Reconstructing Health Monitoring Data of Railway Truss Bridges using One-dimensional Convolutional Neural Networks

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ABSTRACT

Structural Health Monitoring (SHM) system uses sensors to collect information and evaluate the structure, aiming for early damage detection. For many reasons, data from sensors can be corrupted, affecting the assessment results. Reconstructing lost or corrupted data helps complete it, improves structural assessments, and ensures structural safety. Artificial Intelligence (AI) has emerged in recent years as a solution to data problems. This study proposes the use of a One-Dimensional Convolutional Neural Network (1DCNN) to reconstruct lost vibration data during SHM. A complete dataset was used to train the 1DCNN network. After completing the training, the 1DCNN network received incomplete data to return erroneous data. The results of the study show that the proposed method is able to reconstruct vibration sensor data.

Keywords-1-dimensional convolutional neural networks; structural health monitoring; recontruction data

I. INTRODUCTION

Monitoring response to detect structural damage and abnormalities to provide timely solutions and reduce maintenance costs is the main goal of SHM. As a result, structures that benefit from an SHM system typically have an extended lifespan. SHM also ensures the integrity of the system to some extent and can prevent possible future failures by emitting advance warnings about unusual behavior [1]. SHM includes advanced sensing, automation, and AI techniques, allowing to identify damage and predict structural risks [2].

In SHM, accurate and continuous data are crucial for ensuring the safety and sustainability of structures like bridges, buildings, dams, and other infrastructure [3, 4]. However, there are various reasons why the collected data might be imperfect, incomplete, or inaccurate. Thus, data reconstruction becomes an important aspect of the SHM process. SHM often requires continuous data to detect subtle changes or anomalies in structures. Missing data can hinder the detection and prediction of problems, leading to the risk of overlooking early warning signs of structural degradation or failure. In practice, sensors can fail or cease to function, resulting in data loss. Moreover, communication issues or system errors can cause partial or complete data loss. Data reconstruction helps address these gaps and maintain continuity in monitoring. Inaccurate or noisy data can lead to skewed or unreliable results in structural health analyses. Data reconstruction helps restore or clean the data, improving the accuracy and reliability of analyses and predictions. Data reconstruction allows engineers and researchers to create more accurate models of structural behavior. This can improve the ability to predict potential failures and support decision-making for maintenance and repairs [5, 6].

Transport infrastructure is increasingly developing, creating favorable conditions for other industries. Damage to transportation infrastructure, especially large bridges located on vital routes, can seriously affect the economy [7]. Therefore, assessing and monitoring the integrity and early detection of damage to bridge structures is essential [8-10]. In recent years, with the rapid development of sensor technology and information analysis, bridge SHM systems have been installed and support managers in making maintenance and repair decisions. Sensors are installed on bridge structures to collect data and early detect abnormalities in the bridge structure [11, 12]. However, in long-term SHM, sensor errors due to environmental factors, sensor damage due to aging, and data transmission errors may occur. Data reconstruction is becoming an important research area in SHM.

In the recent decade, deep learning techniques have emerged strongly in solving data problems. In the field of SHM data reconstruction, many algorithms have been proposed. Authors in [13] proposed using a deep convolutional generative adversarial network to reconstruct lost health monitoring data. The results of the proposed method have good performance in reconstructing data from sensors, even with a data loss rate of more than 80%. Authors in [14] researched and presented generative adversarial network–based unsupervised learning in SHM data reconstruction. This method is considered a great tool with excellent performance. Authors in [15] demonstrated the effectiveness of a machine learning-based approach in reproducing sensor data in SHM. Authors in [16] used a densely connected convolutional network to reconstruct the dynamic data of an SHM system. Many other studies [17-19] have demonstrated the potential of AI in general and deep learning in particular in reproducing SHM data. In this research, a 1DCNN will be applied to reconstruct vibration data for structural health monitoring.

II. METHODOLOGY

A. The 1DCNN Model

The 1DCNN [20] is a type of neural network designed for processing one-dimensional data, particularly time series data. They are widely used in various applications, including time series forecasting, due to their ability to extract important patterns and features from sequential data. The structure of 1DCNN in time series forecasting includes convolutional layers, pooling layers, flattening layers, and fully connected layers (Figure 1).

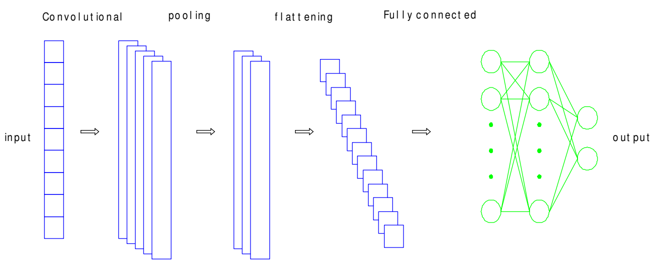

Fig. 1. The 1DCNN architecture.

Convolutional layers use filters to extract features from time series data. The kernel size and stride are important parameters in the convolution process. Pooling layers are used to reduce data size, helping to increase computational efficiency and decrease complexity. Pooling layers are typically used after convolutional layers to summarize information. To create the final prediction, fully connected layers connect all the features that were extracted from the earlier layers. They are usually at the end of the network. The 1DCNN is a powerful tool for time series forecasting, combining computational efficiency with advanced feature extraction capabilities. The convolution process is performed by applying a filter (kernel) to the input data to create an output. If the input is a one-dimensional array x and a one-dimensional filter w, the result of the convolution is a new array y:

$$y(i) = \sum_{j=0}^{k-1} x(i.stride + j).w(j) \tag{1}$$

where $y(i)$ is the value at position i in the output, x is the input, w is the filter, k is the filter size, and *stride* is the step size.

The output size of a convolutional or pooling layer is calculated by:

$$O = \left\lfloor \frac{(I - k + 2.padding)}{stride} + 1 \right\rfloor \tag{2}$$

where O is the output size, I is the input size, k is the filter/kernel size; *padding* is the number of elements added to the start or end of the input, and *stride* is the step size.

Max pooling is the process of taking the maximum value within a window. The general formula to calculate the output value of max pooling is:

$$y(i) = max(x(i.stride) : (i.stride + poolsize)) \tag{3}$$

where *poolsize* is the size of the pooling window, $y(i)$ is the output value at position i, and x is the input.

When the data from the convolutional and pooling layers are fed into the fully connected layer, the output is calculated by:

$$y = W.x + b \tag{4}$$

where y is the output, W is a weight matrix, x is the input (flattened), and b is the bias vector.

B. Reconstruction Process

Data preprocessing steps play an important role in successfully training an AI model. Data preprocessing provides a more general view of the data. The data are explored in this step and a deeper insight will be obtained. At the same time, data preparation in accordance with 1DCNN's input requirements is also performed. Data are normalized and divided. In this study, data from sensors in the monitoring system are used to train 1DCNN. The data obtained from the sensors will be set corresponding to the sensitivity of each sensor in the measurement program. These values will not be of the same standard. Data normalization aims to bring all sensor data to the same value range from 0 to 1.

In the next step, the input and output of the 1DCNN network are determined. The input here consists of data from conventional sensors. The output is the sensor data that are considered to have errors. The data are divided into training set and test set. After dividing the dataset, the training set is first used to train the 1DCNN, so that the network can learn the nonlinear mapping relationship between the regular and the corrupted sensor data. Once the network training process is complete, the test set will be fed into the trained neural network to reconstruct the lost data. The data reconstruction process is shown in Figure 2. The data reconstruction process is performed in Python language with the Scikit-learn, Numpy and Matplotlib libraries. This research leverages resources from Google-Colab with GPUs to perform training

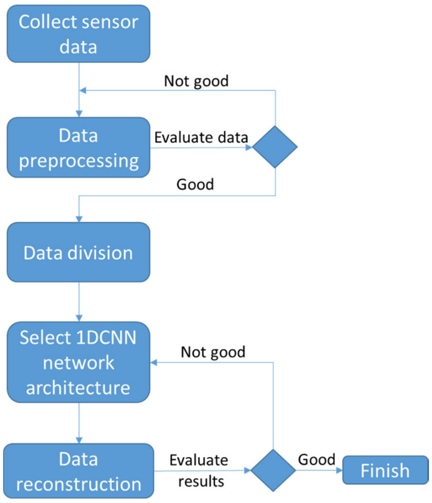

Fig. 2. Data reconstruction process with 1DCNN.

III. CASE STUDY

A. *The Case Study*

In this research, the case study used is the Thang Long Bridge, in Hanoi, Vietnam (Figure 3). The Thang Long Bridge is a steel truss bridge with a continuous structure. The bridge consists of 2 floors: the upper floor is used for cars, the lower floor for railways and rudimentary vehicles on both sides [21].

Thang Long Bridge is designed according to the 22TCN 18-79 standard. The design load for the railway bridge is the T24 train, and the design load for the motorway is H30-XB80 [21]. The main bridge is a steel truss bridge (mainly 10ХСНД low-alloy steel), the approach bridge consists of reinforced concrete beams. The main bridge across the river is 1.688 m long and includes 5 modules, each consisting of 3 continuous steel beam spans.

Having been exploited and used for nearly 50 years, the bridge was inspected, evaluated and majorly repaired in 2020. After repair, the bridge went into stable operation and was only periodically maintained. A thorough bridge inspection was carried out during this study.

B. *Field Data Collection*

A real data set of 5 vibration sensors was collected from one span of the Thang Long bridge (Figure 3). A measuring grid was designed to be deployed with the goal of collecting vibration data from 5 points on the bridge. Five high-sensitivity PCB sensors were used to collect data. The sensors were installed vertically. After arranging and installing the measuring devices and sensors, the collection system begun to collect data.

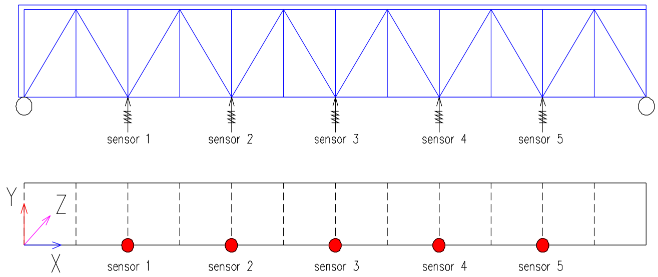

Fig. 3. Sensor arrangement on the bridge.

The data were recorded and saved. A laptop managed the measurement process and collected and recorded the dynamic responses of the sensors (Figure 4). Data collection time was about 20 min with a sampling frequency of 1651 Hz.

(a)

(b)

Fig. 4. Field data collection: (a) sensor installation, (b). control of the measurement process.

C. *Single-Channel Sensor Data Reconstruction*

In the first case study, data from one sensor were considered faulty, while the remaining 4 sensors operated normally. The task was to reconstruct the data from a failed sensor. The sensors' data are numbered from 1 to 5. Sensors 1, 2, 3, and 4 work normally, whereas sensor 5 is faulty.

The proportion of selected training data is 75%, while remaining 25% is the testing data. After being preprocessed, the training data were fed into the 1DCNN network for training. For the case of single-channel data reconstruction, the study uses a 3-layer 1DCNN with 512 filters, selected Kernel size of 2, and ReLu activation function. After each 1DCNN layer, there is a Max-pooling layer to extract data features. Finally, the data were flattened and fed into a densely connected network to produce the output. The loss function chosen is MSE with Adam optimization algorithm. The maximum number of epochs selected was 1000 and the batch size selected was 20. Once finished, the loss converges close to zero in the training dataset. Figure 5 shows the loss during training.

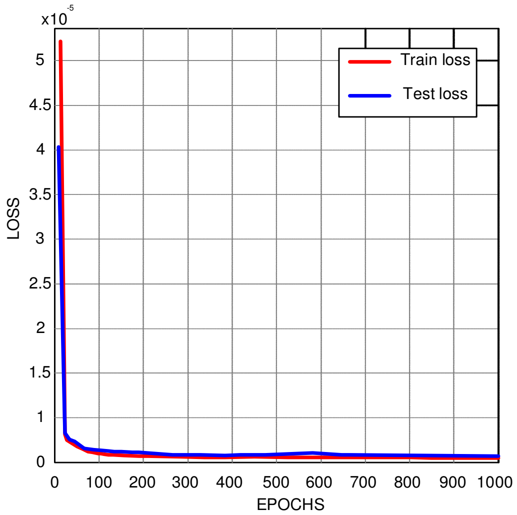

Fig. 5. Single-channel reconstruction training loss.

Figure 6 shows the reconstructed data results compared to the actual data. The results show that the data reconstructed in the single-channel case provide good results. After training, the network has high data reproduction performance and high accuracy. In fact, real data have the presence of noise and unexpected environmental stimuli during the experiment, so reproducing absolutely accurate data is very difficult. The reconstructed data do not match the real data exactly. However, the difference between real data and virtual data is negligible. The reconstructed data and real data match each other up to 93.45%. To retest the performance of the network after training, the test data was utilized. After inputting the data from the error-free sensors, the error data were restored.

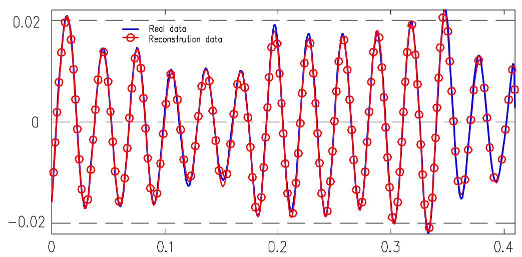

Fig. 6. Comparison of real and reconstructed data of sensor 5.

D. Multiple-Channel Sensor Data Reconstruction

In this scenario, data from sensors 3, 4, and 5 were considered errors, whereas sensors 1 and 2 are considered to be in normal operation. So the input data will be the data of sensors 1 and 2, the output data will be the data of sensors 3, 4, and 5. Data preprocessing operations were performed similarly to the single-channel case. After data preprocessing, the 1DCNN was trained. The network configuration used is similar to case 1 of single-channel data reconstruction. The 1DCNN network was trained for 1000 epochs. The loss during training is shown in Figure 7.

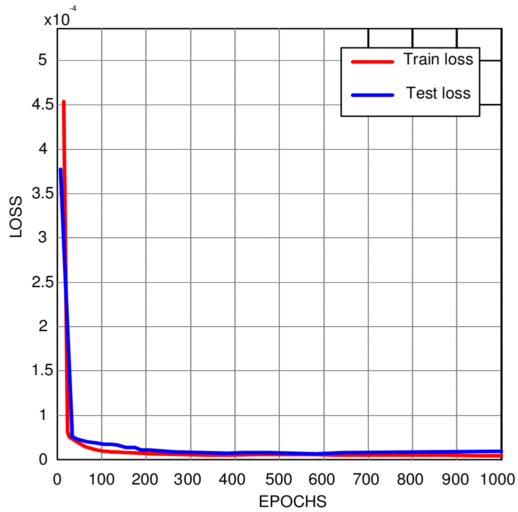

Fig. 7. Multi-channel reconstruction training loss.

(a)
(b)
(c)

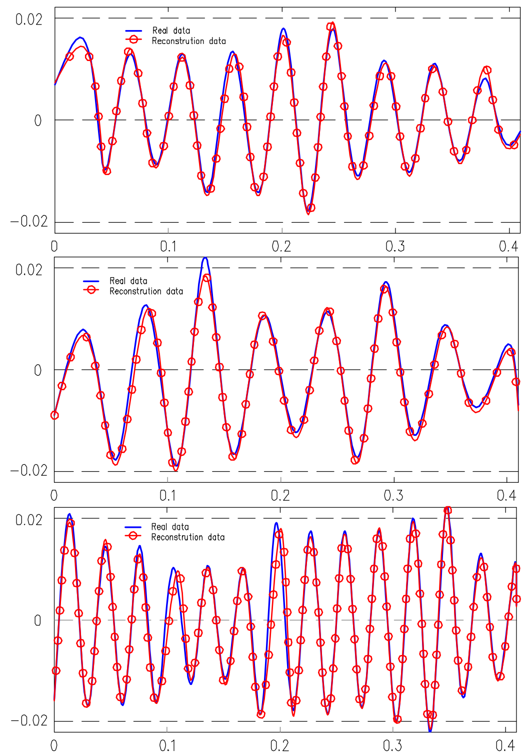

Fig. 8. Comparison of real and reconstructed data: (a) Sensor 3, (b) sensor 4, (c) sensor 5.

The test results with the reconstructed data for sensors 3, 4, 5 are shown in Figure 8. According to the results, the reconstructed data are relatively accurate compared to the real data. The difference is insignificant. Overall, the proposed 1DCNN learned and reconstructed data in case of data loss across multiple channels. The reconstructed data can represent real data for SHM.

IV. CONCLUSIONS

This study proposes a new method based on 1DCNN to reconstruct lost vibration data for structural health monitoring. The implementation process is clearly presented in the study. The effectiveness of the proposed method has been proven through actual test data at the Thang Long bridge. The main conclusions of this study are:

- Data loss is inevitable in structural health monitoring. Appropriate measures need to be taken to overcome this situation. Deep learning, specifically 1DCNN, has the potential to perform this task well.
- The data reconstruction method can be applied either in single channel or in multi-channel data loss. In both cases, the case study shows that the results were in accordance with the requirements for structural health monitoring
- Data preprocessing and data preparation play an important role in training the 1DCNN. Standardized data sources will help improve network performance. At the same time, preprocessed data will help make 1DCNN training time faster and better.
- Further research will focus on improving the effectiveness of the proposed network as well as expanding the functionality of 1DCNN in structural damage detection.

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