Structural Health Monitoring Damage Classification and System Models

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Contributor: Alain Gomez-Cabrera, Ponciano Jorge Escamilla-Ambrosio

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1. Introduction

Structural health monitoring (SHM) is a field of science that focuses its efforts on evaluating and monitoring the integrity of a structure of interest [1]. Structural health monitoring systems are based on the design of sensing systems and structural models to evaluate machines and structures.

Although SHM systems are not a new field of research, computational advances in sensing hardware and the computational power of embedded devices drive the generation of reliable data for developing models based on classification and prediction data, including machine-learning algorithms in SHM systems. Moreover, sensors, such as accelerometers, are inexpensive compared to other sensors and can be effectively deployed in a sensing system to implement vibration-based SHM systems [2]. Accelerometers, or when combining them with other sensors, are the dominant sensing approaches for these SHM applications [3]. Because vibration-based systems date back to the late 1970s [4], technological advances represent a field of opportunities to improve existing solutions in the field of damage identification.

2. Damage Classification in SHM

SHM covers several application areas and the assets monitored range from small components to huge civil structures and complex machines. Building SHM systems focus on measuring changes in the physical parameters to assess the current state of the structure and, in some cases, predict the building's response to future seismic excitations. To make these predictions, it is necessary to identify the natural frequencies of the buildings [5]. In the case of buildings, the structure is subjected to the effects of static and dynamic loads, so the complexity of the analysis presents a challenge in giving an accurate model that includes all these known and unknown effects.

SHM systems are composed of several hardware and software elements. An overview of the main components of SHM systems as defined by Farrar and Worden [6] are:

- Operational assessment: The aspect related to damage conceptualization and operational conditions.
- Data acquisition: The sensor system design and data preprocessing.
- Feature extraction: The selection of sensitive damage features according to the damage identification capabilities of the desired SHM system.
- Statistical model development: The design and implementation of the physics-based or data-based model.

Yuan et al. [1] explored the data acquisition aspect (1) of recent proposals for SHM systems, showing several features of accelerometer sensing systems that are attractive for the structural monitoring and evaluation of SHM systems. This research focuses on areas three and four of SHM systems, analyzing proposals of the physics-based models and the data-based models presented in the literature that belong to these areas. **Figure 1** shows these areas in SHM systems, and the methods, techniques and algorithms involved.

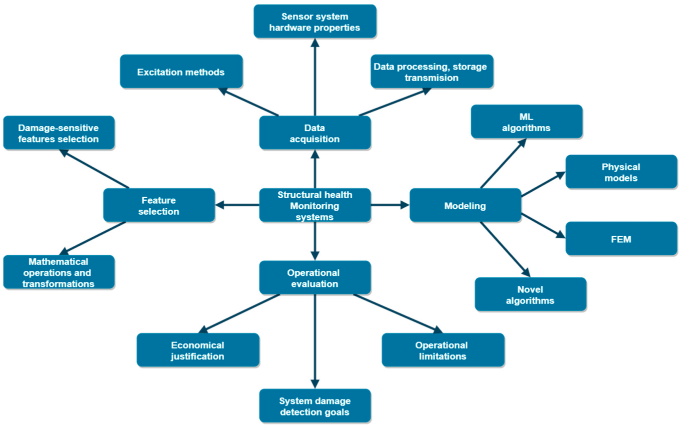

Figure 1. Diagram of structural health monitoring systems areas.

The core of SHM systems is their ability to perform damage identification. Damage is the change in the material's physical properties due to progressive deterioration or as a result of a single event on a structure. This change can detract from the behavior or integrity of a structure. Damage characterization can be conceived in several ways depending on the objectives of the SHM system, and damage states can be defined in terms of extent, severity, remaining operational time, thresholds, and damage index standards. Rytter [7] also presents a damage identification classification in SHM systems, as shown in **Table 1**.

Table 1. Damage characterization levels.

Damage Characterization Level	Description
I: Detection	The SHM system can decide if there is any damage to the structure of interest.
II: Localization	The SHM system can determine the existence and location of damage in the structure of interest.
III: Assessment	The SHM system can estimate the extent of damage in the structure of interest.
IV: Prediction	The SHM system can estimate the remaining lifetime of the structure.

3. SHM System Models

3.1. Physics-Based SHM Systems

In the case of physical asset monitoring, there are two main branches of modeling: physics-based modeling, also known as physical-law modeling, and data-driven modeling. Physics-based modeling aims to describe phenomena by formulating mathematical models that integrate interdisciplinary knowledge to generate models that replicate observed behavior. Models are commonly presented in differential equations whose complexity increases as more factors become involved. Several terms and parameters must be defined to fully describe the system phenomena. Initial and boundary conditions must be identified to obtain physics equation solutions, and the computational cost associated with this operation can be very time-consuming for complex phenomena.

In SHM systems, these models are implemented to assess the condition of an asset under operating conditions to monitor changes that may indicate the presence of damage and shorten the remaining useful life of the asset. Finite element modeling (FEM) software implements well-known analyses, such as modal analysis, and allows the simulation of different structures and initial and boundary conditions straightforwardly. FEM software includes physical law models integrated into software libraries to perform damage analysis on a virtualized model of structures efficiently.

The complexity of modeling building structures under seismic excitation is caused by the intervening factors that can modify the behavior of these structures and by the difficulty of correctly defining their physical properties. Several works focus on estimating model parameters and uncertainties to improve the model of the structure. For example, Xu et al. [8] estimated the parameters of the structures based on linear and nonlinear regression analyses. These structures' linear and nonlinear parameters, such as elastic stiffness and yield displacement, are obtained for a three-story structure. Gomes et al. [9] addressed an inverse identification problem using numerical models and a genetic algorithm.

Model parameters obtained from experimental and recorded data can increase the model's accuracy compared to the actual measured results. However, environmental and operating conditions do not remain constant throughout the life of the structure. In addition, physical law models have drawbacks that limit their applications in some SHM systems. The time to solve the equations in a real-time SHM system impacts the response time to ensure safety and the reduction of economic losses in response systems for seismic protocols and evacuation procedures. In order to reduce the time costs of performing calculations, optimization algorithms applied to the problem of SHM are encouraged and proposed in the literature [10].

Table 2 lists physics-based proposals for SHM systems in buildings under vibration excitation for multi-story structures. In this table, two types of proposal contributions are shown: the identification of system parameters and damage. According to Farrar's classification, the level of damage identification for the practical proposals is also presented.

Table 2. N-story building structure health monitoring systems based on physical model techniques.

Publication	Structure	Damage Indicator	Algorithm or Analysis Method	Damage Identification and Level		Year
[11]	**An eight-story physical building model in FEM software**	**Stiffness reduction**	**Vibration-based damage methods**	**Damage detection and localization**	**II**	**2018**
[12]	**A 14-story physical building prototype under vibration table**	**Modal frequencies**	**Operational modal analysis**	**Modal identification**	**N/A**	**2017**
[13]	**A five-story physical building prototype under vibration table**	**Stiffness reduction**	**Novel damage localization algorithm based on wave propagation**	**Damage detection and localization**	**II**	**2020**
[14]	**A 51-story building with accelerometers and tilt sensors**	**Modal frequencies**	**Modal parameters estimation through Bayesian algorithm combined with FFT**	**Modal identification**	**N/A**	**2019**
[15]	**A 12-story frame structure**	**Stiffness reduction**	**Hysteresis loop analysis method**	**Damage detection**	**I**	**2017**
[16]	**An 86-story physical building in FEM software**	**Modal frequencies**	**Wave-based damage detection based on propagation analysis**	**Modal identification**	**N/A**	**2018**
[17]	**A three-story frame structure**	**Inter-story displacement**	**Two novel damage indices based on the displacement of the structure**	**Damage detection and localization**	**II**	**2015**

3.2. Data-Based SHM Systems

Machine-learning techniques are a subset of the field of artificial intelligence. Due to their statistical nature, their vision is to address problems of interest in pattern recognition identification and classification tasks. SHM from the ML point of view is a classification problem in which at least two states are compared in SHM systems employing ML techniques: damaged and undamaged states.

A machine-learning model extracts information in the form of features from a given data set and classifies those data features. These data-driven models require large amounts of information to train the model and avoid the overfitting problem. The generalization problem depends on the amount of available data and significant diversity of this training data to avoid overfitting and ensure a reasonable level of generalization. In an idealized situation, the data set should include the samples of the possible range of excitation that can be applied to the structure. In addition, data quality improvement using signal processing techniques, such as normalization and noise filtering, is desirable for the generation of the data set. ML algorithms are applied in the damage identification process and in analyzing the anomalous data obtained from the sensors [18][19], thereby improving data quality. In addition, signal processing techniques, such as WT and HHT also improve data quality and are applied in SHM systems [20][21].

ML techniques can be divided into supervised learning (for regression and classification tasks), unsupervised learning (anomaly detection and clustering) and reinforcement learning. The most popular ML techniques implemented in the construction of SHM solutions are support vector machines (SVMs) and convolutional neural networks (CNNs) [22][23]. In the case of neural network techniques, damage-sensitive feature selection plays a crucial role in the performance of the SHM system. SVM optimally classifies features in linear and nonlinear problems. CNN, a subset of neural network (NN) methods, include convolution operations in the hidden layer of neural networks to classify data, usually in image format. Other techniques, such as PCA, improve the features of the training data set by making them uncorrelated.

The selection of a ML technique is guided by the limitations of each technique and the requirements of SHM in terms of damage identification level and operating conditions. Identifying the modal systems of building structures can also be performed using deep neuronal networks (DNNs) [24][25]. **Table 3** summarizes the ML-based proposals for SHM systems in buildings under vibration excitation for multi-story structures.

Table 3. N-story building structure health monitoring systems based on machine-learning techniques.

Publication	Structure	Data Type Used for Training	Machine-Learning Technique	Damage Identification and Level		Year
[26]	A four-story physical building prototype under vibration table	Acceleration response data from a physical prototype	ANN	Damage existence and localization	II	2016
[27]	An eight-story physical building mathematical model	Artificially generated dataset from an algorithm	FCN	Damage existence and localization	II	2020
[28]	A three-story physical building simulated model	Simulation-generated dataset from OpenSeesMD software	ANN	Damage detection and localization	II	2017
[29]	30 buildings including 3, 5 and 7 stories with different structural parameters	Simulation-generated dataset from Raumoko3D software	ANN	Damage detection and localization	II	2017
[30]	An instrumented main steel frame	Experimental simulation from a physical prototype with modal shaker excitation	CNN	Damage detection and localization	II	2016
[31]	A three-story physical building-simulated model	Simulation-generated dataset from OpenSeesMD software	SVM	Damage existence, localization and severity	III	2019
[32]	A three-story steel frame structure	Intensity-based features	SVM	Damage detection	I	2019
[33]	A seven-story steel structure	Simulation-generated dataset	ANN	Damage existence, localization and severity	III	2018
[34]	A five-story steel structure	Simulation-generated dataset	ANN	Damage detection and localization	II	2008

3.3. Model Type Comparative in Building SHM Systems

Table 4 analyzes the advantages and disadvantages of applying the physics-based model and the data-based model based on reviewing the proposals mentioned above.

Table 4. Advantages and disadvantages of a physics-based model and data-based models in SHM building applications.

Model Approach	Advantages	Disadvantages
Physics-based SHM	• The model parameters have a straightforward physical interpretation. Stiffness changes and displacements are consistent as damage-sensitive features. • It can reach all the levels of damage identification if the parameters are defined or estimated in the building structure. • The effect of the variation of the parameters can be estimated in the final result of the model. Parameter variation allows the simulation of different scenarios, and the structural safety thresholds can be established.	• The calculations of the solution of the model equations may not be feasible for real-time SHM applications, where the complexity of the structure requires long processing times. • The uncertainties and changing parameters may reduce the accuracy of the output model. Therefore, an estimation using other methods, such as model-based techniques, is encouraged.
Data-based SHM	• Noise and environmental effects on the data collected by the sensors can be minimized for the classification performed by the ML model. • Damage identification can be performed even if the parameters of the structure are unknown or cannot be estimated.	• The solution process is hidden from the user, so the rationale for successful damage classification is not explicit. • The training data set must be large enough to avoid overfitting, especially in algorithms such as CNN. In addition, obtaining the training samples of damage states is in most cases limited to an artificially generated dataset from simulations. • Computational training times can be costly for some ML algorithms (SVM, for example). Real-time SHM monitoring systems require faster methods such as NN solutions.

Recent proposals implement hybrid approaches that improve SHM damage identification models and integrate physics-based and data-driven modeling solutions. One of the most common strategies is to build artificial datasets used to train ML models from FEM-generated data. Conversely, FEM parameters can be estimated from the output of an ML regression model and improve a structural virtual model.

References

1. Yuan, F.-G.; Zargar, S.A.; Chen, Q.; Wang, S. Machine learning for structural health monitoring: Challenges and opportunities. Sens. Smart Struct. Technol. Civ. Mech. Aerosp. Syst. 2020, 11379, 1137903.
2. Ibrahim, A.; Eltawil, A.; Na, Y.; El-Tawil, S. A Machine Learning Approach for Structural Health Monitoring Using Noisy Data Sets. IEEE Trans. Autom. Sci. Eng. 2020, 17, 900–908.
3. Sivasuriyan, A.; Vijayan, D.; Górski, W.; Wodzyński, Ł.; Vaverková, M.; Koda, E. Practical Implementation of Structural Health Monitoring in Multi-Story Buildings. Buildings 2021, 11, 263.
4. Kong, X.; Cai, C.-S.; Hu, J. The State-of-the-Art on Framework of Vibration-Based Structural Damage Identification for Decision Making. Appl. Sci. 2017, 7, 497.
5. Valinejadshoubi, M.; Bagchi, A.; Moselhi, O. Structural health monitoring of buildings and infrastructure. Struct. Health Monit. 2016, 1, 50371.
6. Farrar, C.R.; Worden, K. Structural Health Monitoring: A Machine Learning Perspective; Wiley: Hoboken, NJ, USA, 2012.

7. Rytter, A. Vibrational Based Inspection of Civil Engineering Structures. Ph.D. Thesis, Aalborg University, Aalborg, Denm ark, 1993.

8. Xu, C.; Chase, J.G.; Rodgers, G.W. Physical parameter identification of nonlinear base-isolated buildings using seismic response data. Comput. Struct. 2014, 145, 47–57.

9. Gomes, G.F.; de Almeida, F.A.; da Cunha, S.S.; Ancelotti, A.C. An estimate of the location of multiple delaminations on aeronautical CFRP plates using modal data inverse problem. Int. J. Adv. Manuf. Technol. 2018, 99, 1155–1174.

10. Pereira, J.L.J.; Francisco, M.B.; da Cunha, S.S., Jr.; Gomes, G.F. A powerful Lichtenberg Optimization Algorithm: A da mage identification case study. Eng. Appl. Artif. Intell. 2020, 97, 104055.

11. Frigui, F.; Faye, J.; Martin, C.; Dalverny, O.; Peres, F.; Judenherc, S. Global methodology for damage detection and loc alization in civil engineering structures. Eng. Struct. 2018, 171, 686–695.

12. López, J.O.; Reyes, L.V.; Oyarzo-Vera, C. Structural health assessment of a R/C building in the coastal area of Concep ción, Chile. Procedia Eng. 2017, 199, 2214–2219.

13. Morales-Valdez, J.; Alvarez-Icaza, L.; Escobar, J.A. Damage Localization in a Building Structure during Seismic Excitati on. Shock Vib. 2020, 2020, 8859527.

14. Zhang, F.; Yang, Y.; Xiong, H.; Yang, J.; Yu, Z. Structural health monitoring of a 250-m super-tall building and operation al modal analysis using the fast Bayesian FFT method. Struct. Control Health Monit. 2019, 26, e2383.

15. Zhou, C.; Chase, J.G.; Rodgers, G.W.; Huang, B.; Xu, C. Effective Stiffness Identification for Structural Health Monitori ng of Reinforced Concrete Building using Hysteresis Loop Analysis. Procedia Eng. 2017, 199, 1074–1079.

16. Sun, H.; Al-Qazweeni, J.; Parol, J.; Kamal, H.; Chen, Z.; Büyüköztürk, O. Computational modeling of a unique tower in Kuwait for structural health monitoring: Numerical investigations. Struct. Control. Health Monit. 2019, 26, e2317.

17. Isidori, D.; Concettoni, E.; Cristalli, C.; Soria, L.; Lenci, S. Proof of concept of the structural health monitoring of framed structures by a novel combined experimental and theoretical approach. Struct. Control Health Monit. 2016, 23, 802–82 4.

18. Escamilla-Ambrosio, P.; Liu, X.; Lieven, N.; Ramírez-Cortés, J.J.r. ANFIS-Wavelet Packet Transform Approach to Struct ural Health Monitoring. Ratio 2010, 10, 1.

19. Bao, Y.; Chen, Z.; Wei, S.; Xu, Y.; Tang, Z.; Li, H. The State of the Art of Data Science and Engineering in Structural He alth Monitoring. Engineering 2019, 5, 234–242.

20. Escamilla-Ambrosio, P.J.; Liu, X.; Ramírez-Cortés, J.M.; Rodríguez-Mota, A.; Gómez-Gil, M.D.P. Multi-Sensor Feature Extraction and Data Fusion Using ANFIS and 2D Wavelet Transform in Structural Health Monitoring. In Structural Healt h Monitoring—Measurement Methods and Practical Applications; InTech: Houston, TX, USA, 2017.

21. Amezquita-Sanchez, J.P.; Adeli, H. Signal Processing Techniques for Vibration-Based Health Monitoring of Smart Struc tures. Arch. Comput. Methods Eng. 2014, 23, 1–15.

22. Escamilla-Ambrosio, P.J.; Liu, X.; Lieven, N.A.J.; Ramirez-Cortes, J.M. Wavelet-fuzzy logic approach to structural healt h monitoring. In Proceedings of the 2011 Annual Meeting of the North American Fuzzy Information Processing Society, El Paso, TX, USA, 18–20 March 2011.

23. Flah, M.; Nunez, I.; Ben Chaabene, W.; Nehdi, M.L. Machine Learning Algorithms in Civil Structural Health Monitoring: A Systematic Review. Arch. Comput. Methods Eng. 2020, 28, 2621–2643.

24. Liu, X.; Lieven, N.; Escamilla-Ambrosio, P. Frequency response function shape-based methods for structural damage l ocalisation. Mech. Syst. Signal Process. 2009, 23, 1243–1259.

25. Bao, Y.; Li, H. Machine learning paradigm for structural health monitoring. Struct. Health Monit. 2021, 20, 1353–1372.

26. Smarsly, K.; Dragos, K.; Wiggenbrock, J. Machine learning techniques for structural health monitoring. In Proceedings of the 8th European Workshop on Structural Health Monitoring (EWSHM 2016), Bilbao, Spain, 5–8 July 2016; pp. 5–8.

27. Rosafalco, L.; Manzoni, A.; Mariani, S.; Corigliano, A. Fully convolutional networks for structural health monitoring throu gh multivariate time series classification. Adv. Model. Simul. Eng. Sci. 2020, 7, 38.

28. Vazirizade, S.M.; Nozhati, S.; Zadeh, M.A. Seismic reliability assessment of structures using artificial neural network. J. Build. Eng. 2017, 11, 230–235.

29. Morfidis, K.; Kostinakis, K. Seismic parameters' combinations for the optimum prediction of the damage state of R/C bu ildings using neural networks. Adv. Eng. Softw. 2017, 106, 1–16.

30. Abdeljaber, O.; Avci, O.; Kiranyaz, S.; Gabbouj, M.; Inman, D.J. Real-time vibration-based structural damage detection using one-dimensional convolutional neural networks. J. Sound Vib. 2017, 388, 154–170.

31. Sajedi, S.O.; Liang, X. A data-driven framework for near real-time and robust damage diagnosis of building structures. Struct. Control Health Monit. 2020, 27, e2488.
32. Sajedi, S.O.; Liang, X. Intensity-Based Feature Selection for Near Real-Time Damage Diagnosis of Building Structures. In Proceedings of the IABSE Congress, New York, NY, USA, 4–6 September 2019.
33. Chang, C.-M.; Lin, T.-K.; Chang, C.-W. Applications of neural network models for structural health monitoring based on derived modal properties. Measurement 2018, 129, 457–470.
34. González, M.P.; Zapico, J.L. Seismic damage identification in buildings using neural networks and modal data. Comput. Struct. 2008, 86, 416–426.