Steel and Composite Structures, Vol. 9, No. 6 (2009) 557-568
DOI: http://dx.doi.org/10.12989/scs.2009.9.6.557

Prediction on the fatigue life of butt-welded specimens using artificial neural network

Kim, Kyoung Nam[1], Lee, Seong Haeng[2]* and Jung, Kyoung Sup[1]

[1]School of Civil Engineering, Chungbuk National University, Cheongju, Korea
[2]Department of Civil Engineering, Pusan National University, Busan, Korea

(Received November 22, 2007, Accepted November 17, 2009)

Abstract. Fatigue tests for extremely thick plates require a great deal of manufacturing time and are expensive to perform. Therefore, if predictions could be made through simulation models such as an artificial neural network (ANN), manufacturing time and costs could be greatly reduced. In order to verify the effects of fatigue strength depending on the various factors in SM520C-TMC steels, this study constructed an ANN and conducted the learning process using the parameters of calculated stress concentration factor, thickness and input heat energy, etc. The results showed that the ANN could be applied to the prediction of fatigue life.

Keyword : prediction; fatigue life; fatigue strength; artificial neural network.

1. Introduction

A high cost is involved with a fatigue test, since acquisition of data needed in the determination of factors affecting fatigue is an expensive process. Therefore, if prediction of fatigue life and strength can be carried out with simulation tools such as an artificial neural network (hereafter, ANN), a great deal of time and money could be saved.

It has been noted that there is a reduction in static and dynamic strength in thermo-mechanical control steel (hereafter, TMC steel) due to various influential factors. And no definite solution has yet been found for the prediction of the fatigue strength and life of this type of steel.

Various science journals have reported a great deal of research carried out on the prediction of fatigue strength and life. In particular, when predicting the strength and life of material, Majidian and Saidi (2007) calculated the maximum wall reduction rates of boiler tubes by using two schemes, the Fuzzy logic function and the ANN (by applying numerical calculation) with the Genetic Algorithm. They reported that since the ANN method has several input data, it is able to predict remaining lifetime more accurately than the Fuzzy logic method.

Bezazi, *et al.* (2007) conducted a flexural test on a total of 27 specimens of sandwich composite materials and found that the Bayesian evidence based approach provided a superior and smoother fit to the experimental data.

Also, Fathi and Aghakouchak (2007) used the ANN method to carry out the prediction of the weld magnification factor for the weld toe cracks in T-butt joints under membrane and bending loading with

* Corresponding Author, Email: lsh77@pusan.ac.kr

four multi-layer perceptron (hereafter, MLP) networks. Kang, *et al.* (2006) utilized back-propagation (hereafter, BP) ANN for fatigue life prediction under multi-axial random loading and reported that the ANN gave superior results when searching for critical locations.

Conversely, using alternative methods to predict fatigue life, Ayala-Uraga and Moan (2007) presented reliability-based models to characterize the safety of a welded joint, including SN models, fracture mechanics linear/bi-linear models. In addition to these studies, many researchers have conducted studies on the fatigue life prediction model (Amanullah, *et al.* 2002; Li, *et al*. 2006; Lee, *et al.* 2007). And also the Studies using a ANN are various in assessment of behavior of steel structures (Yi, *et al.* 2003; Al-jabri, *et al.* 2007; Kim, *et al.* 2008).

This paper constructed a MLP-ANN applied BP learning algorithm. And this ANN was verified on the basis of data collected from fatigue experiments on welded SM520C-TMC steel materials. Subsequently, this study conducted the prediction of fatigue life according to parameters such as stress concentration factor (hereafter, SCF) and thickness, etc. It was confirmed that the ANN could be applied to the prediction of fatigue life and could be used effectively for the improvement of weld details.

2. Artificial neural network

2.1 Organization of ANN

An artificial neural network consists of many networks that are linked to other networks or many neurons such as node or processing elements. The structures of a neuron and MLP-ANN are shown in Figs. 1 and 2, respectively (Do, *et al.* 2001).

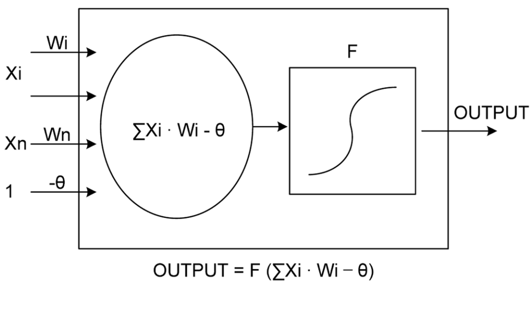

Fig. 1 Scheme of neuron in ANN

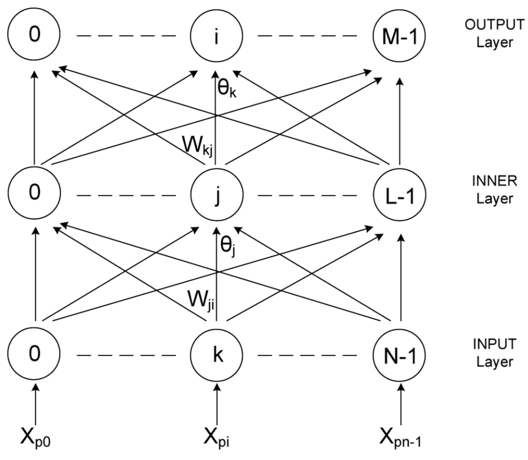

Fig. 2 Organization of MLP-ANN

One neuron has 'n' connection line such as $X_1, X_2, ..., X_n$. Each element of connection is multiplied by connection weight W_i, and if the multiplied value is more than the threshold, then the neuron can be active. The output value of an active neuron can be applied as variable x of the transfer function $F(x)$. The transfer functions frequently used in ANN are the hard-limiter, threshold and sigmoid functions.

The output value of one neuron is applied for input value of another neuron.

2.2 Back-propagation learning algorithm (Rumelhart, et al. 1986)

A MLP-ANN has one or more hidden layers between the input layer and the output layer. The error BP learning algorithm is used to teach this. This algorithm is designed to minimize the value of the cost function, E, by the gradient-descent method. Cost function E is defined as the sum of the squares of errors between the desired target value and the actual output value.

3. Modeling of ANN

3.1 Composition of layers

General parameters for the prediction of fatigue strength are shown in Table 1. Though there may be more influential factors than the parameters presented here, this study assumed that influences are only exerted by the parameters of the Table 1.

The parameters related to the shape of the welded joint are able to correspond to the SCF. Calculated SCFs are therefore used for input data, as shown in Fig. 3.

Finally, the training data of the ANN is as follows:

Training data: the acquisition data from the fatigue test of SM520C-TMC steel

1) Fabrication data: material property, thickness, input heat energy

2) Test data: stress range loaded

3) Weld zone data: SCF

A hidden layer is inserted to take into consideration the efficiency and calculation speed. The number of hidden nodes is also selected to take into account the fact that there are five types of input nodes and a total of 71 data (Kang, *et al.* 2006).

A sigmoid function is most widely used as a transfer function in the construction of the ANN. This function is suitable for this study since it can be differentiated and it has a successive output and a

Table 1 General parameters for prediction of fatigue strength

Layer	Input layer	Output layer
Parameter	Materials, thickness, geometry of welded joint, stress range, area, root gap, angle of groove, welding rod, welding method, the number of passes, input heat energy, impact absorb energy, the position of fracture, the ratio of fatigue area in fracture surface	Fatigue life

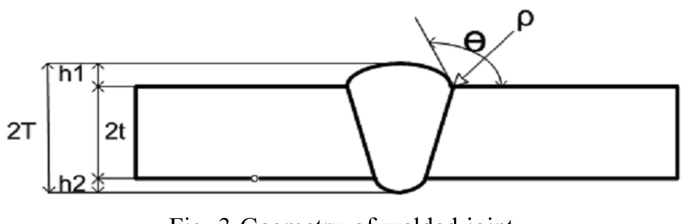

Fig. 3 Geometry of welded joint

Table 2 The number of neuron of ANN in present study

layer	Input(i) layer	Inner(j) layer	Output(k) layer
The number of neurons	5	10	1

simple form, too. Additionally, ANN using hard-limiter function was also built and then compared against the former.

$$E' = \frac{E}{n}, \qquad E = \sum_{p=0}^{n} E_p \left(E_p = \frac{1}{2}\sum_{k=0}^{M-1} \delta_{pk}^2\right) \tag{1}$$

Here, E' : Final accumulated error sum
E_p : Error of the pth data set
n, M : The number of data set and output neuron, respectively
δ_{pk} : The difference of target data d_{pk} and obtained data O_{pk}

Learning is performed through a back-propagation algorithm. In applying a back-propagation algorithm, the initial connection weight and bias are selected at random. The errors between the obtained output and the target data are the sum of the squares of the errors, which are defined as Eq. (1). To minimize this, the gradient descent method is applied and the momentum is not considered. The same learning rate of 0.3 was used for both j and k layer. The maximum number of repeated learning was 1,000,000 cycles. The error tolerance was set at 0.01, and 10 hidden nodes were used.

3.2 Training

In Table 3, the data used in this training is listed. The stress ranges were 1.0, 1.25 and 1.5 times that of the fatigue limit strength of the grade B fatigue category, and they were set at 110, 137.5 and 165 MPa, respectively (ASSHTO 2002). These are the fatigue test results using SM520C-TMC (Kim, *et al*. 2009). Pre-processing is conducted to eliminate the test results that are likely to act as a noise to the training of ANN. Test specimens such as 20-S-02 is also included in the eliminated test results. In the pre-processing work, test specimens that showed a shorter life expectancy than that obtained by subtracting the standard deviation from the average value were eliminated. For choosing one standard deviation, the polluted data can make away with the result efficiently. Finally 58 screened learning data were determinated. Of these, 34 data were trained repeatedly. The remaining 24 data were reapplied to verify the performance of the trained ANN.

Normalized fatigue life (hereafter, NFL) is presented in table 4 and defined as Eq. (2).

$$NFL = \frac{Number.of.cycle.tested}{prdicted.fatigue.life} \tag{2}$$

And a transfer function is assumed as the sigmoid function. On the other hands, a hard limiter function based on the satisfaction or dissatisfaction of fatigue life also is applied.

In Table 4, NFL in test results is the value of dividing actual life by expected life. Because the tests are exhausted at 4 million cycles, the five times of expected fatigue life is assumed as the upper limit of

Table 3 Test data set

Predicted fatigue life*	No. of specimen	Number of cycle tested	Remarks*	No. of specimen	Number of cycle tested	Remarks*
2,952,667	20-S-01	4,000,000	RUN-OUT	40-S-01	4,000,000	RUN-OUT
	20-S-02	fail	Error	40-S-02	4,000,000	RUN-OUT
	20-S-03	4,000,000	RUN-OUT	40-S-03	4,000,000	RUN-OUT
1,511,765	20-S-04	4,000,000	RUN-OUT	40-S-04	2,448,000	The weld toe
	20-S-05	4,000,000	RUN-OUT	40-S-05	2,148,264	The weld toe
	20-S-06	1,074,423	The weld toe	40-S-06	815,927	The root
874,864	20-S-07	570,567	The weld toe	40-S-07	898,597	The root
	20-S-08	702,550	The root	40-S-08	1,366,523	The root
	20-S-09	4,000,000	RUN-OUT	40-S-09	1,262,508	The root
2,952,667	20-F-01	4,000,000	RUN-OUT	40-F-01	4,000,000	RUN-OUT
	20-F-02	4,000,000	RUN-OUT	40-F-02	4,000,000	RUN-OUT
	20-F-03	1,096,739	Compression	40-F-03	4,000,000	RUN-OUT
1,511,765	20-F-04	4,000,000	RUN-OUT	40-F-04	4,000,000	RUN-OUT
	20-F-05	4,000,000	RUN-OUT	40-F-05	1,658,000	The weld toe
	20-F-06	4,000,000	RUN-OUT	40-F-06	3,173,730	The weld toe
874,864	20-F-07	1,251,038	Fracture at base	40-F-07	472,947	The root
	20-F-08	1,219,100	The weld toe	40-F-08	1,004,429	The weld toe
	20-F-09	666,410	The weld toe	40-F-09	1,288,944	The root
2,952,667	60-S-01	4,000,000	RUN-OUT	80-S-01	4,000,000	RUN-OUT
	60-S-02	3,803,494	The weld toe	80-S-02	2,916,289	The weld toe
	60-S-03	2,790,600	The weld toe	80-S-03	1,921,081	The root
1,511,765	60-S-04	4,000,000	RUN-OUT	80-S-04	4,000,000	RUN-OUT
	60-S-05	758,919	The weld toe	80-S-05	1,328,836	The weld toe
	60-S-06	4,000,000	RUN-OUT	80-S-06	1,285,323	The root
874,864	60-S-07	662,632	The weld toe	80-S-07	602,251	The weld toe
	60-S-08	671,844	The weld toe	80-S-08	763,380	The weld toe
	60-S-09	817,602	The root	80-S-09	814,332	The weld toe
2,952,667	60-F-01	3,621,395	The root	80-F-01	1,778,786	The root
	60-F-02	1,337,714	The root	80-F-02	2,692,391	The root
	60-F-03	3,875,629	The root	80-F-03	2,504,981	The root
1,511,765	60-F-04	3,816,287	The weld toe	80-F-04	690,601	The root
	60-F-05	1,480,159	The root	80-F-05	1,149,148	The root
	60-F-06	1,545,866	The weld toe	80-F-06	1,153,713	The root
874,864	60-F-07	1,137,200	The weld toe	80-F-07	460,410	The weld toe
	60-F-08	274,507	The root	80-F-08	497,512	The root
	60-F-09	1,054,956	The weld toe	80-F-09	475,457	The root

※ Here, predicted fatigue life can be calculated as an expression (AASHTO specification). And the remarks indicated crack initiated position (The weld toe weld, the root) or exhausted (“run-out”).

Table 4 Scaled test results and output results of ANN

No. of Specimen	Test result	"YN" model output		"Real number" model output	
	NFL	Output	Verification	Output	Verification
20-F-02	1.347	1	T	1.280	T
20-F-05	2.632	1	T	2.620	T
20-F-06	2.632	1	T	2.605	T
20-F-08	1.385	1	T	1.605	T
20-S-03	1.347	1	T	1.465	T
20-S-05	2.632	1	T	2.375	T
20-S-08	0.798	1	F	0.825	T
20-S-09	4.545	1	T	4.540	T
40-F-02	1.347	1	T	1.155	T
40-F-03	1.347	1	T	1.610	T
40-F-06	2.088	1	T	1.945	T
40-F-09	1.465	1	T	1.160	T
40-S-02	1.347	1	T	1.395	T
40-S-03	1.347	1	T	1.325	T
40-S-05	1.413	1	T	2.040	T
40-S-09	1.435	1	T	1.455	T
60-F-03	1.305	1	T	1.195	T
60-F-05	0.974	1	F	1.235	F
60-F-06	1.017	1	T	1.145	T
60-F-09	1.199	1	T	0.745	F
60-S-02	1.281	1	T	1.125	T
60-S-06	2.632	1	T	1.435	T
60-S-08	0.763	0	T	0.970	T
60-S-09	0.929	0	T	0.930	T
80-F-03	0.843	0	T	0.930	T
80-F-06	0.759	0	T	0.845	T
80-F-08	0.565	0	T	0.690	T
80-F-09	0.540	0	T	0.700	T
80-S-02	0.982	0	T	0.915	T
80-S-03	0.647	0	T	0.720	T
80-S-05	0.874	0	T	1.040	F
80-S-06	0.846	0	T	1.150	F
80-S-08	0.867	0	T	0.870	T
80-S-09	0.925	0	T	0.960	T

※ Here, "YN" model is applied hard limit as transfer function. And "real number" model is applied sigmoid function.

output of ANN. And in "YN" model output, 1 indicates satisfaction and 0 indicates dissatisfaction for fatigue life. In real number model output, the output represents the NFL from ANN. With regards to verification, when the test results are consistent with the expected results, the outcome becomes T

(True) and when the test results are inconsistent with the expected results, the outcome becomes F (False). At the completion of training, the error of Eq. (1) was E' = 0.416 in the YN model at 1,000,000*th* iteration. In the real number model, It was satisfied the allowance of 0.01 at 749,780*th* iteration and converged. Fig. 4 shows the distributions for the training results of "real number" model.

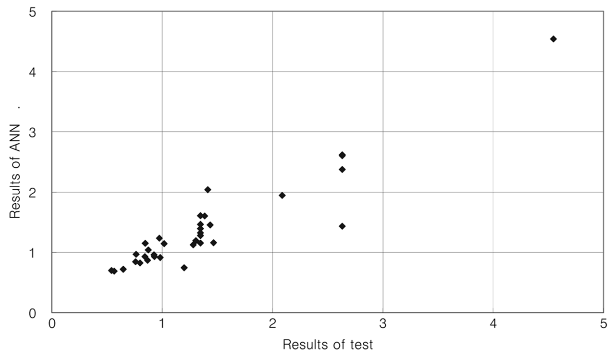

Fig. 4 Distribution of the NFL results in "real number" model

4. Verification and application

4.1 Verification

The verification of the ANN was performed by using the remaining 24 data in the actual fatigue test data of Table 3 that were not used for the ANN training. Table 5 shows the verification results of the ANN.

In the case of "YN" model, the judgment of the satisfaction of fatigue strength was recording a right prediction ratio of approximately 83 percent. In terms of the prediction results of 20-S-07 and 80-S-04, there were large differences between the actual results and the output results of the ANN. This implies that there are additional factors to be considered in the prediction of fatigue life, in addition to the factors considered in this study. This is either due to the influence of the shortage of the shock absorption energy or to the internal residual cracks (caused by faults that were not confirmed by MT(magnetic test), RT(radiographic test) or UT(ultra sonic test)), could not be considered as factors in the ANN.

In the "real number" model, the results are shown in Fig. 5. Among the total of 24 cases, the 21 outputs of trained ANN are satisfied with real test results for yes or no. So, the satisfaction for the fatigue life and strength can be predicted with 87.5% (21/24*100%). And in the table 5, the standard error between inputs and outputs was calculated with 0.589 (the range of inputs and outputs is from 0.0 to 5.0). Therefore, the prediction of 75% falls into the scatter-band of +/- one standard error.

And this study uses the results of the "real number" model ANN, since the output of "real number" model can be better than that of "YN" model.

4.2 Application and estimation of results

4.2.1 The grinding effects of the weld toe

The trained ANN can be used to predict the fatigue life of the butt welding test specimen of Fig. 6. The ANN used here represents the results of learning of all 58 data and is expected to make a prediction

Table 5 Verification results for outputs of ANN

No. of specimen	Test result	Result of "YN" model		Result of "Real number" model	
	NFL	Output	Verification	Output	Verification
20-F-01	1.347	1	T	1.460	T
20-F-04	2.632	1	T	2.620	T
20-F-07	1.422	1	T	1.565	T
20-S-01	1.347	1	T	1.905	T
20-S-04	2.632	1	T	2.300	T
20-S-07	0.648	1	F	1.525	F
40-F-01	1.347	1	T	1.505	T
40-F-04	2.632	1	T	2.035	T
40-F-08	1.141	1	T	1.125	T
40-S-01	1.347	1	T	2.075	T
40-S-04	1.611	1	T	2.055	T
40-S-08	1.553	1	T	1.120	T
60-F-01	1.219	1	T	1.065	T
60-F-04	2.511	1	T	1.155	T
60-F-07	1.292	1	T	0.755	F
60-S-01	1.347	1	T	1.300	T
60-S-04	2.632	1	T	1.430	T
60-S-07	0.753	0	T	0.900	T
80-F-02	0.907	0	T	0.895	T
80-F-05	0.756	0	T	0.820	T
80-F-07	0.523	0	T	0.650	T
80-S-01	1.347	0	F	1.000	T
80-S-04	2.632	0	F	1.120	T
80-S-07	1.162	0	F	0.895	F

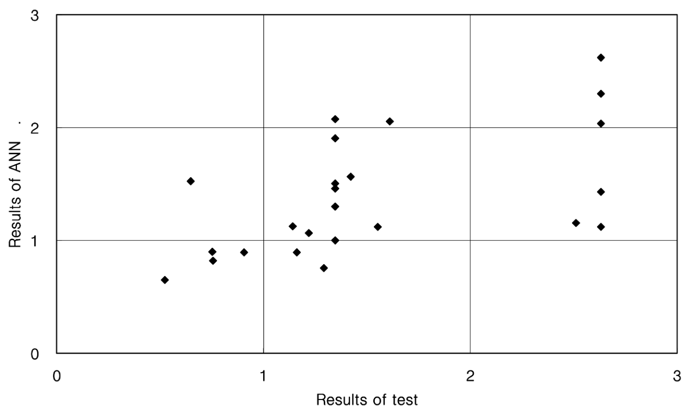

Fig. 5 Distribution of the verification results in "real number model"

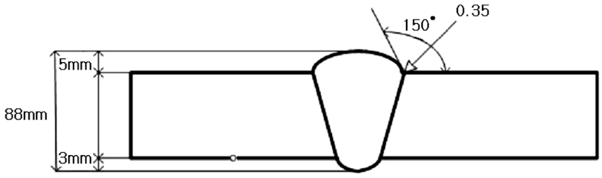

Fig. 6 Geometry of welded joint

with a higher level of accuracy than the case of learning of the 34 data. When the training of ANN was completed, the error item was 0.01 and the repetition cycle was 197,741.

1) Fabrication data: SM520C-TMC, thickness 80mm, SAW (input heat energy 45 kJ/cm)
2) Test data: stress range loaded = 1.0 (σ_{fl} = 110 MPa, fatigue classification B')
3) Weld zone data: As-Welded, SCF (stress concentration factor) K_t = 6.05

Where, SCF is the value K_t from the geometry of the weld zone (Nishida 1971) obtained from Eq. (3).

$$K_t = 1 + \left[\frac{1-\exp\{-0.9\sqrt{T/h}\times(\pi-\theta)\}}{1-\exp\{-0.9\sqrt{T/h}\times\pi/2\}}\right]\times\left(\frac{1}{2.8T/t-2}\times\frac{h}{\rho}\right)^{0.65} \quad (3)$$

Here, T: (specimen thickness + bead height) / 2 = 44 mm
h: (h1+h2)~(bead height) = 8 mm
t: (specimen thickness) / 2 = 40 mm
ρ: Radius of curvature of the weld toe = 0.35 mm
θ: Tangential angle = 150° = 2.62 radian

So, SCF of this detail in Fig. 6 is calculated as 6.05. Above values entered into the trained ANN. Then, the NFL is 0.84 and the fatigue life predicted = $0.84 \times 2.97 \times 10^6 = 2.49 \times 10^6 \le 2.97 \times 10^6$cycles. This result cannot satisfy the required fatigue life.

A prediction can be made for the same test specimen with the results of the case where the weld toe was grinded, instead of the 'as-welded' test specimen. If the radius of curvature (ρ) of the weld toe changed from 0.35 mm to 2 mm with the grinding of the weld toe, the SCF decreases from 6.05 to 2.626. Then, the fatigue life can be calculated as $2.49 \times 10^6 \times 5 \ge 2.97 \times 10^6$cycles over.

This result shows the same as a general rule - when the radius of curvature (ρ) was increased, by grinding the weld toe (rather than by using the welded test specimen of Fig. 6), the life of the structure details can be improved. So the fatigue classification may be enhanced. However, the prediction results of the fatigue life extension, from a change in the radius of curvature, shows something different limit. The graph in Fig. 7 displays on the effects of increases in the fatigue life calculated according to the radius of curvature with changing SCFs.

Figs. 8 and 9 indicate the effects for the test specimens of 60mm and 40mm, where conditions are the same as in Fig. 7.

According to Figs. 7~9, the maximum value of NFL is 5. However, the longer lives exist in reality. In the test result of present study, the limit value of fatigue life was the five times of the expected fatigue life in a structure detail with "B" fatigue classification. Therefore, in the details with a low SCF and a large radius (such as NFL ≥5), the prediction results of the ANN may not realistic due to the limits of the test method.

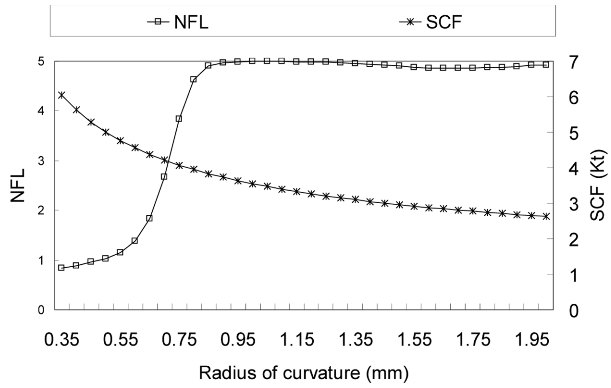

Fig. 7 Prediction of NFL according to the radius of curvature (thickness 80mm)

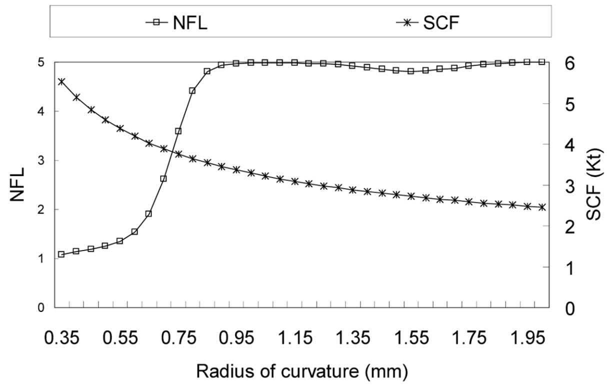

Fig. 8 Prediction of NFL according to the radius of curvature (thickness 60 mm)

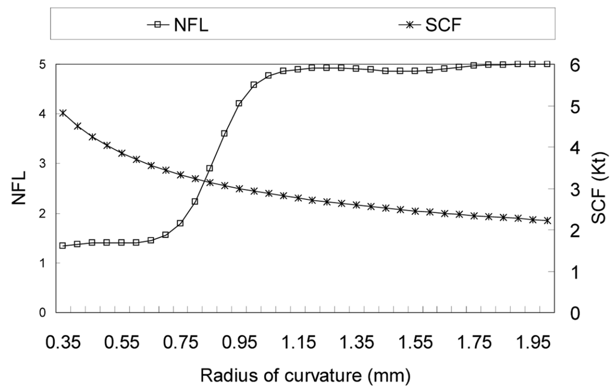

Fig. 9 Prediction of NFL according to the radius of curvature (thickness 40mm)

4.2.2 Thickness effect at butt-welded joints

The same ANN that was applied in Section 4.2.1 can be used to make a prediction for fatigue life,

Table 6 Averaged SCF according to thickness

Thickness	Averaged the radius of curvature (ρ)	Averaged SCF	Remarks
20 mm	0.32	3.222	
40 mm	0.33	3.962	
60 mm	0.33	4.831	
80 mm	0.35	5.333	

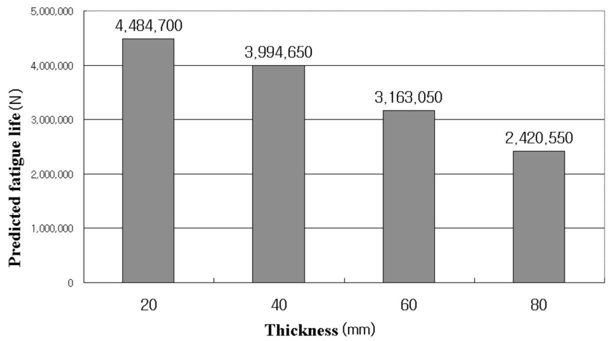

Fig. 10 Prediction of fatigue life with trained ANN according to thickness

depending on the change in thickness. In the ANN, calculation is conducted for FCAW (flux cored arc welding) only.

1) Fabrication data: SM520C-TMC, thickness 20~80 mm, FCAW (input heat energy 30kJ/cm)

2) Test data: stress range loaded = 1.0 (σ_{fl} = 110 MPa, fatigue classification B')

3) Weld zone data: As-Welded, Averaged SCF (refer to Table 6)

Here, the averaged SCFs for each thickness were obtained by the test shown in Table 6 were applied as the SCFs.

According to Fig. 10, the fatigue life decreases in accordance with the thickness. These results are similar to previous study (Kim, *et al.* 2009).

5. Conclusion

In order to verify the thickness effects of fatigue strength in SM520C-TMC steels, this study constructed an ANN and conducted its learning process. Through the ANN, this study also calculated SCF and thickness effects and the results were verified by actual data.

The fatigue tests of extremely thick plates require a great deal of fabricating time and are expensive. Therefore, if predictions could be made through simulation models such as ANN, a great deal of time and money could be saved.

The analysis and examination of the above research results came to the following conclusions.

1) Through an ANN, predictions of approximately 87 (21/24*100%) percent were made for the good judgment of the fatigue strength of the butt-welding applied to SM520C-TMC steel.

2) The major factors affecting fatigue life from quantitative evaluation was thought as thickness, welding methods, and weld shapes. Their effects were evaluated using an ANN, as follows.

- When the SCF of the weld zone was improved by changing the radius of curvature through grinding of the weld toe, it brings the fatigue classification to an upgrade of one grade or more.
- In terms of the thickness effect, the fatigue life decreased as the thickness increased, which is similar to what occurred in the experiment expression that used actual test data.

In this study, the materials learned by the ANN include only the details for the butt-welding of SM520C-TMC. For this reason, it is necessary to conduct studies on fillet welding or other steels, in addition to continuous accumulation of fatigue test data with their geometric data. Furthermore, additional data could be transformed into more effective fatigue strength prediction model through the learning of the ANN. It is hoped that the results of this study could provide a foundation for the planning of future studies.

References

AASHTO LRFD Bridge Design Specification (2002), U.S. Units 2002, Interim Revisions.

Al-Jabri, K.S. and Al-Alawi, S.M. (2007), "Predicting the behavior of semi-rigid joints in fire using an artificial neural networks", *Int. J. Steel Struct.*, **7**(3), 209-217.

Amanullah, M., Siddiqui, N.A., Umar, A. and Abbas, H. (2002), "Fatigue reliability analysis of welded joints of a TLP tether system", *Steel Compos. Struct*., **2**(5), 331-354.

Ayala-Uraga, E. and Moan, T. (2007), "Fatigue reliability assessment of welded joints applying consistent fracture mechanics formulations", *Int. J. fatigue*, **29**, 444-456.

Bezazi, A., Gareth Pierce, S., Worden, K. and Harkati, E.H. (2007), "Fatigue life prediction of sandwith composite materials under flexural tests using a Bayesian trained artificial neural network", *Int. J. fatigue*, **29**, 738-747.

Do, Y.T., Kim, I.G., Kim, J.W. and Park, C.H. (2001), *Artificial intelligence-Concept and Application*, Scitech Media, Korea.

Fathi, A. and Aghakouchak, A.A. (2007), "Prediction of fatigue crack growth rate in welded tubular joints using neural network", *Int. J. fatigue*, **29**, 261-275.

Kang, J.Y., Choi, B.I., Lee, H.J., Kim, J.S. and Kim, K.J. (2006), "Neural network application in fatigue damage analysis under multiaxial random loadings", *Int. J. fatigue*, **28**, 132-140.

Kim, J.T., Park, J.H., Koo, K.Y. and Lee, J.J (2008), "Acceleration-based neural networks algorithm for damage detection in structures", *Smart Struct. Syst*., **4**(5), 583-603.

Kim, K.N., Lee, S.H. and Jung, K.S. (2009), "Evaluation of factors affecting the fatigue behavior of buttwelded joints using SM520C-TMC Steel", *Int. J. Steel Struct*., **9**(3), 185-193.

Lee, Y.L., Tjhung, T. and Jordan, A. (2007), "A life prediction model for welded joints under multiaxial variable amplitude loading histories", *Int. J. fatigue*, **29**, 1162-1173.

Li, B., Reis, L. and Freitas, M.D. (2006), "Simulation of cyclic stress/strain evolutions for multiaxial fatigue life prediction", *Int. J. fatigue*, **28**, 451-458.

Majidian, A. and Saidi, M.H. (2007), "Comparison of Fuzzy logic and Neural Network in life prediction of boiler tubes", *Int. J. fatigue*, **29**, 489-498.

McCulloch, W.S. and Pitts, W. (1943), "A Logical Calculus of the Ideas Imminent in Nervous Activity", *B. Math. Bio*., **5**, 115-133.

Nishida, M. (1971), Stress Concentration, Morikita Ink, Japan.

Rumelhart, D.E., Hinton, G.E. and Williams, R.J. (1986), *Learning Internal Representation by Error Propagation*, Parallel Distributed Processing, Vol. 1, MIT Press.

Yi, J.H., Yun, C.B. and Feng, M.Q. (2003), "Model updating and joint damage assessment for steel frame structures using structural identification techniques", *Int. J. Steel Struct.*, **3**(2), 83-94.

CC