Damage detection of bridges by means of neural network-supported FEM

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1. Introduction

There are currently about 730,000 bridges in Japan, of which about 660,000, or more than 90%, are managed by local governments and local public agencies. Approximately 34% of them are over 50 years old. This is expected to increase to about 59% in 10 years. Of the 27938 structures inspected between 2018 and 2021, 13833 (49.5%) have been identified as having abnormal deformation, and they need to be observed for a certain period [1]. Therefore, the maintenance of bridges is a serious problem.

The structural integrity of engineering structures such as bridges and buildings exposed to man-made and natural environments is constantly changing due to various factors. To ensure the safety of the structure, close-up visual inspections should be carried out once every five years [2-3], as well as conducting the Finite Element Method (FEM) based SHM. However, even with improvements in computing and sampling methods, updating the complicated finite element (FE) model with higher degrees of freedom is time-consuming. The large uncertainties can lead to large discrepancies between the measured physical response and the response from FEA, which can reduce the reliability of the predictions. This study aims to propose SHM using a data-driven FE model that combines machine learning and FEM to avoid updating the FE model, reduce the amount of FE calculation, and increase the validity of the prediction. The artificial neural network (ANN) is adopted to solve the problem of inconsistency between the results of FEA and observed data. The feasibility of the proposed method is discussed using data from laboratory experiments on a model bridge and FEA.

2. Methodology

In this research, a method with three main processes, 'Training', 'Matching', and 'Predicting' is developed (**Fig.1**). Computation time of the FEA is reduced by avoiding FE model updates. Discrepancies between measured physical response and FEA response are solved using a scaling operator. Damage detection could be achieved without the need for data collection through the creation of a library of FEA results. The updating of the model is achieved by updating the scaling operator, which is completely separate from the ANN and the FEM.

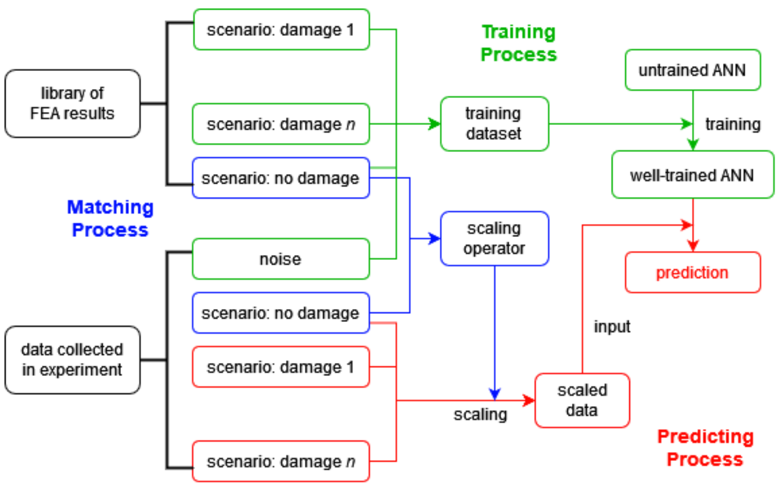

Fig.1 System of the proposed method.

3. Target bridge

The bridge in the experiment (**Fig.2**) is a simply-

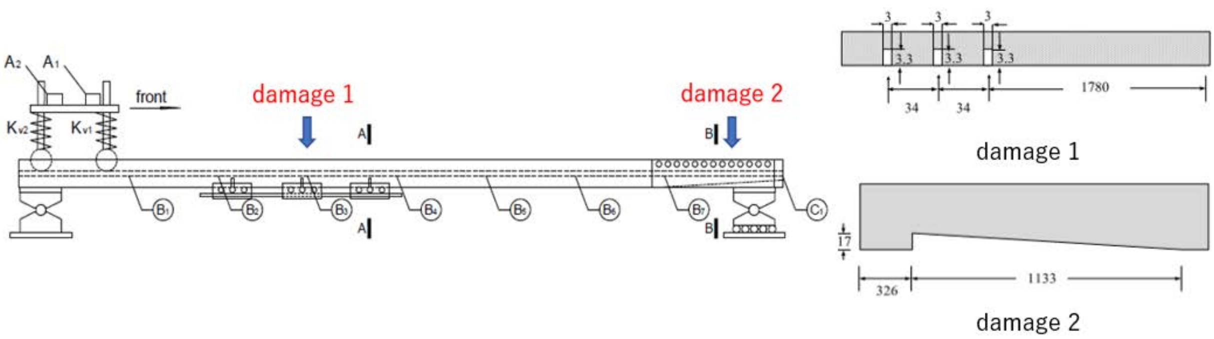

Fig.2 Bridge model for the in-house experiment.

keyword artificial neural network; damage detection; finite element method, scaling operator
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supported steel bridge with a span length of 5.4 m. A vehicle moves on the bridge at a speed of 9.4m/s. Sensors are set the under the bridge to collect real-time acceleration and displacement. The sampling frequency of the measurement was 200 Hz. Reinforcements were installed on the bridge. The damage on the bridge is simulated when reinforcement is removed.

4. The surrogate model (ANN)

The ANN has three hidden layers of 512, 128, and 32 neurons. The input layer is a flattened 62×7 matrix. The number of rows is determined by the time step in FEA, and the number of columns is determined by the number of sensors. The learning rate is 0.001.

The activate function is the rectified linear unit (ReLU), and the error function is a combination of softmax and means square error (MSE).Updating of the weight $\boldsymbol{W}$ in the ANN from layer Q to layer R could be summarized as:

$$w_{ij}^R(k+1) = w_{ij}^R(k) + \eta \nabla w_{ij}^R(k) \tag{1}$$

$$\nabla w_{ij}^R = \begin{cases} p_i(1-p_i)(p_i-\hat{y}_i)\cdot p_j & \text{R is the output layer} \\ t_i(t_i-\hat{y}_i)\cdot t_j & \text{if } t_i > 0 \\ 0 & \text{if } t_i \le 0 \end{cases} \tag{2}$$

where w_{ij}^R is the weight of the jth neuron in layer Q on the ith neuron in layer R, η is the learning ratio, and k is the epoch of the calculation.

A scaling operator consists of a kernel and a Hadamart operator. The expression of the kernel $\boldsymbol{K}$ is given by:

$$B(i,j) = \sum_{dx=1}^{m} \sum_{dy=1}^{n} K(dx,dy)\cdot A(i-dx+p, j-dy+q) \tag{3}$$

The expression of the Hadamart operator $\boldsymbol{H}$ is given by:

$$B(\boldsymbol{A} \circ \boldsymbol{H})_{ij} = (\boldsymbol{A} \odot \boldsymbol{H})_{ij} = A_{ij}\cdot H_{ij} = B_{ij} \tag{4}$$

The model updating is independent of the FE model and the ANN (**Fig.3**). It prevents updating complicated FE models as well as unknown internal parameters in the ANN.

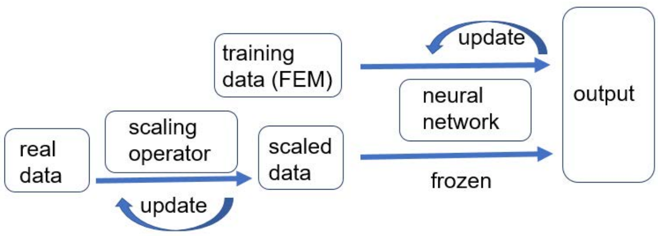

Fig. 3 Updating of scaling operator.

5. Result of prediction

To prevent overfitting, the training was stopped at the 23rd epoch. After that, the ANN is never updated. By updating the scaling operator, the model can detect damages in different scenarios. The accuracy of the prediction is shown in **Table 1**.

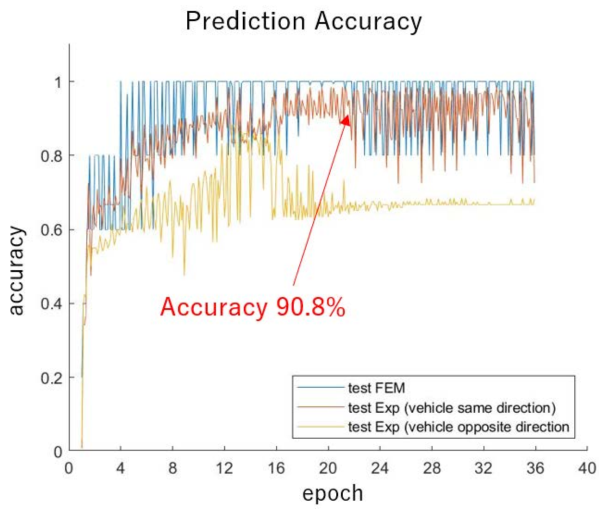

Fig. 4 Accuracy of prediction by using ANN.

Table 1. Accuracy of prediction.

bridge condition	Damage detection	accuracy
no damage	damage 1 and 2	90.8%
damage 1	damage 2	95.0%
damage 2	damage 1	96.7%

6. Conclusions

The study investigates a method to detect damage using ANN-supported FEM. A scaling operator independent from both systems takes on the task of model updating. It is demonstrated that it is possible to detect damage under different conditions by updating the scaling operator. It greatly reduces FEA's computing time and avoids adjusting the ANN's internal parameters. The accuracy of prediction is quite satisfactory.

References

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