AUSTRALIAN NETWORK OF STRUCTURAL HEALTH MONITORING

Newsletter

Issue 26, December 2020

Contents

President Message

Tommy Chan

Professor in Civil Engineering, Queensland University of Technology

Dear All,

In this month, it is heartened to know that many of ANSHM Executive Committee members and Advisory Board members receiving ARC funding supports, totalling an amount of $3,079,762.00!

Congratulations to Alex, Hong Guan, Jun, Mehri and Tuan, Wenhui and Stewart!

This is the first time in ANSHM history that so many of us received an award of ARC projects in the same round of Discovery Projects and also many of the projects that are related to SHM are awarded in the rounds for Discovery Projects and DECRA Projects. This indicated that after many years of the effort of all of us, ANSHM has helped the community to realise the significance of the field by promoting the research and development in the field of SHM. I expect more and more SHM projects will be awarded in the future under the Australian Competitive Grants category and other categories. I feel excited not only because so many of us got awarded an ARC project, I am encouraged because Alex, Hong Guan, Jun, Mehri and Tuan have been serving ANSHM as its committee members for that many years and same as other Executive Committee members, they are all passionate for the SHM technologies and have devoted so much to the organisation. Similarly, Wenhui and Stewart have been our Advisory Board Members for many years. I should thank them and other Advisory Board Members who have been so supportive and helpful to ANSHM for that many years.

I always state that SHM is not about placing sensors randomly on a structure to acquire data. SHM research should include 3 categories: (i) system development; (ii) sensors/measurement and (iii) applications. System development is research about how we develop a system to select and deploy sensors, collect, transmit, store and retrieve data effectively. Sensors/measurement is about development of new sensor and/or measurement technology to measure the loads and responses of a structure. Application is about how to make sense of the data collected for health status evaluation and performance monitoring. It is interesting that in this round, we have Mehri's project related to System Development, Alex's project related to sensors/measurement and Jun's project related to Applications, covering all the three categories of SHM researches. Besides Tuan and Hong's project on the development of innovative structural systems could also include using SHM technologies collecting information to improve future design of composite systems with enhanced resilience to extreme loads. I believe for the projects of Wenhui and Stewarts, their development will also be helpful to the field of SHM for better understanding of Artificial Intelligence (AI) application in concrete technology and providing assessment for terrorist risks respectively. I look forward to having their presentations in future ANSHM Workshops reporting their progresses and reading their publications generated from these projects.

Although it is common for our Executive Committee members and Advisory Board members to have an ARC project being awarded, this round is very unusual that we have so many successes in one round! Below are extracts of the information from the corresponding page from ARC Grant Outcomes (https://www.arc.gov.au/grants/grant-outcomes).

Dr Mehrisadat Makki Alamdar	Developing an Advanced Drive-by Bridge Inspection Technology - Funding Awarded: $ 430,075.00 - Scheme: ARC DECRA (DE210101625) 72% of bridges in Australia were constructed before 1976. Currently bridges are inspected by biennial visual inspection which is expensive, time consuming and subjective. Considering the large number of defective bridges in Australia and around the world and the limited budget of road authorities, this project aims to develop a low-cost and robust bridge monitoring framework by advanced data analytics, solely based on the response of a moving vehicle passing over the bridge, with no equipment to be installed on the bridge. The project is significant because it opens a new direction for sustainable monitoring of such ageing infrastructure, consequently resulting in the lower costs of maintenance, enhanced safety and extended asset life.
Prof Tuan Ngo, Prof Alex Remennikov, Prof Hong Guan, and A/Prof Benoit Gilbert	Innovative composite systems with enhanced resilience to extreme loads - Funding Awarded: $ 381,244.00 - Scheme: ARC Discovery Projects (DP210102499) The rapidly increasing global population (projected to be 9.8 billion by 2050) and global urbanisation have created a demand for the construction industry, thereby increasing the pressure on our planet's limited resources for the construction industry. This high demand can yield detrimental effects to the environment due to the high carbon footprint of conventional construction materials, and is amplified by the threat of accidental or deliberate extreme loadings to buildings, which can trigger fatal progressive collapse events. The proposed project aims to develop an innovative structural system with that possesses superior structural resilience to extreme loads and progressive collapse using lightweight eco-friendly materials.
A/Prof Ching Tai (Alex) Ng and Prof Andrei Kotooussov	Next generation nondestructive inspection using guided-wave mixing - Funding Awarded: $ 440,624.00 - Scheme: ARC Discovery Projects (DP210103307) This project aims to develop a novel approach for early damage detection. It relies on a systematic experimental investigation of nonlinear ultrasonic interaction between different input wave modes in the presence of damage, so as to identify optimal mode selections and operating parameters that will maximise the sensitivity to particular forms of structural damage. The effects of in-service loading on wave-mixing response, and non-contact detection suitable for hard-to-inspect surface conditions, will also be investigated. The new developments will help transform existing schedule-based maintenance practice to a condition-based maintenance paradigm, to achieve significant cost savings in maintenance.

A/Prof Jun Li, Prof Ling Li, and Dr Senjian An	AI Assisted Probabilistic Structural Health Monitoring with Uncertain Data - Funding Awarded: $ 355,331.00 - Scheme: ARC Discovery Projects (DP210103631) This project aims to develop an advanced Artificial Intelligence (AI) assisted probabilistic structural health monitoring approach for civil engineering structures. The developed approach applies novel deep learning techniques with a large amount of data measured from uncertain and complex environment, for reliable structural condition monitoring and performance prediction. This project expects to make a step change in data mining and interpretation. Expected outcomes of the project include novel AI assisted approaches to conduct probabilistic structural condition monitoring with sensitive features and future structural performance prediction. This will provide significant benefits to infrastructure asset owners to reduce maintenance costs.
Prof Wenhui Duan, Prof Yan Zhuge, Prof Jay Sanjayan, and Prof Ling Li	Hydrogen carbon waste into concrete: AI assisted nanoscience approach - Funding Awarded: $ 768,927.00 - Scheme: ARC Discovery Projects (DP210100020) The carbon waste from hydrogen production will be converted into carbon nanosheets on abundant construction materials for the creation of stronger and more durable concrete. Cutting-edge nanoscience-based experiments, as well as sophisticated modelling techniques including machine learning and finite element modelling, will be employed. The findings will drive advances in clean hydrogen production, carbon waste utilisation, cement hydration, nanotechnology and concrete technology for the next generation of an upskilled workforce and the promotion of a circular economy. This project will be carried out in collaboration with Australian and international renowned experts in computational modelling, nanomaterials and concrete materials.
Prof Mark Stewart	Stochastic Assessment of Terrorist Blast and Fragmentation Casualty Risks - Funding Awarded: $ 703,561.00 - Scheme: ARC Discovery Projects (DP210101487) The project will develop probabilistic models to predict the likelihood and extent of casualties and other losses from terrorist car bombing threats. Car bombs comprise a large quantity of explosives, and produce primary fragments such as wheels, engine block, parts of door panels and other shrapnel that pose a serious safety hazard to people exposed in a street or other mass gatherings. An improved understanding of safety risks will assist in setting safe evacuation distances. A quantitative assessment of terrorism risks will also allow the effectiveness of security measures to be assessed to provide cost-effective levels of protection that are acceptable to society.

We should also congratulate Mehri for her involvement in the design and development of a real time Structural Health Monitoring System for the Sir Leo Hielscher Bridge (the Gateway Bridge) in Brisbane, which is the winner for the Intelligent Transport Systems (ITS) Australia award (Smart Transport Infrastructure Award) this year. The collaborators of the project include Data61, Transurban, UNSW, CISCO and Rockfield. Congratulations to all of them. I am so pleased to let you know that, Ben and Khoa of Data61 together with Mehri will give a presentation of the this award winning SHM system in our 12th ANSHM Workshop. I am so delighted to see that the importance of SHM has been recognised not only within academic community as demonstrated in the successes of SHM projects in recent ARC Discovery and DECRA rounds, but also in the industry. It is really encouraging to all of us as ANSHM members.

The West Gate Bridge collapsed 50 years ago on 15 Oct 1970. In October this year, to commemorate that tragedy ABC Radio Melbourne interviewed Colin, our another Executive Committee member. He made use of this good opportunity to promote the benefits of SHM for public safety. Please read the full article via:

https://www.abc.net.au/news/2020-10-15/bridge-safety-50-years-on-from-westgate-tragedy/12740628.

Below are the updates of the month.

12th ANSHM Workshop

As mentioned in the last update, the 12th ANSHM Workshop, will be conducted in an online mode from 7 to 8 Dec 2020. This event could be considered as a CPD event for Engineers Australia for your CPD and Practice Review. The Workshop Organising Committee has been working extremely hard for preparing this workshop. I really appreciate Lei, John and Xinqun and other organising committee members for their effort and hard work, especially this is the first time we organise this ANSHM important annual event online. We have will have around 20 presentations including the presentation on the SHM System for the Gateway Bridge mentioned earlier. The presentations are arranged into 5 sessions as follows:

1. Bridge Structural Health Monitoring
2. Data-driven Structural Health Monitoring
3. Non-destructive Techniques
4. Big Data Analytics for Structural Health Monitoring
5. Advanced Sensing Technology

Besides, we will also have a session called Industry Workshop entitled Structural Health Monitoring Practices. Same as previous years, we will also have an industry forum which I believe will be a highlight of the Workshop.

We will ensure this workshop to be as good as a face to face workshop or even better. Both the delegates and the presenters will find it very easy to attend and present respectively. More details including the program and attending link will be forwarded by the organising committee in the following few days. At the moment, you just need to mark your calendars and save the dates of 7 to 8 December 2020 for this important ANSHM annual event and register your attendance using this link: https://forms.gle/UYMgx1NuJLuT8teg6 if you have not done so. If you like, you could also send the registration link to your HDR students, colleagues or others especially in the industry you think they would be interested.

Look forward to meeting you all in the workshop.

13th ANSHM Workshop
Hopefully our 13th ANSHM Workshop could be held in Sydney as originally planned for the 12th Workshop but has been postponed to next year because of COVID-19. Further details will be discussed in the forthcoming Advisory Board Meeting and the organiser of the 13th ANSHM Workshop will give us some introduction on this Workshop during the Closing Session of 12th ANSHM Workshop on 8 December 2020.

ANSHM Advisory Board Meeting and Annual General Meeting
Please be kindly reminded that we will have our ABM and AGM during the 12th ANSHM Workshop. The details for the two meetings are as follows:

ABM (Only for the ANSHM Advisory Board Members and Executive Committee Members):
Date: 7 December 2020
Time: 15:00 to 17:00 (AEST)
Zoom details have been provided to all the members of the Advisory Board.
Please email me (tommy.chan@qut.edu.au) if you are unsure of the link.

AGM (For any ANSHM Members):
Date: 8 December 2020
Time: 11:00 to 11:40 (AEST)
Registration for AGM will be conducted from 10:30 to 11:00 (AEST)

Zoom details will be same as that for the 12th ANSHM Workshop which will be provided in due course.

You should have received my message dated 17 November 2020 on *the Proposed Change of ANSHM Rules Cl 6.3* in order to avoid future issue in the definition of the term "venue". Such amendment will be voted upon at the coming AGM on 8 December 2020 according to the Rules of ANSHM.

Election of Executive Committee Members

Besides, you should have received my message dated 17 November 2020 on *the Call for Nominations for Election of Executive Committee Members*. As the message sated, the nomination can be made by sending an email to me (tommy.chan@qut.edu.au) by 3 December 2020. According to the Rules of ANSHM, the Nominations shall be called at least 14 days prior to the election during the forthcoming Annual General Meeting on 8 December 2020. The election will be conducted using a secure online voting system. For this time, the two-year term of office of the following EC members will be completed:

1. Tommy Chan (President)
2. Jianchun Li (Deputy President)
3. Hong Guan
4. Xinqun Zhu
5. Tuan Ngo

All these five Executive Committee members are happy to continue their service in the Executive Committee and are willing to be re-elected. In the upcoming Advisory Board Meeting, we will also review the Executive Committee including the number of members required.

Annual Membership Renewal

We need to renew our membership around the time of AGM. Regarding this, our Membership Officer Alex will act on the followings:

- Email you if you are ANSHM members to confirm whether you would like to renew their (ordinary) membership.
- Review the commitment, e.g. attendance of the annual workshops, and then contact you if you would like to be/renew core membership. After that we can then discuss in EC meeting to approve this.

Publication generated from the 11th ANSHM Workshop

Nova Science Publishers has accepted our book proposal and sent us the proposed contract for our ANSHM 11th Workshop publication. They've suggested the most suitable publication type:

Title - Recent Advances in Structural Health Monitoring Research in Australia
Type - Edited Collection
Binding – Hardcover

We will discuss the conditions with the Executive Committee during the forthcoming Advisory Board meeting. We have 14 days (**by 10th Dec the latest**) to respond to Nova with our signed contract.

ANSHM Mini-Symposium (MS26) in SHMII-10

Please note that the call for papers for this Mini-Symposium is still on. Please submit your paper directly through the link (https://web.fe.up.pt/~shmii10/submission/paper-submissions/) and select theme no. 26 - Latest advances on SHM and smart structures in Australia/Oceania. Please follow the format rules according to the templates downloadable via this link. The deadline of submission is **10 January 2021**. According to the most recent update from SHMII10 conference chair, the conference will be held in a hybrid mode so that authors can be certain that the conference will go ahead. Late submission authors (who haven't submitted abstracts by the final deadline) could contact Andy Nguyen Andy.Nguyen@usq.edu.au or me for possible straight full paper submission.

Research Collaboration

The application for the proposed ARC Research Hub for Resilient and Intelligent Infrastructure Systems in Urban, Resources and Energy Sectors (RIIS) was submitted on 18 November 2020. The outcome will be announced in the 3rd quarter of 2021. Bijan and I will determine how ANSHM can be involved in RIIS, if successful. Building 4.0 CRC may have some interesting projects to involve ANSHM for 2021. SmartCrete CRC involves 46 projects and we look to having some projects led by ANSHM members.

The ANSHM Newsletter

In order to formulate an article collection plan, Mehri statistically summarised all the articles published in the Newsletter since the first issue in Sep 2014 and prepared a chart showing the number of articles contributed by a particular organization. Please see Figure 1. The Editorial Team will use this information as a guidance to formulate their article collection plan and those universities or from the industry which have not published earlier to realise the importance of publishing their articles in the Newsletter to update others about their research development in SHM, their experiences in applying SHM or what they expect SHM could help.

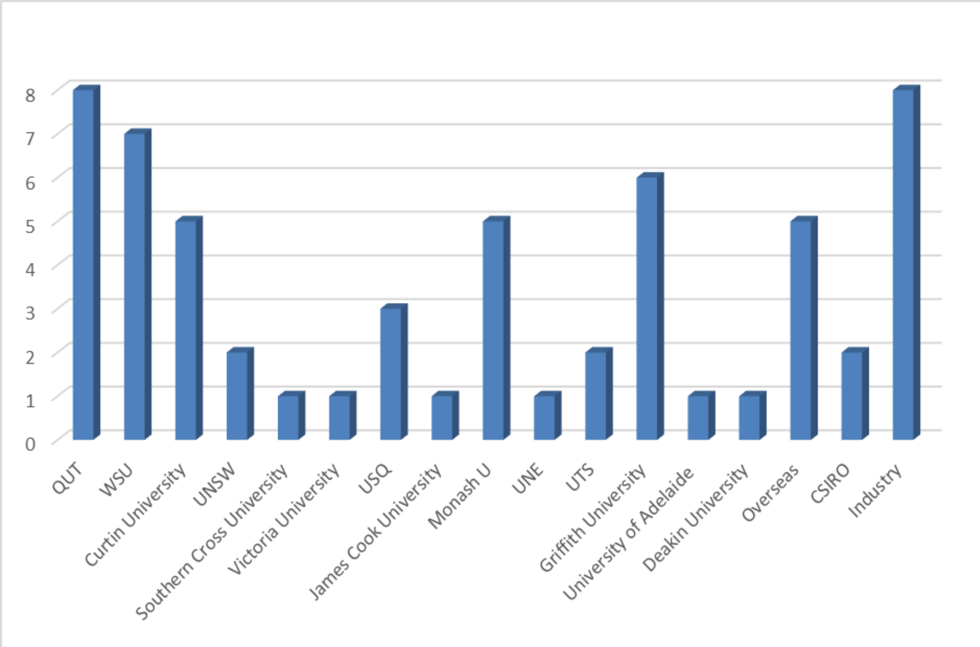

Figure 1 The Source of Articles Published in the ANSHM Newsletter

Thanks Jun for looking after this issue of the Newsletter. In the next sections of this Newsletter, Dong and Li of UTS propose an intrinsically self-sensing cement-based sensors for concrete structural health monitoring by collecting the changes of electrical resistivity. Moreavej et al. of QUT conducted structural performance assessment using vibration based probabilistic model updating and reliability analysis.

With kind regards,

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President, ANSHM
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Research profile | **Research publications** | **Google Scholar citations**

Intrinsically self-sensing cement-based sensors for concrete structural health monitoring: an Australian perspective

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Introduction

Traditional concrete structures with steel reinforcement are provided with extremely high compressive and tensile strengths, durability and severability, thus widely applied in the constructions of buildings, pavements, dams, and bridges, etc. (Dong et al., 2019). Different from the traditional concrete, the novel cementitious composite incorporating electrically conductive fillers are given multiple functions including but not limited to the self-sensing, self-heating and self-healing characteristics (Chung, 2020). In particular, the self-sensing property of concrete enables itself to monitor the stress/deformation automatically, by recording the electrical resistivity/conductivity of the cementitious composite. Therefore, when modify the concrete with conductive fillers such as carbon nanotube or carbon fibre, in addition to the enhanced mechanical properties and durability, the extra property of self-sensing can be an intrinsic technique for structural health monitoring in comparison to the traditional sensing methods such as surveillance camera and strain gauge (Konsta-Gdoutos et al., 2010).

Research objectives

The objectives of the research are to:

(1) Figure out the relationship between the electrical resistivity of cement-based sensors and the stress/strain of monitored concrete structures.

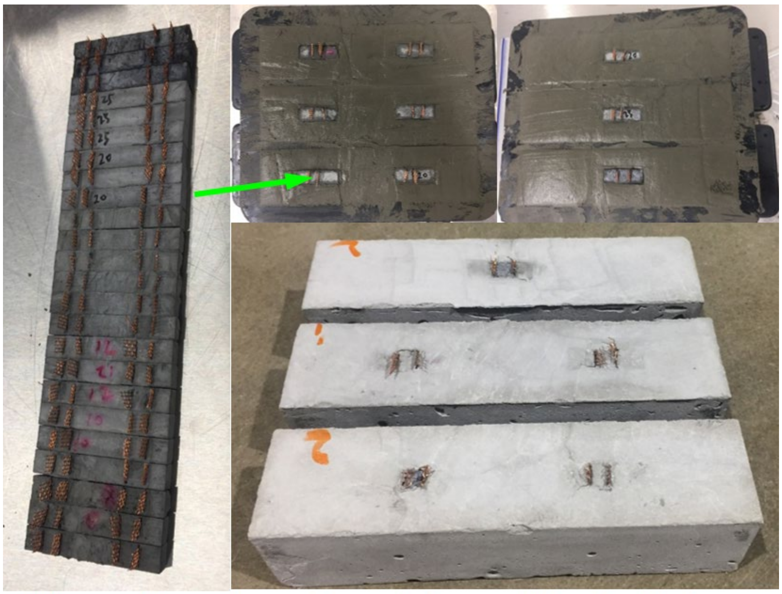
(2) Improve the intelligence, serviceability, mechanical and durable properties of concrete structures.

(3) Develop a novel intrinsic self-monitoring system for the concrete structures.

(4) Reduce the engineering cost regarding to the concrete structural health monitoring.

Concrete beam with embedded cement-based sensors

To evaluate the self-sensing efficiency of cement-based sensors, the concrete beams are cast when the cement-based sensors are manually embedded. Figure 1 shows the cement-based sensors and the concrete beams with embedded sensors. To ensure good cohesion between sensors and beams, the mix proportion of cement-based sensors and the concrete beams is completely identical, except for the addition of conductive carbon black in the cement-based sensors. The addition of carbon black improves the electrical conductivity of cementitious composite and provides the composite with self-sensing ability or piezoresistivity.



CB/cement-based sensor | Concrete beam with embedded cement-based sensors

Figure 1. Diagram of CB/cement composite, CBCS manufacturing and concrete beam embedded with CB/cement-based sensor (CBCS)

Experimental test setup

Figure 2 shows the experimental setup for the test, including the details of concrete beams, cement-based sensors, compression equipment and the data collection systems. The cement-based sensors are embedded in the central of tension zone, where the tensile stress reaches the largest values during three-point-bend test. The compressed force and deformation of concrete beam can be detected through the compression machine, while the electrical resistance of the embedded cement-based sensor can be recorded using a digital multimeter. The changes of the electrical resistivity of cement-based sensors are found possessing firm relationship to the applied force, thus the electrical resistivity changes can be a reliable signal to monitor the compressive/flexural stress and strain on the concrete structures.

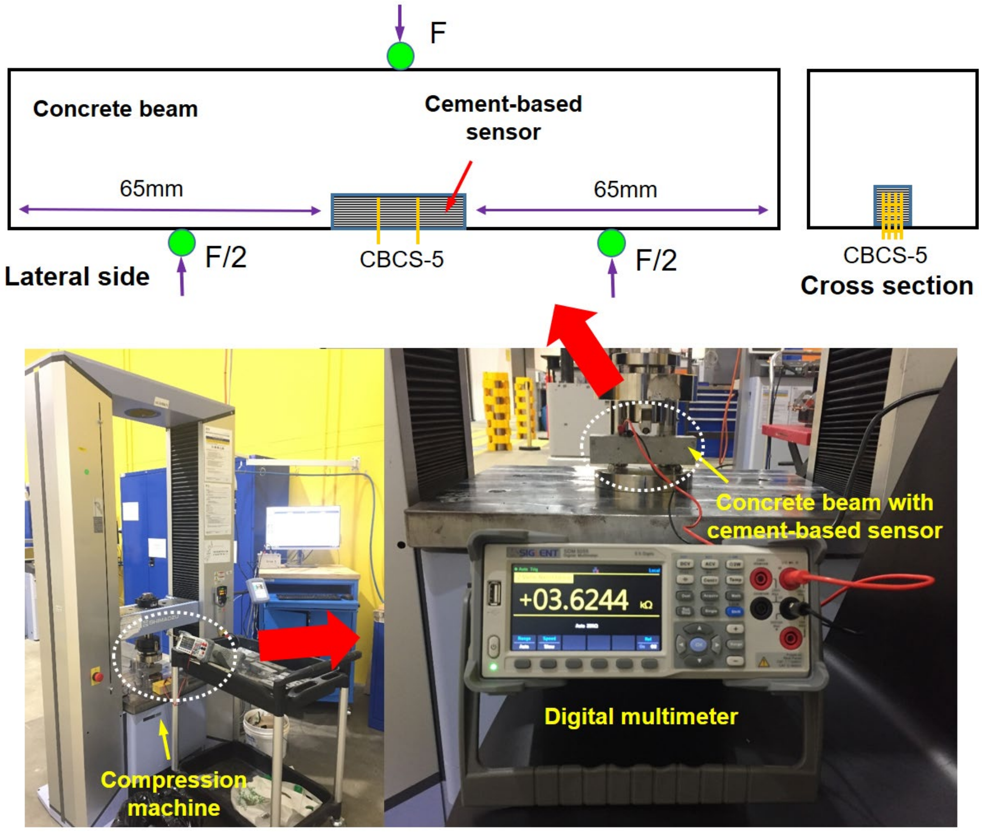
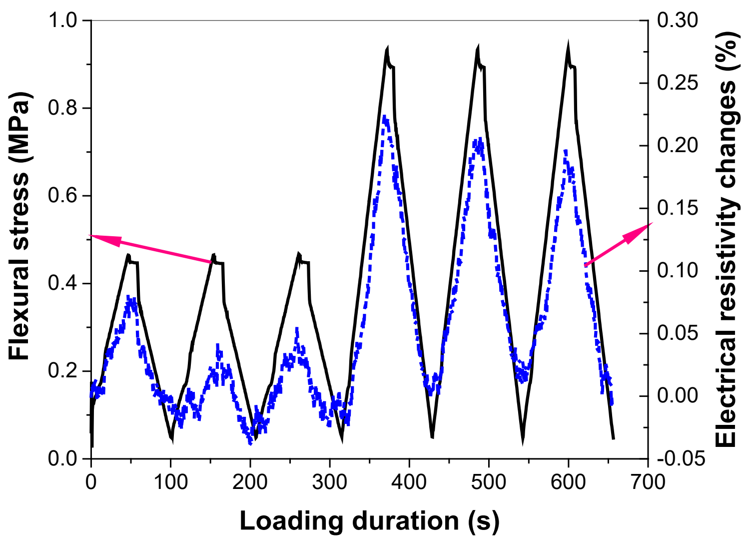


Figure 2. Experimental test setup for the concrete beam with embedded cement-based sensor

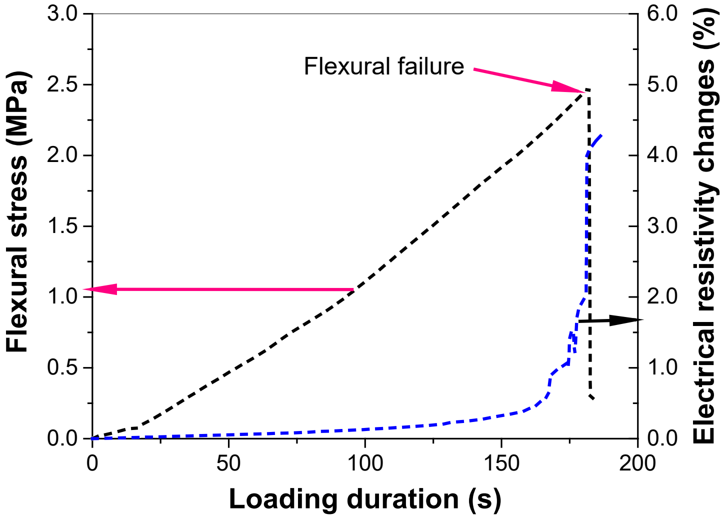
Results and discussion

The measured electrical resistivity changes of cement-based sensors embedded in concrete beams subjected to cyclic and monotonic flexural loadings are plotted in Figure 3. The cyclic loading pattern can reflect the stress sensing ability and repeatability, while the monotonic loading pattern can assess the flexural failure monitoring of cement-based sensors. It was found that the electrical resistivity of cement-based sensors increased in the loading stage and decreased in the unloading stage (Dong et al., 2020). Given the cement-based sensors are tensioned in the tension zone, the distance of conductive carbon black increases and damages the conductive passages in the cement-based sensors, which leads to the increased electrical resistivity. On the contrary, in the unloading process, the carbon black nanoparticles reconnect to each other and regenerate the conductive passages to decrease the electrical resistivity. Therefore, because of the good correlation between electrical resistivity changes and flexural stress, the electrical resistivity of cement-based sensors can be the parameter to monitor the flexural stress.

In terms of the performance of cement-based sensors embedded in concrete beams under monotonic loading, the electrical resistivity continually increased with the increase of flexural stress. The changing rate of electrical resistivity of cement-based sensors significantly increased at the flexural failure point. This is mainly due to the cracks in the cement-based sensors that block the conductive passages and increase the electrical resistivity (Liu et al., 2018). At the failure point, the cracks are firstly formed in the tension zone of concrete beams because of the low tension strength of concrete, and then the cracks propagate to the cement-based sensors. Overall, it means the cement-based sensors are capable to detect the flexural failure of concrete beams by collecting the changes of electrical resistivity.



(a) cyclic flexural loading



(b) Monotonic loading

Figure 3. Electrical resistivity changes of cement-based sensors in concrete beams under cyclic and monotonic loadings

Acknowledgement

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STRUCTURAL PERFORMANCE ASSESSMENT USING VIBRATION-BASED PROBABILISTIC MODEL UPDATING

Hans Moravej[1], Tommy HT Chan[1], Khac Duy Nguyen[1], Andre Jesus[2]

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Bayesian model updating applying Gaussian process metamodel

Structural health monitoring data has been widely acknowledged as a significant source for evaluating the performance and health conditions of structures. However, information that is directly extracted from the monitored data is usually susceptible to uncertainties and not reliable enough to be used for structural investigations. Further, a holistic framework that efficiently incorporates monitored data into structural identification, and in turn, provides a realistic life-cycle performance assessment of structures is yet to be established. Finite element model updating (FEMU) is an accredited framework, which aims to improve the accuracy of the finite element models of real structures and reduce the discrepancy between the outputs of the numerical models and experimental measurements [5]. So far, a large number of FEMU algorithms have been proposed. Amongst them, approaches using vibration properties have been extensively studied and broadly applied to a number of practical applications of infrastructure. However, FEMU faces some significant barriers, which prevent it from reaching its peak efficiency. The first one is the computational burden, especially in the case of complex structures, making this technique cumbersome. Another challenge in updating a model relates to addressing different sources of uncertainties, such as structural parameters, computer model bias and measurement errors. Neglecting to account for these factors result in unreliable structural identifications. To overcome the problem of uncertainties consideration, probabilistic approaches, which are more reliable than deterministic ones, have been introduced despite they are mostly computationally tedious.

Accordingly, this research proposes a FEMU method for calibrating the FEMs of structures with addressing uncertainties while it is computationally efficient. Firstly, Bayesian framework and Gaussian process metamodel are applied for calibrating numerical models, then by integrating the FEMU method and structural reliability analysis, a new framework for structural performance assessment is proposed. In this framework, Gaussian process metamodels are replaced with a finite element model and its associate discrepancy function to provide a computationally efficient and all-round uncertainty quantification. Herein, the structural parameters that are most sensitive to measured structural dynamic characteristics are investigated and used to update the numerical model. Sequentially, the updated model is applied to compute the structural capacity with respect to loading demand to evaluate its as-is performance. The proposed framework's feasibility is investigated and validated on a large lab-scale box girder bridge (BGB) in two different health states, undamaged and damaged, with the latter state representing changes in structural parameters resulted from overloading actions.

A comprehensive equation of the model updating process in Eq (1) denotes the output of the processes within the domain of a calibrated status $\theta = \theta^*$, which implies the best fit compared with the observed data [1].

$$\mathbf{Y}^{e}=(\theta^{*})+\boldsymbol{\delta}+\varepsilon \tag{1}$$

In this equation, $\boldsymbol{\delta}$ is a discrepancy function, which represents the difference between the numerical model and the real process. $\mathbf{Y}^{m}(\theta^{*})$ is the numerical model's output and θ^{*} is an r-dimensional vector of the true structural parameters and ε is the observation error.

Gaussian process (GP) metamodel is an interpolation approach that considers uncertainty highly efficient even when data are limited. By applying interpolations and extrapolations, this approach offers a predicted GP that is fitted on all observation points. To generate the GP, the mean function and covariance function of fitted model is required to be obtained, which exists at every design input point without uncertainty. In the spaces located between or outside the design input points, the GP will produce either a possible interpolation or extrapolation from the existing data points.

In the GP, the prior mean function is supposed to be a member of a hierarchical structure of linear functions. It can be generalized as the form $\mathbf{M}=\mathbf{H}\boldsymbol{\beta}$. Herein, matrix $\mathbf{H}$ comprises N polynomial constant regression functions and the matrix of regression coefficient $\boldsymbol{\beta}$ for each term included in matrix $\mathbf{H}$ and each fitted response in $\mathbf{Y}$. That is, $\mathbf{H}$ is a row vector of regression functions and $\boldsymbol{\beta}$ is a column vector of regression functions. The prior covariance function of the GP for the model and discrepancy function can be formulated as:

$$\mathbf{V}=\sum{}^{2}\otimes\mathbf{R} \tag{2}$$

where $\mathbf{V}$ is the covariance function, $\boldsymbol{\Sigma}^{2}\in\mathbb{R}^{g\times g}$ is a non-temporal variance matrix, $\mathbf{R}\in\mathbb{R}^{N\times N}$ is a temporal correlation matrix, and $\otimes$ is the Kronecker product operation on the two matrices. The parameters of mean function and covariance function need to be estimated for generating the GP metamodel. These parameters are called GP hyperparameters.

Modular Bayesian Approach (MBA), against with fully Bayesian approach, separates the updating process into four steps (modules) to reduce the computational cost. Herein, the hyperparameters of the GP are estimated separately and sequentially [2]. In this approach, at first, several data sets from a computer model are prepared. In application of MBA, GP models are replaced with the numerical model, experimental response and discrepancy function. Following the relation between the observations and the numerical model shown in Eq (1), the GP model for an experimental response is the summation of the GP models for a discrepancy function and a computer model. Subsequently, this GP model will be applied to find the experimental response at any point. The MBA method used in this study is summarized as follows:

- In the first module, a GP is replaced with the simulated model; and to estimate its hyperparameters, the GP model will be fitted to pass through all simulation data point.

- In the second module, by using the simulation data, the measured experimental data and the estimates of the hyperparameters from module 1 and the prior for the calibration parameters, hyperparameters of the GP model for discrepancy function are obtained.
- In the third module, the posterior distribution of the calibration parameters is calculated based on the experimental data, the simulations data, and the estimated hyperparameters from modules 1 and 2. The posterior distribution is obtained by using Bayes theorem as expressed as follows:

$$P(\boldsymbol{\theta}|\boldsymbol{d},\hat{\varnothing}) \; \alpha \; P(\boldsymbol{d}|\,\boldsymbol{\theta},\hat{\varnothing}) \; P(\boldsymbol{\theta}) \tag{3}$$

where $\hat{\varnothing}$ is denoted as the estimates of hyperparameters of model and discrepancy; **d** stands for all experimental and numerical responses; p(**θ**) is the prior distribution of the calibration parameter vector **θ**. It is worth noting that the posterior distribution of **θ** and the hyperparameter estimates from modules 1 and 2 influence the prediction of the experimental response. After gathering the experimental and simulation data and obtaining the hyperparameters in the first and the second module, and by applying a specific value of **θ**, the conditional posterior distribution of the experimental response can be obtained at any point, with mean and covariance functions. Consequently, the posterior distribution of the experimental response involves all sources of uncertainty, including parameter uncertainty, model discrepancy, interpolation uncertainty and experimental uncertainty.

- In the fourth module, the measured responses are using the test data, estimated hyperparameters and updated parameters obtained from modules 1, 2 and 3, respectively. In this module, the posterior response from updated model as well as the updated discrepancy function can be resulted [2]. It is worth noting that simulated data points have been collected using Latin Hypercube Sampling (LHS) approach. In addition, it is assumed that the measured responses are independent of time, temperature variation, and other operational effects.

Structural Performance Assessment integrating FEMU and Reliability Analysis

The calibrated numerical model in the previous stage of this framework is applied to investigate the performance of structure in its current condition by using reliability analysis. In general terms, structural reliability theory regards all basic variables, such as loading conditions, material and geometrical properties, as random with specifying their probability distributions obtained from the research background or by applying tests. In regard to computing structural reliability, performance function Z for each limit state can be generated as follows:

$$Z = R - E \tag{4}$$

The above expression illustrates the relation between the resistance of structure, R, and the action effect that applies to the structure, E. The fundamental task of structural reliability is to provide the conditions for the following requirement:

$$E < R \tag{5}$$

The principal target of the theory of reliability is the evaluation of the probability of failure Pf. For the state of inequality in Eq (5), the probability of failure will be accordingly written as,

$$P_f = P(E > R) = P(Z < 0) = \int_{Z(X)<0} K(X)dx \quad (6)$$

The random nature of the load action effect and the resistance is denoted in terms of suitable parameters such as force, strain and deflection, which are generally defined by the applicable distribution functions $\phi E(X)$ and $\phi R(X)$, respectively, where $X=(X_1, X_2,\ldots,X_n)$ represents the random variables such as deflection or normal stress. Apparently, to preserve the probability of failure P_f within adequate limits, the distributions of E and R need to fulfil certain conditions. Here, K(X) is the joint PDF of X. Since the direct calculation of the integration is computationally expensive and beyond engineering applicability, analytical techniques to solve the problem are not effective. It is also unfeasible to perform numerical techniques to find an answer as a result of high levels of dimensionality in engineering practice. So the application of approximation techniques is required. FORM is the most applicable approximation technique in structural reliability, which makes the probability integration to be solved by simplifying the integrand K(X) and approximating the integration boundary Z(X) = 0 by using the first-order Taylor series expansion. This simplification is applied through the conversion of an original, random space into a standard normal distribution space from X to U. This type of conversion is carried out by using Rosenblatt's transformation, which requires the cumulative distribution function (CDF) of a random variable is remained unchanged after the transformation.

Numerical Results and Discussion

In this study, the performance of a BGB has been inspected in two states: undamaged and damaged phases. The BGB represents a typical in-service hollow-core bridge deck in Australia. It is 6 m long, and its cross section consists of three parts that were cast separately as the top slab, the bottom slab, and the two parallel webs. The geometry of the BGB and properties of the materials used in construction of the structure are presented in Fig. 1 and Table 1, respectively [10]. The bridge model is simply supported at its two ends using roller and pin supports.

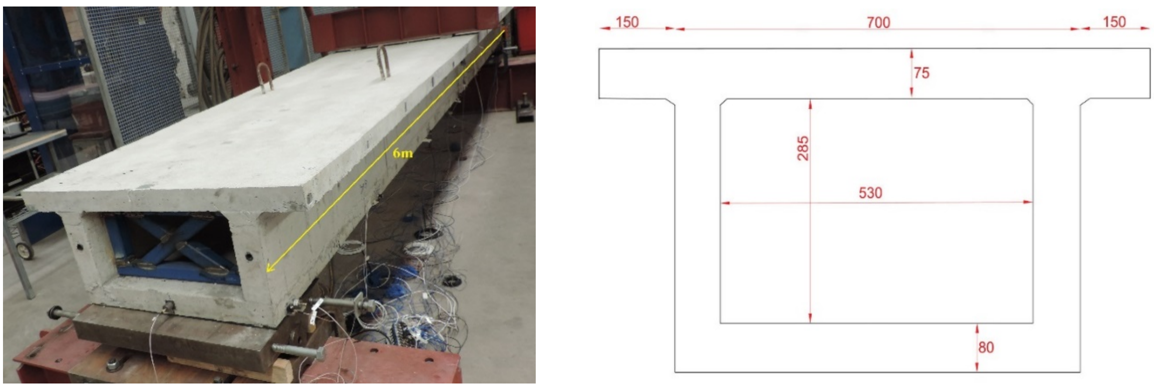


Figure 1. The dimensions of Box Girder Bridge (Adopted from [3]).

Table 1. Material properties used in FE model of the BGB (Adopted from [3]).

Parameter	Material	Nominal value
Young Modulus E (GPa)	Concrete	32
	Reinforcement	200
Mass Density ρ (Kg/m^3)	Concrete	2400
	Reinforcement	7850

The initial condition of the structure is considered as the undamaged state, in spite of some minor cracks observed on the bottom slab. The damaged state represents the condition after a point load together with a cyclic load were applied at the mid-span and generated some cracks. The structural details of the BGB, such as material and geometrical properties and support conditions were chosen according to the design details and applied to build an initial FE model using ABAQUS software package.

In this study, the BGB was subjected to a random excitation by applying an impact hammer at multiple locations. Vibration data points have been collected using a data acquisition setup [8 & 9]. The acceleration responses of the structure in the two states were recorded and applied in the FEMU process. To commence the process of updating, sensitivity analysis has been applied to select the most sensitive parameters and responses. In relation to the experimental responses, the four modal frequencies were nominated as sensitive responses.

As mentioned before, in the initial FE model, both ends of the BGB were modeled as simple support with full fixity in vertical displacement. Based on the sensitivity analysis, the five most sensitive parameters were selected as Young's moduli for the bottom slab, the webs, and the top slab (E_{cBot}, E_{cWeb}, and E_{ctop}), as well as the vertical spring stiffness coefficients of the two supports (K_{roller} & K_{pin}). It is worth noting that in the damaged state, the Young's moduli of the three parts would decrease and the boundary conditions of both supports would not be affected. At each state, an MBA is carried out to provide the calibrated parameters to be applied in the reliability analysis. Thus, in module 1 and 2, two GP metamodels are replaced with the FE model and the discrepancy function, respectively, and their hyperparameters are estimated accordingly. In module 3, given the GP models of FE model and discrepancy function from the previous modules, and by applying Bayesian approach and MCMC, the PDF of calibrated parameters are obtained.

In this study, to integrate the FEMU into reliability analysis, the PDF of calibrated parameters was obtained at each state (undamaged and damaged) by applying an MBA, and used to quantify the probabilistic distribution of both structural resistance and load action effect arising from a moving load, which is a common demand applied to bridge structures. The moving load MS1600, as the most commonly used moving load specification in Australian bridge design code (AS 5100.2, 2017), has been used in this study. This load specification comprises two different loading cases as M1600 and S1600. The reliability analysis was conducted in an SLS, since, at both states, the structural materials were in the linear elastic region and had not yielded. Regarding the reliability analysis, two structural features, deflection and strain, were considered as the two separate variables in the performance function. The analysis stops when a serviceability limit (i.e. the maximum deflection) is reached (AS 5100.2, 2017). The corresponding maximum normal strain at this increment is also recorded as the strain resistant of the structure. Consequently, the reliability analysis is conducted based on the changes in the two features. Consequently, at each state, with obtaining the distribution of resistant capacity and the loading action, the performance equation is calculated using FORM to determine the reliability index, and in turn, the probability of failure.

Applying the MBA in the first health state, the calibrated parameters have been obtained, as shown in Table 2 and Fig. 2. No significant variations are observed in Young's moduli of the top slab and web after updating for the undamaged state. However, Young's modulus of the bottom slab is reduced slightly, and this reduction can be considered a result of the minor cracks observed underneath the BGB. Regarding the boundary conditions, there is a noticeable change (60% drop) in the vertical spring stiffness at the roller support, implying an overestimation of this support in the initial FE model.

By obtaining the calibrated distribution of parameters for the undamaged state, the updated model is analysed with the aforementioned moving load cases to ascertain the maximum deflection and strain, which represent the effect of the loading action on the structure. Further, the structural resistance is obtained after the incremental analysis has caused the allowable maximum deflection to reach the specified limit. According to the observation of results, both maximum deflection and strain occur at the mid-span regardless of the load case used. The results for strain and deflection by applying MS1600 are shown in Table 3.

Table 2. The Likelihood and Posterior distribution for calibrated parameters in the undamaged state (Adopted from [3 & 6]).

	Before updating		After updating	
Part	Mean	Coefficient of Variation (%)	Mean	Coefficient of Variation (%)
E_{cBot}	32 GPa	7.13	30.84 GPa	8.3
E_{cWeb}	32 GPa	7.13	32.69 GPa	2.9
E_{cTop}	32 GPa	7.13	33.67 GPa	5.2
K_{Roller}	5×10^7 N/m	9×10	1.68×10^7 N/m	2.02×10^2
K_{Pin}	5×10^7 N/m	9×10	9.53×10^7 N/m	3.82×10^2

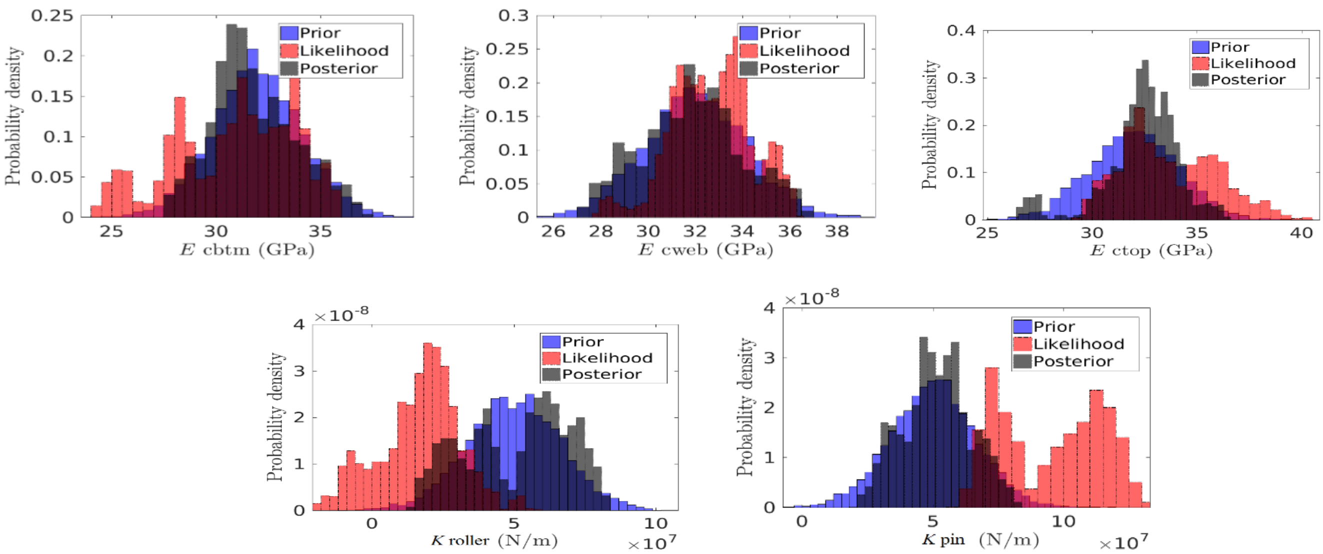


Figure 2. Calibrated parameters in undamaged state (Adopted from [3 & 6]).

Table 3. Deflection and strain responses for load case MS1600 in undamaged state (Adopted from [4]).

	Strain (%)				Deflection (mm)			
	Before updating		After updating		Before updating		After updating	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
S1600 (Load action)	0.01175	0.0048	0.014	0.0041	8.24	1.62	9.41	1.55
M1600 (Load action)	0.00985	0.0041	0.01107	0.0038	6.67	1.48	7.72	1.41

Overall, the impact of S1600 load action is higher than that of M1600, which aligns with the previous observations of these loading cases. The distributions of deflection and strain before and after updating for the two loading cases are illustrated in Fig. 3. Even though the observed change is not significant at this health state, FEMU's significant role in updating the performance of structures is highlighted.

The MBA is also applied for the damaged state, wherein some significant cracks are observed on the bottom slab and the webs of the BGB. It is worth mentioning that the number of calibrated parameters is reduced to three (i.e., Young's moduli of the concrete parts) because it is assumed that the applied impacts will not affect the boundary conditions of the damaged structure. The distributions of the updated parameters for the damaged state are shown in Table 4. As shown in the table, a significant change in Young's modulus of the bottom slab is observed for the damaged state, indicated by a reduction of about 40% and a new mean value of 20.63 GPa. Further, the decrease in Young's modulus of the web section is noticeable, showing an updated mean value of 27 GPa. The impact forces have little effect on the top slab, and its updated Young's modulus is almost the same as its initial value. It is worth noting that the reduction in Young's moduli for the bottom slab and the webs is well matched to the cracks observed in the damaged state.

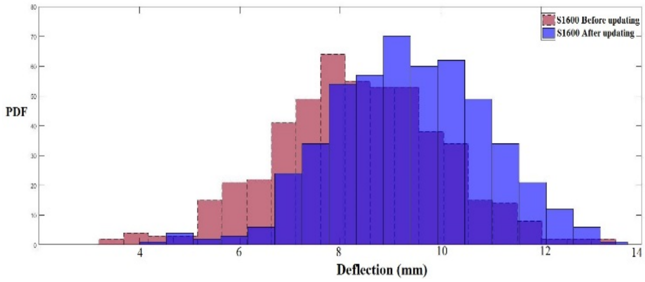
The calibrated model of the damaged state with the updated parameter distributions is analysed to obtain the loading action on the structure as well as the structural resistance. The results for strain and deflection after updating are shown in Table 5.

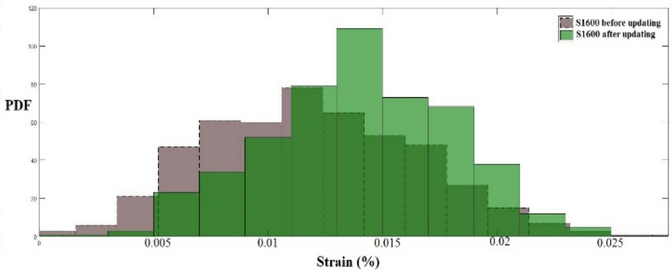
Table 4. Distribution of calibrated parameters in damaged state (Adopted from [3]).

Part	Mean	Coefficient of Variation (%)
E_{cBot}	20.63 (GPa)	25.59
E_{cWeb}	27.82 (GPa)	5.99
E_{cTop}	30.54 (GPa)	35.45

Table 5. Deflection and strain responses for load case MS1600 in Damaged state (Adopted from [4]).

	Strain (%)		Deflection (mm)	
	Mean	Standard Deviation	Mean	Standard Deviation
S1600	7.20E-02	8.10E-03	17.02	2.03
M1600	5.79E-02	9.20E-03	14.8	1.87





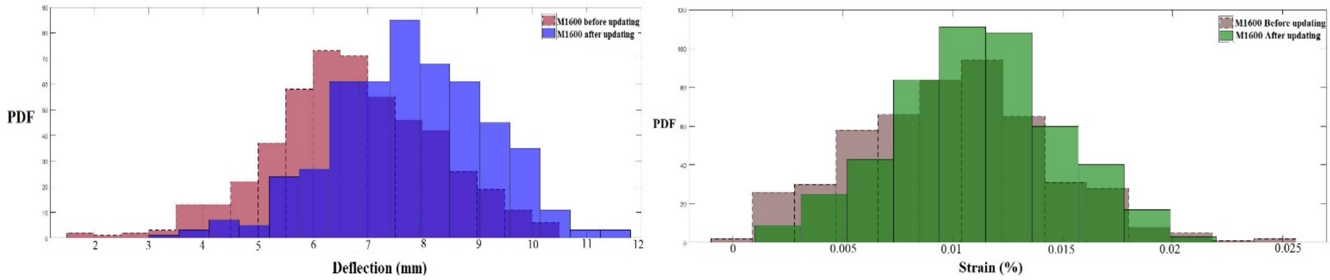


Figure 3. Results of deflection and strain for both loading cases in the undamaged state before and after updating (Adopted from [4]).

It can be noticed that the variations in deflection and strain between both health states. It can also be inferred that the load effects in the damaged state are more scattered than those in the undamaged state. This is because the variation of the calibrated parameters in the damaged phase is greater compared with the undamaged phase. Both the deflection and normal strain obtained from the loading case S1600 are more conservative than those obtained from M1600. However, in both loading cases, significant increases can be clearly identified in the deflection and strain of the BGB, which implies that the structure's performance has been compromised. Therefore, the reliability analysis is conducted to determine how far the current condition is from the expected safety margin. So, FORM is applied for both states, and the results are shown in Fig. 4.

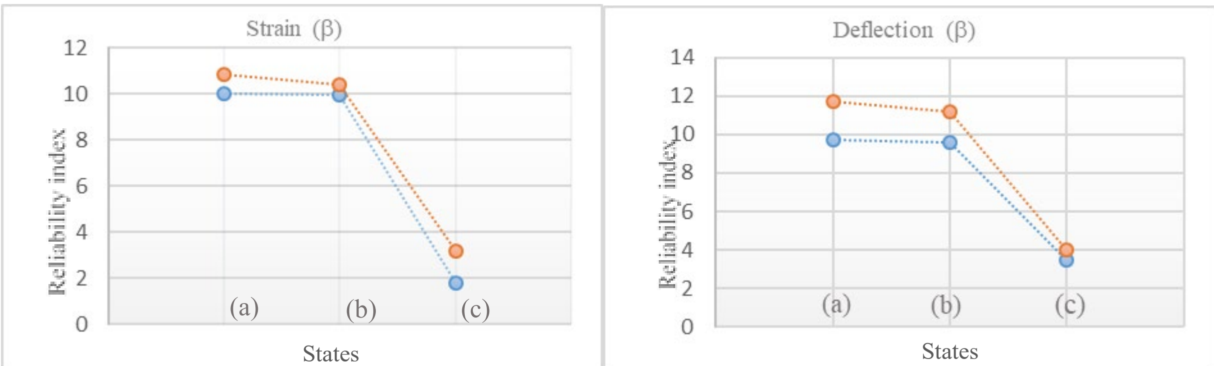


Figure 4. Results of Reliability index for S1600 (blue) and M1600 (orange) in: (a) undamaged before updating, (b) undamaged after updating and (c) damaged after updating (Adopted from [4 & 7]).

As can be seen in the above figure, the reliability index for both deflection and strain, even in the damaged state, still stay in the safe regions. However, the result for the damaged state illustrates noticeable drops in both reliability indices, which is feasible since the stiffness of BGB in the damaged state reduced by 40% and it led to the detectable cracks generated on the body of structure. According to Eurocode (EN 1990), the recommended reliability index for SLS is 1.5, corresponding to P_f= 6.7e-2, for the design's operational life of 50 years. According to the results obtained in this study, the strain reliability index in S1600 is estimated as 1.79 for the damaged state (corresponding to P_f= 0.03673), which is very close to the Eurocode's recommendation, and this could be considered as a threat to the performance of the structure.

In summary, this study addressed the performance assessment of a BGB by integrating FEMU with reliability analysis. For the first time, an approach was proposed that integrates MBA, the most comprehensive probabilistic FEMU technique, with reliability analysis to monitor point-in-time structural performance, which in turn improves the accuracy of structural maintenance decisions. This work offers proof that FEMU is a robust tool for calibrating structural properties under uncertainty, while it is computationally efficient. Accordingly, the lifetime reliability of structures can be updated based on as-is evidence obtained from FEMU, which is more trustworthy than using prediction techniques and non-destructive testing. In addition, this research can provide insights into a comprehensive assessment framework that can improve the current assessment approach, considering the absence of well-developed assessment guidelines in structural codes of practice.

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Conference News

- The 10th Australasian Congress on Applied Mechanics (ACAM10), to be held at The University of Adelaide, Adelaide, Australia, 2021. Chair: Assoc. Prof. Alex Ng. Webpage: https://acamconference.com.au/

- Mini Symposium "Latest advances on SHM and smart structures in Australia/Oceania" in the Tenth International Conference on Structural Health Monitoring of Intelligent Infrastructure, Porto, Portugal, from 30 June to 2 July 2021. Organized by Dr Andy Nguyen, Assoc. Prof. Alex Ng, Prof. Tommy Chan.

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- Mini Symposium MS05: " Innovative data-driven techniques for Structural Health Monitoring" in the Tenth International Conference on Structural Health Monitoring of Intelligent Infrastructure, Porto, Portugal, from 30 June to 2 July 2021. Organized by Assoc. Prof. Jun Li, Prof. Ting-Hua Yi.

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