A Neural Network and Post-processing for Estimating the Values of Error Data

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Abstract: A sensor network is a key factor for successful structural health monitoring (SHM). Although stable sensor network system is deployed in the structure for measurement, it is often inevitable to face measurement faults. In order to secure the continuous evaluation of targeted structure in cases where the measurement faults occur, appropriate techniques to estimate omitted or error data are necessary. In this research, back-propagation neural network is adopted as a basic estimation method. Then, a concept of post-processing is proposed to improve an accuracy of estimation obtained from the neural network. The results of simulation to verify performance of estimation are also shown.

1 INTRODUCTION

A structural health monitoring (SHM) is gradually gathering attention to guarantee safety or serviceability in various technical fields including civil, mechanical, and aeronautical engineering. Most of SHMs are initiated with composition of a sensor network designed for its purpose, and then progress based on acquired data. Although a stable sensor network is the primary element for further progression of SHM process, unfortunately many cases where acquisition of normal data is impossible exist due to malfunction, problem in power supply, and(or) obstacles in communication. In these cases, normal evaluation on the status of structure, which is an ultimate objective of SHM and sensor network, becomes difficult until proper maintenance.

There may be two possible approaches for continuous evaluation in case where measurement faults occur: 1) evaluaitng a state of structure through available data. 2) estimating the values of unavailable data which indicates omitted or unusable data, and then evaluating a state. This paper deals with a proper process for estimating the values of error data caused by measurement faults to secure continuous SHM. A back-propagation neural network (BPNN) which is robustly and successfully used among various artificial neural network (ANN) methods is adopted as a basic technique into estimation. It allows a model-free estimation since it only requires data for forming neural network. Additionally, post-processing of BPNN leading to more accurate estimation will be presented. The post-processing is motivated from how to compose training sets. Finally, a simulation utilizing finite element (FE) program (OpenSees) and its results will be discussed in regards to the performance.

2 APPLICATION OF BPNN

To achieve a final goal of this research, which is to find an effective and model-free estimation technique, a concrete idea is established as: to discover the direct relationship between two types of data sets acquired from stable sensor network in advance to the occurrence of measurement faults. Herein, first set is obtained from the sensors which will face measurement faults and second set is obtained from the sensors which will survive from the faults. This approach enables model-free estimation, and thus enhances applicability. However, it is almost impossible to set the relationship as a form of function if considering complex systems such as building structures, whereas ANN is most suitable for such systems.

An ANN has been widely applied on various fields including engineering and business in order to find the relation between inputs and outputs for the

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complex or ambiguous systems. BPNN utilized in this study is based on multi-layer perceptron with back-propagation algorithm, and is most robustly applied among various ANN techniques. The references for BPNN are readily available thanks to a large number of researches on BPNN and its applications being conducted.

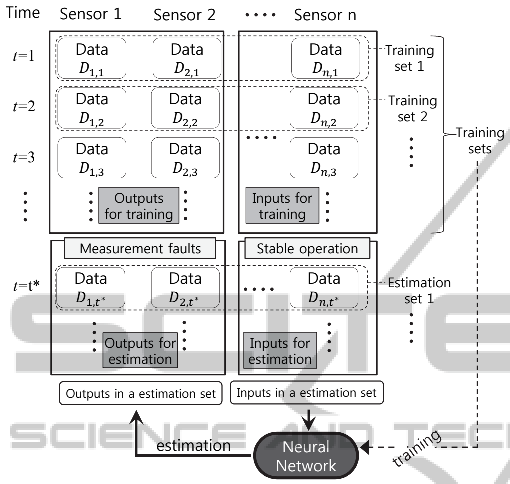

Figure 1: Typical training sets for neural network.

3 TRANING SETS

3.1 Typical Training Sets

The training sets directly influence the quality of neural network. Inputs and outputs for BPNN are composed of measured values obtained from stable sensor network. Figure 1 illustrates composition of training sets which is regarded as a typical case in this research. Inputs in typical training sets consist of the values from active sensors that will survive after malfunction occurrence at $t = t^*$ and outputs consist of the values from unstable sensors that will be inactive due to errors in the sensors or network.

3.2 Self-referential Training Sets

Second type of training sets has different outputs from those of typical training sets, but has identical inputs. The outputs include input components as shown in figure 2 and this type is named as self-referential training sets. In case of building structure, for example, if measurement faults occur at two sensors among three sensors which are deployed in close proximity, expected values of data from two unavailable sensors can be forecasted within acceptable range in consideration with the value from one surviving sensor. This characteristic gives a possibility that input components in outputs may work as a controller to make estimated values more acceptable.

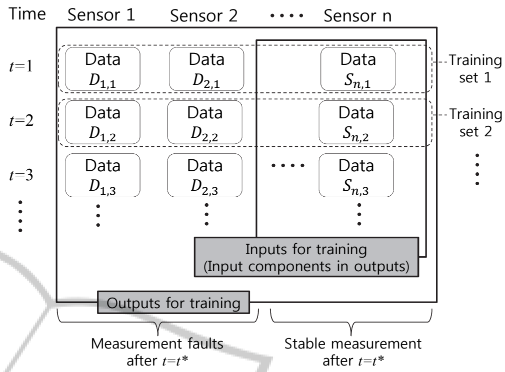

Figure 2: Self-referential training sets.

4 A POST-PROCESSING

A neural network trained by self-referential sets takes inputs and then reversely gives those estimated values. Note that outputs include input components. Nonetheless, estimated inputs and real inputs are not identical since training of the network progresses toward the direction of minimum error on total estimation, but not on input components. Instead, this point implies the opportunity to improve an accuracy of the estimation through appropriate adjustment processe which makes the values of estimated and real inputs same. Thus, post-processing of BPNN trained by self-referential sets can be expected to improve overall accuracy of estimation.

A concept of the post-processing is illustrated in Figure 3. The post-processing is basically based on the neural network trained by self-referential sets. First work is numbering the outputs in accordance with a rule that the smaller difference between data numbers means the stronger correlation between data. For instance, displacements of every story show simple serial topology of correlation as shown in Figure 3. Then, in accordance with correlation topology, the intervals are determined by setting k number of input components as nodes of intervals. The key concept of post-processing is that the data being closer to the centre of interval means the bigger change occurs. This concept corresponds with the expectation that extent of the correlation between dead and surviving data will be stronger as distance being closer each other. Regarding serial topology of correlation, adjustment function $g_j(i)$ for i data in j

interval is derived as Equation (1) and illustrated in Figure 4.

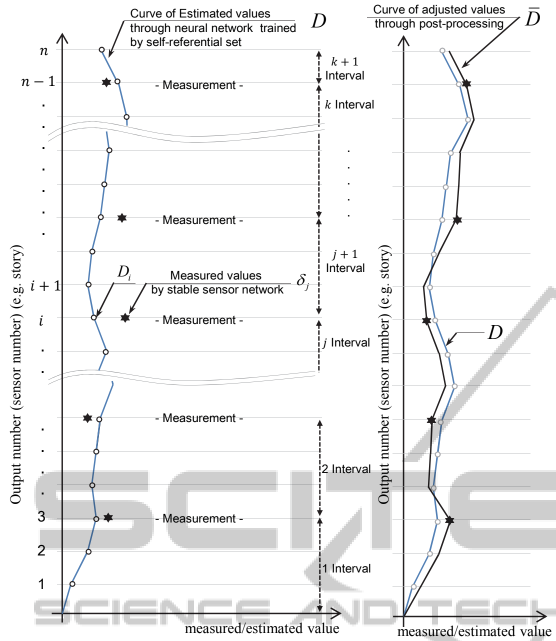

Figure 3: A concept of post-processing.

for $i = J_j + 1$ to J_{j+1}

$$g_j(i) = \frac{d_j}{J_{j+1} - J_j}\left[-\frac{J_{j+1} - J_j}{2\pi}\sin\left\{ \frac{2\pi}{J_{j+1} - J_j}\left(i - J_j\right)\right\} + \left(i - J_j\right)\right] \quad (1)$$

with

$$J = \left\{0, I_1, I_2, \ldots, I_k\right\} \quad (2)$$

$$\overline{\delta} = \left\{0, \delta_1, \delta_2, \ldots, \delta_k\right\} \quad (3)$$

$$d_j = \left(D_{J_{j+1}} - D_{J_j}\right) - \left(\overline{\delta_{j+1}} - \overline{\delta_j}\right) \quad (4)$$

where, I is an index vector consisting of numbers of the available data and δ_i is i-th estimated value by neural network. Finally, adjusted estimation data $\overline{D}_i$ in j-th interval are given by:

for a j-th interval : $J_j < i \leq J_{j+1}$

$$\overline{D_i} = D_i + g_j(i) + \left(\overline{\delta_j} - D_{J_j}\right) \quad (5)$$

5 SIMULATION

To verify a performance of estimation, a simulation was conducted. The simulation will yield two findings: 1) accuracy of estimation by only BPNN and 2) performance of post-processing. OpenSees, which is FE program, and MATLAB® were utilized for simulation. Figure 5 displays the properties of targeted structure. In this simulation, relative horizontal story displacements at every story are set as measurands. A scenario was designed as follows; relative displacements of every story were being stably obtained and then measurement faults occurred at every story except 6, 12, 18, 24, 30, 36, 42, and 48 stories. In order to make a time history of the structural response, vertical loads were stochastically determined in each iteration according to the uniform distribution. Thus, training sets could be acquired by setting number of iteration as time. This variable loads were also applied on a structure after occurrence of measurement faults. In addition, locations of nodes were randomly determined in every iteration within limit range. Since real structures show an uncertain and non-theoretical behaviour, random dimensions were intentionally used to reflect the uncertainty of structural behaviour. An example of estimations is shown in Figure 6.

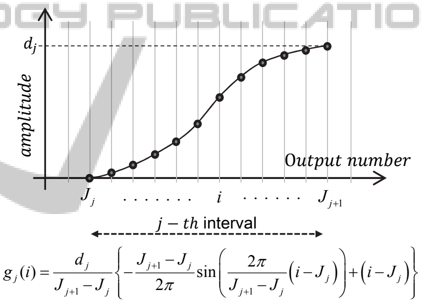

Figure 4: Adjustment function for serial topology of correlation.

Figure 7 shows accuracies of 500 estimations through BPNN trained by 200 typical sets. Root mean square (*RMS*) of real displacements at every story and root mean square error (*RMSE*) of estimated displacements are used to show the applicability of BPNN to estimation.

Meanwhile, Figure 8 expresses the performance of post-processing compared to other cases where the post-processing is not applied. A dashed and thin solid lines indicate the normalized *RMSE* of estimated displacements in prior to and after post-processing, respectively. Normalized *RMSE* (*N.RMSE*) is defined as:

$$N.RMSE = \frac{RMSE \text{ befor or after post-processing}}{RMSE \text{ in case of typical training}} \quad (6)$$

If a value of *N.RMSE* after post-processing is one, it means that the extent of reduced error is zero. Estimation was executed for 500 times.

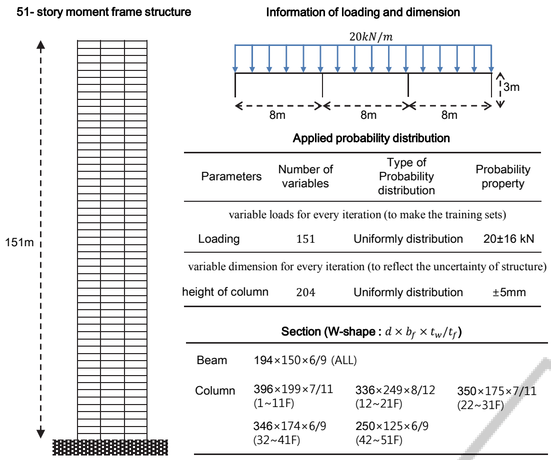

Figure 5: The framed structure in simulation.

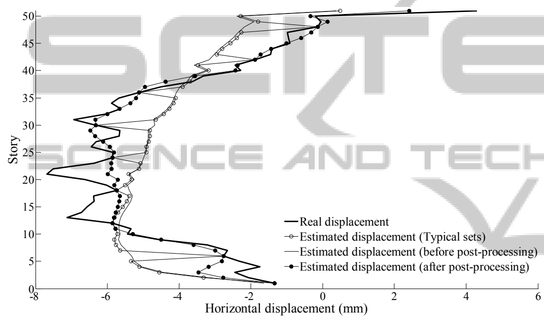

Figure 6: An example of estimations.

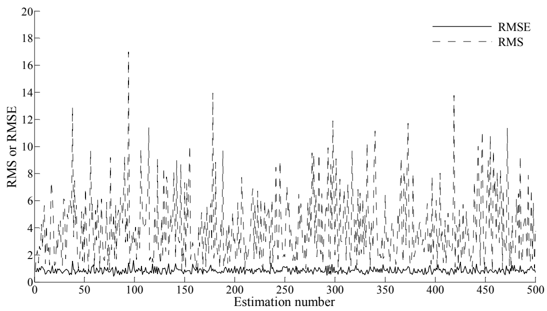

Figure 7: Accuracies of estimated displacements through BPNN trained by 200 typical sets.

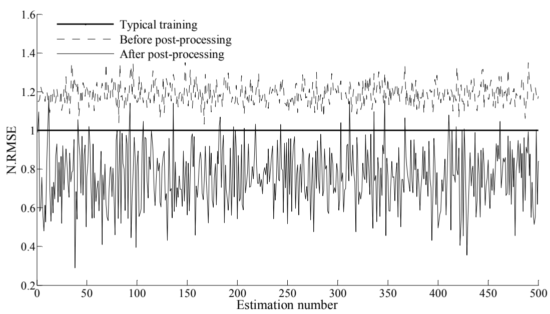

Figure 8: Performance of post-processing.

6 CONCLUSIONS

In this paper, a technique for estimating the values of error data was dealt with in order for the stable SHM to continue. BPNN was selected as basic tool for model-free estimation. An efficient post-processing of BPNN was then developed. After neural network trained by typical sets gives first estimated values of error data, the adjustment process, which is a post-processing, makes those values more accurate. Finally, the performances of BPNN and its post-processing were verified by conducting the FE simulation.

From the results of simulation, the estimation through only BPNN had a stable RMSE with small variation whatever measurand is large or not. The presented post-processing was able to increase an accuracy of estimation about 20% when compared the case where BPNN is only used.

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