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Editorial

Artificial-Intelligence-Based Methods for Structural Health Monitoring

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1. Introduction

Intelligent and resilient infrastructure and smart cities make up a rapidly emerging field that is redefining the future of urban development and ways of preserving the existing infrastructure against natural hazards. Sensing, and especially networked sensing and monitoring, has been an integral part of a growing field. The analysis and interpretation of a large volume of data (collected by the sensor network or digital images) and the extraction of critical information that can determine the state of health, reliability, and safety, as well as the life cycle assessment of these infrastructures (including feature extraction), require advanced and more realistic computational models to be developed, as well as analysis tools that can predict the behavior of these systems under complex and even hazardous loading environments and identify potential sources of damage and deterioration in real time.

Over the past several years, a series of artificial-intelligence-based methodologies, including machine learning methods, have been proposed for model updating, diagnostics, data interpretation, and feature extraction for the heath monitoring of infrastructure systems. This rapidly emerging field of research has demonstrated superiority within system identification, feature extraction, damage identification, and even the direct response prediction of dynamical systems, and has shown promises for a wide range of practical applications. A typical integrating structural control and health monitoring structure is shown in Figure 1.

This Special Issue aims to stress the importance of developing and introducing AI-based methodologies for the structural health monitoring of infrastructure systems and the analysis and feature extraction of sensor data.

The keywords of this Special Issue are as follows:

- Structural health monitoring;
- Deep learning;
- Artificial intelligence;
- Data analytics;
- Damage detection;
- System identification;
- Feature extraction;
- Machine learning;
- Sensor network;
- Intelligent infrastructure systems.

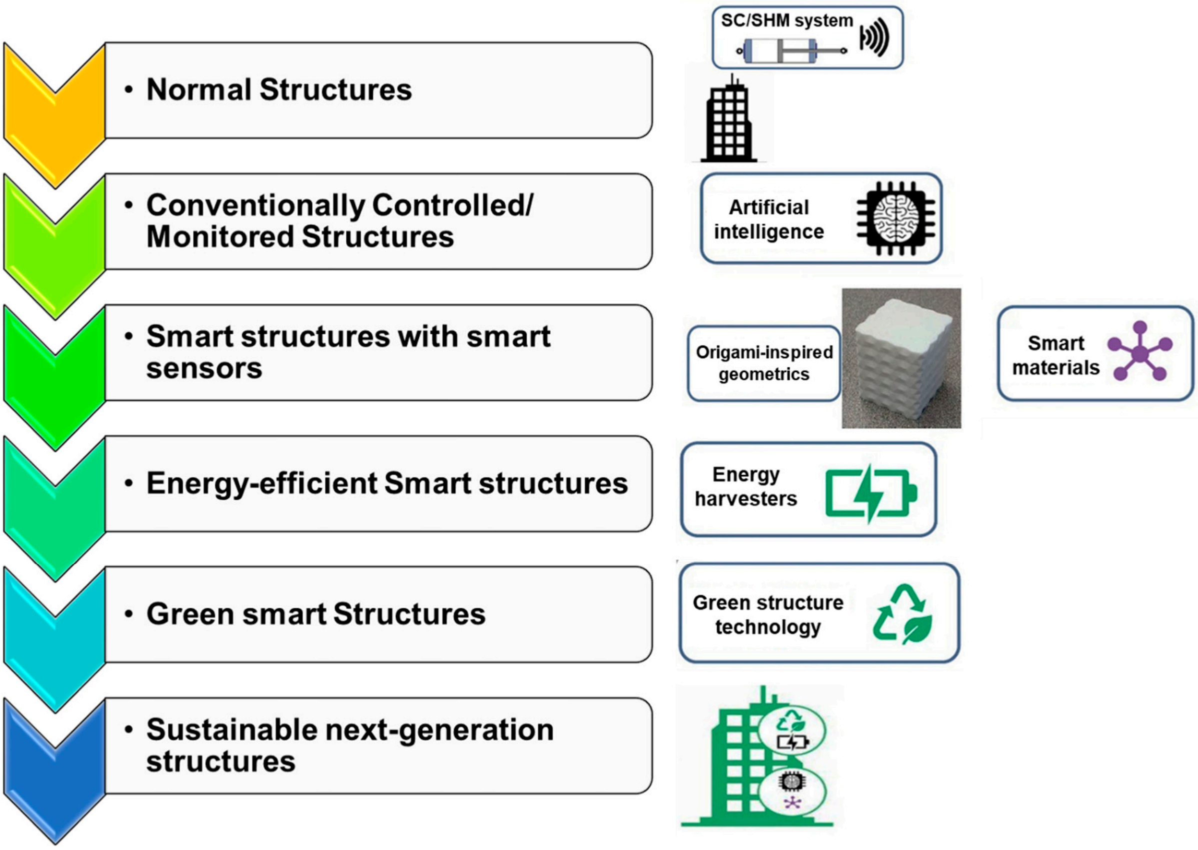

Figure 1. The main stages of typical integrating structural control and health monitoring systems.

Given the interdisciplinary nature of this topic, the proposed Special Issue will be a collection of contributions from scholars in several fields, and will cover topics such as: artificial neural networks; deep learning neural networks; system identification; Big Data in infrastructure systems; optimization; probabilistic methods for SHM combined with AI methods; and dynamic response prediction via AI methodologies.

2. Contributions

This Special Issue, comprising a total of sixteen research articles, is dedicated to recent developments in artificial-intelligence-based methods for structural health monitoring. The first two studies explored the bridges' cable monitoring system. Lu et al. [1] proposed a novel and intelligent approach for reliably evaluating the system of cable-supported bridges under stochastic traffic load by utilizing deep belief networks (DBNs). They introduced the theoretical basis for utilizing DBNs to approximate the structural load, and presented a computational framework to illustrate the procedures followed to evaluate the bridge system reliability via DBNs. Hou et al. [2] proposed a novel method for identifying time-varying cable tension based on the variational mode decomposition (VMD) method. This recent method decomposes signals and adaptively estimates instantaneous frequencies combined with the Hilbert–Huang transform method, where the time-varying modal frequencies were identified from stay cable acceleration data, and then the time-varying cable tension was identified by the relationship between cable tension and identified fundamental frequency.

The next two research articles [3,4] of the Special Issue proposed a non-probabilistic surrogate model based on wavelet weighted least squares support vector machine (WWLS SVM) to address the problem of uncertainty in vibration-based damage detection. The input data for WWLSSVM consist of selected wavelet packet decomposition (WPD) features of the structural response signals, and the output is the Young's modulus of structural elements.

For damage segmentation purposes, Shi et al. [5] proposed ways to improve the damage segmentation framework using two methods to train VGG-Unet models. They collected and manually labeled 200 corrosion images of steel and 500 crack images of rubber bearing to build the training dataset. The first method involves squashing segmentation to input squashed images from high resolution directly into the VGG-Unet model, while the second method, cropping segmentation, uses cropped images with a size of 224 × 224 as the input images. Meanwhile, in the study by Hoskere et al. [6], the structure damage segmentation was used alongside an open-source software platform "InstaDa" for the fast pixel-wise annotation of damage by utilizing binary masks to aid user input. They described details of InstaDam's software architecture and presented some of its key features. They also proposed several benefits of InstaDam by comparing it to the Image Labeler app in Matlab, and various comparisons were made between the InstaDam results. Moreover, experiments were conducted where two employed student annotators were given the task of annotating damage levels in a small dataset of images using Matlab.

Yazdchi et al. [7] is investigated the effect of nano-MgO on the durability of normal concrete under freeze–thaw conditions. They also created a total of 98 cubic 10 × 10 × 10 concrete samples for the compressive strength test, while 78 cylindrical concrete 10 × 20 samples were considered for the tensile strength and permeability tests to build the training dataset for gene expression programming (GEP) algorithm. They then applied GEP and three formulations were derived to predict the mechanical properties of concrete containing nano-MgO by randomly using 80% of the dataset for the training process and 20% for formulation testing.

Machine learning (ML)-aided structural health monitoring (SHM) can rapidly evaluate the safety and integrity of the infrastructure. The next two research articles [8,9] in this Special Issue introduced the framework of applying the ML algorithm for damage identification purposes. Muin et al. [8] used low dimensionality, namely cumulative absolute velocity (CAV)-based features, to enable the use of ML for rapid damage assessment. This experiment was performed to identify the appropriate features and the ML algorithm using data from a simulated single-degree-of-freedom system. Gao et al. [9] combined time series (TS) modeling and ML classification to automatically extract damage features and overcome the limitation of non-stationarity. They also proposed a two-stage framework, namely auto-regressive integrated moving-average machine learning (ARIMA-ML) with modules for pre-processing, model parameter determination, feature extraction, and classification.

The research article of Altabey et al. [10] proposed a novel deep learning framework for the crack identification for steel pipelines by extracting features from 3D shadow modeling. They also developed a novel deep neural network to process the 3D images from 3D shadow maps. The proposed automatic crack identification method successfully and efficiently processed 3D images and accurately diagnosed corrosion cracks.

Moreover, Finotti et al. [11] used a deep learning algorithm, called the sparse auto-encoder (SAE), to evaluate the algorithm when applied to characterize structural anomalies. They also explored the SAE's performance in a supervised damage detection approach to consolidate its application in the structural health monitoring (SHM) field, especially when dealing with real-case structures.

For the long-term management and monitoring of bridges, the next two works [12,13] featured in the Special Issue proposed new techniques for monitoring vehicle–bridge interactions and for the long-term management of bridge networks. The proposed decision support system used advanced prediction models, decision trees, and incremental machine learning algorithms to generate an optimal decision strategy.

Damage identification methods based on structural modal parameters were influenced by the structure form, the number of measuring sensors, and noise, resulting in insufficient modal data and low damage identification accuracy. Su et al. [14] and Zhang et al. [15] introduced a new framework for structure damage identification using new methods such as the bat algorithm (BA) [14] and virtual bass method based on damage sparsity [15].

The last article by Tang et al. [16] provided a framework for understanding natural disaster scenes from mobile images using deep learning. The authors investigated the problem of understanding disaster scenes through a deep learning approach. Two attributes of images were considered, including hazard types and damage levels. Three deep-learning models were trained, and their performance was assessed.

3. Conclusions

The articles in this Special Issue promote research to evaluate artificial-intelligence-based methods for structural health monitoring mostly via numerical approaches. As a Guest Editor, I believe that the overall quality of the methodologies and achievements presented in this Special Issue helps to progress our understanding of damage identification in intelligent and resilient infrastructure and smart cities using different artificial intelligence algorithms, consequently aiding the future design and optimization of advanced intelligence-based structures.

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