Fatigue Prediction of Hybrid Joints and Perforated Plates Using Neural Network

Ali Yousefnezhad Oskooi[1*], Vahid Pourmohammad[2] ,Karim Samadzamini[1], Firooz Esmaeili Goldarag[1]
[1]Department of Computer Engineering, University College of Nabi Akram, Tabriz, Iran
[2]Department of Mechatronics Engineering University College of Nabi Akram, Tabriz,Iran
Email: ali_yousefnezhad@yahoo.com(corresponding author)
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Abstract

Hybrid connections (bolts, glue) and perforated plates are one of the most important topics in various industries, including aerospace. This type of process occurs due to the growth of small cracks in the metal structure as a result of cyclic or intermittent loading. Since failures occur suddenly, terrible accidents such as plane crashes, shipwrecks, bridge collapses, and toxic radioactive fallout can occur. To prevent these incidents, fatigue tests are performed on a sample of parts that is similar to the real part, so that the fatigue life can be obtained through this method. However, because fatigue tests are time-consuming and expensive, artificial intelligence methods have been used in this research to estimate the fatigue life of hybrid joints and perforated plates. In the experimental part of this research, plates made of aluminum alloy 2024-T3, which is one of the widely used materials in aerospace, the used materials are screws made of Hex head M5 and a special adhesive made of Loctite 3421 (Henkel ltd). Fatigue tests are extracted as input and output data from the related article. Out of a total of 71 fatigue tests, 35 tests were performed for perforated plates, 18 tests for hybrid joints, and 18 tests for bolted joints. Also, according to the number of data, the best result was when 80% of the data was considered for training the network and 20% was used as test data to evaluate the performance of the network. Finally, the predicted output was compared with the actual output and it was seen that the best performance of the neural network was after normalizing the data, that the error value was close to zero.

Keywords: hybrid connections, bolt connections, perforated plates, artificial intelligence, neural network

1. Introduction

Fatigue of metals occurs when the metal is subjected to vibration and mechanical forces and the parts are weakened by repeated forces over a period of time leading to the sudden failure of the part. This sudden factor is one of the most dangerous types of metal damage, namely metal fatigue which causes many injuries and damage to life and property. In recent decades, engineers in this field have focused research on fatigue life instead of static resistance analysis. There are many methods to predict fatigue life and a lot of research has been done in this field. For example, Ce Xiao et al. (14) used an artificial neural network (ANN) in estimating fatigue failure in composites with high lamination. Fatigue cracks have small apertures that result in low-contrast images and make the segmentation of cracks difficult. The phase contrast in synchrotron sources improves crack detection but also increases image complexity and human intervention is usually used to assist traditional segmentation methods. In this research, an image segmentation method based on a convolutional neural network is developed to replace user interpretation of images. This method, together with the "Hessian matrix" filter, can successfully extract the three-dimensional shapes of internal fatigue cracks in metals. In 2021, T.G.Sreekanth et al (12) conducted another research. In this research, an image separation method based on the convolutional neural network was developed to replace the user's interpretation of images. This method, together with the "Hessian matrix" filter, can successfully extract the three-dimensional shapes of internal fatigue cracks in metals. In 2021, Xinran Ma et al. (13) showed that the trained network can provide satisfactory predictions without any prior knowledge. NN-based boost learning method can perform well with a small amount of data.abst. An incremental learning method based on a fully connected neural network is proposed to predict fatigue crack growth at medium stress, M(T), of aluminum 7 B04 T6 and titanium alloy TA15 specimens under constant amplitude stress. Usually, fatigue crack growth rate measurement is labor-intensive and time-consuming, and fatigue cracks growth data sets are small. Backpropagation neural networks are not good at training on small datasets. Here we design network inputs that use multiple gain information to overcome this shortcoming. Given the data of the first part of crack growth in a sample, the trained network can predict the residue for both aluminum alloy and titanium alloy without any prior knowledge. The trained network learns the basic rules in experimental crack growth data. Our method shows its superiority over conventional proportional formulas and common neural networks such as recurrent neural networks and long-term-short-term memory methods. Our work demonstrates the capacity of the neural network and provides an alternative method for fatigue crack growth prediction.

2. Related Works

In 2013, Esmaili et al.[15] investigated the effect of screw preload force on the fatigue life of bolted sheets using a volumetric method. The comparison between the displacement results and the results obtained from the volumetric method in samples under different preload forces showed that there is a very good correlation between them. Also, the fatigue life of the bolted plates is improved due to the compressive stress created around the plate hole as a result of the preload force.

In another article by Esmaili et al. in 2014, the fatigue life obtained in the hybrid connection was compared by the volumetric method with the results of existing laboratory tests. The research shows that there is a good relationship between the fatigue life predicted by the volumetric method and the experimental results for samples with different tightening torques. The results obtained from the experimental analysis showed that the hybrid connection has better fatigue resistance than the simple connection. It has two sides. In addition, the volumetric method and experimental results showed that the fatigue life of both types of connections is improved by increasing the preload force caused by the tightening torque due to the compressive stresses created around the hole.

Experimentally, compressive residual stresses increase the fatigue life and tensile residual stresses decrease the fatigue life. This issue can be related to the closing of the crack tip due to compressive stress or its opening due to tensile stresses [2].

To estimate the fatigue life, there are fatigue testing devices, and to use the fatigue devices, a piece that is similar to the final product is required to be tested on, but due to the fact that in one test, the analysis may be insufficient or not performed correctly, it is necessary to perform a lot of tests which is costly and time-consuming, and for this reason, these tests cannot be performed most of the time, and fatigue life estimation is used for ease of work. In this article, ANN has been used to estimate the fatigue life of three parts of hybrid joints, bolts, and perforated plates in MATLAB software. Neural networks (artificial intelligence) needs data. These data are performed through fatigue tests by fatigue testing machines on test parts that are similar to real parts. The results of these fatigue tests will be determined using an artificial neural network by changing the layers and neurons of a model. The goal is that the training input data is sent to the perceptron network. Then these inputs are weighted by the hidden layers, the sum with the biases is applied to the transfer function and the output is obtained. Our algorithm should train this data so that the predicted output value is close to the actual output. The closer it is to the actual output, the better the network is trained.

3. Methods

To train the perceptron neural network, input and output data are needed. As mentioned in the introduction, all the data previously performed by the fatigue testing machines, and all the data of the hybrid connections and nut bolts in the s-n diagram of Figure (1) were extracted from the article [10,2

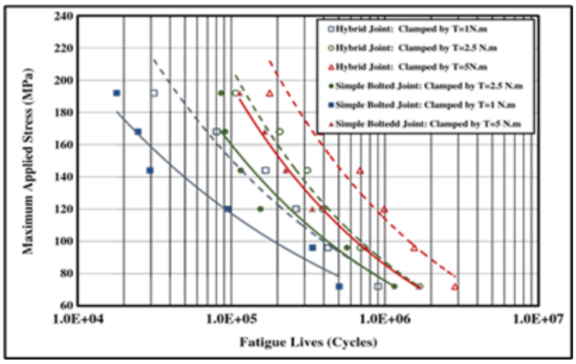


Fig. 1. diagram s-n tests of nut and hybrid connections [10]

]The graph in Figure (1) shows the results of fatigue life and the vertical axis shows the maximum stress. The hollow shapes show hybrid connections and the filled shapes show screw connections. In total, out of 36 tests, 18 fatigue tests were performed for screw connections and 18 tests for connections. It is a hybrid. And from these tests, data has been sent for training the network as input and output. The maximum stress torque value as input, and the fatigue life results as output are introduced to the network . In the following, all the data are written in tables 1 and 2, as well as the tests performed for the fatigue life of perforated plates, which can be seen in table number 3. The results of 35 fatigue tests are extracted from the article [], as shown in table number 3. The torque of the screw, the amount of force as the input, and the fatigue of the perforated plates are written as the output.

Artificial neural network architecture is determined by changing the layers and neurons. The number of inputs and outputs will be considered first, and in this title, from the three parts of the fatigue test on bolts, hybrid joints and hole plates has been done. According to the amount of data in the hybrid and screw connections, all these data are written in the form of 18X3 matrix in MATLAB software, where the first and second lines are input data (value of force, torque) and the last line are output matrix (Fatigue life). This indicates that in the network architecture, it has 2 inputs and one output, the same conditions are also in perforated plates. In perforated plates, out of 35 data written in 35x3 matrix format, the first and second lines are input data (bolt torque stiffness, amount of force) and the third line is output data (fatigue life of perforated plates). After specifying the number of input and output by changing the number of hidden layers, the best model is selected after several changes. Every time the input and output of the network are changed, the percentage of test, validation, training, and determination of the type of algorithm is sent. The algorithm prediction that the neural network performs should be close to the actual output, which is further explained in the regression diagram. The network model consists of two layers, in the first layer, the sigmoid tangent transfer function, and in the second layer, linear transfer functions are used. Of course, many changes have been made to these functions, and the best result for the network architecture seen in Figure (2) has been selected.

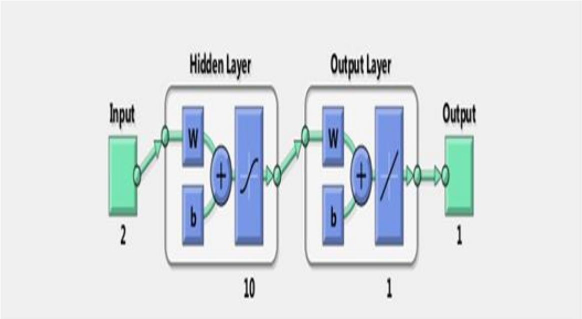


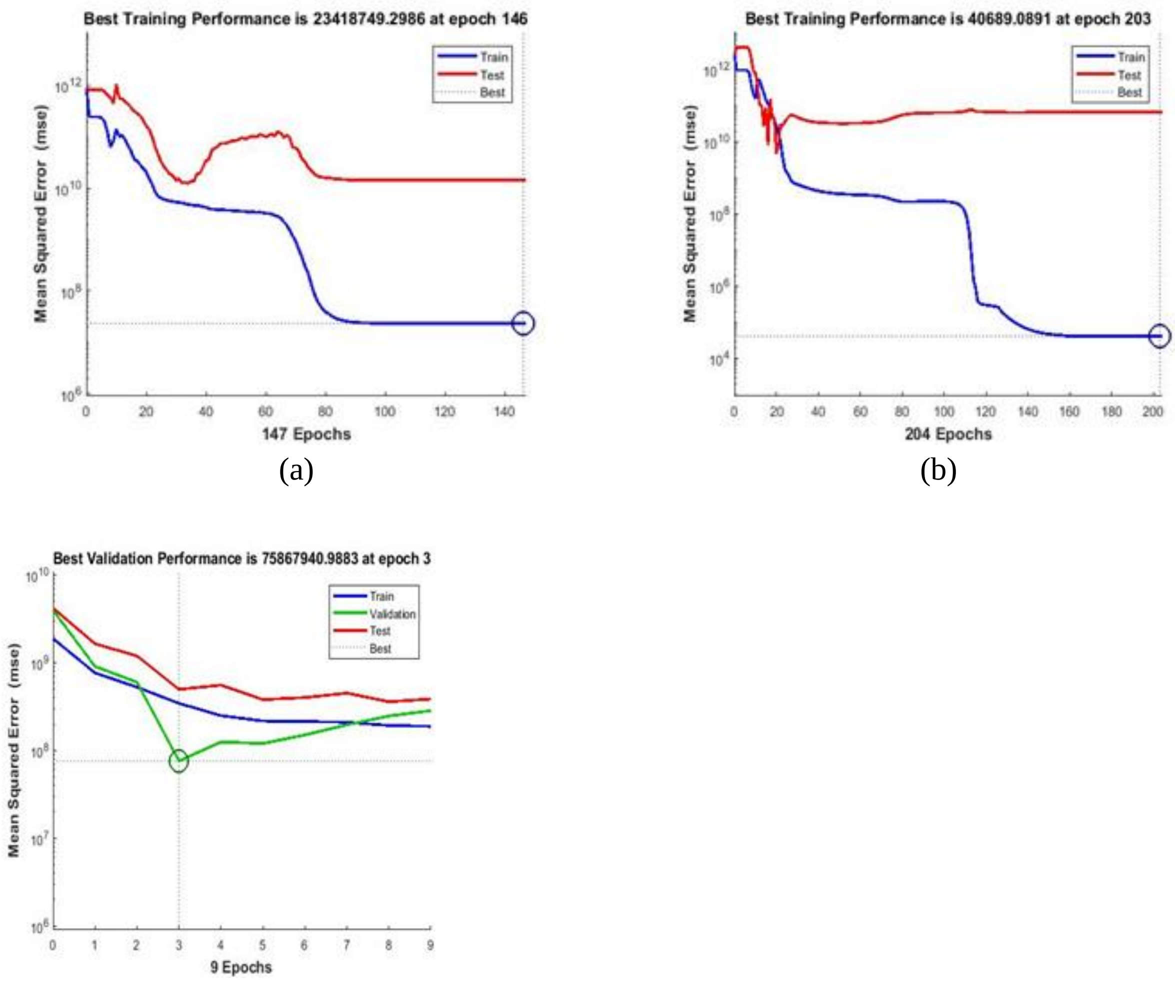
Fig. 2. Neural network architectur

4. Results

After designing the perceptron neural network, to use the network, the input data must be sent to the perceptron algorithm. Then the data is weighted by hidden layers, by choosing the type of algorithm, it can learn, in the sense that it must have the correct number of inputs and outputs so that the network can imitate it. Learning in the network is happens this way: it produces an output, compares the output with the expected output, and adjusts itself a little to get closer to the output. As the results of fatigue tests are written in the table (4, 5, 6), the simulation was done in MATLAB software, and its results are written in Tables (4) and (5). Table (4) results of the connection test Hybrid. Table (4) shows the percentage of validation, test, percentage of training, the type of algorithm, and the results of the graphs. Experiments have also been performed on the number of different neurons. In this table, the experiments were performed on the number of 10 and 5 neurons, then with changes in the percentage value of validation, test, training, and the number of layers of the three algorithms in the network. From the three algorithms of B.R., S.G., L.M. B.R algorithm has had better results in hybrid and bolt connections, ML algorithm has had better results in perforated plates than other algorithms, and in the following experiments, the results of 5 neurons and 10 neurons are the results of 10 neurons. It has been better than 5 neurons, although more than 10 neurons were tested, which did not have good results. And the results of the performance and regression charts are written in the following tables so that the neural network is well trained. The value of the square error (performance) is closer to zero, which is an example of the best result obtained along with the square error chart of Each will be explained.

4.1.Comparing the amount of error in the graph *(*performance)

As mentioned in the previous topic, it can be seen in the graphs below that the number of error squares is far from zero, as a result, the network is not trained well. In Figure (3), the vertical axis below shows the average error squares and the horizontal axis shows the repetition. Diagram (a)shows the error value of the bolt connection network. The value of squared error is close to 108 and the best performance of the network in epoch 146 is 2986/23418749. Figure (b) shows the error value of hybrid connections. The network in hybrid connections is not well trained, the number of error squares is close to 105 and the best performance of the network in figure (b) of hybrid connections was in epoch 204 01/40689. Also in figure (c) the amount of error in perforated plates. It shows that the neural network has not been well trained due to the high error squared value, and the error squared value is close to 108, and the best performance of the network is 9883/7586794 in epoch 3, so the network has a good result, all the data It should be normalized and it is explained below to normalize the data.



(a)

(b)

(c)

Fig. 3 Diagram of error squares (a) Diagram of error squares of bolt connections (b) Diagram of error squares of hybrid connections (c) Error squares in perforated plates

4.2. Fatigue tests after normalization

In the previous tests, the performance chart had more errors. In order for the performance error to be closer to zero and for the neural network to be trained well, all the data is normalized. In other words, all the data is in the range (1 and -1). and the neural network can analyze all the data. The results of the tests after normalization are written in Tables 7 and 8 for hybrid connections, nut patch and Table 9 for perforated plates, as seen in Tables (7, 8, 9), the number of hidden layers is 5 and 10. The result of 10 neurons is better than 5 neurons. The number of hidden layers in the following tables is written from the left side of the second row, and the percentage of test and validation can also be changed and the rest is used for training. Three algorithms ML, BR, SB are used and the best results are highlighted in the following tables, which are in table (7,8) for hybrid connections and screw nuts for both in the 18th row of the table, where 80% of the data is for training the network and 10% for validation and 10% for testing were selected with 10 neurons in the B.R algorithm and the best result for perforated plates in the 3rd table which is based on the ML algorithm and the same value of 80% for network training and for testing and validation Each 10% with the number of 10 neurons that was in the 6th row was selected

Table 1. test results for nut samples

Test no.	Tightening torque (Nm)	P_{max} (KN)	σ_{max}(MPa) σ	Cycles to failure
1	1	9.6	192	18012
2	1	8.4	168	24754
3	1	7.2	144	29561
4	1	6	120	94294
5	1	4.8	96	339326
6	1	3.6	72	503812
7	2.5	9.6	192	85918
8	2.5	8.4	168	91177
9	2.5	7.2	144	115356
10	2.5	6	120	154934
11	2.5	4.8	96	566670
12	2.5	3.6	72	1156236
13	5	9.6	192	113460
14	5	8.4	168	165774
15	5	7.2	144	226709
16	5	6	120	337656
17	5	4.8	96	756868
18	5	3.6	72	1666757

Table 2. Fatigue test results for hybrid samples

Test no.	Tightening torque (Nm)	P_{max} (KN)	σ_{max}(MPa) σ	Cycles to failure
1	1	9.6	192	31437
2	1	8.4	168	80440
3	1	7.2	144	167480
4	1	6	120	264569
5	1	4.8	96	425690
6	1	3.6	72	905361
7	2.5	9.6	192	106817
8	2.5	8.4	168	207211
9	2.5	7.2	144	313655
10	2.5	6	120	395430
11	2.5	4.8	96	694468
12	2.5	3.6	72	1685609
13	5	9.6	192	178158
14	5	8.4	168	381540
15	5	7.2	144	690820
16	5	6	120	992365
17	5	4.8	96	1556689
18	5	3.6	72	2866557

Table 3. Fatigue test results of perforated plates

Test no.	Tightening torque (Nm)	Amount of force	Tightening torque (Nm)
1	0	183	2980
2	0	174	4000
3	0	165	5500
4	0	156	9000
5	0	147	12000
6	0	138	15000
7	0	129	18000
8	1	183	23000
9	1	174	27000
10	1	165	31000
11	1	156	38000
12	1	147	42000
13	1	138	41000
14	1	129	51000
15	1.5	183	40000
16	1.5	174	45000
17	1.5	165	57000
18	1.5	156	51000

Test no.	Tightening torque (Nm)	Amount of force	Fatigue of perforated plates
19	1.5	147	50000
20	1.5	138	72000
21	1.5	129	130000
22	2	183	40000
23	2	174	47000
24	2	165	50000
25	2	156	55000
26	2	147	70000
27	2	138	58000
28	2	129	120000
29	4	183	40000
30	4	174	42000
31	4	165	42000
32	4	156	48000
33	4	147	51000
34	4	138	60000
35	4	129	98000

Table 4. the results of hybrid connection network training

Number	N.H.N	validatin	testing	traning	algorithm	performance	regression
1	5	%15	%15	%70	LM	1524157259.09	0.99944
2	5	%15	%10	%75	L.M	2886082129.9882	0.97542
3	5	%10	%15	%75	L.M	20609372415.3552	0.99377
4	5	%10	%10	%80	L.M	39895804977.2836	0.82736
5	5	%5	%15	%80	L.M	1009658268653.794	0.69285
6	5	%15	%5	%80	L.M	35386803689.6459	0.98095
7	5	%15	%15	%70	B.R	40689.0891	0.99068
8	5	%15	%10	%75	B.R	620594.1936	0.99995
9	5	%10	%15	%75	B.R	1.6277e-08	0.98724
10	5	%10	%10	%80	B.R	1328861.4597	0.99831
11	5	%5	%15	%80	B.R	14452.5066	0.99359
12	5	%15	%5	%80	B.R	428797.7436	0.8
13	5	%15	%15	%70	S.G	3386360812.693	0.9318
14	5	%15	%10	%75	S.G	65836263587.5626	0.85327
15	5	%10	%15	%75	S.G	2196030508.224	0.96728
16	5	%10	%10	%80	S.G	349820149481.9205	0.13938
17	5	%5	%15	%80	S.G	1644737.4912	0.98018
18	5	%15	%5	%80	S.G	108936516843.3392	0.96933

19	10	%15	%15	%70	L.M	32066695399.8161	0.95624
20	10	%15	%10	%75	L.M	434843485478.9235	0.845458
21	10	%10	%15	%75	L.M	58320826162.068	0.96146
22	10	%10	%10	%80	L.M	15761320039.6585	0.97794
23	10	%5	%15	%80	L.M	66650497597.8943	0.9252
24	10	%15	%5	%80	L.M	352226526307.7443	0.92379
25	10	%15	%15	%70	B.R	0.00018161	0.99959
26	10	%15	%10	%75	B.R	2.0969e-05	0.99989
27	10	%10	%15	%75	B.R	2.4818e-19	0.9981
28	10	%10	%10	%80	B.R	1.012e-14	0.99892
29	10	%5	%15	%80	B.R	4.9822e08	0.9846
30	10	%15	%5	%80	B.R	3.28e-05	0.7
31	10	%15	%15	%70	S.G	37335083749.1339	0.9273
32	10	%15	%10	%75	S.G	1328271573223.701	0.72914
33	10	%10	%15	%75	S.G	2584812290.4907	0.76985
34	10	%10	%10	%80	S.G	1073445139466.074	0.85591
35	10	%5	%15	%80	S.G	138645737701	0.16678
36	10	%15	%5	%80	S.G	4275838744.7895	0.97766

Table 5. the results of the training of the screw connection network

Number	N.H.N	validatin	testing	traning	algorithm	performance	regression
1	5	%15	%15	%70	L.M	9944323805.5336	0.78586
2	5	%15	%10	%75	L.M	16139269271.1231	0.56321
3	5	%10	%15	%75	L.M	1558761127.5191	0.92859
4	5	%10	%10	%80	L.M	1475226428.214	0.98278
5	5	%5	%15	%80	L.M	512094420.4716	0.91419
6	5	%15	%5	%80	L.M	377596262.6848	0.99637
7	5	%15	%15	%70	B.R	23418749.2986	0.99643
8	5	%15	%10	%75	B.R	4932495.666	0.99944
9	5	%10	%15	%75	B.R	370780711.9148	0.95832
10	5	%10	%10	%80	B.R	751150870.6076	0.97554
11	5	%5	%15	%80	B.R	3.4285e-20	0.956
12	5	%15	%5	%80	B.R	5473269.8214	0.99987
13	5	%15	%15	%70	S.G	73696380676.8622	0.95442
14	5	%15	%10	%75	S.G	30890266407.3768	0.95164
15	5	%10	%15	%75	S.G	23331703968.5906	-0.66566
16	5	%10	%10	%80	S.G	310393940361.4228	0.81436
17	5	%5	%15	%80	S.G	1895575907.6977	0.99657
18	5	%15	%5	%80	S.G	24818729450.3776	0.8694
19	10	%15	%15	%70	L.M	28938616644.8197	0.98616

20	10	%15	%10	%75	L.M	106319912581.1056	0.95058
21	10	%10	%15	%75	L.M	9605015212.4574	0.99629
22	10	%10	%10	%80	L.M	4189467460	0.90759
23	10	%5	%15	%80	L.M	11959693990.6972	0.94138
24	10	%15	%5	%80	L.M	288820865.0721	0.9998
25	10	%15	%15	%70	B.R	0.00021452	0.97845
26	10	%15	%10	%75	B.R	129519693.131	0.99968
27	10	%10	%15	%75	B.R	2574297383.3995	0.94339
28	10	%10	%10	%80	B.R	1472350193.398	0.99353
29	10	%5	%15	%80	B.R	377858268.4144	0.95769
30	10	%15	%5	%80	B.R	3867636.5793	0.99991
31	10	%15	%15	%70	S.G	1643993808.327	0.96912
32	10	%15	%10	%75	S.G	136235302264.4328	0.91755
33	10	%10	%15	%75	S.G	34383145314.8029	0.98774
34	10	%10	%10	%80	S.G	51822563546.4756	0.95308
35	10	%5	%15	%80	S.G	1667898013.0198	0.87831
36	10	%15	%5	%80	S.G	142039347641.4664	0.72788

Table 6. the results of tests performed on perforated plates

Number	N.H.N	validatin	testing	traning	algorithm	performance	regression
1	5	%15	%15	%70	L.M	124862150.2265	0.74309
2	5	%15	%10	%75	L.M	120480221.8054	0.91812
3	5	%10	%15	%75	L.M	8458073.6448	0.92038
4	5	%10	%10	%80	L.M	13032901.8457	0.7841
5	5	%5	%15	%80	L.M	96953357.6679	0.90696
6	5	%15	%5	%80	L.M	47161201.7672	0.93853
7	5	%15	%15	%70	B.R	290511145.2338	0.70999
8	5	%15	%10	%75	B.R	332322674.7204	0.71064
9	5	%10	%15	%75	B.R	91614941.1008	0.9433
10	5	%10	%10	%80	B.R	96616067.487	0.94421
11	5	%5	%15	%80	B.R	340023245.6748	0.71067
12	5	%15	%5	%80	B.R	83424040.9014	0.94913
13	5	%15	%15	%70	S.G	789234141.3632	0.81897
14	5	%15	%10	%75	S.G	75867940.9883	0.79145
15	5	%10	%15	%75	S.G	3420311031.2436	0.81977
16	5	%10	%10	%80	S.G	103452625.7334	0.88286
17	5	%5	%15	%80	S.G	82406295.8605	0.62238
18	5	%15	%5	%80	S.G	8382212227.4293	0.84168
19	10	%15	%15	%70	L.M	441935339.4853	0.90201
20	10	%15	%10	%75	L.M	852549816.7116	0.87663
21	10	%10	%15	%75	L.M	37967641.7954	0.79959

22	10	%10	%10	%80	L.M	557005769.2931	0.93565
23	10	%5	%15	%80	L.M	3606196.7008	0.95632
24	10	%15	%5	%80	L.M	374217359.1938	0.90301
25	10	%15	%15	%70	B.R	41857211.2098	0.9453
26	10	%15	%10	%75	B.R	67162777.4324	0.96269
27	10	%10	%15	%75	B.R	38553281.6042	0.96889
28	10	%10	%10	%80	B.R	429393915.8181	0.71065
29	10	%5	%15	%80	B.R	33370103.3916	0.95596
30	10	%15	%5	%80	B.R	48803414.3211	0.97091
31	10	%15	%15	%70	S.G	539388763.4981	0.79757

Table 7. results of network training after normalized hybrid connections

Number	N.H	test	valideion	traing	algoritm	pefromns	regression
1	5	%15	%15	%70	M.L	0.001436	0.991
2	5	%10	%10	%80	M.L	0.00013944	0.989
3	5	%15	%10	%75	M.L	0.0085635	0.9808
4	5	%10	%15	%75	M.L	0.1409	0.961
5	5	%15	%15	%70	B.R	9.36662e-15	0.9998
6	5	%10	%10	%80	B.R	6.5675e-07	0.99
7	5	%15	%10	%75	B.R	2.3091e-07	0.99
8	5	%10	%15	%75	B.R	4.6875e-07	0.998
9	5	%15	%15	%70	S.G	0.0003905	0.76
10	5	%10	%10	%80	S.G	0.00132	0.945
11	5	%15	%10	%75	S.G	0.285	0.874
12	5	%10	%15	%75	S.G	0.001104	0.987
13	10	%15	%15	%70	M.L	0.0207	0.92
14	10	%10	%10	%80	M.L	0.00122	0.949
15	10	%15	%10	%75	M.L	0.0103	0.955
16	10	%10	%15	%75	M.L	0.0121	0.951
17	10	%15	%15	%70	B.R	9.6533e-15	0.97
18	10	%10	%10	%80	B.R	1.8452e-06	0.9993
19	10	%15	%10	%75	B.R	9.3276e-014	0.97
20	10	%10	%15	%75	B.R	9.5401e-06	091
21	10	%15	%15	%70	S.G	0.1048	0.42
22	10	%10	%10	%80	S.G	0.03101	0.94
23	10	%15	%10	%75	S.G	0.0053	0.853
24	10	%10	%15	%75	S.G	0.00154	0.991

Table 8. results of network training after normalized screw connections

Number	N.H	test	valideion	traing	algoritm	pefromns	regression
1	5	%15	%15	%70	M.L	0.0153	0.782
2	5	%10	%10	%80	M.L	0.178	0.976
3	5	%15	%10	%75	M.L	0.011	0.7701
4	5	%10	%15	%75	M.L	0.0534	0.875
5	5	%15	%15	%70	B.R	5.9794e-1	0.998
6	5	%10	%10	%80	B.R	0.0011483	0.9987
7	5	%15	%10	%75	B.R	0.00123	0.974
8	5	%10	%15	%75	B.R	7.2361e-16	0.9968
9	5	%15	%15	%70	S.G	0.31355	0.241

10	5	%10	%10	%80	S.G	0.00326	0.838
11	5	%15	%10	%75	S.G	0.0408	0.92
12	5	%10	%15	%75	S.G	0.288	0.907
13	10	%15	%15	%70	M.L	0.1534	0.963
14	10	%10	%10	%80	M.L	0.0338	0.94
15	10	%15	%10	%75	M.L	0.01035	0.95
16	10	%10	%15	%75	M.L	0.0795	0.66
17	10	%15	%15	%70	B.R	9.544e-07	0.9984
18	10	%10	%10	%80	B.R	8.846e-15	0.9999
19	10	%15	%10	%75	B.R	0.00367	0.944
20	10	%10	%15	%75	B.R	1.1857e-05	0.998
21	10	%15	%15	%70	S.G	0.01359	0.977
22	10	%10	%10	%80	S.G	0.000887	0.96
23	10	%15	%10	%75	S.G	0.0132	0.632
24	10	%10	%15	%75	S.G	0.00981	0.82

Table9. results of tests of normalized perforated plates

number	n.h	test	vakidion	traing	algoritm	pefromns	regression
1	5	%15	%15	%70	LM	%0429	%959
2	5	%15	%10	%75	LM	%144	%892
3	5	%10	%15	%75	BR	%0017	%945
4	5	%10	%10	%80	BR	%0046	%91
5	10	%15	%15	%70	LM	%029	%937
6	10	%15	%10	%75	LM	%0273	%739
7	10	%10	%15	%75	BR	%0206	%948
8	10	%10	%10	%80	BR	%0119	%94
9	15	%15	%15	%70	LM	%0267	%857
10	15	%15	%10	%75	LM	%0134	%962
11	15	%10	%15	%75	BR	%0215	%942
12	15	%10	%10	%80	BR	%026	%77
13	20	%10	%10	%80	LM	%39	%803
14	20	%10	%10	%80	BR	%025	%929

Table 10. calculation of neural network output error percentage in bolt connections

percentage error	Expected output	Actual output	Number
0	-1	-1	1
2.0165	-0.99182	-0.9918	2
0.04	-0.985	-0.9854	3
0.43	-0.9136	-0.9176	4
0.79	-0.904	-0.9112	5
0.011	-0.9076	-0.9075	6
1.07	-0.8937	-0.8842	7
4.32	-0.8438	-0.8819	8
4.68	-0.8832	-0.8438	9
0.023	-0.8337	-0.8339	10
0.04	-0.7471	-0.7468	11
0.06	-0.6119	0.6123	12
0.228	-0.6109	-0.6123	13
0.121	-0.4102	-0.4107	14
0.2	-0.3338	-0.3345	15
0.19	-0.1039	-0.1037	16
0.1	0.3803	0.3807	17
0	1	1	18

Table 11. calculation of neural network output error percentage in hybrid connections

percentage error	Expected output	Actual output	Number
0	-1	-1	1
0.01	-0.9653	-0.9654	2
0.01	-0.9469	-0.9468	3
0.011	-0.904	-0.9041	4
0.0022	0.89652	-0.8965	5
0.0114	-0.876	-0.8761	6
0.0119	-0.8356	-0.8355	7
0.012	-0/8009	-0.801	8
0.013	-0.7531	-0.753	9
0.013	-0.7432	-0.7433	10
3.84	-0.7219	-0.7508	11
1.27	-0.5475	-0.5348	12
0.0018	-0.53231	-0.5323	13
0.0078	-0.3835	-0.38353	14
0.031	-0.3222	-0.3221	15
0	0.0759	0.0759	16
0.05	0.1669	0.167	17
0	1	1	18

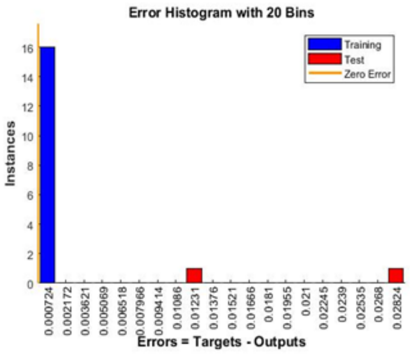
Table12.percentage of network output error

Number	Actual output	Expected output	percentage error
1	-1.014	-1.013	0.98
2	-1.151	-1.149	1.7
3	975	968	7.97
4	980	985	5.1
5	-963	-968	5.1
6	147	-149	1.36
7	825	-822	3.6
8	-76	-766	7.8
9	-64	-654	2.187
10	517	537	3.86
11	435	451	3.67
12	465	482	3.65
13	36	377	4.72
14	39	392	5
15	375	385	2.66
16	32	304	5
17	27	274	1.48
18	27	269	37
19	179	178	55
20	192	192	1.05
21	06	069	1.5
22	016	015	6.2
23	02	021	5
24	29	298	3.44
25	87	879	1.03
26	231	23	4
27	14	149	6.4
28	135	139	2.9
29	269	269	0
30	207	208	4.8
31	139	145	4.3
32	163	16	1.8
33	15	156	4
34	14	148	5.7
35	1.2	1.07	1.3

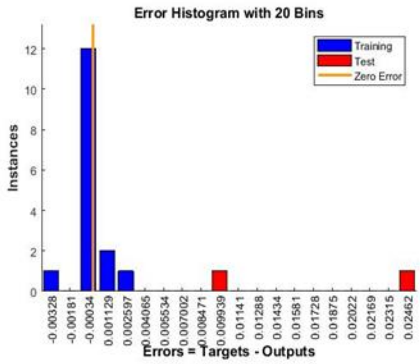
4.2. Fatigue tests after normalization4.3. Error histogram

The error histogram diagram shows the training data in which the degree of belonging to different error members in each group of data is examined. The blue, green, and red bars show the training data, validation data, and test data, respectively.

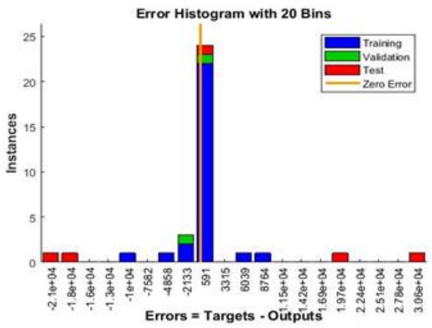
In figure (4), the amount of histogram is the error after normalization. The tallest column should be close to the orange zero error line, and the amount of errors should be centered on that line. If it is like this and the other columns have a lower height than the tallest column, it shows that the network has less erro



(a)



(b)



(c)

Fig.4.error histogram after normalization (a) error histogram of hybrid connections (b) bolt connections (c) perforated plates

Fig. 6.Output features after wavelet transformation implementation

4.4. Comparing the error value after normalization

Figure (5) shows the value of squared error after normalization. In the graph of Figure (a), the error value recorded in the hybrid connections after normalization shows that the performance of the squared error (mse) which can be seen on the vertical axis is 106 and the best performance of the network is epoch 2741 6-e8452/1, which+h shows that the network is well trained. Figure (b) shows the squared error of the bolt connections. Its error value (mse) is 1015 and the performance of the epoch323 network is 8246/15-e and its value is closer to zero. As a result, the neural network is well trained and finally, Figure (c) is the square diagram of the error in the perforated plates, where the error value is 102, and the function of the epoch8 network is 0.028794, which is closer to zero. In perforated plates, the best result is obtained from the M.L algorithm

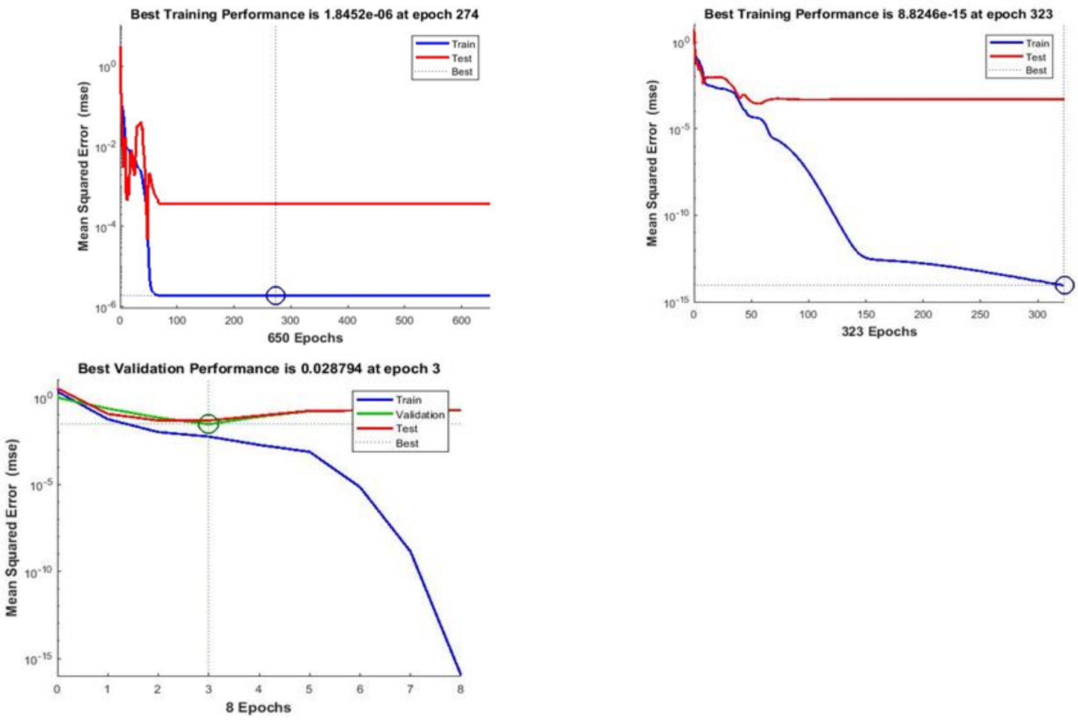


Fig.5. Square error diagram after normalization (a) hybrid connections (b) screw connections (c) perforated sheets

5. Conclusion

In the regression diagram of Figure (6), the value of the actual output and the predicted output were used to evaluate the network that is compared. In this diagram, Figure (6) shows that the closer the value of R is to one, the closer the predicted output predicted by the neural network is to the actual output. This result means that the neural network can predict with less error. In this regression diagram, the vertical axis shows the output predicted by the neural network and the horizontal axis shows the actual output shown by the tests. It is seen that the fatigue has been achieved and this graph compares the predicted output with the actual output. T*he empty circles show the results of the data in the coordinates of the regression diagram. In figure (a) and (b), respectively, the hybrid connections and nut bolts selected from the BR algorithm, the total regression value (ALL) is R=0.999 in bolt connections, as well as the hybrid connections, the total regression value in figure (b) is R=0.99993 because the value of R is close to 1, the neural network has been able to bring the predicted output closer to the actual output, and finally, graph (c) shows the regression of the perforated plates, which is used by the ML algorithm, the value of R=0.95192 Finally, the R value is closer to one in the connections of nut bolts, hybrids and perforated plates, so in three modes the neural network can predict the output with less error.

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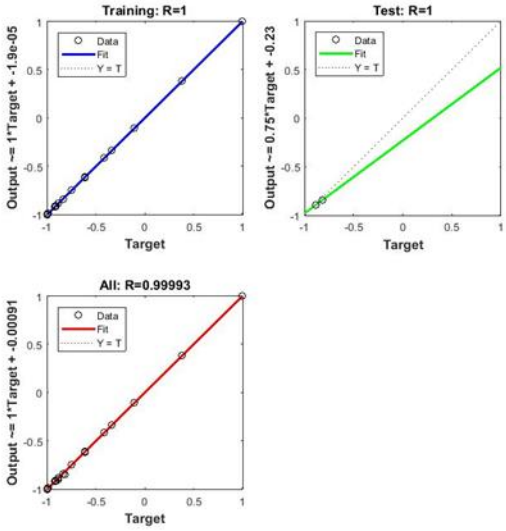
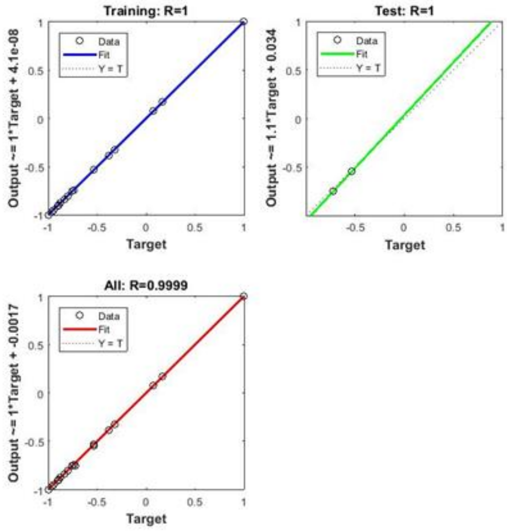
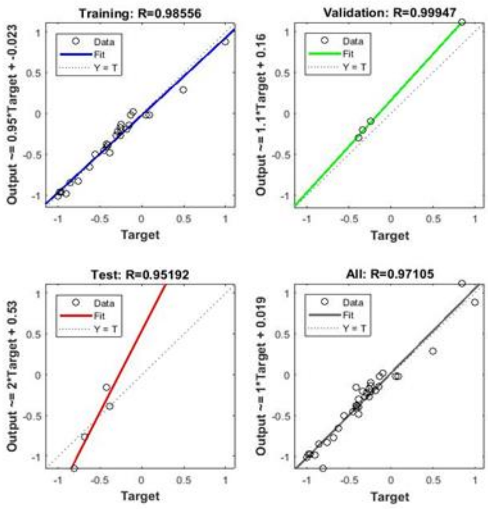


(a)



(b)



(c)

Fig.6. regression diagram after normalizing the data (a) hybrid connections (b) bolt connections (c) perforated plates

In figure (7), where the horizontal axis shows the data and the vertical axis shows the fatigue life, the output of the neural network is compared with the actual output,. Extract the coordinates of the predicted output from the regression chart and compare the normalized output with the actual output, because the normalized data is in the range of -1 and 1, it cannot be compared with the actual output, so the normalized data must be returned to the initial state. (Denormalized) means to remove it from the range of 1 and 1 so that it can be compared with the real output.

In the rest of the outputs obtained from the training, the data is compared with the actual output and the result indicates that there is a slight difference between the output of the neural network and the actual data, and this research will be the percentage of the difference. Figures (14) and (15) show the actual output and the predicted output of the network. In the diagrams of all three figures, the network output is shown with a red line, and the actual output is shown with a blue line.

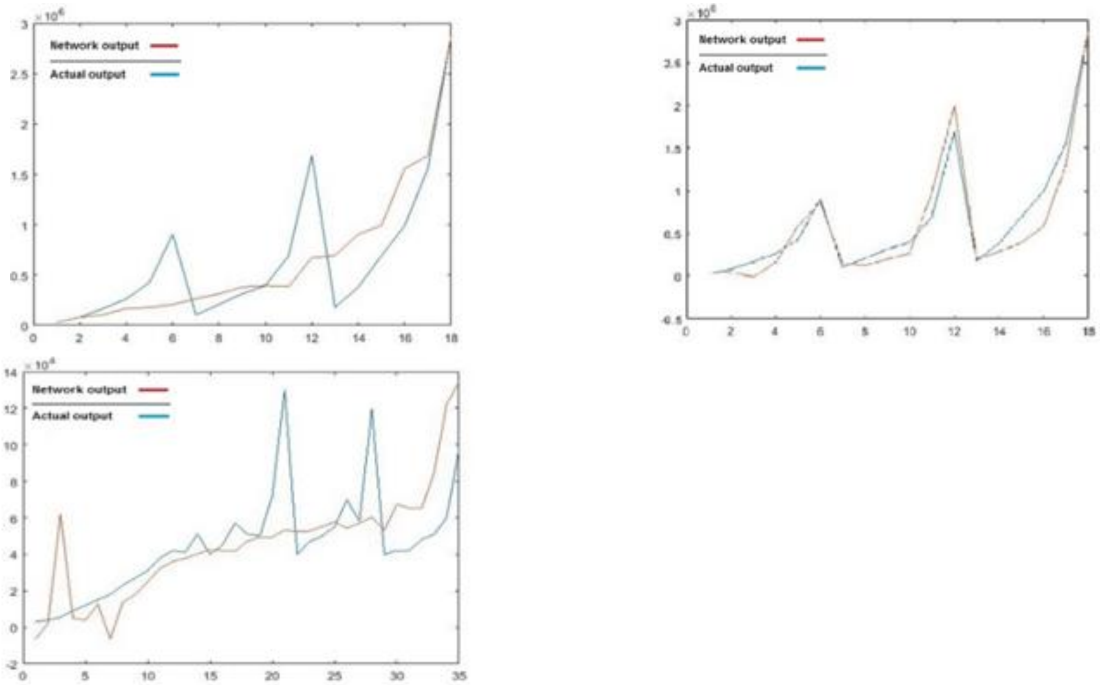


Fig.7.comparing the predicted output with the actual output (a) hybrid connections (b) bolt connections (c) perforated sheets

In this part, as the previous one, we have four graphs for four clusters. Regarding all four graphs, the area under the graph is almost equal to 1 which is considered as the best status. Thus, this graph represents the very great result of the proposed program.

$$\text{Percentage error}\ \frac{\text{Actual output}-\text{Expected output}}{\text{Actual output}} = \times 100 \qquad (1)$$

All the actual output data and the predicted output are compared with this method, the actual output is compared with the output of the neural network, and according to the forecast data and the actual outputs are placed in the above formula, and the result is the error percentage, and all the results are in the tables. It is written below. Table No. (10) is the percent error of bolt and nut connections. To calculate the percentage of errors, all the data were extracted from the regression chart and the error percentage was calculated from each data. In table (11), the results of the error percentage of hybrid connections are written, the highest error is in row 11, the highest error percentage in hybrid connections is 3.84. Finally, in the perforated sheets, the percentage of error results are written in Table 3, where the highest error percentage is 5.7.

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