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Study of the nonlinear behavior of prestressed concrete girders by a neural network

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Abstract

For the performance design of a bridge, improvement of the hysteresis model of prestressed concrete (PC) members is necessary in order to carry out checking and design in considering the superstructure nonlinearity. However, new functions and parameters must be investigated to appropriately express features of the PC superstructure hysteresis loop, for example 'the origin directionality by the prestress' and 'the asymmetry of the configuration of the strands', therefore, the modeling is very complicated. Then, it was shown that nonlinear hysteretic behavior of a PC member could be simply modeled using the ability of a neural network to approximate function in this study. The cyclic loading test using 1/8 test specimens of the superstructure of an actual bridge was conducted to acquire the data for learning of a neural network.

1 Introduction

In the Hyogo-ken Nanbu Earthquake in 1995, much damage was caused to various bridges in the Han-Shin and Awaji districts. Research found that the superstructure of prestressed concrete rigid-frame bridges designed at the old specifications showed the nonlinear behavior exceeded yield moment of the PC member under such seismic force[1)]. Furthermore, in statically indeterminate structures of high order in which behavior is complicated by earthquakes, such as rigid-frame bridges with unequal bridge piers, arch bridges and cable stayed bridges, the nonlinear behavior of the superstructure may have a large effect on damage balance of the total bridge system.

Therefore, it is very important to accurately model the nonlinearity of the PC superstructure for the simulation of behavior of the whole bridge when subjected to earthquakes.

In recent years, studies about the application of neural networks to engineering problems became popular. A neural network is based on artificially creating a structure which performs similarly to the nervous system of the human brain. The brain nervous system is assumed as connected units of cells.

In this study, based on the pattern recognition ability of neural network, nonlinear hysteretic behavior was modeled by the network directly without replacing it with a mathematical model. The effectiveness and applicability of the network in numerical analysis were evaluated.

The cyclic loading test using 1/8 specimens of the superstructure of the actual bridge was conducted to acquire the data for the neural network.

2 The cyclic loading test of PC specimens

The cyclic loading test was conducted to acquire the data for learning of neural network in this chapter.

2.1 Test specimens

Test specimens consist of one room box girder with 1200mm width, 500mm height, chosen in consideration of the capacity of the loading jack. They assume the inflection point of an rigid-frame bridge with 80 - 140m center span, and are correspondent to 1/1.8 of the PC superstructure of the existing bridge. The material properties are shown in table 1.

2.2 The test case

The test case noticed the degree of introduced prestress and eccentricity of the strand. As an experimental parameter, the degree of the introduced prestress set average axial compression intensity of stress by the prestress at 2.4 - 6.0MPa based on the existing bridge. On the shear reinforcement, the interval of the shear reinforcement was decided so that shear failure may not be preceded. The examination case is shown in table 2, and the sectional view is shown in figure 1.

Table 1: The material property

Material	Property
Concrete	σck=40N/mm2
Reinforcement	SD295 (D6, D13)
Strand	1S15.2A

Table 2: The examination case

Case	introduced prestress	The number of the strand	The configuration of the strand.
A	3.6	6	The symmetrical configuration
B	3.6	6	The upper configuration
C	3.6	6	The lower configuration
D	6	10	The symmetrical configuration
E	2.4	4	The symmetrical configuration

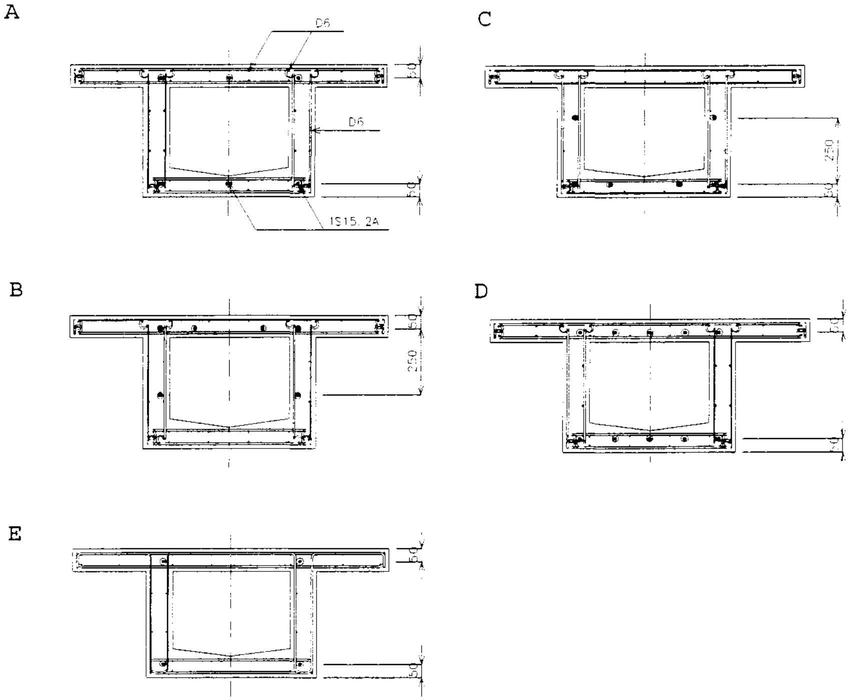


Figure 1 : The bar arrangements

2.3 The loading method

The loading method was the cyclic loading of the simple bending (the 2 point force). That loading span is 600mm (within span length 4000mm). The front view is shown in figures 2, the test equipment and the specimen installation condition are shown in figure 3 and picture 1. Next, using the oil jack of push and pull 980kN, the displacement as longitudinal reinforcement yielded was set with $\delta y0$, and it loaded like figure 4 ($\pm 2\ \delta y0, \pm\ 3\ \delta y0, \pm\ 4\ \delta y0$ ....).

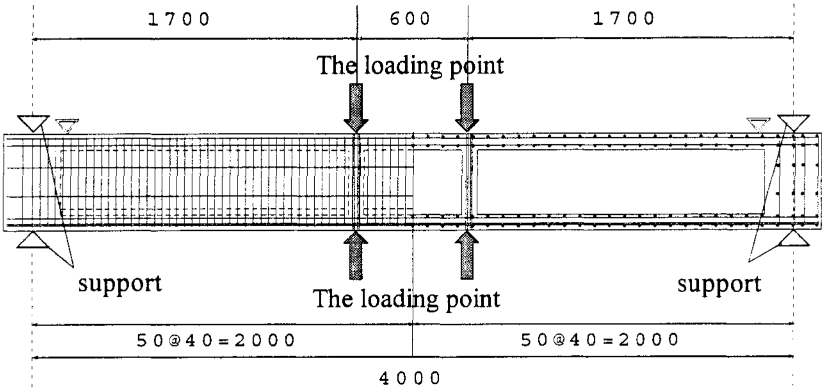


Figure 2 : The front view of specimen

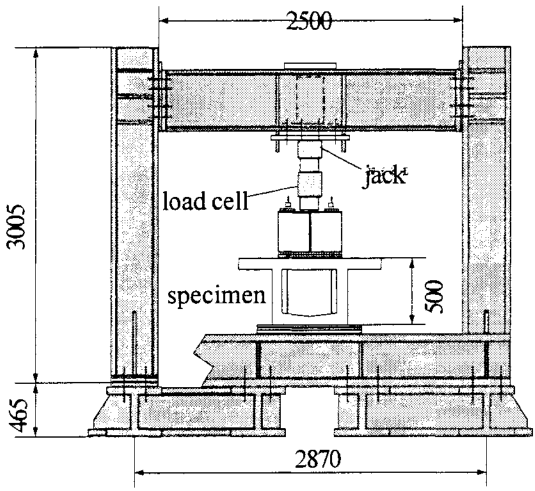
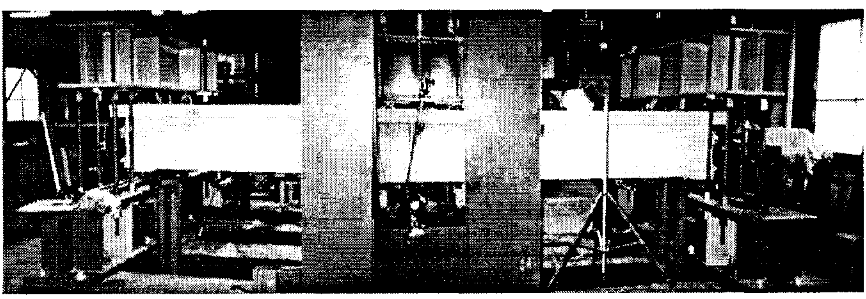


Figure 3 : Test equipment and the specimen installation condition



Picture 1 : Test equipment and the specimen installation condition

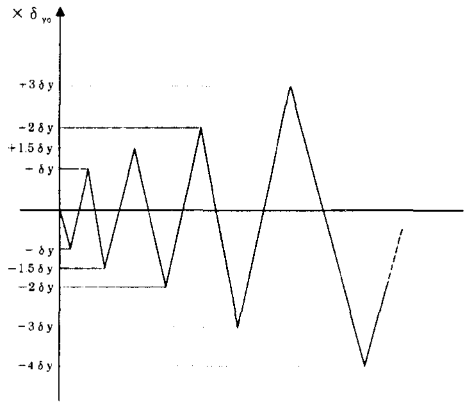


Figure 4 : The input displacement

2.4 The experimental result

The load-displacement (P- δ) hysteresis loops of specimens got by experimenting, is shown in figure 5 and features of the load curve of each specimen are described in the following.

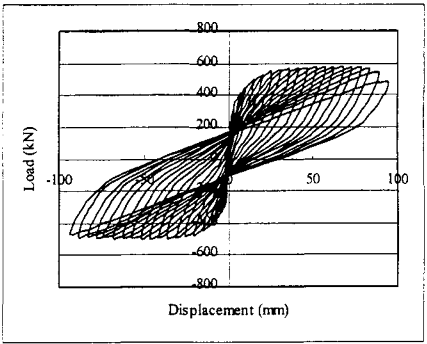
1) In case A, proof stress gently rises to the largest proof stress, and the rigidity in the unloading becomes small with the lowering of the load. It is considered that the strand remains long in the region before the yield because the yield strength and strain of the strand is high in comparison with that of the reinforcement. Therefore, the residual displacement is small, and the hysteresis loop directs at the near origin.
2) In case B which placed the strand to the upper, and case C which placed the strand to the lower respectively, the proof stress increased to the side where the strand was eccentric. Additionally, in case B, the damage was remarkable in the lower part, and, in case C, the damage was remark able in the upper part.
3) Comparing the difference between the quantity of introduced prestress; in case D, the largest proof stress increased about 40%, and in case E, it decreased about 25% for case A.

3 The construction of neural networks

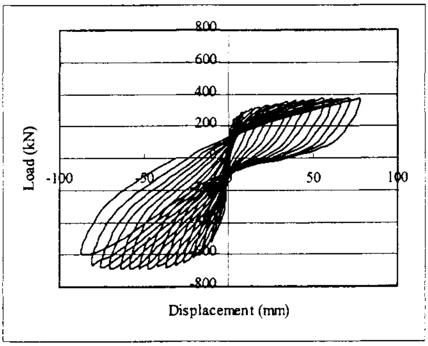
In this chapter, the experimental result in the tip was taken to be the data for learning, and the simulation of the load was done. But as space is limited in this paper, the modeling was only examined of case A.

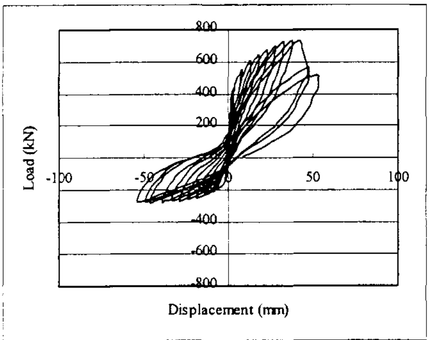
3.1 Selection of input units, output units and structure of neural network

In this study, the multiple layered neural network shown in figure 6 was adopted.



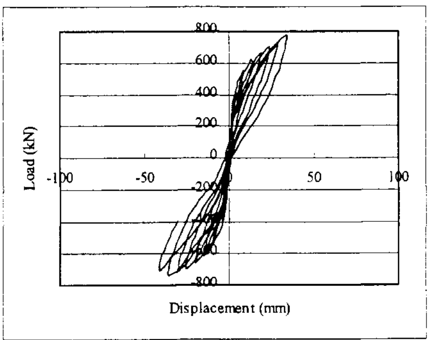
Case A (3.6MPa, The symmetrical configuration)

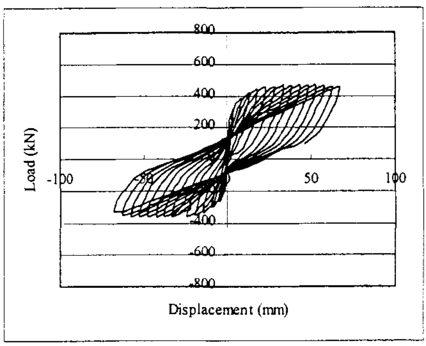




Case B
(3.6MPa, The upper configuration)

Case C
(3.6MPa, The lower configuration)





Case D
(6.0MPa,The symmetrical configuration)

Case E
(2.4MPa,The symmetrical configuration)

Figure 5 : The experimental results

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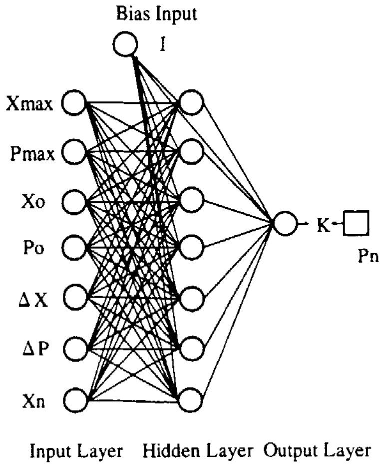

X_{max} : maximum experienced displacement
P_{max} : maximum experienced load
X_o : the latest displacement turning point
P_o : the latest load turning point
ΔX_{n-1}: increase of displacement in Δ t sec($=X_{n-1}-X_{n-2}$)
ΔP_{n-1}: increase of load in Δ t sec($=P_{n-1}-P_{n-2}$)
X_n : present displacement
P_n: present load

Figure 6 : The structure of the network

The neural network transmits the signals from the input layer to the output layer by way of the hidden layer when the input signals is received, and finally output the output signals. When an error between these output signals and the data for learning occurred, the weight of connection was modified to reduce this error. This modification process is equivalent to learning by neural network. Modification is proceeded to minimize the error toward the input layer from the output layer in learning the algorithm.

The input units were decided upon based on past research[2)]. Obtained hysteretic curve forms the most outer loop renewing the maximum experienced point. When maximum displacement isn't renewed, the hysteresis curve goes toward for opposite maximum experienced point. Maximum experienced point and latest turning point are important as the inputs for the input layer. Increases of previous displacement and previous load were added as inputs. Above six units and present displacement were defined as inputs for the input layer. The output layer has one unit of present load. Structure of the network was three layers network with one hidden layer.

3.2 Neuron model

Neuron is the nervous cell system of a creature. The neuron model shown in figure 7 can simulate the information processing of this brain nervous system industrially. This information processing organization is called a unit in the following. The characteristic of this unit has multiple inputs and single output. J unit shown in figure 6 receives the input signal from n units. These input values are $x_1, x_2, \ldots, x_i, \ldots, x_n$. W_{ij} shows strength of connection between unit i and unit j, and is called the weight of connection. I is the bias input to restrain or accelerate the output of unit.

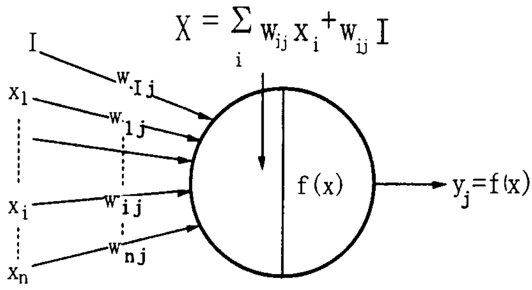

Figure 7 : The neuron model

Because I is regarded as a unit to output value 1 at all times in a calculation, I is treated as the weight of connection W_{Ij} between j unit and the bias input like other weights of connection. Input signals $x_1 \sim x_n$ to unit j are amplified or reduced by the weight of connection, and are summed up as internal potential X. X is transformed to output value Y_j through response function. Function f (X) is called response function or input output function here, and it is monotonic increase function to normalize internal potential. Sigmoid function shown in formula (1) was used as response function in this study.

$$f(X) = \frac{1}{1 + \exp(-X / Tn)} \tag{1}$$

Tn is called the temperature constant that controls activity of a neuron. f (X) to various Tn are shown in figure 8.

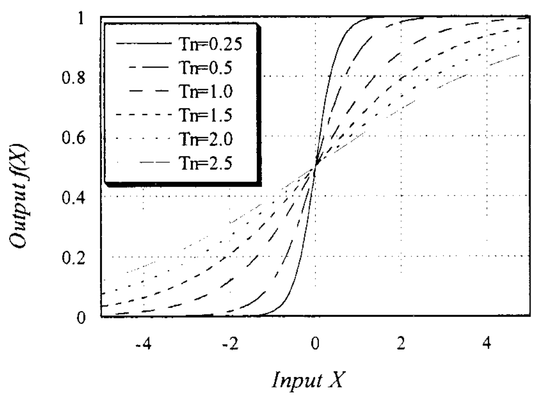

Figure 8 : The Sigmoid function

3.3 Error Back Propagation method

Error Back Propagation Method (BP method in the following) is used as a learning algorithm developed by Rumelhart[3)] in this study. The BP method is the most general learning algorithm for neural networks. In this study, average coefficient α and learning velocity coefficient η were introduced to control the adjustment of the weight. The number of learning iteration was five-thousand, average coefficient α was 0.9, learning velocity coefficient η was 0.5. Twenty five cases of analysis were conducted. The data of nine hundred and thirty five sets for learning was selected from the hysteretic curve shown in figure 4 (Case A).

4 Analytical result

The comparison of time history of the load between the output of the network and the data for learning is shown in figure 9, and the comparison of each hysteresis curve is shown in figure 10. When we compare the load of experimental result and the load of analytical result using learned neural network, some errors occur when the direction of loading is changed, but they are not very large. Both results agree well qualitatively and quantitatively. From the above, the modeling method that uses function approximation ability of the neural network directly is applicable to evaluate the hysteresis loop obtained from the experiment which is difficult to model. It has some errors, but is effective to simulate the complex phenomenon.

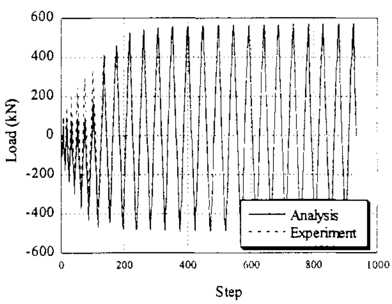

Figure 9 : Recognized result by the network (Time histories)

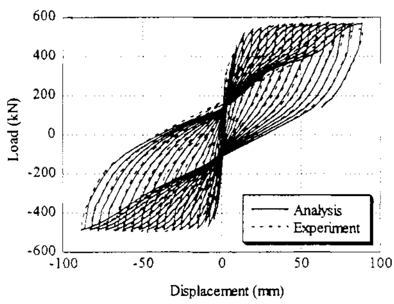

Figure 10 : Recognized result by the network (hysteresis loop)

5 Conclusions

The function approximation ability of the neural network was evaluated through comparing with experimental hysteretic behavior, as a result, the following became clear.

1) The cyclic loading tests, which noticed origin directionality and asymmetry of the PC member were carried out and the data about nonlinear behavior was obtained.
2) By constructing the similar function using the neural network, complicated nonlinear hysteresis behavior of the PC member was able to be simulated.

Applicability of the neural network as a subroutine for numerical analysis will be confirmed by shaking table test, using this test specimen in future.

Acknowledgment

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