A New Benchmark Problem for Structural Damage Detection: Bolt Loosening Tests on a Large-Scale Laboratory Structure

Onur Avci, Osama Abdeljaber, Serkan Kiranyaz, Mohammed Hussein, Moncef Gabbouj, and Daniel Inman

Abstract Monitoring the structural performance of engineering structures has always been pertinent for maintaining structural health and assessing the life cycle of structures. Structural Health Monitoring (SHM) and Structural Damage Detection (SDD) fields have been topics of ongoing research over the years to explore and verify different monitoring techniques and damage detection and localization procedures. In an attempt to compare performances of different methods, benchmark datasets are valuable resources since the data is made available to researchers enabling side-by-side comparisons. This paper presents a new experimental benchmark dataset generated from tests on a large-scale laboratory structure. The primary goal of the authors was to explore brand-new damage detection and quantification methodologies for efficient monitoring of structures. For this purpose, a large-scale steel grid structure with footprint dimensions of 4.2 m $\times$ 4.2 m was constructed in laboratory environment and it has been used as a test bed by the authors. The structural members of the structure are all IPE120 hot-rolled steel cross sections. The simulation of structural damage was simply loosening the bolts at one of the beam-to-girder connections, which is a slight change of rotational stiffness at the joint of the steel grid structure. The authors shared the dataset for 1 undamaged and 30 damaged conditions and published it on a public website as a new benchmark problem for structural damage detection at http://www.structuralvibration.com/benchmark/ so that other researchers can use the data and test algorithms. The authors also shared one of the damage detection tools they used, One-Dimensional Convolutional Neural Networks (1D-CNNs). The application codes, configuration files, and accompanied components of the 1D-CNNs package are available for viewers at http://www.structuralvibration.com/cnns/.

Keywords Benchmark problem · Structural Damage Detection · Structural Health Monitoring · Damage localization · Damage quantification · Damage identification · Steel structures

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1 Introduction

The traditional way of monitoring civil infrastructure is based on visual inspections [1, 2]. Along with the computing and sensing technologies, dynamic response of structures has started to be used for condition evaluation [3–11] and serviceability assessment [12–20] of engineering structures. Structural Health Monitoring (SHM) and Structural Damage Detection (SDD) have emerged as research fields targeting efficient monitoring of structures [21–29] for which Machine Learning (ML) and Deep Learning (DL) algorithms have been implemented [30–38] to facilitate and optimize the identification and localization processes. Before the researchers apply newly developed damage detection and damage quantification methods on real structures, it is important that they verify the methodologies experimentally in laboratory. Yet, building a laboratory structure, arranging the logistics for data collection and processing, is not always easy. This is why benchmark datasets are made available to researchers to benefit from existing data. Benchmark datasets are useful resources for comparing the performances of various damage detection/localization/quantification procedures. Such datasets are convenient because the data becomes accessible to all, and since everybody uses the same data, the performance comparisons are systematic and more efficient.

In this paper, the authors are presenting a new experimental benchmark dataset generated by tests on a large-scale laboratory structure. The primary goal of the authors was to explore and test brand-new damage detection and quantification methodologies on the laboratory structure. It was later decided to share the dataset in a benchmark format so that other researchers can use the data and test their own methodologies. The One-Dimensional Convolutional Neural Networks (1D-CNNs) code package was also published on a website about the same time, by the authors.

The benchmark structure used to simulate the damage conditions was an inclined steel grid structure with footprint dimensions of 4.2 m × 4.2 m (Fig. 1). By loosening the bolts at the beam-to-girder connections, 31 different damage conditions were created on the benchmark structure. Acceleration data was carefully collected for each damaged and undamaged condition. The collection of the acceleration recordings formed the Benchmark dataset, providing SHM and SDD researchers with a new test bed for verifying newly developed vibration-based damage detection algorithms.

The steel frame consists of hot-rolled members (4 columns, 25 filler beams, 8 girders and brace elements to stabilize the columns). While the length of the 20 typical filler beams is 77 cm, the 5 cantilevered filler beams are about 1 m long (Fig. 1). The length of the girders is 4.6 m. As per grandstand specifications, there is a 20° inclination on the structure. All structural

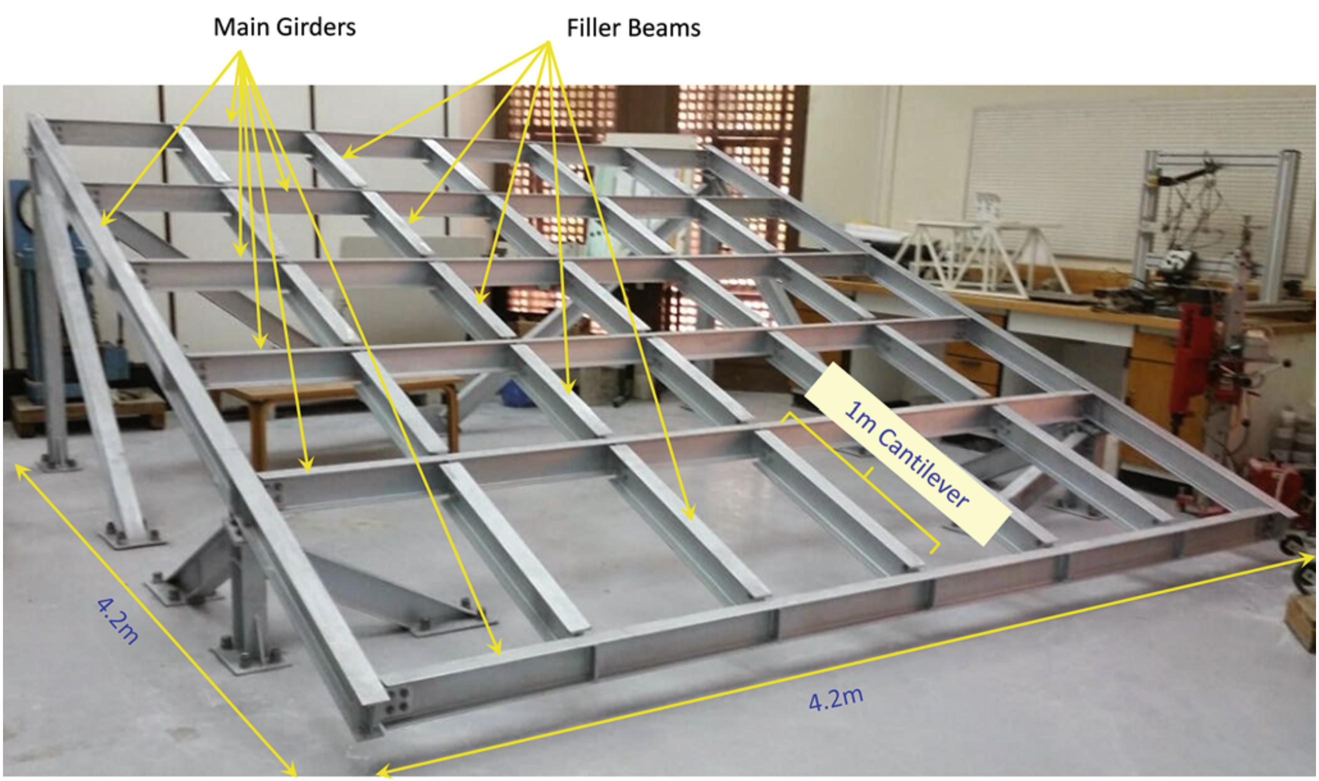

Fig. 1 The Benchmark structure

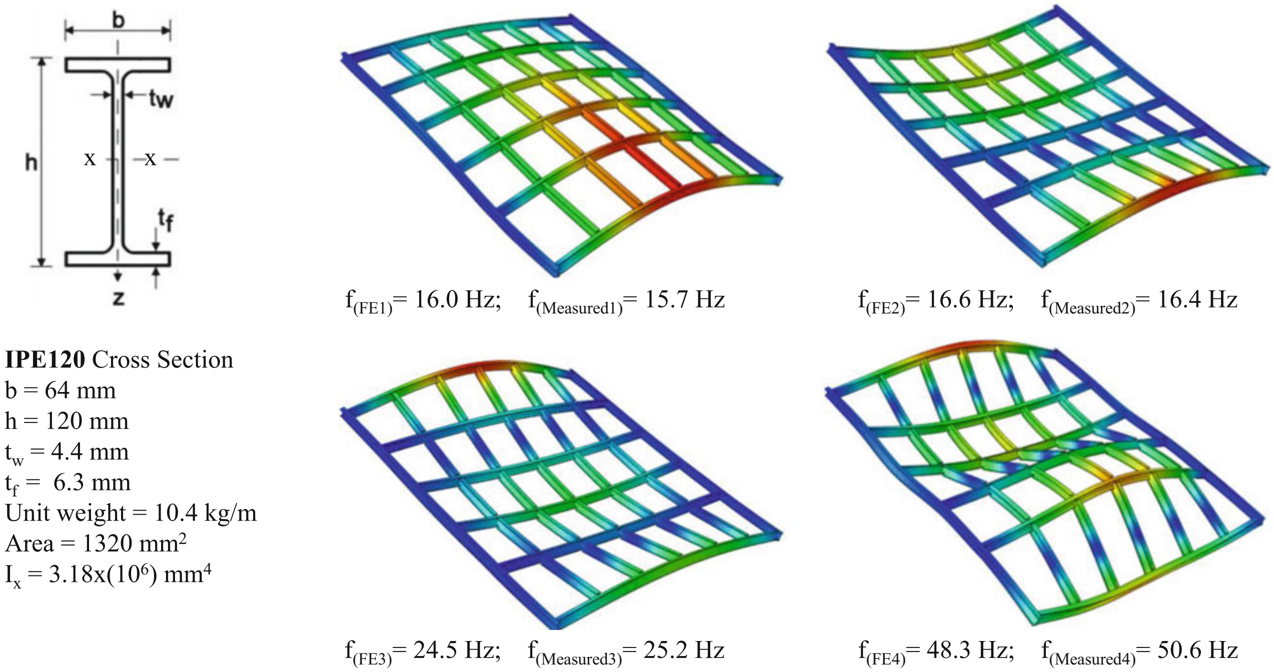

Fig. 2 IPE120 cross section and the first four bending modes

members are IPE120 cross sections (Fig. 2). Based on the structural drawings, a finite element model is created in Abaqus using C3D20R quadratic brick elements with 27 integration points (using 210 GPa for modulus of elasticity of steel), and the resulting first four governing bending mode shapes and corresponding modal frequencies are determined (Fig. 2). The measured frequencies per modal testing are processed in MEScope software and the values are shown in Fig. 2.

The total number of joints where the filler beams are being connected to the main girders is 30 (Fig. 3). One accelerometer was assigned for each joint and data was collected under various dynamic excitations without moving accelerometers between tests. Brüel & Kjær (model 8344) and PCB (model 393B04) accelerometers were used to record acceleration data, along with other dynamic testing equipment such as SmartAmp 2100E21-400 power amplifier, a dual 16-channel data acquisition system (DT9857E-16), and a modal shaker (Model 2100E11). Based on the type of dynamic excitation, a modal impact hammer or a shaker was utilized to create dynamic excitations as inputs.

For structural damage, the reference condition was considered as the undamaged state when all bolts are fully tightened (Fig. 4). Thirty additional conditions were individual bolt loosening at each joint shown in Fig. 3 (corresponding to 30 independent damage conditions). Loosening the bolts might be considered as a very slight damage, may be no damage at all. The authors wanted to consider bolt loosening as a damage based on the idea that when the damage detection methodology is sensitive enough to recognize and locate this slight damage condition and quantify it, this would be an indication of success for the methodology.

2 The Benchmark Website

The Benchmark dataset includes accelerations for each damage condition. The website address for the Benchmark dataset is:

- http://www.structuralvibration.com/benchmark/

  The main page of the Benchmark website includes links for additional information on the overview of the dataset package; grandstand simulator; instrumentation; damage scenarios; dataset descriptions; and downloading links (Fig. 5a). Users can navigate through the menu options on the left side of the main window. In addition to the Benchmark dataset, the damage detection tool used by the authors, One-Dimensional Convolutional Neural Networks (1D-CNNs) application codes and accompanied files are shared on this website:
- http://www.structuralvibration.com/cnns/

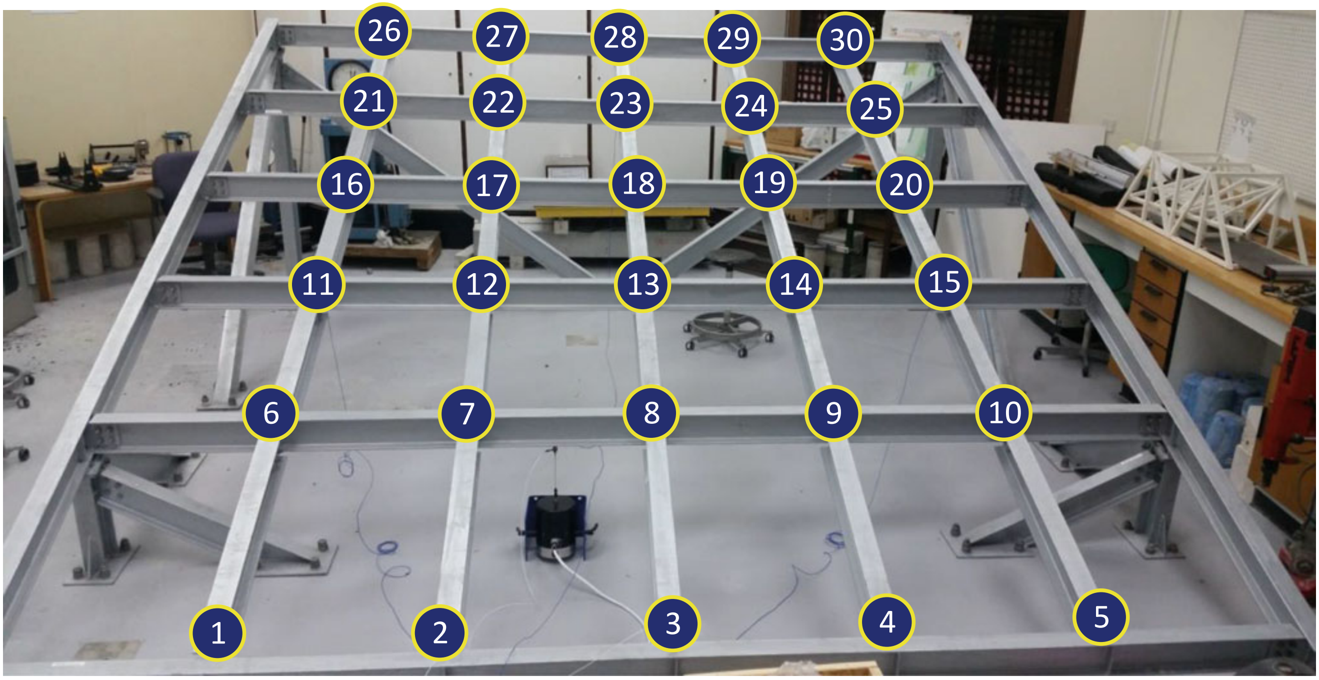

Fig. 3 Joint numbering on the Benchmark structure

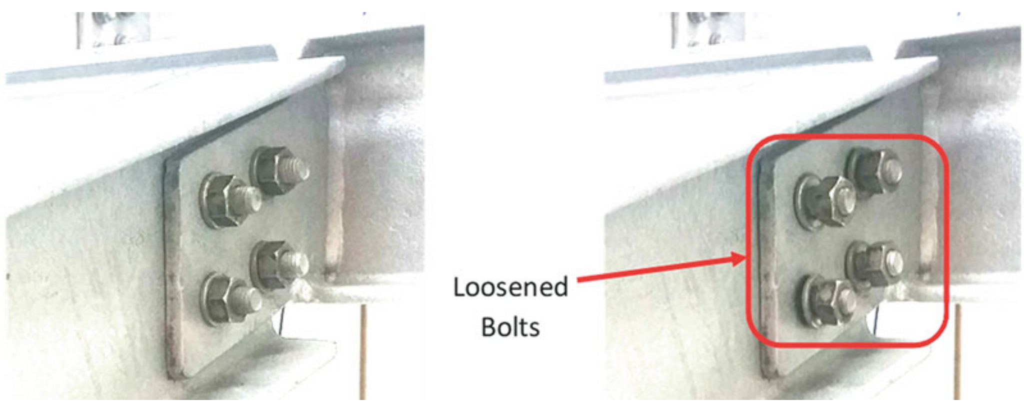

Fig. 4 The “damage” is introduced to the benchmark structure by loosening the bolts at the joints

Similarly, through the menu on the left side of the main window, the users can access information on back-propagation, and 1D-CNN package which includes the C++ Windows Console application; Matlab code; CDF files; configuration file; and downloading links (Fig. 5b).

After successful use of the original 2D version applications of CNNs [39–47], the 1D-CNNs were also proven to be an accurate and reliable tool used in various fields [48–51]. They are implemented as a damage identification/localization tool with the built-in adaptive architecture, merging the steps of feature extraction and classification into one compact unit. The first civil/structural engineering application of 1D-CNNs was conducted on the Benchmark structure, by the authors. The procedure runs directly on the raw acceleration signal, making the methodology available for real-time use.

The authors have conducted extensive analytical and experimental research on the Benchmark structure, mostly focusing on damage detection methods. Some of the publications produced based on the work on the Benchmark structure are [52–56], followed by a patent on the 1D-CNN SDD methodology [57]. Based on the success of the 1D-CNNs on the Benchmark structure as a damage detection and localization tool, the authors tested 1D-CNNs on other structures. For example, on another benchmark structure [58], 1D-CNNs showed excellent performance on identifying and quantifying the damage [59, 60]. In addition, the 1D-CNN code was also successful on damage identification on bearings as a rotating machine element [61, 62].

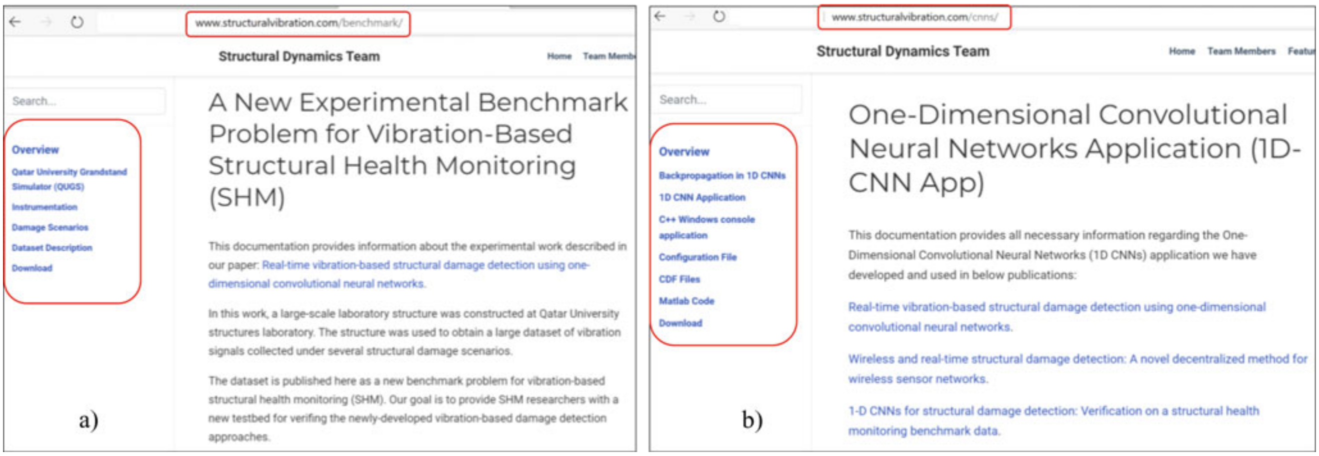

Fig. 5 Website views for (**a**) Benchmark dataset; (**b**) 1D-CNNs Application

3 Benchmark Dataset Description

The Benchmark dataset comprises two datasets to be downloaded (Dataset A and Dataset B). One dataset is for training and the other one is for testing purposes. The datasets include 31 TXT files (a total of 62 TXT files). Among the 31 files in one dataset, 30 files are dedicated to the damaged (untightened bolts) condition for each joint shown in Fig. 3. One additional TXT file is for the undamaged condition of the Benchmark structure. For each damaged condition, the accelerations were recorded for 256 s at each joint subjected to a white noise shaker excitation at a sampling frequency of 1024 Hz. This results in signals containing $256 \times 1024 = 262{,}144$ samples. For one dataset, this procedure was repeated 31 times, therefore resulting in 31 TXT files. The data collection process was done twice, resulting in two different datasets: Dataset A and Dataset B.

The naming of the TXT files is explained below:

Dataset A
- zzzAU.TXT: Undamaged condition
- zzzAD1.TXT: Damage at Joint 1
- zzzAD2.TXT: Damage at Joint 2
- ...
- zzzAD30.TXT: Damage at Joint 30

Dataset B
- zzzBU.TXT: Undamaged condition
- zzzBD1.TXT: Damage at Joint 1
- zzzBD2.TXT: Damage at Joint 2
- ...
- zzzBD30.TXT: Damage at Joint 30

Each TXT file contains 31 columns
- Column 1: timestamp.
- Column 2: Signal measured at Joint 1.
- Column 3: Signal measured at Joint 2.
- ...
- Column 31: Signal measured at Joint 30.

4 Conclusions

A new experimental Benchmark dataset generated from dynamic tests on a large-scale laboratory structure is presented in this paper. The Benchmark structure is a large-scale steel grid structure with footprint dimensions of 4.2 m × 4.2 m. It was constructed in a laboratory and has been used as a test bed for several publications by the authors. All structural members are hot-rolled steel IPE120 cross sections. For the structural damage detection studies, the damage was introduced at the joints of beam-to-girder connections by loosening the bolts. Even though bolt loosening is a slight change of rotational stiffness at the joints of the steel structure, the authors were able to detect, locate, and quantify it in their studies. The authors posted the dataset for 31 structural damage conditions on a public website as a new benchmark problem for structural damage detection at http://www.structuralvibration.com/benchmark/. The authors also shared the damage detection tool they used: One-Dimensional Convolutional Neural Networks (1D-CNNs). The 1D-CNNs package (application codes and accompanied files) is posted at http://www.structuralvibration.com/cnns/. The authors would appreciate feedback from other researchers on the Benchmark data and the 1D-CNNs package.

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