Prediction Fatigue Life of Aluminum Alloy 7075 T73 Using Neural Networks and Neuro-Fuzzy Models

Dr. Mustafa S. Abdullatef
Electromechanical Engineering Department, University of Technology/Baghdad
Email: Mustafa 1989oc@yahoo.com
Dr. Nazhat . AlRazzaq
Electromechanical Engineering Department, University of Technology/Baghdad
Mustafa M. Hasan
Electromechanical Engineering Department, University of Technology/Baghdad

Received on: 26/3/2015 & Accepted on: 12/11/2015

ABSTACT

In present paper the fatigue life of aluminum alloy 7075 T_{73} under constant amplitude loading is predicted using ANN and ANFIS models. Many neural networks models are used for this purpose and also different neuro-fuzzy models are built for predict fatigue life. The classical power law formula is most common used to find fatigue behaviors of materials. In present study, two techniques are used to find coefficients of the formula linear and nonlinear regression. For comparison the fatigue life curves of soft computing methods are plotted together with two conventional methods. The neural network and neuro-fuzzy models give good results compared with two conventional methods. Also it is shown that neural network model which is trained using Levenberg-Marquardt algorithm is best neural network models compared with other NNS models. Also, it is found ANFIS models with input trapezoidal membership function is best performance from other membership function types to predict fatigue life. It can be stated that neuro-fuzzy models are better models than neural network and conventional methods to predict fatigue life of the maintained alloy.

Keywords: Neural networks, Neuro-Fuzzy, Fatigue life, Aluminum alloy, 7075 T_{73}.

تخمين عمر الكلال لسبيكة الالمنيوم 7075 T73 بأستخدام نماذج الشبكات العصبيه والضبابيه العصبيه التكيفية

الخلاصه:

هذا البحث يهدف لتخمين عمر الكلال لسبيكة الالمنيوم 7075 T73 تحت احمال ثابتة بأستخدام نموذج الشبكة العصبيه و الضبابية العصبية التكيفية.عدة نماذج من الشبكات العصبيه والضبابيه العصبيه التكيفية بنيت لهذا الغرض.عادة العلاقات الأسية التقليدية هي الاكثر استخداما لأيجاد عمر كلل المعادن. استخدمت طريقتين لايجاد معاملات هذه العلاقه بشكل تقليدي هما الانحدار الخطي واللاخطي. رسمت منحنيات تصرف الكلال لطرق الحساب البرمجية سويا مع الطريقتين التقليديتين لغرض المقارنه تبين من النتائج بان نماذج الشبكات العصبية والضبابية العصبية قد اعطت نتائج جيده بالمقارنة مع الطرق التقليدية. كذلك تبين بأن نموذج خوارزمية Levenberg-Marquardt أفضل نموذج لتمثيل تصرف الكلال بالمقارنة مع نماذج الشبكات العصبية الاخرى. كذلك وجد نموذج ANFIS الذي بني باستخدام دالة عضوية على شكل شبه منحرف أفضل أداء من الدوال العضوية الاخرى لتمثيل تصرف السبيكة.

https://doi.org/10.30684/etj.2016.112624
2412-0758/University of Technology-Iraq, Baghdad, Iraq

NOMENCLATURE:

A,d,E	Corson equation constants.
ANN	Artificial neural network.
ANFIS	Adaptive neuro-fuzzy inference system.
a,b	Dengel and Basquin equation constants.
a_i	Predicted value.
CF	Cascade forward network.
FFN	Feed forward neural network.
Log, Lin	Logistic and linear activation function respectively.
MSE	Mean square error.
MAE	Mean absolute error.
n	Number of data set.
N_f	Number of cycles to failure.
NN	Neural network.
RMSE	Root mean square error.
R^2	Coefficient of determination.
S-N	Stress versus number of cycles to failure curve.
Tan	Hyperbolic activation function.
t_i	Experimental value.
σ	Amplitude stress.

INTRODUCTION

The S-N fatigue tests which are called wöhler tests are most common types of fatigue testing. These tests are represented fatigue life of component and provide valuable information to engineer during design process. Because of it's affected by many factors and nonlinearity, it is built using empirical formulas of experimental data [1]. Many empirical formulas are used to find S-N curves such as Dengel representation with two parameters a and b, Basquin equation with logarithmic scale and two parameters a and b, Stromeyer with two parameters, Palmgren the same method with inflection point that allows us to improve the quality of the data adjustment, Corson with three parameters *A, E* and d and Weibull equation with four parameters but these methods are inaccurate, even inconsistent greatly [2]. So obtaining fatigue S-N curve is very difficult for a long time, it is perfect goal that designers get fatigue S-N curve fully and reliably [3]. Artificial neural networks are one of artificial intelligent tools that have been used successfully in various engineering applications. Due their massively parallel structure, ANN can be able to represent multivariable nonlinear mathematical modeling accurately which classical analytical methods is very difficult to obtain. ANNs are very capable when it comes to describing fatigue phenomena, many researchers are used it to predict fatigue life of materials. For example T. Pleune et al. [4] used artificial neural networks to predict the fatigue life of carbon and low-alloy steels .They found ANN models have standard error lower than statistical model where artificial neural networks show great potential for predicting environmentally without depending on preconceptions. Also Júnior et al. [5] demonstrated the applicability of artificial neural networks on building constant life diagrams of fatigue. They found that the use of ANNs on building constant life diagrams is very promising, mainly because it is possible to have satisfactory results using a few number of S–N curves. Other researchers used other types of network architecture such as Freire et al. [6] used of new network architectures in modeling and building of constant life diagrams, they assumed the use of modular networks for modeling the fatigue life and show more satisfactory results than the use of FNN. Although ANNS have been successfully predict fatigue behavior of materials but on the negative side they have the negative assign of the "black box" .ANFIS combines the advantages of ANNS and fuzzy logic without having any of their disadvantages therefore it is used to solve complex problems of fatigue phenomena. One of the first papers which is used ANFIS models to predict fatigue behavior is published by Jarrah et al. [7] .They modeled the fatigue behavior of unidirectional glass fiber/epoxy composites with good performance. Vassilopoulos et al. [8] used adaptive neuro-fuzzy inference system for modeling fatigue behavior of a multidirectional composite laminate.

In this work, fatigue life of aluminum alloy 7075 T_{73} is predicted fatigue using conventional methods, ANN and ANFIS models then comparing between all these methods.

Experimental procedure

The material used in this study is aluminum alloy 7075 T73. Chemical composition of the alloy has been tested using (Foundary –Master Expert) testing device and found to be as listed in table (1). The mechanical properties of this alloy are listed in Table (2) according to ASTM standards. The fatigue test was done using Avery 7305 test machine under constant amplitude stress with stress ratio (R=-1) under laboratory conditions .The specimen of this test are shown schematically in figure (1) according to ASTM. It is used three specimens A1, A2 and A3 are used each stress level to find fatigue life by plotting S-N curve. The results of fatigue test which are found show in table (3).

S-N Curve of the aluminum alloy

The S-N curve can be obtained using power law equation $\sigma = a(N_f)^b$; the curve fitting is used to find the coefficients of this equation. There are two methods to find the constants of this equation as follows:

1-Direct method:

In this method, curve fitting is used directly without any transformation of power law equation. The trust region method is used to find coefficients. After calculations, the equation becomes:

…(1)

2-Transformation method:

In this method, the power law equation is transformed to linear equation be taking logarithm to the base 10 for both side then use linear least square method to find constant of this equation. After calculations, the equation becomes:

…(2)

Artificial neural networks

An artificial neural network is an information processing system that has certain performance characteristics in common with biological neural networks. A neural net consists of many of simple processing elements called neurons, units, cells, or nodes. Each neuron is connected to other neurons by direct communication links, each with an associated weight. The weights represent the information being used by the net to solve a problem [9].

ANN and ANFIS model design

The fatigue life of aluminum alloy 7075 T73 is predicted using neural networks and Neuro-Fuzzy models. To design both models, the number of cycles to failure is used as input and amplitude stress is used as output in both models. To avoid over fitting, the data is divided in two sets for training and testing with percent 75% and 25% respectively. Because the range of data set is very wide, the data set is normalized between -1 to 1 for NN model while is taken logarithmic base 10 then divided by 7 for input and 3 for output for ANFIS model. Different neural network models are designed with three architectures feed forward ,cascade forward and Elman network, different hidden neurons and training algorithms, these models are found in table (4).Also ANFIS model is designed using different number and types of membership functions. The ANFIS models are found in table (5).

Results and Discussion

MATLAB 2013b [10] is used to design, train and test ANNS and ANFIS models. To evaluate the performance of models the following error analysis criteria is used for this purpose:

$$-\sum \quad)^2 \quad . \quad \ldots (3)$$

$$\sqrt{-\Sigma} \qquad ...(4)$$

$$\frac{\Sigma_i^n}{\Sigma_i^n \quad -\bar{t_i})} \qquad .... (5)$$

$$-\Sigma \quad (|t \qquad |) \qquad ...(6)$$

Feed forward neural networks are used to predict fatigue life, Fig. (3), Fig. (4), Fig. (5) and Fig.(6) show fatigue life of two conventional methods vs. feed forward neural network models. According to the results obtained, it can be stated, the feed forward neural networks models are better than both conventional methods. The mean absolute error of the network has been calculated and found to be for FF2 is 2.56614, FF5 is 3.22939, FF9 is 3.032515 and FF32 is 3.308468 while the mean absolute error of the nonlinear least square is 11.53639 and linear least square method is 13.87119. This difference is very high if it is known that difference of fatigue strength between some aluminum alloys is less than this difference. It can be calculated that using of the feed forward neural networks models are more efficient than conventional methods in all different training algorithms and activation functions. The prediction of fatigue life using cascade forward neural network vs. conventional methods is shown in Fig. (7), Fig.(8) and Fig. (9).

It can be shown from these results that cascade forward neural networks give good results. The mean absolute error of the networks has been calculated and found to be for CF1 is 2.889331, CF26 is 2.61722 and CF29 is 2.46155. Both conventional methods give a mean absolute error less than these values, also cascade forward neural network models have accurate results than feed forward in most cases because of additional weight that is used in this networks which may be increase the accuracy of the network.

Conventional methods vs. Elman network results are shown in Fig. (10), Fig.(11) and Fig. (12).The mean absolute error of the networks are calculated and found to be EL2 is 2.0782, EL8 is 2.107116 and EL34 is 2.5579 .From the previous results, the Elman neural networks are better than both neural networks FF and CF however it are still slower than both networks because these networks are used delay feedback in their architectures. It can be stated that, the Levenverg Marqurted training algorithms gives best prediction of fatigue life than all other training algorithms that are used in this work. This is due the technique which this method is used it. It is designed to approach second-order training speed without computing the Hessian matrix. From all the results are found in table(4.46), it is found the best neural networks to represent fatigue behavior at these condition is EL2 and worst network from network that is found in Table (6) is FF32

Comparison between conventional methods and ANFIS results is shown in Fig. (13), Fig. (14), Fig.(15) and Fig. (16).The results of using this model shows that the neuro fuzzy model is better than neural networks where the mean absolute error of the networks ANFIS4 is 1.56141, ANFIS5 is 1.48258, ANFIS7 is 1.57910, ANFIS9 is 1.69237 and ANFIS15 is 3.18612.The neural networks models as noted from above shows mean absolute error less than these values. The other advantages of using neuro-fuzzy model are the representation of the input and output by membership function which was not found in neural networks models where these models are not represented by any function and represented by black-box model. It has been found that the neuro-fuzzy models are best method to represent fatigue life model from both neural networks and conventional methods because ANFIS models have less mean absolute errors from other models. Although all these advantages of neuro-fuzzy and neural networks models but these methods still cannot extrapolate any predictions outside the data base. This is one of big disadvantage in ANN and ANFIS models. To solve this problem, the suitable range of data must be used, in the fatigue phenomena, the range of the number of cycles to failure must be exceed the endurance limit, this limit is very important for the designer. Another approach may be used to solve this problem, is the extrapolating of the data before design soft computing models then used this data to train and test models, this process will increase the range of the data. Many researchers and papers try to find solution of this problem but all methods until now are still unable to do this. These problems may be solved in the future. The results of conventional methods and two soft computing methods are sown in table (6) .

CONCLUSIONS

ANNS and ANFIS models are used to represent fatigue life of aluminum alloy 7075 T_{73}.It can be stated from the results both for neural networks and neuro-fuzzy models are very promising with compare conventional methods that are based on empirical formula. The following conclusions are obtained from this work:

1-Neuro-Fuzzy models are better than neural networks models.

3-Elman neural network model is best performance of other types of neural network architecture although it is slowest of other networks.

4- Levenberg-Marqurted training algorithm is best training algorithm which is used to train of neural network models to represent this problem.

REFRENCES

[1] Yung L.L ,Jwo P. ,Richard B. H. & Mark B. , “Fatigue Testing And Analysis (*theory and practice*) ” , Elsevier Inc.,USA,2005.

[2] Claude Bathias and André Pineau, Fatigue of Materials and Structures, John Wiley and Sons Inc.2010.

[3] Yi WAN and Chengwen W.U, “A new intelligent design method for building material fatigue S-N curve” ,International Conference on E-Learning, E-Business, Enterprise Information Systems, and E-Government, 2009.

[4] T. Todd Pleune and Omesh K. Chopra,“Using artificial neural networks to predict the fatigue life of carbon and low-alloy steels”, Nuclear Engineering and Design vol. 197, 2000.

[5] Raimundo C. S., Adrião D. D. & Eve M. F. “Building of constant life diagrams of fatigue using artificial neural networks” , International Journal of Fatigue vol. 27, Elsevier Inc.,USA, 2005.

[6] Raimundo C. S. , Adrião Duarte Do ria Neto & Eve Maria Freire de Aquino , “Use of modular networks in the building of constant life diagrams”, International Journal of Fatigue vol. 29, Elsevier Inc.,USA, 2007.

[7] Jarrah, M. A., Al-Assaf, Y., & El Kadi, H. “ Neuro-fuzzy modeling of fatigue life prediction of unidirectional glass fiber/epoxy composite laminates”. Journal Computational Materials, vol.36, p.p685–699. 2002.

[8] A. P. Vassilopoulos and R. Bedi, “Adaptive neuro- fuzzy inference system in modelling fatigue life of multidirectional composite laminates”, Computational Materials Science vol.43 ,2008.

[9] S. Haykin, Neural Networks A Comprehensive Foundation, Prentice-Hall, 1999.

[10] http://www.mathworks.com/products/new_products/release2013b.html

[11] Mustafa Mahmood,“ Prediction Fatigue Life of Aluminum Alloy 7075 T_{73} Using Neural Networks and Neuro-Fuzzy Models” , MSC Thesis, University of Technology of Electromechanical of Engineering, Electromechanical systems, Iraq,2015.

Table (1) - Chemical composition of aluminum alloy 7075 T73

Si%	Fe%	Cu%	Mn%	Mg%	Cr%	Zn%	Ti%	Other%	Al%
0.028	0.221	1.59	0.01	2.18	0.18	5.61	0.021	0.025	Remainder

Table (2) - Mechanical properties of aluminum alloy 7075 T73

Tensile strength (Mpa)	Yield strength (Mpa)	Elongation%	Brinel hardness (HB)	Vickers hardness (HV)
482.5	415.5	16.27	138.95	154.33

Table (3) - Stress and number of cycles to failure of the aluminum alloy 7075 T73

Nf(A3)	Nf(A2)	Nf(A1)	Nf(average)	Stress (Mpa)
3000	3000	2000	2666.6	325.45
5000	4000	4000	4333.3	321.95
6000	5000	5000	5333.3	314.96
6000	7000	8000	7000	311.46
12000	9000	10000	10333.3	304.46
15000	16000	12000	14333.3	300.96
40000	34000	30000	34666.6	290.46
56000	68000	72000	65333.3	276.46
89000	79000	93000	87000	265.96
125000	100000	117000	114000	258.96
145000	139000	133000	138666.6	244.96
213000	230000	223000	222000	234.47
350000	353000	346000	349666.6	230.97
463000	449000	423000	445000	227.47
553000	555000	560000	556000	220.47
674000	677000	686000	679000	213.47
733000	735000	720000	729000	209.97
1005000	998000	1010000	1004333	206.47
1136000	1150000	1100000	1126666	199.47
1466000	1550000	1430000	1482000	192.47
2210000	2244000	2200000	2218000	185.47
3119000	3120000	3095000	3111333	171.47
3510000	3576000	3416000	3501333	164.47
4211000	4300000	4233000	4248000	150.48
6000000	5866000	5553000	5806333.3	139.98

Table (4) - Neural network models

Model	Architecture	Hidden neurons	Training algorithms	Activation functions
FF2	Feed forward	١٢	Levenberg- Marqurted	Log-Lin
FF5	Feed forward	8	Scaled conjugate gradient	Log-Lin
FF9	Feed forward	٧	Quasi newton	Tan-Tan
FF32	Feed forward	٧	Conjugate gradient with Powell-Beale	Log-Lin
CF1	Cascade forward	٦	Levenberg- Marqurted	Tan-Lin
CF26	Cascade forward	١٤	Conjugate gradient with Fletcher-Reeves	Log-Lin
CF29	Cascade forward	١٩	Conjugate gradient with Polak-Ribiére	Log-Lin
EL2	Elman	9	Levenberg- Marqurted	Log-Lin

EL8	Elman	7	Quasi newton	Log-Lin
EL34	Elman	7	One step secant	Tan-Lin

Table (5) - ANFIS models

Model	NO. of nodes	NO. of membership functions	Types of membership functions
ANFIS5	20	4	Gaussian type
ANFIS7	16	3	Bell type
ANFIS9	16	3	Gaussian combination
ANFIS15	16	3	Trapezoidal type

Table (6) - Performance of all data set of all models

Model	MAE	MSE	R^2	No. epochs
Equation 1	13.87119	255.9	0.97291	-
Equation 2	11.53639	185.67	0.97187	-
FF2	2.56614	13.17794	0.99831	30
FF5	3.22939	17.02091	0.99751	250
FF9	3.03251	18.12798	0.9971	100
FF32	3.30846	16.59620	0.9972	140
CF1	2.88933	14.18841	0.9977	50
CF26	2.61722	15.503199	0.9972	120
CF29	2.46155	13.42572	0.99789	70
EL2	2.0782	7.70750	0.9993	5000
EL8	2.10711	8.91438	0.99855	5000
EL34	2.5579	11.30531	0.99817	5000
ANFIS5	1.48258	3.57388	0.99948	200
ANFIS7	1.57910	4.26498	0.99934	100
ANFIS15	1.23528	3.18612	0.99954	300

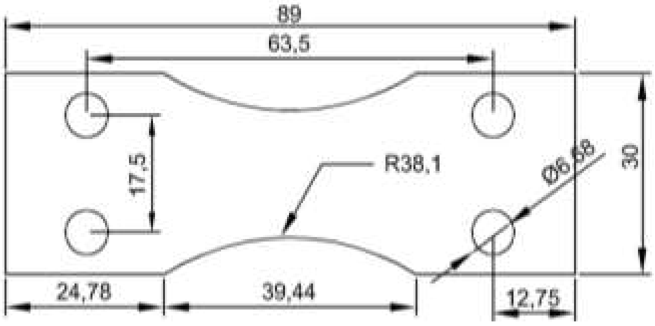


Figure (1) - Schematic of fatigue specimen

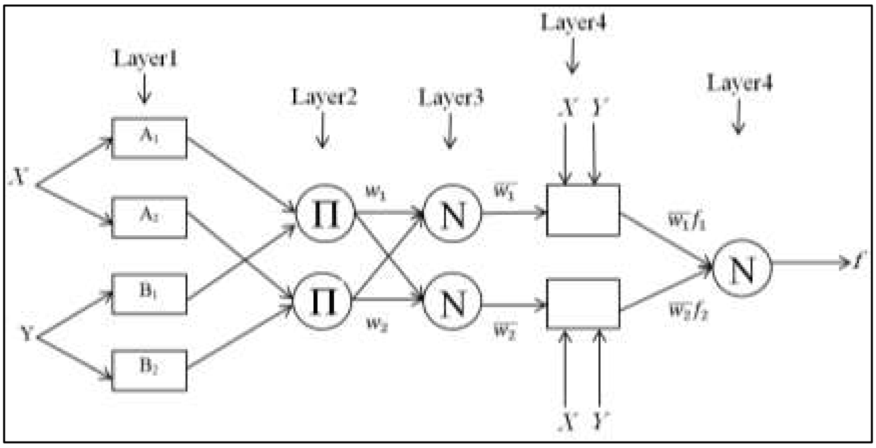


Figure (2) - First order Takagi-Sugeno ANFIS model

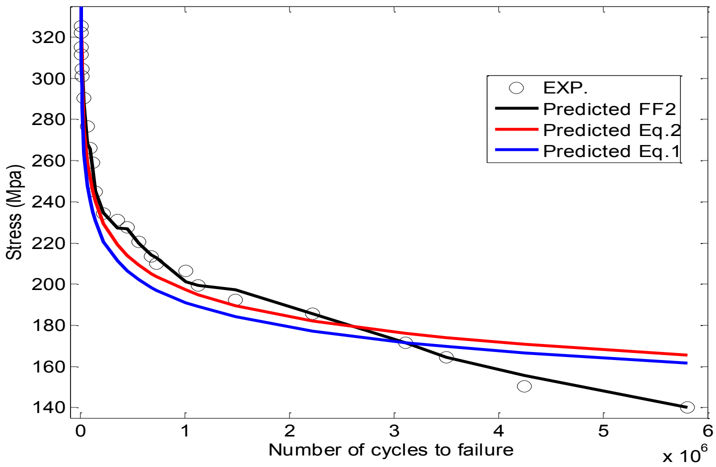
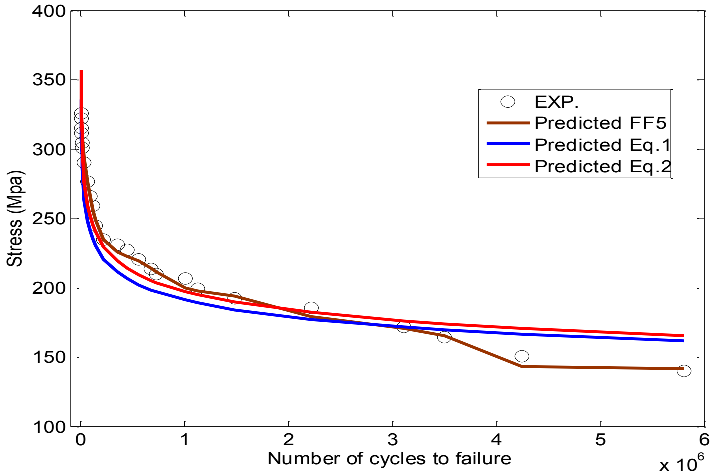


Figure (3) - Fatigue behavior using neural network FF2



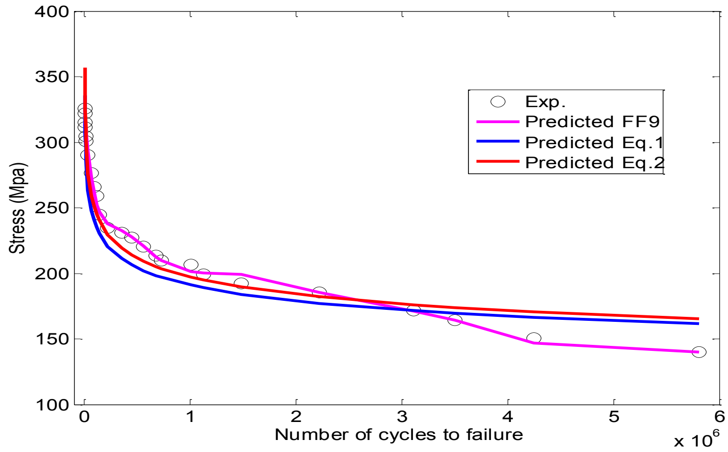


Figure (5) - Fatigue behavior using neural network FF9

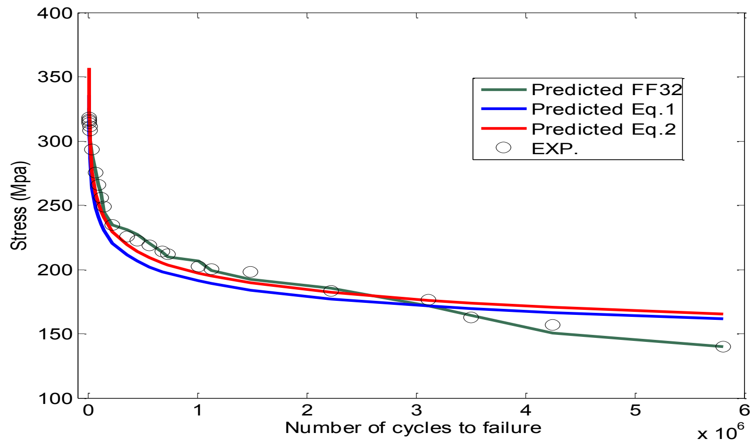


Figure (6) - Fatigue behavior using neural network FF32

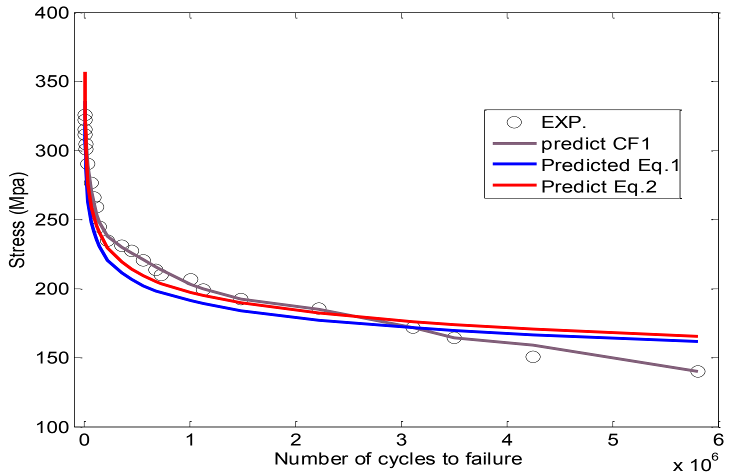


Figure (7) - Fatigue behavior using neural network CF1

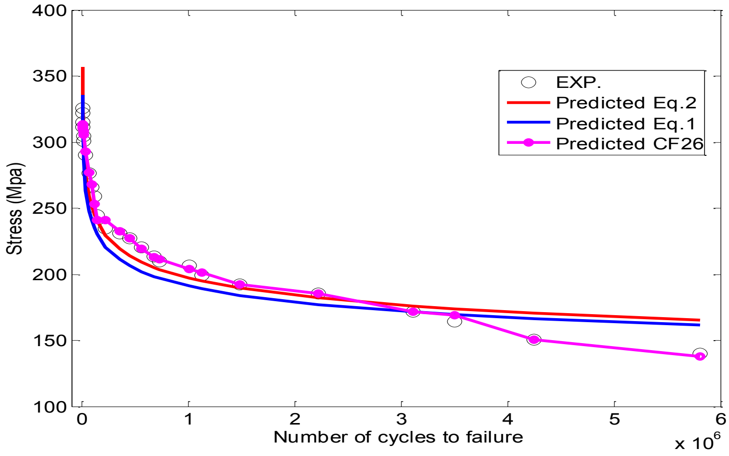


Figure (8) - Fatigue behavior using neural network CF26

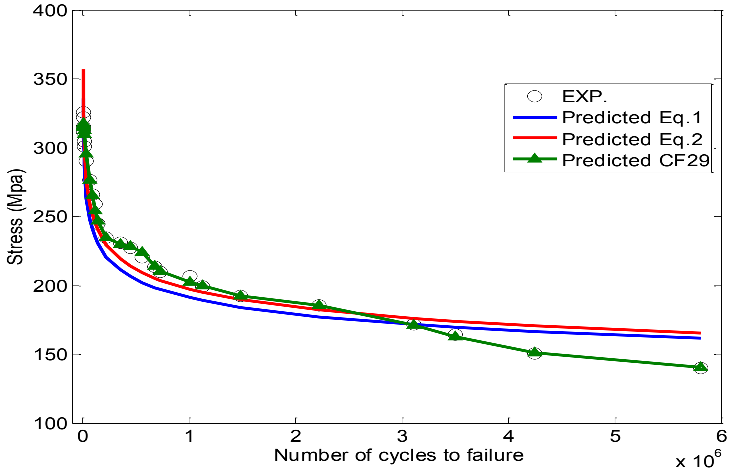


Figure (9) - Fatigue behavior using neural network CF29

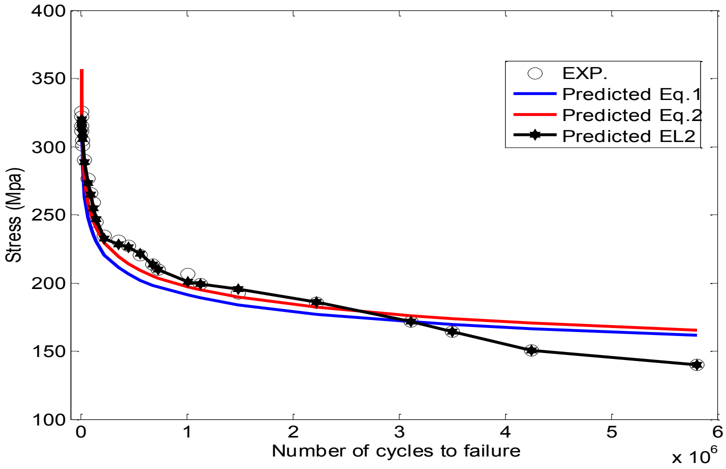


Figure (10) - Fatigue behavior using neural network EL2

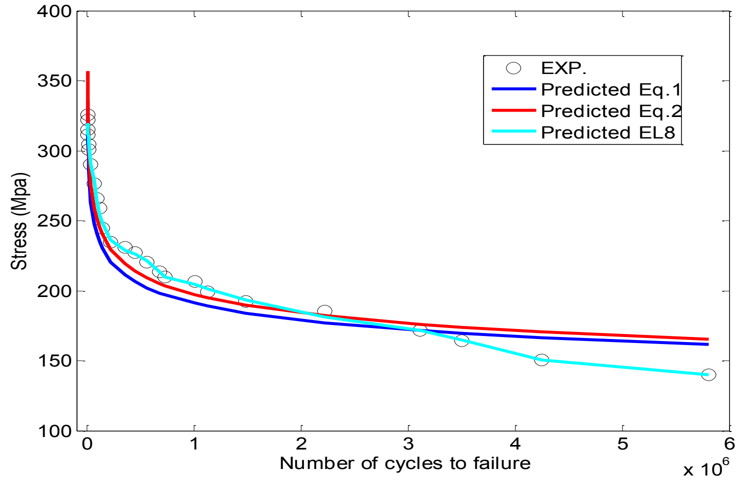


Figure (11) - Fatigue behavior using neural network EL٨

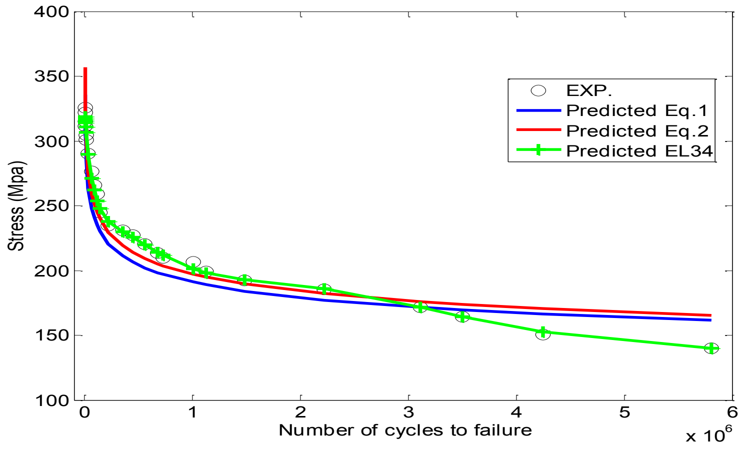


Figure (12) - Fatigue behavior using neural network EL34

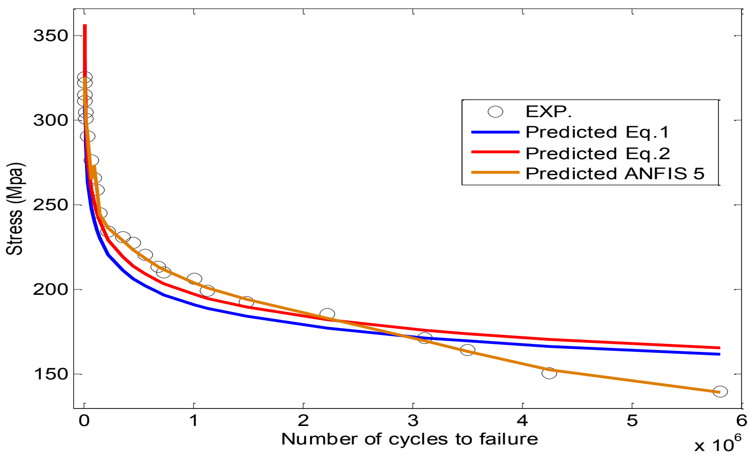


Figure (13) – Fatigue behavior using neuro-fuzzy network ANFIS5

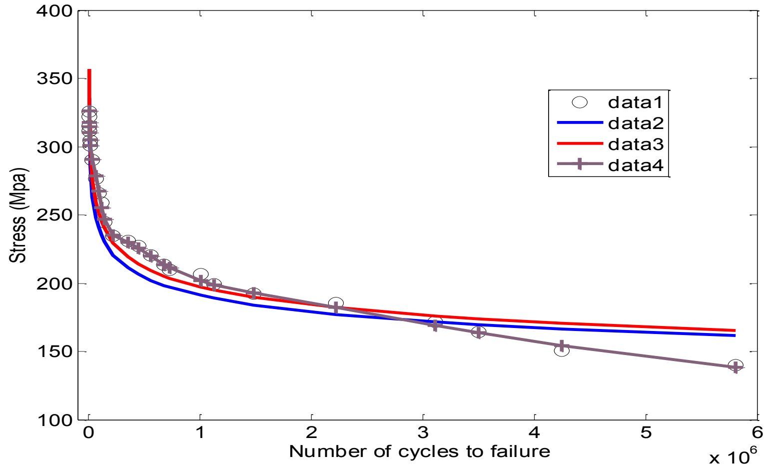


Figure (14) - Fatigue behavior using neuro-fuzzy network ANFIS7

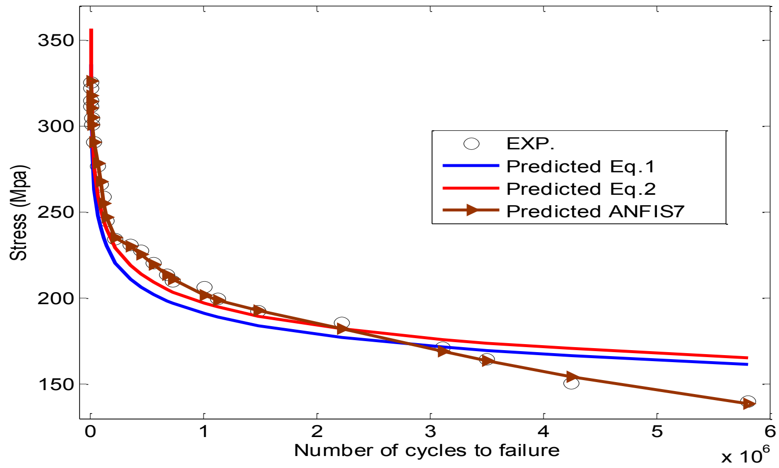


Figure (15) - Fatigue behavior using neuro-fuzzy network ANFIS9

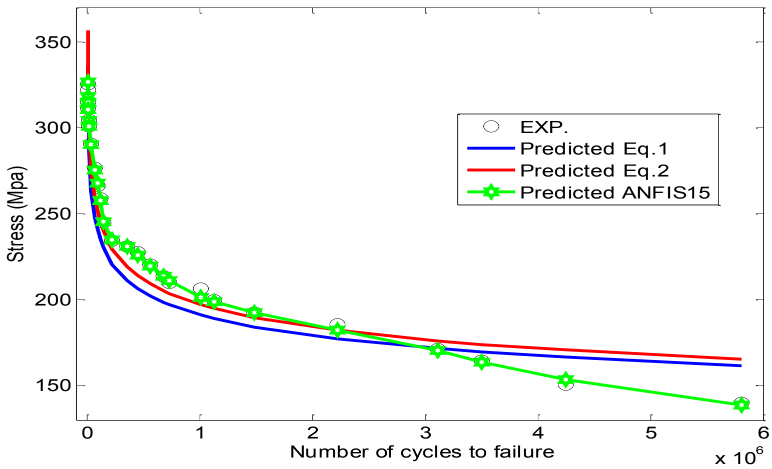


Figure (16) - Fatigue behavior using neuro-fuzzy network ANFIS15