating the vehicle, track, tunnel, and subgrade. The aim is to systematically reveal the mechanisms and macroscopic patterns under different wind – rain conditions on key operational safety indicators, providing qualitative and quantitative references for subsequent prevention and control strategies. Using a typical high-speed train as the study object, a multibody vehicle dynamics model and a finite-element track – structure model were established. System coupling was achieved through wheel – rail contact, enabling unified consideration of both the structural characteristics of the portal transition zone and external wind – rain loads. To capture the critical influence of rainfall on wheel – rail interaction, an adhesion correction model describing dry-to-wet transitions at the contact interface was introduced to adjust tangential force calculations, thereby reflecting adhesion degradation due to rainfall in the dynamic analysis. The overall model and methodology were rigorously validated against experiments. The simulation results agreed well with field measurements in terms of trends and amplitude ranges, confirming the model’s validity and reliability for assessing operational safety in complex wind – rain tunnel-portal scenarios. Based on the validated model, the study first examined the effect of rainfall intensity. As rainfall intensity increases, the effective wheel – rail adhesion coefficient decreases continuously, significantly influencing the train’s dynamic response. Under heavy rainfall, the wheel load reduction rate increases markedly and may exceed safety limits under extreme precipitation, directly demonstrating the substantial threat of intense rainfall. Meanwhile, the derailment coefficient also shows a clear upward trend, indicating that adhesion deterioration exacerbates derailment risk. Comparisons among different car positions further reveal that the

leading car is the most sensitive under windy and rainy conditions, exhibiting the greatest deterioration in safety indicators, consistent with its exposure to stronger aerodynamic disturbances during portal passage. The study also investigated the effect of wind speed. Under fixed rainfall conditions, increasing wind speed similarly worsens operational safety indicators. Owing to the aerodynamic interference flow field during portal passage, the right-side wheels generally exhibit more severe responses than the left-side wheels, with higher indicator values and stronger fluctuations. When wind speed exceeds a certain level, abrupt variations in right-side wheel loads lead to sharp increases in the wheel load reduction rate and derailment coefficient, potentially exceeding safety thresholds in sequence. This highlights high wind speed as another key risk factor for operational safety in tunnel-portal regions. In summary, by establishing and validating a model that comprehensively captures coupled wind – rain effects and system dynamic responses, this study systematically clarifies how rainfall intensity and wind speed influence high-speed train safety during tunnel-portal passage. The results indicate that heavy rainfall and strong winds can substantially increase the risks of wheel load reduction and derailment through the combined pathways of degraded wheel – rail adhesion and intensified aerodynamic interference, posing a particularly severe threat to the leading car and the right-side wheel – rail system. These findings provide an important theoretical basis and analytical framework for understanding and assessing operational safety risks under complex meteorological conditions.

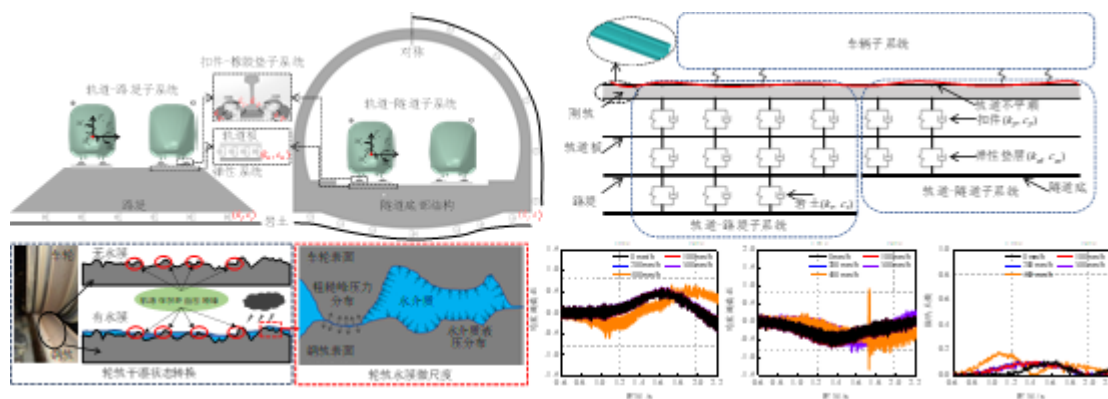


Fig 2.154 Schematic framework for calculating the dynamic response of a high-speed train considering wheel–rail dry–wet state transitions

2.3 Research Outcomes

In 2025, CNERC-Rail (HK Branch) published 101 SCI papers, delivered 9 theme reports, attended conferences 37 times, received 8 awards, submitted 6 patents, and 7 authorized patents.

2.3.1 International Journal Publications

1. Zeng, Z.X., Tan, Y.K., Deng, E., Ni, Y.Q., Zhang, Q.L., and Yang, B. “Uncertainty-aware Bayesian time series framework for probabilistic imputation”, *Advanced Engineering Informatics*, 70, No. 104153 (2026).
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13. Yang, C., Wang, X., Chen, H., Wang, Q., Ni, Y., and Ou, J. “Design method of high-rise fully MiC with simplified models of grouted joints”, *Journal of Constructional Steel Research*, 235, No. 109891 (2025).
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15. Li, S., Zhang, W., Ding, S., Lu, J., and Ni, Y.Q. “A comprehensive review on energy-absorbing mechanical metamaterials: From mechanisms to applications”, *Composites Part B: Engineering*, 113222 (2025).
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2.3.2 Theme Reports

1. Ni, Y.Q. (2025), Keynote speaker: The 2nd International Workshop on Intelligent Tropical-Storm-Resilient Systems for Coastal Cities (INTACT 2025), Hong Kong, China.
2. Ni, Y.Q. (2025), Keynote speaker: The 11th National Conference on Structural Vibration Control and Health Monitoring, November 1, 2025, Wuhan University of Technology, Wuhan, China.
3. Ni, Y.Q. (2025), Keynote speaker: 2025 Greater Bay Area International Rail Transit Exhibition (GGRTE 2025 GBA), November 21, 2025, Guangzhou, China.
4. Ni, Y.Q. (2025), Keynote speaker: The 1st International Workshop on Scientific Machine Learning and Large-Language-Model-Enabled Civil Engineering Application (SMLLM2026 Working Group), November 24, 2025, Hong Kong, China.

5. Ni, Y.Q. (2025), Keynote speaker: "PolyU Research Pioneers: Fortifying Urban Resilience Against Extreme Weather", November 27, 2025, Hong Kong, China.
6. Ni, Y.Q. (2025), Forum Participant: NSFC–BHKAEC Frontier Academic Forum on “Wind Energy Utilisation and Wind Disaster Mitigation”, December 1-3, 2025, Chongqing, China.
7. Su, Z.Q. Keynote speaker: Augmenting ultrasound for continuous glucose monitoring via a wearable acoustically readable microneedle patch (2025 International Conference on Advanced Materials Technology (ICAMT 2025); 15-16, November 2025; Guangzhou, P. R. China).
8. Su, Z.Q. Keynote speaker: The 14th International Conference on Structural Integrity and Failure (SIF 2025); Presentation title: Optoacoustic characterization of three-dimensional, nanoscopic interior features of microchips using ultrafast laser; 28-30, May 2025; Sydney, Australia; Chairs: Wang, C. and Gludovatz, B.
9. Su, Z.Q. Keynote speaker: The 2025 SPIE Conference on Smart Structures/NDE (Health Monitoring of Structural and Biological Systems XIX); Presentation title: An annular photoacoustic tweezer for manipulation of bioparticles, 17-20, March 2025; Vancouver, Canada; Chairs: Su, Z., Peters, K., Ricci, F. and Rizzo, P.

2.3.3 International Conferences

1. Member of Scientific Committee of the 13th International Conference on Structural Dynamics, 27 September – 1 October 2026, Hannover, Germany;
2. Member of Scientific Committee of the 4th International Conference on Industrial Aerodynamics, 17-19 October 2025, Qingdao, China;
3. Member of Scientific Committee of the 13th International Conference on Structural Health Monitoring of Intelligent Infrastructure, 1-5 September 2025, Graz, Austria;
4. Member of International Advisory Board of the 9th International Conference on Structural Engineering, Mechanics and Computation, 1-3 September 2025, Cape Town, South Africa;
5. Chairman of the 2nd International Workshop on Intelligent Tropical-storm-resilient System for Coastal Cities (INTACT 2025), 25-26 August 2025, Hong Kong;
6. Zhou, H., Luo, T., and Ni, Y.Q. (2025), “MS-TFNet: An unsupervised deep learning method for multi-frequency GPR data fusion in tunnel lining inspection”, 13th International Workshop on Advanced Ground Penetrating Radar (IWAGPR) Thessaloniki, Greece, 2025.

7. Ni, Y.-Q., Duan, H.-F., Zhu, S.-Y., Lai, S.-K., Zhai, G.-H., Wang, J.-Y., Ghafoor, I., and Lu, B. (2025), “The 2nd International Workshop on Intelligent Tropical-Storm-Resilient Systems for Coastal Cities (INTACT 2025),” Workshop, August 25–26, 2025, Hong Kong, China.
8. Ni, Y.-Q. (2025–2030), “Appointment to Advisory Committee of the Institute for Disaster Prevention and Mitigation in the Guangdong–Hong Kong–Macao Greater Bay Area (GDUT),” Appointment, October 2025–October 2030, Guangzhou, China.
9. Zhou, H. (2025), “An Obstacle Intrusion Detection Method for Complex Environment Tracks Based on Manifold Regularization,” The 13th International Workshop on Advanced Ground Penetrating Radar (IWAGPR 2025), July 2–4, 2025, Thessaloniki, Greece.
10. Zhou, H. (2025), “MS-TFNET: An Unsupervised Deep Learning Method for Multi-Frequency GPR Data Fusion in Tunnel Lining Inspection,” The 13th International Workshop on Advanced Ground Penetrating Radar (IWAGPR 2025), July 2–4, 2025, Thessaloniki, Greece.
11. Zeng, Y.-J. (2025), “Prediction of Urban Wind Speed During Tropical Cyclones Using a Novel Deep Learning-Based Spatiotemporal Model,” The 13th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII), September 1–5, 2025, Graz, Austria.
12. Li, P.-L. (2025), “Solving Structural Dynamics with Uncertainty Quantification via Evidential Neural Operators,” The 13th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII), September 1–5, 2025, Graz, Austria.
13. Zhai, G. (2025), “Bidirectional Graphics-Based Digital Twin (BiGBDT): Concept and Implementation in Post-Earthquake Structural Assessment,” The 5th Digital Twin International Conference (DigiTwin 2025), October 14–18, 2025, Garmisch-Partenkirchen, Germany.
14. Chen, Z.-W. (2025), “Research on Aerodynamic Characteristics and Dynamic Safety of High Speed Maglev Trains Under Complex Wind Conditions,” The 4th International Conference on Industrial Aerodynamics (ICIA 2025), October 17–19, 2025, Qingdao, China.

15. Liu, W.-Q. (2025), “An Obstacle Intrusion Detection Method for Complex Environment Tracks Based on Manifold Regularization,” The 15th International Workshop on Structural Health Monitoring (IWSHM), September 9–11, 2025, Stanford, CA, USA.
16. Lyu, L. (2025), “Noise Tomography Based Urban Ground Collapse Monitoring Using Distributed Acoustic Sensing,” The 15th International Workshop on Structural Health Monitoring (IWSHM), September 9–11, 2025, Stanford, CA, USA.
17. Lu, J.-H. (2025), “Kolmogorov–Arnold Network Aided Design of Conch Shell Inspired Acoustic Metamaterial for Rail Noise Mitigation,” The 15th International Workshop on Structural Health Monitoring (IWSHM), September 9–11, 2025, Stanford, CA, USA.
18. Ni, Y.-Q. (2025), “Integrated Air–Space–Ground Monitoring for Typhoon Early Warning of High Rise Building Clusters in Coastal Cities,” Invited Keynote at the 11th National Conference on Structural Vibration Control and Health Monitoring, November 1, 2025, Wuhan, China.
19. Ni, Y.-Q. (2025), “AI Empowered Rail Transit: A New Paradigm for Talent Development,” Invited Keynote at the Global Rail Talent Development Forum, GGRTE 2025, November 21, 2025, Guangzhou, China.
20. Ao, V. W. K. (2025), “AI Driven Railway Technologies: CNERC Rail Research Achievements,” Merck KGaA and OASES Delegation Meeting, November 21, 2025, Hong Kong, China.
21. Ni, Y.-Q., Ao, V. W. K., Hu, Y., Lu, J.-H., and Lu, Y.-H. (2025), “Excellence Award – 2nd International Innovation Competition on Structural Health Monitoring for Railway Systems (ECAV Ensemble for Impact Localisation and Energy Prediction),” Competition, November 17, 2025, Singapore.
22. Ni, Y.-Q. (2025), “A Multi Source Data Driven Intelligent Disaster Mitigation System for Typhoons and Associated Hazards in Coastal Cities,” Invited Keynote at the NSFC—BHKAEC Frontier Academic Forum, 2025, Hong Kong, China.
23. Ding, S.-Q. (2025), “2025 Building Materials Industry Science and Technology Innovation Conference (Second Prize: Intrinsic Self Sensing Cement Based Composites and Their Intelligent Structures),” Conference, 2025, Ningbo, China.
24. Su, Z.-Q. (2025), “Optoacoustics-enabled nondestructive evaluation for turbofan engine blades” (Global Power and Propulsion Society (GPPS) Technical Conference Shanghai 2025; 4-6, September, 2025; Shanghai, P. R. China).

2.3.4 Patents and Awards

Patents:

1. Chinese invention patent “Image analysis system, method and device suitable for track detection” (Inventors: S.M. Wang; C.L. Liao; Y.Q. Ni; Patent number: ZL202011059164.3; Grant date: January 3, 2025) (Fig. 2.160 left)
2. Chinese invention patent “Vehicle Control Method, Device and Controller for Maglev System” (Inventors: S.M. Wang; M.H. Zhang; Q. Zhu; Y.Q. Ni; Patent number: ZL 20221 1013918.0; Grant date: March 28, 2025) (Fig. 2.160 right)
3. Chinese invention patent “Maglev control system and control method” (Inventors: Y.Q. Ni; S.M. Wang; Y. Lu; Patent number: ZL 202011058051.1; Grant date: July 22, 2025) (Fig. 2.161 left)
4. Chinese invention patent “A Main Beam Structure for Wind Turbine Blades” (Inventors: K. Zhou; Y.Z. Nian; S.Q. Ding; Y.Q. Ni; Y.W. Wang; Patent number: ZL 202510258961.0; Grant date: July 25, 2025) (Fig. 2.161 right)
5. Chinese invention patent “Flow Field Prediction Method, Device, Terminal Equipment and Storage Medium” (Inventors: Z.W. Chen; Y.Q. Ni; E.Z. Rui; G.Z. Zeng; Patent number: ZL 202311252989.0; Grant date: September 30, 2025) (Fig. 2.162 left)
6. Chinese invention patent “Foam concrete for low-height sound-absorbing barriers in rail transit and its preparation method” (Inventors: S.Q. Ding; S.F. Dong; X.H. Xi; B.G. Han; Y.Q. Ni; Patent number: ZL 202510678913.7; Grant date: November 11, 2025) (Fig. 2.162 right)
7. US Patent “Methodology for Vibration and Noise Control Using Modular Rail Particle Damper in Rail Transit Systems” (Inventors: Seyed Masoud Sajjadi Alehashem; Y.Q. Ni; C. Zhang; Patent number: US 12,480, 261 B2; Grant date: November 25, 2025) (Fig. 2.163 left)

Awards

1. Prof. Yi-Qing Ni, Dr. Su-Mei Wang, Dr. Wen-Qiang Liu and Ms. Xin-Yue Xu received the Silver Medal at the 50th International Exhibition of Inventions, New Techniques and Products in Geneva (Fig. 2.163 right)
2. Dr. Xin-Yu Zhou’s team received the Third Place of the Flash Competition at 2025 IEEE MTT-S International Wireless Symposium (Fig. 2.164)

3. Dr. Xin-Yu Zhou's team received the First Place in the Student Design Competition on PCB Based Bandpass Filter at the 2025 International Microwave Symposium (Fig. 2.165)
4. Dr. Wai Kei Ao, Dr. Yao Hu, Mr. Jia-Hao Lu, and Mr. Yu-Hang Lu received the Excellence Award at the 2nd International Innovation Competition on Rail Structural Health Monitoring for Railway System (Fig. 2.166)
5. Dr. Su-Mei Wang received the IEEE SA Emerging Technology Award (Fig. 2.167)
6. Dr. Si-Qi Ding received the Second Prize for Basic Research in the Building Materials Science and Technology Awards (Fig. 2.168)
7. Prof. Yi-Qing Ni received the Top Patents Filing Award 2024 on September 25, 2025 (Fig. 2.169)
8. Prof. Yi-Qing Ni received the Editorial Contribution Award 2025 by Springer Nature Group in recognition of his outstanding performance as an Associate Editor of Journal of Civil Structural Health Monitoring (Fig. 2.170)

Recognitions

1. Prof. Yi-Qing Ni elected as Fellow by the American Society of Civil Engineers (ASCE) (Fig. 2.171)
2. Nine members of CNERC-Rail (HK Branch) selected into the list of World's Top 2% Scientists released by Stanford University (Prof. Yi-Qing Ni; Prof. Li Cheng; Prof. Zhongqing Su; Prof. Jiannong Cao; Prof. Siu Wing Or; Prof. You Dong; Prof. Hwa Yaw Tam; Prof. Songye Zhu; Prof. Zhen Leng) (Fig. 2.172)
3. Prof. Yi-Qing Ni received the Certificate of Outstanding Advisor for Excellence Award of 2nd International Innovation Competition on Structural Health Monitoring for Railway System (Fig. 2.173)



Fig. 2.160 Patent certificates: Image analysis system, method and device suitable for track detection (left); Vehicle Control Method, Device and Controller for Maglev System (right)



Fig. 2.161 Patent certificates: Maglev control system and control method (left); A Main Beam Structure for Wind Turbine Blades (right)



Fig. 2.162 Patent certificates: Flow Field Prediction Method, Device, Terminal Equipment and Storage Medium (left); Foam concrete for low-height sound-absorbing barriers in rail transit and its preparation method (right)

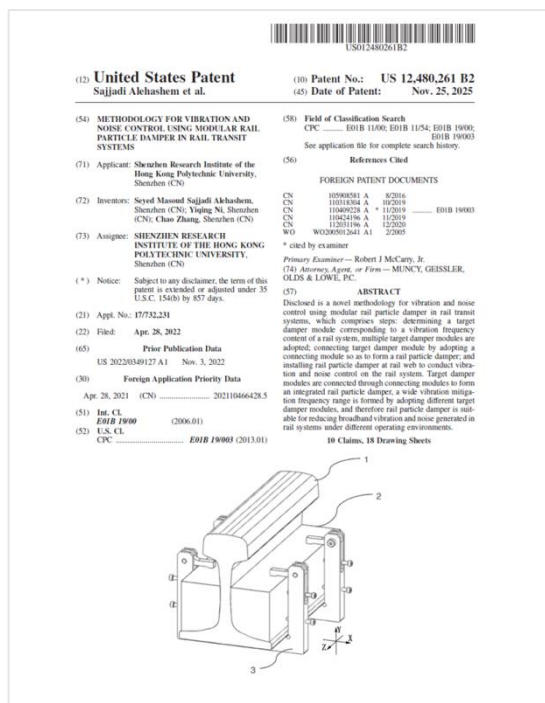


Fig. 2.163 Patent certificate: Methodology for Vibration and Noise Control Using Modular Rail Particle Damper in Rail Transit Systems (left); Silver Medal at the 50th International Exhibition of Inventions, New Techniques and Products in Geneva (right)



Fig. 2.164 Dr. Xin-Yu Zhou’s team received the Third Place of the Flash Competition at 2025 IEEE MTT-S International Wireless Symposium



Fig. 2.165 Dr. Xin-Yu Zhou’s team received the First Place in the Student Design Competition on PCB Based Bandpass Filter at the 2025 International Microwave Symposium



Fig. 2.166 Dr. Wai Kei Ao, Dr. Yao Hu, Mr. Jia-Hao Lu, and Mr. Yu-Hang Lu received the Second Prize at the 2nd International Innovation Competition on Rail Structural Health Monitoring for Railway System



Fig. 2.167 Dr. Su-Mei Wang received the IEEE SA Emerging Technology Award



Fig. 2.168 Dr. Si-Qi Ding received the Second Prize for Basic Research in the Building Materials Science and Technology Awards



Fig. 2.169 Prof. Yi-Qing Ni received the Top Patents Filing Award 2024 on September 25, 2025



Fig. 2.170 Prof. Yi-Qing Ni received the Editorial Contribution Award 2025 by Springer Nature Group in recognition of his outstanding performance as an Associate Editor of Journal of Civil Structural Health Monitoring

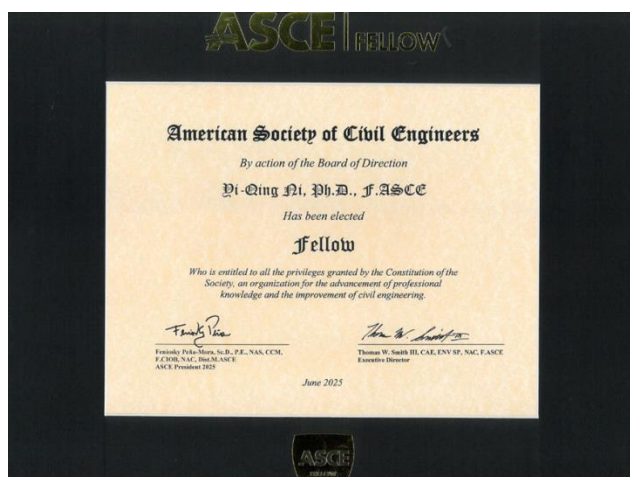


Fig. 2.171 Prof. Yi-Qing Ni elected as Fellow by the American Society of Civil Engineers (ASCE)

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1	authid	inst_name	inst_country	ng6024	firstyr	lastyr	rank (m)	nc6024 (m)	h24 (m)	ngs (m)	ncs (m)	cpst (m)	ncst (m)	ngstl (m)	ncstl (m)	c (m)	ngcstl (m)	ncstl (m)	ng6024 cit sc%	U	
71101	Cheng, Li	The Hong Kong Polytechnic University	hkg	508	1992	2025	71,100	9,829	53	30,815.1	5	73	24	461	306	5,655	3,5926	7,099	1,3846	385	20.42
74752	Ni, Yi-Qing	The Hong Kong Polytechnic University	hkg	566	1992	2025	74,751	11,840	56	27,2468	9	8	86	3,154	269	6,055	3,5751	9,070	1,3054	457	16.25
133520	Su, Zhongqing	The Hong Kong Polytechnic University	hkg	345	1999	2025	142,578	7,820	46	25,9008	3	2	49	2,812	184	4,599	3,3106	5,765	1,3545	270	18.59
144403	Cao, Jiannong	The Hong Kong Polytechnic University	hkg	1,069	1995	2025	159,033	16,830	42	29,3349	5	0	128	645	374	3,996	3,2946	15,116	1,1134	813	12.58
153175	Or, Siu-Wing	The Hong Kong Polytechnic University	hkg	264	1996	2025	173,675	6,087	39	15,8294	1	41	26	408	74	1,479	3,2597	5,036	1,2087	227	14.13
158316	Dong, You	The Hong Kong Polytechnic University	hkg	189	2011	2025	182,782	2,700	27	15,8611	1	97	27	990	90	1,584	3,2384	2,177	1,2402	140	32.67
174618	Tam, Hwayaw	The Hong Kong Polytechnic University	hkg	744	1989	2021	214,901	13,757	58	29,4187	3	0	25	148	341	5,052	3,1706	11,095	1,2399	531	14.79
182612	Zhu, Songye	The Hong Kong Polytechnic University	hkg	228	2003	2025	233,201	5,799	42	24,9167	0	0	21	828	141	3,955	3,1357	4,042	1,4347	183	19.81
204992	Leng, Zhen	The Hong Kong Polytechnic University	hkg	224	2008	2025	302,910	4,957	42	15,1317	0	0	22	1,004	63	1,661	3,0210	3,779	1,3138	191	18.27

Fig. 2.172 Nine members of CNERC-Rail (HK Branch) selected into the list of World's Top 2% Scientists released by Stanford University

(Prof. Yi-Qing Ni; Prof. Li Cheng; Prof. Zhongqing Su; Prof. Jiannong Cao; Prof. Siu Wing Or; Prof. You Dong; Prof. Hwa Yaw Tam; Prof. Songye Zhu; Prof. Zhen Leng)



Fig. 2.173 Prof. Yi-Qing Ni received the Certificate of Outstanding Advisor for Excellence Award of 2nd International Innovation Competition on Structural Health Monitoring for Railway System

2.3.5 Professional Activities

1. Prof. Yi-Qing Ni, Co-Editor-in-Chief of Journal of Infrastructure Intelligence and Resilience (Publisher: Elsevier).
2. Prof. Yi-Qing Ni, Co-Editor-in-Chief of Intelligent Transportation Infrastructure (Publisher: Oxford University Press).
3. Prof. Yi-Qing Ni, Academic Editor of Structural Control and Health Monitoring: An International Journal (Publisher: Wiley & Hindawi Partnership).
4. Prof. Yi-Qing Ni, Associate Editor of Journal of Vibration and Control (Publisher: SAGE Publications).
5. Prof. Yi-Qing Ni, Associate Editor of Journal of Civil Structural Health Monitoring (Publisher: Springer).
6. Prof. Yi-Qing Ni, Editor of IEEE Std 3352-2025 – IEEE Standard for Test Specification of Short Primary Maglev Vehicles.
7. Prof. Yi-Qing Ni, Author of “Technical Specification for Intelligent Nondestructive Testing of Building Enclosure Systems” (Code: T/CECS 1884-2025).
8. Prof. Yi-Qing Ni, Author of Technical requirements of noise reduction ring for urban rail transit vehicles.
9. Prof. Yi-Qing Ni, Member of National Key Laboratory of Green and Long-Life Road Engineering in Extreme Environments (Shenzhen).

10. Prof. Yi-Qing Ni, Member of Advisory Board for International Journal of Railway Research (Publisher: Iran University of Science and Technology Press).
11. Prof. Yi-Qing Ni, Member of Editorial Advisory Board for Journal of Intelligent Manufacturing and Special Equipment (Publisher: Emerald Publishing).
12. Prof. Yi-Qing Ni, Member of Editorial Board for Engineering Structures (Publisher: Elsevier).
13. Prof. Yi-Qing Ni, Member of Editorial Board for Smart Structures and Systems: An International Journal (Publisher: Techno-Press).
14. Prof. Yi-Qing Ni, Member of Editorial Board for Advances in Structural Engineering: An International Journal (Publisher: SAGE Publications).
15. Prof. Yi-Qing Ni, Member of Editorial Board for Advanced Steel Construction: An International Journal (Publisher: The Hong Kong Institute of Steel Construction).
16. Prof. Yi-Qing Ni, Member of Editorial Board for Structural Monitoring and Maintenance: An International Journal (Publisher: Techno-Press).
17. Prof. Yi-Qing Ni, Member of Editorial Board for Transportation Safety and Environment (Publisher: Oxford University Press).
18. Prof. Yi-Qing Ni, Member of Editorial Board for Advances in Bridge Engineering (Publisher: Springer Nature Group).
19. Prof. Yi-Qing Ni, Member of the Advisory Committee of the Institute for Disaster Prevention and Mitigation in the Guangdong–Hong Kong–Macao Greater Bay Area at Guangdong University of Technology.
20. Prof. Yi-Qing Ni, Member of Editorial Board of Journal of Railway Science and Technology (Publisher: KeAi).
21. Prof. Yi-Qing Ni, ScholarGPS Lifetime Highly Ranked Scholars List (top 0.05% of scholars worldwide) 2025.
22. Prof. Songye Zhu, Member of Editorial Board for Advances in Structural Engineering (Publisher: SAGE Publications).
23. Prof. Songye Zhu, Associate Editor of International Journal of Smart and Nano Materials (Publisher: Taylor & Francis).
24. Prof. Zhongqing Su, Editor-in-Chair of Journal of Ultrasonics (Publisher: Elsevier).
25. Prof. Zhongqing Su, Associate Editor of Structural Health Monitoring: An International Journal (Publisher: SAGE Publications).
26. Dr Siu-Kai Lai, Associate Editor of Journal of Vibration Engineering & Technologies (Publisher: Springer).

27. Dr Siu-Kai Lai, Member of Editorial Board for International Journal of Dynamics and Control (Publisher: Springer).
28. Prof. Siu-Wing Or, Member of Editorial Board for Processes (Publisher: MDPI).
29. Prof. Zhi-Zhao Liu, Member of Editorial Board for GPS Solutions (Publisher: Springer).
30. Prof. Zhi-Zhao Liu, Member of Editorial Board for Satellite Navigation (Publisher: Springer Open).
31. Prof. Zhen Leng, Editor-in-Chair of Cleaner Materials (Publisher: Elsevier).
32. Prof. Zhen Leng, Member of Editorial Board for Journal of Cleaner Production (Publisher: Elsevier).
33. Prof. Zhen Leng, Member of Editorial Board for Journal of Transportation Engineering, Part B: Pavements (Publisher: ASCE).
34. Prof. Zhen Leng, Member of Editorial Board for Journal of Materials in Civil Engineering (Publisher: ASCE).
35. Prof. Zhen Leng, Member of Editorial Board for Road Materials and Pavement Design (Publisher: Taylor & Francis).
36. Prof. Zhen Leng, Member of Editorial Board for Transportation Research Part D: Transport and Environment (Publisher: Elsevier).
37. Prof. Zhen Leng, Member of Editorial Board for International Journal of Transportation Science and technology (Publisher: Elsevier).
38. Prof. Jiannong Cao, Member of Editorial Board for ACM Computing Surveys (Publisher: Association for Computing Machinery).
39. Prof. Jiannong Cao, Member of Editorial Board for ACM Transactions on Cyber-Physical Systems (Publisher: Association for Computing Machinery).
40. Prof. Jiannong Cao, Member of Editorial Board for ACM Transactions on Sensor Networks (Publisher: Association for Computing Machinery).
41. Prof. Jiannong Cao, Member of Editorial Board for Chinese Journal of Electronics (Publisher: Chinese Institute of Electronics).
42. Prof. Jiannong Cao, Member of Editorial Board for Peer-to-Peer Networking and Applications (Publisher: Springer).
43. Prof. Li Cheng, Associate Editor of Journal of Sound and Vibration (Publisher: Elsevier).
44. Prof. Li Cheng, Associate Editor of Journal of the Acoustical Society of America (Publisher: Acoustical Society of America).
45. Prof. Li Cheng, Associate Editor of Structural Health Monitoring: An International Journal (Publisher: SAGE Publications).

46. Prof. Li Cheng, Associate Editor of Nonlinear Dynamics (Publisher: Springer).
47. Dr. Su-Mei Wang, Editors of IEEE Std 3351-2025- IEEE Standard for Levitation System of Electromagnetic Suspension-type Maglev Vehicles. 27 March 2025.
48. Dr. Wai Kei Ao, Author of Technical requirements of noise reduction ring for urban rail transit vehicles.
49. Dr Wen-Qiang Liu, Member of Editorial Board for IEEE Transactions on Instrumentation and Measurement (Publisher: IEEE).
50. Dr E Deng, The Third Youth Editorial Committee Member of Journal of Central South University.
51. Dr E Deng, Youth Member of Editorial Board for Advances in Wind Engineering (Publisher: KeAi).
52. Dr E Deng, Youth Member for Technical Committee on Aerodynamics of Orbital Vehicles in Discipline of Dynamic Effect of Orbital Transport Systems in Division of Rail Transit at the Third Division Committee of World Transport Convention (WTC).
53. Dr Yue Dong, Youth Member of Editorial Board for Advances in Wind Engineering (Publisher: KeAi).
54. Dr Si-Qi Ding, Guest Editor of Communications Engineering (Publisher: Nature Portfolio).

3. Collaborations & Exchanges of CNERC-Rail (HK Branch) in 2025

3.1 Collaboration Agreements

3.2 Conferences

3.3 Cross Institutes Technical Exchanges

3.4 Organised Seminars

3.5 Visiting Scholars & Delegations

3.6 Media Interview



3. Collaborations & Exchanges of CNERC-Rail (HK Branch) in 2025

3.1 Collaboration Agreements

3.1.1 Strategic agreements with China Railway Electrification Group to establish joint research laboratory

On April 30, 2025, the Hong Kong Polytechnic University (PolyU) and China Railway Electrification Engineering Group Co., Ltd. (CREEG) recently held a signing ceremony for a strategic cooperation agreement on technology research and application, as well as the unveiling of a joint laboratory in Beijing. Through the Beijing-Hong Kong technology cooperation mechanism, both parties aim to cultivate high-quality talents with innovative theories and practical experience, and to create a global hub for rail transit innovation and a model for industry-education integration. This collaboration will support the national strategy of "strengthening the country through transportation" and contribute to the coordinated development of the Beijing-Tianjin-Hebei region and the construction of a global digital economy benchmark city.

CREEG, a key member of China Railway Group Limited, a dual Fortune Global 500 company, is the national team and main force in the construction of electrified railways and urban rail transit in China. This partnership will leverage the strengths of both parties to build a highland of innovation in rail transit.

Prof. Yi-Qing Ni, Chair Professor of Intelligent Structures and Rail Transit in the Department of Civil and Environmental Engineering at PolyU, also signed a strategic cooperation agreement on technology research and application with Mr. Yu-Bing Li, Chief Engineer of the Electrification Company of CREEG. Professor Ni is the Director of the National Engineering Research Center for Railway Electrification and Automation (Hong Kong Branch) and Dean of the PolyU Hangzhou Technology Innovation Institute.

PolyU representatives visited the Electric Traction Equipment Research and Development Center of Beijing Electric Traction Company of CREEG for an on-site inspection. They gained detailed insights into CREEG's latest developments and innovative achievements in intelligent construction, digital technology application, and intelligent operation and maintenance systems

for rail transit. In-depth technical exchanges and discussions were held on the intelligent and digital development of rail transit.



Fig. 3.1 Strategic agreements with China Railway Electrification Group to establish joint research laboratory

3.1.2 Strategic research collaboration with Zhuzhou Guochuang Rail Transit Technology Co., Ltd. to jointly tackle key technological challenges in hydrogen-lithium hybrid power systems for low-altitude aircraft

On September 29, 2025, the CNERC-Rail (HK Branch) has entered into a strategic research collaboration with Zhuzhou Guochuang Rail Transit Technology Co., Ltd. to jointly tackle key technological challenges in hydrogen-lithium hybrid power systems for low-altitude aircraft.

This partnership, under the prestigious National Key R&D Program "Strategic Scientific and Technological Innovation Cooperation," aims to develop a long-endurance, highly reliable, and intelligent hybrid power solution for unmanned aerial vehicles (UAVs). The project, titled "Hydrogen-Lithium Hybrid Power Low-Altitude Aircraft Power Electronics Technology," is supported by the Mainland and Hong Kong Joint Funding Scheme for Research and Development.

The collaborative research will focus on three core areas: building high-precision simulation models for the hybrid power system, developing advanced temperature prediction and safety monitoring technologies for hydrogen storage and supply, and achieving integrated system control with intelligent energy management strategies.



Fig. 3.2 Strategic research collaboration with Zhuzhou Guochuang Rail Transit Technology Co., Ltd.

3.1.3 Forge AI Partnership to Advance Regional Rail Intelligence with the Infrastructure Inspection Institute of China Academy of Railway Sciences

On August 20, 2025, CNECR-Rail and the Infrastructure Inspection Institute of China Academy of Railway Sciences Group Co., Ltd. have signed a cooperation agreement to jointly develop next-generation AI technologies for regional rail infrastructure.

The collaboration, targeting a 2025 International (GBA) Joint R&D Program grant from the Beijing Municipal Science & Technology Commission, will focus on creating intelligent perception and maintenance solutions for metropolitan rail systems using advanced AI models.

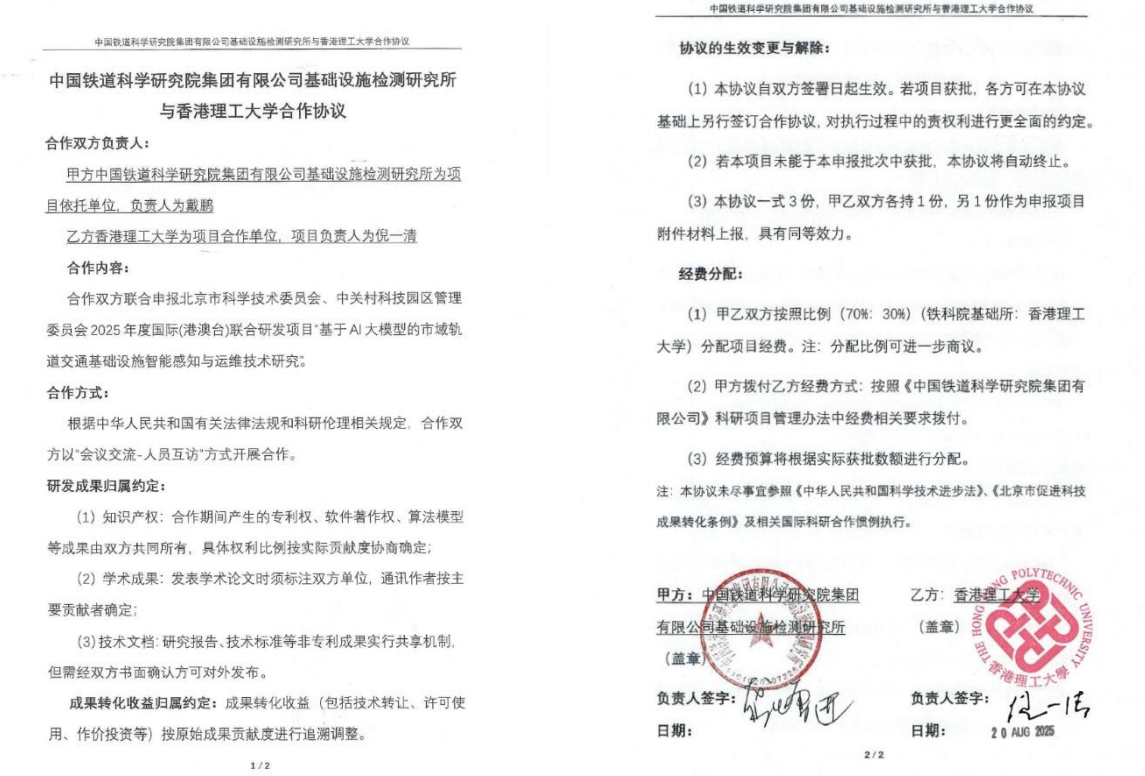


Fig. 3.3 Forge AI Partnership to Advance Regional Rail Intelligence with the Infrastructure Inspection Institute of China Academy of Railway Sciences

3.1.4 Establish Structural Health-Monitoring Partnership for the Shenzhen Galaxy Twin Towers

On December 1, 2025 CNERC-Rail entered into a formal service cooperation agreement with the owner/developer of the Shenzhen Galaxy Twin Towers to deploy a comprehensive structural health monitoring (SHM) system for the twin towers. Under the agreement, the Center is responsible for designing, installing and commissioning an integrated monitoring suite — including multi type sensors (accelerometers, strain gauges and anemometers), a vehicle mounted and fixed LiDAR network for urban wind mapping, data acquisition and edge processing units, and a cloud based analytics platform. The partnership aims to deliver real time structural response data during extreme events (typhoons and seismic incidents), support long term performance assessment for façade and structural elements, and provide actionable outputs for building owners and emergency managers. The arrangement includes provisions for joint data sharing, co-authored research, operational training for facility engineers, and

periodic performance reviews to validate monitoring outcomes and inform maintenance strategies. This collaboration both advances city scale resilience research and creates a living laboratory for translating CNERC-Rail's sensing, modelling and digital twin technologies into operational practice.

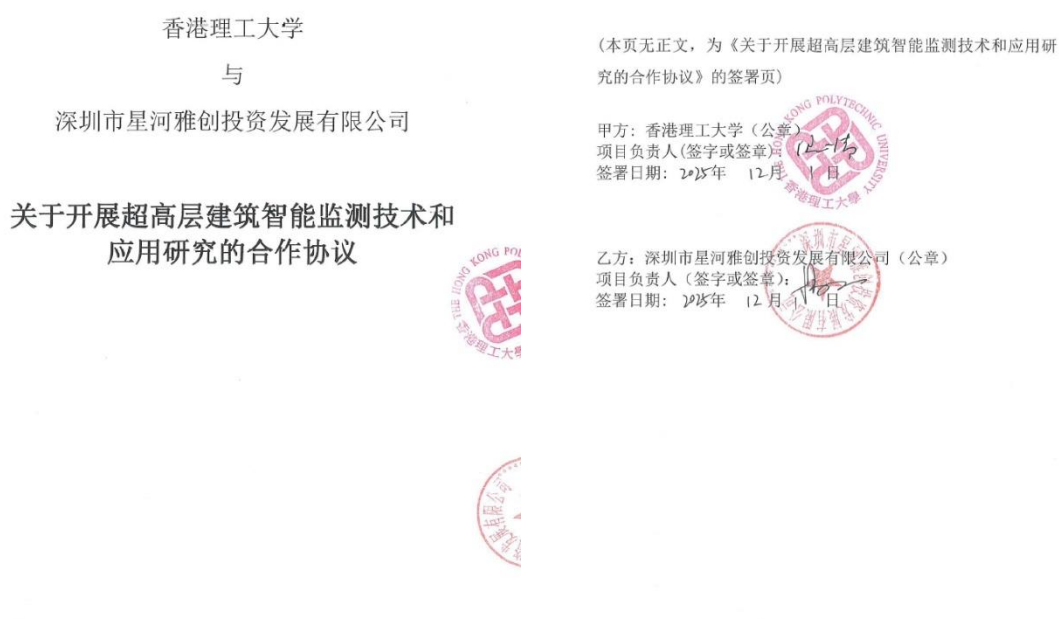


Fig. 3.4 Establish Structural Health Monitoring Partnership for the Shenzhen Galaxy Twin Towers

3.2 Conferences Hosted and Attended

3.2.1 Hosted the 1st International Workshop on Bayesian Approach in Civil Engineering (IWOBA 2025)

The National Rail Transit Electrification and Automation Engineering Technology Research Center (Hong Kong Branch) and the Department of Civil and Environmental Engineering at the Hong Kong Polytechnic University are thrilled to announce the successful conclusion of the 1st International Workshop on Bayesian Approach in Civil Engineering (IWOBA 2025), which took place from 10th -12th January 2025. This esteemed event brought together 120 participants from 10 countries and regions, including the United States, United Kingdom, Greece, Germany, Italy, Singapore, Japan, Mainland China, Hong Kong, and Macau. The workshop served as an active platform for international collaboration and knowledge exchange, focusing on the application of Bayesian methods in various civil engineering disciplines.

Throughout the workshop, nearly 70 academic presentations were delivered, covering a broad spectrum of topics such as probabilistic risk assessment, uncertainty quantification, and Bayesian machine learning methods.

These speeches and discussions highlighted the latest research advancements and innovative applications of Bayesian approaches, demonstrating their merits in addressing complex challenges in civil engineering.



Fig. 3.5 1st International Workshop on Bayesian Approach in Civil Engineering (IWOBA 2025)



Fig. 3.6 Welcome speech by Prof. Yi-Qing Ni

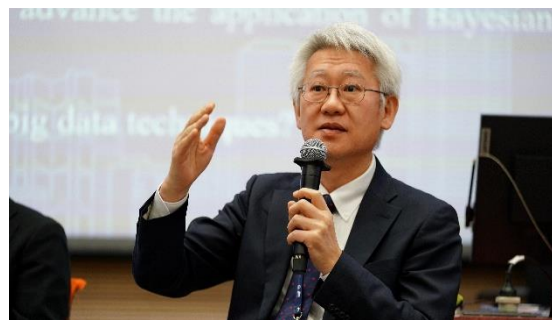


Fig. 3.7 Keynote speeches and panel discussions

3.2.2 Hosted the 2nd International Workshop on Intelligent Tropical-Storm-Resilient Systems for Coastal Cities (INTACT 2025)

The Department of Civil and Environmental Engineering successfully hosted the 2nd International Workshop on Intelligent Tropical-Storm-Resilient Systems for Coastal Cities (INTACT 2025) on 25th -26th August, 2025. Building upon the success of last year's event, INTACT 2025 served as a premier platform dedicated to addressing escalating challenges posed by tropical storm disasters and advancing climate-adaptive urban systems. The workshop was chaired by Prof. Yi-Qing Ni and co-chaired by Prof. Huan-Feng Duan, Prof. Song-Ye Zhu, Prof. Siu-Kai Lai, Dr. Guang-Hao Zhai, Dr. Jia-Yao Wang, Dr. Imran Ghafoor, and Dr. Bin Lu. Prof. You Dong, Dr. E Deng, and Dr. Yue Dong served as workshop secretaries. The workshop also constitutes a key component of a five-year project funded by the Hong Kong Research Grants Council Theme-based Research Scheme.

Over 100 researchers, experts, and industry leaders from Hong Kong, Mainland China, Canada, Australia, and other regions participated in the two-day event. Prof. Yi-Qing Ni extended a warm welcome to participants during the opening ceremony, highlighting the workshop's significant achievements. These included the development of a LiDAR network for enhanced cyclone forecasting, AI-powered prediction models developed in collaboration with NVIDIA, and notable advances in structural health monitoring and climate risk assessment.

The program featured four keynote speeches from distinguished scholars, including Prof. Kenny Kwok (The University of Sydney), Prof. Ming-Feng Huang (Guangxi University), Prof. Johnny C. L. Chan (City University of Hong Kong), and Prof. Ashraf El Damatty (Western University), as well as presentations by young researchers from leading universities and industry partners. Technical sessions showcased the latest progress and future directions of the project's main research tasks, facilitating in-depth discussions among participants. The workshop successfully promoted knowledge exchange, collaboration, and the development of innovative strategies to enhance safety and resilience in coastal cities facing climate change challenges.

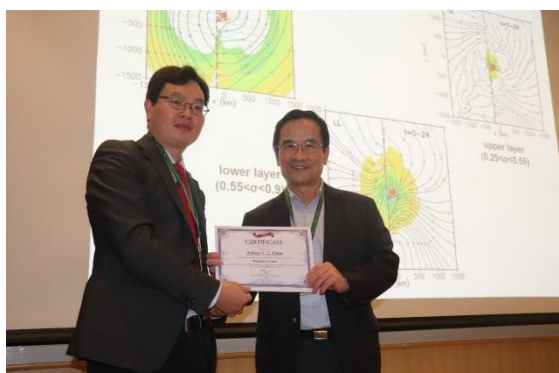




Fig. 3.8 Participants in workshop

3.2.3 Attended the 13th International Workshop on Advanced Ground Penetrating Radar (IWAGPR2025)

Huaiyuan Zhou attended the 13th International Workshop on Advanced Ground Penetrating Radar (IWAGPR2025), Aristotle University of Thessaloniki, 2nd to 4th July in Thessaloniki, Greece. ZHOU presented the paper, entitled “An Obstacle Intrusion Detection Method for Complex Environment Tracks Based on Manifold Regularisation”. “MS-TFNET: an Unsupervised Deep Learning Method for Multi-Frequency GPR Data Fusion in Tunnel Lining Inspection.”



Fig. 3.9 Presentation by Mr. Huai-Yuan Zhou at IWAGPR2025

3.2.4 Attended the 13th International Conference on Structural Health Monitoring of Intelligent Infrastructure in Graz, Austria

The 13th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII-13) was held in Graz, Austria, from 1st to 5th September, 2025. As a leading global forum, the conference gathered researchers and practitioners to exchange cutting-edge advancements in intelligent monitoring technologies for civil infrastructure.

Dr. Yuan-Jiang Zeng presented their paper, entitled “Prediction of urban wind speed during tropical cyclones using a novel deep learning-based spatiotemporal model.”

Furthermore, Ms Pei-Lin LI presented the paper, entitled “Solving structural dynamics with uncertainty quantification via evidential neural operators”



Fig. 3.10 Presentation by Dr. Yuan-Jiang Zeng at SHMII-13



Fig. 3.11 Presentation by Ms. Pei-Lin LI at SHMII-13

3.2.5 Attended the 5th Digital Twin International Conference (DigiTwin 2025)

Dr. Guang-Hao Zhai attended the 5th Digital Twin International Conference (DigiTwin 2025), 14th to 18th October, 2025, in Garmisch-Partenkirchen, Germany

Zhai presented the paper: Bidirectional graphics-based digital twin (BiGBDT): concept and implementation in post-earthquake structural assessment



Fig. 3.12 Presentation by Dr. Guang-Hao Zhai at DigiTwin 2025

3.2.6 Attended the 15th International Workshop on Structural Health Monitoring (IWSHM), Stanford University

The 15th International Workshop on Structural Health Monitoring (IWSHM) was held at Stanford University, CA, USA, from 9th -11th September, 2025. This prestigious event brought together global experts to advance the state of the art in monitoring the condition of infrastructure.

Dr. Wen-qiang Liu attended the conference and presented the paper, entitled “An Obstacle Intrusion Detection Method for Complex Environment Tracks Based on Manifold Regularisation”.

The paper introduced an innovative method designed to enhance the safety of railway and tram tracks. By employing manifold regularisation, an advanced machine learning technique,

the proposed solution improves detection accuracy for obstacle intrusions in complex, real-world environments where traditional systems may be challenged.

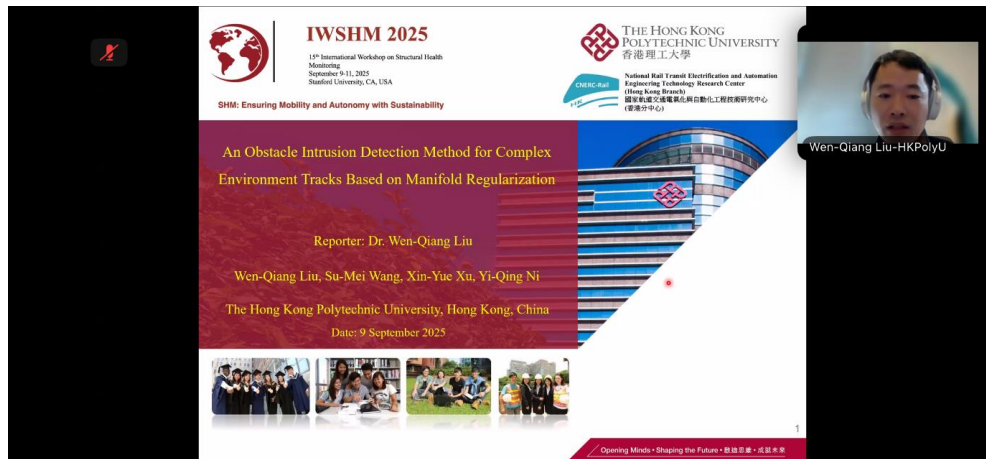


Fig. 3.13 Dr. Wen-qiang Liu attended the 15th IWSHM

Mr Liang LYU presented the paper, entitled “Noise Tomography Based Urban Ground Collapse Monitoring Using Distributed Acoustic Sensing”. This study demonstrates the feasibility of shallow S-wave tomographic imaging using ambient noise data, providing reliable prior information for engineering construction, urban underground space utilisation, and infrastructure disaster prevention monitoring.

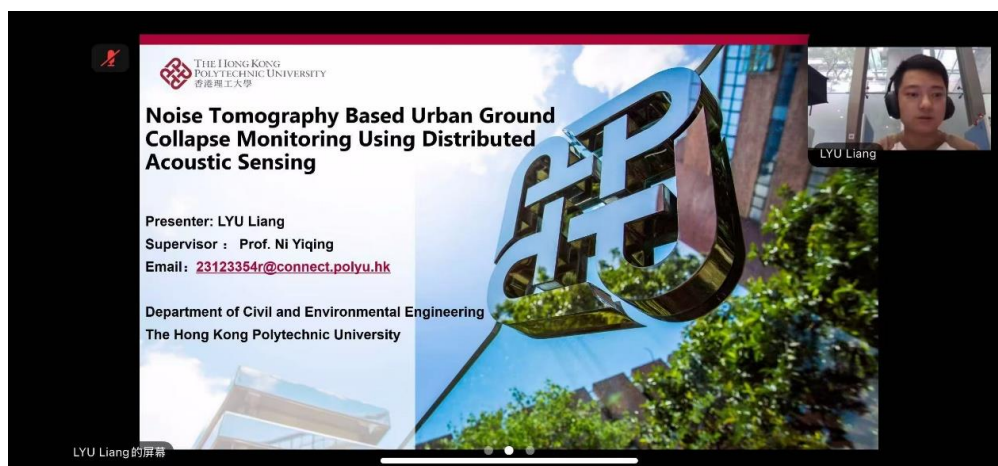


Fig. 3.14 Liang LYU attended the 15th IWSHM

Mr Jia-hao Lu presented the paper, entitled “Kolmogorov-Arnold Network-Aided Design of Conch Shell-Inspired Acoustic Metamaterial for Rail Noise Mitigation”.

This study presents a novel approach to AMM design, leveraging biomimetic principles and advanced machine learning techniques to address urban transportation noise challenges. By integrating conch shell-inspired cavity structures with porous sound dissipation mechanisms and employing KAN with PSO, we have developed an AMM that achieves broadband sound absorption. The optimised design consistently demonstrates absorption coefficients exceeding 0.8 across the critical 500-2000 Hz frequency range, significantly outperforming traditional noise mitigation strategies. Our methodology not only provides a framework for advanced acoustic material development but also demonstrates the potential of interdisciplinary approaches combining machine learning, biomimicry, and materials engineering in solving complex acoustic challenges.



Fig. 3.15 Mr. Jia-Hao Lu attended the 15th IWSHM

3.2.7 PolyU Technology Transfer Conference & Inaugural Annual Symposium of the Technology Innovation Institute

On 13th -14th December, 2025, to deepen industry–academia–research integration and promote the commercialisation of research outcomes, The Hong Kong Polytechnic University, in collaboration with the Hong Kong and Macao Affairs Office of the People’s Government of Fujian Province, held a two-day “PolyU Technology Transfer Conference & Inaugural Annual Symposium of the Technology Innovation Institute” in Jinjiang, Fujian.

A highlight of the showcase was the Foamed-Concrete Metamaterial Near-Track Sound Barrier, a core product developed under the RAISe+ Scheme of Hong Kong’s Innovation and

Technology Commission (ITC). The project, led by Prof. Yi-Qing Ni, our Center Director, was presented alongside its incubated spin-off company, Meta-Noise Technology Co., Ltd. Our center members, Dr. Si-Qi Ding and Dr. Xiao Wang were on-site to engage with attendees. They delivered comprehensive presentations on the technology’s innovative principles, key performance advantages, real-world applications, and commercial potential. The exhibit garnered significant interest and received enthusiastic feedback from industry experts, investors, and government officials.



Fig. 3.16



Fig. 3.17

3.2.8 Attended the 4th International Conference on Industrial Aerodynamics (ICIA 2025) in Qingdao

The 4th International Conference on Industrial Aerodynamics (ICIA 2025) was held in Qingdao, Shandong from 17th – 19th October, 2025.

The conference aimed to exchange the latest research advances and innovative achievements in the fields of wind engineering and industrial aerodynamics. It focused on key areas such as next generation high-speed trains, high-speed maglev trains, new concept vehicles, intelligent aerodynamics, structural wind engineering, air pollution control, and wind energy development and utilisation.

It showcased significant breakthroughs and cutting edge results achieved in recent years both domestically and internationally, promoted interdisciplinary integration and industry academia research collaboration, and facilitated the broad application of wind engineering and industrial aerodynamics in major equipment, green energy, smart transportation, environmental protection, and other fields. The conference also strengthened academic exchanges among researchers, educators, designers, and industry professionals from around the world, jointly contributing to the high quality innovative development of wind engineering and industrial aerodynamics.

Research Assistant Professor Zheng-Wei Chen attended ICIA 2025 as an invited guest and participated in the special session on “Aerodynamics of Maglev Transportation.” In this session, he delivered a presentation entitled “Research on Aerodynamic Characteristics and Dynamic Safety of High Speed Maglev Trains Under Complex Wind Conditions.”



Fig. 3.18 The 4th International Conference on Industrial Aerodynamics



Fig. 3.19 Research Assistant Professor Zheng-Wei Chen attended ICIA 2025

3.2.9 Prof. Yi-Qing Ni Delivers Keynote at National Conference on Structural Vibration Control

On 1st November, 2025, at the 11th National Conference on Structural Vibration Control and Health Monitoring in Wuhan University of Technology, Prof. Ni delivered an invited keynote titled “Integrated Air–Space–Ground Monitoring for Typhoon Early Warning of High Rise Building Clusters in Coastal Cities.” He shared his team’s latest advances in applying structural health monitoring technologies to high speed rail. The talk sparked lively discussion among experts, underscoring CNERC-Rail’s leadership in the field and enhancing the center’s academic impact while offering valuable guidance for industry technology development.

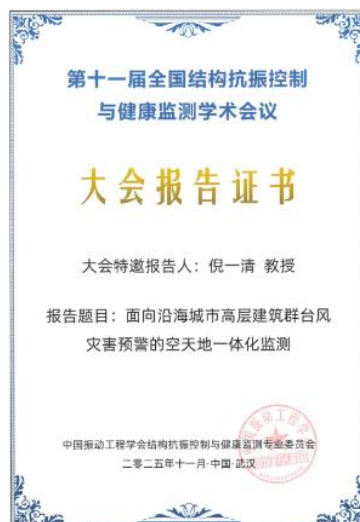


Fig. 3.20 Prof. Yi-Qing Ni’s certificate received from the 11th National Conference on Structural Vibration Control and Health Monitoring

3.2.10 Prof. Yi-Qing Ni Delivers Keynote on AI-Empowered Railway Talent Development at GGRTE2025

In the morning of 21st November 2025. Prof. Yi-Qing Ni from The Hong Kong Polytechnic University was invited to speak at the “Global Rail Talent Development Forum” of the Greater Bay Area International Rail Transit Exhibition (GGRTE2025). Prof. Yi-Qing Ni delivered a keynote speech titled “AI-Empowered Rail Transit: A New Paradigm for Talent Development,” sharing the team’s latest advances in maglev intelligent Q&A systems, tunnel defect detection, and acoustic metamaterial noise-reduction technologies. Prof. Ni highlighted that future rail transit professionals must integrate engineering fundamentals with data literacy, AI competence, and systems thinking. The conference presented Prof. Ni with an academic recognition certificate, and Dr Xiao Wang accompanied him throughout the event.



Fig. 3.21 Prof. Yi-Qing Ni Delivers Keynote on AI-Empowered Railway Talent Development at GGRTE2025

3.2.11 Prof. Yi-Qing Ni Delivers Keynote on the NSFC—BHKAEC Frontier Academic Forum

On 27 November, Prof Yi-Qing Ni was invited to attend and delivered a keynote titled “A Multi Source Data Driven Intelligent Disaster Mitigation System for Typhoons and Associated Hazards in Coastal Cities”, which sparked enthusiastic discussion and won unanimous acclaim from delegates.

With the theme of “Wind Energy Utilisation and Wind Disaster Mitigation,” the forum brought together experts and scholars from China and abroad to exchange ideas and discuss key scientific issues, including wind resource development and utilisation, prediction of complex wind fields and wind power optimisation, enhancement of wind power facilities’

performance under extreme disasters, integration of intelligent operation and maintenance technologies, and wind-resistant design of wind-sensitive structures.



Fig. 3.22 Prof. Yi-Qing Ni Delivers Keynote on the NSFC—BHKAEC Frontier Academic Forum

3.2.12 2025 Building Materials Industry Science and Technology Innovation Conference

On 3 December, Dr. Si-Qi Ding, a Research Assistant Professor of CNERC-Rail, attended the 2024 Building Materials Industry Science and Technology Innovation Conference held in Ningbo. Centering on the theme of “Innovation-Driven, Green Development: Promoting the Transformation of the Building Materials Industry System through High-Quality Development”, the conference aimed to pool industry wisdom, strengthen technical exchanges

and cooperation, and advance the in-depth integration of scientific and technological innovation and industrial innovation in the sector. The project “Intrinsic Self-Sensing Cement-Based Composites and Their Intelligent Structures”, in which Dr. Si-Qi Ding participated as a core member, was awarded the Second Prize for Basic Research in the Building Materials Science and Technology Awards.



Fig. 3.23 Dr. Si-Qi Ding attended the workshop and won the award

3.2.13 Prof. Yi-Qing Ni Delivers Keynote on the NSFC—BHKAEC Frontier Academic Forum

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Fig. 3.24 Prof. Yi-Qing Ni Delivers Keynote on the NSFC—BHKAEC Frontier Academic Forum



Fig. 3.25 CNERC-Rail won the Second Prize (Excellence Award)

3.2.14 Summary of Attended Conferences

Table 3.1 Summary of attended conferences

No	Conference	Host	Venue	Time	Participants
1	The 1st International Workshop on Bayesian Approach in Civil Engineering (IWOBA 2025)	CNERC-Rail	Hong Kong, China	2025.1.10-12	Prof. Yi-Qing Ni, Prof. Yong Huang, Dr. Bin-Bin Li, Dr. Hong-Wei Li
2	The 2nd International Workshop on Intelligent Tropical-Storm-Resilient Systems for Coastal Cities (INTACT 2025)	Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University	Hong Kong, China	2025.8.25-26	Prof. Yi-Qing Ni (Chair), Prof. Huan-Feng Duan, Prof. Song-Ye Zhu, Prof. Siu-Kai Lai, Dr Guang-Hao Zhai, Dr Jia-Yao Wang, Dr Imran Ghafoor, Dr Bin Lu, Prof. You Dong, Dr E Deng, Dr Yue Dong
3	International Workshop on Advanced Ground	Aristotle University of Thessaloniki	Thessaloniki, Greece	2025.7.2-4	Huaiyuan Zhou

	Penetrating Radar (IWAGPR2025)				
4	The 13th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII 13)	SHMII 2025 Organising Committee	Graz, Austria	2025.9.1-5	Dr Yuan-Jiang Zeng, Ms Pei-Lin Li, Dr Yuan-Jiang Zeng
5	The 5th Digital Twin International Conference (DigiTwin 2025)	DigiTwin 2025 Organising Committee	Garmisch-Partenkirchen, Germany	2025.10.14-18	Guanghao Zhai
6	The 15th International Workshop on Structural Health Monitoring (IWSHM 2025)	Stanford University	Stanford, CA, USA	2025.9.9-11	Dr. Wen-Qiang Liu, Liang Lyu, Jia-hao Lu
7	PolyU Technology Transfer Conference & Inaugural Annual Symposium of the Technology Innovation Institute	Hong Kong and Macao Affairs Office of the People's Government of Fujian Province	Fujian, China	2025.12.13~14	Prof. Yi-Qing Ni
8	The 4th International Conference on Industrial Aerodynamics (ICIA 2025)	ICIA 2025 Organising Committee	Qingdao, Shandong, China	2025.10.17-19	Dr. Zheng-Wei Chen
9	The 11th National Conference on Structural Vibration Control and Health Monitoring	Wuhan University of Technology	Wuhan, China	2025.11.1	Prof. Yi-Qing Ni
10	Global Rail Talent Development Forum, GGRTE 2025	Greater Bay Area International Rail Transit	Guangzhou, China	2025.11.21	Prof. Yi-Qing Ni

		Exhibition (GGRTE 2025)			
11	NSFC—BHKAEC Frontier Academic Forum	NSFC— BHKAEC Frontier Academic Forum Organising Committee	Hong Kong, China	2025.11.27	Prof. Yi-Qing Ni
12	2025 Building Materials Industry Science and Technology Innovation Conference	Conference Organising Committee	Ningbo, China	2025.12.3	Dr. Si-Qi Ding
13	CNERC-Rail Research Team Won the Second Prize (Excellence Award) at the 2nd International Innovation Competition on Structural Health Monitoring for Railway Systems	Under the guidance of the China Railway Society and CRRC Corporation Limited, and jointly organized by CRRC Qingdao Sifang Co., Ltd. and Central South University.	Singapore	2025.11.17	Prof. Ni Yi-Qing, Dr. Ao Wai Kei, Dr. Hu Yao, Mr. Jia-Hao Lu, and Mr. Yu-Hang Lu.

3.3 Cross Institute Technical Exchanges

3.3.1 City University of Hong Kong (CityU)

On January 22, 2025, Dr. E Deng, Dr. Yue Dong, Mr. De-Hui Ouyang, Mr. Xin-Yuan Liu, and Mr. Qian Xiang from CNERC-Rail (HK Branch) visited the City University of Hong Kong (CityU) for a research discussion meeting with Johnny C. L. Chan. During the meeting, the team presented and discussed their recent research progress. Prof. Chan expressed his recognition of the research achievements attained by the team and provided insightful suggestions on mechanistic interpretation, offering valuable guidance for subsequent studies.



Fig. 3.25 Prof. Johnny C. L. Chan in discussion with TRS project members

3.3.2 NVIDIA HK Ltd.

On April 15, 2025, the TRS project team of CNERC-Rail (HK Branch) and the NVIDIA team conducted a technical exchange at The Hong Kong Polytechnic University. During the meeting, members of the NVIDIA team provided detailed introductions to PhysicNeMo, data visualisation, and digital twin technologies, sharing recent advances in their applications to complex physical modelling and engineering practice. Subsequently, the TRS project team

reported on the recent progress in the development of the intelligent tropical storm mitigation system for coastal cities, with a focus on meteorological data storage and visualisation, the development and training of urban meteorological prediction models for Hong Kong, and the localised deployment and fine-tuning of DeepSeek. In the discussion session, both parties engaged in in-depth exchanges on intelligent analysis of multimodal meteorological data, three-dimensional meteorological visualisation and digital twin applications, as well as the training and optimisation of city-scale meteorological prediction models based on NVIDIA server platforms, laying a solid foundation for future collaboration on AI-enabled urban climate resilience research.



Fig. 3.26 NVIDIA HK Ltd. visited CNERC-Rail (HK Branch)

3.3.3 Zhejiang Communications Construction Group Co., Ltd.

On April 28, 2025, Zhejiang Communications Construction Group Co., Ltd. held an exchange meeting with the Department of Civil and Environmental Engineering (CEE) at The Hong Kong Polytechnic University (PolyU) in The Hong Kong Polytechnic University (PolyU). The meeting aimed to strengthen cooperation between the two parties in the field of engineering technology.

Participants: Zhejiang Communications Construction Group Co., Ltd.: Ms. Yanyan Liu (Deputy Party Secretary, Executive General Manager), Dr. Dong Liu (Deputy Chief Engineer, Director of the Quality and Technology Department (Research Institute)), Dr. Chunlin Xu (Director of the Quality and Technology Department (Research Institute)) and Dr. Tie Chen (Staff Member of the Quality and Technology Department (Research Institute)). Zhejiang Communications Investment Hong Kong Representative Office: Mr. Dehua Wang (Chief Representative) and Dr. Jian Bao (Director of Science and Innovation). Department of CEE, PolyU: Prof. Song-Ye Zhu (Associate Head (Research) and Professor), Prof. Zhen Leng (Professor, Associate Director of Research Center for Resources Engineering towards Carbon Neutrality), Dr. Ning Zhang (Research Assistant Professor), Dr. Si-Qi Ding (Research Assistant Professor), Dr. Wai Kei Ao (Research Assistant Professor), Dr. Qiu-Chan Meng (Research Assistant Professor), Dr. Zi-Xuan Liang (Postdoctoral Fellow, Department of Electronic and Information Engineering) and Dr. Lu Bai (Postdoctoral Fellow, Department of Aeronautical and Aviation Engineering).

Both parties engaged in an in-depth discussion on cutting-edge technologies such as intelligent transportation and green buildings, reaching a preliminary agreement on cooperation. They plan to promote technological innovation through resource sharing.



Fig. 3.27 Zhejiang Communications Construction Group Co., Ltd. visited CNERC-Rail (HK Branch)

3.3.4 Shenzhen Galaxy Twin Towers

On 12 May 2025, Dr. E Deng, Mr. Zi-Xuan Zeng, Mr. Hang Du, Mr. Ao Zheng, Ms. Ling-Yi Diao, and Mr. Min Deng from CNERC-Rail (HK Branch) visited the Shenzhen Galaxy Twin Towers to carry out the third phase of sensor installation. The team completed the installation of two accelerometers, an ultrasonic anemometer on the rooftop of the East Tower, and a near-infrared camera, followed by system inspection and commissioning. During the visit, the team met with Jian-Hua Gong (Vice President, Galaxy Industrial Group) and provided a detailed introduction to the research significance and engineering value of the monitoring system, as well as exchanged views on its subsequent operation and application.



Fig. 3.28 CNERC-Rail (HK Branch) members visited Shenzhen Galaxy Twin Towers

3.3.5 Shenzhen Metro Group Co., Ltd.

On 29 May 2025, Dr. Xiao-Ming Tan from CNERC-Rail (HK Branch) held a technical exchange on near-rail sound-absorbing low barriers with Mr. Keke Wang (Director, Shenzhen Metro Group Co., Ltd.). The discussion focused on key issues related to the engineering application of near-rail sound-absorbing low barriers in metro systems, including the structural stability of the barriers and their mounting brackets under metro-induced vibrations, the durability of foam concrete under long-term exposure to acid rain and solar radiation, the potential impacts of installation schemes on viaducts and track slabs, and compatibility with line maintenance and repair operations. It was further agreed to consolidate maintenance practices across all lines of Shenzhen Metro Group Co., Ltd., and to provide comprehensive installation and experimental plans (including relevant qualifications and assessment reports) for internal evaluation. Finally, the project team applied to conduct on-site inspections and identify suitable installation locations along the metro lines after the Dragon Boat Festival, which was approved by the counterpart.



Fig. 3.29 CNERC-Rail (HK Branch) members visited Shenzhen Metro Group Co., Ltd.

3.3.6 Shenzhen Metro Group Co., Ltd.

On 4 June 2025, a delegation comprising Dr. Si-Qi Ding, Dr. Wei-Ji Ou, Dr. Xiao-Ming Tan, Dr. Yun-Fan Yang, and Dr. Jia-Hao Lu from CNERC-Rail (HK Branch) conducted an on-site inspection and research visit. The team visited Shenzhen Metro Line 11 and subsequently toured Taizhou Dongdian Rubber Co., Ltd., including its production workshops and laboratories. The visit focused on systematically examining the manufacturing processes and

performance testing methods of rail transit rubber pads, providing practical references for related engineering applications and future research.



Fig. 3.30 CNERC-Rail (HK Branch) members visited Shenzhen Metro Group Co., Ltd. (Line 11).

3.3.7 Shenzhen Metro Group Co., Ltd.

On August 13, 2025, Dr. Si-Qi Ding, Dr. Xiao-Ming Tan, Dr. Shuo Hao, and Mr. Yu-Ling Wang from CNERC-Rail (HK Branch) visited the Shenzhen Metro repair center to meet with engineers led by Mr. Xin-Lei He. The meeting focused on the research and development of near-rail foam concrete noise barriers, as well as the installation plan and noise testing strategy for Line 11.

Mr. He and the three other engineers expressed their approval of the current proposal and agreed to report it to their leadership to advance the application of the noise barriers on Line 11.



Fig. 3.31 CNERC-Rail (HK Branch) members visited the Shenzhen Metro repair center

3.3.8 Guangzhou Metro Group Co., Ltd.

On August 21, 2025, Dr. Wai Kei Ao, Mr. Yu-Hang Lu, and Mr. Guang Zhou from CNERC-Rail (HK Branch) visited the Guangzhou Metro Line 3 depot alongside to review the installation plan for an ATC beam on a Guangzhou Metro train body. They also assessed the feasibility of deploying an FBG sensing system on the beam to detect potential deformations once installed on the bogie (pending final confirmation from the client, Guangzhou Metro). This marks the first application of fibre-reinforced lightweight materials in a bogie component for Guangzhou Metro. A six-month FBG-based monitoring plan will be implemented to ensure stability and safety.



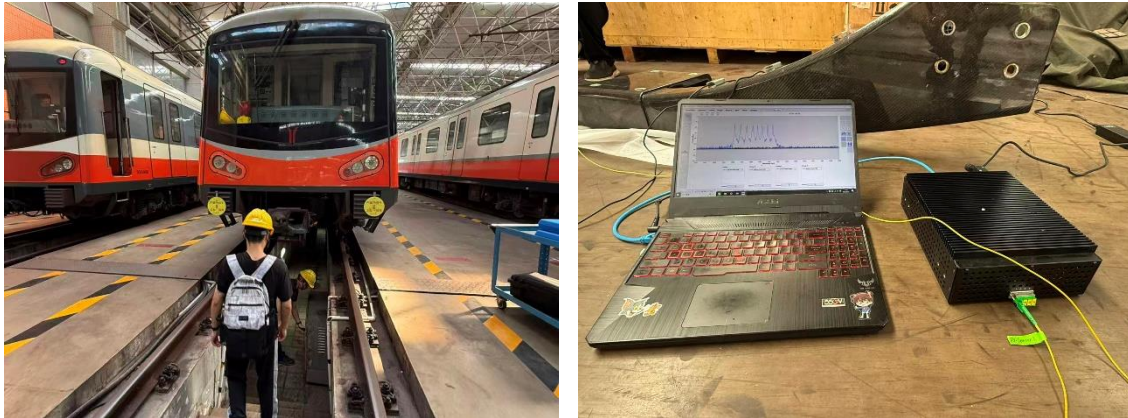


Fig. 3.32 CNERC-Rail (HK Branch) members visited the Guangzhou Metro Line 3

3.3.9 Prof. Ashraf El Damatty

On August 28, 2025, Prof. Ashraf El Damatty held an academic exchange meeting with members of the TRS project team of the CNERC-Rail (HK Branch), including Dr. E Deng, Dr. Yue Dong, Dr. Xiu-Yu Chen, Dr. Guang-Hao Zhai, Dr. Imran Ghafoor, Mr. Lei Yuan, Mr. De-Hui Ou-Yang, Mr. Huan Yue, Mr. Xin-Yuan Liu, Mr. Zi-Xuan Zeng, Mr. Wei-Jia Zhang, and Mr. Min Deng. During the meeting, the team systematically presented several recent research advances. These included the development and operation of the real-time monitoring system for the Shenzhen Galaxy Twin Towers, featuring multi-source measurements of wind speed, wind pressure, structural acceleration, and displacement, which successfully captured structural responses during the Qingyuan earthquake in 2025 and Typhoon Wipha. The team also reported on the rainfall monitoring system and observations during black rain events, highlighting the pronounced spatial variability of rainfall in Hong Kong and the public's demand for more effective early-warning capabilities. In addition, progress on a high-resolution meteorological database and forecasting system was introduced, integrating data from LiDAR, ground meteorological stations, and satellite observations within a WRF-based data assimilation framework to construct a 40-year, 1-km-resolution comprehensive meteorological database, together with a tiered forecasting approach from the global scale (27 km) to the city scale (1 km). The team further presented findings on coastal stalling typhoons, noting a marked increase over the past 44 years and attributing this trend to the characteristics of near-shore wind fields and moisture structures.

In the discussion session, Prof. El Damatty focused on the implications of climate change for future structural design codes, suggesting the use of large-scale meteorological models to predict wind-speed evolution over the next 50 years. Regarding the performance of the tuned

liquid dampers installed in the Shenzhen Galaxy Twin Towers, he recommended the installation of wave probes to monitor liquid-level variations. In terms of collaboration, Prof. El Damatty proposed initiating an online academic exchange meeting to share research outcomes and clarify potential collaboration directions, followed by data sharing by the TRS team in compliance with relevant requirements to further advance joint research. The meeting featured in-depth discussions and fruitful exchanges, laying a solid foundation for future collaboration in areas such as structural resilience, assessment of climate-change impacts, and multi-source monitoring integration.



Fig. 3.33 Prof. El Damatty visited CNERC-Rail (HK Branch)

3.3.10 Shenzhen Metro Qiaochengdong Rolling Stock Depot

On September 3, 2025, Dr. Zheng-Wei Chen and Dr. Jun Peng from CNERC-Rail (HK Branch) visited the Qiaocheng East Depot Overhaul Center of Shenzhen Metro. They held detailed discussions and conducted an on-site survey with key personnel, including Mr. Yongkui Duan (Deputy General Manager of the Overhaul Center, Shenzhen Metro), Mr. Xianglin Zeng (Supervisor at the Shenzhen Metro Overhaul Center), Mr. Zhengyi Liu (Secretary-General of the Southwest Jiaotong University Guangdong Alumni Association and System Architect at Huawei's Transportation Corps), and Dr. Suping Li (Researcher at the Southwest Jiaotong University Shenzhen Research Institute and the Chief Technology Officer of the MTR-Shenzhen & SWJTU SZRI Rail Transit Innovation Base). The discussions focused on core issues such as the project requirements, technical solutions, and intellectual property ownership arrangement for the 2025 Jie Bang Gua Shuai (i.e., Open Innovation Challenge) Project - Intelligent Bogie Inspection Sub-Project" of Shenzhen Metro Group. The meeting pinpointed the pain points and core demands in the depot's maintenance operations, charting the course for potential future in-depth collaboration.



Fig. 3.34 CNERC-Rail (HK Branch) members visited Qiao cheng-dong Depot

3.3.11 CRRC Corporation Limited (CRRC)

On September 10, 2025, a delegation led by Mr. Yin Tian (Director of the Technology Department) and Mr. Haichuan Tang (Head of the Artificial Intelligence Research Office from the CRRC Research Institute) visited CNERC-Rail (HK Brnch) for technical cooperation and exchange (Fig. 3.35). CNERC-Rail members including Dr. Wen-Qiang Liu, Dr. Zhi Li, Dr. Si-Yi Chen, Dr. Da-Zhi Dang had a meeting with the delegation.

The parties held in-depth discussions on technologies such as energy harvesting and large models for bridges and tunnels. They also explored future project collaboration models and technical implementation plans.



Fig. 3.35 Delegation from CRRC visited CNERC-Rail (HK Branch)

3.3.12 Huizhou City Wing Hong Shun Construction Materials Co., Ltd.

On September 16, 2025, Dr. Xiao Wang, Dr. Si-Qi Ding, Mr. Jia-Hao Lu, and Mr. Yu-Ling Wang from CNERC-Rail (HK Branch) visited Huizhou City Wing Hong Shun Construction Materials Co., Ltd. for an inspection and survey. They discussed the mass production of foam concrete near-rail sound-absorbing low walls with Factory Director Ms. Julian Lee.



Fig. 3.36 CNERC-Rail (HK Branch) members visited Huizhou City Wing Hong Shun Construction Materials Co., Ltd.

3.3.13 Qiaocheng East Depot Overhaul Center of Shenzhen Metro

On October 15, 2025, CNERC-Rail postdoctoral researchers Dr. Jun Peng, Dr. Xiao Wang, Dr. Hongmin Zhu, and Dr. Dazhi Dang from CNERC-Rail (HK Branch) visited the Qiaocheng East Depot Overhaul Center of Shenzhen Metro. They held detailed discussions at Shenzhen Metro Qiaocheng East Depot regarding key issues regarding the bogie handover details and contract signing milestones for the under 2025 Jie Bang Gua Shuai Project - Intelligent Bogie Inspection Sub-Project" of Shenzhen Metro Group.

The meeting confirmed that the project recruitment will call for submissions in December 2025, with group discussions scheduled for January 2026 and the contract signing set for February 2026. It was further communicated that the bogies would initially be transported to The Hong Kong Polytechnic University Shenzhen Research Institute on a loan basis (delivery within one week after signing the loan agreement) and later formally included as essential research equipment through a supplementary agreement in the project recruitment contract.

Additionally, an on-site assessment was conducted to evaluate the feasibility and specific details of the ultrasonic inspection solution.

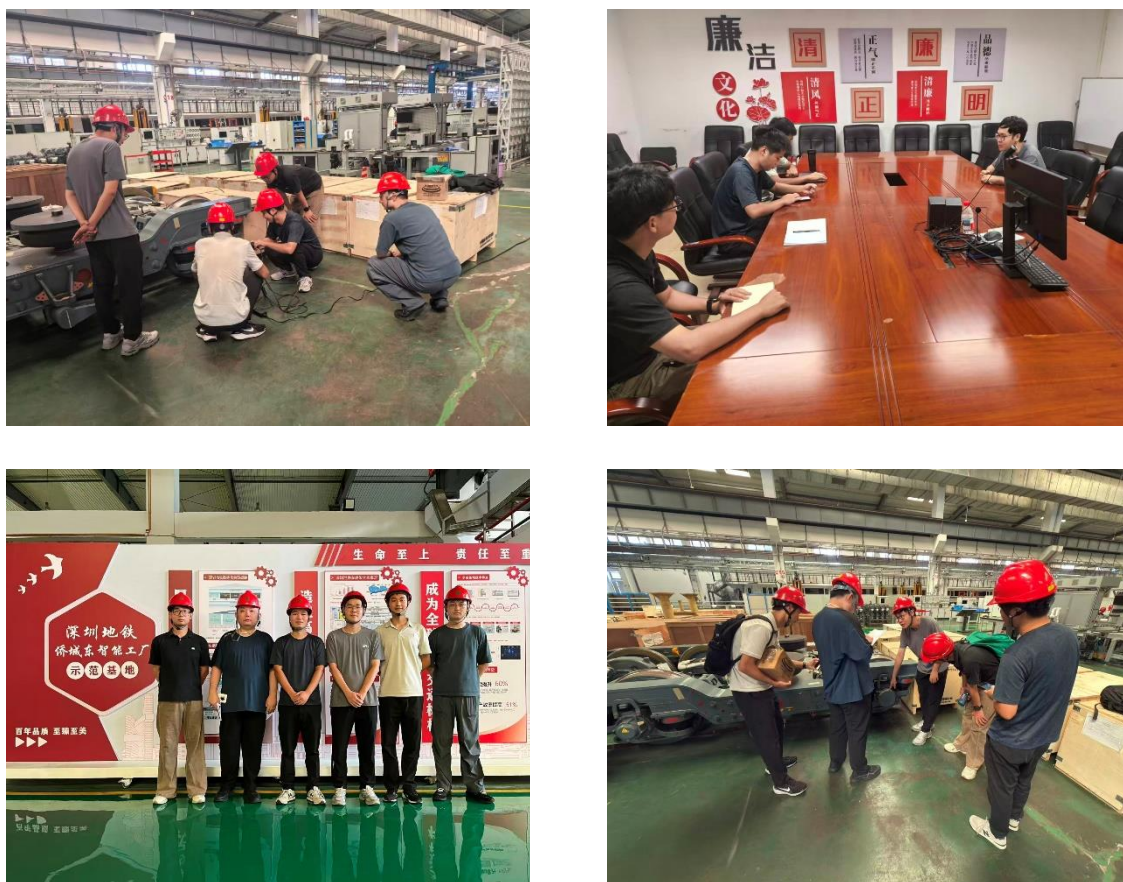


Fig. 3.36(b)

3.3.14 Delegation from Research Grants Council (RGC)

On October 21, 2025, the RGC panel members visited CNERC-Rail (HK Branch) to conduct a mid-cycle review of the TRS project (Fig. 3.37). Project members from the CNERC-Rail and other collaborating institutions reported the progress and key achievements of each research task, demonstrating the urban LiDAR observation network, UAV monitoring equipment, and glass impact test results, and engaged in in-depth discussions with the review experts.



Fig. 3.37 RGC Expert Delegation Visits the Hong Kong Polytechnic University

3.3.15 The Hong Kong Polytechnic University Hangzhou Technology and Innovation Research Institute

On November 10, 2025, Dr. E Deng from CNERC-Rail (HK Branch) visited The Hong Kong Polytechnic University Hangzhou Technology and Innovation Research Institute and met Mr. Xiu-Ming Yang. They conducted tests on thin-film wind pressure sensors and discussed relevant technical details as well as current challenges.



Fig. 3.38 Technical Testing and Discussion on Thin-Film Wind Pressure Sensors at Hangzhou Research Institute

3.3.16 Taizhou Xingkong Zhilian Technology Co., Ltd.

On November 11, 2025, Prof. Yi-Qing Ni, Director of CNERC-Rail (HK Branch), and Dr. E Deng (Research Fellow) from CNERC-Rail (HK Branch) visited Taizhou Xingkong Zhilian Technology Co., Ltd. for technical exchange. Taizhou Xingkong Zhilian Technology Co., Ltd. is a technology innovation enterprise under Zhejiang Geespace Technology Co., Ltd. During the visit, they toured the company's satellite manufacturing facility and presented the specific technical service and product requirements of the TRS project related to satellite applications. Subsequently, both parties engaged in detailed discussions regarding these needs.



Fig. 3.39 CNERC-Rail (HK Branch) members visited Taizhou Xingkong Zhilian Technology Co., Ltd.

3.3.17 Qiaotou Station on Shenzhen Metro Line 11

On November 20, 2025, Dr Si-Qi Ding, Dr Xiao Wang, Dr Xiao-Ming Tan, Mr. Jia-Hao Lu, and Mr. Yu-Ling Wang from CNERC-Rail (HK Branch) visited Qiaotou Station on Shenzhen Metro Line 11 to conduct an on-site survey. Based on field observations, the installation environment at Qiaotou Station is overall superior to that at Shajing Station, with

more favorable conditions. In light of the site realities, we have preliminarily formulated an installation plan for sound-absorbing low walls suitable for this station.

Next, we will maintain close coordination with Shenzhen Metro and the contractor to complete the construction safety agreement and obtain the construction permits as soon as possible.



Fig. 3.40 Site Investigation Conducted at MTR Line 11 Qiaotou Station for Acoustic Barrier Installation Planning

3.3.18 Delegation from the Merck KGaA and OASES

On November 21, 2025, a delegation from the Merck KGaA and OASES visited CNERC-Rail (HK Branch) (Fig. 3.41). Dr. Wai Kei Ao (Research Fellow) presented the latest research achievements related to ongoing Hong Kong MTR projects, vibration and acoustic-based health monitoring, Maglev, camera–LiDAR vision–based monitoring techniques, noise-mitigation technologies, and more, with a particular emphasis on the development and application of AI-driven solutions.



Fig. 3.41 Delegation from the Merck KGaA and OASES

3.3.19 NVIDIA HK Ltd.

On November 26, 2025, Dr. Charles Cheung, Dr. Ivan Au-Yeung and Dr. Ginny from NVIDIA visited CNERC-Rail (HK Branch) (Fig. 3.42). Dr. Guan-Hao Zhai, Dr. E Deng, Dr. Yue Dong, Dr. Xiao Wang, Dr. Xiao-Ming Wang, Dr. Si-Ying Chen, Dr. Yao Hu, Dr. Zhi Li, Dr. Qi-Wu Zhu, Dr. Wei-Jia Zhang, Dr. Lei Yuan, Mr. Huan Yue, Mr. Huai-Yuan Zhou, Mr. Yi-Ting Xiang and Mr. Jian Wang from CNERC-Rail (HK branch) warmly welcomed them and had a meeting. The meeting focused on presenting the latest research progress in large-scale meteorological models and discussing the implementation framework and key considerations for AI Agents. In addition, participants engaged in in-depth exchanges on the applications of large models in areas such as high-rise buildings, bridges and tunnels.



Fig. 3.42 Delegation from NVIDIA

3.3.20 Delegation from Qingdao Leice Transient Technology Co., Ltd

On December 8, 2025, Prof. Song-Hua Wu (Chairman of Qingdao Leice Transient Technology Co., Ltd.) led a delegation and visited CNERC-Rail (HK Branch) for a technical

collaboration meeting (Fig. 3.43). The delegation includes Mr. Rong-Zhong Li (General Manager), Dr. Qi-Chao Wang (Deputy General Manager), Ms. Li-Li Jia (Deputy General Manager), Ms. Fang Tan, and Mr. Wei Zhou.

Prof. Yi-Qing Ni, Dr. E Deng, Dr. Yue Dong, Dr. Xiu-Yu Chen, and members of the TRS project team, Prof. Ruo-Yu You (BEEE) and Dr. Yu Wang (BEEE) attended the meeting. The discussion centered on LiDAR-based monitoring technologies in the fields of meteorology, environmental science, wind energy, and aviation. Prof. Yi-Qing Ni and Prof. Song-Hua Wu also exchanged views on the application prospects of LiDAR in Hong Kong's Northern Metropolis, paving the way for deeper collaboration in the future.



Fig. 3.43 Delegation from Qingdao Leice Transient Technology Co., Ltd.

3.4 Organised Lectures

3.4.1 Lecture by Prof. Zhi-Shen Wu from Southeast University

On January 3, 2025, Prof. Zhi-Shen Wu from Southeast University, invited by CNERC-Rail (HK Branch), presented a lecture titled "Fiber-Optic FRP Self-Sensing Technologies and Innovative Applications: Structural Enhancement and Health Monitoring". He introduced a

series of key technologies associated with basalt fibers, aiming at achieving superior performance, stabilisation, and large-scale production.



Fig. 3.44 Prof. Zhi-Shen Wu at the lecture venue

3.4.2 Lecture by Prof. Michael Beer from Leibniz University of Hanover

On April 2, 2025, Prof. Michael Beer, the director of the Institute of Risk and Reliability at Leibniz University of Hanover, Germany, invited by CNERC-Rail (HK Branch), presented a lecture titled "Keys to Successful Publication," sharing important experiences and strategies for academic publishing.



Fig. 3.45 Prof. Michael Beer at the lecture venue

3.4.3 Lecture by Prof. Bill Spencer from the University of Illinois Urbana-Champaign

On May 2, 2025, Prof. Bill Spencer from the University of Illinois Urbana-Champaign, invited by CNERC-Rail (HK Branch), presented a lecture titled "Energy-efficient Autonomous Framework for Monitoring Railroad Bridges in the U SA using Wireless Smart Sensors".

Prof. Bill Spencer, a renowned expert in structural health monitoring and cyberinfrastructure applications, introduced an innovative monitoring system for railway bridges using wireless smart sensors. This system overcomes the challenges of remote data acquisition and autonomous operation to provide a cost-effective and efficient solution for bridge monitoring.



Fig. 3.46 Prof. Bill Spencer at the lecture venue

3.4.4 Lecture by Prof. Fernando Moreu from the University of New Mexico

On May 12, 2025, Prof. Fernando Moreu, an Associate Professor at the University of New Mexico visited CNERC-Rail (HK Branch) and presented a lecture titled “Integration and Control of Dynamics and Pattern Recognition with Immersive Platforms”.

Prof. Fernando Moreu, a distinguished expert in structural dynamics, control, and cyber-physical systems, presented his latest research on human-computer interfaces for quality inspection aided by robotics applications. This research enhances human decision-making through AI and machine-enabled visual analysis, providing innovative solutions for structural health monitoring and robotic programming.



Fig. 3.47 Prof. Fernando Moreu at the lecture venue

3.4.5 Lecture by Dr. Jun Yang from Loughborough University

On May 21, 2025, Dr. Jun Yang from Loughborough University visited CNERC-Rail (HK Branch) and presented a lecture titled “Safety-Critical Control Under Disturbances.” He introduced the importance of safety-critical control, control methods based on control barrier functions (CBF), and their applications in robotics and port automation.



Fig. 3.48 Dr. Yang Jun at the lecture venue

3.4.6 Lecture by Prof. Zhen-Lei Chen from the Ningbo University

On August 25, 2025, Prof. Zhen-Lei Chen from the Ningbo University visited CNERC-Rail (HK Branch) and presented a lecture titled “Thermo-Compensation for CNC Machine Tools via Fluid–Structure Interaction and Deep Learning”. He presented his team’s innovative achievements in high-speed and high-precision machining environments. By developing deep learning models, the team successfully predicted machine tool thermal growth and workpiece errors, derived real-time thermal compensation formulas, and ultimately developed a practically applicable compensation system.





Fig. 3.49 Prof. Zhen-Lei Chen at the lecture venue

3.4.7 Lecture by Prof. De-Zong Zhao from the University of Glasgow, UK

On 1 Sep 2025, Prof. De-Zong Zhao from the University of Glasgow, UK, invited by CNERC-Rail (HK Branch), presented a lecture titled “Efficient, Safe, Trustworthy and Causal Autonomous Systems”. The event featured who presented his team’s latest advances in multi-source perception, trustworthy modelling and real-time decision-making for autonomous driving and robotic systems. Prof. Zhao also outlined prospects for deploying digital twins and smart-transport solutions.



Fig. 3.50 Prof. De-Zong Zhao at the lecture venue

3.4.8 Lecture by Prof. Der-Shen Yang from Tongji University

On October 3, 2025, Prof. Der-Shen Yang from Tongji University, invited by CNERC-Rail (HK Branch), presented a lecture titled “Smart Sensing of Bridges under Vehicle–Bridge Interaction”. The event featured, who delivered an insightful presentation on recent advances in inclined bridge dynamics, dual-resonance mechanisms in vehicle–bridge systems, and damage detection techniques based on elliptic filtering and wavelet transforms.

During the seminar, Prof. Yang further explored emerging applications of AI and lightweight sensing in structural health monitoring, stimulating active discussion among participating faculty and students. The Q&A session provided a productive exchange of ideas on intelligent sensing and its engineering implementation. The seminar served as a valuable platform for academic dialogue and was well received by the audience.

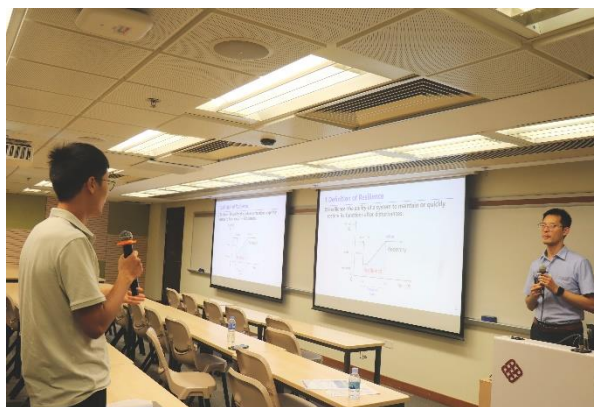
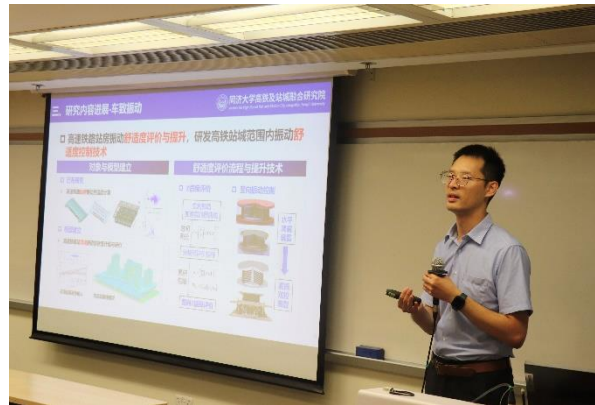




Fig. 3.51 Prof. Der-Shen Yang at the lecture venue

3.4.9 Lecture by Prof. Yi-Qing Ni at the Global Rail Talent Development Forum

On November 21, 2025, Prof. Yi-Qing Ni, Director Of CNERC-Rail (HK branch), delivered a presentation titled “AI-Empowered Rail Transit: A New Paradigm for Talent Development” at the forum. In his talk, he introduced the team’s latest research achievements in areas including intelligent Q&A systems for maglev transportation, tunnel damage identification, and acoustic metamaterial noise-reduction technologies. Prof. Ni emphasised that future rail transit professionals should possess integrated capabilities combining solid engineering fundamentals, data literacy, and artificial intelligence competence, highlighting the importance of interdisciplinary talent development for the next generation of rail transit systems.





Fig. 3.52 Prof. Yi-Qing Ni at the lecture venue

3.4.10 Lecture by Prof. Solomon Tesfamariam from the University of Waterloo

On December 3, 2025, Prof. Solomon Tesfamariam from the University of Waterloo, Canada, invited by CNERC-Rail (HK Branch), presented a lecture titled "Tall Timber Buildings: Past, Present and Future." The seminar featured as the keynote speaker. He systematically presented the current development of tall timber buildings, the advantages of new CLT and glulam systems in mid- to high-rise construction, as well as the applicability and limitations of NBCC 2020 performance-based design in hybrid timber structures.

During the lecture, Prof. Tesfamariam further shared insights into multi-hazard design philosophies for earthquakes, wind, and fire, and discussed future resilience-based design directions for timber structures, which sparked strong interest among the attending faculty and students. The lecture provided a valuable platform for academic exchange in the field and was highly praised by all participants.



Fig. 3.53 Prof. Solomon Tesfamariam at the lecture venue

3.4.11 Other Lectures

Table 3.2 Summary of other lectures

Time	Theme	Lecture	Conference	Venue
2025-07-15	Guided Wave Testing and Evaluation for Railway Tracks	Prof. Yi-Qing Ni	14th Asia-Pacific-Euro Summer School on Smart Structures Technology (APESS2025)	Hong Kong, China
2025-11-28	Enhancing Acoustic Comfort in Urban Rail Systems: A Metamaterial-empowered Holistic Approach	Dr. E Deng, Dr. Si-Qi Ding	Robot Dexterous Applications & Iontronic E-Skin Technology Seminar	Shenzhen, China

3.5 Visiting Scholars & Delegations

3.5.1 Delegation from the Office for Attracting Strategic Enterprises (OASES) and HollySys Transportation International Limited

On 12 March 2025, Mr. Eric Leung, Deputy Chief Manager (Advanced Manufacturing and New Energy Technology) from OASES, which is under The Government of the Hong Kong Special Administrative Region of the People's Republic of China, and Mr. Jia-Yuan Zhou, Deputy General Manager and Business Development Director) from HollySys Transportation International Limited, which is under Beijing HollySys Co., Ltd., visited the CNERC-Rail (HK Branch) (Fig. 3.55).

Dr. Su-Mei Wang (Research Assistant Professor) and Dr. Wai Kei Ao (Research Assistant Professor) have introduced related research of CNERC-Rail. The OASES, HollySys and CNERC-Rail had engaged in an in-depth discussion.



Fig. 3.54 Mr. Eric Leung from OASES and Mr. Jia-Yuan Zhou from HollySys Transportation International Limited

3.5.2 Delegation from South China University of Technology

On March 14, Prof. Hongwu Tang, President and Deputy Party Secretary of South China University of Technology, led a delegation to visit the CNERC-Rail (HK Branch) (Fig. 3.56). The delegation includes Prof. Xiaohu Yao (Dean of the School of Civil and Transportation Engineering), Prof. Guangming Chen (Professor of the School of Civil and Transportation Engineering) and Prof. Nengwu Zhu (Executive Vice Dean of the School of Environment and Energy). Prof. Yi-Qing Ni, the center's director, Dr. Su-Mei Wang (Research Assistant Professor) and Dr. Si-Qi Ding (Research Assistant Professor) warmly welcomed the delegation and introduced the center's key research areas, latest achievements, and related research facilities.



Fig. 3.55 Delegation from South China University of Technology

3.5.3 Delegation from China Tower

On March 17, 2025, a delegation from China Tower visited the CNERC-Rail (HK Branch) (Fig. 3.57). The delegation includes Mr. Xiaobing Fang (Independent Non-Executive Director), Mr. Chunbo Dong (Independent Non-Executive Director), Ms. Wei Zhang (Independent Non-Executive Director), and Ms. Huazi Liu (General Manager of Human Resources Department,

Guangdong Branch). Both sides engaged in discussions on issues such as the transformation of research achievements and engineering innovation.



Fig. 3.56 Delegation from China Tower

3.5.4 Delegation from CITIC Group

On March 27, 2025, a delegation of senior leaders from CITIC Group visited the CNERC-Rail (HK Branch) (Fig. 3.58). The delegation includes Mr. Guo-Hua Xi (Chairman of CITIC Group), Mr. Wenwu Zhang (President of CITIC Group), Mr. Guoquan Wang (Vice President of CITIC Group), Mr. Dan Liang (Director of General Office, CITIC Group), Mr. Lei Zhao (General Manager of Technology and Digitalisation Department of CITIC Group), and Mr. Hanqi WU (Chairman of CITIC Heavy Industries), among others. Both sides had an in-depth exchange on the latest research results in railway electrification and automation technology, future cooperation directions, and industry development trends, aiming to promote cooperation between industry, academia, and research and technological innovation.



Fig. 3.57 CITIC Group

3.5.5 Delegation from the Zhejiang's Hangzhou City

On April 14, 2025, a delegation from Zhejiang's Hangzhou City visited the CNERC-Rail (HK Branch) (Fig. 3.59). The delegation includes Mr. Biao Hu (Deputy Director of the Hangzhou Science and Technology Bureau), Ms. Yanfang Xuan (Director of the Education, Science, and Culture, Hangzhou Finance Bureau), Mr. Zhang Ruikai (Director of the Gongshu District Science and Technology Bureau), Mr. Zifa Chen (Level II Researcher of Hangzhou Science and Technology Bureau), Ms. Weixia Shen (Deputy Director of the Shangcheng District Science and Technology Bureau, Hangzhou), Mr. Jianzhi Shen (General Manager of Hangzhou West Port·Great Future Technology Co., Ltd), Mr. Yebiao Xu (Deputy General Manager), and Mr. Jiawei Jin (General Manager of the CETC Innovation Fund). Both parties engaged in an in-depth dialogue on the cutting-edge breakthroughs in railway electrification and automation technology, collaborative innovation pathways among industry, academia, and research, and industry upgrading trends. They focused on discussing technical transfer application plans and the framework for strategic cooperation, jointly committing to building a joint technological innovation entity.



Fig. 3.58 Delegation from the Hangzhou Municipal Government

3.5.6 Delegation from Phoenix TV

On April 16, 2025, Mr. Li Qi (Executive Vice President and Chief Operating Officer of Phoenix TV), Mr. Haibo Huang (Deputy Head and Director of Chief Editor's Office, the Chinese Channel; Head of Movie Channel), and Mr. Xinxin Xu (CEO of Phoenix Show) visited the CNERC-Rail (HK Branch) (Fig. 3.60). Prof. Yi-Qing Ni, the director of the Center, received the guests and introduced in detail the Center's cutting-edge research achievements in railway electrification and automation.



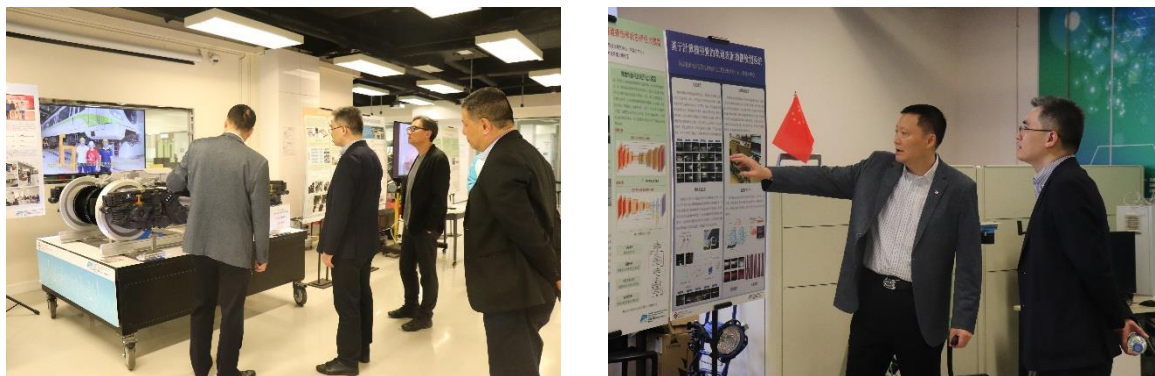


Fig. 3.59 Delegation from Phoenix TV

3.5.7 Delegation from School of Civil Engineering and Mechanics, Lanzhou University

On May 16, 2025, Prof. Jizeng Wang led a delegation from the School of Civil Engineering and Mechanics at Lanzhou University visited the CNERC-Rail (HK Branch) (Fig. 3.61). Dr. Su-Mei Wang warmly received the delegation and provided a detailed introduction to the Center's cutting-edge research achievements and future development directions in the relevant fields. The visiting team expressed high admiration for the Center's research capabilities and achievements and conveyed their strong interest in further cooperation and exchange.



Fig. 3.60 Delegation from School of Civil Engineering and Mechanics, Lanzhou University

3.5.8 Delegation from CRRC Corporation Limited (CRRC)

On June 6, 2025, members of the CRRC delegation, including Mr. Mingming Yang (Deputy Director of CRRC Science and Technology Department), Mr. Mingyuan Zhao (Deputy Director of CRRC Research Institute), Mr. Baibo Liu (Deputy Director of Technology Department, CRRC Research Institute), and Mr. Jinfeng Zhao (General Manager of CRRC Sifang Hong Kong Branch), visited the CNERC-Rail (HK Branch) (Fig. 3.62). Dr. You-Wu Wang, Dr. Si-Qi Ding, Dr Wai Kei Ao, and Dr. Wen-Qiang Liu warmly received the visiting team and introduced the center's cutting-edge research achievements and development direction in relevant fields. The visiting team highly praised the center's research strength and achievements and expressed their willingness to further cooperate and exchange.



Fig. 3.61 Delegation from CRRC

3.5.9 Delegation from Guangzhou City University of Technology Green Intelligent Transportation School

On July 7, 2025, a delegation from the Green Intelligent Transportation School of Guangzhou City University of Technology, including Haoyu Zhang (Associate Dean), Shen Na (Vice President), Xiqun Lin (Secretary of the Party Branch and Vice President of the School of Automotive and Transportation Engineering), Weihua Li (Deputy Secretary of the Party Branch and Vice President of the School of Civil Engineering), Ye He (Teacher), Tang Wenjun (Teacher), and student representatives, visited CNERC-Rail(HK Branch) (Fig. 3.63).

Dr. Wai Kei Ao (Research Assistant Professor) from CNERC-Rail warmly received the delegation. The purpose of this activity was to learn about cutting-edge achievements in railway transportation, promote academic exchanges, enhance professional quality, and promote the development of the school.



Fig. 3.62 Delegation from Guangzhou City University of Technology Green Intelligent Transportation School

3.5.10 Delegation from Shanghai University of Applied Sciences

On July 10, 2025, a delegation from Shanghai Shanghai University of Applied Sciences, including Prof. Xiaofan Wang (President), Prof. Qingchang Chen (Director of International

Exchange Office), and Prof. Li Peigang (Vice President of the School of Rail Transit Engineering), visited CNERC-Rail (HK Branch) (Fig. 3.64). They met with Prof. Jin-Guang Teng (President of PolyU), Prof. Yi-Qing Ni (Director of CNERC-Rail (HK Branch) and Chair Professor from Department of Civil and Environmental Engineering), Prof. Cheng-Qi Zhang (Chair Professor of the Department of Data Science and Artificial Intelligence), Prof. You Dong (Associate Professor from Department of Civil and Environmental Engineering), Prof. Kai Zhou (Assistant Professor from Department of Civil and Environmental Engineering), and Prof. Haitian Lu (Director of Mainland Development Office) to discuss cooperation. The visit promoted understanding and cooperation between Shanghai University of Applied Sciences and Hong Kong Polytechnic University, with in-depth discussions on future cooperation opportunities and a preliminary consensus reached. The delegation expressed gratitude for the warm reception by Hong Kong Polytechnic University and looked forward to further cooperation.



Fig. 3.63 Delegation from Shanghai Institute of Technology

3.5.11 Delegation from China University of Mining and Technology

On July 23, 2025, Prof. Qi-Ang Wang led a delegation from the School of Mechanics and Civil Engineering at the China University of Mining and Technology visited the CNERC-Rail (HK Branch) (Fig. 3.65). Dr. Zheng-Wei Chen and Dr. Hong-Wei Li from CNERC-Rail (HK Branch) warmly welcomed the group.

During the meeting, both parties discussed intelligent railway power supply, infrastructure health monitoring, and low-carbon operation and maintenance (O&M) in depth. The visitors were then given a tour of CNERC-Rail laboratories, where Dr. Chen and Dr. Li showcased the TRS project, self-sensing concrete, vibration-energy harvesters, and the intelligent train-bogie monitoring system.

Prof. Qi-Ang Wang noted that the visit offered top-tier students' invaluable exposure to frontline international research and expressed the hope of working closely with PolyU to advance high-quality national rail-transport development.



Fig. 3.64 Delegation from China University of Mining and Technology

3.5.12 Delegation from Liaison Office of the Central People's Government in the Hong Kong S.A.R.

On July 31, 2025, Mr. Ji Zhou (Director for liaison office of central gov't in HKSAR), led a delegation from liaison office visited the CNERC-Rail (HK Branch) (Fig. 3.66).

Prof. Yi-Qing Ni, Director of CNERC-Rail (HK Branch) accompanied the visit and gave an introduction.



Fig. 3.65 Liaison Office of the Central People's Government in the Hong Kong S.A.R.

3.5.13 Delegation from College of Civil Engineering and Architecture of Zhejiang University

On 25 August 2025, a delegation of from College of Civil Engineering and Architecture of Zhejiang University visited CNERC-Rail (HK Branch) (Fig. 3.67). Dr. Hong-Wei Li (Research Fellow) delivered an overview of PolyU and the Center, followed by in-depth discussions on cutting-edge research directions. The delegation toured the Center's laboratories, fostering a vibrant academic atmosphere and productive exchanges.

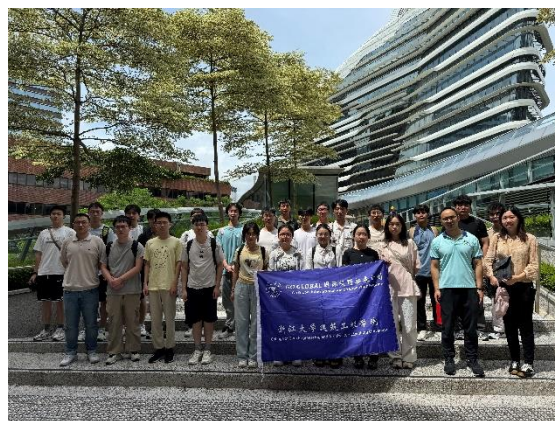




Fig. 3.66 Academic Exchange with Zhejiang University College of Civil Aviation & Transportation

3.5.14 Delegation from Shenzhen Metro

On August 26, 2025, a delegation from Shenzhen Metro visited the Shenzhen Research Institute of The Hong Kong Polytechnic University for an exchange activity. The delegation was received by the team led by Prof. Yi-Qing Ni, Director of CNERC-Rail (HK Branch). Centered on the theme “Technology Serving People’s Livelihoods, Digital Innovation for the Future”, the exchange focused on discussions of rail transit vibration and noise mitigation technologies. During the visit, the team introduced key technologies and devices, including particle dampers and near-track sound-absorbing low walls, and exchanged views on their engineering application prospects and implementation pathways. The discussions were productive and constructive, and the visit concluded successfully with positive outcomes.



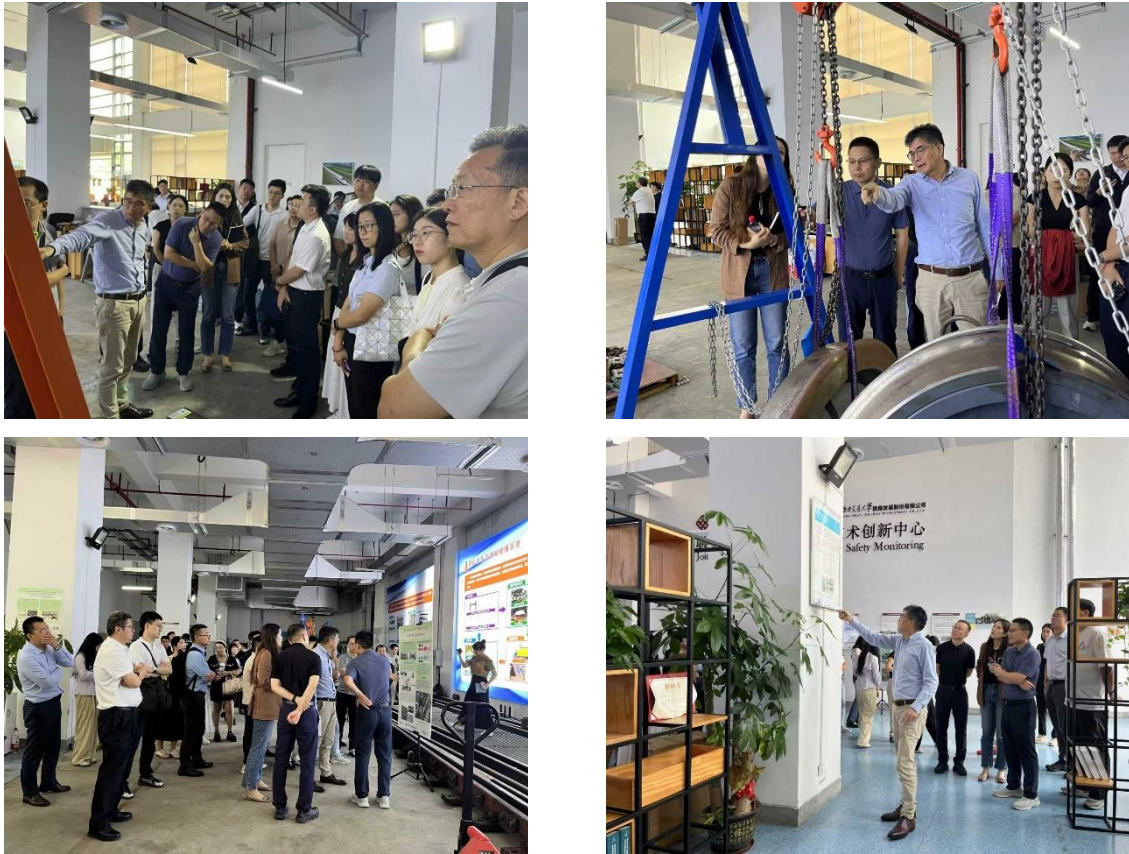


Fig. 3.67 Shenzhen Metro visited CNERC-Rail (HK Branch)

3.5.15 Guangdong Teng Yue Construction Engineering Co

On September 4, 2025, Mr. Xu Bo (Vice President of Country Garden Group - Tengyue Construction Technology Group) visited CNERC-Rail (HK Branch) (Fig. 3.69). He was received by center members including Prof. Zhou Kai, Dr. Si-Qi Ding, and Dr. Xiao Wang. Both parties engaged in in-depth discussions on topics such as intelligent building construction, engineering safety technologies, and automated construction techniques.

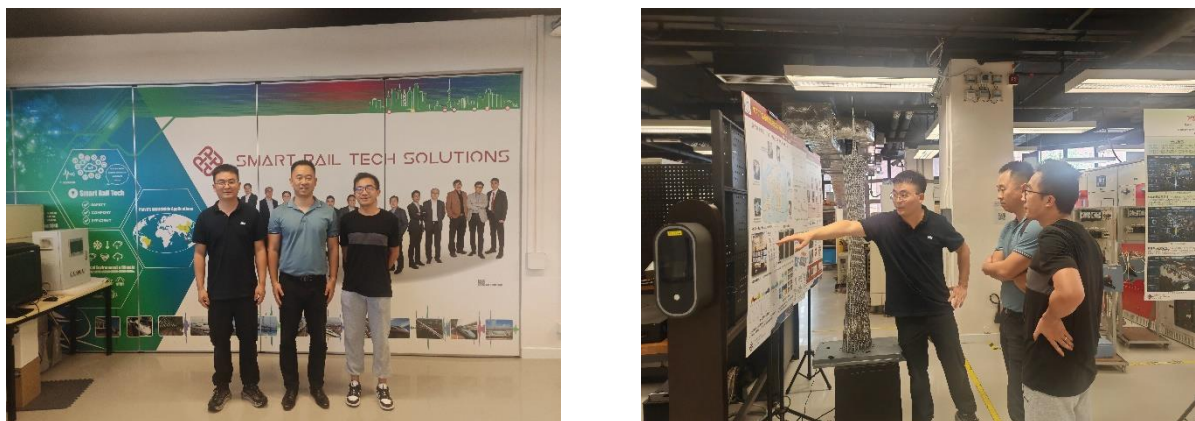




Fig. 3.68 Smart Construction & Safety Tech Talk – Country Garden Tengyue Visit

3.5.16 Prof. Badreddine Assouar from Université de Lorraine

On 11 September 2025, Prof. Badreddine Assouar from Université de Lorraine visited CNERC-Rail (HK Branch) (Fig. 3.70). Dr. Wai Kei Ao conducted a laboratory tour for Prof. Assouar, which included the PolyU Industrial Center (IC) 3D printing workshop and the IC railway corner. Prof. Assouar expressed particular interest in ongoing MTR projects and the development of metamaterials for noise absorption in railway applications.



Fig. 3.69 Prof. Badreddine Assouar from Université de Lorraine

3.5.17 Delegation from Shenzhen Metro

On September 15, 2025, Mr. Xiang-Lin Zeng (Supervisor from the Overhaul Center of Shenzhen Metro Operations Group Co., Ltd.), Engineer Kun Liu, and Mr. Zheng-Yi Liu (Secretary-General of the Southwest Jiaotong University Guangdong Alumni Association) visited CNERC-Rail (HK Branch) (Fig. 3.71). Prof. Yi-Qing Ni, Director of the CNERC-Rail, Dr. Zheng-Wei Chen (Research Assistant Professor) and Dr. Jun PENG (Postdoctoral Fellow)

introduced the center's leading research focuses, latest achievements, and related research facilities.

The meeting focused on in-depth discussions regarding the project requirements, technical approach, and intellectual property rights pertaining to the “Smart Bogie Inspection Sub-Project” under 2025 Jie Bang Gua Shuai (i.e., Open Innovation Challenge) Project - Intelligent Bogie Inspection Sub-Project" of Shenzhen Metro Group. Both parties confirmed the “Call for Proposals” model as the framework for collaboration, identified bolt fastening condition detection as the key research focus, and jointly agreed that CNERC-Rail (HK Branch) will lead the technology development and draft a detailed cooperation agreement, while Shenzhen Metro will provide bogies and experimental sites.

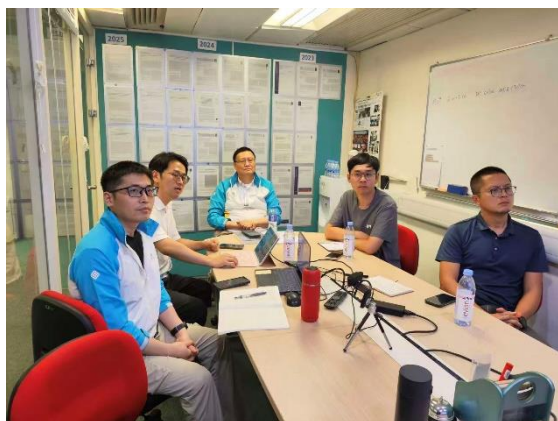


Fig. 3.70 PolyU and Shenzhen Metro Finalise Collaboration Plan for Smart Bogie Inspection Sub-Project

3.5.18 Delegation from Taizhou CPPCC and Hong Kong-based Entrepreneurs from Taizhou

On October 15, 2025, Mr. Lingxiang Zhou (Vice Chairman of Taizhou Municipal Committee of CPPCC in Zhejiang Province) with Hong Kong-based entrepreneurs from Taizhou, visited CNERC-Rail (HK Branch) (Fig. 3.72). They were accompanied by Dr. Laura Lo (Associate Vice President (Institutional Advancement)) and Prof. Yi-Qing Ni, Director of CNERC-Rail (HK Branch) warmly welcomed the delegation and introduced the center's research and related facilities.



Fig. 3.71 Delegation from Taizhou CPPCC and Hong Kong-based Entrepreneurs from Taizhou

3.5.19 Delegation from the Policy Unit of the Chief Executive of the Hong Kong Special Administrative Region Government & Hong Kong Chiu Chow Chamber of Commerce

On December 8, 2025, a delegation from the Policy Unit of the Chief Executive of the Hong Kong Special Administrative Region Government & Hong Kong Chiu Chow Chamber of Commerce visited CNERC-Rail (HK Branch) (Fig. 3.73). During the visit, they toured

CNERC-Rail's exhibition hall at PolyU's Industrial Center, as well as the 3D Printing Technology Center, the Nano 3D Concrete Printing Research Center, and the Maglev Train Laboratory, where they observed the latest achievements in rail transit and construction printing.

Dr Wai Kei Ao (Research Fellow) from CNERC-Rail (HK Branch), provided a comprehensive guided briefing and held in-depth discussions with Mr. Albert Lee, Dr Francis Cheung (Vice President Mr. Kenneth Chan, and others on research translation and development opportunities in the Northern Metropolis. Toward the end of the event, guests moved to Ju Yin House for a dinner meeting and further exchanges with CNERC-Rail Director, Chair Prof. Yi-Qing Ni, further consolidating the government–business–academia collaborative innovation network and earning unanimous praise from participants.

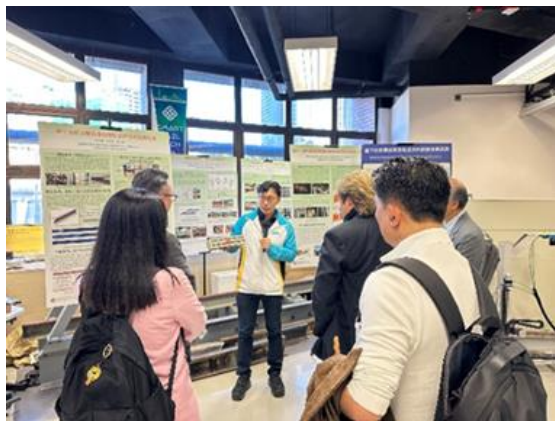


Fig. 3.72 Delegation from the Policy Unit of the Chief Executive of the Hong Kong Special Administrative Region Government & Hong Kong Chiu Chow Chamber of Commerce

3.6 Media Interviews

3.6.1 Hong Kong 21st Century Economic Report Interviews Prof. Ni from The Hong Kong Polytechnic University

On June 10, 2025, a reporter from the Hong Kong 21st Century Economic Report visited The Hong Kong Polytechnic University (PolyU) and conducted an exclusive interview with Prof. Ni. As a renowned scholar at PolyU, Prof. Ni has extensive influence in both academic and industrial circles. During the interview, he shared his insights on the current trends in technological development and highlighted the efforts of PolyU in promoting technological innovation and talent cultivation.

Prof. Ni pointed out that, with the rapid advancement of global technology, PolyU is actively strengthening its cooperation with domestic and international research institutions, aiming to achieve more breakthroughs in the fields of railway electrification and automation. He also emphasised the importance of integrating industry, academia, and research, believing that close collaboration with enterprises can better transform research outcomes into practical applications and drive industrial upgrading.

When discussing talent cultivation, Prof. Ni stated that PolyU focuses on fostering students' innovation and practical abilities, encouraging them to actively participate in research projects and international exchanges. He believes that this educational model can cultivate more high-quality talents who meet the demands of future social development.

This interview not only showcased PolyU's outstanding achievements in research and education but also reflected Professor Ni's sense of responsibility and forward-thinking as a scholar. The Hong Kong 21st Century Economic Report will continue to follow the development of PolyU and Prof. Ni's latest research findings in relevant fields.



Fig. 3.73 Hong Kong 21st Century Economic Report Interviews Prof. Yi-Qing Ni, director of CNERC-Rail (HK Branch)

大湾区观察 | GBA Observation

专访香港理工大学倪一清： 为高铁磁浮装上“感知神经”



本报记者 袁思杰 香港报道

在香港，青马大桥的自适应概率神经网络精准捕捉大桥“心跳”的细微异常。即使环境噪声完全掩盖了损伤本身的微弱信号，依然能实现85%以上的精准定位，就像在暴雨夜的喧闹中清晰分辨出一片落叶坠地的声响。

默默守护这个标志性项目结构安全的核心技术，源自香港理工大学土木及环境工程学系智能结构与轨道交通讲座教授倪一清在结构健康监测领域的一系列开创性科研成果。

“对于任何一个运动系统，我们都希望能够实现对其的有效控制。”倪一清对记者说。

倪一清表示，过去数十年，其团队依托大数据与人工智能技术开发了一系列分析算法，使系统能快速诊断结构性能问题，如裂缝形成、局部可靠度下降等关键指标，实现实时计算反馈。

倪一清是国际著名结构健康监测专家，连续5年在土木工程领域位列全球前2%高被引科学



目前我国高铁技术“出海”时，通常需要与当地签署协议，确保系统按中国标准制造和使用。但部分国家要求技术产品必须通过本地相关规范和认证。香港可发挥独特优势。

倪一清

技术，对在里约奥运会期间运行的地铁4号线列车结构部件展开全面监测，在4天时间内累计监测行车里程500公里。

除保障结构安全外，如何减少高速行驶下的列车产生的噪声也是研究中心的科研重点。为解决噪声问题，研究中心团队通过3D打印技术制作声学超材料吸声屏障，可实现宽频高效吸声。此外，团队还研发了铁路噪声控制智能颗粒阻尼器，安装后轨道近场噪声可降低3-5分贝，远场噪声可降低1-3分贝。

目前，这两项技术已经在香港地铁和深圳地铁投入测试和使用。

倪一清指出：“我们不仅关注

学术时期的研究方向，我的本科毕业论文也是和动力学相关。在浙江大学攻读硕士学位期间，我亦从事振动控制方向的研究。

我一直对控制非常感兴趣，而火车的运行过程本质上就是动力系统的运行过程。对于任何一个运动系统，我们都希望能够实现对其的有效控制。

《21世纪》：你为何没有留在美国，而是回到香港发展？

倪一清：香港在大桥结构健康监测领域处于世界领先地位。当时，这些大桥已经开始建设长期、永久性的结构健康监测系统。

我们将监测系统永久性地安装在大桥上，实现实时监测和预警，而国外多以一座桥梁为对象，

采用智能材料，如石墨烯、碳纤维管，通过3D打印技术制造具有优异吸声性能的非天然材料，即声学超材料，以实现噪声的有效控制。此类技术不仅适用于高铁和磁悬浮列车，也可推广用于高速公路的噪声治理。

AI赋能轨道交通安全

《21世纪》：你主导的高铁安全监测系统已实现从“轨道”到“轮子”的监测延伸，并计划拓展至管道隧道等。可否分享一下团队在轨道交通安全检测方面的研究成果？这些技术是如何在超高速交通系统中保障安全和提升稳定性？

倪一清：我们研发了一系列特制传感器。由于现有的光纤传感器，其采样频率一般仅能检测5000赫兹以内的信号，而在声发射或超声波检测中，检测频率远高于此。

我们发现，超声波检测在裂缝检测方面极为有效。超声波沿结构表面传播时，遇到裂缝会产生反射和折射，信号特征明显不同。

因此，我们开发了专用的超声波光纤传感器。其优点在于：首先，可在多点布设传感器；其次，每个测点无需单独供电。由于高铁

Fig. 3.74 Prof. Yi-Qing Ni, Director of CNERC-Rail (HK Branch), featured in 21st Century Economic Report (Hong Kong)

3.6.2 PolyU Holds Media Briefing on Enhancing Urban Resilience Against Extreme Weather

On November 27, 2025, Prof. Yi-Qing Ni and Dr. E Deng participated in a media briefing themed "PolyU Research Pioneers: Fortifying Urban Resilience Against Extreme Weather."

At the event, Prof. Ni presented the latest research achievements of the TRS project, including the LiDAR monitoring system and the high-rise building monitoring system. Prof.

Ni also addressed questions from journalists on how these innovations can benefit residents in Hong Kong and other coastal cities, explaining potential applications and community impact.

The briefing highlighted PolyU's ongoing commitment to developing practical technologies that enhance urban resilience in the face of escalating extreme-weather events.

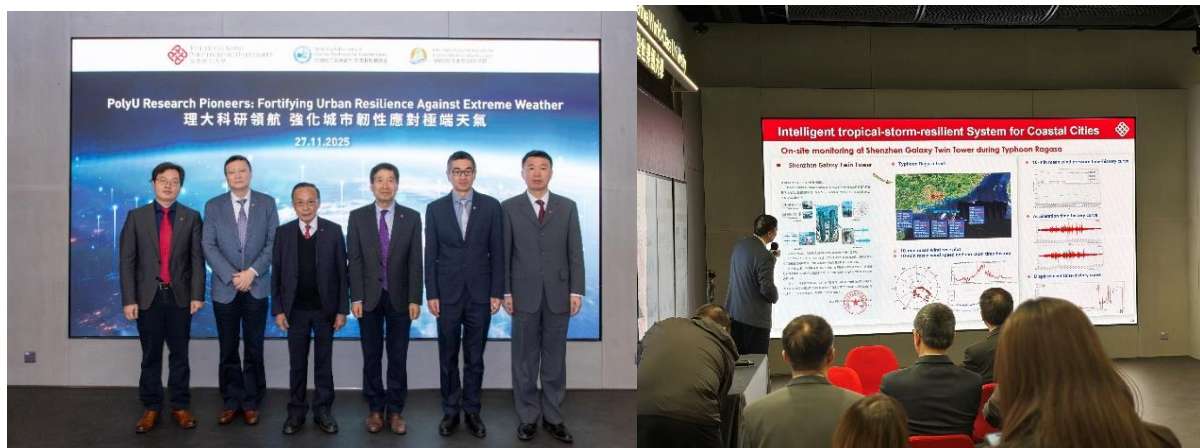


Fig. 3.75 PolyU Holds Media Briefing on Enhancing Urban Resilience Against Extreme Weather

3.6.3 Sing Tao Interviews Prof. Ni on INTACT

On December 11, 2025, Prof. Yi-Qing Ni was interviewed in Room U301 by Ms. Chan Ka Yuen, Maggie, Education Section News Editor of Sing Tao Daily. Ms. Hazel Cheng (CPA), Dr. E Deng, Mr. Huan Yue, Mr. Xin-Yuan Liu, Mr. De-Hui Ouyang, Mr. Hang Du, Mr. Zi-Xuan Zeng, Mr. Jian Wang, and Mr. Min Deng attended the event.

Prof. Yi-Qing Ni introduced the project overview and explained how the project outcomes serve the public in Hong Kong and neighboring regions, and Dr. E Deng demonstrated the functions of the relevant instruments and the monitoring results.





Fig. 3.76 Sing Tao Interviews Prof. Ni on INTACT

Appendix

A.1 Equipment Purchased

No.	Device/Sensor	Quantity
1	"Keysight 001" DC Bias Option	1
2	"Keysight 16089A" Test Fixture A	1
3	"Keysight 16089B" Test Fixture B	1
4	"Keysight BV0014B" Software	1
5	"Keysight E4980A" LCR Meter	1
6	Annual Software Maintenance Package (ASMP) for 2 years	1
7	Annual Support Package (ASP) for 2 years	1
8	M3704B six-axis force sensor at nacelle-tower connection	1
9	M3815E2 six-axis force sensor at tower-platform connection	1
10	Provision of foreign object intrusion monitoring system test in rail transit	1
11	Software License fee	1
12	"Campbell / CR1000Xe" wind speed and pressure monitoring system	1
13	"In-situ High-tech / CIS-JH-4.0-F" Plasma Joule Heating System and Material Processing System	1
14	"ZY-DMSIC-01" deformation monitoring system based on inertial camera vision	1
15	"ITS p2+" Electrical Impedance Tomography system with phantom tank	1
16	deformation monitoring system based on inertial camera vision	1

17	FORMLABS FORM 4L 3D printer for fabricating precise acoustic and mechanical metamaterial samples	1
18	Hong Kong Rail Transport Safety Meteorological Warning System	1
19	In-Situ High-Tech CIS-JH3.3-P Joule heating device	1
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A.2 News Reports

理大與中鐵電氣化局集團簽訂技術研發與應用戰略合作協議共建聯合實驗室 | 香港理工大學



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理大與中鐵電氣化局集團簽訂技術研發與應用戰略合作協議共建聯合實驗室

2025年5月2日

科研與創新發展

知識轉移及創業處



▲ 理大與中鐵電氣化局日前於北京舉行技術研發與應用戰略合作協議簽訂暨聯合實驗室揭牌儀式。雙方與會代表包括：賈保信先生（右四）、林大輝博士（右五）、王少鋒先生（左五）、郭樹祥先生（右三）、趙汝恒教授（右四）、中鐵電氣化局副總經理李磊先生（右二）、倪一清教授（左三）、林雲志先生（左二）、理大人工智能講座教授、理大深圳研究院院長張成奇教授（左一）及理大內地發展處總監、會計及金融學院香港可持續技術基金會會計及金融教授陸海天教授（右一）。

香港理工大學（理大）與中國中鐵電氣化局集團有限公司（中鐵電氣化局）日前於北京舉行技術研發與應用戰略合作協議簽訂暨聯合實驗室揭牌儀式。雙方將通過京港科技合作機制，培育兼具創新理論與實踐經驗的高質素人才，並實現優勢互補，共同將聯合實驗室打造成為全球軌道交通創新高地和產教融合典範，以科技賦能「交通強國」戰略，助力京津冀協同發展及全球數碼經濟標竿城市建設。

中鐵電氣化局集團是世界企業和世界品牌雙500強——中國中鐵股份有限公司的重要成員企業，是中國電氣化鐵路和城市軌道交通建設的國家隊和主力軍，是次合作將發揮雙方優勢，共築軌道交通創新高地。

在中鐵電氣化局集團黨委書記兼董事長賈保信先生和理大校董會主席林大輝博士見證下，由中鐵電氣化局集團總工程師林雲志先生及理大副校長（研究及創新）趙汝恒教授簽署戰略合作協議。此外，在林大輝博士、賈保信先生、趙汝恒教授及林雲志先生見證下，理大土木及環境工程學系智能結構與軌道交通講座教授、嚴、麥、郭、鍾智華結構冠名教授、理大國家軌道交通電氣化與自動化工程技術研究中心香港分中心主任兼理大杭州技術創新研究院院長倪一清教授亦與中鐵電氣化局集團電氣化公司總工程師李育冰先生簽署技術研發與應用戰略合作協議。

賈保信先生在致辭中指出，理大和中鐵電氣化局將以聯合實驗室為起點，通過「基礎研究—技術攻關—產業轉化」的創新鏈深度融合，打造軌道交通領域的產教融合典範。雙方將依託京港兩地的政策與區位優勢，建立「科學家+工程師」聯合團隊培養機制，共建實訓基地與博士後工作站，培育支撐行業轉型升級的複合型人才。

专访香港理工大学倪一清：
为高铁磁浮装上“感知神经”

本报记者 袁思杰 香港报道

在香港，青马大桥的自适应概率神经网络精准捕捉大桥“心跳”的细微异常。即使环境噪声完全掩盖了损伤本身的微弱信号，依然能实现85%以上的精准定位，就像在暴雨中的喧闹中清晰分辨出一片落叶坠地的声响。

默默守护这个标志项目结构安全的核心技术，源自香港理工大学土木及环境工程学系智能结构与轨道交通讲座教授倪一清在结构健康监测领域的一系列开创性科研成果。

“对于任何一个运动系统，我们都希望能够实现对其的有效控制。”倪一清对记者说。

倪一清是国际著名结构健康监测专家，连续5年在土木工程领域位列全球前2%高被引科学家，曾获国家科技进步二等奖和日内瓦国际发明展金奖及特别大奖。自1990年代起，他主导了香港青马大桥、广州塔、深圳证券交易所等超大型工程的结构监测系统研发，为建筑物进行全寿命期的健康监测。

基建项目的“隐形卫士”

1990年代在浙江大学研究生毕业后，由于浙大当时还未设立结构动力学相关的博士学位，倪一清选择远赴香港理工大学攻读博士学位，担任研究员，并开始参与政府主导的桥梁结构安全监测项目，包括为1995年开始建设的香港青马大桥安装传感器。

“香港在大型结构健康监测领域处于世界领先地位。当时，这些大桥已经开始建设长期、永久性的结构健康监测系统。我们将监测系统永久性地安装在大桥上，实现实时监测和预警，而国外多以一座桥梁为对象，进行一至两个月的临时监测，二者的概念存在明显区别。”倪一清指出。

倪一清先后参与了一系列新建桥梁的结构安全监测工作。

2010年，倪一清开始参与大桥安全监测项目，从结构下不解之患，并扎根这一领域，将其在土木工程领域的科研成果，通过跨学科合作进行落地转化。

2015年10月，经科技部部长批准，国家轨道交通工程化与自动化工程研究中心（香港理工大学）在香港理工大学正式成立，主要聚焦应用于轨道交通领域的先进传感、智能振动控制、轨道交通噪声控制、机器学习及大模型等先进技术研发。

迄今，倪一清团队在研究和应用领域硕果累累，代表性研究包括轨道交通智能运维系统、铁路异常入侵监测系统、光纤光栅传感器等。

其中，光纤光栅传感器是倪一清团队在结构安全监测方面最具代表性的科研成果之一。

这一智能传感器，通过一条细如发丝的光纤即可传递信号。结合超声导波等技术，光纤传感器能够精准捕捉裂缝、温度及振动等细微信号。

该技术已护航全球多个标志性基建项目。在高铁领域，京沪高铁与兰新高铁率先部署传感器网络，实时监测提升安全运营水平。在2016年，该技术输出到宁波地铁，成为首条海外铁路应用。

同年，倪一清团队利用这项



倪一清

技术，对在里约奥运会期间运行的地铁4号线列车结构部件展开全面监测，在4天时间累计监测行程500公里。

除保障结构安全外，如何减少高速行驶的列车产生的噪声也是研究中心的科研重点。为解决噪声问题，研究中心团队通过3D打印技术制作声学超材料吸声港地铁和深圳地铁投入测试和使用。

倪一清指出：“我们不仅关注结构安全性，更强调用户体验维度，例如在铁路应用中，我们会把乘坐舒适性和噪音控制作为核心指标纳入监测体系。”

人工智能“保驾护航”

作为国家轨道交通工程化与自动化工程研究中心香港分中心主任，倪一清正积极推动人工智能在铁路领域结构健康监测领域的研究与运用。

AI的发展为结构健康监测注入“先知直觉”。基于图像以及激光雷达技术，倪一清建立了异常监测系统，即使是一根桥梁未检测到铁轨上也能精准识别。“这个系统是完全采用深度学习算法建立起来的，一般的算法做不到这样快速的识别。”倪一清表示。

目前，智能监测云平台已经在新加坡地铁、香港地铁和内地高速铁路等轨道交通场景安装使用，反响良好。

倪一清建议，攻读土木工程专业的学生，不能只学专业知识，更重要的是接触人工智能、材料科学和信息系统等方向相关的先进技术。“人工智能将来会在每个领域广泛应用，大学生现在就应该开始接触相关课程。”

在土木工程材料革新方面，研究中心团队也在积极推动智能感知与AI的深度融合。其研发的自感知混凝土材料，具备实时感知和承载能力，目前正在上海铁路局开展应用测试。

人工智能的赋能不仅还可以守护轨道交通安全，还可以应对复杂城市环境面对极端风暴带来的风险。

2023年，倪一清领导的团队获得研究资助局拨款近5000万港元支持，开发了“INTACT：沿海城市智能式热带风暴减灾系统”。这项系统以激光雷达测风技术为核心，构建了全球首个面向高层建筑群的实时台风风险预警模型。

倪一清表示，该系统突破了传统气象监测局限，通过弹性评估模型与台风路径深度融合，结合卫星遥感、地面传感、历史风速等多源数据源，动态更新算法，实现了台风对关键建筑结构的破坏力定量预测。

“火车梦”引领动力学研究之路

《21世纪》：可否分享一下您是如何一步步走向结构动力学研究之路的？

倪一清：火车动力学是我大

目前我国高铁技术“出海”时，通常需与当地签署协议，确保系统按中国标准制造和使用。但部分国家要求技术产品必须通过本地相关规范和认证。香港可发挥独特优势。

倪一清

学时期的研究方向，我的本科毕业论文也是和动力学相关。在浙江大学攻读硕士学位期间，我亦从事振动控制方向的研究。

我一直对控制非常感兴趣，而火车的运行过程本质上就是动力系统的运行过程。对于任何一个运动系统，我们都希望能够实现对其的有效控制。

我们将监测系统永久性地安装在大桥上，实现实时监测和预警，而国外多以一座桥梁为对象，进行一至两个月的临时监测，二者的概念存在明显区别。

除青马大桥外，还有港珠澳大桥、汀九大桥、后来的昂船洲大桥、深圳湾公路大桥（西部通道大桥）、直落港珠澳大桥，我均有幸参与了这些大桥结构监测系统的建设。彼时我也意识到，未来还会有更多新桥的建设，因此我非常希望能够回国，继续参与这些大桥结构健康监测的相关研究工作。

中国高铁技术世界领先

《21世纪》：作为我国轨道交通发展的见证者，您如何看待中国在轨道交通领域，特别是高铁、地铁、城际列车等方面的技术实力及其国际竞争力？

倪一清：过去十来年，我国在轨道交通领域取得了巨大的技术进步。目前，我国轨道交通技术已处于世界先进水平。比如高铁，我国的运营里程居世界首位。尽管出于安全考虑，部分线路将列车时速控制在300至350公里，但近年来如京沪高铁等线路，部分列车时速已提升至400至450公里，车速已达到世界领先水平。

但在管理和运营方面，部分领域仍有提升空间。以往我们更侧重于技术层面，而国际上则更加注重乘客舒适度、高铁车站人流规划等科学方面。

在磁悬浮方面，我国已具备时速600公里的磁悬浮列车，但目前尚需建设一条实际运营的高速磁悬浮试验线。只有建成这条试验线，我国高速磁悬浮技术才能真正实现运营。

《21世纪》：从您的研究领域出发，实现上述目标还存在哪些关键技术难题亟待攻克？

倪一清：就车速而言，我认为已不存在重大技术障碍。但在提升舒适度等方面，如噪声控制，仍是亟需解决的挑战。如何进一步降低噪声对乘客及沿线居民的影响，是当前面临的重要课题。

有观点认为，由于磁悬浮列车消除了轮轨摩擦，噪声问题将大为缓解。然而，空气动力噪声依然存在。在时速600公里为例，这相当于飞机起飞时的噪声。众所周知，飞机起飞时的噪声非常大。因此，如何在如此高的速度下有效降低空气动力噪声，是磁悬浮技术面临的重要挑战之一。

我所在的国家工程技术研究中心的主要研究领域之一，就是利用先进技术降低噪声。例如，

AI赋能轨道交通安全

《21世纪》：您主导的高铁安全监测系统已实现从“轨道”到“轮子”的监测延伸，并计划拓展至管道磁浮。可否分享一下团队在轨道交通安全防护方面的研究成果？这些技术是如何在超高速交通系统中保障安全并提升稳定性？

倪一清：我们研发了一系列特制传感器。由于现有的光纤传感器，其采样频率一般仅能检测5000赫兹以下的信号，而在声波或超声波检测中，检测频率高达数兆赫兹。其优点在于：首先，可在多点布设传感器；其次，每个测点无需单独供电。由于高铁沿线（除站台区及道岔位置外）普遍无电源，若需为检测设备单独供电，将极为不便且成本高昂。

《21世纪》：人工智能和各行各业深度融合是现在的一大趋势。您的研究团队在应用人工智能方面有哪些最新实践？

倪一清：我所在的国家工程技术研究中心重点研究方向之一是磁悬浮控制系统，包括控制算法的研发。目前，磁悬浮控制系统在模拟环境下运行稳定，但在遭遇台风等极端天气时，悬浮控制的鲁棒性（稳健性）仍面临挑战。为提升控制系统在不稳定干扰下的稳定性，我们引入了人工智能算法。例如，采用深度学习、迁移学习、图神经网络等方法，提升系统对不确定性干扰的适应性和鲁棒性，从而确保在极端天气下也能实现良好控制。

另一个实例是应对异物侵入，如落轨导致的石块、泥沙堵塞轨道，可能导致脱轨事故。对此，我们开发了人工智能的异物侵入监测系统。该系统结合数码相机和激光雷达，通过图像识别技术，可在动态环境下实现实时监控，能够准确识别异物，或其他车辆闯入，并及时预警列车驾驶员，实现列车及时减速或停车，从而保障运行安全。该系统完全依赖人工智能智能感知，能够实时快速识别并即时响应，是传统算法无法实现的。

《21世纪》：近年来，我国轨道交通业加快了出海步伐，特别是在“一带一路”共建国家市场方面落地建设项目。这其中，香港可以扮演哪些角色？

倪一清：香港在这一过程中可以扮演独一无二的角色。例如，香港已建立铁路领域的认证中心。香港已与全球一百多个国家和地区签署了互认协议，即在港完成的认证，在这些国家和地区均可直接获得认可，无需再次认证。

目前我国高铁技术“出海”时，通常需与当地签署协议，确保系统按中国标准制造和使用。但部分国家要求技术产品必须通过本地相关规范和认证。在这种背景下，香港可发挥独特优势。出海项目在香港完成技术认证后，凭借互认协议，该认证即能被相关国家直接认可，无需在当地重新检验认证。

（实习主笔 刘欣、副主编 报道者 袁思杰）

（编辑：李玲霞）

专访平安资管车强：
泡泡玛特行情未完

车强建议投资者在港股市场采用“红铃式配置”策略，即一端配置高息股，另一端配置成长股。他认为，这种策略能够有效应对市场不确定性，并在不同市场环境下捕捉投资机会。



车强

（十年期国债收益率约1.6%），港股高息股对配置型资金吸引力显著。

对于成长类板块而言，年初以来DeepSeek带动的情绪溢价，成为成长类板块带来了良好的刺激。若未来AI进一步发力，有望带动内地数字经济快速增长。具体而言，我们看好一些科技类以消费类板块的布局。此外，我们对创新药板块保持相对乐观。近期创新药领域政策利好支持力度加大，包括纳入医保目录等举措，为相关股票提供良好支撑。同时，该板块过去几年的估值也处于历史低位水平。

化表现尤为明显。港股持续跑输A股主要有几个方面的原因。政策层面，内地监管机构鼓励优质企业赴港上市，宁德时代、海天味业等相继登陆港股，优质公司的加入进一步丰富了港股市场的多样性。同时，许多优质成长型公司也集中于港股，例如腾讯、美团等代表性企业主要集中在港股上市。

此外，港股的估值相较于A股更具吸引力。以高息股为例，港股银行的价格相较于A股价格有所折价，股息率更高。因此，对于希望配置高息类股票的投资者而言，港股的吸引力明显更大。

最后，从资金流来看，海外市场出现美元化的趋势，海外资金出现回流迹象。部分资金回流港股为港股提供了流动性支持。

《21世纪》：刚才提到高息股的走势。高息股自2022年至今经历了一波显著上涨，不少股票的价格已有所回调。你认为高息股未来是否会受到青睐？

车强：高息股股票目前来看依然具备持续吸引力。综合估值优势、资金流向及政策导向等多重因素，高息类股票的投资价值仍将持续。

南向资金支持仍将持续

《21世纪》：今年以来，港股呈现震荡上行的态势。您如何看待下半年港股的投资机会？哪些板块有望实现超额收益？

车强：如果展望下半年，我们认为市场波动仍将持续，主要有几个原因。首先，从外部环境来看，全球地缘政治仍较为动荡，这对港股的估值形成一定压力。其次，从整体经济环境的角度来看，目前内地经济仍面临一定压力。展望下半年，我们认为中国的政策工具箱中应该仍有后手。

从资金流角度来看，今年港股获得了较为有力的支持，尤其是南向资金流入表现突出。年初至今，南向资金流入已超过6500亿港元。相比去年全年仅8000多亿港元的流入量，今年上半年的流入量已接近去年全年的80%。我们认为南向资金的支持仍将持续。当前港股估值已回升至过去十年平均水平，总体而言，我们判断下半年市场波动性可能加大。

“红铃式”配置策略应对波动

《21世纪》：对于投资者而言，你认为下半年在港股投资方面应采取怎样的策略？

车强：我建议采取“红铃式”配置策略。具体而言，若一端配置高息资产，另一端则配置成长型资产。红铃式配置策略的优势在于：当市场出现较大波动时，配置部分高息股能够在一定程度上起到保值的作用；而若经济持续改善，且政策支持力度超预期，成长型股票则有望带来超额收益。

对于高息股配置而言，市场波动加剧背景下，高息股个股能提供较好安全边际，叠加内地较低收益率环境

湾区金融大咖说

本报记者 张伟泽 香港报道

“泡泡玛特虽然从底部上涨不少，我认为目前这波行情仍未走完。”平安资管（香港）股票投资主管车强在专访中对21世纪经济报道记者表示。

年初以来，以泡泡玛特为首的新消费板块受到市场热捧，“新消费F4”——老铺黄金、泡泡玛特、毛戈纳销售模式区别于传统消费对渠道销售的依赖。他指出，基于这些核心特质，新消费赛道仍有巨大的发展空间。

谈及港股市场在2025年下半年的走势，车强指出，目前港股的估值已经达到过去10年的平均水平。展望下半年，市场波动仍将持续。然而，尽管外部环境复杂，港股市场仍有其内在的支撑力量。他特别提到，南下资金的持续流入是今年港股的强劲支持，预计今年南向资金将超过1万亿元。

面对市场的波动性，车强建议投资者在港股市场采用“红铃式配置”策略，即一端配置高息股，另一端配置成长股。他认为，这种策略能够有效应对市场不确定性，并在不同市场环境下捕捉投资机会。

对于AI对企业盈利的影响，车强认为短期内可能不会在上市公司报表中立即体现，但长期来看，AI在降本增效方面将带来显著帮助。他预测，从明年开始，AI有望在降本增效和人力节省方面逐步发挥作用，尤其是在制造业行业以及创新药、工业等领域。

外资有回流迹象

《21世纪》：刚才也提到了，外资对内地市场的配置窗口仍有所收窄。您觉得什么时候外资对内地市场的配置可能回归到历史平均水平？这将为港股带来多少增量？

车强：去年以来，我们观察到外资有一些回流的迹象，但规模尚不显著。根据我们的数据来看，目前外资整体对内地市场仍处于低配状态，低配幅度约为2-3个百分点，而此前曾达3-4个百分点。据我们测算，每回流一个百分点，约可带来200亿美元的资金流入。

我认为想要真正观察到外资回流的话，就要满足几个关键条件。第一，内地的经济要持续复苏，投资者要相信内地经济目前面临的压力是可以解决的。第二，今年年初市场的反弹也体现投资者对AI在内地的发展潜力有信心。目前，我们认为只有中国内地和美国有足够的力量去建设AI，内地在AI领域拥有较强的产业优势。AI如何能进一步提升内地的劳动生产率，也是外资关注的重点。

《21世纪》：年初，DeepSeek的推出引发热议，您认为AI将如何影响企业的盈利能力？

车强：AI对企业盈利的影响是一个长期趋势。若大模型技术能进一步提升，特别是在降本增效方面取得突破，未来几年有望逐步显现其成本优势。尤其是人力成本的节约效应。尽管AI技术尚处于早期阶段，短期内的收益可能难以在多数上市公司财报中体现，但我预计在未来一两年内，部分科技类公司可能将逐步展现出AI技术对其利润率的积极提升作用。

（编辑：李玲霞）

文匯網 專題 香港 教育 理大與杭州杭港地鐵及杭州申昊科技合作 推動軌道交通智能技術創新

理大與杭州杭港地鐵及杭州申昊科技合作 推動軌道交通智能技術創新

2025-08-28 19:54:42 教育



在理大校董會主席林大輝（後排中）、副校長（研究及創新）趙汝恒（後排左）及杭州杭港地鐵總經理吳偉鴻（後排右）見證下，由理大杭州技術創新研究院院長、軌道交通智慧中心主任、土木及環境工程學系智能結構與軌道交通講座教授倪一清（前排左）及杭州杭港地鐵副總經理謝志明（前排右）簽署合作協議。（理大圖片）

香港文匯報訊（記者 姜嘉軒）香港理工大學杭州技術創新研究院分別與杭州杭港地鐵有限公司及杭州申昊科技股份有限公司簽署合作協議，開發軌道交通智能運維技術，及建立人工智能科技實驗室，為國家鐵路技術發展與智能化注入新動力。

兩項簽署儀式均於上周三（20日）在杭州舉行。其中，理大杭州技術創新研究院及杭州杭港地鐵的合作將聚焦軌道浮置板震動分析、受電弓狀態檢測、綠能震動發電、DAS系統應用等多項軌道交通智能運維技術開展聯合開發。雙方將發揮各自優勢，推動科研成果轉化，提升企業創新動力與科技水平，助力軌道交通運維技術升級。



在林大輝、趙汝恒、杭州申昊科技董事長陳如申及董事兼CEO曹光客見證下，由倪一清及杭州申昊科技副總裁李濤簽署合作協議。

（理大圖片）

另一方面，理大杭州技術創新研究院將聯同杭州申昊科技、北京申昊電算集成科技有限公司及萬卷軌交智能科技（杭州）有限公司，共建人工智能科技實驗室，在大模型垂類應用與智能化運維等領域開展深度合作，協同推進人才培養。雙方將重點布局軌道交通智能運維和政務私有化部署等應用場景，全面提升國產化技術競爭力。

此行，理大代表亦到訪兩間公司，參觀並交流軌道交通領域的創新技術與發展方向。理大期望透過是次合作，把在軌道交通累積的研究成果與杭州的產業深度融合，轉化為國家基礎設施的創新技術，助力發展國家新質生產力。

理大研極端天氣下 加強港基建安全



▲理大從應用及基礎科研兩方面，加強本港在極端氣候下的基建安全。
(朱永倫攝)

【本報記者何峻新報道】極端天氣日益頻繁，理工大學今年成立潘樂陶韌性基礎設施研究院，並與科技大學共建沿海城市氣候韌性全國重點實驗室，從應用及基礎科研兩方面加強本港在極端氣候下的基建安全，以適時協助政府制定相關政策。

長期監察氣候變化 對大橋影響

理大表示，兩個實驗室均會就極端天氣展開研究。建設及環境學院院長李向東指，潘樂陶研究院將偏向應用層面，例如研究如何避免「黃大仙地鐵站再度淹水」等實際問題；至於全國重點實驗室則聚焦基礎科研。

科研項目其中一項是監察氣候變化對跨海大橋影響，已進行逾20年。青馬大橋於1997年啟用

後，理大科研團隊在橋身安裝近300個傳感器，監測溫度、風力等氣候因素對橋梁造成的影響，亦是全球首個在跨海大橋上進行長期氣候監測項目。

研究數據顯示，1997年至2025年期間，青馬大橋橋面溫度平均每年上升0.05度，颱風襲港時間每年增加約3.6小時。團隊指，這些數據可以用以預測大橋會否變形，有助制定維修保養建議。相關技術已應用至港深多個大型橋梁，包括將軍澳跨灣大橋、深圳灣大橋、深中通道及港珠澳大橋等。

理大亦於上一年度研究沿海城市高層建築的抗颱風表現，去年在鶴嘴、沙田、沙頭角、元朗、龍鼓灘及貝澳安裝激光雷達監察儀，並與天文台共享測風數據。團隊表示，相關監測技術未來有望應用於北部都會區發展。✎

理大兩大重點科研平台聯動

強化城市氣候韌性防線

氣候變化帶來的極端天氣事件頻發，對全球城市安全構成嚴峻威脅。香港理工大學積極以科研應對挑戰，先在今年四月成立「潘樂陶韌性基礎設施研究院」，八月再獲國家科技部授牌，與香港科技大學共建「沿海城市氣候韌性全國重點實驗室」。理大期望透過結合兩大科研平台下多個研究項目，強化香港本土抵禦氣候風險的能力，同時冀將技術與經驗延伸至其他城市。

理大代表日前唔傳媒，分享多個研究項目進展和成果。大力支持理大成立「潘樂陶韌性基礎設施研究院」、並為督導委員會成員的潘樂陶表示，氣候變化的挑戰無分國界，亟需全球攜手應對。「國家在綠化環境及再生能源方面已投入大量資源與努力，但單靠少數國家去推動，很難在短時間內扭轉局面，未來二、三十年，極端氣候情況將愈發頻繁，對人類安全的威脅也將持續加劇。」有見及此，他與理大決定合力成立研究院，以創新方案應對氣候變化。

身兼該研究院院長、沿海城市氣候韌性全國重點實驗室主任的理大建設及環境學院院長李向東，指出兩大平台雖然均針對氣候變化與極端天氣、城市基建與韌性、鄉村社區與災害應對等範疇，但在方向上卻有不同。「研究院側重的是能夠『落地』的工程應用項目，主力建構一個具氣候韌性的香港，而全國重點實驗



理大研究利用蠔殼製作防波堤置於水底，減弱海浪衝擊。



潘樂陶（左三）、李向東（右三）等介紹潘樂陶韌性基礎設施研究院及沿海城市氣候韌性全國重點實驗室的研究方向。

室則以國家和全球發展戰略為導向，就基礎科研發表高水平科研文章，並跟內地其他重點實驗室合作，共同促進科技創新協同發展。」

多個科研項目解決氣候問題

其中一個重點研究，是全球首個在跨海大橋上進行氣候變化監測的項目。團隊自 1997 年至今，透過於青馬大橋上的近 300 個傳感器，收集及分析氣候變化對大橋的影響，發現大橋溫度平均每年上升攝氏 0.05 度；颱風襲港時間則每年增加約 3.6 小時。團隊根據結果提出維修及保養建議，確保大橋的安全及延長使用壽命。相關技術已應用至其他大型基建項目，例如港珠澳大橋，自 2018 年起，理大亦參與大橋的長期安全監測。

另外，自 2024 年起，理大在港九新界六個地點設置激光雷達風力監測儀，並與天文台共享風力數據，令颱風預測更準確。今年九月超強颱風樺加沙襲港時，研究團隊更出動搭載激光雷達儀的工程專車，遊走全港檢測不同地點的風速，加強數據準確度。未來計劃將監測儀安裝至其他地點，包括北部都會區。

在海岸保護方面，理大其中一項突破性方案，是研究利用蠔殼作為物料製成防波堤置於水底，減低海浪形成而有效保護沿岸居民的安全。由於蠔殼取自海洋，屬自然物料，較混凝土等物料更環保，對生態影響極低。目前研究團隊正調整防波堤形狀、密度及擺放位置，希望能得出最有效的方案。

新成立兩科研平台 針對極端氣候研究 理大開發颱風風險實時預警系統

近年香港屢遇極端天氣，包括「500年一遇」暴雨、自1964年以來再次於一年內兩度出現10號颱風信號等。為應對氣候變化帶來的多重挑戰，香港理工大學今年成立「沿海城市氣候韌性全國重點實驗室」及「潘樂陶韌性基礎設施研究院」，負責氣候相關科研項目。理大於上周舉行記者會，介紹兩個科研平台多項針對極端氣候的研究，包括開發颱風風險實時預警與管理系統，以提升沿海城市高層建築的抗颱風能力。

■ 記者鍾緯盈 ■

理大建設及環境學院院長李向東向記者表示，理大今年8月獲國家科技部授牌，與香港科技大學共同成立「沿海城市氣候韌性全國重點實驗室」，專注於基礎科學研究，探討香港及大灣區極端天氣之成因與潛在危害。同時，理大亦獲支持於今年4月正式成立「潘樂陶韌性基礎設施研究院」，側重於工程應用與科研成果轉化。他亦會同時擔任研究院院長及全國重點實驗室主任。

全港6地點設激光雷達監測儀

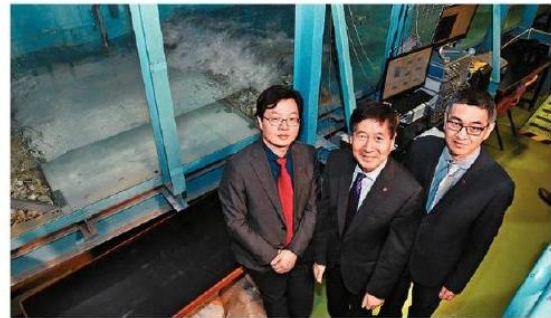
李向東指，兩大科研平台將聯合推動多項重點研究，其中，理大獲研究資助局2023/24主題研究計劃撥款近5000萬元，支持項目「INTACT：沿海城市智能式熱帶風暴減災系統」，針對沿海城市高層建築抗颱風問題，開發颱風風險實時預警與管理系統。自

2024年起，理大在港九新界6個地點（鶴咀、沙田、沙頭角、元朗、龍鼓灘、具澳）設置激光雷達監測儀，研究團隊師生更組成「理大流動測風隊」，於颱風期間運用車載3D激光雷達監測儀，實時追蹤風力變化，並持續與天文台共享風力數據，提升風力預測精確度與可靠性。

“近年全球極端氣候事件日益頻繁，期望推動相關研究，以應對氣候變化所帶來的衝擊。”

理大潘樂陶韌性基礎設施研究院
督導委員會成員潘樂陶

理大亦建立全球首個在跨海大橋上進行氣候變化監測的系統，以確保



■ 李向東(中)稱，理大團隊正在校園內的水利工程實驗室模擬海浪拍岸的過程，探索創新方法減低波浪衝擊力。
何健勇攝

橋身結構安全並延長使用壽命。自青馬大橋於1997年啟用以來，理大已在橋身安裝近300個不同類型的傳感器，通過監測各項數據，分析氣候變化對橋樑的影響，並提出維修及保養建議。研究結果顯示，1997年至今，大橋溫度平均每年上升攝氏0.05度；颱風襲港時間則每年增加約3.6小時。團隊稱相關技術亦已應用至港珠澳大橋。

此外，理大團隊正進行沿岸安全研究，利用校園內的水利工程實驗室先進設施，模擬海浪拍岸的過程，探索創新方法以減低波浪衝擊力，例如



■ 李向東(右)指，理大自2024年起，在港九新界6個地點設置激光雷達監測儀，監測全港風力變化。左為潘樂陶。

在水底鋪設以綠殼等環保物料製成的防波堤，藉此大幅削弱海浪衝擊力，保護沿岸居民的生命及財產安全。

「海陸空」防線強化城市韌性 理大雙科研旗艦應對極端天氣

為應對氣候變化對城市的威脅，香港理工大學今年8月獲國家科技部正式授牌，合建「沿海城市氣候韌性全國重點實驗室」；此前，理大亦獲支持成立「潘樂陶韌性基礎設施研究院」。

理大科研團隊正運用兩大世界級平台資源，推進多個科研項目，包括跨海大橋氣候變化監測、激光雷達颱風監測網絡及基於自然的海岸保護方案等，兩平台分別承擔基礎科研與工程轉化職能，並深化與內地頂尖科研機構的合作，為香港及其他城市構築氣候韌性防線。

大公報記者 邱梓茵

理大建設及環境學院院長李向東，同時兼任沿海城市氣候韌性全國重點實驗室主任及潘樂陶韌性基礎設施研究院院長。他表示：「沿海城市氣候韌性全國重點實驗室」側重基礎科研，聚焦全球及港澳大灣區極端天氣的出現成因與潛在危害，構建氣候變化影響的基礎理論體系。

大橋傳感器網絡分析氣候

而「潘樂陶韌性基礎設施研究院」偏重於工程應用，致力於推動科研成果落地轉化。李向東舉例說明：「以黃大仙港鐵站發生的淹水事件為鑒，研究院將針對此類風險研發具體防範措施，日後市民透過手機應用程式，不僅可查閱颱風信號，還能實時掌握所在區域的實際風力數據。這類技術就是要完全能在實際生活中應用，真正貢獻社會。」

理大粵港海洋基礎設施聯合實驗室主任夏勇在介紹重點項目進展時，闡述其領導的跨海大橋氣候變化監測項目，指出青馬大橋上安裝了近300個各類傳感器，讓團隊可分析溫度、風力等氣候因素對橋樑結構的影響。「1997年至2025年間，大橋平均溫度每年上升攝氏0.05度，颱風影響時間每年增加約3.6小時。基於數據，團隊預測未來氣候變化對橋樑的影響，提出維修保養

建議，並推動香港橋樑設計邁向更高標準。」

目前，相關技術亦已成功應用於港珠澳大橋，自2018年起，理大團隊為該橋搭載無線傳感器網絡，運用邊緣計算技術實現實時數據處理，相比傳統有線系統更靈活高效。

研颱風風險實時預警管理系統

激光雷達颱風監測網絡項目同樣成果顯著。理大杭州技術創新研究院院長倪一清介紹，團隊獲研究資助局主題研究計劃撥款近5000萬元，針對沿海城市高層建築抗颱風問題，開發颱風風險實時預警與管理系統。自2024年起，團隊已



▲「理大追風隊」及搭載激光雷達儀的工程車。

在港九新界六大地點設置激光雷達監測儀，並持續向天文台共享風力數據。

由師生組成的「理大追風隊」，於颱風期間更會駕駛搭載激光雷達儀的工程車，實時採集不同區域的風速數據，進一步提升風力預測精準度。團隊將運用機器學習方法優化系統，未來計劃應用於北部都會區等新發展區及大型基建項目。

環保物料製水底防波堤

在基於自然的海岸保護方案項目，理大沿海城市氣候韌性全國重點實驗室副主任、潘樂陶韌性基礎設施研究院副院長段煥豐透露，團隊利用水利工程實驗室的先進設施，模擬海浪拍岸過程，研發創新型防護技術。

段煥豐表示，其中一項突破性成果為水底防波堤，採用綠殼等環保物料鋪設，可大幅削弱海浪衝擊力，保障沿岸居民生命財產安全。

實驗室學生現場演示了波浪生成過程，有關設備不僅能調控浪高大小，更可模擬「破碎」級別的強浪，用於測試不同孔隙率的綠殼防波堤對波浪的緩衝效果。段煥豐解釋：「不同孔隙率的物料，對波浪的反射與削弱效果存在明顯差異，這為優化防護方案提供了科學依據。」

▲講解科研項目目的理大團隊包括（左起）段煥豐、倪一清、潘樂陶、李向東、朱松濤及夏勇。



▲理大水利工程實驗室進行大浪衝擊測試。

理大科研平台介紹

沿海城市氣候韌性全國重點實驗室

理大獲國家科技部於今年8月授牌批准正式成為全國重點實驗室。為應對氣候變化和災害風險，實驗室旨在深度融入國家戰略格局與全球發展倡議，聚焦韌性城市構建及災害應急管理，致力於提升沿海城市基礎設施韌性，以應對氣候變化引發的多重挑戰。理大與香港科技大學共建的實驗室重點研究領域包括：氣候變遷與極端天氣、城市基礎設施與韌性、城市複合災害與演變、極端暴雨災害與綠色防控、海岸工程與技術，以及氣候變化風險感知預警與因應政策管理。

潘樂陶韌性基礎設施研究院

理大獲潘樂陶慈善基金會慷慨捐助，於今年4月成立該研究院，旨在成為全球領先的研究與發展機構，致力為城市與鄉郊地區提供韌性和可持續性的解決方案，以應對全球氣候變化所帶來的挑戰。研究院提供一個跨學科研究平台，構建高效協同的科學智庫，達成「政、產、學、研、用」深度融合，為香港、國家乃至全球的可持續發展貢獻力量，並致力於四大研究方向：氣候變化與極端天氣、城市基建與韌性、鄉村社區與災害應對，以及氣候適應政策與實施。

責任編輯：曾明達 美術編輯：蕭景崇

理大開發颱風風險實時預警系統 新成立兩科研平台針對極端氣候研究

近年香港屢遇極端天氣，包括「500年一遇」暴雨、自1964年以來再次於一年內兩度出現10號颶風信號等。為應對氣候變化帶來的多重挑戰，香港理工大學今年成立「沿海城市氣候韌性全國重點實驗室」及「潘樂陶韌性基礎設施研究院」，負責氣候相關科研項目。理大於上週舉行記者會，介紹兩個科研平台多項針對極端氣候的研究，包括開發颱風風險實時預警與管理系統，以提升沿海城市高層建築的抗颱風能力。

■ 記者鍾緯盈 ■

理大建設及環境學院院長李向東向記者表示，理大今年8月獲國家科技部授牌，與香港科技大學共同成立「沿海城市氣候韌性全國重點實驗室」，專注於基礎科學研究，探討香港及大灣區極端天氣之成因與潛在危害。同時，理大亦獲支持於今年4月正式成立「潘樂陶韌性基礎設施研究院」，側重於工程應用與科研成果轉化。他亦會同時擔任研究院院長及全國重點實驗室主任。

全港6地點設激光雷達監測儀

李向東指，兩大科研平台將聯合推動多項重點研究，其中，理大獲研究資助局2023/24主題研究計劃撥款近5000萬元，支持項目「INTACT：沿海城市智能式熱帶風暴減災系統」，針對沿海城市高層建築抗颱風問題，開發颱風風險實時預警與管理系統。自2024年起，理大在港九新界6個地點（鶴咀、沙田、沙頭角、元朗、龍鼓灘、貝澳）設置激光雷達監測儀，研究團隊師生更組成「理大流動測風隊」，於颱風期間運用車載3D激光雷達監測儀，實時追蹤風力變化，並持續與天文台共享風力數據，提升風力預測精準度與可靠性。

理大亦建立全球首個在跨海大橋上進行氣候變化監測的系統，以確保橋身結構安全並延長使用壽命。自青馬大橋於1997年啟用以來，理大已在橋身安裝近300個不同類型的傳感器，通過監測各項數據，分析氣候變化對橋樑的影響，並提出維修及保養建議。研究結果顯示，1997年至今，大橋溫度平均每年上升攝氏0.05度；颱風襲港時間則每年增加約3.6小時。團隊稱相關技術亦已應用至港珠澳大橋。

此外，理大團隊正進行沿岸安全研究，利用校園內的水利工程實驗室先進設施，模擬海浪拍岸的過程，探索創新方法以減低波浪衝擊力，例如在水底鋪設以蠔殼等環保物料製成的防波堤，藉此大幅削弱海浪衝擊力，保護沿岸居民的生命及財產安全。

近年全球極端氣候事件日益頻繁，期望推動相關研究，以應對氣候變化所帶來的衝擊。理大潘樂陶韌性基礎設施研究院督導委員會成員潘樂陶

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Our Ref: HKOG 1/50/41

11 August 2025

Ir Prof. Yi-Qing Ni
Chair Professor of Smart Structures and Rail Transit
Department of Civil and Environmental Engineering
The Hong Kong Polytechnic University
Kowloon, Hong Kong, China

Dear Ir Professor Yi-Qing Ni's Team of The Hong Kong Polytechnic University,

Acknowledge Letter

On behalf of the Hong Kong Observatory, we would like to express our sincere appreciation to Prof. Yi-Qing Ni and his team for their continued provision of data from the Hong Kong LiDAR network monitoring system, which was designed and installed by your team (Annex).

Since the commencement of its operation, the Observatory has issued three No. 8 or higher tropical cyclone warning signals—for Yagi, Toraji, and Wipha. Over the past year, your system has delivered timely and invaluable data, including wind profiles, wind direction, turbulence intensity, pressure, temperature and humidity.

These high-quality datasets have greatly enhanced our capability to analyze the structure and evolution of typhoons, and to conduct three-dimensional observations of the urban boundary layer wind fields across Hong Kong.

Yours sincerely,



(Dr P W Chan)

Director of the Hong Kong Observatory



尊敬的香港理工大学倪一清教授团队：

衷心感谢贵团队为我集团运营的深圳·星河双子塔设计并安装的极端气象条件下结构安全智能监测系统（见附图）。该系统现已于今年6月完成安装调试，并投入常态化运行。



系统运行以来，在近期经历的两次关键外荷载事件中表现卓越：

1. 2025年6月23日18时48分，广东清远发生M4.3级地震，系统完整记录了塔楼振动响应数据，为事后的安全评估与复盘提供了可靠依据；
2. 7月20日，今年第6号台风“韦帕”在粤港澳大湾区附近登陆，系统通过实时采集塔体风致响应数据并快速分析，为台风期间结构安全保障提供了关键决策依据。

作为“中国最高的等高双子塔”地标性建筑，星河集团始终将建筑结构安全置于首位。贵团队研发的该系统显著提升了我集团对双子塔结构安全管控的自动化水平，优化了运营效率，并节约了相关运营成本。

深圳市星河智慧园区运营管理有限公司

2025年8月



科研團隊構建「地圖」預測不同地區高廈氣流走向 理大AI減災系統為城市做「體檢」防風險

AI輔助風災減災系列
理大專訪

為應對颱風可能帶來的災害，有本港科研團隊開發「智能式熱帶風暴減災系統」，通過分析多項颱風相關的數據，包括風速、風向等，結合人工智能（AI），構建「風的城市地圖」，以預測本港不同地區、高樓大廈不同樓層在颱風吹襲時所面對的風險。領導研究的香港理工大學學者倪一清接受《星島》專訪時表示，團隊期望通過新系統為城市做「精密體檢」，準確分析風在樓宇之間的走向，提前預測哪些地區的風險最高，並作出預警。

記者陳嘉倫 鍾錦盈

今年颱風「韋帕」及超強颱風「樺加沙」吹襲香港期間，天文台兩次發出10號風球警告，是相隔逾半世紀以來，天文台再度於一年內兩次發出10號風球。風暴期間造成多人受傷，令外界關注防災減災的議題。不過，理大土木及環境工程學系智能結構與軌道交通講座教授倪一清指出創建的「INTACT」：沿海城市智能式熱帶風暴減災系統，則與不少人記憶猶新「2018年襲港的「山竹」有異。

高樓密集環境 局部風力超預期

「山竹」吹襲期間，本港一度懸掛10號風球，並錄得數百宗玻璃窗或玻璃幕牆損毀的報告，另造成最少458人受傷。倪一清向本報記者表示，提出INTACT系統與「山竹」等超強颱風的影響密切相關。「我們在研究中發現，傳統防風方法在香港這種高樓密集的現場存在局限，風在高樓之間會形成複雜的氣流，導致局部風力遠超預值」。他指出，建立系統的初衷就是為城市做「精密體檢」，「（系統）不僅能預測風速強度，更能精準分析風在樓宇間的實際走向，提前判斷哪些區域風險最高」。

我們通過在關鍵建築物設置感測器，即時收集風壓等資料，再讓AI學習資料背後的規律，就像教懂電腦看「風的城市地圖」。當新的颱風來臨時，系統就能結合即時資料，預測出不同區域、不同樓層的具體風險。

理大學者倪一清

倪一清表示，傳統風災預警着重「風威有多大，往哪裏去」，而INTACT系統能進一步顯示「風在樓群間怎麼走，對哪些建築物影響最大」。由他領導、為期5年的INTACT項目，於研究資助局2023/24年度研究計劃中獲得4829萬元撥款，目前已展期兩年。

流動測風降風車載儀器「追風」

研究團隊在本港6個地點設置「激光雷達監測儀」（LIDAR），並利用團隊新研發的系統，監測風速、風向、溫度等數據，與天文台實時分享，用作天氣和風災預警。

為取得第一手數據，提升風力預測的精確度與可靠性，團隊更組成「理大流動測風隊」。於「樺加沙」9月23日及24日襲港期間，使用車載雷達LIDAR，途經沙田、新瀾潭路、理大、黃埔、小西灣、坑口、紅磡、西貢、屯門、東涌、汲水門橋等地點，實時監測風向及風速等數據，並持續與天文台共享風力數據。

倪一清解釋，團隊通過不同方法收集與風災相關的數據，包括LIDAR、天文台提供過去40年的相關數據等，以打造「香港氣象大模型」。構建風災風險地圖，並以此實時預測風災未來一小時的風力變化等。他指即使LIDAR未能涵蓋的地點，團隊也可以通過結合AI及數據主導（data-driven）的方式，重構相關數據，「我們希望可以做到（覆蓋）整個香港」，未來可提供「實時城市風災風險預警」。

計劃維港沿岸北都開展試點

團隊計劃在未來一、兩年內，首先在維港沿岸等地點，以及即將發展的北部都會區開展試點，包括為部分樓宇率先提供系統的風險預警功能，再逐步推廣至更廣泛的應用場景。倪一清在訪問中描繪願景，「我們設想的不是「分級預警、分區推送」的模式，在颱風來臨前24小時，系統會生成動態風險地圖，通過天文台、手機等渠道向公眾發布區域風險等級。對於高風險樓宇的業主和管理方，還可收到更具體的提示資訊，例如建議加強某座向的窗戶防護」。



研究團隊在本港6個地點設置「激光雷達監測儀」（LIDAR），並利用團隊新研發的系統，監測風速、風向等數據。

積極配合建設國際創科中心 推動知識轉移

INTACT系統工作重點(部分)

- 研究團隊在本港6個地點設置「激光雷達監測儀」（LIDAR），分別位於元朗區、北區、屯門區、離島區、沙田區及港島區，並利用團隊新研發的系統，監測風速、風向、溫度等數據。
- 為取得第一手數據，研究團隊組成「理大流動測風隊」，於「樺加沙」9月23日及24日襲港期間，使用車載雷達LIDAR，途經沙田、新瀾潭路、理大、黃埔、小西灣、坑口、紅磡、西貢、屯門、東涌、汲水門橋等地點，實時監測風向及風速等數據。

資料來源：理大提供、本報整理



政府及學界近年大力推動知識轉移，香港理工大學土木及環境工程學系智能結構與軌道交通講座教授倪一清認為，自己作為學者，除了從事學術研究，亦期望研究成果可以應用於業界。然而，他指出「香港沒有那麼多industry（產業），我們也要有application scenario（應用場景）」，坦言這是推動知識轉移工作的主要挑戰。

與輝達商討合作空間

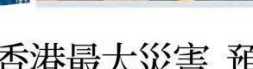
對於政府致力把香港建設為國際創科中心，倪一清表示認同並積極配合，「政府很重視這件事，希望我們把做出來的成果用在不同國家、不同城市，可以提升香港在創科方面的reputation（聲望）。他舉例，他和研究團隊計劃把「智能式熱帶風暴減災系統」推廣至其他沿海城市，期望香港可以發揮牽頭作用。

他透露，團隊正與晶片巨頭Nvidia（輝達）商討合作空間，期望通過Nvidia把新建的系統推廣至全球。他指Nvidia屬全球知名公司，若新系統能配合他們的硬件或軟件，將有助推動知識轉移的工作，「這是香港的科學家希望做的，我們希望可以做到（推廣）去全世界」。

問及推動知識轉移面對哪些挑戰，他坦言挑戰很多，其中是否有足夠的應用場景，屬於主要的挑戰，「香港沒有那麼多industry（產業），我們也要有application scenario（應用場景），才可用到新系統」。

他指出，維港北部都會區即將發展，新系統可先應用於北都，其後逐步推廣至內地城市，「首先在香港應用，接着我們到大灣區用」。

「理大流動測風隊」於「樺加沙」襲港期間，實時監測風向及風速等數據，左圖為「樺加沙」風眼。



倪一清：颱風是香港最大災害 預警研究相當重要

在香港理工大學從事教研工作多年的倪一清，早於1990年代起，便參與香港大型橋樑結構健康監測（SHM）技術研究，其研究範疇亦涵蓋感測器與驅動器、高速鐵路與磁懸浮安全等。倪一清接受《星島》專訪時表示，綜觀多個研究項目，開發實時城市風災風險預警的項目，在他眼中相當重要，於氣候變化之下，預料有助本港未來防災減災的工作。

倪一清是理大土木及環境工程學系智能結構與軌道交通講座教授，以及嚴、麥、郭、鍾晉賢、鍾國強、於土木工務領域、SHM與震動控制領域知名學者。他於2017年獲《國際結構健康監測雜誌》評選為「結構健康監測年度人物」，並於2020

年至2024年連續5年入選由史丹福大學發布的「全球前2%頂尖科學家」名單（土木工務領域），亦曾獲國家科學技術進步二等獎、日內瓦國際發明獎金獎及特別大獎等多個獎項。

連續5年獲「全球前2%頂尖科學家」

今次領導團隊研發「INTACT」：沿海城市智能式熱帶風暴減災系統項目，倪一清表示，與風有關的研究相當重要，「因為對於香港來說，最大的hazard（災害）是颱風」。

他又指，他和研究團隊正與相關政府部門探討，讓城市風災風險預警的資訊未來既能及時傳達給市民，又不會造成「不必要的恐慌」，達到「精

準預警，有效應對」的平衡。

根據香港天文台的資料，今年有10多個熱帶氣旋需要發出熱帶氣旋警告信號，打破自1946年以來年內「掛淡」次數的最高紀錄。倪一清認為，今年襲港颱風的數量多，與氣候變化有關，並坦言「更加需要去做（相關研究）」，以及早應對颱風可能為市民帶來的災害和影響，「我們希望可以幫助整個香港及香港市民」。

倪一清指出，除了颱風之外，本港近年亦曾發生嚴重水浸，例如商場及港鐵站在暴雨下出現水浸情況等。他期望其研究項目在收集有關的數據外，可以同时收集雨量等數據作監測用途，協助減低暴雨對市民的影響。



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