



Fracture Strength Evaluation of AA 2219-T87 Weldment using Artificial Neural Network

S.Rajakumar¹ and N.Murugan²

¹Professor of Mechanical Engineering, Thanthai Periyar Government Institute of Technology,
Vellore-632002, India.

²Professor of Mechanical Engineering, Coimbatore Institute of Technology,
Coimbatore -641014, India.

Abstract: Fracture strength equation of any structural configuration is a non-linear relation of considerable complexity. Any new research on fracture strength requires lots of experimental works which consumes cost and time. In order to minimize these efforts an alternative approach of modelling and simulation concepts have been introduced. Neural networks toolbox available in MATLAB 7.5 was used to predict fracture strength of AA2219-T87 tensile specimens with surface cracks in the weldment. The results obtained are compared with experimental results.

Keywords: Centre surface crack, tensile specimen, Fracture strength, AA2219-T87, artificial neural networks.

Nomenclature

a	Crack depth
c	Half crack length
K_{IFM}, δ_{aci}	Fracture parameters in equation (1)
t	Specimen thickness
W	Specimen width
σ	Applied far field stress
σ_{NC}^{∞}	Fracture strength of a wide specimen
σ_{NC}	Fracture strength of finite width specimen
σ_0	Ultimate tensile strength (unnotched strength)

1. Introduction

The significant parameters affecting the size of a critical crack in a structure are the applied stress levels, the fracture toughness of the material, the location of the crack and its orientations. Since the intensity of the stress at the crack tip, K is a function of load, geometry and crack size, it is more appropriate to have a relationship between the critical stress intensity factor at failure and the failure stress from the fracture data of cracked specimens for the estimation/prediction of the fracture strength to any cracked configuration. For cracked configurations, a relation between the critical stress intensity factor (K_Q) and the corresponding stress (σ_{NC}^{∞}) at failure is obtained from modified inherent flaw model (IFM) as [1]-[2]:

$$K_Q = K_{IFM} \left\{ 1 - \delta_{aci} \frac{\sigma_{NC}^{\infty}}{\sigma_0} \right\} \sqrt{1 - \left(\frac{\sigma_{NC}^{\infty}}{\sigma_0} \right)^2} \quad (1)$$

Where, σ_{NC}^{∞} is the failure stress normal to the direction of the crack in a wide specimen and σ_0 is the ultimate stress of the material. Equation (1) represents a failure assessment diagram useful for fracture strength evaluation of different cracked configurations. The fracture Strength (σ_{NC}^{∞}) of the center crack wide tensile specimen is obtained from that of a finite width specimen (σ_{NC}) as

$$\sigma_{NC}^{\infty} = \sigma_{NC} Y \quad (2)$$

Where the finite width correction factor [3] is,

$$Y = \sqrt{\sec\left(\frac{\pi c}{W}\right)} \quad (3)$$

Where 'c' is half the crack length and W is the specimen width.

For the determination of two fracture parameters (K_{IFM} and δ_{aci}), test results of simple laboratory specimens like compact tension specimens, center crack specimens etc. can be utilized. In order to evaluate fracture strength of any other structural configuration, the stress intensity factor corresponding to that geometry is to be used in (1) to develop the necessary fracture strength equation. As developing fracture strength equation is a cumbersome work, neural networks can be used as a tool to predict fracture strength of any material. A neural network is capable of realizing a greater variety of non-linear relation of considerable complexity.

Fracture data [4] have been compiled for AA2219-T87 useful for aircraft applications. The objective of this article is to apply neural network as a tool to predict fracture strength of AA2219-T87 tensile specimens with surface cracks in the weldment.

II. Artificial Neural Network

Feed-forward ANNs allow signals to travel in one direction only and there is no feedback signal. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is used in the present study. The width of the plate, thickness of plate, crack depth, crack length, temperature and ultimate strength are taken as input variables. All of these input variables (Table-1) influence the fracture strength which is the output variable. The fracture strength can be represented as a general empirical formula of variables that are commonly acknowledged to be important in influencing the fracture strength of a material.

One of the most popular learning-algorithms is the back propagation (BP) algorithm. In this present study, Feed-forward ANN with BP algorithm is used with one hidden layer. The architecture of ANN used in this study is 6-6-1, with 6 corresponding to the input values, 6 to the number of neurons in the hidden layer and 1 to the output. Using ANN for system simulation requires a handful of experimental data's.

A. Data's for Training

Any ANN work needs some experimental data for modeling. The amount of data used will decide the accuracy of the model. In order to model the network, experimental data's [4] have been used. Data are presented to the network in the form of input and output parameters. The width of the plate, thickness of plate, crack depth, crack length, temperature and ultimate strength are taken as input variables. The fracture strength is the required output parameter. The network was fed with an input of 100 data given in Table 2 to Table 6. The neural network after successful training was used to predict the fracture strength of welded joints of AA2219-T87 alloy within the trained range.

B. Training

The 6-6-1 architecture (Fig.1) has been used to train the system. Neural networks operate much as a "black box" model, requiring no detailed information about the system. On the other hand, they learn the relationship between the input and the output. According to Soteris A. Kalogirou et al. "Training is the process of modifying the connection weights, in some orderly fashion, using a suitable learning method" [6]. The learning process consists of identifying the weights that produce the best fit of the output data over the entire training data set. An important stage of a neural network is the training step, in which an input is introduced to the network together with the desired output and in this the weights of the network are continuously adjusted, based on the error signal generated by the deviation between the output data computed through the network and the data from the database used in the training examples [5] so that the network attempts to produce the desired output. The outputs are the dependent variables that the network produces for the corresponding input. All the information needed for the network is supplied to the network as a data set. After the network has run through all the input patterns, if the error is still greater than the maximum desired tolerance, the ANN runs through all the input patterns repeatedly until all the errors are within the required tolerance [7]. When a satisfactory level of performance is reached, the training stops, and the network uses the weights to make decisions [8]. The network in effect tries out many kinds of relationships in its search for an optimum fit. The search for the optimum representation can be computer intensive, but once the network is trained the estimation of output is very rapid.

C. Testing

In ANN modeling the network accuracy must be tested (Fig.2). In the training step, the network produces error in the root mean square form. In training, supervised modeling technique is used, since both input and the corresponding output are given. Hence it is very much desirable to test the network accuracy with unsupervised modeling by introducing some input data alone in the network. Then the network will produce the output based

on the adjusted weights and bias values stored in the neurons during training. The tested Data, ANN Output and the relative error (%) are given in Table-7.

III. COMPARISON WITH TEST RESULTS

It is noticed that ANN s performs well than the other techniques, when highly non-linear behavior is the case. Also, this technique can build an efficient model using a small number of experiments; however the technique accuracy would be better when a large number of experiments are used to develop a model. A neural network is capable of realizing a greater variety of non-linear relationships of considerable complexity. On the other, the ANN model itself provides little information about the design factors and their contribution to the response if further analysis has not been done. Test Data and ANN Data for AA2219-T87 tensile specimens are compared in Fig.3

IV. RESULTS AND DISCUSSION

Fracture data [4] of AA2219-T87 with surface cracks in the weldment is utilized in the present study to verify the validity of the fracture criterion. Table 7 gives the comparison of fracture strength estimations with the test results for AA2219-T87. The standard error is found to be less than 0.1, which indicates that the fracture strength estimations utilizing ANN can be expected within $\pm 10\%$ of the test results.

A standard error (SE) between analytical and test results is obtained from

$$SE = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(1 - \frac{\text{Analysis result}}{\text{Test result}} \right)^2} \quad (4)$$

Where N is the number of test specimens. The relative error (%) is computed as

$$\text{Relative error (\%)} = 100 \left(1 - \frac{\text{Analysis result}}{\text{Test result}} \right) \quad (5)$$

Fracture data of AA2219-T87 with surface cracks in the weldment have been analyzed using a neural network technique. Fig.3 shows that most of the fracture strength estimations are within $\pm 10\%$ of the test results for ANN analysis.

V. CONCLUDING REMARKS

The ANN is used to predict the fracture strength of AA2219-T87 with surface cracks in the weldment. The prediction possibility of the material fracture strength is valuable for manufacturers and constructors. The relative error between the predicted and experimental values is found to be within $\pm 6\%$. It is within acceptable limit. As most of the input data has material with ultimate strength from 263 to 647 MPa, the developed network produces good results only if the testing material has ultimate strength in this range.

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Table-1: Process parameters and their ranges used in this study

S.No	Variable	Range	Mean
1	Width (W), mm	64 to 762	247.47
2	Thickness (t), mm	1.6 to 26.2	11.22
3	Crack Depth (a), mm	1.12 to 22.58	7.60
4	Crack Length (2c), mm	8.15 to 151.64	46.90
5	Temperature (T), K	20 to 295	117.60
6	Ultimate strength (σ_o), MPa	263 to 647	516.95

Table-2: Input data [4] used in this study

S. No	Specimen Dimensions (mm)						Fracture strength σ_{NC} (MPa) (Sih 1973)
	Width W	Thickness t	Crack Depth a	Crack length 2c	Temperature K	Un-notched strength σ_o (MPa)	
1	228.52	16.33	7.52	61	295	477.1	290.97
2	558.93	16.33	15.24	145.41	295	477.1	148.93
3	139.75	15.87	6.88	16.61	295	477.1	373.02
4	171.4	16.28	6.07	15.27	295	477.1	379.22
5	139.7	16.26	8.61	23.42	295	477.1	330.96
6	171.42	15.85	9.91	29.21	295	477.1	323.38
7	228.5	16.26	6.98	61.72	77	592.3	314.41
8	228.09	16.21	6.91	62.2	77	592.3	306.14
9	279.48	16.43	9.52	91.82	77	592.3	245.46
10	367.94	16.08	11.43	117.09	77	592.3	193.75
11	558.65	15.93	14.22	147.7	77	592.3	160.65
12	558.67	16.33	14.1	140.33	77	592.3	146.86
13	139.62	16.33	6.27	24.66	77	592.3	390.95
14	139.67	16.03	6.65	24.84	77	592.3	393.01
15	228.68	16.21	8.92	33.1	77	592.3	314.41
16	304.9	16.31	11.94	44.45	77	592.3	247.53
17	304.88	16.08	12.19	45.21	77	592.3	275.8
18	305.03	15.9	14.35	52.58	77	592.3	237.88
19	304.95	16.41	14.1	51.56	77	592.3	217.19
20	139.7	16.43	6.32	15.54	77	592.3	424.04

Table-3: Input data [4] – continued

S.No	Width W	Thickness t	Crack Depth a	Crack length 2c	Temperature K	Un-notched strength σ_o (MPa)	Fracture strength σ_{NC} (MPa)
21	139.65	16.28	7.9	22.58	77	592.3	368.19
22	139.75	16.18	9.37	24.49	77	592.3	350.96
23	154.3	16.41	10.97	29.72	77	592.3	315.79
24	171.4	16.05	10.59	29.59	77	592.3	339.92
25	171.45	16.05	12.34	34.62	77	592.3	303.38
26	304.57	16.31	13.87	34.82	77	592.3	260.63
27	304.88	15.9	14.07	35.66	77	592.3	280.63
28	228.6	16.26	5.71	61.59	20	646.8	342.68
29	228.5	16.33	5.79	61.72	20	646.8	341.99
30	279.6	16	9.52	91.31	20	646.8	233.05
31	367.97	16.31	11.68	118.62	20	646.8	184.1
32	367.97	16.28	11.68	117.98	20	646.8	179.96
33	368.02	16.28	12.7	136.52	20	646.8	162.03
34	367.89	16.33	13.21	139.95	20	646.8	161.34
35	139.7	16.38	5.69	15.01	20	646.8	464.72

Table-4: Input data [4] - continued

S.No	Width W	Thickness t	Crack Depth a	Crack length 2c	Tempe- -rature K	Un-notched strength σ_o (MPa)	Fracture strength σ_{NC} (MPa) (Sih 1973)
36	139.45	15.85	5.49	14.96	20	646.8	473.69
37	139.6	15.87	8.94	23.62	20	646.8	392.33
38	171.4	16.28	10.72	29.87	20	646.8	344.06
39	171.45	16.08	10.41	29.49	20	646.8	353.02
40	171.37	16.31	12.09	34.57	20	646.8	305.45
41	171.32	15.93	12.09	34.82	20	646.8	308.9
42	63.7	1.7	1.37	27.69	295	468.17	252.36
43	63.68	1.65	1.4	27.69	295	468.17	244.77
44	171.63	1.63	1.42	27.18	295	468.17	326.82
45	171.63	1.7	1.32	27.08	295	468.17	331.65
46	304.8	1.7	1.3	27.43	295	468.17	330.96
47	171.4	1.75	1.45	28.65	295	468.17	308.9
48	171.4	1.68	1.47	28.35	295	468.17	313.72
49	171.35	1.75	1.27	25.55	295	468.17	315.1
50	171.32	1.6	1.27	24.05	295	468.17	319.24
51	139.73	1.7	1.42	8.53	295	468.17	362.68
52	139.73	1.7	1.27	9.4	295	468.17	374.4
53	139.73	1.65	1.35	9.63	295	468.17	359.92

Table-5: Input data [4] - continued

S.No	Width W	Thickness t	Crack Depth a	Crack length 2c	Tempe- -rature K	Un-notched strength σ_o (MPa)	Fracture strength σ_{NC} (MPa) (Sih 1973)
54	171.35	1.73	1.32	25.4	77	583.32	381.29
55	171.45	1.7	1.3	25.4	77	583.32	381.29
56	171.32	1.65	1.4	26.21	77	583.32	385.43
57	171.4	1.78	1.4	27.94	77	583.32	370.26
58	171.45	1.75	1.45	28.45	77	583.32	379.22
59	171.63	1.73	1.3	26.92	77	583.32	366.12
60	171.5	1.6	1.17	23.95	77	583.32	390.95
61	171.37	1.65	1.22	24.59	77	583.32	377.85
62	139.73	1.73	1.19	8.64	77	583.32	460.59
63	139.78	1.63	1.3	8.71	77	583.32	444.73
64	139.8	1.63	1.45	9.37	77	583.32	441.28
65	171.4	1.73	1.12	20.04	20	647.44	417.84
66	171.35	1.7	1.5	20.5	20	647.44	407.49
67	171.45	1.65	1.37	26.03	20	647.44	393.7
68	171.45	1.7	1.47	26.31	20	647.44	379.22
69	171.42	1.73	1.4	28.09	20	647.44	384.74
70	171.4	1.57	1.27	23.88	20	647.44	399.22
71	171.37	1.57	1.3	24.18	20	647.44	406.8
72	139.65	1.7	1.19	8.15	20	647.44	484.72
73	139.7	1.68	1.32	9.12	20	647.44	466.1
74	139.75	1.63	1.27	9.55	20	647.44	466.79

Table-6: Input data [4] - continued

S. No	Specimen Dimensions (mm)						Fracture strength σ_{NC} (MPa) (Sih 1973)
	Width W	Thickness t	Crack Depth a	Crack length 2c	Temperature K	Un-notched strength σ_o (MPa)	
75	609.6	25.96	17.53	105.54	295	263.4	157.21
76	761.75	25.83	18.41	126.87	295	263.4	142.73
77	342.9	25.58	17.68	60.38	295	263.4	162.03
78	406.91	25.53	19.63	64.34	295	263.4	159.27
79	406.65	25.53	21.08	72.39	295	263.4	152.38
80	406.65	25.53	22.58	76.45	295	263.4	148.24
81	507.29	25.58	11.86	84.58	77	379.2	169.62
82	609.73	25.86	18.03	107.82	77	379.2	136.52
83	406.65	20.04	19.99	65.63	77	379.2	148.93
84	406.4	25.6	21.36	71.93	77	379.2	168.24
85	508.25	25.65	15.75	105.79	20	433.01	119.28
86	762	25.65	21.34	151.64	20	433.01	79.98
87	342.19	25.76	18.03	59.31	20	433.01	139.28
88	406.68	25.58	19.68	63.25	20	433.01	142.73
89	406.63	25.4	22.1	75.82	20	433.01	117.21
90	152.78	3.1	1.42	22.64	295	263.4	226.16
91	95.35	3.12	1.6	12.6	295	263.4	204.09
92	95.25	3.1	2.08	15.98	295	263.4	209.61
93	152.5	3.1	1.12	24.94	77	379.2	251.67
94	241.63	3.12	2.06	47.37	77	379.2	228.91
95	95.35	3.12	1.17	8.74	77	379.2	275.11
96	95.35	3.12	1.98	12.4	77	379.2	248.91
97	95.15	3.17	2.39	18.97	77	379.2	229.6
98	152.25	3.2	1.32	27.05	20	433	302.69
99	190.7	3.12	1.78	36.96	20	433	228.91
100	95.22	3.17	2.03	15.87	20	433	256.49

Table -7 Comparisons between experimental [4] and analytical (ANN) fracture strength of AA 2219-T87 tensile specimens with surface cracks in the weldment

S. No	Specimen Dimensions (mm)						Fracture strength σ_{NC} (MPa)		Relative Error (%) & Crack Location	
	Width W	Thickness t	Crack Depth a	Crack length 2c	Temperature K	Un-notched strength σ_o (MPa)	Test [4]	ANN Analysis		
1	139.8	15.9	9.19	24.41	295	477.1	335.1	337.1	-0.6	BM
2	305.1	1.7	1.30	27.41	295	468.2	336.5	334.6	0.6	BM
3	139.8	1.6	1.40	8.59	295	468.2	366.1	367.5	-0.4	BM
4	342.9	25.6	17.68	60.38	295	263.4	162.0	170.0	-4.9	WM
5	95.3	3.1	2.08	15.98	295	263.4	209.6	200.8	4.2	WM
6	558.9	16.3	13.33	137.29	77	592.3	148.2	151.3	-2.1	BM
7	228.8	15.9	8.81	33.63	77	592.3	350.2	350.3	-0.0	BM
8	139.6	16.0	5.71	14.91	77	592.3	422.0	441.5	-4.6	BM
9	171.5	16.0	11.99	34.80	77	592.3	305.5	308.4	-1.0	BM
10	171.4	1.8	1.40	27.94	77	583.3	370.3	380.1	-2.7	BM
11	139.8	1.7	1.32	9.40	77	583.3	439.9	445.2	-1.2	BM
12	342.7	25.6	17.86	60.30	77	379.2	174.4	166.5	4.5	WM
13	95.2	3.1	2.18	16.03	77	379.2	237.2	233.7	1.5	WM
14	279.5	16.0	9.02	91.69	20	646.8	237.9	246.1	-3.5	BM
15	171.3	15.9	12.09	34.82	20	646.8	308.9	326.2	-5.6	BM
16	171.4	1.7	1.42	26.57	20	647.4	391.0	391.2	-0.1	BM
17	139.8	1.8	1.32	8.61	20	647.4	469.6	479.4	-2.1	BM

Standard error = 0.03
Legend: BM- Base Metal; WM- Weld Metal

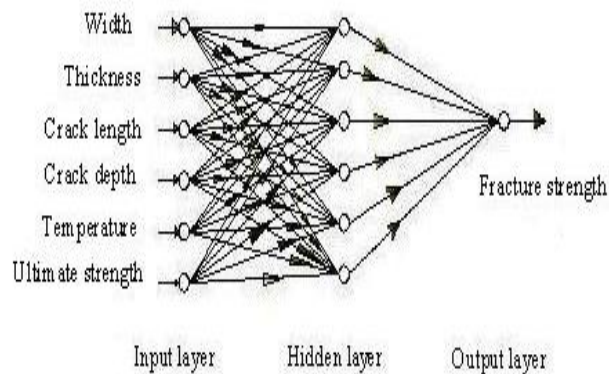


Fig.1 Layout of selected ANN architecture

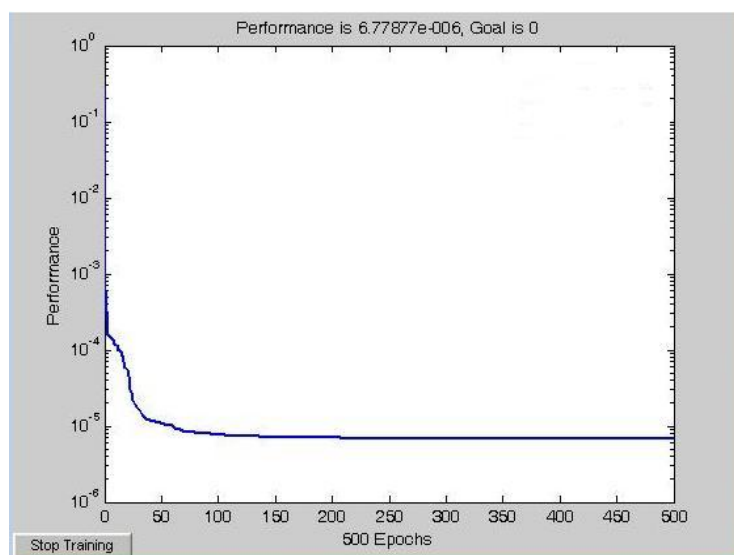


Fig. 2 Training curve for 6-6-1 network

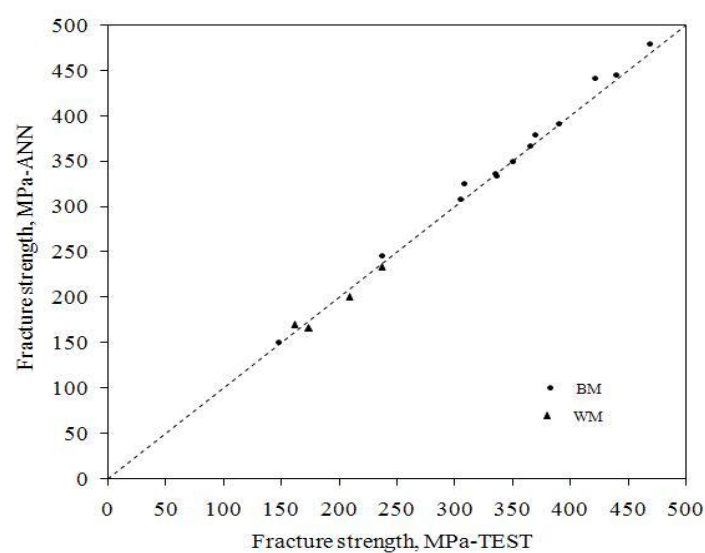


Fig. 3 Comparison between TEST and ANN