AUSTRALIAN NETWORK OF STRUCTURAL HEALTH MONITORING

Newsletter

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Contents

President Message

Tommy Chan

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Dear All,

First of all, I would like to extend our warmest welcome to Dr Moustafa Al-Ani, Lead Advisor Structures of NZ Transport Agency who replaced Barry Wright to serve on the ANSHM Advisory Board for NZTA. Barry suggested Moustafa replace him since his retirement on 5 May 2023. The suggestion was endorsed by the ANSHM Executive Committee (EC) in the last EC meeting on 8 May 2023. Many thanks to Barry for his service to ANSHM for those many years and we wish him another bright chapter of his life, and may it be even more fantastic than the previous chapter!

Moustafa, welcome on board!

In our 14th ANSHM Workshop, we kept hearing various panellists in the panel discussions of the workshop, especially those from the industry mentioned the Smart Infrastructure Policy. Because of this, we identified the first task of ANSHM in 2023 to "review the NSW Smart Infrastructure Policy and plan accordingly".

The NSW State Government released the Smart Infrastructure Policy (refers as the Policy hereafter) in July 2020, a vital component of the state's Smart Places Strategy and Australia's national Smart Cities Plan. As stated in 1.10 of the Policy, *All NSW public sector Secretaries and Chief Executives are responsible for ensuring that this policy is applied within their agencies*. Hence, this Policy mandates the integration of sensors and smart technologies in all new and upgraded public sector infrastructure starting from 1 July 2020. Its implementation aims to enhance infrastructure efficiency and create more connected communities, fostering improved planning, design, construction, and operation of infrastructure assets in NSW.

This 22-page of Policy document consists of 3 Sections. Section 1 is the Policy Statement listing the purpose, scope, exemptions, compliance and audience of the policy, and the definition, benefits, challenges, and design principles of Smart Infrastructure. Section 2 states the requirements for Smart Infrastructure and Section 3 is an Appendix describing the successful examples of Smart Infrastructure on the Sydney North West Metro and Smart Infrastructure at John Hunter Hospital.

Section 1 of the Policy gives definitions of some terms related to Smart Infrastructure as follows:

Infrastructure *means a system of physical and digital assets that enable the delivery of the services that are the foundation for a successful economy and society (e.g. transport modes, street furniture, bridges, hospitals, schools, parks, waterways, green spaces, prisons etc.).*

Smart Infrastructure *is infrastructure that uses technology and data to optimise performance, increase capacity and achieve a greater return on investment. It uses smart technology (e.g. sensors, computing algorithms) to generate meaningful insights for service and infrastructure providers (including Government, businesses, partners and consumers) who can make better-informed decisions about service outcomes for their customers, places (or communities) and the asset(s).*

Smart Technology *is comprised of devices that can be connected or interconnected. It is comprised of hardware and other physical assets that are embedded with processors, sensors, data storage, software and connectivity that allow data to be exchanged between the product and its environment, manufacturer, operator/user, and other products and systems.*

Section 1 continues to state that Smart Infrastructure will help the NSW Government to realise benefits like improved customer outcomes and productivity improvement, information-driven decision making and whole-of-lifecycle asset management. These again reinforce the direction of the SHM systems developed or implemented on a structure that should be for delivering these benefits. It is an important reminder, and I am so pleased to see that ANSHM has been working on these since its establishment. The aims of the two ARC Industrial Transformed Training Centres that we proposed in 2018 and 2019 respectively align exactly with what the Policy is heading. It is a pity that we are a bit too early and realised such importance ahead of the Policy which was released one year later. The Challenges mentioned in Section 1 refer to the security challenges and privacy challenges which after some serious cyberattack events happened in Australia become a 'must' of consideration for any systems involving IoTs. Regarding the design principles, it states 5 principles govern the design and deployment of smart infrastructure:

i. Customer-centred and inclusive infrastructure
ii. Open and accessible
iii. Interoperability and flexibility
iv. Resilience and sustainability
v. Managing risks and ensuring safety

Section 2 states that from 1 July 2020, in order to achieve interoperability and standardization, which are crucial for realizing the benefits of a smart place in smart infrastructure, smart connected systems are needed to build blocks to combine the following layers:

- Security
- Application & Hosting layer
- Data & Intelligence layer
- Connectivity layer
- Sensor layer

After defining each of these layers in Section 2.2, Section 2.3 states the general requirements which apply to all layers and then specifically states the requirements and why they are important for each layer. In the requirements, "Must" (which are mandatory) are distinguished from "Should" (are recommended (note: if these requirements are not followed, agencies may be at risk of not meeting the Government's commitment to smart places), and the Smart Technology could be applied to the following infrastructure types stated in 2.3.1:

- Power
- Water
- Waste

- Ground & Air Quality
- Public spaces (safety & capacity)
- Building management
- Transport
- Agriculture

Although the Policy does not mention the term Structural Health Monitoring, Smart Technology definitely includes the technologies in SHM and it will give insights to us working in the areas of Structural Health Monitoring, like the following

i. Federal vs State

From this Policy document, it could be seen that Australia is one of the pioneers in promoting Smart Technology to achieve Smart Infrastructure. Although the Policy is just applicable to New South Wales, I anticipate and also strongly recommend that it will become a Federal Policy as well, so that the whole country could be benefited from implementing Smart Technology for the national Smart Cities Plan.

ii. "Smart" vs "Intelligent"

Actually, we are doing something that is ahead of other countries, including the USA. In the past, the infrastructure with smart technologies like SHM will be referred to as Intelligent Infrastructure in North America, e.g. International Society for Structural Health Monitoring of Intelligent Infrastructure (ISHMII), the International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII) series. Even in the year 2021, an advocate for incorporating smart technology in civil infrastructure, Prof Stephen Goldsmith of Harvard Kenney School, refers to this kind of structure as Intelligent Civil Structure[1]. However, in Australia, we take the lead to call this kind of structure a Smart Infrastructure as clearly reflected in the Smart Infrastructure Policy that we are discussing, or the national Smart Cities Plan in 2016. Recently this kind of infrastructure has been

[1] Goldsmith, Stephen, Betsy Gardner, and Jill Jamieson. 2021. "Toward a Smarter Future Goldsmith, Stephen and Gardner, Betsy and Jamieson, Jill A, Toward a Better Future: Building Back Better with Intelligent Civil Infrastructure — Smart Sensors and Self-Monitoring Civil Works (September 10, 2021). HKS Working Paper No. RWP21-023.

referred to as 'Smart' rather than 'Intelligent' as well in the USA[2]. In this PolicyCast, Prof Goldsmith distinguishes "Smart" from "Intelligent" by stating,

…upgrading our infrastructure will not only require spending all that money intelligently, but spending it on infrastructure that is itself smart—full of sensors that can anticipate problems before they require costly repairs and that have multiple functions instead of just one.

However, in this PolicyCast, we could see that the Democrats are seeking support from the Republicans in the US to consolidate the US 2021's Bipartisan Infrastructure Investment and Jobs Act and the 2022's Inflation Reduction Act for the upgrading the existing infrastructure and build the new infrastructure, towards Smart Infrastructure.

iii. Investment vs Expenses

I agree without any hesitation that the budget allows for upgrading our infrastructure or building new infrastructure should be considered a Smart investment as stated in the Policy, *it will also make sure we use these assets to their full potential, ensuring we get the best return on the Government's $97.3 billion infrastructure commitment*. The US was also prepared as much as *$800 billion in spending in the coming years on everything from roads and bridges to water treatment to public transit to climate readiness to clean energy to internet access.*[2]

For examples of the benefits of having Smart Infrastructure, please refer to Section 3 of the Policy.

iv. Physical Infrastructure vs Soft Infrastructure.

It is encouraging to see the Government realise the importance of the investment in infrastructure. After the Policy, it is expected that the NSW government will budget more money for the building of Smart Infrastructure and hopefully, it will give a positive impact

[2] https://www.hks.harvard.edu/faculty-research/policycast/why-smart-infrastructure-smart-investment-even-republicans-era-historic

on the Federal Government. However, all these could be considered investments in the Physical infrastructure. Investments in Soft infrastructure are equally important, which the Policy has not clearly stated. As Prof Goldsmith highlighted in the PolicyCast[2] that was mentioned above, we should not miss the investments in Soft Infrastructure. He considered Job Training and Education for Smart infrastructure as Soft Infrastructure. I totally agree with him. I would like to include Research and Development should be included in the Soft Infrastructure as well. Hopefully, the Policy could direct the governments, State and Federal t**o invest a sufficient amount for the building up of Soft Infrastructure, i.e. Job Training, Education, Research and Development,** so that the benefits of Smart Infrastructure could be delivered effectively, realistically and practically.

Below are the updates for the month.

SHMII-12

As mentioned in the last monthly updates, the 12th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII-12) will be held from Oct. 19 – 22, 2023, in Hangzhou, Zhejiang, China. Some details are given below:

- Call for Full Papers/Ext. Abstracts (submission system is open): May 1, 2023
- Deadline: Full Papers/Ext. Abstracts submission: June 15, 2023

In the last EC Meeting, we decided to have A/Prof Jun Li, A/Prof Xinqun Zhu and myself organise an ANSHM Special Session, entitled "Towards Sustainable and Resilient Infrastructure"

If you would like to join this special session, when submitting papers/extended abstracts using the conference's official link, https://www.shmii-12.com/, please choose the special session under Australian Network of Structural Health Monitoring (ANSHM): Towards Sustainable and Resilient Infrastructure.

If you have already submitted your paper and would like to join our special session, please resubmit your paper to the Special Session and send an email to any of us (Jun Li junli@curtin.edu.au, Xinqun Zhu Xinqun.Zhu@uts.edu.au, Tommy Chan tommy.chan@qut.edu.au), so that we could inform the organiser that your paper will be for ANSHM Special Session.

ANSHM 15th Workshop

Please find below the details of the Workshop that have been confirmed so far:

Title: The 15th Australian Network of Structural Health Monitoring Workshop & The Smart Infrastructure Summit 2023
Theme: Infrastructure Digitisation for Net Zero Transition
Hosts: Rockfield Technologies Australia Pty Ltd and James Cook University
Organizers: Dr Govinda Pandey, the CEO of Rockfield, and
A/Prof Ragbin Tuladhar, Head of Engineering,
College of Science and Engineering, JCU
Dates: 23rd and 24th of November, 2023
with the 25th (Saturday) as an optional day trip to Magnetic Island
(Please mark the dates on your calendar)
Venue: Townsville (exact location to be advised)

Dr Govinda Pandey and A/Prof Rabin Tuladhar will form an organising committee soon and we will keep updating you with the information on the Workshop in the forthcoming monthly dates.

Specifications for SHM

In Issue 34 of the ANSHM Newsletter, A/Prof Colin Caprani of Monash University, our Coordinator of the SHM Specifications Task Force presents his Model Specifications for Structural Health Monitoring aiming at starting the consultation process. He states clearly the aim of the Specifications as:

> *A model set of specifications for SHM will provide a uniform basis for both client expectations and supplier commitments. This should encourage the market in SHM, thereby fostering more and more meaningful installations for improved asset management and the enhancement of public safety.*

If you have not read the articles, please download a copy of ANSHM Newsletter Issue 34, and refer to P.43 to 45 for the article.

The article lists 8 “Shoulds” and “Shouldn’ts” as Goals of the Model Specifications and the proposed Contents of the specifications.

Your feedback will be more than welcome so that the Task Force could continue to work on the development accordingly. For example, the article considers "That SHM seemingly over-promises is partly due to the misnomer of "health" monitoring, which infers the detection of damage." Actually, this is always something we would like to help researchers and engineers working in the field not to mix up structural health monitoring with damage detection. As early as more than 12 years ago, in a chapter of ANSHM 1st Monograph, we have already addressed the issue, by stating that[3],

> *…However, from our experience in Hong Kong, SHM should not be confined to damage detection only. Sometimes, one could even find that existing damage detection approaches will not be effective in the SHM of large complicated civil structures.*

And then we give a much more appropriate definition of SHM as[1],

> *Structural Health Monitoring should be defined as the use of on-structure sensing system to monitor the performance of the structure and evaluate its health state. Hence Structural Health Monitoring should be composed of two components: Structural Performance Monitoring (SPM) and Structural Safety Evaluation (SSE)…*

I don't think the confusion is caused by the "misnomer" of the term "health" monitoring. It is mainly due to the mixed-up of SHM with damage detection. More importantly, it is crucial to give a correct definition and keep the term SHM as the article concludes. Hence, our definition of SHM consisting of two components was then adopted in the Australian Standards for SHM and modified as,

> *Structural Health Monitoring (SHM) involves the use of various sensing devices and ancillary systems to monitor the in-situ behaviour of a structure to assess the performance of the structure and evaluate its condition.* (AS5100.7:2017 Cl 3.15)

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[3] Chan, T.H.T., Wong, K.Y., Li, Z.X. and Ni, Y.Q. (2011) "Structural Health Monitoring for Long Span Bridges – Hong Kong Experience & Continuing onto Australia" Chapter 1 in *Structural Health Monitoring in Australia*, edited by Chan, T.H.T. and Thambiratnam, D.P., Nova Publishers, New York.

Your feedback in any form is welcome!

Research Collaboration

Other than the ARC Hub we mentioned above, there are other collaboration opportunities for us. CRC Building 4.0 just announced the Express of Interest (EOI) process for researchers from the University of Melbourne, Monash University, and Queensland University of Technology. The submission link is given here.

In the next sections, we will have two articles from our members. The first article is from UNSW on simultaneous energy harvesting and sensing using cantilever-type piezoelectric devices to infer the speed of traffic on bridges. The second article is again from UNSW on Hilbert transform optimisation to detect damage in composite laminate structures.

With kind regards,

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Simultaneous energy harvesting and sensing using cantilever-type piezoelectric devices to infer the speed of traffic on bridges

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Abstract

There is growing evidence that piezoelectric energy harvesters (PEHs) not only generate energy from traffic-induced vibration on bridges to supply small sensors, but their voltage signals can also be utilised simultaneously to sense various events of interest. In this paper, using an extensive vibration dataset collected from a real-world cable-stayed bridge, we investigate the simultaneous energy harvesting and vehicle speed sensing performance using a neural network framework of PEH devices with different geometrical shapes. Our results reveal that both energy harvesting efficiency and sensing accuracy depend significantly on the shape of the PEH, and there exist configurations with more favourable harvesting and sensing performances. This finding leads us to propose a framework for jointly optimising energy harvesting and sensing for PEH devices.

Keywords: Energy harvesting; Bridges; Structural Health Monitoring; Piezoelectric; Convolutional Neural Networks; AlexNet

1. Introduction

Bridges are crucial elements in transportation systems due to their high cost, the connectivity that they add to the network, and the severe consequences of their collapse. Consequently, ensuring their safer and durability is vital. In this way, monitoring the bridge-crossing traffic is indispensable because it provides reliable data for management and decision-making [1]. Whatever selected technology for this task, it will require a power source. In some contexts, cabling can become inflexible, expensive and unsafe. Meanwhile, the periodic replacement of chemical batteries can be particularly difficult or unfeasible, limiting a system's service life to a battery's service life. For this reason, Piezoelectric Energy Harvesters (PEHs) have arisen as a promisor alternative to provide energy supply for sensors on bridges converting the traffic-induced vibration into electrical power [2].

Recently studies have shown the feasibility of the use of PEHs for bridges to supply continuous or intermittent measurement operations due to their high-power density [3]. While the primary function of PEHs is power generation from vibration sources, there is a growing interest in using the same device as a sensor to detect various environmental contexts. In this way, studies have demonstrated that the voltage signal from piezoelectric devices under a bridge not only can be used to characterise events of interest. For example, detecting times of vehicle entry and exit [4], identifying train passages [5] or even identifying bridge damage [6]. A key benefit of using a PEH as a sensor is that it eliminates the need for a separate dedicated sensor, and hence the produced energy can be utilised to more efficiently power other parts of the system. This concept was coined as a Simultaneous Energy Harvesting and Sensing (SEHS) system [7].

Although significant progress has been made in designing efficient PEH from the energy harvesting point of view [8], a SEHS system is required to be designed with the dual purpose of achieving efficient energy harvesting and high sensing accuracy. However, little is known about the impact of PEH design parameters, such as its geometrical shapes, on its sensing performance. Therefore, the objective of this work is to explore PEH design spaces to understand the impact of design configurations on both energy harvesting as well as sensing accuracy. To reach this goal, we evaluated both energy harvesting efficiency and vehicle speed sensing accuracy of different cantilever-type PEH with different lengths fed by an extensive vibration dataset collected from a large-scale operating cable-stayed bridge. Based on the study's findings, a joint optimization framework for energy harvesting and sensing for PEH is explored.

2. Case Study: A Cable-Stayed Bridge

The study will carry out on a cable-stayed bridge located over the Great Western Highway in the state of New South Wales (NSW), Australia (Fig. 1a). The bridge has one traffic lane and one pedestrian lane. The bridge has one accelerometer sensor (A1), and two pairs of strain sensors (SS1:SS4) installed under the deck, as shown in Fig. 1b. The collected data from the A1 will be employed to estimate the potential harvested energy from the passing traffic, and further infer the corresponding traffic speed. Additionally, the two pairs of strain gauge sensors are used to estimate the ground-truth velocity following the procedure proposed in [9].

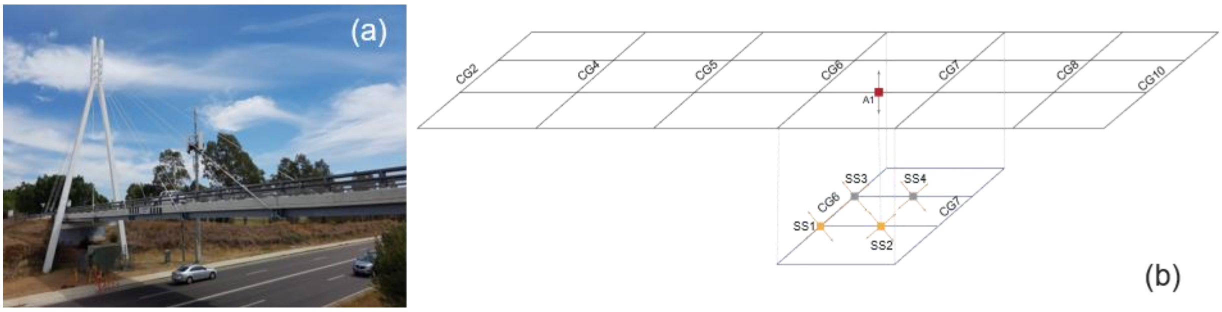


Figure 1. *(a)* Overview Cable-stayed bridge located in the state of NSW *(b)* Illustration of the sensors under the deck.

3. Piezoelectric Energy Harvester Model

The selected model to describe the dynamic response of a cantilever-type piezoelectric device installed under the bridge is the Iso-Geometric Analysis (IGA) framework for PEHs because it was shown to be highly accurate at reasonable computational costs [10]. Fig. 2 presents a schematic of the PEH adopted in this study.

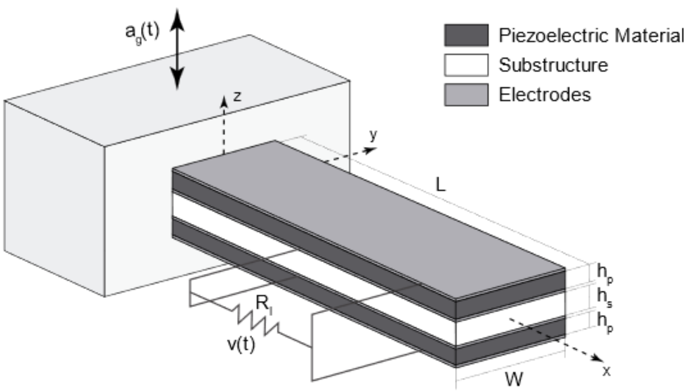


Figure 2. Illustration of the piezoelectric energy harvester.

The model formulation is based on the Kirchhoff-Love plate theory and Hamilton's generalized principle for electro-mechanical bodies. The model is solved numerically using the IGA method, where B-Splines functions are used to describe the device's domain and, also estimate the deflection field $\boldsymbol{w}$, which can be approximated by a truncated modal expansion of the first k mode shape vectors $\boldsymbol{w}_0 = \boldsymbol{\Phi}_0\boldsymbol{\eta}$. Here, $\boldsymbol{\Phi}_0 \in \mathbb{R}^{k\times N}$ is the matrix which contains the k first mode shape vectors

$\boldsymbol{\phi}_i \in \mathbb{R}^{k\times1}$ and $\boldsymbol{\eta} \in \mathbb{R}^{k\times1}$ denotes the modal coordinates. Therefore, the procedure leads to a coupled system of differential equations of the form,

$$\ddot{\boldsymbol{\eta}} + \boldsymbol{c}\dot{\boldsymbol{\eta}} + \boldsymbol{k}\boldsymbol{\eta} - \boldsymbol{\theta}v(t) = \boldsymbol{f}a_b(t) \tag{1a}$$

$$C_p\dot{v}(t) + \frac{v(t)}{R_l} - \boldsymbol{\Theta}^T\boldsymbol{\Phi}_0\dot{\boldsymbol{\eta}} = 0 \tag{1b}$$

Here, $\boldsymbol{k} \in \mathbb{R}^{k\times k}$ is the reduced stiffness matrix, $\boldsymbol{c} \in \mathbb{R}^{k\times k}$ is the reduced mechanical damping matrix, $\boldsymbol{f} \in \mathbb{R}^{k\times1}$ is the mechanical forces vector, $\boldsymbol{\theta} \in \mathbb{R}^{k\times k}$ is the reduced electro-mechanical coupling vector, $\boldsymbol{\Theta} \in \mathbb{R}^{N\times1}$ is the electro-mechanical coupling vector; C_p is the capacitance and R_l is the external electric resistance. From the differential equations (1a) and (1a) using an explicit Runge-Kutta (RK) method, it is also possible to estimate the response voltage signal when the piezoelectric device is subjected to the acceleration measured from a vibrating bridge because of passing traffic. Note that once $v(t)$ is estimated, the harvested energy E can be achieved according to the following equation,

$$E = \int_{t_1}^{t_2}\frac{v^2(t)}{R_l}dt \tag{2}$$

4. Deep Learning Approach

A deep-learning-based framework is proposed to infer a passing vehicle's speed from the generated voltage signal by a PEH installed under the bridge. The framework consists of two main parts as indicated in Fig. 3. The first one is the sample generation, where the initial step is to extract the time window corresponding to a passing vehicle (denominated event), and subsequently, obtain the corresponding acceleration and strain signal responses from the sensors attached to the bridge. Next, the vehicle speed labels are estimated from the strain signals following the procedure explained in [9]. Meanwhile, the voltage signal response is calculated from the acceleration signal using the numerical model presented previously in section 3. Further, the raw time signals of the voltage are post-processed using the Continuous Wavelet Transformation (CWT) with Morlet-type wavelets following the recommendation in [11]. CWT images are used to extract traffic-dependent information.

The second part of the methodology is the Convolutional Neural Network (CNN) for training and testing. The first step is to build a database following the procedure of sample generation. The data is divided into sets of training and testing, containing 70% and 30% of the samples, respectively. The selected architecture for CNN in this paper is AlexNet [12] due to its excellent ability to extract local and multilevel features in different applications, and its successful implementation in vehicle classification in earlier work [11]. AlexNet requires a vast database for its training; for this reason, the Transfer Learning method [12] is incorporated into the framework to reduce the size of the required databases. In this method, an alternative data is used to train lower-level layers, which are responsible for extracting the generic features of the input data. While, the real data is used to train the last layers, which carry out the classification task. Finally, the trained model accuracy is estimated using the validation dataset.

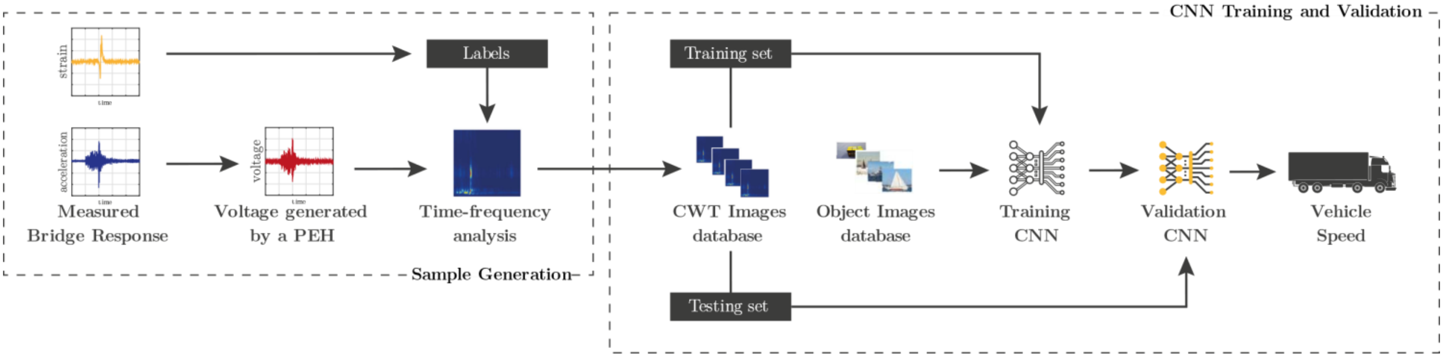


Figure 3. Overview of deep learning framework comprised of two main parts: sampling generation and Convolutional Neural Network training and validation.

5. Results

In this study, different PEH devices are studied to establish the relationship between energy harvesting and detection performance. On one hand, five 12-hour continuous time windows of acceleration response, from five separate days, are used to estimate the average energy generated, using equation 2. On the other hand, the full framework proposed in section 4 is implemented in the six PEH designs. In each implementation, the training/testing process is performed multiple times to reduce the stochastic factors. The database is classified into three different labels, as presented in Table 1. To deal with the long computational times to estimate the sensing accuracy and energy harvesting performance of a single PEH, Kriging surrogate models are implemented following the guidelines discussed in [10].

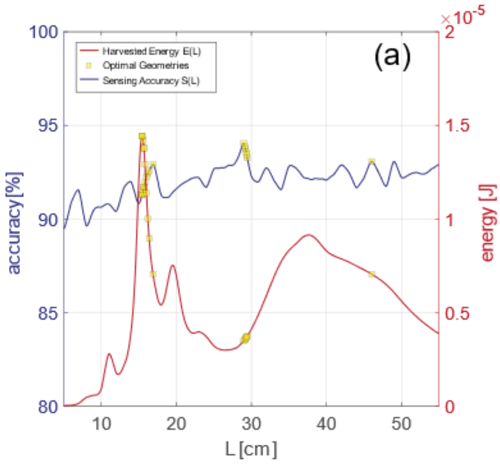
The devices share the same geometric parameters, except for the length L, which is considered the design variable. Meanwhile, the width W, piezoelectric thickness h_p and substructure thickness h_s are 5 cm, 0.25 mm and 0.50 mm, respectively. The materials of the devices are PZT5A and brass [10]. Another important consideration is the external electrical resistance of $R_l = 100\ \Omega$.

Table 1. Definition of the classification labels.

Label	Parameters	# samples
30 km/h	Speed $\in [30, 38]$ km/h	649
40 km/h	Speed $\in [42, 48]$ km/h	490
50 km/h	Speed $\in [52, 60]$ km/h	126

Fig. 4a presents the sensing performance of the PEH devices together with the corresponding energy harvesting performance. From this figure, it is implied that there is no correlation between the optimal geometries in terms of sensing performance and energy harvesting performance, i.e. we cannot identify a device, which is optimal for both, energy harvesting and sensing. This finding opens an opportunity for joint optimisation of sensing/harvesting performances of PEH devices. The optimisation problem is formalised as,

$$L^* = \arg\max_{L \in X}\{E(L), S(L)\} \tag{3}$$



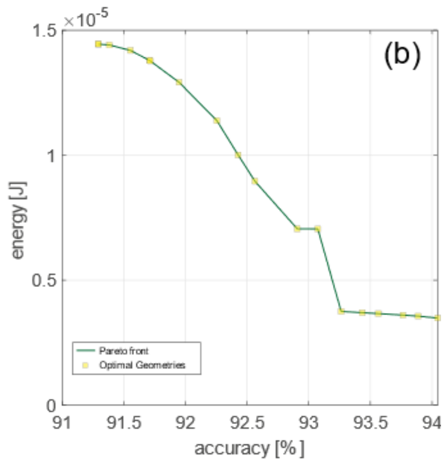


Figure 4. *(a)* Harvested energy and sensing Accuracy for different PEH Designs. *(b)* Pareto front with optimal geometries for the maximization of harvested energy and sensing accuracy

Here the average amount of produced energy and the sensing accuracy are denoted by $E(L)$ and $S(L)$, respectively. A Genetical Algorithm (GA) based on a variant of NSGA-II [14] is the selected optimisation method due to its good Pareto front convergence and its diversification of the candidate solutions. The Pareto front results from the multi-objective optimisation are present in Fig. 4b. It is possible to state that no single configuration simultaneously maximises both and there is a trade-off between its energy harvesting and sensing performances. When no additional information is available from the context, all the Pareto front solutions are considered equally good, despite some being better in one objective but at the same time worse in the other objective, than the other Pareto front points.

6. Conclusion

A comprehensive study case in a real-world application was carried out to correlate energy harvesting and sensing performance for a PEH. We found that there is no clear correspondence, in other words, an optimum harvester may not necessarily act as an optimum sensor. This finding motivated the development of a design framework for joint optimisation of dual-function PEH to obtain a manifold of optimal geometries (Pareto front). Ultimately, the designer is the one who decides which geometry to select based on the design requirements.

Although the optimisation framework is a good tool for understanding the trade-off between the multi-functionalities of a PEH, more studies are needed to improve the sensing performance using PEH, e.g., novel NN models. This work is the first effort to study the impact of a PEH shape on simultaneous energy harvesting and sensing and encourage future works in this direction.

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Hilbert Transform Optimisation to Detect Damage in Composite Laminate Structures

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Abstract

Dealing with incomplete and noisy measurements poses a challenge for many structural health monitoring (SHM) methods. However, this challenge can be dealt with by combining signal processing and optimisation techniques. Here, a new method for detecting damage in laminated composite plates with varying ply orientations is proposed for incomplete and noisy condensed frequency response function (CFRF) measurements. Notably, the proposed method considers damping during simulations presenting a distinguishing feature. To extract a damage-sensitive feature (DSF) from the measured CFRF matrix, an algorithm based on Empirical Mode Decomposition (EMD) is developed. Subsequently, a new objective function is formulated using the constructed DSF matrix as input. The Reptile Search Algorithm (RSA) updates the unknown structural damage indexes in a finite element (FE) model based on the constructed objective function. A composite laminate plate is used as an example of a system with closely-spaced eigenvalues to demonstrate the capabilities of the proposed method. Furthermore, a comparison is made with a technique from the literature, highlighting the superior performance of the proposed approach.

Keywords - Hilbert Transform Optimisation; Empirical Mode Decomposition; Reptile Search Algorithm; Structural Health Monitoring,

Introduction

A variety of strategies and methods have been developed for SHM in response to individual structures' objectives, aims, and constraints. Generally, SHM strategies fall into two categories: model-based and data-driven (1). Model-based SHM methods employ a structural model for identifying and assessing structural damage and predicting how the structure will react in the future when subjected to loading conditions and system configurations. In these methods, the properties of a structure can be updated and compared with their real properties to determine damage. In data-based SHM, measurements from previous data are used to assess the current condition of a system. Detecting anomalies in structural behaviour is the primary goal of these strategies, and pattern recognition is the principle behind them. Data-driven techniques can determine variations in configuration or conditions of loading, including damage to structural elements. A difference between measurements over the previous period indicates abnormalities. Unlike model-based SHMs, data-based SHMs are simple to implement and do not require system behaviour modelling. A number of strategies are employed in these models, including data reduction and representation, feature extraction, and abnormality detection. These methods can also address the effects of environmental and operational conditions (EOC) variations.

Model updating is a model-based technique for improving the accuracy of numerical models that simulate the behaviour of structures. FE model updating methods aim to modify the unknown parameters of a structure's FE model through iteration until the measured responses match the results obtained from the updated FE model. Model updating methods based on optimisation, a goal function based on the difference between analytical and measured structural responses, is optimised to update the unknown physical parameters. Using computational techniques, an optimisation algorithm provides the best solution to these objective functions. Optimisation algorithms, including linear programming, integer programming, nonlinear programming, and metaheuristic algorithms, can solve these problems (1). Using two sub-objectives, flexibility matrix change (FMC) and modal assurance criterion (MAC), Dinh-Cong et al. (2) proposed a novel damage detection approach based on FE model updating. An optimisation problem was solved using the multi-objective cuckoo search (MOCS) algorithm, leading to Pareto-optimal solutions.

Various structural responses have been used to update models, including strain responses, modal information, Frequency Response Functions (FRFs), time histories, dynamic responses, and modal data combined with static data. Complex structures like composite structures and 3D trusses have closely spaced modal information. In the presence of such a phenomenon, it is difficult to detect damage to these structures since there is a significant amount of uncertainty in their response. Small variations in mass or stiffness can significantly affect the modal data in such structures. Due to this, these data would not be a good choice for use in damage detection as damage-sensitive features (DSF). Despite their use as a better alternative to measuring damage on structures with closely-spaced eigenvalues, FRFs are also highly susceptible to measurement errors. The detection of damage to such structures remains challenging when using noisy FRF data. In order to overcome this problem, advanced signal processing techniques are used to produce a signal capable of capturing damage-induced variations in FRF data, even in the presence of high noise levels. In complex structures such as bridges and composites, vibration-based damage detection requires advanced signal processing because signals in the real world are nonlinear and nonstationary. As such, the Hilbert–Huang transform can be applied to facilitate the estimation of damage. A time-frequency signal processing approach extracts sub-signals from an input signal on the basis of two assumptions: (1) the decomposed sub-signals are monocomponent, meaning they oscillate in one single mode only. Due to this, the frequency of these sub-signals fluctuates within a narrow band around the centre frequency. And (2) the original signal is constructed from the sum of the sub-signals. Due to their first property, such sub-signals can be defined as instantaneous frequency, phase, and amplitude. An instantaneous signal can be obtained by adding such properties to the decomposition results. Several time-frequency signal processing approaches can be used to identify structural damage, including Wavelet transformations, empirical mode decompositions (EMD), ensemble empirical mode decompositions (EEMD), and variational mode decompositions (VMD). Denoising can also be facilitated using these methods. Composite structures with closely-spaced eigenvalues are particularly challenging in this regard. The application of a complete ensemble EMD with an adaptive noise technique was investigated by Mousavi et al. (3) to detect damage in steel truss bridge models.

This paper addresses the damage detection problem for composite laminate structures with closely-situated eigenvalues. A model-updating problem based on optimisation updates the damage indices using condensed FRFs (CFRFs). In the EMD algorithm, the sum of the decomposed CFRF signal's Unwrapped Instantaneous Hilbert Phase (SUIHP) is used to reduce measurement noise on the condensed FRF. In the case of composite laminate structures with varying numbers and orientations of layers, the proposed method is demonstrated to detect damage when the CFRFs are highly contaminated by noise with closely-situated eigenvalues. As part of a model updating process, various techniques may be used to update the damping matrix in damage detection methods, including direct optimisation of damping the coefficients, modification based on FRFs, or use of Bayesian regularization to improve damage identification accuracy. A structure's damping matrix is an important parameter affecting its dynamic response, which can be changed by damage. Changes in the structure's dynamic response due to damage can be better captured with an updated damping matrix, thereby leading to a more accurate assessment of the damage's location and extent. Here, we consider updating the damping matrix with each iteration. This paper uses a metaheuristic optimiser known as Reptile Search Algorithm (RSA) (4), which is inspired by crocodile hunting behaviour. To evaluate the performance of the proposed method, three performance criteria have been used: relative error (RE), closeness index (CI), and mean sizing error (MSE). The proposed method is also superior to a method from the literature based on a comparison.

Damage Detection Based on Optimization Algorithms

The proposed method uses a CFRF signal to update the model via an optimisation-based equation. Therefore, we replace each column of CFRF with its UIHP to obtain a signal that is less susceptible to noise. However, it is essential to note that the UIHP is typically well-defined for monotonic signals, representing a single oscillation mode of the original signal. Given that the columns of the CFRF may not satisfy this condition, it is advisable to follow the following procedure:

1. Since each column of the CFRF consists of a signal that may not be considered a single-component signal, it is necessary to decompose it into its constituent mono-component oscillation modes. This decomposition can be achieved by employing an adaptive signal decomposition algorithm that generates Intrinsic Mode Functions (IMFs). To this end, we use the EMD algorithm.

2. For further analysis, the initial and final IMFs obtained from the EMD are disregarded. This exclusion is primarily motivated by the fact that the first IMF represents high-frequency components associated with signal noise, while the last IMF represents the residual components that are assumed not to contain relevant in- formation about the damage. The UIHP values of the remaining IMFs are then summed to derive the SUIHP signal.
3. The resulting SUIHP signal is used to replace the corresponding column.

In general, to obtain the proposed reconstructed signal, (1) the CFRF signal is decomposed using an EMD algorithm, and (2) the SUIHP of its modes is obtained with the EMD algorithm (see Figure 1). In Figure 2, a flowchart showing how an EMD algorithm works with CFRF signals is shown. Using the function EMD in MATLAB, a signal can be decomposed as follows:

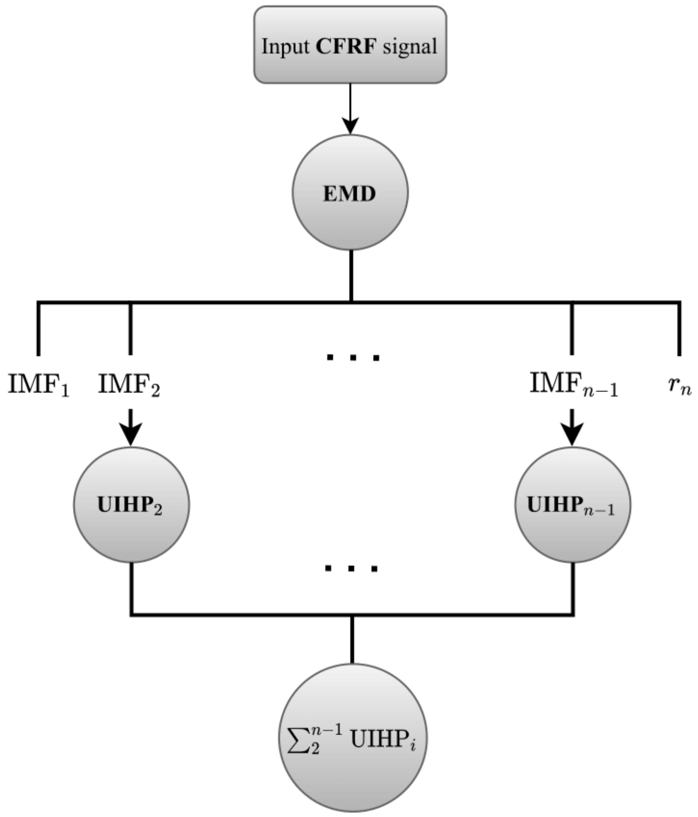


Figure 1. An overview of the process of obtaining the proposed SUIH (5).

In an n-DOF structure, CFRF $(\bar{H})$ can be calculated as follows:

$$\bar{H}(\omega) = (-\omega^2\bar{M} + j\omega\bar{C} + \bar{K})^{-1} \qquad [1]$$

$\bar{K}, \bar{C}$, and $\bar{M}$ represent the compressed stiffness matrix, damping matrix, and mass matrix respectively. This equation uses the Rayleigh damping model of the form $[\bar{\mathbf{C}}] = a[\bar{\mathbf{M}}] + b[\bar{\mathbf{K}}^{\mathrm{d}}]$ in Eq.[1]. This was accomplished by considering a damping ratio of 5% for the two lowest modes of the structure, b and $a. \bar{H}(\omega)$ is also referred to as:

$$\bar{H}(\omega) = \frac{\bar{X}(\omega)}{\bar{F}(\omega)} \qquad [2]$$

$$\bar{X}(\omega) = \bar{H}(\omega)\bar{F}(\omega) \qquad [3]$$

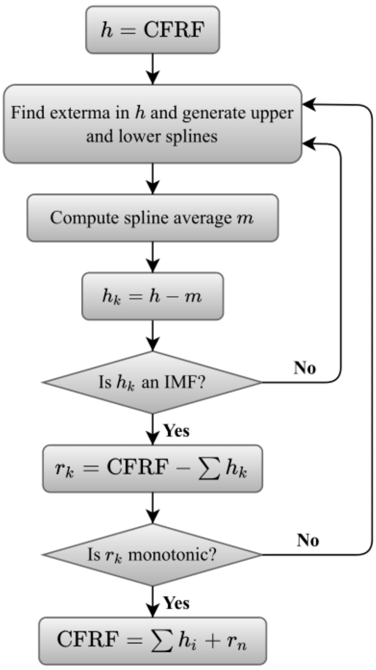


Figure 2. A flowchart showing the EMD algorithm applied to CFRFs (5).

Using the measured and computed structural responses, we can obtain an objective function as follows:

$$G(\hat{\alpha}) = \| \epsilon \|^2 = \|\bar{X}_{\mathrm{m}}(\alpha, \omega_k) - \bar{X}_c(\hat{\alpha}, \omega_k)\|^2 \quad [4]$$

The function $G(\hat{\alpha})$ indicates the error related to $\hat{\alpha}$, which represents the estimated unknown vector. $\bar{X}_{\mathrm{m}}(\hat{\alpha}, \omega_k)$ and $\bar{X}_c(\hat{\alpha}, \omega_k)$ denote the measured and calculated structural responses of the system when excited by k^{th} frequency ω_k, while α signifies the estimated unknown vectors obtained through $\hat{\alpha}$. Consequently, ϵ represents the residual vector. To further elaborate on Eq.[4], a first-order Taylor series expansion can be used as follows:

$$\bar{X}_{\mathrm{m}}(\alpha, \omega_k) \simeq \bar{X}_c(\hat{\alpha}, \omega_k) + \frac{\partial X_c(\hat{\alpha}, \omega_k)}{\partial \hat{\alpha}} \delta \hat{\alpha} \quad [5]$$

As a function of the estimated unknown vector, α^, the derivative of the calculated response vector is as follows:

$$\begin{aligned} \frac{\partial \bar{X}_c(\hat{\alpha}, \omega_k)}{\partial \hat{\alpha}} &\simeq -\bar{H}_c(\hat{\alpha}, \omega_k) \\ &\times \left(-\omega^2 \frac{\partial \bar{M}}{\partial \hat{\alpha}} + j\omega \frac{\partial \bar{C}}{\partial \hat{\alpha}} + \frac{\partial \bar{K}}{\partial \hat{\alpha}}\right) \bar{X}_c(\hat{\alpha}, \omega_k) \end{aligned} \quad [6]$$

Eq.[6] can be substituted into Eq.[5] as follows:

$$\begin{aligned} \epsilon &= \bar{X}_{\mathrm{m}}(\alpha, \omega_k) - \bar{X}_c(\hat{\alpha}, \omega_k) \\ &\simeq \left[-\bar{H}_c(\hat{\alpha}, \omega_k)\left(-\omega^2 \frac{\partial \bar{M}}{\partial \hat{\alpha}} + j\omega \frac{\partial \bar{C}}{\partial \hat{\alpha}} + \frac{\partial \bar{K}}{\partial \hat{\alpha}}\right) \right. \\ &\left. \times \bar{X}_c(\hat{\alpha}, \omega_k)\right] \delta \hat{\alpha} \end{aligned} \quad [7]$$

Due to the fact that Eq.[7] avoids the higher order of Taylor series expansion, it does not obtain an exact solution. Using the CFRF measurements, the changes in the structural response are given as follows:

$$\begin{aligned} \delta \bar{X}_c(\hat{\alpha}, \omega_k) &\simeq -\bar{H}_{\mathrm{m}}(\alpha, \omega_k) \\ &\times (-\omega^2 \delta \bar{M} + j\omega \delta \bar{C} + \delta \bar{K}) \bar{X}_c(\hat{\alpha}, \omega_k) \end{aligned} \quad [8]$$

Eq.[8] can be interpreted as the sum of the partial derivatives of stiffness and mass matrices with respect to damage indices:

$$\delta \bar{K} = \sum_{i=1}^{n} \frac{\partial \bar{K}}{\partial \hat{\alpha}_i} \delta \hat{\alpha}_i \qquad [9]$$

$$\delta \bar{M} = \sum_{i=1}^{n} \frac{\partial \bar{M}}{\partial \hat{\alpha}_i} \delta \hat{\alpha}_i \qquad [10]$$

n is the structure's FE element number. Eq.(9) can be substituted with Eq.[10] and Eq.[8]:

$$(\omega) \simeq [S^{\bar{K}} S^{\bar{M}}] \begin{bmatrix} \delta \hat{\alpha} \\ \delta \hat{\alpha} \end{bmatrix} \qquad [11]$$

where

$$S^{\bar{K}} = \left[-\bar{H}_{\mathrm{m}}(\omega) \left(\frac{\partial \bar{K}}{\partial \hat{\alpha}_1} \right) \bar{X}_c(\omega), \ldots, -\bar{H}_{\mathrm{m}}(\omega) \left(\frac{\partial \bar{K}}{\partial \hat{\alpha}_n} \right) \bar{X}_c(\omega) \right] \qquad [12]$$

and

$$S^{\bar{M}} = \left[-\bar{H}_{\mathrm{m}}(\omega) \left(\frac{\partial \bar{M}}{\partial \hat{\alpha}_1} \right) \bar{X}_c(\omega), \ldots, -\bar{H}_{\mathrm{m}}(\omega) \left(\frac{\partial \bar{M}}{\partial \hat{\alpha}_n} \right) \bar{X}_c(\omega) \right] \qquad [13]$$

where

$$S = [S^{\bar{K}} S^{\bar{M}}] \qquad [14]$$

Eq.[11] can be expressed as an objective function as follows:

$$J(\hat{\alpha}) = \| \delta \bar{X}(\omega) - S \delta \hat{\alpha} \|^2 \qquad [15]$$

In this paper, Eq.[15] is proposed to detect damage in structures with close eigenvalues. Eq.[15] is solved in iterations using RSA, where $\hat{\alpha}_t$, the value of $\hat{\alpha}$ at iteration t, is updated as

$$\hat{\alpha}_t = \hat{\alpha}_{t-1} + \delta \hat{\alpha}_t.$$

Numerical Example

The new damage detection method is demonstrated on numerical models of a composite laminate plate. For this purpose, we adopted the structure and mechanical properties of the composite plate from (6).

The following two configurations of the plate are considered:

- Laminate composite plate with three layers (NoL=3) with ply orientation of LA= (0°/90°/0°).
- Laminate composite plate with six layers (NoL=6) with ply orientation of LA= (0°/45°/0°).

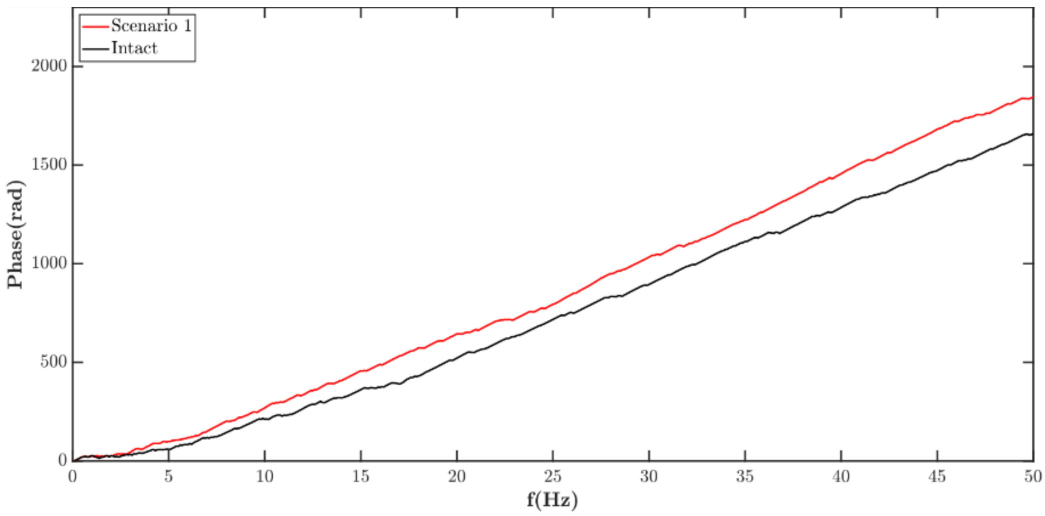
245 degrees of freedom are available at each node of each plate, consisting of three translational DOFs and two rotational DOFs. Following the imposition of boundary conditions, 125 DOFs remain active. This method is examined concerning two different damage scenarios as listed:

- Scenario 1: Damage is present in elements 3, 16, 20, and 31, with stiffness reductions of 0.20, 0.25, 0.30, and 0.15, respectively.
- Scenario 2: Damage is present in elements 6, 10, 11, and 35, resulting in stiffness reductions of 0.25, 0.3, and 0.15.

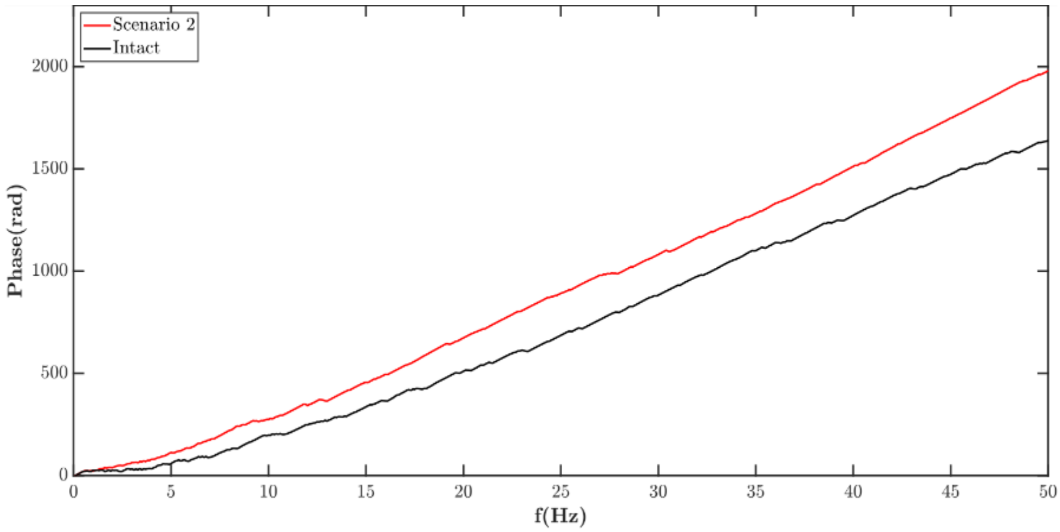
Table 1 lists the natural frequencies of the ten lowest composite laminate plates for each damage scenario. Figure 3 depicts SUIHP for healthy and damaged scenarios of the three-layer (0°/90°/0°) composite laminate plate. Figure 4 depicts the fitness results obtained by solving our proposed objective function (Eq.[15]) using the optimisation algorithm for all damage scenarios. According to the figure, our proposed objective function converges after only a few iterations, indicating the chosen optimisation algorithm (RSA) is appropriate. By applying CFRF and SUIHP as inputs, different accuracy indices are used to quantitatively assess the algorithm's performance (see Table 2). In addition to CFRF and SUIHP, the method's superiority is further demonstrated by comparing it with a method from the literature by Vo-Duy et al. (7). It is noted that we adopted the damage indices of MSE, CI, and RE from Dos Santos et al. (8). The results show that using SUIHP yields significantly more accurate results for damage detection in all cases when compared to CFRF. Our algorithm is further superior to the method proposed by Vo-Duy et al. (7) It is important to note that acceptable damage indices lie within the following range: MSE close to 0, RE close to 0, and CI close to 1.

Table 1. Natural frequencies of compossssite laminate plates with various configurations (first ten modes).

Scheme of lamination		Mode number									
		1	2	3	4	5	6	7	8	9	10
Intact	NoL = 3, LA = (0°/90°/0°)	7.40	11.14	14.32	16.23	18.74	21.42	23.32	23.90	25.74	26.29
	NoL = 6, LA = (0°/45°/0)	7.64	11.53	14.74	16.82	19.07	21.99	23.78	24.90	25.78	26.60
Case 1	NoL = 3, LA = (0°/90°/0°)	7.26	11.02	14.12	16.13	18.50	21.20	22.90	23.71	25.32	26.06
	NoL = 6, LA = (0°/45°/0°)	7.50	11.39	14.52	16.69	18.85	21.76	23.38	24.65	25.38	26.23
Case 2	NoL = 3, LA = (0°/90°/0°)	7.35	10.98	14.27	16.00	18.53	21.09	23.09	23.58	25.41	25.88
	NoL = 6, LA = (0°/45°/0°)	7.63	11.42	14.64	16.61	18.81	21.75	23.53	24.45	25.50	26.12

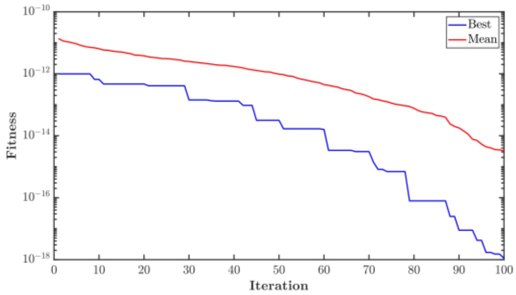


(a) Case 1

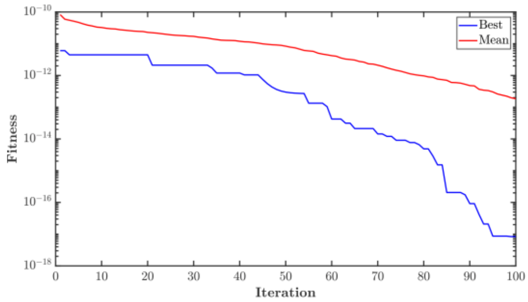


(b) Case 2

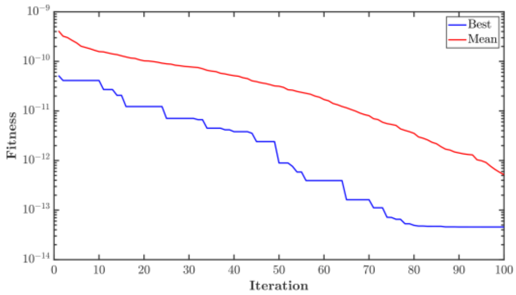
Figure 3. SUIHP of the intact and damaged composite laminate with noise percent (NP)=30%.



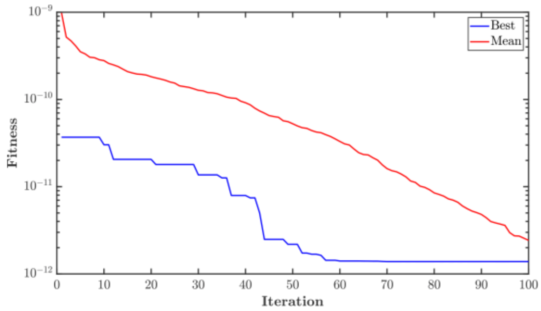
(a) Case 1, LA = (0°/90°/0°), NoL = 3



(b) Case 1, LA = 0°/90°0°), NoL = 3



(c) Case 1, LA = (0°/45°/0°), NoL = 6



(d) Case 1, LA = (0°/45°/0°), NoL = 6

Figure 4. Convergence trace of the optimisation problem for 100 iterations for damage cases 1 and 2 with (NP)=30%.

Table 2. Summary of error indices for different damage cases in composite laminate plates with various configurations when 30% noise is introduced to the CFRF data.

Case #	**Applied method**	**NoL = 3, LA = (0°/90°/0°)**			**NoL = 6, LA = (0°/45°/0°)**		
		MSE	**RE**	**CI**	**MSE**	**RE**	**CI**
1	SUIHP	0.0068	-0.2899	0.8543	0.0069	-0.1999	0.8567
1	CFRF	0.0456	-1.6643	0.7866	0.0657	-1.4999	0.0071
1	MSRCR (7)	0.0178	-0.499	0.7078	0.0065	-0.3988	0.7156
2	SUIHP	0.0067	-0.2666	0.8555	0.0066	-0.1890	0.8452
2	CFRF	0.0499	-1.7098	0.6233	0.0306	-1.3899	0.1007
2	MSRCR (7)	0.0169	-0.4455	0.7852	0.0067	-0.4998	0.7052

Concluding remarks

This article presented an optimisation-based damage detection method for analysing noise-polluted signals. A decomposed condensed FRF (CFRF) is utilized as an input parameter in the proposed method by summing the Unwrapped Instantaneous Hilbert Phase (SUIHP). The algorithm was validated on a numerical laminated composite plate model and compared to a method using the original CFRFs and a state-of-the-art approach from the literature. The results demonstrated that utilizing the SUIHP in the method of model updating based on optimisation yields significantly improved damage detection outcomes compared to using CFRFs when the input data (columns of FRF) are heavily influenced by noise.

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