A R C H I V E S O F M E T A L L U R G Y A N D M A T E R I A L S
Volume 59 2014 Issue 1
DOI: 10.2478/amm-2014-0016

I. UYGUR*, A. CICEK**, E. TOKLU*, R. KARA***, S. SARIDEMIR****

FATIGUE LIFE PREDICTIONS OF METAL MATRIX COMPOSITES USING ARTIFICIAL NEURAL NETWORKS

PRZEWIDYWANIA TRWAŁOŚCI ZMĘCZENIOWEJ KOMPOZYTÓW METALOWYCH PRZY UŻYCIU SZTUCZNYCH SIECI NEURONOWYCH

In this study, fatigue life predictions for the various metal matrix composites, R ratios, notch geometries, and different temperatures have been performed by using artificial neural networks (ANN) approach. Input parameters of the model comprise various materials (M), such as particle size and volume fraction of reinforcement, stress concentration factor (Kt), R ratio (R), peak stress (S), temperatures (T), whereas, output of the ANN model consist of number of failure cycles. ANN controller was trained with Levenberg-Marquardt (LM) learning algorithm. The tested actual data and predicted data were simulated by a computer program developed on MATLAB platform. It is shown that the model provides intimate fatigue life estimations compared with actual tested data.

Keywords: MMCs, Fatigue life prediction, Artificial neural networks

Zastosowano sztuczne sieci neuronowe (ANN) do przewidywania trwałości zmęczeniowej dla różnych kompozytów metalowych, parametrów R, geometrii karbu, i różnych temperatur. Parametry wejściowe modelu obejmowały: różne materiały (M), o różnym rozmiarze cząstek i objętości frakcji zbrojącej, współczynnik koncentracji naprężeń (Kt), stosunek parametru R (R), naprężenie szczytowe (S), temperaturę (T), natomiast dane wyjściowe składały się z liczby cykli awarii (SSN). Kontroler ANN był trenowany z użyciem algorytmu uczenia Levenberga-Marquardta (LM). Badane dane rzeczywiste i dane przewidywane symulowane były przez program komputerowy opracowany na platformie MATLAB. Wykazano, że model zapewnia oszacowanie trwałości zmęczeniowej bliską rzeczywistym danym badanym.

1. Introduction

In engineering terminology, fatigue refers to the progressive mechanical failure of a material subjected to a fluctuating or repeated stress or strain when applied monotonically would not result in fracture. Fatigue is the most common mode of failure in engineering components. Over 80% of service failures due to mechanical causes can be attributed to fatigue. The process of fatigue may be considered as consisting of three main stages: crack initiation, crack propagation and final fast fracture. Most of fatigue data are commonly used to characterize the stress-fatigue life relationship using plain or notched specimens. Tests can be carried out under various R ratios. The results are normally plotted using stress amplitude or maximum applied stress against the number of cycles to failure, generally known as the S-N curve. The S-N curve is determined by taking several specimens and subjecting each one to a different cyclic stress until it fails. Discontinuously reinforced metal matrix composites (MMCs) are excellent candidates for structural components in the aerospace and automotive industries, where they are usually subjected to cyclic loads. The fatigue behavior of these composites has been received quite reasonable attention. The tensile responses [1], High Cycle Fatigue (HCF) responses [2], and Low Cycle Fatigue responses (LCF) [3] of Al-SiC$_p$ composites were extensively investigated. An extensive review about the fatigue of materials and structures can be found in detail by Schijve [4]. The fatigue response of these MMCs has been influenced by the following properties: reinforcement type (continuous, whisker or particulate), volume fraction of reinforcement, composition, heat treatment, notch behavior, elevated temperatures, environment, processing technique (casting or powder metallurgy) and R ratios that defines the developed stress station the specimen [5]. Fatigue analysis has become an early simulation in the product development process of a growing number of industries. In general, LCF involves large cycles with high amounts of plastic deformation and relatively short life. However, HCF is associated with low stresses and long life in which stresses and strains are largely confined to the elastic region. Fatigue analysis refers to three methodologies: i) local strain or crack initiation, ii) stresses life, and iii) crack growth or damage tolerance analysis. Most

* DUZCE UNIVERSITY, FACULTY OF ENGINEERING, DEPARTMENT OF MECHANICAL ENGINEERING, 81620, DUZCE, TURKEY
** YI LDIRIM BEYAZIT UNIVERSITY, FACULTY OF ENGINEERING AND NATURAL SCIENCES, DEPARTMENT OF MECHANICAL ENGINEERING, ANKARA, TURKEY
*** DUZCE UNIVERSITY, FACULTY OF ENGINEERING, DEPARTMENT OF COMPUTER ENGINEERING, 81620, DUZCE, TURKEY
**** DUZCE UNIVERSITY, FACULTY OF TECHNOLOGY, DEPARTMENT OF MANUFACTURING ENGINEERING, DUZCE, TURKEY

of fatigue life estimations depend on the methodology data mentioned above. It is almost impossible to avoid the defect, environment and notches for most of engineering components. Recently ANN has offered as a new branch of computing, convenient for applications in a various fields. It is also a new type of computer system which is based on the primary understanding of the organization, structure, function and mechanism of the human brain. ANN were originally developed to solve pattern based problems but they can be used as failure analysis, non-destructive testing, welding technology etc. Ates [6] showed the possibility of the use of ANN for the calculation of the mechanical properties of welded low alloy steel using GMA method. ANN offers to solutions of multi-variable problems for which a certain mathematical models do not exist or difficult and time consuming to solve. The most suitable applications for ANN have a large data, difficult to solve problems by existing mathematical models and incomplete data. Fatigue has all of these characteristics and therefore it seems to be suitable for neural network analysis [7]. Fatigue life predictions based on the critical strain life approach for the MMCs under various conditions have been discussed elsewhere [8]. Although, good predictions can be obtained at high stress levels by critical strain approach, there are serious problems at low stress levels. Also, the method can be applied under the limited conditions. Thus, in this study, the ANN is used for the modeling fatigue life of metal matrix composites.

2. Experimental fatigue data

This work addresses the behavior of particulate reinforced 2xxx series aluminum metal matrix composites subjected to tension-tension fatigue loads. All the fatigue data collected from a variety of published investigations [1-5] are used to test the suitability of the ANN in predicting the fatigue lives. Experimental details, specimen configurations, and materials characteristics were given in detail in Reference 5. Table 1 shows the materials and variables of the experimental data used. It is seen that five different materials (LMMC17, LMMC25, MMC17, MMC25, MMC00), various maximum stress levels, two different R ratios (0.1, 0.5), three different temperatures (21, 200, 250^{o}C) were used to predict fatigue lives of composites. For the materials "L" refers large particles, only MMC refers small particulate reinforced metal matrix composites, and 00, 17 and 25 refers to volume percentages of particles.

2.1. Configuration and designing ANN controllers

ANNs are popular and there are many industrial situations where they can be easily applied. They are suitable for modeling various manufacturing functions due to their ability to learn complex non-linear and multivariable relationships between process parameters [9]. ANN consists of a combination of artificial neural cells (neurons). This combination should be regular and usually is constructed as layers. ANN consists of three main layers, namely input, hidden and output layers. The neurons in input layer transfer the data from the external world into hidden layer [10]. The output is generated using summation and activation functions along with data transferred from input layer and the neuron called bias in the hidden layer. The summation function is a function which calculates the net input of the cell. Summation function used in this study is given in Eq. 1.

$$NET_i = \sum_{j=1}^{n} w_{ij} \times x_j + w_{bi} \tag{1}$$

Where NET_i is the weighted sum of the input to the ith processing element. w_{ij} is the weights of the connections between ith and jth processing elements. X_j is the output of the jth processing element. w_{bi} is the weights of the biases between layers. Activation function provides a curvilinear match between input and output layers. In addition, it determines the output of the cell by processing net input to the cell. Selection of appropriate activation function significantly affects network performance. The common transfer functions in ANNs are linear, step/signum, threshold, logistic sigmoid, hyperbolic tangent sigmoid functions, etc. Recently, logistic sigmoid transfer function has been commonly used as an activation function in multilayer perception models, because it is a differentiable, continuous and non-linear function. For this reason, the logistic sigmoid transfer function was used as the activation function in this study. Logistic sigmoid transfer function of ANN model used is expressed as follows;

$$f\,(NET_i) = \frac{1}{1 + e^{-NET_i}} \tag{2}$$

The hidden layer may be more than one. In this case, each hidden layer sends its outputs into the next hidden layer. In the output layer, the output of network is generated by processing the data from the last hidden layer and the outputs are sent to the external world. In this study, the training and testing data for ANN were prepared by use of 58 experimental data collected from fatigue life responses of MMCs. These experimental data are shown in Table 1.

TABLE 1
All experimental fatigue data of MMCs

Materials	*Maximum Applied Stress (MPa)*	*R ratio*	K_t	*Temperature (°C)*	*Tested N_f (Cyles)*
LMMC17	400	0.1	1.8	21	11458
	350	0.1	1.8	21	24877
	300	0.1	1.8	21	42296
	275	0.1	1.8	21	43469
	250	0.1	1.8	21	127245
LMMC25	450	0.1	1.8	21	9448
	350	0.1	1.8	21	26366
	300	0.1	1.8	21	66626
	250	0.1	1.8	21	121259
MMC00	450	**0.5**	1.8	21	32132
	400	**0.5**	1.8	21	44606
	350	**0.5**	1.8	21	117130

cd TABLE 1

1	2	3	4	5	6
MMC00	400	0.1	1.8	21	3869
	350	0.1	1.8	21	14471
	300	0.1	1.8	21	67366
	275	0.1	1.8	21	70948
	250	0.1	1.8	21	140000
MMC00	350	0.1	1.8	**250**	6450
	250	0.1	1.8	**250**	28222
	200	0.1	1.8	**250**	99500
MMC17	450	0.1	1.8	21	9693
	400	0.1	1.8	21	13954
	375	0.1	1.8	21	21250
	350	0.1	1.8	21	26996
	300	0.1	1.8	21	62814
	275	0.1	1.8	21	115485
	250	0.1	1.8	21	135483
MMC25	450	0.1	1.8	21	5840
	400	0.1	1.8	21	12500
	350	0.1	1.8	21	29000
	325	0.1	1.8	21	83063
	300	0.1	1.8	21	131317
	275	0.1	1.8	21	180000
	250	0.1	1.8	21	950000
MMC25	550	**0.5**	1.8	21	14571
	500	**0.5**	1.8	21	58735
	450	**0.5**	1.8	21	62723
	400	**0.5**	1.8	21	87461
	350	**0.5**	1.8	21	500000
MMC25	350	0.1	**2.7**	21	12650
	325	0.1	**2.7**	21	17884
	300	0.1	**2.7**	21	45343
	285	0.1	**2.7**	21	63000
	275	0.1	**2.7**	21	100000
	255	0.1	**2.7**	21	215000
MMC25	530	0.1	**1.4**	21	6950
	500	0.1	**1.4**	21	12000
	475	0.1	**1.4**	21	28268
	450	0.1	**1.4**	21	30000
	400	0.1	**1.4**	21	37512
	375	0.1	**1.4**	21	55225
	365	0.1	**1.4**	21	699501
MMC25	350	0.1	1.8	**200**	7248
	250	0.1	1.8	**200**	40406
	200	0.1	1.8	**200**	120000
MMC25	250	0.1	1.8	**250**	1723
	200	0.1	1.8	**250**	18973
	150	0.1	1.8	**250**	108528

In the construction of the architecture of ANN, determination of training and testing data ratios has an important place. In separation of the experimental samples into training and testing samples, there is no general rule that is followed to determine the ratio between the amounts of training and testing samples. The studies performed in the literature used a certain ratio between training and testing samples for separation [11-14]. The ratio of training and testing samples in the literature is taken as 90%: 10% [15,16], 85%: 15% [12], 80%: 20% [17], 75%: 25% [18], 70 %: 30% [19,20]. In this study, the ratio was taken as 80%: 20%. For this reason, they were randomly selected 12 testing data and 46 training data from all experimental data. Number of cycles until failure (Nf) was selected as the output data, five different materials, various maximum stress levels, two different R ratios and three different temperatures were used into the network as input data. Although all neural network models share common operational features, input requirements and modeling and generalization abilities are different. Thus, each hypothesis would have advantages and disadvantages depending on the particular application and selecting the appropriate network class with convenient parameters is crucial to ensure a useful application. In the back propagation (BP) model, normalization of input and output data affects the performance of network. The normalization regularly makes the distribution of values ??of the samples. This study used logistic sigmoid transfer function as mentioned above. This function always generates a value between 0 and 1 only. Therefore, the input and output values were normalized between 0.1 and 0.9 in this study.

$$nv_i = 0.8 \times \left(\frac{v_{min} - v_i}{v_{min} - v_{max}} \right) + 0.1 \tag{3}$$

Eq 3 was used to provide the ideal distribution between 0.1 and 0.9 in the normalization of the fatigue life cycles and temperatures, since difference between minimum and maximum life cycles and temperatures of MMCs was very large. The materials, peak stress, R ratio, stress concentration factor were normalized by dividing with 7, 700, 0.6 and 3.5 respectively. The digits for the composite material types to be entered into the artificial neural networks were determined as LMMC17 = 1, LMMC25 = 2, MMC00 = 3, MMC17 = 4 and MMC25 = 5 because they do not have numerical values. There are many learning model used to determine the weights in ANN. One of the most widely used learning models is the back propagation (BP) model. The BP model performs the updating of weights based on the difference between the experimental results and outputs of network. Learning parameter used in the BP model plays an important role in reaching to optimal results. There are various learning algorithms that have been applied by the previous studies, such as SCG (Scaled Conjugate Gradient) [15, 21] and LM [15, 18, 19]. In this study, in consequence of a number of trials performed for both SCG and LM learning algorithms, it was found that LM learning algorithm and ANN architecture with two hidden layers became the best to train the network (Fig. 1).

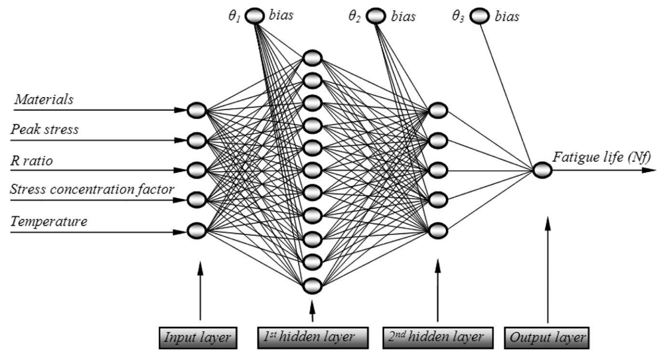

Fig. 1. ANN architecture with two hidden layers

As shown in the Fig. 1, the ANN model has been set up for fatigue life predictions using five neurons in the input layer, eleven neurons in the first hidden layer, five neurons in the second hidden layer and a neuron in the output layer. These processing elements or neurons process information by their dynamic state response to external inputs. After determination of learning algorithm and architecture, the numbers of iterations were entered and the training process was started. Data obtained after training of ANN were compared with data obtained from experiments to confirm reliability of prediction. RMSE, AFV and MEP values were used for comparisons [21, 22]. These values are calculated as follows;

$$RMSE = \left(\left(\frac{1}{p}\right) \sum_j \left|t_j - o_j\right|^2 \right)^{1/2} \tag{4}$$

$$AFV = 1 - \left(\frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \tag{5}$$

$$MEP = \frac{\sum_j \left((t_j - o_j)/t_j\right) \times 100}{p} \tag{6}$$

Where, t is the goal value, and o is the output value. *RMSE* is the root mean square error. *AFV* is the absolute fraction of variance, and *MEP* is the mean error percentage.

3. Results and discussions

The aim of using the ANN model is to test the prediction capability of fatigue life of metal matrix composites. Comparison and statistical evaluation of tested actual and predicted fatigue life cycles for testing and training data is shown in Fig. 2. It is observed in Fig. 2 that AFV values are very close to 1 for both training and testing data. RMSE values are smaller than 0.0075. During the training and testing period, the maximum mean relative errors were found to be 2.203173% and 4.039562%, respectively. These results show that MEP values are within acceptable error limits (±5).

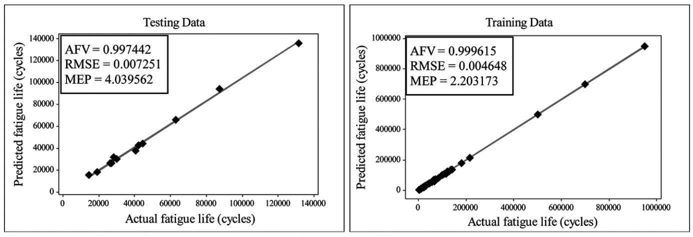

Fig. 2. Comparison of tested actual and predicted fatigue life cycles for testing and training data

Fatigue life formula derived via ANN is given in Eq. 7. Also, fatigue cycles of MMCs can be accurately calculated by this formula. It is seen that most of the predicted values are very close to the experimental results.

$$Nf = \frac{1}{1 + e^{-(9.9493\times \mathbf{F1} + 6.7870\times \mathbf{F2} - 8.5051\times \mathbf{F3} + 17.5272\times \mathbf{F4} + 0.1072\times \mathbf{F5} - 0.1866)}} \tag{7}$$

where Nf and F_i are the activation functions and are calculated with the equations in Table 2. Activation function F_i for fatigue life predictions is calculated using weights between first and second hidden layers after calculation of function N_j using weights between input and first hidden layers due to two layered ANN architecture. The weight values among layers for fatigue life cycles are given in Table 2.

Depending on the materials type, fatigue life predictions by ANN are given in Table 3. An increasing volume fraction of SiC particles from 0% to 25% in the composites has significant effects on the fatigue life response. It is clear from the results that the neural controlled prediction of fatigue life follows the experimental results very closely. The MEP is as small as %3.3. In Table 3, both actual and predicted fatigue life cycles are given. The grayscaled rows show testing data and others show training data.

TABLE 2

Weights among layers for fatigue life cycles

Weights values between first and second hidden layers											
$Fi = \frac{1}{1 + e^{-(w_1\times \mathbf{N1} + w_2\times \mathbf{N2} + w_3\times \mathbf{N3} + w_4\times \mathbf{N4} + w_5\times \mathbf{N5} + w_6\times \mathbf{N6} + w_7\times \mathbf{N7} + w_8\times \mathbf{N8} + w_9\times \mathbf{N9} + w_{10}\times \mathbf{N10} + w_{11}\times \mathbf{N11} + \theta_i)}}$											
i	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}	w_{11}	θ_i
1	1.1468	1.9973	-3.1987	8.4416	2.8185	5.8917	-5.6907	-4.2849	8.3510	1.8492	0.8297	-10.258
2	5.7843	-2.3207	3.2836	-7.5497	-4.5456	2.9591	-2.7651	5.8475	1.1614	-0.8113	-0.4439	1.3841
3	-0.9810	-1.9721	12.2135	-6.8420	1.7349	2.2045	-14.336	2.6462	6.9752	2.4324	2.5216	-2.7403
4	6.2171	-0.5358	9.9621	-20.094	-37.346	-0.1719	6.5075	3.2057	-3.1112	1.5450	1.6760	3.1143
5	-1.7286	0.8961	-2.2724	2.5430	-2.1708	-0.4300	2.7201	0.3266	-2.3212	2.6122	-1.3355	-2.5391

cd TABLE 2

Weights between input and first hidden layers						
$Nj = \frac{1}{1+e^{-(w_1\times\mathbf{M}+w_2\times\mathbf{S}+w_3\times\mathbf{R}+w_4\times\mathbf{Kt}+w_5\times\mathbf{T}+\theta_j)}}$						
j	w_1	w_2	w_3	w_4	w_5	θ_j
1	-4.4969	-1.1884	-0.8528	2.3030	-10.2732	8.8182
2	0.1502	3.3473	-3.4849	4.4230	3.9960	-11.1368
3	2.2816	20.6636	-6.9340	-0.5252	-6.7692	-4.3309
4	1.9633	20.5162	4.2308	19.7896	-5.3064	-19.3525
5	-20.0306	16.0203	5.3404	29.1958	3.9843	-7.5659
6	2.7358	-0.8131	4.4361	0.1962	2.5030	-7.4714
7	0.7859	-10.3145	-6.9449	0.5783	-2.7124	5.1394
8	1.1360	-11.9094	-0.9475	-2.2060	0.8913	10.5268
9	6.9233	-16.2169	3.0354	8.5648	1.9061	-5.4547
10	-1.9359	5.7881	-1.0552	-4.5398	4.1760	-6.2736
11	1.6483	-3.5112	-2.2898	-2.2776	6.3572	8.9385

TABLE 3

The influence of materials type on actual and the predicted fatigue cycles

Materials	*Maximum Applied Stress (MPa)*	*R Ratio*	*Kt*	*Temperature °C*	*Tested Nf (Cyles)*	*ANN predicted Nf (Cycles)*
LMMC17	400	0.1	1.8	21	11458	11711
	350	0.1	1.8	21	24877	25336
	300	0.1	1.8	21	42296	42262
	275	0.1	1.8	21	43469	46086
	250	0.1	1.8	21	127245	125784
LMMC25	450	0.1	1.8	21	9448	9266
	350	0.1	1.8	21	26366	26163
	300	0.1	1.8	21	66626	59718
	250	0.1	1.8	21	121259	123858
MMC00	400	0.1	1.8	21	3869	4106
	350	0.1	1.8	21	14471	15480
	300	0.1	1.8	21	67366	64171
	275	0.1	1.8	21	70948	74217
	250	0.1	1.8	21	140000	136798
MMC17	450	0.1	1.8	21	9693	9601
	400	0.1	1.8	21	13954	13544
	375	0.1	1.8	21	21250	20025
	350	0.1	1.8	21	26996	26362
	300	0.1	1.8	21	62814	68357
	275	0.1	1.8	21	115485	110686
	250	0.1	1.8	21	135483	136734
MMC25	450	0.1	1.8	21	5840	6023
	400	0.1	1.8	21	12500	12477
	350	0.1	1.8	21	29000	30336
	325	0.1	1.8	21	83063	80491
	300	0.1	1.8	21	131317	135865
	275	0.1	1.8	21	180000	180007
	250	0.1	1.8	21	950000	949493

The effect of R ratios on the fatigue lives and prediction are shown in Fig. 3 where the ANN predictions are shown with continuous lines. In general, the addition of SiC particles significantly improves fatigue lives at both stress ratios. Fatigue lives can be improved as much as 50% by addition of ceramic particles in the matrix material. It was reported that increasing the number of R ratios improved the accuracy of the prediction method [7].

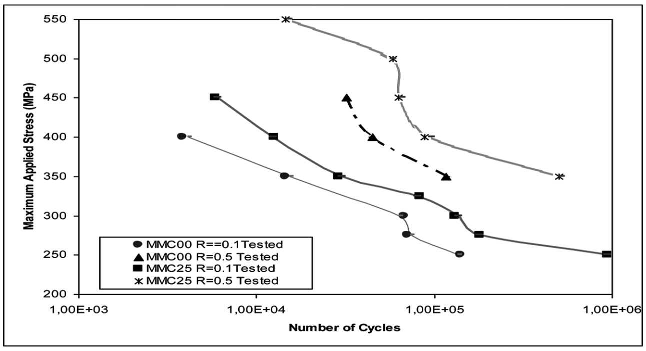

Fig. 3. The influence of R ratio on fatigue life and ANN predictions

The effect of stress concentration factor (Kt) on the fatigue life predictions for MMC25 composites are shown in Fig. 4. The graphs show how the fatigue life of MMC25 composite material decreased with increasing stress concentration factor. The continuous lines are shown the predictions made by the ANN. It can be seen that very good predictions can be obtained by the ANN model. The MEP is only 1.71%. This means that the ANN model can perfectly predict the fatigue life of these composites.

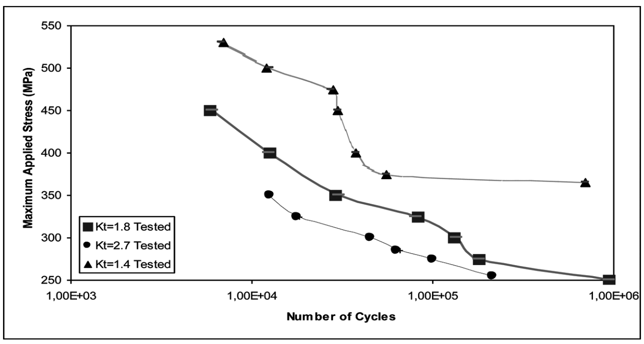

Fig. 4. The influence of Kt on fatigue life and ANN predictions

The effect of testing temperature on the fatigue life predictions for MMC25 composite are shown in Fig. 5. The downward shift in stress-life curve with increasing temperature is evident. At equivalent values of stresses, the degree of degradation in cyclic fatigue life was in the range 50-500%. The reduction in fatigue response is consistent with decreased values of the tensile properties. The MEP is 2.5%.

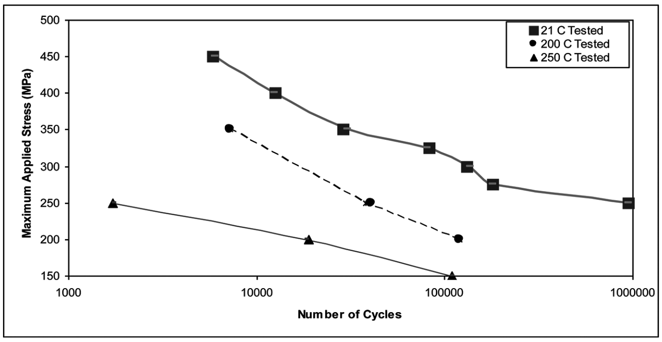

Fig. 5. The effect temperature on the fatigue life and predictions

All the figures show that the proposed neural network model successfully predicts fatigue life with the least error. The figures also show shift between the experiments and the predicted values along the fatigue lives. This might be due to the significantly different failure modes, number of tested specimens and materials characteristics etc. With the larger number of experiments used in the training, this could cause the ANN, not only predict the trend of fatigue behaviour but also the many variations within the experimental data used in training. Different neural network architectures using a variety of functions resulted different amount of the MEP values prediction of fibber reinforced composite materials [23]. Also, the neural networks can be used as an alternative way for calculating the gas mixtures according to the presented conventional calculation method [24]. In general it was noted that the reliability of the network was improved by increasing the number of variations for which training data were used. However, the ANN method using experimental data from two different material system and proved that constant life diagrams which are very useful for the design of structures can be efficiently modelled using a much smaller set of experimental data compared to that needed for the development of life diagrams by the conventional way [25]. It is interesting to notice that a generalization of ANN using only three S-N curves. It showed that the ANN has great potential in predicting the life at fatigue of composite materials [26].

4. Conclusions

The applicability of ANNs for the fatigue life predictions of metal matrix composites was investigated. To train the network, the particle size and volume fraction of reinforcement, stress concentration factor, R ratio, peak stress and temperatures are used as the input layer, while the output is a number of failure cycles. Using some of the experimental data for training, an ANN model based on standard back-propagation algorithm for the fatigue life predictions was developed. Then, the performance of the ANN predictions were measured by comparing the predictions with the experimental results which were not used in the training process. It is shown that AFV values are 0.999615 and 0.997442 for the training and testing data respectively; RMSE value is equal to 0.007251; and mean error is equal to 4.039562% for the testing data. It is observed that the results are within the acceptable error limits. The relationships between input and output variables for metal matrix composites can be determined by using the network. For this reason, the usage of ANNs can be considerably recommended to predict the failure cycles instead of expensive, complex and time-consuming experimental studies. This study shows that the ANN can be used to precisely predict the failure cycles of metal matrix composites.

REFERENCES

[1] I. Uygur, Iranian J. Sci. Technol. **28B2**, 239 (2004).
[2] I. Uygur, W.J. Evans, M.R. Bache, B. Gulenc, Metallo. Novei. Tekhnol. **26**, 927 (2004).
[3] I. Uygur, M.K. Kulekci, Turk. J. Eng. Env. Sci. **26**, 265 (2002).
[4] J. Schije, Int. J. Fatigue **25**, 679 (2003).
[5] I. Uygur, PhD Thesis (Swansea: University of Wales: 1999).
[6] H. Ates, Mater. & Design **28**, 2015 (2007).
[7] J.A. Lee, D.P. Almond, B. Harris, Composites **30A**, 1159 (1999).
[8] I. Uygur, Archives of Metal. & Mater. **56**(1), 109 (2011).
[9] D. Karayel, Journal of Materials Processing Technology **209**, 3125 (2009).
[10] E. Oztemel, Artificial Neural Network. Istanbul, Papatya Publishing, 2003.
[11] G. Najafi, B. Ghobadian, T. Tavakoli, D.R. Buttsworth, T.F. Yusaf, M. Faizollahnejad, Applied Energy **86**, 630 (2009).
[12] N. Pasadakis, S. Sourligas, C. Foteinopoulos, Fuel **85**, 1131 (2006).
[13] G. Liu, L. Wang, H. Qu, H. Shen, X. Zhang, Fuel **86**, 2551 (2007).
[14] E. Jorjani, S.C. Chelgani, S. Mesroghli, Fuel **87**, 2727 (2008).
[15] M. Nalbant, H. Gokkaya, I. Toktas, G. Sur, Robotics and Computer-Integrated Manufacturing **25**, 211 (2009).
[16] E. Arcaklıoğlu, I. Çelikten, Applied Energy **80**, 11 (2005).
[17] B. Ghobadian, H. Rahimi, A.M. Nikbakht, G. Najafi, T.F. Yusaf, Renewable Energy **34**, 976 (2009).
[18] A. Parlak, Y. İslamoğlu, H. Yaşar, A. Eğrisöğüt, Applied Thermal Engineering **26**, 824 (2006).
[19] T.F. Yusaf, D.R. Buttsworth, K.H. Saleh, B.F. Yousif, Applied Energy **87**, 1661 (2010).
[20] C. Sayın, H.M. Ertunç, M. Hosoz, I. Kılıçaslan, M. Çanakcı, Applied Thermal Engineering **27**, 46 (2007).
[21] A. Kurt, Expert Systems with Applications **36**, 9645 (2009).
[22] I. Korkut, A. Acır, M. Boy, Expert Systems with Applications **38**, 11651 (2011).
[23] M. Al-Assadi, H. El-Kadi, I.M. Deiab, Appl. Compos. Mater. **17**, 1 (2009).
[24] H. Ates, Mater. & Design **28**, 2015 (2007).
[25] A.P. Vassilopoulos, E.F. Georgopoulos, T. Keller, Int. J. Fatigue **30**, 1634 (2008).
[26] J.C.S.F. Junior, A.D.D. Neto, E.M.F. Aquino, Int. J. Fatigue **272**, 746 (2005).

Received: 20 April 2013.