AUSTRALIAN NETWORK OF STRUCTURAL HEALTH MONITORING

Newsletter

Issue 34, December 2022

Contents

President Message

Tommy Chan

Professor in Civil Engineering, Queensland University of Technology

Dear All,

This year the announcement of ARC Discovery Project outcomes is earlier than last year. It was announced on 24 November 2022, on the 1st day of the 14th ANSHM Workshop, just before our Advisory Board Meeting. Once again, it is heartened to know that many of the ANSHM Executive Committee members and Advisory Board members receiving ARC funding supports in this round totalling an amount of $ $1,212,653.00.

Congratulations to Brian, Hong Guan, Jianchun, Tuan and Xinqun!

A/Prof Xinqun Zhu; **Prof Jianchun Li**; Asso. Prof Yang Wang	**Real-time bridge performance evaluation based on crowdsourcing and learning.** - Funding Awarded: $ 360,000.00 - Scheme: ARC Discovery Projects (DP230100806) This project aims to develop a novel strategy utilizing the real-time measurements from moving vehicles and bridges for evaluating the safety and operational performance of bridges based on transfer learning and vehicle-bridge interaction model. This is the first essential study on integrating the bridge-moving load models with transfer learning to extract common knowledge from simulation experiments to support the assessment of damaged status in practice. The project will provide an engineer-friendly low cost monitoring system for its deployment, management and maintenance of existing transport infrastructure. The innovative techniques developed enable the safe operation and reliable evaluation and maintenance of transport infrastructure.
Prof Hong Guan; A/ Prof Benoit Gilbert; A/Prof Minghao Li; Prof Dr Frank Lam	**Safety and robustness of tall timber buildings under extreme dynamic events.** - Funding Awarded: $ 332,633.00 - Scheme: ARC Discovery Projects (DP230100460) This project aims to develop innovative and robust structural connections in tall mass timber buildings by characterising their mechanical behaviour under dynamic loads induced by extreme events like earthquakes or progressive collapse. This project expects to generate new knowledge in the safe, economic, and efficient design of mass timber buildings. Expected outcomes of this project include enhanced robustness design guidelines for the engineering community. This should lead to significant benefits, such as contributing to uptake of viable low-cost timber housing solutions in response to population growth and contributing to net zero emissions in Australia by 2050, and transition to safer and resilient infrastructure in urban development.

A/Prof Huu-Tai Thai; **Prof Brian Uy; Prof Tuan Ngo**	**Fire engineering of prefabricated structural systems of modular buildings.** - Funding Awarded: $ 520,020.00 - Scheme: ARC Discovery Projects (DP230100018) With the speed and cost benefits, modular construction is considered a game-changing solution in response to pandemics and natural disasters, and tackling the affordable housing crisis on a large scale. However, its uptake has been hindered due to recent fire incidents of modular buildings. This project aims to develop novel fire experiments and advanced modelling techniques to evaluate the fire performance of modular buildings. Computational tools and fire safety design guidelines will also be developed to enable modular buildings to be built safer and more economically. This project will promote the widespread adoption of modular buildings to benefit end-users and the wider society, especially the housing sector and low-income households

Engineers Australia – Thought Leaders Series Webinar on SHM

As mentioned in the previous monthly updates, we would like to use my invited presentation for the Engineers Australia (EA) Thought Leaders Series to promote Structural Health Monitoring as well as ANSHM. In order to make the Webinar addressing the current issues on SHM, I invited 5 key persons from Government and private companies to join the panel discussions with Dr Ronan Nguyen, ARC DECRA Fellow to be the moderator of the panel discussion. The 5 panellists have been introduced earlier and are listed here again (names not listed in order):

- Dr Torill Pape, Director (Structures Design, Review and Standards), Queensland Department of Transport and Main Roads
- Dr. Yew-Chin Koay, Structural Engineering Advisor, Major Road Projects Victoria
- Isaac Scot, Contracts and Structures Services Manager, Brisbane City Council
- Dr Govinda Pandey, Chief Executive Officer Rockfield Technologies Australia Pty Ltd
- Peter Runcie, Chief Executive Officer, Natirar Consulting Services

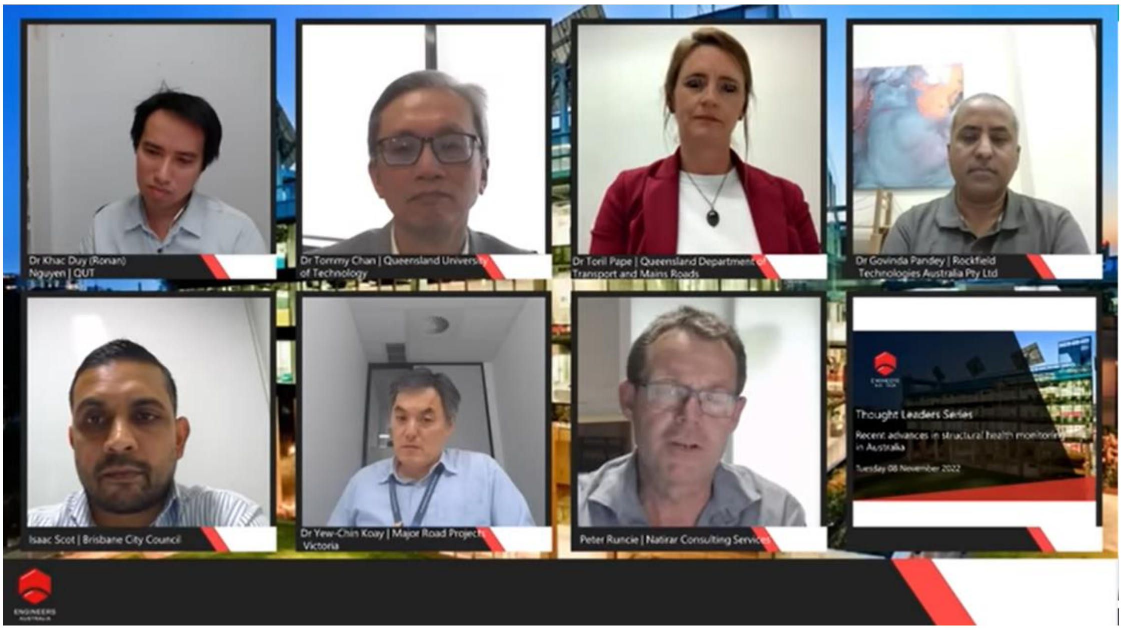

Photo 1 Panel Discussion of the EA Webinar

I am so pleased to let you know the Webinar is extremely successful. It's recording on Youtube (https://www.youtube.com/watch?v=UOAeOPhhLuY&t=142s) has attracted more than 7.5k views in two weeks, which is a record of the series, being the highest number of viewers of the EA Thought Leaders Series. Below I briefly give some highlights of the Webinar.

Presentation on SHM

In my presentation, I gave the definition of SHM to rectify those mistaking SHM being equivalent as damage detection and missing the other aims of SHM like performance monitoring. I also state again SHM is not just placing sensors to collect data, making SHM become costly. Then I described there are 3 areas for SHM research, namely: System Development, Sensors/Measurements Development and Application Development. System Development is to design the SHM system with intended objectives, making the sensors to acquire data with sense, instead of randomly placing the sensors to collect various loading and responses. Sensors/Measurement are about developing some sensors or some measurement method which are either tailor made for civil engineering measurement or some measurements that those sensors available in the market could not acquire. Application Development is on the development of various methods which could be used to analyse or interpret the data acquired to provide information for evidence-based decision making for the asset maintenance or management teams. Based on these 3 areas, I selected 20 examples of the projects that I supervise to illustrate how these projects deliver what it is expected. At the end of my presentation, I also introduce ANSHM and promote the 14th ANSHM Workshop.

The Panel Discussion is after my presentation. The panel discussion is roughly divided into 3 sections.

Panel Discussion I – Value of SHM

In the first part, we discussed about the values of SHM and how Government as asset owners use SHM. Torill stated that TMR had a long history of implementing structural health monitoring or monitoring systems to supplement their decision making. They have various monitoring system to monitor critical components of their assets, e.g. halving joints, on their networks to see how they perform. Also, when big heavy loads need to move around on their Networks, they would also like to use such methods to validate and verify that their structures are performing as they expect. They employed a range of different sensors to help them look at the responses like strains, deflections, temperatures. Recently, they also start to use latest technologies like visual methods using camera. They have also been doing some work with the National Asset Centre of Excellence. Yew-Chin also expressed that SHM is important as it helps evaluate and monitor structural performance especially for high-risk and critical structures. If a SHM system is used correctly, it gives a lot of benefits such as improving safety, reducing maintenance cost and increasing longevity for the structure. Isaac stated that Brisbane City Council manages about 4,000 different civil assets, of which the historical Story Bridge built in 1930s is one of them. They wish to have all their bridges continue to be in service. Their main focuses are to understand the residual life of these structures and how safe they are, and what the most effective and the cost-effective maintenance plans are. A correct SHM system will definitely help them to get the answer. Since the Story Bridge was designed in the 1930s with ink and paper as opposed to CAD drawings and FEA nowadays. With the SHM system installed on the Story Bridge, they know better the actual stresses and actual traffic loads which allow them to be more accurate in their analysis of fatigue life as well as Dynamic amplification. All these processes led them identifying that no members of the Story Bridge including the most critical members will not reach their fatigue life for about another 100 years. From an asset management perspective, it allows them to do some long-term planning for the bridge. Govinda added that the major challenge with public infrastructure assets is not so much about damage detection but more about managing risks associated with critical and non-compliant assets as 70% of the Bridge Assets in Australia are more than 50 years old and over that period the live loads have changed, structures have been degraded and design standards have become more and more stringent. Peter also shared his SHM experiences gained on the installation of SHM system on the Sydney Harbour Bridge, which could probably be Australia's largest SHM installation, in which 3200 sensors were installed to monitor the bridge. He also considered although the Sydney Harbour Bridge and the Story Bridge both use SHM but the two systems are quite different.

Panel Discussion II– Challenges of SHM

Then the next part of the discussion is on the challenges on implementing or managing the structure health monitoring system on a structure. Peter considered SHM might be difficult for small bridges as they are most often operated by local government or small councils but there is not much digital expertise in these organizations and there are 400 councils in the country really struggle with digital technology and understanding how to set these systems up, how to operate them, how to build a business case around them, and how to interpret the data. For large organizations, the challenges would be what changes to the organization are needed to take advantage of the technology because it's a digital transformation. This is a digital transformative technology and how this could integrate to transform business processes including their traditional ways of maintenance moving to a predictive or condition-based maintenance, implying a change in organizational processes and skills will definitely be a challenge. Torill also considered the challenges related to the asset management decision-making cycle and how they can get good decisions based on evidence and make a balance in Cost-risk performance. To get data is not the main focus. The main point is to interpret and use the data in an easy way to make informed decisions. One could create the world's biggest monitoring system but how the data acquired could help to assess the risks. The data could be described as Objective Data. Isaac also emphasised that before one considers installing a SHM system, its objectives have to be really clear. He also made a very good point that the objective of installing a SHM should not be just that "we want to use SHM". Torill then stated another difficulty in Government for applying the SHM which is to influence some of the staff internally without demonstrating the value of SHM. I then raised the current issues on SHM is caused by different expectations or sometimes the service provider over promise what SHM could do. What ANSHM could do is to help the public understand what current SHM methods could deliver. Yew-Chin also considered we need to have competent and skilful people to drive this. ANSHM could help on that.

Panel Discussion III – Future Trends of SHM

In the last part of discussion, we discussed something about how latest technologies like machine learning and optimisation could enhance SHM. We are at a stage of Digital Transformation. Torill considered the digital information using machine learning, etc. still needs to be married with the structural engineering principles that we're trying to manage for and then linking that into the asset and managers decision making process and assessing risks. Peter added that the optimization tools can play a good role as a decision support tool. Govinda added that SHM is more than a system for a single structure. If one has got multiple bridges monitored in a network so if one heavy vehicle is coming from upstream, the information could be helpful for the whole network, and it could be stopped by approaching any critical bridge within the network. This is the main idea of a smart city.

Final Remarks
Then I gave some final remarks that there are some incorrect expectations of SHM which hinders the healthy growth and implementation of the technology. ANSHM could help educate the public and the engineering community to understand what SHM is and have the correct expectations of SHM. ANSHM could also help to train more graduate on the field. Regarding better cooperation among the first SHM users like Road Authorities, Asset Owners and Managers and second the SHM service providers, and third the university researchers, ANSHM will serve as a platform for these three groups to work together and to ensure the SHM research will meet the needs of the industry and to provide expert advice to the SHM users and service providers.

The above are just some highlights of the EA Webinar conducted on 8 November 2022. You are welcome to watch the whole recording on Youtube if you have not done so. Maybe you could find the reason that why it could attract so many views and became a record of the EA Thought Leaders series.

Below are the updates of the month.

14th ANSHM Workshop
Our 14th Workshop was held in Sydney from 24th to 25th November 2022. It was hosted by University of Technology Sydney and organised by Prof Jianchun Li and A/Prof Xinqun Zhu. It was very well attended. We had 42 attended in person and 86 online (day 1) and 92 (day 2). The participants number online may not be accurate since some of the in-person participants were also online. For those who have attended this workshop will definitely agree with me that Prof Jianchun Li and his team have done a great job! Without their well planning and hard work, we could not have such a successful event, particularly it is conducted in a hybrid mode, which is really a challenge. I consider that it is one of the best of the ANSHM Workshops, especially this is the first time we could have an in-person workshop after not having it for two years because of the Covid-19 restrictions.

The first day of the Workshop entitled "Smart Infrastructure Summit" focusing on the use of SHM in the industry and the future trend of digital transformation for the development of smart infrastructure. There were two sessions, two panel discussions, 3 keynote speeches and 4 invited lectures. The second day of the Workshop focused more on the research and development of SHM, with 16 invited presentations arranged into 4 sessions on 4 different areas of SHM. We had very good discussions in the panel discussions. Because of the space in this issue, such discussions could not be described in this issue. Hopefully we could briefly report that in the future monthly updates. Below are some photos taken at the Workshop.

Photo 2 Opening

Photo 3 Keynote 1

Photo 4 Keynote 2

Photo 5 Panel Discussion 1

Photo 6 Panel Discussion 2

Photo 7 Invited Presentation 2 on Day 2

Photo 8 Lunch on Day 2

Photo 9 Group Photo

Election of Executive Committee Officers

As mentioned in the last monthly updates, all the 5 EC members, Jianchun Li, Hong Guan, Tuan Ngo, Xinqun Zhu and myself, whose term of service would be expired by end of the year were all nominated to serve in the EC for another two years (2023-2024). These 5 EC members were re-elected in the recent AGM to serve in the committee for another 2 years.

Hence the Executive Committee in 2023 will consist of the following officers:

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

New Advisory Board Members

In the last Advisory Board Members, we identified a few key persons working in the field of SHM to be invited as our additional Advisory Board members. One of them is Mahesh Ramamoorthy, Associate Director – Bridges & Structures, AECOM, who also attended the 14th ANSHM Workshop. Hence, I could approach him quickly and he is so pleased to accept the invitation. The other one is Nigel Powers, National Leader, Asset Performance of ARRB, who is also pleased to accept the invitation. I believe that Mahesh and Nigel could definitely help ANSHM to know better how SHM could meet the needs of the industry and strengthen our relationship with the industry.

Mahesh and Nigel, welcome on board!

Because of the space, I need to stop here and I will report the other outcomes of the ABM and AGM in the next monthly updates.

In the next sections, we will have two articles from our members. The first article is from UNSW on application of Bayesian Finite Element Model Updating to establish and validate the numerical model of a truss bridge located in Japan. The second article is from Deakin University on evaluation of various machine learning algorithms for the condition assessment of utility timber poles. A/Prof Colin Caprani, our Guidelines and Specifications Task Force in-charge also gives his thought on the Specification development as the first part of model specifications for Structural Health Monitoring.

Stay safe and healthy!

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

Professor Tommy H.T. Chan PhD, ThM, MDiv, BE (Hons I), FHKIE, MIE Aust, CP Eng, NPER, MICE, C Eng, RPE, MCSCE
President ANSHM (www.ANSHM.org.au)
School of Civil & Environmental Engineering, Queensland University of Technology (QUT)
GPO Box 2434, Brisbane, QLD 4001, AUSTRALIA.
Ph. +61 7 3138 6732; Fax. +61 7 3138 1170; email: tommy.chan@qut.edu.au;
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Bayesian Finite Element Model Updating of a Truss Bridge

Shahed Jafarpour*, Mehrisadat Makki Alamdari, Elena Atroshchenko

Centre for Infrastructure Engineering and Safety, School of Civil and Environmental Engineering, University of New South Wales, Sydney, NSW 2052, Australia

*Email: sh.jafarpour@unsw.edu.au;

Abstract

The necessity for economical structural health monitoring requires a surrogate numerical model which can represent the real structure. 3D models of complex large-scale structures, however, are computationally intensive. This study aims at simplifying the full-scale numerical model of the ADA bridge to a 2D model whose response resembles the real structure. Timoshenko beam elements are adopted for finite element structural modeling. Transitional Markov Chain Monte Carlo technique is then applied for Bayesian finite element model updating. The proposed approach proved to reach a high-precision model which can reduce computational time significantly.

Keywords: Bayesian Finite Element Model Updating; Transitional Markov Chain Monte Carlo Method; Steel truss bridge; Structural Health Monitoring

1. Introduction

Bridges are of most important civil infrastructure since they provide vital links in transportation networks. A large majority of bridges are too old, and their mechanical properties have degraded over time. It is therefore necessary to establish a comprehensive inspection and maintenance strategy. Numerical models, such as finite element method (FEM), are critical tools for continuous monitoring of the structure and evaluating its reliability. Model-predicted responses, however, differ from the actual ones, as a result of idealization in connections, boundary condition, section geometrics, and material properties [1]. It is crucial to calibrate the uncertainties associated with the FE model and reduce the numerical simulation errors. Finite Element Model Updating (FEMU) methods have emerged to calibrate the numerical model according to the actual behavior of the structure. The updated FE model produces more accurate and reliable results compared with the real structural data [2]. The FE model updating is generally formulated as an optimization problem whose goal is to minimize the discrepancy between measurement and simulation results. Despite its long history, the development of algorithms for structural model updating is still an active research area in structural dynamics.

FEMU can be generally described as an inverse problem which is broadly categorized as deterministic and probabilistic. Deterministic approaches try to minimize the difference between recorded and model-predicted responses, neglecting inherently involved uncertainties. They yield a single solution and ignore other possible choices which may be of equal importance. They are computationally efficient, however, the updated matrices in this approach lose their physical meaning. Therefore, they have not proved to provide robust outcomes in practical applications [3,4,5]. There are also some inaccuracies in the recorded structural response, as a result of changes in ambient conditions (e.g., temperature and wind), measurement noise, simplifying assumptions in construction of structural FE models, or limited number of sensors for data collection from the structure. Probabilistic model updating provides a more versatile technique to tackle included uncertainties and complexities. Bayesian inference is considered as one of the most powerful and well-established methodologies for probabilistic finite element model updating, system identification, and damage detection. It takes into account any prior knowledge or initial assumptions of the uncertain parameters. The stochastic FEMU then makes use of Bayes' theorem to estimate the posterior probability density function of the updated model parameters, given the measured data [3,5].

The Bayesian approach requires the evaluation of complex multidimensional integrals for which analytical solutions are usually unavailable. The stochastic model updating for real case applications, therefore, relies on the implementation of efficient sampling techniques [6]. Several sampling methods have been used in the literature. The most widely used method is definitely Markov Chain Monte Carlo (MCMC) method along with Metropolis–Hastings (MH) algorithm [7]. However, it is computationally expensive in practice, specially when numerous uncertain parameters to be evaluated. Because the posterior probability density function often concentrates on a much smaller volume than that of the prior. Remarkable studies in the literature have contributed to the development of more efficient algorithms for Bayesian FE model updating. Beck and Au [8] proposed an adaptive Markov chain Monte Carlo simulation technique to evaluate the posterior probability density function. This approach combines the simulated annealing and MH algorithm in a sequential manner so that each target PDF is the posterior PDF considering larger extent of data. The efficiency of the AMH relies on the capability of the proposal PDF to simulate samples for each intermediate PDF. This approach is, however, limited to lower dimensions. Because as the number of uncertain parameters increases, a prohibitively large amount of samples are required to build up a proper proposal PDF with a reasonable acceptance rate [9]. Ching and Chen [10] invoked the idea of sampling from a series of intermediate PDFs that converge to a target PDF, to propose a new sampling algorithm coined as Transitional Markov Chain Monte Carlo (TMCMC). TMCMC adopt the idea behind AMH while they differ in simulating samples. TMCMC uses reweighting and resampling techniques to generate the next target PDF in a sequence, eliminating the difficulty of kernel density estimation, especially in high-dimensional space [9,11,12]. TMCMC has also some potential issues which shall be taken into consideration. Convergence in higher dimensions can be relatively slow using MH algorithm based on MCMC random walk. Cheung and Beck [9] proposed Hybrid Monte Carlo (also referred to as Hamiltonian Markov Chain (HMC) Method) to deal with high dimensional Bayesian model updating problems. Using a deterministic mechanism inspired by the principles of Hamiltonian dynamics for drawing samples from a target distribution it alleviates the deficiencies of the random walk with a consistent exploration of the probability space [13]. The effectiveness of the proposed approach in dealing with many uncertain parameters was studied through the Bayesian model updating of a ten-story building with 31 unknown variables by Cheung and Beck [9]. It has been adopted by some other scholars for structural model updating. Mao et. al. [6] utilized two stochastic algorithms, i.e. Metropolis-Hastings and Hybrid (Hamilton) Monte Carlo method for Bayesian model updating of a 1490m-span suspension bridge called Runyang Suspension Bridge (RSB). They showed that HMC algorithm along with kriging predictor could provide an efficient tool to calibrate large-scale structural models. Baisthakur and Chakraborty [13] adopted Hamiltonian Monte Carlo algorithm for Bayesian finite element model updating of a truss bridge. The efficiency of the proposed method is well demonstrated and comparison is made with the standard MCMC technique. In recent years, some other methods have also been developed in order to improve the convergence rate of Bayesian model updating. The most commonly implemented algorithms are delayed rejection or DR-MCMC, and hybrid DRAM-MCMC. Among all proposed techniques, TMCMC brings both efficiency and ease of implementation, so it has been widely used in the recent structural FE model updating studies. Asadollahi et. al. [1] adopted the TMCMC-based Bayesian inference method for finite element model updating of a long-span cable-stayed bridge which marginalizes prediction-error precisions. Lye et. al. [103] also proposed a comparison between three advanced Bayesian sampling methods, i.e. MCMC, TMCMC, and SMC (Sequential Monte Carlo). They found the TMCMC algorithm to be the most robust algorithm among these three samplers. Its drawback is the long computational time for generating samples from every transitional distribution. Vibration-based Bayesian model updating for damage detection in steel truss bridge was also conducted by Zhou et. al. [12]. Modal properties were extracted using the fast Bayesian FFT. Transitional Markov chain Monte Carlo (TMCMC) sampling method was also implemented to evaluate the posterior distribution.

The majority of existing research focuses on numerical models or simple structural models like cantilever beams or shear buildings. Bayesian FE model updating of full-scale large civil infrastructures based on field data has been rarely reported. Chang and Kim [14] presented the preliminary results of the modal parameter identification as well as damage detection for the steel truss bridge. The collected data as well as 3D structural model is also presented by Kim et. al. [15].

Model updating based on a 3D finite element model may require hundreds of days. This study aims at developing a 2D representative of the ADA bridge which could potentially reduce computational expenses significantly. Accordingly, the structure will be simplified in a 2D model. Timoshenko frame elements will be used to discretize the developed model. TMCMC algorithm will be then adopted to update the model so as to minimize the difference between measured and calculated modal parameters.

2. ADA bridge model

The Old ADA bridge was a simply-supported steel truss structure located in the Nara Prefecture, Japan. It has been in operation for 53 years, since 1959 to 2012. The main span length of bridge was 59.2 m and provided effective width of 3.6 m. The isometric, elevation, top, and bottom plan of the bridge are presented in Figure 1.

Group	Component	Dimension
Top chords	TC1, TC8	Box 318 × 310 × 19 × 10
	TC2, TC3, TC6, TC7	Box 298 × 309 × 9 × 9
	TC4, TC5	Box 298 × 312 × 9 × 12
Top struts	TS1, TS2, TS3, TS4, TS5, TS6, TS7	I 216 × 150 × 8 × 8
Top lateral bracings	TLB2, TLB3, TLB4, TLB5, TLB6, TLB7	T 103 × 150 × 8 × 8
Verticals	V1, V2, V3, V4, V5, V6, V7, V8	I 278 × 170 × 8 × 8
Diagonals	D2, D7	I 278 × 180 × 8 × 8
	D3, D4, D5, D6	Box 278 × 200 × 8 × 8
Bottom chords	BC1, BC2, BC7, BC8	Box 296 × 198 × 8 × 8
	BC3, BC4, BC5, BC6	Box 298 × 202 × 9 × 12
Floor beams	FB1, FB2, FB3, FB4, FB5, FB6, FB7	I 738 × 220 × 9 × 8
	FB end	I 736 × 160 × 8 × 8
Stringers	ST1, ST2	I 721 × 170 × 8 × 10
Bottom lateral bracings	BC1, BC2, BC7, BC8	Box 296 × 198 × 8 × 8
	BC3, BC4, BC5, BC6	Box 298 × 202 × 9 × 12

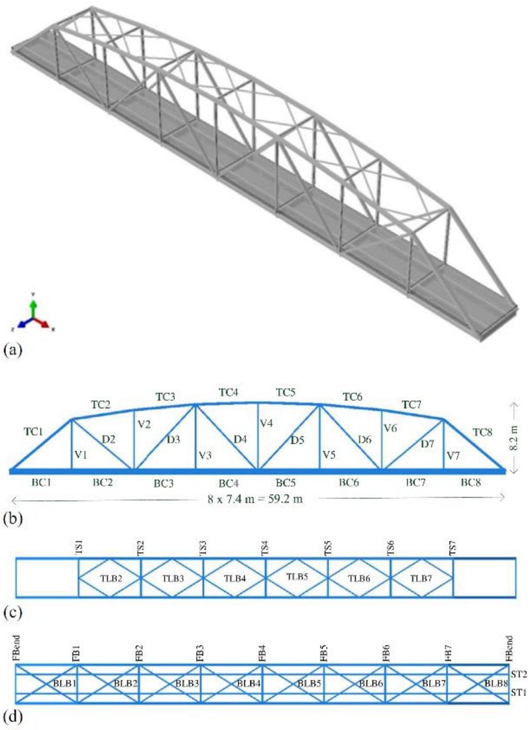

Figure 1: ADA bridge model [15]

(a) Isometric (b) Elevation (c) Top (d) Bottom plan

Design cross sections of ADA bridge are also provided in Figure 1. Note that dimensions are presented in height × width × web thickness × flange thickness. All members are composed of structural steel (density = 7900 kg/m3, elasticity modulus = 200GPa). The deck, however, is constructed by reinforced concrete slabs (density = 2400 kg/m3, elasticity modulus = 21GPa). The 2D model of the ADA bridge has been developed utilizing Timoshenko beam elements. The Timoshenko theory is founded on the assumption that deformed cross-section planes remain plane but not necessarily normal to the neutral axis. It could, therefore account for shear deformation [16,17]. The bending natural frequencies and mode shapes are extracted (Figure 2) and compared with those of [12,14] in Table 1.

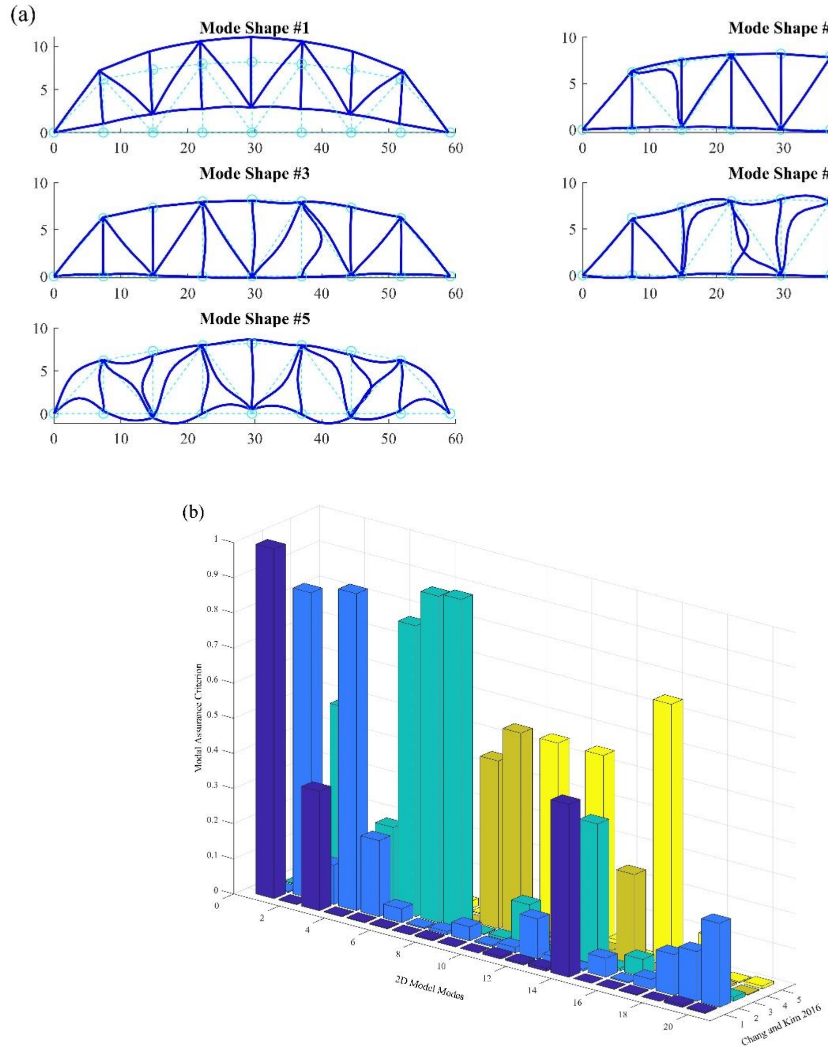

Figure 2: ADA bridge (a) mode shape (b) MAC number

Table 1: ADA bridge natural frequencies

	Field Test	2D Model	
	Freq. (Hz) [12, 14]	Freq. (Hz)	Error (%)
mode 1	2.98	3.18	7.01%
mode 2	6.87	7.32	6.51%
mode 3	9.61	10.14	5.56%
mode 4	10.56	11.05	4.65%
mode 5	13.42	12.78	-4.73%

Table 1 shows that there is a reasonable match between numerical results and field test data. The Timoshenko beam proves great efficiency in modeling the ADA bridge. The inaccuracies result from uncertainties in material properties, and boundary condition as well as deterioration in cross-section properties as a result of corrosion/erosion. Despite the great consistency of results with field data, higher accuracy is required in SHM applications. It is therefore required to apply a Bayesian finite element model updating scheme.

3. ADA bridge model updating

The Bayesian model updating approach is founded on the Bayes' theorem. Based on this framework, conditional probabilities are utilized as estimations of the plausibility of certain statements given other statements. Accordingly, the posterior probability function can be evaluated given the prior distribution function and likelihood function.

$$p(\theta|D) = \frac{p(D|\theta).p(\theta)}{p(D)} \tag{1}$$

In which θ represents the uncertain variables to be updated and D refers to the parameters to be optimized. For the model updating purpose D is taken is the error in the modal parameters of interest e.g. natural frequencies or mode shape. The functions $p(\theta)$, $p(D|\theta)$, and $p(\theta|D)$ also represent the prior, likelihood and posterior functions, respectively. The term $p(D)$ is a normalization factor. [18,19,20]. The likelihood function defines how close the realization are to the modal data. It can be formulated as:

$$p(D|\theta) = c\,\exp\left(-\frac{1}{2}J(\theta)\right) \tag{2}$$

in which

$$J(\theta) = \sum_{m=1}^{N_m}\left[\frac{1}{\delta^2_{\hat{\psi}_m}}\left(1-\frac{\langle\hat{\psi}_m,\phi_m\rangle}{\left\|\hat{\psi}_m\right\|^2\|\phi_m\|^2}\right)+\frac{1}{\delta^2_{\hat{\omega}_m}}\left(1-\frac{\omega_m^2}{\hat{\omega}_m^2}\right)^2\right] \tag{3}$$

In which Nm refers to the number of modes. The terms $\hat{\psi}_m$ and $\hat{\omega}_m$ denote reference mode shape and natural frequency of mth mode. The mode shapes and natural frequencies of the structural model for the mth mode are represented by ϕ_m and ω_m, respectively. The level of uncertainty in the parameters can be determined by $\delta_{\hat{\psi}_m}$ and $\delta_{\hat{\omega}_m}$ terms. Some authors add some multipliers for some modes. Greater multipliers means less C.O.V and consequently less uncertainty. TMCMC sampling algorithm is adopted for Bayaesian FEMU [10,11,21].

Based on the conducted sensitivity analysis the most influential parameters on the frequencies and mode shapes are elasticity modulus and cross-section area. the bridge components are therefore divided into four groups, i.e. bottom chord, top chord, vertical and diagonal members. The mechanical properties of all members in each group are assumed to be the same. Their cross-section also is multiplied by a factor which is also kept same in each group. Moreover, the dynamic properties of the system are significantly affected by the boundary condition. The ideal simply supported boundary condition can never exist in practice. The friction of the system is modeled by a horizontal linear spring, as demonstrated in figure 3.

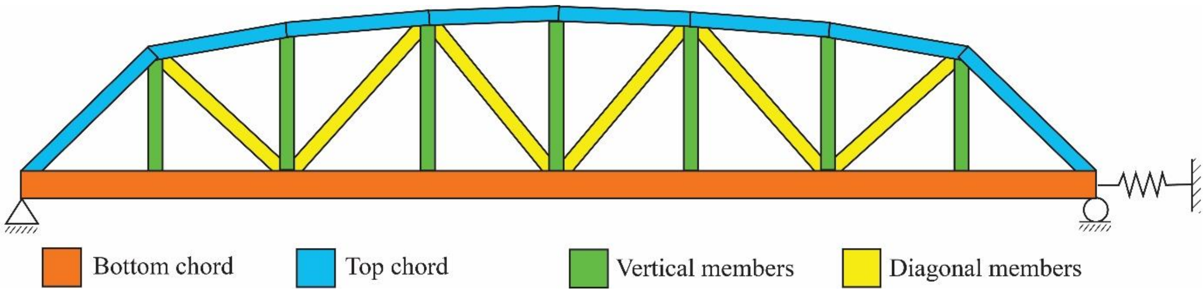

Figure 3: ADA Bridge 2D Model

In the optimization process, it is aimed to minimize the error in the prediction of natural frequencies and mode shapes. In most SHM applications only the first or the second modes are of interest. The developed 2D model is also incapable to capture torsional modes. Therefore, the target of the model updating process has been set to update the model to optimize the first three bending modes. ADA bridge updated natural frequencies are presented in table 2. Mode shape and MAC number of the updated model are also illustrated in Figure 4.

Table 2: Updated natural frequencies

	Field Test	Updated 2D Model	
	Freq. (Hz) [12,14]	Freq. (Hz)	Error (%)
mode 1	2.975	2.988	0.44%
mode 2	6.872	6.907	0.51%
mode 3	9.608	9.622	0.14%

The uncertainty in cross-section areas had been neglected in the original work by zhou et. al. [12]. Despite being ignored, it remarkably affects the dynamic properties of the bridge. It is not surprising because the cross-section areas define the neutral axis and consequently the second moment of inertia of the whole system. Moreover, the axial stiffness of the sections contribute to the overall stiffness matrix. As demonstrated in Table 2 and Figure, there is great compliance between the natural frequencies of the updated model and field test data. The efficiency of the applied TMCMC algorithm is also well established in updating the model with 9 uncertain parameters. The uncertain parameters can also be tuned more so as to reach even higher accuracy. The updated model can, consequently, serve as a surrogate of the structure in structural health monitoring applications.

4. Conclusion

Bayesian Finite element model updating provides an efficient tool for calibration of numerical models and has been widely applied in civil infrastructures. In the current study, the ADA bridge finite element model is updated successfully keeping the first three modes in great compliance with the field test data. The 2D model can therefore represent the real structure keeping the computational effort as low as possible. TMCMC algorithm also proved to be efficient dealing with such a high-dimensional problem. The adopted uncertain parameters also contributed to the accuracy of results.

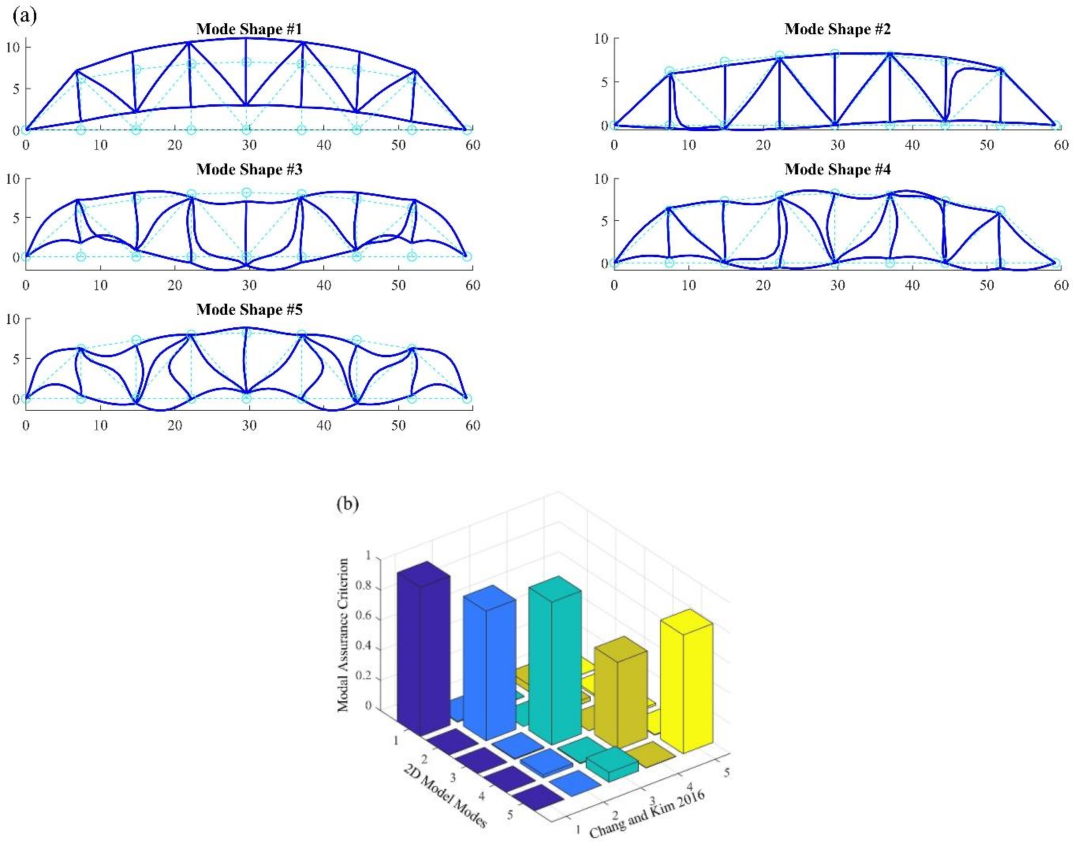

Figure 4: Updated ADA bridge (a) mode shape (b) MAC number

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Evaluation of various machine learning algorithms for the condition assessment of utility timber poles

Ipshita Das, Mohammad Taufiqul Arif, Shamsul Huda, Aman Oo, and Mahbube Subhani*

School of Engineering, Deakin University, Victoria, Australia

*Email: mahbube.subhani@deakin.edu.au;

Abstract

This study focuses on evaluating several machine learning algorithms along with feature selection approaches for the condition assessment of utility timber poles. An efficient feature extraction technique combining Hilbert Huang Transform (HHT) and Wavelet Packet Transform (WPT) is adopted from authors' previous work and implemented to determine damage sensitive features from vibration data related to five serviceable and eight unserviceable in-situ timber poles. Then, these features are pre-processed using correlation heat map analysis for feature selection. Principal component analysis (PCA) is adopted as the final step of pre-processing for reducing noise interference and enhancing the classification accuracy. Afterward, a feature matrix is formed, which is fed into the selected classifiers for pattern recognition. In addition, information gain method is also implemented and compared against PCA to examine the effect of feature selection. Finally, selected classifiers are employed using those dominant features and their performance is evaluated based on six parameters- accuracy, precision, recall, F1-score, confusion matrix and ROC (receiver operating characteristic) curve. The suitability of the selected classifiers is then evaluated to discuss the effect of feature selection.

Keywords: Hilbert Huang Transform; Wavelet Packet Transform; Principal component analysis; Correlation heat map analysis; Information gain method; Machine learning algorithms

5. Introduction

Timber is advantageous to use for electricity poles because of some beneficial properties such as higher heat and electrical insulation, high strength-to-weight ratio, toughness and simplicity in operation [1]. Poles made of timber are commonly used worldwide in power distribution and telecommunication industry due to the accessibility, cost-effectiveness and feasibility than other used alternative materials such as concrete, steel or composites [2]. At present, there are more than 5.5 million in-service timber poles across Australia's telecommunication networks for power supply and communication which covers 80% of total pole population [3]. Despite having some important advantages, condition of these timber poles deteriorates over time due to decay induced by fungus or insect attacks, weather and soil condition.

Vibration based Non Destructive Testing (NDT) method is well established in the pole/ pile industry as this method can examine the whole pole by utilizing its dynamic properties such as natural frequency, mode shapes and damping ratio [4]. However, these dynamic properties are highly affected by the uncertainties of material properties, numerous species of timber, variation in weather and soil condition, environmental factors such as fluctuations in temperature and moisture content. Subsequently, pole assessment outcomes can be inconsistent and unreliable.

Advanced signal processing techniques play a vital role with respect to this problem. Extracting dominant features from the captured broadband signal (induced from impact using modal hammer) is essential to determine the health state of timber poles. In addition, these broadband signals are polluted with noise exist in field testing. The obtained signal is nonstationary and nonlinear which need to be considered while implementing signal processing techniques. Due to this fact, time-frequency analysis is more effective for analyzing field tested broadband signal than conventional signal processing techniques.

Among all the time frequency analysis techniques, Hilbert Huang Transform (HHT) has become more popular in recent times for dealing with such signals. Das et al. [5] adopted vibration based non-destructive technique and successfully utilized an efficient feature extraction technique combining HHT and WPT in order to determine vital features from captured broadband signal [5].

All features extracted using signal processing techniques contributes to the classification but it's important to choose the best feature that are correlated with the damage so that pattern recognition and machine learning process for feature classification can be made more accurate [4]. Feature selection lessens the dimensionality of feature space either through reducing the number of features or combining two features into a new feature or choosing a subset of features [6]. There are many techniques available for feature selection. Among them, Principal Component Analysis [7] is the most commonly used technique.

From the literature, Logistic Regression (LR), K-Nearest Neighbours (KNN), Decision Tree (DT), Support Vector Machine (SVM) and Naive Bayes (NB) are found to be an efficient tool with their pattern recognition and classification ability in complementing vibration-based NDT. This study focuses on investigating the capability of above-mentioned machine learning algorithms using damage sensitive features obtained from improved HHT. For feature selection, correlation heat map analysis, PCA and information gain method are adopted. Furthermore, the results of the classifiers were analyzed and compared based on six parameters namely accuracy, precision, recall, F1-score, confusion matrix and ROC curve.

2. Experimental setup

Equipment

Modal hammer was used to induce energy to the timber poles. Signal / data associated with five serviceable/healthy and eight unserviceable/damaged in-situ timber poles were collected. Since timber is an orthotropic material, its material properties vary in three different directions: longitudinal, radial, and circumferential. Subhani et al. [8] proposed an appropriate sensor set up for the non-destructive assessment of cylindrical type structures which is adopted in this study in order to capture the three dimensional behaviour of timber pole. For field testing, an impact hammer, 12 accelerometers and a data acquisition system were employed. Modal hammer Endevco 2303 was used in this study (1 mV/lbf, 5000 lb range) to generate impact, while Instron 46A16 sensors were used for capturing accelerations which have sensitivity of 100 mv/g (range ±50 g). The NI cDAQ-9133 (1.33 GHz, 16 GB) from National Instrument was used as the data acquisition system with NI 9232 (3 channel, +/30 V, 102.4 kS/s/channel, 24-Bit, IEPE AI C Series) input modules. A total of 12 accelerometers were used and was connected to the pole by mechanically means (as shown in Figure 1 a). Figure 1b depicts the portable device used for the testing.

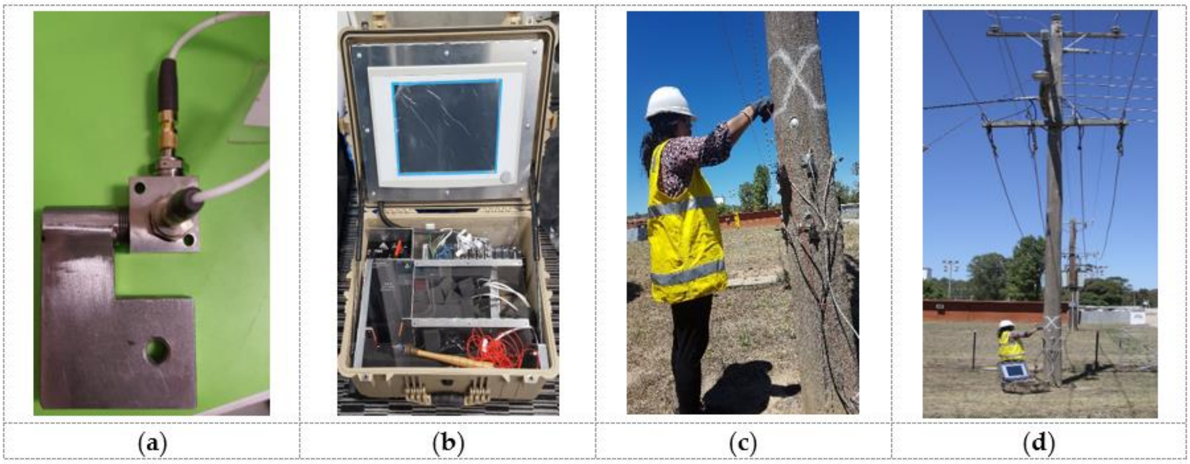


Figure 1 (a) Accelerometer attachment (b) Pole tester (c) Accelerometer arrangement

(d) Field testing.

Testing specimen

Field testing is executed on five serviceable and eight unserviceable in-situ utility timber poles located at Benalla and Wangaratta of Victoria. Detail of the testing specimen is given in Tables 1 and 2.

Table 1. Detail of five in-situ serviceable/healthy timber poles.

	Serviceable Pole 1	**Serviceable Pole 2**	**Serviceable Pole 3**	**Serviceable pole 4**	**Serviceable pole 5**
Timber species	White Stringybark	White Stringybark	White Stringybark	White Stringybark	White Stringybark
Timber type	Hardwood	Hardwood	Hardwood	Hardwood	Hardwood
Cross section	Circular	Circular	Circular	Circular	Circular
Strength class	3	3	3	3	3
Durability class	2	2	2	2	2
Diameter	870 mm	870 mm	980 mm	780 mm	780 mm
Above ground height	9114 mm	9144 mm	10000 mm	9144 mm	9144 mm
Location	Benalla, Victoria	Benalla, Victoria	Benalla, Victoria	Benalla, Victoria	Benalla, Victoria
Chemically treated timber	Yes	Yes	Yes	Yes	Yes

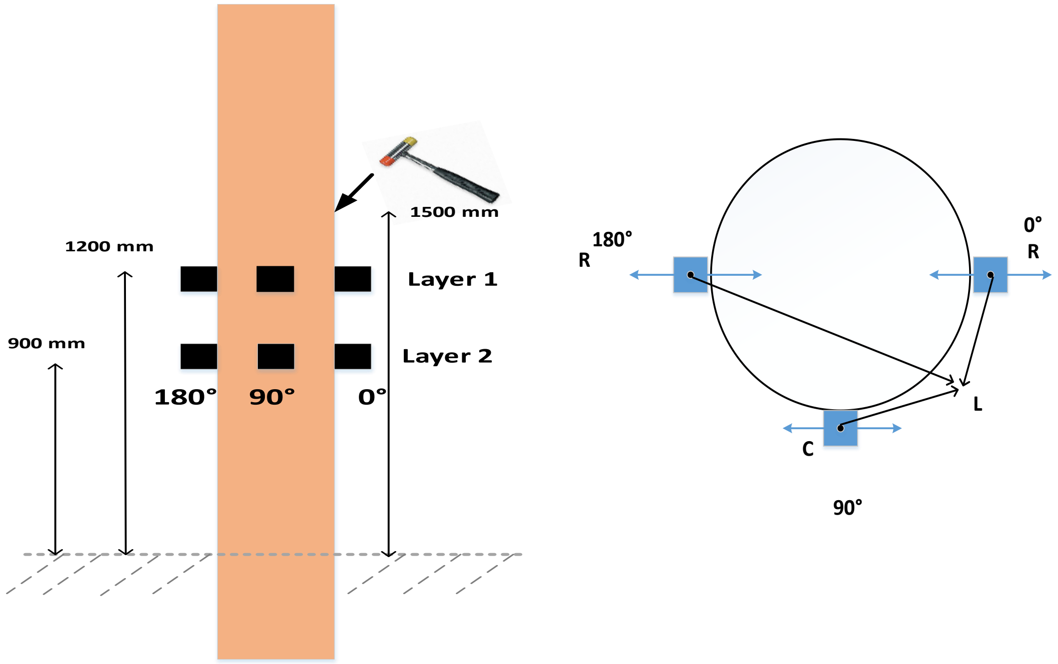
Table 2. Detail of eight in-situ unserviceable/damaged timber poles.

	Unserviceable Pole 1	**Unserviceable Pole 2**	**Unserviceable Pole 3**	**Unserviceable pole 4**	**Unserviceable pole 5**	**Unserviceable pole 6**	**Unserviceable pole 7**	**Unserviceable pole 8**
Timber species	White Stringybark	White Stringybark	White Stringybark	Messmate	Messmate	Grey ironbark	White Stringybark	White Stringybark
Timber type	Hardwood	Hardwood	Hardwood	Hardwood	Hardwood	Hardwood	Hardwood	Hardwood

Cross section	Circular	Circular	Circular	Circular	Circular	Circular	Circular	Circular
Strength class	3	3	3	3	3	1	3	3
Durability class	2	2	2	3	3	1	2	2
Diameter	890 mm	750 mm	1100 mm	1150 mm	1074 mm	890 mm	960 mm	710 mm
Above ground height	9144 mm	9910 mm	15,240 mm	12,000 mm	12,000 mm	12192 mm	12192 mm	10688 mm
Location	Benalla, Victoria	Benalla, Victoria	Benalla, Victoria	Benalla, Victoria	Benalla, Victoria	Wangaratta, Victoria	Wangaratta, Victoria	Wangaratta, Victoria
Chemically treated timber	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Testing setup

Figures 1 and 2 demonstrate the experimental field set up for the vibration testing. Hammer impact was induced at a height of 1500 mm in the radial direction (horizontal). The sampling frequency was set to 100 kHz. Each pole was struck four times. Accelerometers were attached on the pole at 1200 mm and 900 mm from the ground level. Six accelerometers that were located at 1200 mm from the bottom of the pole are designated as Layer 1 accelerometers and the other six accelerometers that were located at 900 mm from the bottom of the pole are designated as Layer 2 accelerometers. For each accelerometer location, three positions along the circumference 0°, 90°, and 180° were taken into account. The accelerometer which is aligned with the impact line is named as 0° and the accelerometer opposite to 0° is called 180°. In the same way, the accelerometer which is located 90° around the circumference is called as 90°. Additionally, at each accelerometer position, the displacement was captured in two orthogonal directions, i.e., in the longitudinal (L), radial (R) for 0° and 180° and longitudinal (L) and circumferential (C) for 90°. The illustration of every accelerometer is named such a way that it represents the location and orientation of that particular accelerometer. For instance, a notation "A90C1" means the accelerometer belongs to Layer 1 (located at 1200 mm from the bottom of the pole) that captured the acceleration in the circumferential direction and located at 90° around the circumference from the impact point.



(a) (b)

Figure 2 (a) Schematic diagram of experimental test set up (b) Horizontal cross section.

3. Approach and methods

Feature extraction using improved HHT

In this study, health assessment of utility timber poles is considered as a pattern recognition problem. Precision of the assessed results exclusively depends on feature extraction. Since features related to damage are often hidden in the captured broadband signals, an efficient feature extraction technique is crucial to reveal the hidden features related to the health state of timber pole. Authors have developed an efficient feature extraction technique in the previous work combining HHT and WPT together for extracting damage sensitive features [5]. This technique is then employed on vibration signals related to five serviceable and eight unserviceable timber poles. A total of 72 features were obtained for each pole as shown in Table 3.

Table 3. Feature description

Feature Name	Feature description
S1IMF1, S1IMF2, S1IMF3, S1IMF4, S1IMF5 S12IMF1, S12IMF2,S12IMF3, S12IMF4, S12IMF5	S1IMF1 denotes the frequency value of Sensor 1, IMF1. There are a total 12 Sensors, and 5 dominant IMFs are considered for the study. Similarly, S12IMF4 denotes the frequency value of sensor 12, IMF4
AVIMF1 ... IMF5	Average frequency of IMF1 ... IMF5 (Described in chapter 4)
DIMF1 ... DIMF5	Standard deviation of IMF1 ... IMF5(Described in
Ins_amp (S8)	Instantaneous amplitude of IMF1 for S8(A0R2)
S8traps(e1)	Area under the curve value for IMF1 S8(A0R2)

Feature selection using correlation heat map

A correlation heat map is generated for feature selection. Figure 3 illustrates a correlation heat map showing correlation among all 72 features. Correlation indicates how one or more input features are related to one another for predicting the target variable. From this correlation heat map, it is observed that frequency values related to each individual IMF from same sensor (For example S1IMF1, S1IMF2, S1IMF3, S1IMF4 and S1IMF5) are positively correlated with each other whereas Ins_ampS8 and S8trapz (e1) have negative correlation with the target, indicating higher instantaneous amplitude and area under the curve of IMF1 relates to unserviceable poles. The less correlated features are removed as they have less impact on the target for enhancing the accuracy of the classifiers reducing the number of features from 72 to 60.

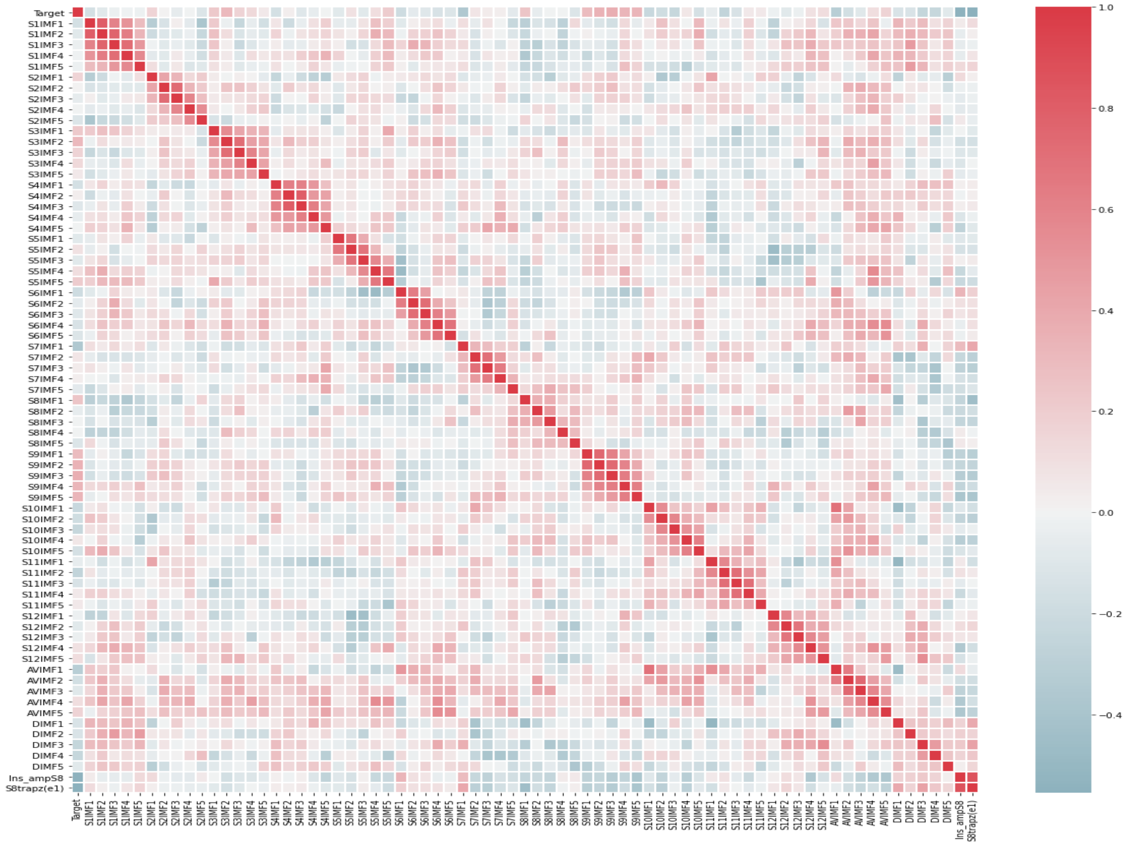


Figure 3 Correlation between different features

Principal component analysis

After correlation heat map analysis, a total of 60 features are selected. Before training those selected features using different classifiers, principal component analysis (PCA) is adopted as the final pre-processing step. Figure 4 shows the individual and cumulative contributions of PCs. It can be observed that the first 30 PCs make up more than 95% of the original data. Therefore, with only a 5% loss of information, 30 correlated PCs are generated which forms the feature vector.

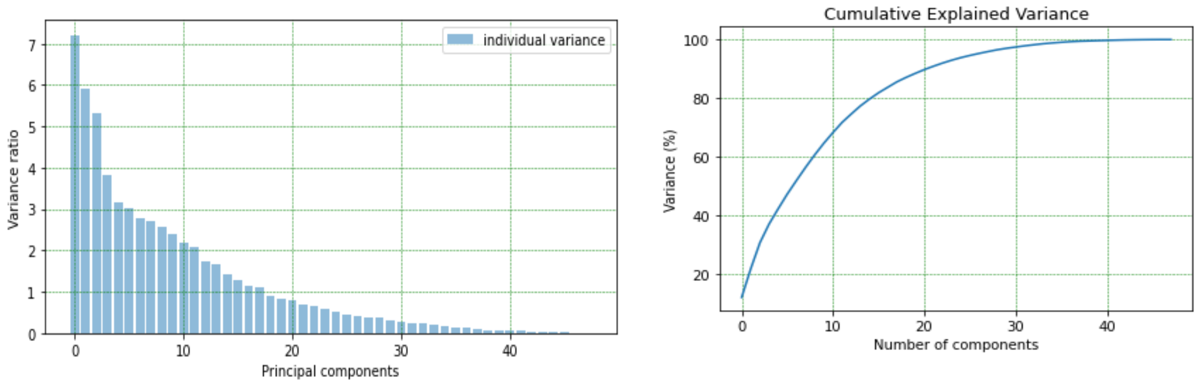


Figure 4 The individual and cumulative contributions of PCs

Feature selection using information gain method

Information gain method utilizes mutual information for feature selection. Mutual information basically measures the dependency of features with the target value which is serviceable or unserviceable in our case. Figure 5 illustrates the dominant features with highest MI score value using information gain method.

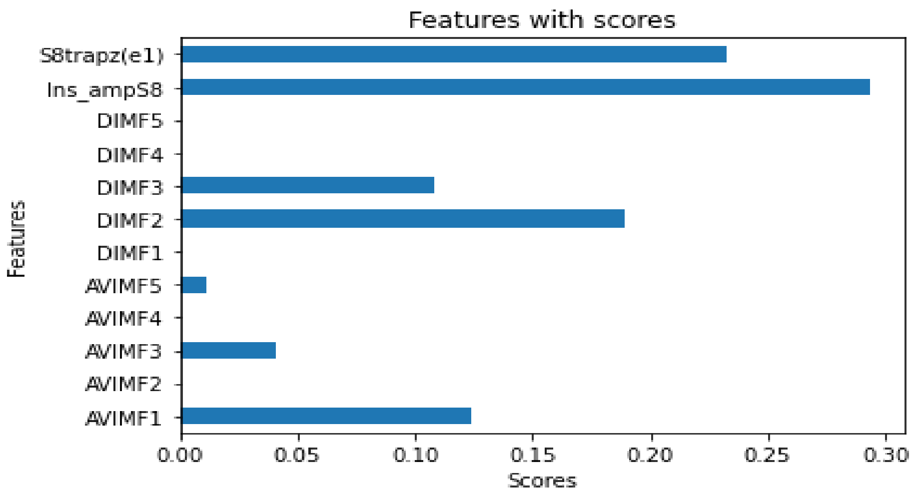


Figure 5 Features with MI score using information gain method

After this analysis, seven features including AVIMF1, AVIMF3, AVIMF5, DIMF2, DIMF3, Ins_ampS8 and S8trapz (e1) are found to be most dominant among all other features having highest MI score. Two approaches are adopted in this study for feature selection. 1st approach combines correlation heat map analysis and PCA from where 30 principal components are obtained. 2nd approach utilizes information gain method for feature selection from where 7 dominant features are obtained. Efficacy of these two feature selection approaches will be explored in Section 4.

4. Results and discussion

In this section, the selected five machine learning algorithms is implemented to assess the health state of utility timber poles using features obtained from feature pre-processing techniques. The dataset is split into two parts randomly. For this study, the dataset is split into 70:30 ratio considering 70% data for training set and 30% data for testing set. In the first step, that 70% randomly selected data was used for training which are fed to the classifiers as input. Once training is completed, the 30% testing data are employed for predicting one of the two classes: Unserviceable (damaged) or serviceable (healthy). In this study, the following machine learning algorithms are selected:

1. Logistic Regression (LR)
2. K-Nearest Neighbours (KNN)
3. Decision Tree (DT)
4. Support Vector Machine (SVM)
5. Naive Bayes (NB)

After implementing the machine learning algorithms, the performance of the classifiers is analysed and compared based on six parameters - accuracy, precision, recall, F1-score, confusion matrix and ROC curve.

Classifier's performance analysis after dataset preprocessing using correlation heat map and PCA

The dataset is pre-processed using correlation heat map analysis and PCA, as described in Section 3. Figure 7 presents the comparison among various algorithms based on accuracy, precision, recall and F1 score using newly obtained feature matrix. From this figure, it is observed that maximum precision, recall and F1 score are observed for DT classifier which also has highest accuracy of 73.33% among all other classifiers. Accuracy of Logistic Regression (LR) classifier has also improved from 53.33% to 60%. However, SVM obtained accuracy of 53.33% and precision of 50% with recall of only 14.29% which indicates, it exhibits imbalanced results in this scenario as well. This phenomenon happened due to the random effect which was not possible to overcome completely due to the limitation of small dataset.

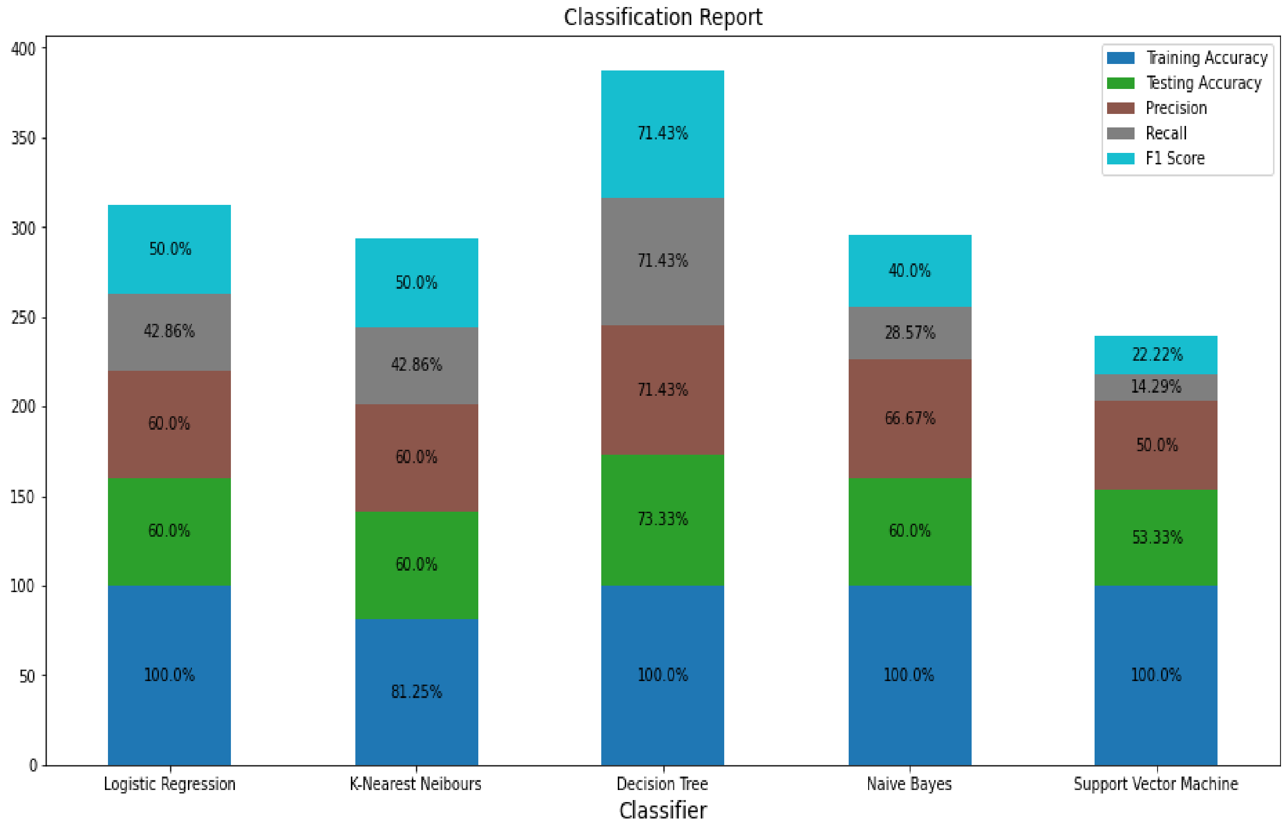


Figure 7 Comparison among various algorithms with accuracy, precision, recall and F1 score using pre-processed data obtained from correlation heat map and PCA

For further investigation, confusion matrix and ROC curve of the best performing classifiers, DT and LR are investigated and shown in Figure 8 and 9. It can be observed that number of misclassified samples are lower in case of DT (Figure 9) compared to other classifiers. For 13 poles, total of 48 tests were conducted. Among 48 tests, 33 test samples are used for training and 15 test samples are used for validation test. A total of 4 samples are misclassified out of total 15 samples in the test data set for DT classifier whereas 6 samples are misclassified by LR classifier. Higher AUC (area under the curve) measured from ROC curve are observed for DT, LR and KNN classifier which is 0.73. Overall, in this scenario, DT is the best performing one considering all the parameters.

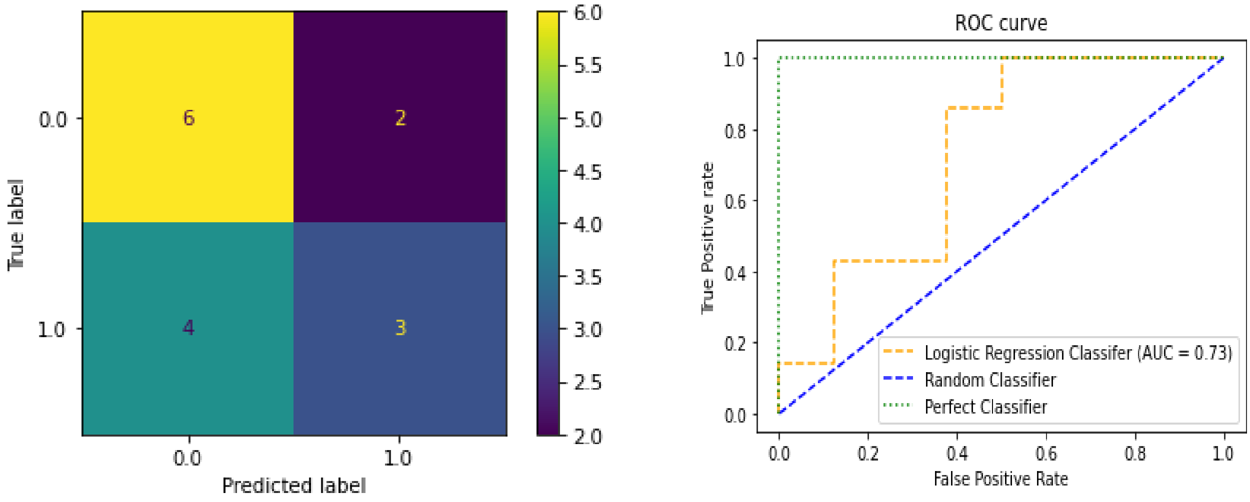


Figure 8 Confusion matrix and ROC curve of Logistic Regression classifier

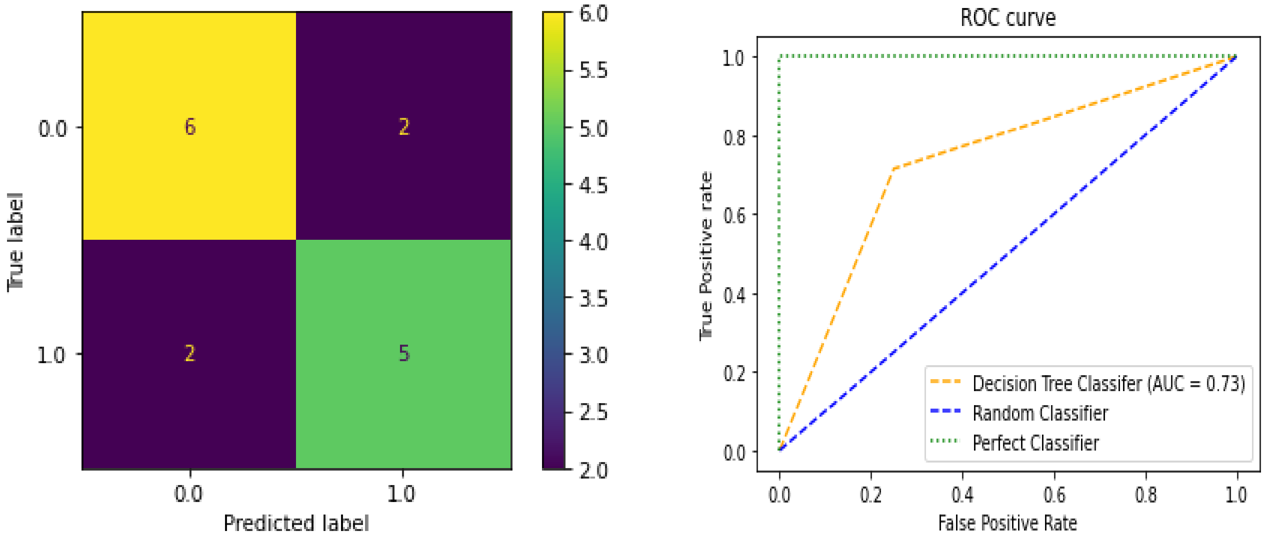


Figure 9 Confusion matrix and ROC curve of Decision Tree classifier

Effect of feature selection using information gain method

In this section, effect of feature selection is investigated for the selected classifiers to explore how the selected features affect classifier's performance. Information gain method utilizing the mutual information is used for feature selection as discussed in Section 3. After selecting 7 dominant features from information gain method, selected machine learning algorithms are implemented, and the performance of the classifiers are observed. All six parameters considering accuracy, precision, recall, F1 score, confusion matrix and ROC curve are compared to examine classifier's performance. Figure 10 represents comparison among various algorithms in terms of accuracy, precision, recall and F1 score. From this figure, it is noticeable that accuracy of KNN, DT and NB has risen above 70%. Maximum accuracy of 86.67% is achieved for LR classifier which is found to be the highest accuracy is considering all scenarios considered above. This indicates that selected 7 dominant features are crucial for model generalization of LR classifier. This is because, LR is low complexity model, and therefore, it works well for dealing with smaller dataset. In classification problems, imbalanced class distribution occurs and accordingly F1-score is a superior metric for assessing classification models. As, F1-score is harmonic mean of precision and recall, higher F1 score indicates better performance in terms of precision and recall. For this scenario, maximum F1 score of 85.71% is obtained for LR classifier which showed significant improvement compared to previous analysis. Though precision is highest in KNN, F1 score is low. Overall, all classifiers except SVM and KNN exhibit balanced results in terms of accuracy, precision, recall and F1 score.

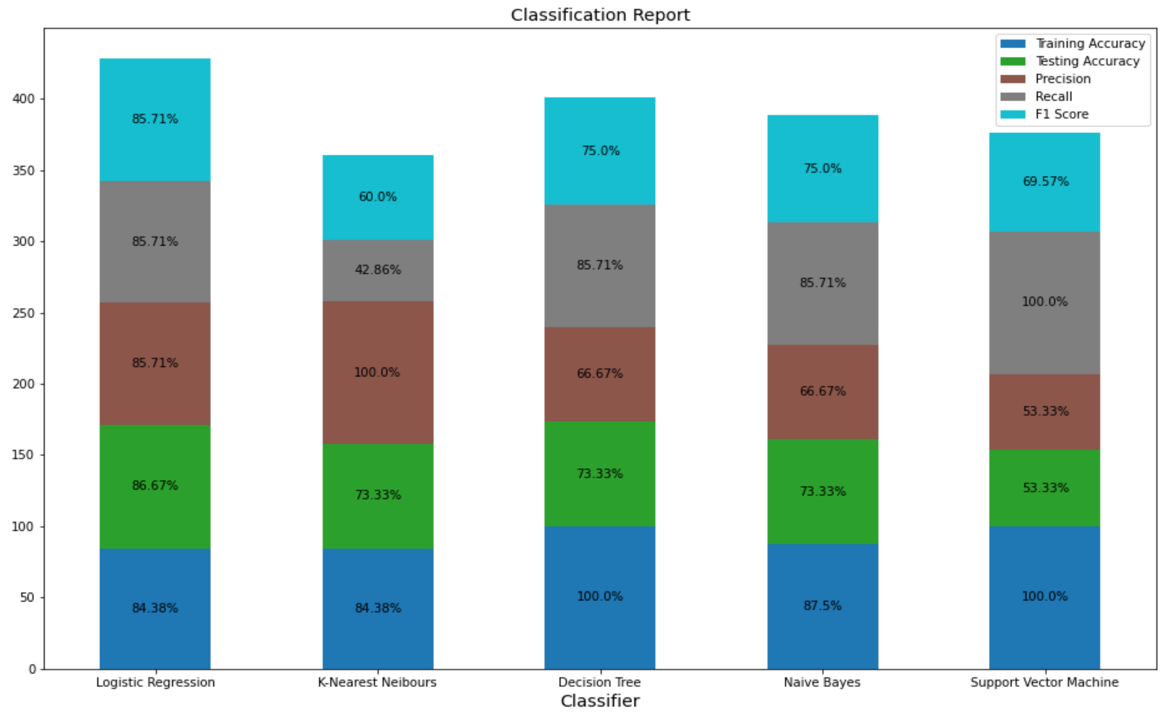


Figure 10 Comparison among various algorithms with accuracy, precision, recall and F1 score when seven most dominant features are selected

For further analysis, confusion matrix and ROC curve of the top three classifiers are shown in Figure (11 – 14). It is noticeable that amount of misclassification has decreased for LR, KNN, DT and NB classifier in this case compared to the previous scenario. For LR classifier, only 2 samples are misclassified (Figure 11) out of total 15 samples in the test data set which is lowest among all the classifiers. It is also observed from the ROC curves that AUC has also improved significantly in this scenario for four of the classifiers except SVM. AUC represents the degree or measure of separability. That means higher AUC indicates that the model is better at predicting serviceable class as serviceable and unserviceable classes as unserviceable. Compared to previous scenario, LR's AUC increased from 0.73 to 0.82, KNN's AUC from 0.73 to 0.86, DT's AUC from 0.73 to 0.74, NB's AUC from 0.68 to 0.88, respectively. Overall, LR model outperforms all the classifiers in this scenario since it performs well for small dataset.

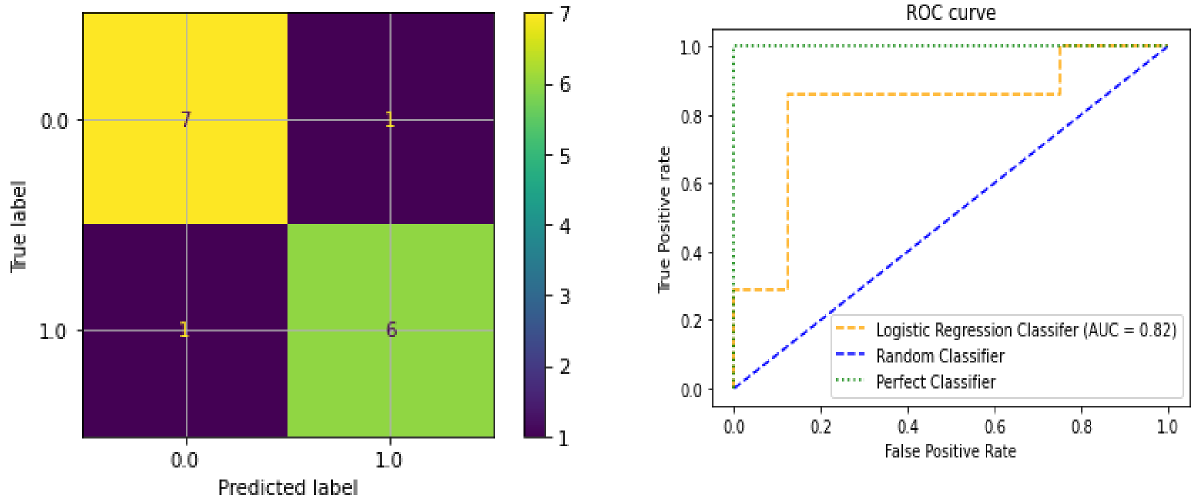


Figure 11 Effect of feature selection on Confusion matrix and ROC curve of Logistic regression classifier

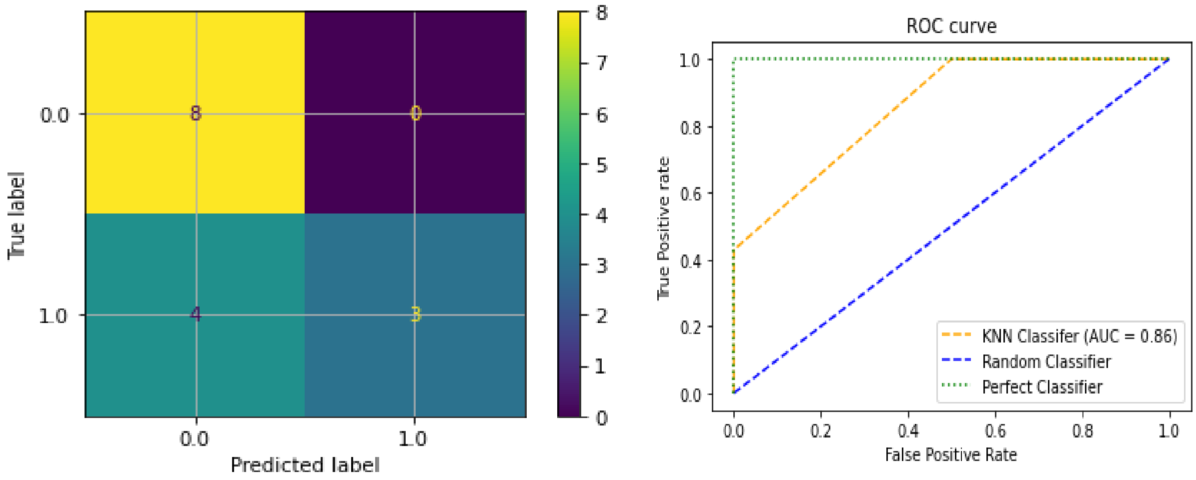


Figure 12 Effect of feature selection on Confusion matrix and ROC curve of K-nearest neighbor classifier

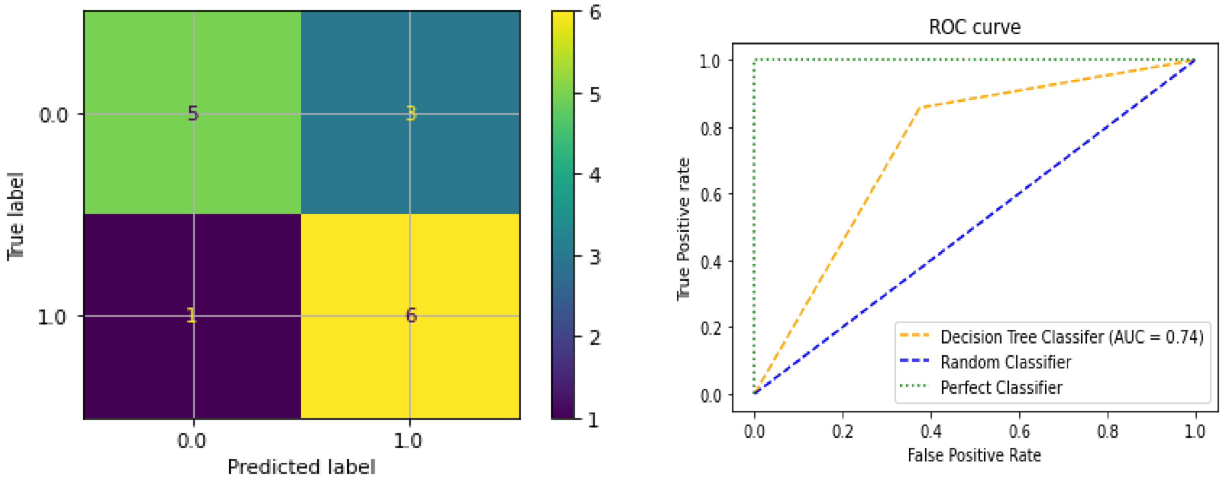


Figure 13 Effect of feature selection on Confusion matrix and ROC curve of Decision tree classifier

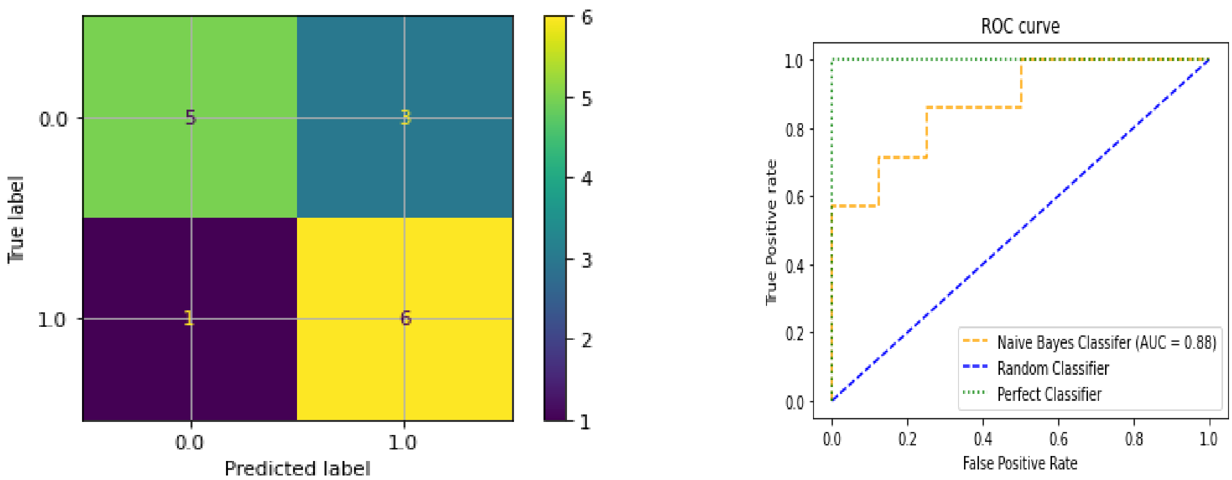


Figure 14 Effect of feature selection on Confusion matrix and ROC curve of Naïve Bayes classifier

Conclusion

In this study, several machine learning algorithms are implemented along with advanced signal processing technique to deal with vibration signals related to thirteen in-situ timber poles. First, features are extracted utilizing improved HHT technique developed in author's previous work where WPT and HHT are employed together. Different feature selection techniques are adopted to choose the best set of features to evaluate which feature set works best. A total of 5 machine learning algorithms – LR, KNN, DT, NB and SVM are investigated along with several features section approaches and their results are compared against accuracy, precision, recall, F1 score and ROC curve. The following outcomes are observed from the study:

- Initially, all the features extracted from improved HHT were utilized for the preliminary investigation. In this scenario, a maximum accuracy and F1 score of 66.67% was achieved for DT algorithm. Overall results are not satisfactory since data pre-processing or feature selection was not utilized.
- To improve the performance, data pre-processing was conducted utilizing correlation heat map analysis and PCA before being fed to the classifier as input. And then, their performance was analysed using processed data. From that analysis, it was found that DT classifier work best for this scenario in order to assess health condition of utility timber poles with a maximum accuracy of 73.33% and AUC of 0.73. Other parameters such as precision, recall and F1 score also demonstrated balanced (approximately equal value of precision, accuracy, recall and F1 score) and improved result.
- It is found that, some classifiers such as SVM, cannot yield satisfactory performance if dataset is small.
- From analysis, it is concluded that information gain method can reduce the number of important features compared to correlation heat map and PCA. Correlation heat map reduced the number of features from 72 to 60, while PCA reduced the number features to 30. In contrast, only 7 features were found to be important to consider while information gain method is implemented.
- The information gain method was found to be very effective to enhance the performance of LR, DT and NB. LR classifier attained maximum accuracy of 86.67%, AUC of 0.82 and F1 score of 85.71%. LR model is simple and it can be implemented easily, thus it performed better than other classifiers in handling smaller dataset. Therefore, LR is recommended for dealing with smaller dataset.

- F1 score is a reliable performance measure while dealing with imbalanced dataset. LR classifier exhibits maximum F1 score of 85.71% considering 7 most dominant features. Therefore, a significant improvement in F1 score is observed compared to previous two scenarios.

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Model Specifications for Structural Health Monitoring: Part 1 – Overview

Colin Caprani, Monash University, colin.caprani@monash.edu

Background

In the age of Smart Cities and the Internet of Things, it is increasingly accepted that the instrumentation and monitoring of the performance of critical infrastructure assets should form a key input to rational decision-making and asset management practices. While many failures occur during construction (e.g. FIU Pedestrian Bridge), due to the bathtub curve of failure rates, developed nations, with mature infrastructure can expect to see an increase in end-of-life failures. This has been tragically highlighted in recent times by the Genoa Morandi Bridge collapse, amongst others. So while the installation of SHM systems into new infrastructure is no doubt recommended, the key asset management benefits emerge from the retrofitting of such systems to existing structures.

Motivation

While the benefits of SHM are appreciated by almost all, there remain some significant hurdles to more widespread adoption. Foremost among these is the value proposition of SHM: while there now exists the techniques to evaluate the expected financial benefit based on Value of Information analysis, nevertheless there is a perception that SHM over-promises and under-delivers.

That SHM seemingly over-promises is partly due to the misnomer of “health” monitoring, which infers the detection of damage. While algorithms exist, this has proven to be yet difficult to achieve in practice. And so a terminology such as structural behaviour measurement or structural performance monitoring is more fitting, though the SHM terminology remains.

That SHM under-delivers is a function of two main causes: it requires a unique combination of technical capabilities, and there is no industry-wide agreed minimum offering to clients from suppliers. The upskilling of engineers to engage in SHM system design and specification, and to properly read and interpret the resulting outputs is certainty vital, and is a challenge to be addressed. However, the need remains for the second of these aspects: by providing an standard industry-wide set of service expectations for clients, the issue of SHM under delivering can be strongly mitigated.

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.

Goals of the Model Specifications

The Model Specifications should:

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

On-site calibration check during late-night installation works.

Outline Contents of the Model Specifications

The Model Specifications should address the following matters:

1) *Monitoring Aims*: guidance should be provided on when to monitor, what to monitor, and any required actions during monitoring, and if or when monitoring should end.
2) *Appropriate Measurements*: different physical quantities are measured to infer different metrics of a structure's condition and performance; appropriately matching the two is essential. Guidance is required on suitable measurement types, locations, sampling rates, and accuracy.
3) *Data Quality*: the validation and calibration of SHM sensors and systems, and environmental conditions, are key factors affecting data quality, and recommendations are required.
4) *Robust Measurement*: installation of SHM systems ought to be robust to vermin and vandalism, and other site-specific conditions.
5) *Site Management*: the installation process itself requires suitable and safe access, and recommendations on access equipment and safety can be outlined.
6) *Data Analysis*: some advice on data summaries and common algorithms can be given.

Feedback

Over the next few articles in this series, I will expand on the individual items in the Outline Contents given above. However, noting the first goal of the Model Specifications given above, this article, and the following articles, will not be prescriptive, and have the simple aim of starting the consultation process. As such, your feedback on this and the subsequent articles is very welcome and sought to the author for possible incorporation in the Model Specifications.

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If you have any comments and suggestions, please contact

Newsletter Editors:

Dr. Mehrisadat Makki Alamdari, University of New South Wales.

Email: m.makkialamdari@unsw.edu.au

Dr. Jun Li, Curtin University.

Email: junli@curtin.edu.au

Prof. Richard Yang, Western Sydney University.

Email: R.Yang@westernsydney.edu.au