Invited Review Paper

RECENT ADVANCES IN HEALTH MONITORING OF CIVIL STRUCTURES

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ABSTRACT

This paper presents a review of recent advances made in vibration-based Structural Health Monitoring (SHM) using responses of the structure to an excitation. The review is divided into parameter and feature estimation based on linear structural behavior, SHM taking into account the nonlinear structural behavior, sensor layout and data collection strategies, integration of SHM with vibration control of structures, wireless monitoring, and application of LIDAR.

Keywords: Structural health monitoring; damage detection; vibrations, System identification; Smart structure

1. INTRODUCTION

Although a structure is designed to resist against all possible loadings during its life span, there still remains many events that are unaccounted for during the design process. Monitoring the integrity and health of a structure remains a subject of great interest to both practitioners and researchers. The process ranges from a simple visual inspection of the structure by a trained engineer to advanced testing and monitoring methods with the goal of detecting any damage early and taking the necessary remedial actions to prevent potential failure or collapse of the structure and avoid human and economic losses. Damage in civil structures may be due to a variety of causes such as excessive movements and loadings, corrosion, crack growth, high temperature changes, and collision by a foreign object.

Sirca and Adeli [1] present a review of representative research in journal articles on structural system identification published in journals during 1995-2012 in the following categories: conventional model-based, biologically-inspired, signal processing-based, chaos theory, and multi-paradigm approaches. This paper presents a review of recent advances in vibration-based Structural Health Monitoring (SHM) using responses of the structure to an excitation. The main concepts and approaches are described briefly. Unlike non-destructive testing (NDT) methods such as those based on acoustic waves or image processing techniques [2-3], vibration based approaches are suitable for global health monitoring of structures even without any *a priori* knowledge of and accessibility to the damage location.

An SHM system includes three main components: 1) sensor type and layout selection and instrumentation, 2) data collection and cleansing, and 3) data analysis, feature extraction, and damage detection. In general algorithms in the last component are divided in two groups, supervised algorithms using damaged structure information and unsupervised algorithms with no need for damaged state information and based on healthy state data only.

The key component of vibration-based SHM technology is system identification which can be divided into parametric and nonparametric methods. In the parametric methods, changes in structural parameters such as natural frequencies, mode shapes, stiffnesses, or dampings are calculated and used to estimate damage existence, location, or severity while in nonparametric methods damage is estimated without the use of these parameters. These parameters are often defined for a linear model of the structure and related eigenvalues. Consequently parametric methods are mostly linear algorithms while nonparametric methods include nonlinear algorithms.

SHM can be implemented at four different levels: 1) identification/detection of damage existence, 2) level one plus finding damage location, 3) level two plus determining damage severity, 4) level three plus prediction of remaining service life of the structure. In general the first two levels of SHM are possible through both supervised and unsupervised methods while the last two levels require information about damaged structure, and an updated finite element (FE) model of the structure is required for level 4 (Figure 1). Approaches used to various SHM levels are reviewed in the paper. Also the types of application, such as a lab experiment, a benchmark problem, or a real life structure are noted for reviewed articles.

2. PARAMETER AND FEATURE ESTIMATION BASED ON LINEAR STRUCTURAL BEHAVIOR

Linear parametric structural health monitoring consists of monitoring the changes of the structural parameters based on the physical characteristics of the structures assuming a linear and time-invariant system. Linear parameter estimation models are based on the assumption of linear structural behavior. The most commonly-used parameters for structural damage identification are structural dynamic properties such as natural frequencies or eigenvalues, masses, viscous damping, mode shapes or eigenvectors, dynamic flexibility, followed by frequency response functions, mode shape-related parameters such as modal assurance criterion (MAC), auto modal assurance criterion (AutoMAC), and mode shape derivatives defined on the basis of linear structural behavior. The process includes a system identification to determine the characteristics of different states of the structure as healthy or damaged. For a robust SHM system, extracted parameters must have high sensitivity towards damage but low sensitivity to noise. Figure 2 shows the unsupervised versus supervised system identification process based on input and output data.

Gul and Catbas [4] use the autoregressive exogeneous (ARX) time series analysis to detect and localize damage in a simple one-story steel frame structure in the lab and in a benchmark problem created for a three-span prestressed concrete overpass bridge in Bern, Switzerland. Ambient vibration was recorded and analyzed using the Random Decrement (RD) method.

Researchers have proposed new parameters for more consistent and effective detection of damage in structures besides widely-used structural parameters such as natural frequency or mode shape. Noting sensitivity to noise and dependence on numerical differentiation as factors for the poor performance of curvature-dependent method based on displacement mode shapes Adewuyi and Wu [5] propose damage detection indices based on normalized Modal MacroStrain (MMS) and apply it to a simple beam structure. Li et al. [6] use the Katz's Fractal Dimension (FD) from the chaos theory [7-9] to measure displacement mode shapes, propose an FD-based damage localization index, and test it to detect single or multiple damages in a simply supported prismatic steel beam. Seyedpoor [10] propose a Modal Strain Energy Based Index (MSEBI) to locate damage in a cantilever beam and 2-D truss structure using simulated data and Particle Swarm Optimization (PSO) [11-15].

Omrani et al. [16] use a time domain eigensystem realization algorithm (ERA) and the subspace state-space system identification method to identify linear story torsional and lateral stiffness matrices of the ASCE (American Society of Civil Engineers) - IASC (International Association for Structural Control) benchmark problem, a quarter scaled 4-story and two by two-bay braced steel model, under both external (hammer strike) and ambient excitations. The method takes advantage of the banded form of stiffness matrices observed in shear and torsional buildings and decomposing the problem into a number of smaller sub-problems.

Yan and Ren's [17] propose Power Spectral Density Transmissibility calculated from PSDs of system outputs to extract natural frequencies and mode shapes and compared it with the peak-picking (PP) and stochastic subspace identification (SSI) method on a five-story shear building and a concrete-filled steel tubular half-through arch bridge in China under ambient vibrations. Qiao et al. [18] use a frequency domain signal processing technique, the fast Fourier transform (FFT) and a time-frequency domain signal processing method, the continuous wavelet transform (CWT) [19], and three pattern-matching algorithms to identify damage features in recorded signals obtained from a small scaled model of a three-story steel building. Jiang et al. [20] use the complex CWT of the slope of the mode shape for crack detection in simply supported and multi-span beams.

Fragility curves are empirically or analytically developed graphs to show the vulnerability or damage level of a structure subjected to a specific hazard. Empirical curves are based on post event damage data but analytical ones are based on numerical modeling analysis results. Torbol et al. [21] use design information in addition to real life data collected from instrumented bridge structures to create updated fragility (the probability of exceeding a given damage state given an intensity measure) curves for three concrete box girder bridges in Southern California. To extract sensitivities of the structures accurately, they update parameters such as stiffnesses of deck, columns, abutment in the finite element model by a generalized pattern search algorithm.

Zhou et al. [22] used the radial basis function based RS models [23] to estimate parameters of a scaled experimental test and an FE model of a cable-stayed bridge. Among parameters to be estimated, they select modulus of elasticity of connection elements to account for changes in materials, dimensions, and boundary conditions at connections. The RS model is created in order to relate some input variables to some output variable using enough sample sets, similar to a neural network [24].

Health monitoring and system identification can also be used for ancient and historical structures where often hardly any blue prints exist. Cimellaro et al. [25] use three system identification methods, frequency domain decomposition, RD technique combined with the ERA method, and the natural excitation technique (NExT) combined with the ERA, to extract dynamic properties of L'aquila City Hall after the 2009 L’Aquila (Italy) earthquake. L'aquila City Hall includes a three-story masonry building and a stone Civic Tower. A network of 15 velocity sensors was placed in three different layouts to estimate the lateral and longitudinal modes. The results were used to update an FE model and evaluate the integrity of the building after the incident. Foti et al. [26] use frequency domain decomposition and the Stochastic Subspace Identification (SSI) algorithms to extract dynamic properties of the Engineering Faculty building, an irregular four-story reinforced concrete (RC) frame structure heavily damaged in the same 2009 L’Aquila (Italy) earthquake from 13 accelerometers. The resulting estimated FE model was used to design retrofitting measures.

Lozano-Galant et al. [27] apply the observability techniques to identification of structural properties such as stiffnesses of a13-story 4-bay frame. Bursi et al. [28] apply the SSI algorithm for ambient vibration and the ERA method for impulse vibration to extract and confirm dynamic properties of the Ponte del Mare curved deck steel footbridge in Pescara, Italy. They tested different sensor placement layouts and chose the best layout based on the AutoMAC value.

Fuggini et al. [29] present identification of a masonry structure retrofitted with *Composite Seismic Wallpaper* through combination of a finite element updating approach and a GA [30]. The wallpaper is a polymeric textile used to improve seismic behavior of masonry structures. They tested the approach on a damaged two story stone building using ambient vibration response.

3. SHM TAKING INTO ACCOUNT THE NONLINEAR STRUCTURAL BEHAVIOR

SHM methods that take into account nonlinear structural behavior are usually based on nonparametric system identification techniques which deal directly with system's input and output and exploit changes in the measured time histories or their corresponding spectra through proper signal processing methods. Unlike parametric SI methods, these features do not estimate any explicit physical-dynamic parameters. Nonlinear damage feature estimation methods make no assumption on linear behavior of the structure. They include a wide range of methods such as nonlinear ARX (NARX), nonlinear Auto Regression Moving Average exogeneous (NARMAX), neural networks [31-34], fuzzy neural networks [35-38], fuzzy wavelet neural network [39], and signal processing methods that can handle nonlinear and nonstationary signals as wavelets [40] and Hilbert-Huang transform [41]. In general, they are more powerful than parametric methods because they incorporate the nonlinear behavior of the structure implicitly. This is significant because damage is often associated with nonlinear behavior. Compared with parametric methods these methods are more effective for large-scale structures with complicated nonlinear behavior and incomplete and noise-contaminated measurements of structural response under extreme loadings [42].

Adeli and Jiang [43] present a novel dynamic time-delay fuzzy wavelet neural network (WNN) model for nonparametric identification of structures with nonlinear behavior using the nonlinear autoregressive moving average with exogenous inputs through adroit integration of dynamic time delay neural networks, wavelets, fuzzy logic [44-47], and the chaos theory [42]. Jiang and Adeli [48] present an adaptive Levenberg-Marquardt-least squares algorithm for training of the dynamic fuzzy WNN model. The model is applied to highrise moment-resisting building structures taking into account their geometric nonlinearities. Jiang and Adeli [49] present a nonparametric system identification-based model for damage detection of irregular highrise building structures subjected to seismic excitations using the dynamic fuzzy WNN model with an adaptive learning algorithm. A multiple signal classification (MUSIC) method is developed to compute the pseudospectrum from the structural response time series. The methodology is validated using the data obtained from a 38-story concrete test model. Osornio-Rios et al. [50] combined the aforementioned MUSIC algorithm introduced by Jiang and Adeli [49] with neural networks [51-53] to identify, locate, and quantify the severity of corrosion and crack damage in a structure using data obtained experimentally on a five-bay truss-type structure with 5 accelerometers.

Some of the common linear system identification algorithms such as state space modeling, transfer function modeling, or linear Auto Regression Moving Average (ARMA) method have also been tested for modeling nonlinear systems. Figueiredo et al. [54] (2011) investigate four different approaches for order approximation of Auto Regressive (AR) models in system identification and damage detection of a scaled three-story base-excited aluminum frame model. The methods include Akaike information criterion, partial autocorrelation function, root mean squared error, and singular value decomposition. Structural response includes nonlinear behavior as a result of damage induced by an impact bump at the top floor. Results show these methods do not yield the same solution in terms of the optimal model order due to operational and environmental variability.

Higher modes play a significant role in detection of local damage in a structure but their determination in frequency domain analysis is sensitive to the noise in sensors, a shortcoming of frequency-based SHM such as the PSD-based algorithm described earlier. Time-frequency domain analysis has been used for better localized damage detections. An example is the Hilbert-Huang transform (HHT) used for nonlinear and nonstationary signals. In this transformation, first the signal is decomposed into intrinsic mode functions (IMF) by the empirical mode decomposition (EMD) followed by determination of the instantaneous frequencies of the signal using the Hilbert transform (HT) [41]. Chanpheng et al. [55] define a degree of nonlinearity based on the difference of the estimated frequency response function of the signal and its HT and apply it to the data obtained from a cable-stayed bridge in Japan in six earthquakes occurring between 2002 and 2005.

Xiang and Liang [56] propose a two-stage crack localization and depth estimation method using the wavelet transform. First, wavelet transform of the modal shape is performed for crack localization. Then, based on the estimated locations, natural frequencies of the beam are estimated for various crack depths using the linear elastic fracture mechanics theory [57-58] while each crack is represented by a weightless rotational spring. They apply the method to a cantilever beam with two cracks

Noh et al. [59] present statistical fragility functions to map wavelet-based damage state features (DSF) to damage states of the structure and estimate the health condition of the building. They use the ratio of the wavelet energy of the dominant scale to sum of energies of all scales in the wavelet transform of the response acceleration vector as DSF and the story drift ratio as the damage index, and apply the method on simulated data of a nonlinear two-dimensional (2D) 4-story steel moment-resisting frame.

4. SENSOR LAYOUT AND DATA COLLECTION STRATEGIES

A key issue in SHM is the number and layout of sensors used to collect time-series data effectively which affects the project cost and accuracy of damage detection. Raich and Liszkai [60] present a multi-objective optimization approach using a genetic algorithm [61-62] with the goal of minimizing the number of sensors while maximizing the sensitivity of the frequency response functions collected at each sensor location. They tested the method on cantilever and simply- supported beams and a three story 2D moment resisting frame.

Enormous amount of time-series data are often generated in SHM systems requiring the application of data compression techniques. Huang et al. [63] use the idea of *compressive sensing* where data are compressed in sensors simultaneously with the sampling, and propose a Bayesian compressive sensing method to reconstruct signals from a compressive sensor. The method is tested using synthesized and actual acceleration data from a bridge SHM system.

5. INTEGRATION OF SHM WITH VIBRATION CONTROL OF STRUCTURES

The idea of smart structures has been advanced through integration of the concept of SHM with passive, semi-active [64], and active vibration control of structures [65-68]. System identification techniques used for SHM also find applications in vibrations control of structures [69-70]. Cho et al. [71] present dynamic parameter identification of secondary mass damping systems installed in highrise buildings based on full-scale field data using the Box-Jenkins state-space system identification method. They apply the methodology to an actual tuned mass damper (TMD) system [72] installed on the top of highrise building structures in Busan, Korea, and an actual tuned liquid column damper (TLCD) system installed on the top of highrise building structures in Incheon, Korea.

Hazra et al. [73] use the second-order blind source identification method [74] for systems with closely-spaced modes or low-energy modes such as TMD-equipped structures. They also address the problem when the number of measurements is fewer than the number of recognized modes (too few sensors). They perform a structural characteristic identification on the Apron Control Tower near Toronto, Canada, which is equipped with a pair of TMDs on the roof. Khalid et al. [75] present nonlinear identification of a magneto-rheological (MR) fluid damper based on a dynamic recurrent neural network [76-77] used for semi-active vibration control of structures [78].

6. **WIRELESS MONITORING**

Long-term monitoring of the integrity of tall buildings and major bridges under various environmental loadings is of particular interest because of their size and importance. Wireless sensors have been proposed to reduce the installation and the long-term maintenance time and cost of SHM (Figure 3). Further, they can be installed in larger numbers and difficult-to-wire locations. They, however, may add to the initial cost of the SHM. Bocca et al. [79] introduce a time synchronized and configurable wireless sensor network to detect modal properties of the structure. The system was tested on a model wooden bridge. Results show identified natural frequencies have accuracies comparable with a wired SHM system.

Hu et al. [80] designed hardware and software requirements of a wireless sensor data collection system for unsupervised SHM of highway bridges. It includes different types of sensors such as accelerometers, strain gauges and temperature sensors. The authors used the Power Spectral Density (PSD) and the ARX methods along with the response surface (RS) statistical approach to estimate the natural frequencies and mode shapes and update the FE model to detect and locate the damage. The system is implemented in Zhengdian prestressed concrete highway bridge in Wuhan, China.

Global Positioning system (GPS) has improved to a great extent in recent years and now the technology allows near real time (100 Hz) positioning with the accuracy in the order of millimeter to centimeter. A GPS for SHM consists of positioning units/sensors and a data monitoring center in addition to the satellites (Figure 4). Yi et al. [81] present a review of GPS applications for health monitoring of tall buildings. GPS can keep track of static and dynamic displacements which makes it a potentially promising technology for SHM. However, its accuracy has to be improved before it can be a reliable technology for SHM.

7. SHM USING LIDAR

Park et al. [82] introduced health monitoring of structures using terrestrial laser scanning, aka Light Detection and Ranging (LIDAR). They tested the model experimentally on a simply-supported steel beam. Truong-Hong et al. [83] present a method to reconstruct building models from LIDAR and validate it on data obtained for three brick buildings in Dublin, Ireland.

8. FINAL REMARKS

Newer technologies for SHM are being explored. Park et al. [84] present a 3D displacement measurement model for SHM using a motion capture system. The effectiveness of the model was demonstrated by comparing the displacements measured in a free vibration experiment of a scaled 3-story structure with laser displacement sensors.

One of the major challenges in SHM of real structures is the effect of changes in unaccounted parameters that are not considered in the model such as ambient temperature or mass of the structure for example the live load in a highrise building or vehicle loads in a bridge.

These parameters create additional nonlinearity or complexity in the SHM system. When these parameters are not considered in the model or are assumed constant the data must be collected and compared in the same conditions. Otherwise the data should be normalized according to different conditions, a subject further SHM research.

The great majority of SHM papers assume linear structural behavior. More research is needed on SHM taking into account the nonlinearity of the complex structure-environment system. Also, more refined modelling of large structures such as highrise buildings including the connection details. Such refined modelling will require significant computational resources such as high-performance computing.

Amezquita-Sanchez and Adeli [41] present a review of signal processing techniques for vibration-based SHM. Development and application of effective signal processing techniques to process a vast amount of time-series data will continue to be an effective area of research. Uncertainty in the SHM modelling is another significant issue which has been addresses by a number of researchers but is beyond the scope of the current review.

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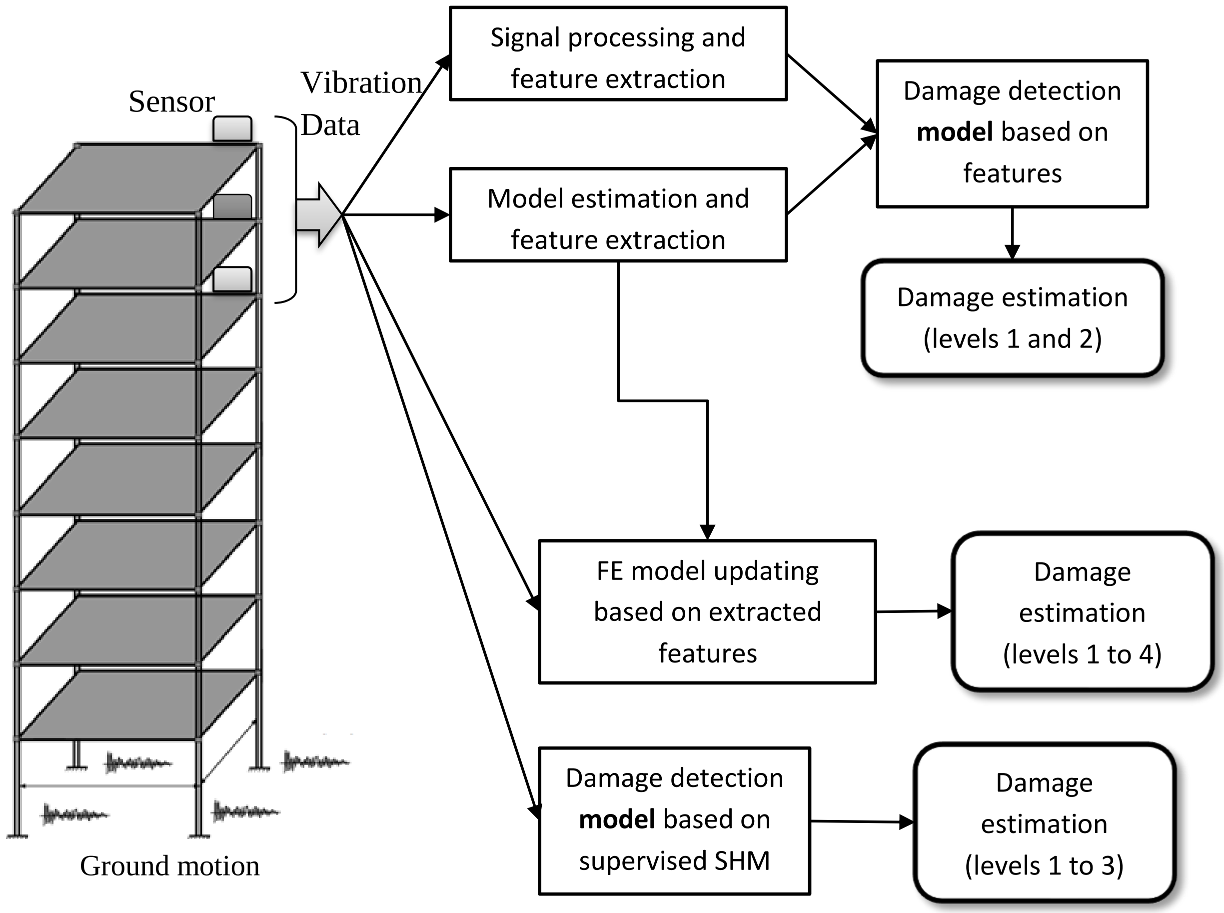
Figure Captions

Figure 1 Typical procedures for different damage estimation levels

Figure 2 Unsupervised (a) versus supervised (b) system identification process

Figure 3 Wireless health monitoring

Figure 4 GPS application for SHM



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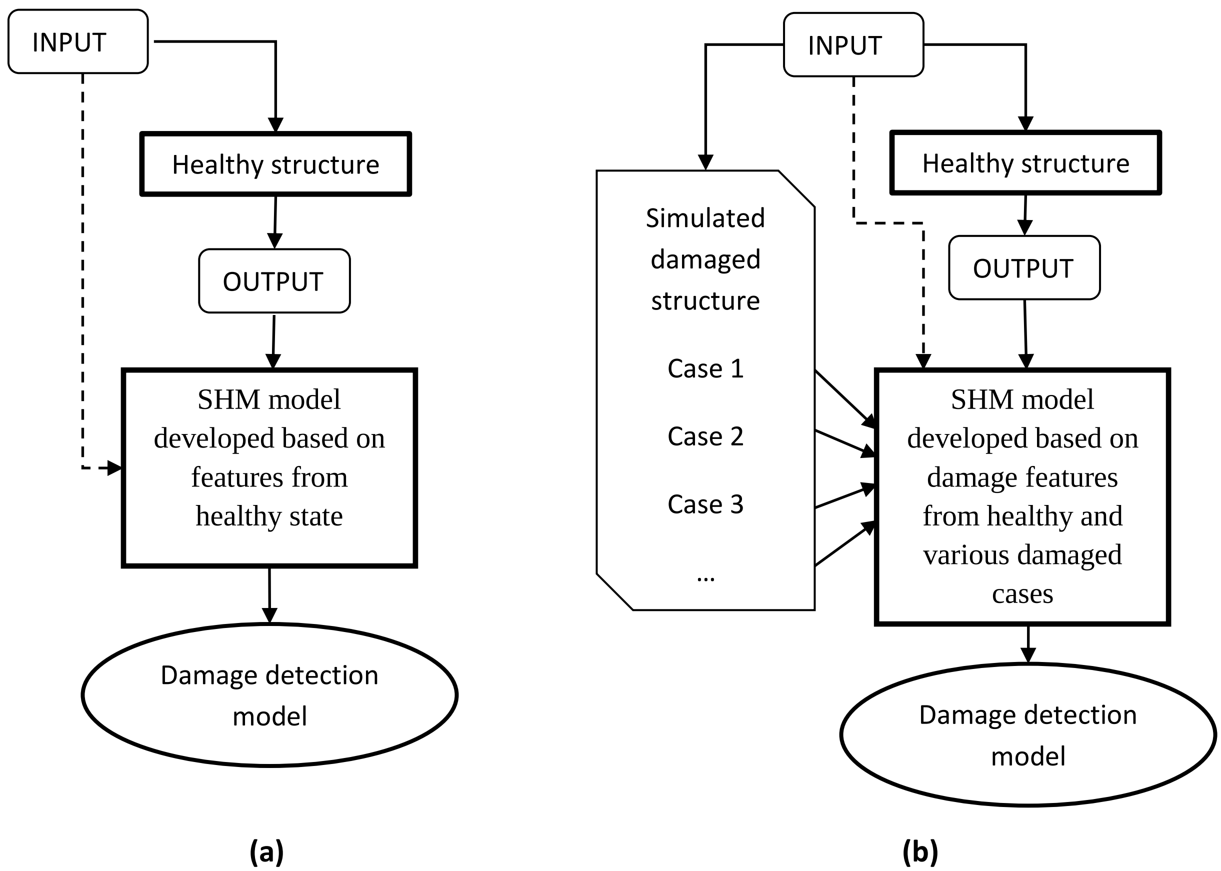


Figure 2 Unsupervised (a) versus supervised (b) system identification process

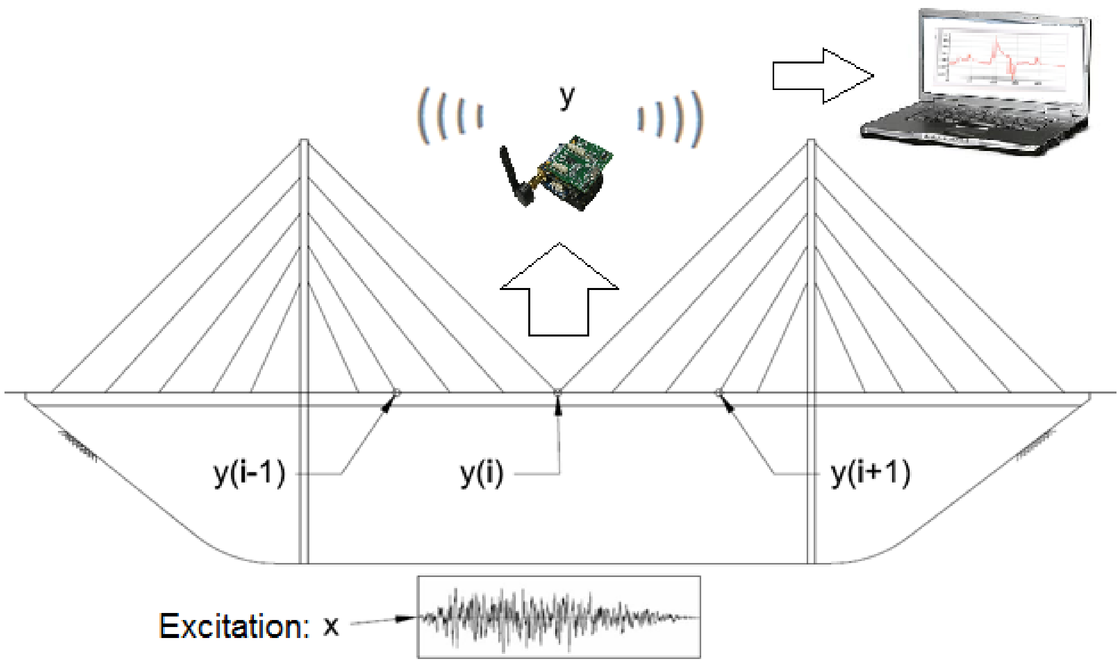
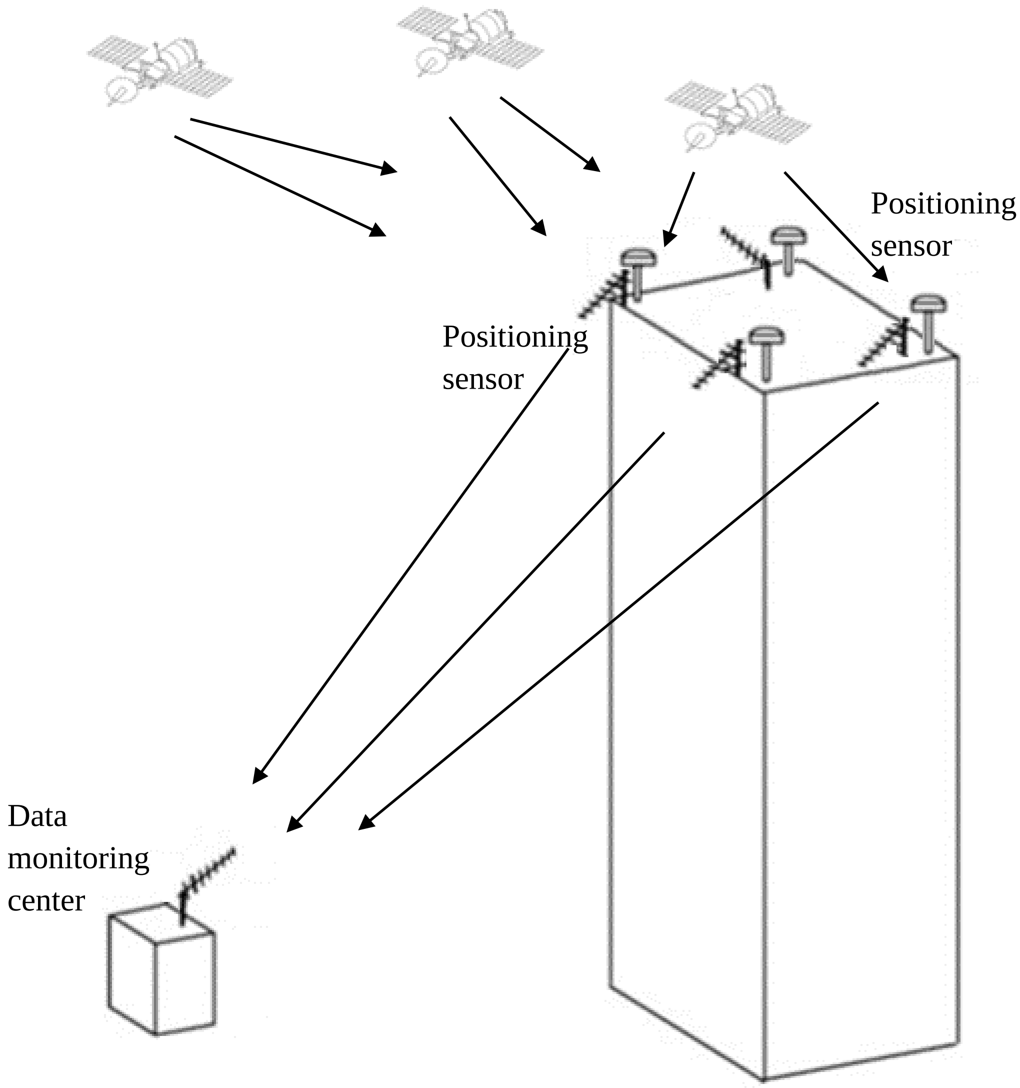


Figure 3 Wireless health monitoring



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