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STRUCTURE HEALTH MONITORING AND MANAGEMENT – A REVIEW

Justin Demetry, Wilson Wang *
* Professor, Dept. of Mechanical Engineering, Lakehead University, Thunder Bay, Ontario, Canada, P7B 5E1

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ABSTRACT
Structural health monitoring (SHM) and management techniques are of great importance in civil and mechanical engineering communities, due to both safety reasons and the economical benefits. The need for detecting damage in complex structures has led to the development of a vast amount of techniques in SHM. This paper will provide a comprehensive review of the state-of-the-art research and development work in this area pertaining to damage detection and health management of civil structures, specifically for bridges. It will address the topics of bridge damage detection in the domains of statistics, time, frequency and time-frequency. It will also systematically discuss the issues related to the implementation of SHM for real-time bridge system monitoring and health management associated with sensors, data acquisition, signal communication, and decision-making. Discussions also include the merits and limitations of these available technologies.

INTRODUCTION
The structural health monitoring (SHM) and management aim to understand the behavior of civil structures (e.g., buildings, bridges and dams), monitor the safety of structures, and establish the lifecycle maintenance strategies, so as to keep the integrity of the structures and ensure public safety [1,2]. This work will focus on SHM of bridge structures, which are regarded as the most critical components in transportation infrastructure systems.

Bridges are subjected to static and dynamic loads along with extreme forces such as natural and man-made hazards. Sudden collapses of bridges can result in extensive human and economic losses [3,4]. For example, the collapse of the Tacoma Narrows bridge could be a well-documented structure failure [5]. Figure 1 describes the moment when it collapsed due to wind-induced resonance instability [6]. Even though the Tacoma Narrow incident is not directly related to SHM, it is an instructive example to show the consequences of neglecting dynamic forces in the design and construction of civil structures such as bridges.

Another severe incident was the collapse of Bridge 9340 on the Interstate 35W Mississippi River in 2007, as illustrated in Figure 2; it is an eight lane steel truss arch bridge across the Saint Anthony falls in Minneapolis, Minnesota, USA [7]. According to the National Transportation Safety Board report in [8], inadequate capacity for the expected loads on the structure initiated the failure of gusset plates in the center portion of the deck truss. The tragic incident has raised many concerns regarding the current health condition of bridges, and also served as reminder of the necessity to develop efficient and practical methods for SHM.

Figure 1: The collapse of Tacoma Narrows bridge on November 7, 1940 [6].

Figure 2: The collapse of 35W bridge on August 1, 2007 [7].

DAMAGE DETECTION IN BRIDGES

Many non-destructive techniques have been proposed in literature for damage detection in bridge structures to identify the presence, location, and the severity of the damage [4,9]. Fault detection can be based on the analysis of information carries such as acoustic emission, eddy current, thermal field, radio-graph, strain data, magnetic quantity, and ambient vibration [10-12]; vibration-based SHM could be the most commonly used techniques due to its ease of measurement and high signal-to-noise ratio. The basic premise of most of these methods is that structural damage manifests itself indirectly through changes in measurable quantities, even though the mechanism may not directly be measurable in most cases. For example, changes in physical properties such as stiffness, damping or mass of the system, will result in changes in the vibration data and also in the modal properties (e.g., frequencies, mode shape and modal damping) [13,14]. Damage detection methods in SHM literature can be classified into physics-based and data-driven methods.

2.1 Finite element analysis
Finite element method is a conventional physics-based approach typically done through computer modeling of the civil structure. It identifies structural parameters using data acquired from the field or laboratory. Physics based methods model the governing equations in order to construct a mathematical abstraction of the physical problem, parametrized by variables that have direct physical meaning, followed by a comparison between predicted and measured vibration outputs to quantitatively assess structure damage [15,16]. While these models have shown to work well in some relatively simple structures, finite element models are usually computationally expensive to build and run especially for large systems.

2.2 Statistical moment analysis for damage detection
Statistical moments such as the mean, variance, skewness, and kurtosis are often used to process raw time-series data for fault detection. Kurtosis is a commonly used indicator for structure damage detection. Kurtosis is the normalized fourth moment that describes the relative spikiness of a distribution, such that

$$K = \frac{E(x-\mu)^4}{\sigma^4} \tag{1}$$

where E is the expectation operator, μ and σ are the mean and standard deviation, respectively. $K = 3$ for the data sets with the pure Gaussian distribution [17]. If the structure is damaged, high peaks are generated and the tails of the distribution function will be modulated; that will result in higher Kurtosis (i.e., greater than 3), which indicates more data far from the mean due to signal peaks.

When used in conjunction with time-series models, statistical process control (SPC) charts [18] are powerful on-line monitoring tools for anomaly detection in SHM applications. Sohn et al. [19] used a univariate SPC control chart for damage detection, where the control limits are constructed based on features constituted from a healthy structure. Wang et al. [20] applied multivariate Hotelling's T2 control charts to monitor progressive damage in reinforced concrete frames. Other studies based on SPC charts include Wang et al. [21,22] proposed an exponentially weighted moving average control chart, Yao et al. [23] utilized Mahalanobis distance and spectral distance measures for damage detection, and Mujica et al. [24] used principal component Q-statistic and T2-statistic for damage detection. Ubertini et al. [25] presented multivariate T2 control charts to track the time evolution of five natural frequencies of structure and applied these charts to monitor a bell tower in Italy. Comanducci et al. [26] proposed a multivariate statistical

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technique for damage detection in the long-span arch Infante D. Henrique bridge, which is the second largest arch bridge in Europe.

2.3 Time-domain approaches for SHM

Time-series modals can be used to characterize the sources that are obtained from the past observations, followed by the future sources [27]. If some clear difference between the predicted and true measurements can be observed, it indicates damage. Once the damage is detected, the model parameters are updated based on the new measurements [28]. A number of linear time series models have been proposed in literature for SHM, but they only consider the linear autoregressive (AR) models as an alternative benchmark to the nonlinear AR models. By its very nature, the AR model specifies that, the output variable depends linearly on its own previous values. Hence, in the time-domain methods, model properties are extracted either from time histories (direct methods), or from impulse response functions (indirect methods) [29]. Another method which uses the similar approach is the Eigen realization algorithm (ERA). It utilizes the structural vibration data to build a state-space system, in which the modal parameters can be identified from the experimental data. In using the ERA method, a matrix containing the measured data is created first; then singular value decomposition is performed to determine the rank of the system and rebuild the reduced matrix, which in turn is used to calculate the state-space matrices. Finally the Eigen values and Eigen vectors (i.e., the modal properties) are determined from the realized state-space matrices. On the other hand, stochastic subspace identification can be considered as an enhanced ERA whereby the input is not measured but assumed to be a stochastic process with white noise [30].

Auto-regressive moving-average (ARMA) models [31-33] and support vector machines (SVM) [33,34] are other examples of data driven tools for damage detection. Sohn et al. [33] presented an AR modeling approach for damage localization using vibration data obtained from an eight degree-of-freedom lumped parameter structure. A more general time series model including ARMA parameters for damage detection and localization was proposed by Nair et al. [31], where the first three AR coefficients were used to derive damage sensitive features. Time series models combined with SVM [34], hidden Markov model [36], and Gaussian mixture model [37] have all been used for feature extraction, damage diagnosis and damage classification. In all these cases, surrogate measures such as Mahalanobis distance, residual error, features extracted from ARMA coefficients have been used in lieu of the physical damage mechanism.

The time domain damage detection approaches do not rely on physical models, they use statistical principles to represent observations, the computational complexity is significantly less than physics based models [38,39]. However, the main drawback of these methods is that the quantity being measured and used for decision-making is often indirectly related to the underlying mechanism of interest, and hence can sometimes obfuscate the presence of damage.

2.4 Frequency domain analysis
Frequency-domain methods make use of the Fourier transform (FT) spectra of measured signals to extract the spectral modal feature properties. As per the basic principles of structural dynamics, a structure will vibrate at one or more of its natural frequencies, or at the frequencies induced as a result of forced vibrations. The resonant vibration will be manifested as peaks in the structural response spectra corresponding to the structural natural frequencies. The peak picking method therefore becomes possible to recognize spectral peaks corresponding to the damped natural frequencies of the structure [40]. Once the natural frequencies are identified, the relative modal amplitudes at different measurement locations can then be computed to estimate the vibration mode shapes [41]. The impediment of this method includes the difficulty to distinguish between peaks that represent natural frequencies from those due to excitation, as well as the difficulty to identify closely spaced modes.

In bridge vibration measurements, it is impossible to measure the time history of the input force due to ambient excitation such as that caused by traffic or wind loading. The response of the structure at one location is then used as a reference to scale the responses at other locations so as to calculate the mode shape. For more accurate estimate of modal properties, the cross power spectrum (CPS) can be used, which is a product of the spectra of a reference accelerometer, and that of another accelerometer [42]. CPS represents the power correlation between two signals having some common frequencies. The peaks retained in the CPS are those common to both signals, and are more likely to be true natural frequencies, which are subsequently used to formulate mode shapes from the relative magnitudes of these peaks at different locations on the structure [43].

2.5 Time-frequency based SHM
The wavelet transform is a commonly used time-frequency technique utilized for transient feature analysis. It has the ability to retain both time and frequency information to solve complicated pattern recognition problems in civil engineering [44,45]. A few researchers also employed the chaos theory and its fractal concept to model complicated structural dynamics, and estimate the fatigue damage such as in Fiber Reinforced Polymer stay cables using acoustic emission technique, and the fractal concept from the chaos theory [46,47].

2.6 Softcomputing tool for SHM
Softcomputing artificial intelligent tools include neural networks (NN), fuzzy logic and their synergetic schemes. In using NNs, after the architecture for the network is chosen, the actual function represented by the NN is encoded by the weights and biases [48]. The appropriate training algorithms (e.g., backpropagation) can be used to adjust the weights and biases by minimizing the error between the predicted and measured outputs until some criterion for training is satisfied [49,50]. Likewise, the accuracy of the NN models depends on how it is trained to solve new problems. The issue associated with the softcomputing tool is that, a poorly trained model using sparse or corrupt data could lead to inaccurate results [51]. Synergetic approaches integrate two or more computing paradigms such as NNs, fuzzy logic, evolutionary genetic algorithm (GA), for complex problem modeling and SHM applications [52,53]. On the other hand, most of the reviewed softcomputing tools suffer from some common drawback, that is, they require a

large and accurate representative data sets from both the undamaged and damaged structures for training, which may be hardly available from real world bridge structures.

BRIDGE SYSTEM MONITORING AND MANAGEMENT

3.1 Specific considerations in real-time SHM applications

In general, the long-span bridges accommodate a number of vehicles concurrently, and therefore, are subjected to strong bridge-vehicle dynamic interactions. On the other hand, traffic loads on the long-span bridges such as the cable-stayed and suspension bridges are subjected to wind excitations, which make them experience complicated dynamic loads from both the bridge stochastic traffic and wind [54]. The stochastic nature of wind and traffic, as well as the dynamic interactions as listed below, has a significant impact on its strength and serviceability and creates fatigue damage on bridges during their lifetime:

- Bridge and vehicle interactions;
- Bridge and wind interactions;
- Vehicle and wind interactions;
- Wind and vehicle interactions.

In recent years, there has been an increasing interest in long-term monitoring of bridges, as the research community has been alarmed by some tragic events and collapses of bridges. Essentially, a SHM system includes the following modules: sensing unit, data acquisition, signal transmission, data management, signal processing, safety evaluation and alarm. A SHM system also contains functions such as a user interface, software developing configurations, and software operational environment configurations [55].

Figure 3 shows the general flowchart of the instrumentation for a real time SHM system [56]. Essentially, static and dynamic types of sensors could be used for each monitoring project, whose data lines can be connected to the main data acquisition center at the bridge site. The data center can function 24 hours a day, 365 days a year, and should be capable of acquiring all the data concurrently, then synchronize and transfer the data to any remote location over an internet gateway. The data center needs to have the capability of recording the data locally based on the preset trigger conditions. A real-time and continuous software based analysis can be carried out at one or more remote monitoring centers [56].

3.2 Sensors and sensing technologies

The design of sensory module of SHM for cable-stayed bridges comprises of the variable type, the sensor type, and the positioning of the installed sensors. The monitored variables can be categorized into three types: loads and environmental actions, global responses, and local responses. As discussed in [55], the loads and the environmental actions mainly include vehicle loads, wind velocity, earthquake ground motion, vessel collisions, temperature, humidity, rainfall intensity, and chloride ion concentration. The acceleration, deformation, and tilt are global response variables, whereas the strain, cable tension force, displacement and wears of joints and bearings, fatigue and crack of elements, corrosion of elements, and scour around piers are the local response variables. The vehicle loads including the weight of each axle, number of axles, and vehicle speed are frequently measured by weigh-in-motion (WIM) systems embedded in all lanes at a cross section of a cable-stayed bridge; the WIM systems can provide the vehicle load information at one cross section only [55].

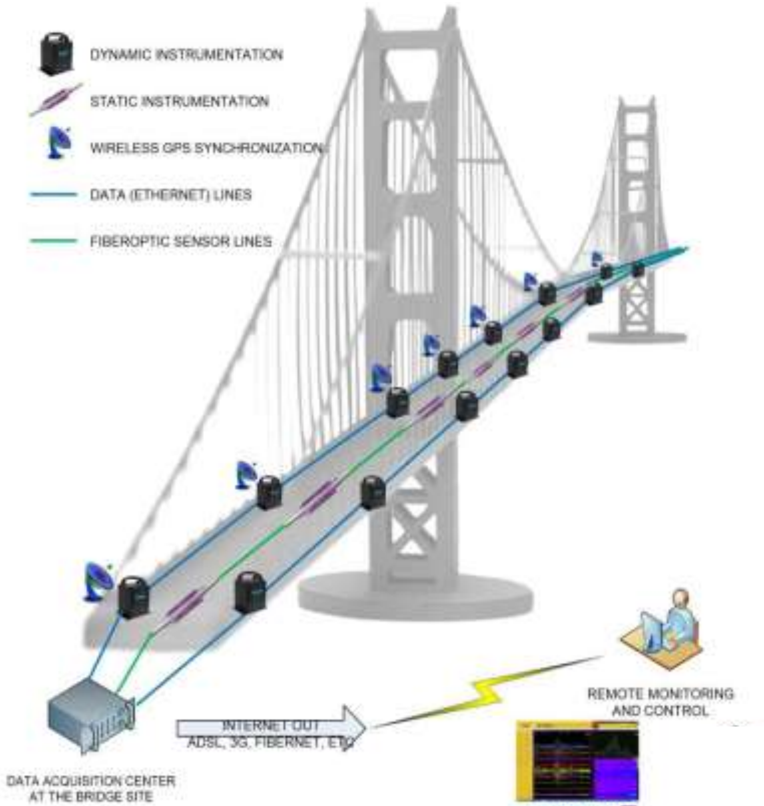

Figure 3: An illustration of the proposed real-time SHM system

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Bao et al. [41] proposed an approach to identify the spatial–temporal distribution of vehicle loads on a cable-stayed bridge based on monitoring of the cable tension force. In order to improve the estimation accuracy, Chen & Cai [54] proposed an identification method of the spatial-temporal distribution of vehicle loads on a cable-stayed bridge by combining WIM systems with cameras that is validated through the identification of location and time of heavy trucks on the Hangzhou Bay Bridge, which is a cable-stayed bridge in China.

The earthquake ground motion in three directions can be monitored by seismometers; however, the seismometers should be installed in the free-field away from the bridge, and on the piles of bridge piers. For long-span cable-stayed bridges, seismometers should be installed at more than one pier so as to investigate the travel wave effects. The vessel collisions can be measured by accelerometers, or by the seismometers on the piles of bridge piers [14,67].

Wind is one of the critical loads for long-span cable-stayed bridges; it excites vortex induced vibration of the decks and cables. Anemoscopes or ultrasonic anemoscope can be used for fluctuating winds, whereas propeller anemoscope can be employed to measure wind velocity. Due to rain-wind-induced stay cables vibration, rainfall intensity is a critical variable which can be measured by a rainfall gauge installed on the bridge without any shield [57].

For temperature measurements, thermocouples or optical fiber Bragg grating (FBG) sensors are frequently employed to measure the temperature around and inside the bridges. To ensure the survival of FBG sensors during construction of the civil structures, Ou and Li [58] proposed embedded FBG sensors into fiber reinforced-polymer bars, which results in FRP bars with self-sensing properties and better mechanical performances. The location of temperature sensors is determined based on thermodynamic analysis of the bridge.

The temperature sensor arrays should be embedded into the concrete elements to obtain the temperature gradient along at least one cross-sectional height. Due to the temperature compensation requirement of a strain gauge, temperature sensors should be installed close to strain sensors. On the other hand, the humidity is frequently monitored by hygrometers installed inside a box on the bridge girders. The chloride ion concentration can be measured by electrode probes, whose arrays are embedded in the cover of reinforced concrete piers [55].

Displacement or acceleration should be monitored for cable-stayed bridges by accelerometers with low-frequency bands. The location of accelerometers on the bridge deck can be determined by some placement optimization approaches. Accelerometers should be attached to the long cables rather than the short cables because long cables are more prone to dramatic vibrations [55]. Transportation Research Board of the National Academies in the USA [59] has indicated that security cameras mounted on the tower are suggested to monitor vibration of stay cables; however, there have been no indication of this technique practically used in monitoring of rain-wind induced vibration of stay cables.

For the tower, accelerometers should be attached to the top of the towers in two horizontal directions. The deformation of the tower can be measured by a global positioning system (GPS) and a tilt meter, whereas the deformation of a girder is usually monitored by GPS and hydraulic pressure connecting the pipe system [15]. Since strain is one of the most important variables for direct safety evaluation, fatigue assessment, and validation of the design, strain can be monitored using traditional strain gauges, vibrating-wire strain gauge, and the FBG strain sensors. Vibrating-wire strain gauges can only measure the static strain, which is why, in China, FBG strain sensors have been installed on many cable-stayed bridges for strain monitoring, such as the one installed on the Shandong Binzhou Bridge, a 3-tower cable-stayed bridge, as well as Jiashao Bridge that is a 6-tower cable-stayed bridge [60].

Dascotte [61] proposed a method to derive strain from the displacement measured by a GPS system for accumulated fatigue assessment; however, the location of the strain sensors needs to be determined based on a structural analysis and fragility analysis. It further stated that, stay cables are the most critical elements in cable-stayed bridges because of their effect on steel wires and anchorage. The monitoring variables of the stay cables include vibration, tension force, fatigue damage, and corrosion.

Load cells can be installed at the anchorage of the cable, or a single strand; however, these cells are hard to replace. Zhang et al. [62] proposed a method that employs smart sensors based on the elasto-magnetic (EM) and magneto-electric effect to monitor the stress of steel cables. The design theory of the sensor involves the EM coupling effect and magneto-electric coupling effect [62].

The sensor life-span is estimated for 50 years, whereas the operational temperature range is between -20 to +80 °C, and the sampling rate can be 10 seconds [63]. Although the EM sensor can be easily replaced, it can only measure the static cable tension force, and cannot monitor the cable tension force in real time because of the demagnetization effect; that is why the Fiber optical sensors have been proposed to monitor cable tension force [63].

Another solution for monitoring cable frequencies from large distance is using laser vibrometer [64], which can speed up the vibration process. The assumption on the chord may not reflect the actual cable boundary conditions and nonlinearity of cables caused; therefore, Kurz et al [64] analyzed the existing non-destructive testing methods, and commented on a suitable approach for different scenarios of cable elements. Methods for the accessible parts include magnetic inspection and acoustic emission monitoring. Suitable techniques for monitoring the non-accessible parts include ultrasonic guided waves - particularly for anchorage zones, magnetic flux leakage inspection, micro magnetic method, and the acoustic emission method.

Corrosion of reinforced bar in concrete can be monitored based on the electrochemical response mechanism. Qiao et al. [65] developed corrosion sensors, recognition algorithms, and corrosion control actuators for the internet-based durability monitoring. These components realize the assessment of safety, maintenance and reinforcement, as well as the performance-based design of the major infrastructures. Alternatively, Zhao et al. [66] proposed to wrap the optical fiber sensors on reinforced bars to measure the expansion of concrete caused by corrosion, so as to diagnose corrosion locations and corrosion extent of reinforced bars.

3.3 Data acquisition and transmission

The design of data acquisition (DAQ) module includes DAQ devices, the transmission technology, and the sampling modes. Analog signals can be transmitted to DAQ devices directly through shielded cables before analog-digital (A/D) conversion. Since the transmission distance should be limited because of the signal attenuation, direct analog signal transmissions are often used over short distances. For the long transmission distance range, analog signals can be first converted to a digital signal, and then transmitted through industrial communication buses such as ethernet, PROFIBUS, RS-485, and wireless transmission techniques [55]. The communication bus can also be used by other automatic devices. Wireless transmission techniques have been applied in SHM including WiFi and ZigBee, whereas for the long distances, microwave communication is more appropriate [55].

DAQ devices contain signal conditioning devices; however, non-standard signals must first be conditioned through amplification, filtering, isolation, and any other processes. DAQ devices are determined according to the type and number of sensors and signals, and proper sampling rates, whereby, they can be connected with analog signals and digital signals when they are extended to the other interfaces [55]. For example, signals from FBG sensors may be collected by DAQ, whereas the static signals such as the strain and temperature can be collected by serial devices like the RS-232-based devices.

An appropriate sampling rate is required to avoid huge and redundant data in the following fashion: data are sampled at specific time period each day, sampled when exceeding the threshold only, and sampled when a special event occurs. For instance, data are sampled after a typhoon, earthquake, vessel collision, or attack to the bridge. On the other hand, only typical data are saved and the remaining data are deleted [55]. For the dynamic and wave propagation signals, the sampling rate should follow the Nyquist sampling theorem. For the case of the static signal, the sampling rate can be determined according to the variation characteristics of the signals [55].

CONCLUSION

SHM and management techniques are of great importance in bridge structures. There are many techniques and tools proposed in literature for bridge SHM and health management, each having its own merits and limitations. This paper has provided a comprehensive review of the state-of-the-art research and development technologies in this area. The damage detection techniques are classified in the domains such as statistics, time, frequency, time-frequency and softcomputing. It has also systematically discussed the issues related to the implementation of SHM for real-time bridge monitoring and health management; detailed discussions are related to sensor selection criteria, data acquisition devices, signal communication, and decision-making. Discussions also include the merits and limitations of these available technologies.

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