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Structural Health Monitoring of Bridges

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Amendment Version #	Date Reviewed	Clause	Description of Amendment
1.0	05 Apr 24		First issue: illustrates an effective roadmap for the practical SHM of bridges.

Table of Contents

1 Introduction

1.1 Purpose

The purpose of this guideline is to provide general recommendations for effective Structural Health Monitoring (SHM) of bridges to ensure that:

- Fit-for-purpose SHM plans are well investigated, analysed, and outlined before implementation to achieve tangible and cost and time-effective results.
- State-of-the-art developments are reviewed and incorporated into the SHM plans to enhance effectiveness, reduce processing time, cost, and future human contributions, as well as increase bridge safety throughout the bridge lifecycle.

1.2 Scope

This guideline includes recommendations for the implementation of state-of-the-art, and cost and time-effective SHM plans throughout the bridge lifecycle.

1.3 Document Owner

The Head of Engineering Standards is the Document Owner. Queries should be directed to standards@artc.com.au in the first instance.

1.4 Definitions

The following terms and acronyms are used within this document:

Term or acronym	Description
AI	Artificial Intelligence
ARMA	Autoregression Moving Average
BIM	Building Information Modelling
BMS	Bridge Management System
BWIM	Bridge Weigh In Motion
CWT	Continuous Wavelet Transform
DAF	Dynamic Amplification Factor
DLA	Dynamic Load Allowance
DoF	Degree of Freedom
DSF	Damage Sensitive Feature
DT	Digital Twin
DWT	Discrete Wavelet Transform
EFDD	Enhanced Frequency Domain Decomposition
FDD	Frequency Domain Decomposition
FE	Finite Element
FEA	Finite Element Analysis
FFT	Fast Fourier Transform

Term or acronym	Description
FRF	Frequency Response Function
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GWN	Gaussian White Noise
IoT	Internet of Things
IRF	Impulse Response Function
LiDAR	Light Detection And Ranging
LVDT	Linear Variable Differential Transformer
MAC	Modal Assurance Criterion
NExT	Natural Excitation Technique
PP	Peak Picking
PSD	Power Spectral Density
RSI	Rail Structure Interaction
SAR	Synthetic Aperture Radar
SHM	Structural Health Monitoring
SLS	Serviceability Limit State
SM	Structural Monitoring
SNR	Signal to Noise Ratio
SSI	Stochastic Subspace Identification Soil Structure Interaction
SVD	Singular Value Decomposition
TPD	Truck performance Detector
UAV	Unmanned Aerial Vehicle
WSN	Wireless Sensor Network

2 Structural Monitoring versus Structural Health Monitoring

2.1 General

While Structural Monitoring (SM) can be conducted to monitor a structural member under loading and acquire field data, Structural Health Monitoring (SHM) can be defined as the comprehensive process of acquiring and analysing data from sensing equipment to evaluate the health state of the structure. An effective SHM cannot be fulfilled without understanding structural performance and behavior under various static and dynamic load cases in all phases (numerical, experimental, or practical levels) or without extracting and analysing sensitive health or anomaly patterns to enable detecting health/undamaged states against damaged ones.

Generally, the SHM process is implemented in five key steps, of which only the first three steps can be applied to an SM:

- Data acquisition
- System Identification
- Condition monitoring and safety assessment
- Damage detection, localisation, and qualification
- Decision-making [1]

Before commencing an SM or an SHM process, the aim of such a process needs to be well-defined and purpose-driven so that the involvement of further detailed investigation and understanding of the performance and behavior of critical structural elements using sensors is justifiable.

In general, the SM or SHM process is more important for tracking the health state of existing old bridges in their as-is condition or when they are very close to a site where new construction occurs than for tracking the performance or behavior of newly constructed bridges. The increasing volume of vehicle tonnage and cycles over existing old bridges or constructing new structures adjacent to older bridges can cause sudden structural damage or even catastrophic failure of these bridges, as these bridges may not have been constructed with significantly higher design capacity or required structural redundancy nor be in perfect structural condition.

A successful SHM can supplement the effectiveness of:

- Structural modelling and numerical analysis that may be compromised or conservatively simplified. In this case, the lack of accuracy in numerical analysis may lead to unrealistic low-calculated load rating factors or high-calculated stresses (fatigue) in critical structural members. If no SHM or SM is considered, any decision might have costly or adverse consequences on network efficiency or the business, e.g., it might result in bridge, lane, or track closure, barricade installation, speed and mass restriction, or an incorrect estimation of the remaining fatigue life.
- Physical inspections that may be compromised by limited human resources, delayed discovery of damages, a lack of knowledge, and the subjectivity of inspectors [2].
- Performance or condition tracking of safety-critical, heritage, or significant bridges that are not likely to be replaced or have a high economic impact on the business.
- Performance or condition tracking of bridges located in strategic regions that have higher importance levels or a higher annual probability of exceedance that are mostly

susceptible to natural disasters, e.g., earthquakes, winds, or flooding, and require an immediate recovery after such an event.

- Verification and validation of an actual load case or effect applied to existing lower-capacity bridges that causes a significant cost in bridge upgrading or strengthening in case these bridges need to comply with the current bridge design codes.

Carbon dioxide emissions can significantly be reduced as a result of bridge maintenance without the need for bridge reconstruction or new bridge construction [3, 4] once older bridges' behavior is monitored, and their end-of-service life estimated more realistically.

The use of SHM of bridges includes below but is not limited to:

- Strain, displacement, and temperature data acquisition.
- Force estimation for verifying and validating designs, assessments, and safety and regulatory compliance requirements.
- Modal parameter identification (acceleration responses).
- Bridge condition monitoring and safety assessment.
- Damage or anomaly detection, localisation, and qualification.
- Numerical modelling or Finite Element (FE) model validation and updating.
- Data-driven SHM, and machine and deep learning techniques [1].

Areas of expertise involved in an effective SHM process include but may not be limited to:

- Bridge engineers, especially those with a proven track record in structural dynamics, practical bridge design, Finite Element Analysis (FEA), and signal processing
- Experts in numeric computing and/or programming language platforms
- Artificial Intelligence (AI) specialists
- Structural inspection and maintenance specialists
- Project managers
- Data integration and management specialists
- Contractors, providers of sensing services, or SHM specialist technicians

2.2 Sensors for SHM

SHM needs to collect accurate real-time data from structural members and transmit this information to the control system while it should signal necessary warnings with anomaly conditions.

The latest advances in sensing technology for SHM have resulted in various types of sensors which are divided into two categories:

- Contact sensor types
- Noncontact sensor and remote sensing types

2.2.1 Contact Sensor Types

Table 1 below lists some of the most common contact sensors used in bridge monitoring [5]:

Table 1: Common Sensor Types

Physical quantity	Sensor
Strain	Conventional and embedded strain transducer
	Optical strain gauge
	Vibrating wire
Displacement	Linear Variable Differential Transformer (LVDT)
	Long gauge fibre optics
	Optical e.g., Fiber Bragg grating
	Laser vibrometer
Temperature	Electrical resistance thermometer
	Thermocouple
	Thermistor
	Fibre optic-based sensor
Acceleration	Piezoelectric accelerometer
	Capacitive accelerometer
	Force-balanced accelerometer
	Seismometer
	MEMS
Force	Electrical resistance load cells
	Piezoelectric load cells

2.2.2 Noncontact Sensor and Remote Sensing Types

In some situations, a significant number of measurement locations may be required as the bridge is more complex, or sometimes access to some of the locations is restricted. In these cases, noncontact sensors may be of high interest. A noncontact system can be remote sensing-based and is when a measurement is conducted with absolutely no contact or probing to a structural member. Noncontact systems are primarily based on laser, radar, vehicle, GPS, video technologies, and digital cameras [5].

The SHM can provide remote condition monitoring by transmitting data to data analysis centres. The transmission using networking technologies, such as Wireless Sensor Networks (WSN)s allows the development of a cheaper continuous and autonomous measurement system for bridge SHM than a cable-based measurement system. WSN can perform independent activities, such as preliminary data processing of the acquired data, self-monitoring of supply energy and communication links, and scheduling of the measurements. However, the WSN nodes are battery-powered, and thus power management is vital to maximize their durability [6].

In recent years, more effective remote sensing has been established as an innovative, effective, and cost-efficient option for the provision of high-quality information to decision-makers to update their plans and/or take actions toward the mitigation of the risks involved in bridges. In this context, many practical SHM for railway and road bridges have been developed based on:

- Global Navigation Satellite System (GNSS)
- Synthetic Aperture Radar (SAR)
- Light Detection And Ranging (LiDAR)
- Unmanned Aerial Vehicle (UAV) [7]

Thus far, many SHMs have successfully integrated remote sensing technologies with in place sensors (contact and/or noncontact) on Internet of Things (IoT) cloud platforms to obtain real bridge data (e.g., dynamic displacements or ambient acceleration responses). In some cases, the need to install heavy instrumentation and therefore the overall cost of SHM for complex bridges have been reported to be significantly reduced. The obtained information has been analysed by a computer decision support system to develop unique signatures of bridge conditions.

Although rapid advances in noncontact, vision-based, or remote sensing equipment have made this sensing equipment a promising alternative to conventional contact sensors for data collection, it is necessary to fully investigate:

- sensor accuracy,
- required sampling rate,
- field data magnitude range of interest,
- natural frequency and resonant area and amplitude of interest,
- involved time and cost in sensor(s) installation, implementation, data post-processing, and removal,
- required expertise and ease of use of sensors at the bridge site, and
- other potential environmental obstacles,

before selecting a sensor to ensure the effectiveness of an SHM.

3 Data Acquisition

Field testing on a temporary/quick or permanent/ongoing basis can be conducted to acquire data depending on the required SM or SHM purpose. These tests are undertaken to obtain information about structural responses to loads. During the field test, real-time data such as strain, displacement, temperature, acceleration, and velocity responses of the structure under static or dynamic loads can be obtained.

Figure 1 illustrates different types of field tests and bridge excitation methods based on the characterisation of the test. Depending on the SHM problem, one or a combination of these field tests can be used.

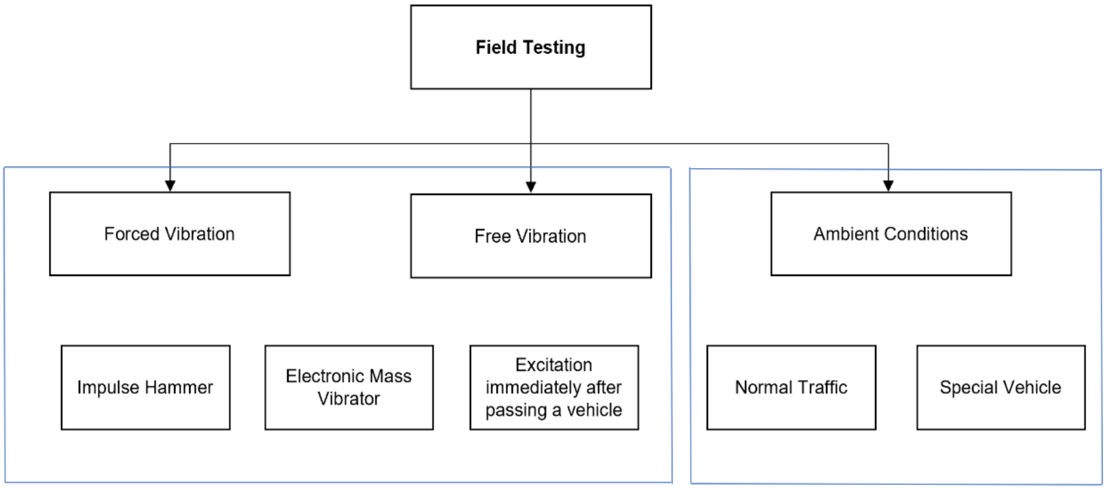


Figure 1: Different types of field testing [5]

It should be mentioned that along with sensor installation and field data acquisition, some tests may be conducted to obtain information about materials or specimens' strength e.g., tensile, compressive, torsion, weld, bolt, fatigue, or creep, etc. These tests can provide good information when a SHM plan is designed for a specific bridge or structural member.

3.1 Strain, Displacement, and Temperature

Strain, displacement, and temperature data can be acquired from a field test in the time domain. Some applications of this data are as below:

- Permanent monitoring or quick field test to collect strain or displacement data of a member (under ambient conditions). This may be used for force estimation in a design code to verify and validate its magnitude, fatigue life estimation, FE model updating (static stress, strain, or displacement), structural connections, constraints, and stiffnesses check, member's elastic behavior, composite steel-concrete effects, or etc.
- Ongoing environmental data acquisition to investigate e.g. relationship between temperature variations with displacements or strains in members during time.
- Tracking structural members' stress, strain, or displacement e.g., where new constructions occur adjacent to older bridges.

- Verification of restraints' stiffnesses (boundary conditions) in a FE model
- Investigation of elastic, elastoplastic, or plastic strain
- Investigation of Rail Structure Interaction (RSI)
- Pile test, monitoring, and Soil Structure Interaction (SSI)
- Field verification of dynamic effects in the form of Dynamic Amplification Factors (DAF)s or Dynamic Load Allowances (DLA)s in Serviceability Limit State (SLS) by crossing a special vehicle or a group of known vehicles over a bridge at various speeds to further investigate vehicle-bridge interactions in e.g., an FE model updating problem.

3.2 Modal Parameter Identification

The basic principle of a modal parameter identification test is that any structural damage would result in changes in the multi Degree of Freedom (DoF) linear structural dynamic responses of a system.

To track these changes, signal processing should be carried out to extract modal parameters from the acceleration responses of a member using modal parameter identification methods in frequency, time, or time and frequency domains (such as wavelets). Modal parameter identification is the study of a system's dynamic nature that is defined independently of the loads (excitation) given to the system and the system's response [5]. Some applications of this vibration data and modal test are as below:

- Extraction of bridge's natural frequencies and mode shapes immediately after a vehicle passes over a bridge or immediately after being excited by an impact hammer or an eccentric mass vibrator (applied only to small-size bridges or footbridges). The free vibration data can be processed to extract the system's stiffness, mass, or damping ratios, and to validate numerical dynamic frequency or modal analysis.
- Carrying out FE model updating (modal, harmonic, or transient dynamic analysis) using field acceleration responses from a special vehicle or vibrator.
- Investigation of seismic or wind responses of bridges.
- Vehicle bridge interaction in FE model updating problem.

It should be noted that most practical damage or anomaly detection, and health decision-making SHMs obtain modal parameters at some stages to investigate the system's behavior and performance under dynamic loading.

3.2.1 Frequency-Domain Methods

Frequency-domain methods have a broader spectrum of applications than time-domain methods in SHM.

These input-output modal parameter identification tests can estimate the Frequency Response Functions (FRF)s or the corresponding Impulse Response Functions (IRF)s using a Fast Fourier Transform (FFT) method. The FRF is used to measure and characterize the dynamic behavior of a bridge structure. The FFT algorithm is also used to transfer the structure's output response (such as strain, displacement, velocity, and acceleration) from the time domain to the frequency domain.

It should be noted that real-time data is normally required to be transformed into a frequency domain for various SHM purposes.

Some of the most applicable frequency domain methods are listed in Table 2:

Table 2: Some of the Frequency-Domain Methods [5]

Method	Application
Peak Picking (PP)	A simple and fast method to extract modal parameters i.e. peaks from the Power Spectral Density (PSD) computed over a time history. This method can be enhanced by the Singular Value Decomposition (SVD) of PSD for each DoF.
Frequency Domain Decomposition (FDD)	A simple algorithm that constructs output spectrum or half-spectrum matrices from measured dynamic responses. This method decomposes modes that are closely spaced.
Enhanced Frequency Domain Decomposition (EFDD)	This method is an extension of the FDD method, and it can integrate damping and give a better estimation of both natural frequencies and mode shapes.

3.2.2 Time-Domain Methods

Time-domain methods rely on a single DoF to carry out calculations.

The SVD of the output correlation matrix is used to extract the undamped mode forms concerning the sensor positions. The PP approach is then used to extract the natural frequencies and damping ratios from a single DoF signal, after the retrieval of the mode shapes.

Some of the most applicable time-domain methods are listed in Table 3:

Table 3: Some of the Time-Domain Methods [5]

Method	Application
Natural Excitation Technique (NExT)	A time-domain-based method that generates IRFs using cross-spectra of ambient vibration response rather than forced vibration test.
Autoregression Moving Average (ARMA)	A time-domain-based method that can forecast a time series of current values based on previous values and a prediction error. This method is an extended model of a linear time-invariant system stimulated by white noise, with the measured response assumed to be stationary.
Stochastic Subspace Identification (SSI)	This method is a prominent method that is capable of estimating, a linear time-invariant state-space model from correlated sequences of observed data using conventional linear algebra techniques.

3.2.3 Time and Frequency Domain Methods

Time and frequency domain methods are signal processing methods that include both time and frequency data at the same time. These time and frequency domain methods include Wavelet transforms that can be classified into two broad classes:

- Continuous Wavelet Transform (CWT)
- Discrete Wavelet Transform (DWT)

Wavelets are effective tools for analysing data over different scales by decomposing temporal signals into a summation of time-domain functions for measuring time-frequency energies of spectral components [8]. Wavelets have been widely used to detect sudden damages to bridges such as those caused by earthquakes or winds.

4 Model-Based Structural Safety Assessment

Figure 2 illustrates a model-based approach to adopt the structural safety levels for a bridge structure.

To design effective safety levels of bridges, the first phase involves the development of an initial FE model from a bridge based on the available drawings and accurate site measurements. This stage is to ensure that there is a general understanding of members' elastic behavior or critical members' stresses or displacements under SLS load cases in ambient conditions with and without e.g., standard or field-verified DAFs or DLAs as well as the system's stiffness and mass which shows itself in the bridge's natural frequencies and mode shapes. FE modelling is essential for complex bridges to ensure the best locations are selected for sensing. This is very important because the number of available sensors may be limited in an SHM, or adding more sensors may cause increased cost, time, or complexity of installation, data post-processing, or analysis. Installation of sensors at insensitive locations will result in a misinterpretation of the bridge's behavior or the ineffectiveness of SHM. Therefore, selecting insensitive locations for sensing can be as impractical as having no SHM plan. Normally, vibration responses of structures should be obtained from important locations to fully update or validate an FE model with field-testing data. In theory, if one could install an unlimited number of accelerometers, they would acquire a full shape of the bridge occurring at each mode of vibration. This vibration data helps validate the natural frequencies and mode shapes of a bridge for various SHM purposes. It would be impractical to install sensors or conduct field testing without an initial understanding of the expected system's stiffness, or stress levels due to the various load cases. In the absence of as-built drawings or where structural members cannot fully be measured at the site (such as embedded concrete members with unknown reinforcement arrangements), permanent field tests may be conducted to obtain e.g., strain levels in the extreme concrete fibres to investigate safety levels in the elastic zone.

After an initial FE model development, various data types can be collected from critical locations obtained from numerical analysis in ambient conditions during normal operations or using special known vehicles. Vibration data (such as accelerations) can also be collected from the excited structure to calibrate the developed FE model to a reference state of the structure. In railway bridges, data from trains can be collected from the wayside monitoring centre during field testing. Other ways to collect data may include Bridge Weigh In Motion (BWIM) or Truck performance Detectors (TPD)s. For example, wayside data can obtain axle tonnage and accurate spacings as well as the speed of the train at the bridge which can be simulated carefully in the FE model to further update the model until it reaches a good and acceptable agreement with the field collected data. The wayside data should always be reviewed and checked carefully to make sure they are consistent with the design and load capacity of the bridge as well as safety and regulatory compliances before further work on an SHM plan. These field-collected data can be used to initially update an FE model through deterministic or stochastic algorithms [9]. A common way to further validate an FE model is to identify and calibrate modal parameters of a bridge using modal parameter identification tests (Section 3) and altering structural properties such as Young's modulus, material densities, boundary conditions, members, or FE elements constraints through a rigorous sensitivity-based approach or a deterministic or stochastic algorithm until the FE model represents the actual structure with a good approximation [10, 11]. Some of the common FE model updating methods include Gaussian, Bayesian, and nonlinear methods. When calibrating an FE model using modal parameter identification methods, it is strongly recommended mode shapes are also extracted to ensure that natural frequency belongs to the same mode of vibration. The Modal Assurance Criterion (MAC) is one of the most common methods that can be used to determine the similarity of two mode shapes [12]. In the context of FE model updating process, the FE model can be validated only once at the beginning, or it can be kept validated during the SHM process while bridge is under various loads. While the former way is more common and cost-effective, the latter is more reliable for online SHM of bridges (refer to Section 6).

As an example in an FE model updating process; the model updating target may be optimisation of $f(u_n)$ as Equation 1:

$$f(u_n) = Min\ |u_{n-FE-model} - u_{\text{n-field}}| \quad (1)$$

where $f(u_n)$ refers to optimised function of elastic nodal displacement difference in FE and field at node,n, through the FE model updating process. The same approach can be developed for updating natural frequencies, stresses, strains, temperatures, etc. It should be noted that in many cases, FE model updating can be a complex process and may need optimisation algorithms such as numerical or data driven based algorithms to improve accuracy. An FE model should always be analysed in different noisy and unnoisy conditions (by linking the FE model to a numeric computing or programming platform), with model anomalies, material sensitivities, etc. to ensure the model can well represent the behavior of the real bridge in different conditions. For simulating noise, Signal to Noise Ratios (SNR)s with different intensities may be applied to the theoretical FE model outputs before and/or after signal processing to pollute these outputs to simulate real data. For FE model updating and validation using acceleration data, Gaussian White Noise (GWN) [13] may be used to excite the FE model to obtain modal parameters in the structural free vibration zone. These parameters can then be calibrated through modal and transient dynamic analysis after comparing and validating them using obtained free acceleration data from the field testing [10].

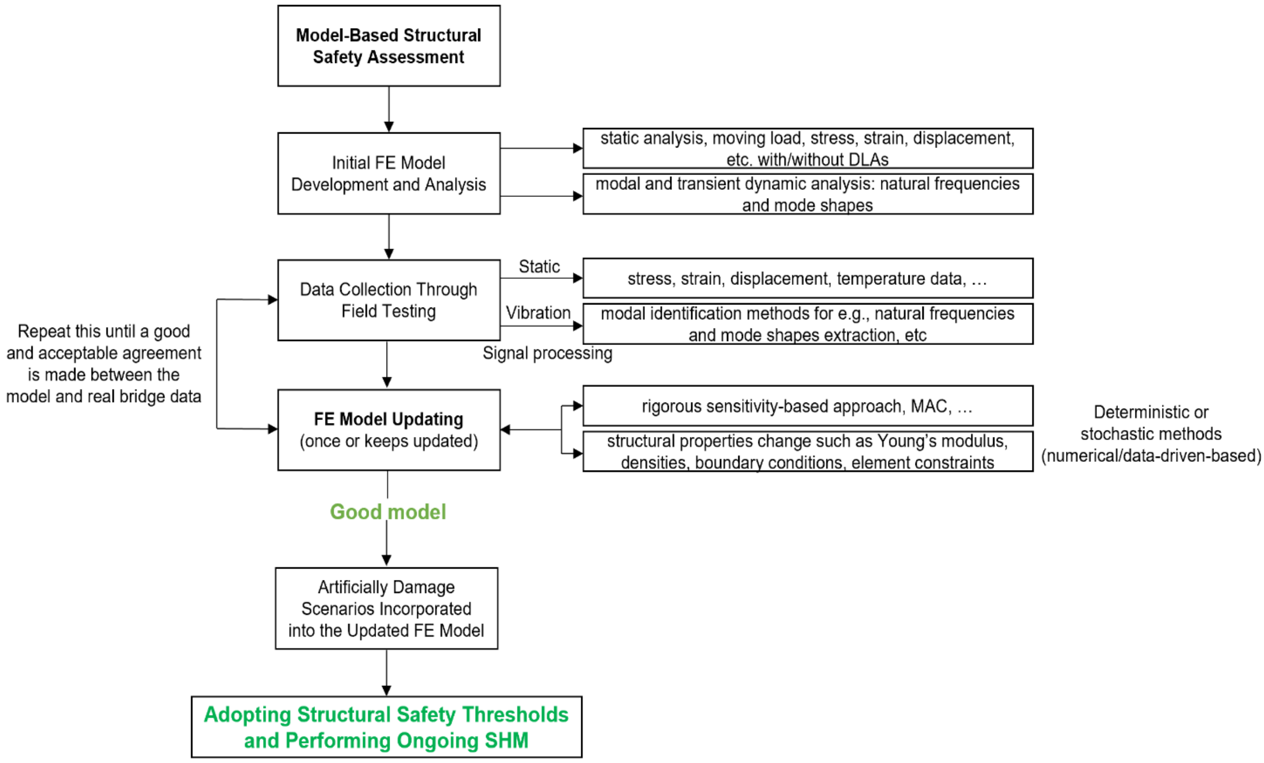
In the complementary stage and after FE model has reached a good and acceptable agreement with field data, and errors are acceptable, the FE model can be used to simulate artificially damaged or anomaly scenarios resulting from static or dynamic loading to predict damaged structural responses at different locations including where no actual sensor is available.

For example, a flexural rigidity damage index, D_i, which reflects the level of the beam's rigidity damage can simply be expressed as Equation 2:

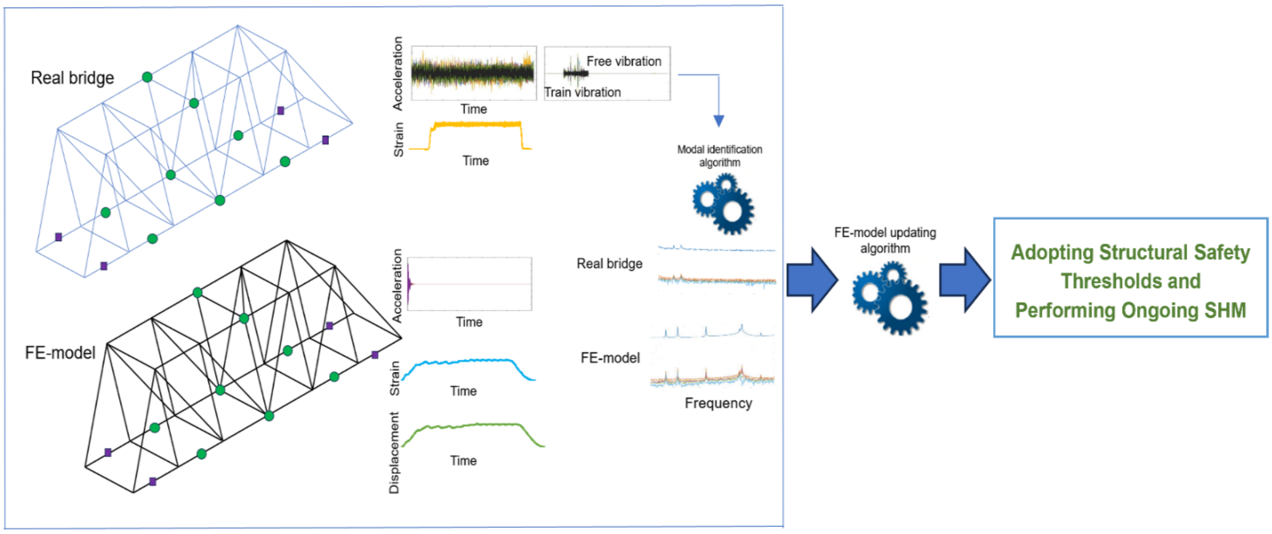
$$D_i = \frac{\Delta(EI)}{(EI)_0} \times 100\% \quad (2)$$

where $\Delta(EI)$ refers to the variation in flexural rigidity between the base and compromised beam's cross-section; and $(EI)_0$ indicates the beam's undamaged cross section's initial rigidity.

These results can finally specify structural safe zones and adopt safety boundaries and thresholds. Using this approach, one can track the structural responses and detect damages or anomalies due to e.g. a unfavourable change in the structural performance or a structural failure.



(a)



(b)

Figures 2: (a) A flowchart and (b) a simple schematic to adopt a model-based SHM

5 Damage Detection, Localisation, and Qualification

Structural damage is predominantly prone to propagate due to various environmental and mechanical factors. The short and long-term damages cause the structures to age and shorten the service design life which makes the SM and SHM an important aspect of structures [14]. Damage in bridges is defined as a change in the geometric or material characteristics of the bridge that adversely affects its performance, safety, reliability, and operational life [15, 16]. Damage does not always indicate a complete failure of a bridge or a structural member, yet a comparative deterioration of the system functionality causing a suboptimal performance [17, 18]. If no remedial action is taken, damage may accumulate until reaching the failure state. The bridge may fail gradually or suddenly depending on the type of damage, members' material, and load [19].

Generally, damage detection, localisation, and qualification techniques are categorized into two types:

- Conventional model-based approaches
- Modern approaches utilising AI

The conventional model-based approaches use static data or vibration responses due to undamaged and damaged cases to adopt structural safety levels (explained in Section 4).

Modern approaches, which can be model or non-model-based, include data-driven methods that use signal processing and then AI such as machine and deep learning techniques to extract Damage Sensitive Features (DSF)s and formulate the relationship between the change of structural properties due to damages or anomalies and DSFs to finally diagnose and prognosticate damages [20, 21].

5.1 Feature Extraction Utilising Machine Learning

In general, AI techniques allow computer systems to learn the knowledge required for carrying out a specific task by analysing enough relevant data samples in a systematic form.

Machine learning, as a subset of AI, requires data processing in advance to extract certain DSFs that represent the most characteristic pieces of information. This important pre-processing step is called "Feature Extraction" which is a dimensionality reduction process by which the sizable data is reduced to more meaningful groups for further processing [22]. Feature extraction is a key step to make sure that the damage detection system is reliable and directly affects the effectiveness and accuracy of a fault diagnosis system [23].

Some of the common DSFs in SHM of bridges include but are not limited to; displacement [24, 25], natural frequencies and mode shapes [26, 27], modal damping [28, 29], modal curvature [30, 31], modal strain energy [32, 33], modal flexibility [34, 35], coordinate modal assurance criterion [36, 37], frequency response function curvature [12, 38], and energy features in wavelet transforms [11, 39]. It should be noted that there are many advantages and disadvantages to the above-mentioned DSFs. Some DSFs are only sensitive to global failures rather than localised failures in complex structures (e.g., natural frequencies). This can limit their applications in a real practical SHM. Some other DSFs may widely be affected by noise or environmental factors which also limit their applications to only numerical, experimental, or laboratory samples. To tackle this, recently some practical DSFs have been developed as a combination of a couple or more DSFs to increase the accuracy and effectiveness of damage detection [11]. Novel DSFs can also be developed and extracted from bridge data for adopting proper safety boundaries. It is strongly recommended that DSFs are well-investigated, verified and validated before utilising them for a real bridge to avoid misperception of results and the design of ineffective safety thresholds and boundaries in ongoing SHMs.

Machine learning mainly requires complicated signal processing or complex structural engineering knowledge before using the application to manually extract proper hand-crafted DSF(s). In recent years, deep learning techniques, as a part of the broader family of machine learning, have proven to be more effective in the practical SHM of railway bridges [10, 40, 41]. Deep learning does not require a user to manually select a highly sensitive feature to damages or anomalies as the input, i.e. it can select and process DSFs through its complex nonlinear layers [42, 43]. Although deep learning is more effective in most cases than traditional machine learning techniques i.e., it uses complex nonlinear data-driven techniques that can practically be effective in both complicated data and image processing; the decision to select an AI technique in an SHM depends on the obtained data, simplicity of DSFs, specific expertise of SHM experts, and SHM problem to be resolved.

It should be noted that damage detection using AI needs to be performed stage-by-stage rather than hypothetically designed for complex bridges or a group of bridges. In many cases, the detection, localisation, or qualification of damages such as surface cracks, minor deformations, cross-section losses, or even local failures in complex bridges may be challenging using available AI techniques; therefore, it is necessary to clarify the SHM's target and set expectations from AI techniques rather than overcommitment from the beginning.

5.2 Types of Machine Learning or Deep Learning SHMs

The outcomes of machine learning or deep learning SHM can be one of the following:

1. Classification: A classifier SHM can be designed to determine which category the data belongs to e.g., whether the data is healthy or anomaly. As an example, such SHM can be used to comply with safety and regularity management systems such as distinguishment between defect categories and required action according to AS7636 [10, 11].
2. Regression: The goal here is to model the relationship between the inputs and outputs. The only difference between regression and classification is the format of the outputs. As an example, an ongoing regression SHM can be designed to adopt safety or alarm levels when e.g., displacements or strains are excessive, or real-time data are not within the safe boundaries.
3. Prediction: Prediction is a special type of regression in which the objective is to foresee the future values of a given time. A predictor SHM can be designed to predict the magnitudes of new data if train operations alter in the future.
4. Clustering: The target of clustering is to divide the input dataset into clusters with similar examples [44]. Unlike classification, regression, and prediction tasks which are performed using supervised methods, clustering is conducted in an unsupervised manner such as self-organizing maps [22].

Figure 3 shows AI, machine learning, and deep learning and their subsets.

The developed machine learning and deep learning SHM can completely be model-based, non-model-based, or a combination approach depending on the field data and SHM problem. When the FE model is developed, the model should be analysed with different noisy and unnoisy conditions, model anomalies, material sensitivities, etc. to ensure the model can well represent the real bridge's behavior in different conditions.

Figure 4 illustrates a schematic of an SHM classification problem (case 1 above) that can be resolved utilising machine learning and deep learning algorithms.

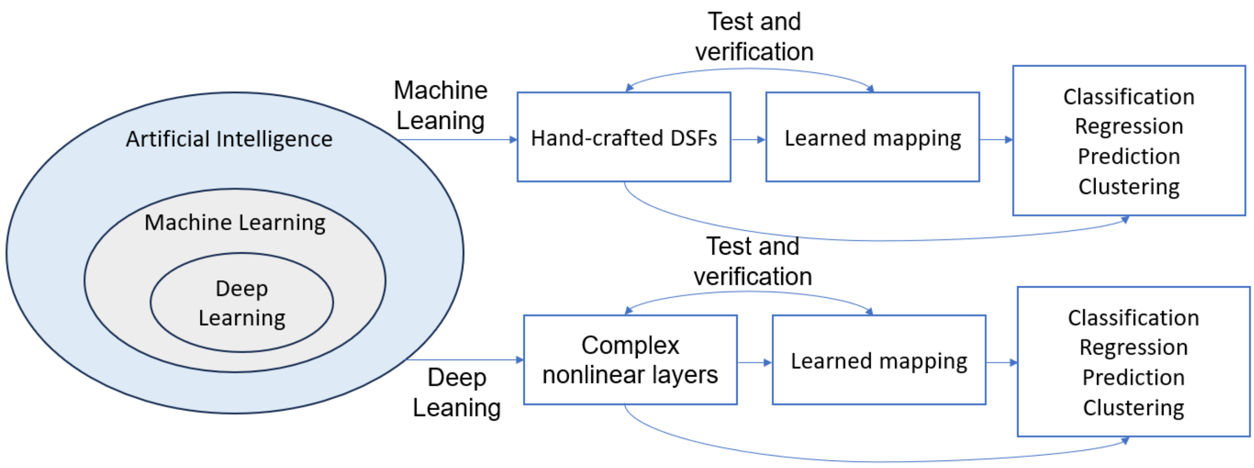


Figure 3: AI and its subsets

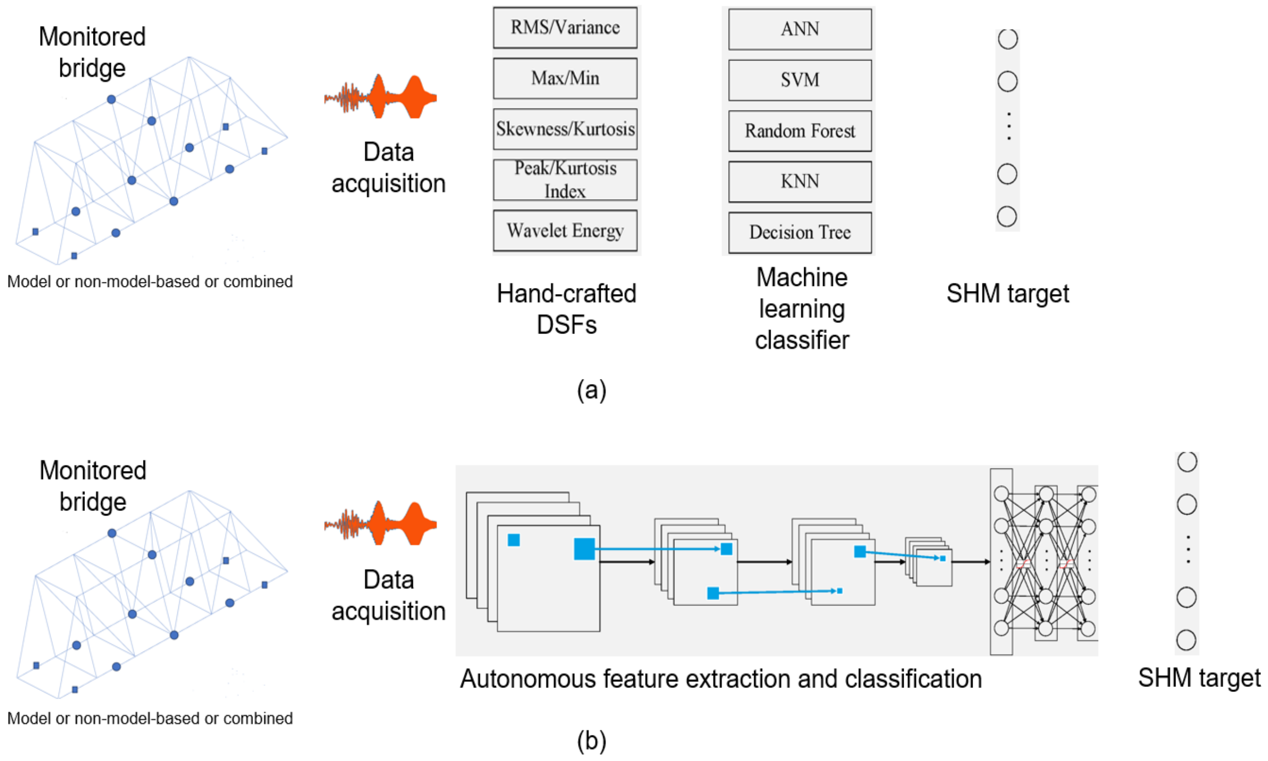


Figure 4: An SHM classification problem using (a) machine learning and (b) deep learning

6 Possible Future Innovations

Possible future innovations in the field of SHM of bridges are discussed generally in this section. Although past sections of this document can practically be implemented for a specific case without any requirements; the context explained in this section will require future developments in all five pillars of SHM (explained in Section 2) depending on the overall future decision-making outlook in the field of asset (including bridges) management.

6.1 Ideal Hybrid SHM of Railway Bridges

Designing a comprehensive SHM system, which can correctly identify all the structural failures in different types of bridge structures has not yet been proposed. To increase the practicality and effectiveness of SHM of bridges, some SHM experts have proposed hybrid SHM (Figure 5). A hybrid SHM is an ideal decision-making system which tries to assess the health state of the bridges by merging different types of information or data, which can come from multiple sources (e.g. data from track, train, and bridge) and of different types (e.g. ongoing processed data, inspection, maintenance records and measurements of the track quality, etc.) [45]. This ideal SHM will not successfully be fulfilled unless there is a real-time processing database between all the track and civil disciplines that can monitor and update the bridge conditions anytime.

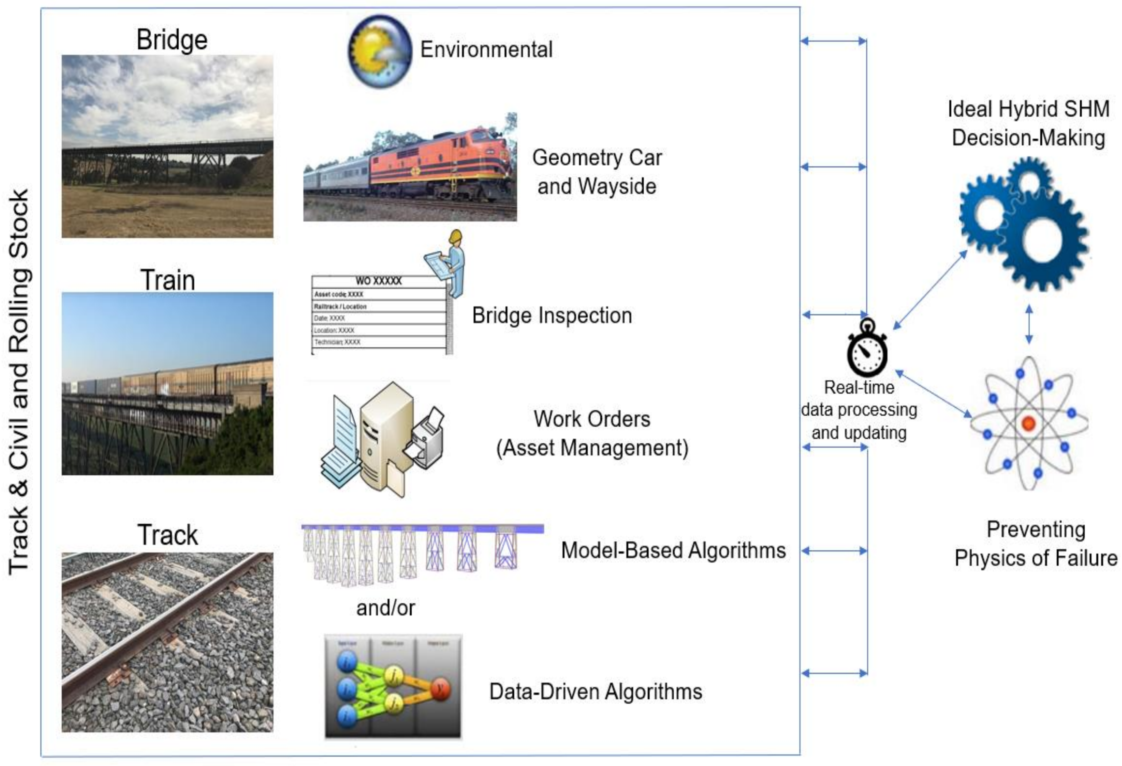


Figure 5: A schematic to an ideal hybrid SHM of railway bridges

6.2 Digital Twin Lifecycle Management Tool

Within the context of designing innovative SHMs in the future and in the absence of ideal hybrid models, enabling a Digital Twin (DT) perspective for important bridges can be crucial for safety and operative reasons to allow for optimised condition-based and predictive maintenance practices, inspection, and management planning throughout bridge’s lifecycle health [46]. Building Information Modelling (BIM) has been playing a pivotal role in bringing systematic changes in bridge engineering. When BIM merges into the DT technology and applies from the construction phase to the operation and maintenance phases, it has a great potential to shape a DT-enhanced BIM framework to fully enable whole digital lifecycle of bridges [47].

DT technologies for the management of the bridge lifecycle have been rapidly growing in recent years and will be a promising alternative to the current bridge maintenance tools (static conventional Bridge Management System, BMS) soon [48, 49, 50]. The following framework can be outlined to apply the DT-enhanced BIM framework concept to bridge lifecycle management. Not all this information needs to be available before building such a framework, however, the information can gradually be fed into the tool during the time and in a planned and systematic manner.

1. A 3D geometry model (DT model) based on the as-built drawings of the existing bridge. This DT model includes the following information but is not limited to:
    a. A reverse 3D-surface model with the bridge's status (reality twin model) which is created through the 3D scanning procedure, a combination of scanned photos using e.g., UAV of the lateral and top surface models and laser scanning cloud data for the bottom surface model.
    b. An FE model developed using a standard FE package and updated using deterministic and/or stochastic algorithms (the same FE package is preferable to be used for all the SHMs for future integration of all the separate SHMs and ease of coding).
2. Image processing and image tracing technology (raster-to-vector conversion) for automating existing and future inspection reports.
3. The required upgrade, repair, or strengthening work is specified and completed, and all archived data right after repair work is imported into the management tool.
4. Environmental data, including temperature, humidity history, etc. to include in the tool.
5. Current and historical loading and speeds from vehicles, any speed restriction and accident history, etc. for predicting the consequent performance of the structural member.
6. Bridge analytical results, members, damages, as-is conditions, etc. (using FE model) are updated and reported based on numerical or data-driven algorithms (refer to Sections 4 and 5).

The general procedure for this DT-enhanced BIM management tool is a closed loop of interactive processes. This means that this process is continuously repeated and updated throughout the service life of the bridge.

Figure 6 shows a simple illustration of the above-explained closed-loop.

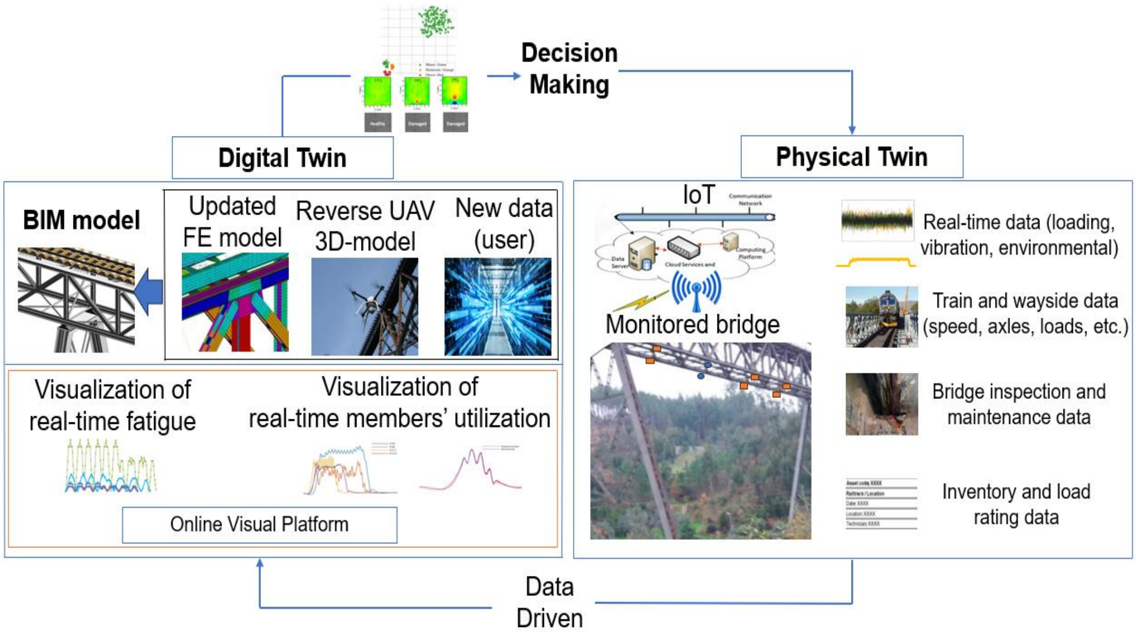


Figure 6: A simple illustration of a closed-loop DT-enhanced BIM management tool

7 References

[1] M. Q. F. D. Feng, Computer Vision for Structural Dynamics, New York: Wiley, 2021.

[2] G. A. W. D. D. R. B. A. G. M. M. B. M. Phares, “Routine Highway Bridge Inspection Condition Documentation Accuracy and Reliability,” Bridge Engineering, vol. 9, no. 4, 2004.

[3] B. A. A. M. D. J. T. F. Raeisi, “Reducing carbon dioxide emissions through structural health monitoring of bridges,” Civil Structural Health Monitoring, pp. 11: 679-689, 2021.

[4] L. C. T. S. P. S. J. H. H. Pu, “Minimizing costs and carbon emissions in railway alignment optimization: A bi-objective model,” Transportation Research Part D: Transport and Environment, vol. 1160, no. 103615, 2023.

[5] A. J. S. A. K. N. M. A. M. A. A. S. S. Saidin, “An Overview: The application of vibration-based tecniques in bridge structural health monitoring,” International Journal of Concrete Structures and Materials, p. 16:69, 2022.

[6] R. R.-P. J. A. M. Vagnoli, “Railway bridge structural health monitoring and fault detection: State-of-the-art methods and future challenges,” Structural Health Monitoring, vol. 17(4), pp. 971-1007, 2018.

[7] V. M. K. N. P. P. G. A. Kyriou, “Review of Remote Sensing Approaches and Soft Computing for Infrastructure Monitoring,” Geomatics, vol. 3(3), pp. 367-392, 2023.

[8] A. M. D. C. E. O. L. P. P.C. Fitzgerald, “Drive-by scour monitoring of railway bridges using a wavelet-based approach,” Engineering structures, vol. 191, pp. 1-11, 2019.

[9] Q. Z. S. H. G. W. S. Chen, “Two-stage stochastic model updating method for highway bridges based on long-gauge strain sensing,” Structures, pp. 1165-1182, 2022.

[10] M. K. M. C. T. N. A. H. S. J. Q. S. A. Ghiasi, “Damage classification of in-service steel railway bridge using a novel vibration-based convolutional neural network,” Engineering Structures, pp. 264-114474, 2022.

[11] C. T. N. A. H. S. A. Ghiasi, “Damage detection of in-service steel railway bridges using a fine knearest machine learning classifier,” Structures, pp. (45)190-1935, 2022.

[12] H. J. C. L. J.H. Kim, Application of the modal assurance criteria for detecting and locating structural faults, 1992.

[13] L. A. L. J. D. H. Z. G. Xia Z, “Model updating of an existing bridge with high-dimensional variables using modified particle swarm optimization and ambient excitation data,” Measurement, vol. 159, no. 107754, 2020.

[14] Y. Q. N. H. P. Chen, Structural Health Monitoring of Large Civil Engineering Structures, Wiley , 2018.

[15] G. M. E. Cosenza, “Damage indices and damage measures,” Progress in Structural Engineering and Materials, vol. 2(1), pp. 50-59, 2000.

[16] J. P. C. D. M. Frangopol, “Effects of Damage and Redundancy on Structural Reliability,” Structural Engineering, vol. 113, 1987.

[17] D. C. Z. M. Kaouk, “Structural damage assessment using a generalized minimum rank perturbation theory,” AIAA, 2012.

[18] M. K. D. C. Zimmerman, “Structural Damage Detection Using a Minimum Rank Update Theory,” Vibration and Acoustics, pp. 222-231, 1994.

[19] K. W. R. Farrar, “An introduction to structural health monitoring,” Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, pp. 303-315, 2006.

[20] Y. R. Q. H. Z. F. Z. T. W. C. B. L. X. Xu, “Anomaly detection for large span bridges during operational phase using structural health monitoring data,” Smart Materials and Structures, no. 045029, p. 29, 2020.

[21] X. L. S.O. Sajedi, “Vibration-based semantic damage segmentation for large-scale structural health monitoring,” Computer-Aided Civil and Infrastructure Engineering, no. 12523, 2019.

[22] O. A. S. K. M. H. M. G. D. I. O. Avci, “A review of vibration-based damage detection in civil structures: From traditional methods to machine learning and deep learning applications,” Mechanical Systems and Signal Processing, no. 147:15:107077, 2021.

[23] A. S. R. S. E. F. C. C. J. M.F. Silva, “Damage-sensitive feature extraction with stacked autoencoders for unsupervised damage detection,” Structural Control and Health Monitoring, p. 28(5):e2714, 2021.

[24] S. A. J. T. S. Rana, “A statistical index based damage identification method of a bridge using dynamic displacement under moving vehicle,” Stuctures , vol. 43, pp. 79-92, 2022.

[25] W. X. R. S. Z. W. Y. He, “Damage detection of beam structures using quasi-static moving load induced displacement response,” Engineering structures, vol. 145, pp. 70-82, 2017.

[26] B. S. P. C. R.D. Adams, “A vibration technique for non-destructively assessing the integrity of structures,” Mechanical Engineering Science, no. 20(2), pp. 93-100, 1978.

[27] L. K. H. O. C.H. Jenkins, “Sensitivity of parameter changes in structural damage detection,” Shock and Vibration, vol. 4:807239, 1996.

[28] C. Beards, Structural Vibration: analysis and damping, 1995.

[29] D. J. J. H. A.D. Nashif, Vibration Damping, 1985.

[30] M. B. A.K. Pandey, “Damage detection from changes in curvature mode shapes,” Sound and Vibration, vol. 145(2), pp. 321-332, 191.

[31] G. D. R. W.M.M. Abdel, “Damage detection in bridges using modal curvatures: Application to a real damage scenario,” Sound and Vibration, vol. 226(2), pp. 217-235, 1999.

[32] Y. R. H. C. N. S. J.T. Kim, “Damage identification in beam-type structures: frequency-based method vs mode-shape-based method,” Engineering Structures, no. 25(1), pp. 57-67, 2003.

[33] S. L. L. Z. Z.Y. Shi, “Structural damage localization from modal strain energy change,” Sound and Vibration, no. 218(5), pp. 825-844, 1998.

[34] M. B. A.K. Pandey, “Damage Detection in Structures Using Changes in Flexibility,” Sound and Vibration, no. 169(1), pp. 3-17, 1994.

[35] A. A. T. Toksoy, “Bridge-condition assessment by modal flexibility,” Experimental Mechanics, vol. 34:2, pp. 271-278, 1994.

[36] D. B. R.J. Allemang, A correlation coefficient for modal vector analysis, Computer Science, 1982.

[37] J. D. C. C. N. A. W. R. Allemang, “Damage Detection Using Flexibility proportional coordinate modal assurance criterion,” in 31st IMAC, A conference on structural dynamics, 2013.

[38] D. M. R. K. A. Kumar, “Application of frequency response curvature method for damage detection in beam and plate like structures,” in Materials Science and Engineering, 2016.

[39] Z. J. C. Q. N. Y. Y. Lei, “Drive-by bridge damage detection based on wavelet analysis of residual contact response of a moving vehicle,” Acta Mechanica , 2023.

[40] M. S. A. K. G. P. P. P. M. H. D. C. Nguyen, “Vibration-based SHM of Dębica railway steel bridge with optimized ANN and ANFIS,” Constructional Steel Research, vol. 108505, 2024.

[41] D. Hajializadeh, “Deep-Learning-Based Drive-by Damage Detection System for Railway Bridges,” Infrastructures, no. 7(6), p. 78, 2022.

[42] A. S. o. D. L. S. Poyanfar et al., “Algorithms, Techniques, and Applications, Advancing Computing as a Science & Profession,” Advancing Computing as a Science & Profession, p. 10.1145/3234150., 2018.

[43] J. P. G. Toh, “Review of Vibration-Based Structural Health Monitoring Using Deep Learning,” Applied Science Mdpi, p. 10(5)1680, 2020.

[44] M. D. J. V. L. J. M. J. B. S. da Silva, “Structural damage detection by fuzzy clustering,” Mechanical Systems and Signal Processing, vol. 22, no. 17, pp. 1636-1649, 2008.

[45] U. K. R. V. C. A. J. D. Galar, “Hybrid Prognosis for Railway Health Assessment: An Information Fusion Approach for PHM Deployment,” in 4th IEEE Conference on Prognostics and System Health Management (PHM), 2013.

[46] M. T. S. M. A. M. K. E. W. M. Torzoni, “A digital twin framework for civil engineering structures,” Computer methods in applied mechanics and engineering, vol. 418, no. 116584, 2024.

[47] Y. G. L. H. Z. T. J. A. S. Honghong, “Digital twin enhanced BIM to shape full life cycle digital transformation for bridge engineering,” Automation in Construction, vol. 147, no. 104736, 2023.

[48] S. K. N. V. S. A. H. T. hielsher, “A neural network based digital twin model for the structural health monitoring of reinforced concrete bridges,” Structures , vol. 57, no. 105248, 2023.

[49] H. S. W. Z. Y. L. L. Sun, “Hybrid monitoring methodology: A model-data integrated digital twin framework for structural health monitoring and full-field virtual sensing,” Advanced Engineering Informatics, vol. 60, no. 102386, 2024.

[50] M. M. F. A. P. d. C. N. T. N. Bittencourt, Digital transformation of bridges inspection, monitoring and maintenance processes, Taylor & Francic Group, 2021.