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Neural Network Prediction of Failure Load in High Strength Composites Using Acoustic Emission Method

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***Abstract* - The objective of this paper was to predict the failure load of carbon/epoxy composite test specimens using an online acoustic emission (AE) monitoring and artificial neural networks (ANN). The test specimens were Carbon/epoxy rings made of carbon T700 fibers and Epoxy resins these rings were tested in BISS 300KN Servo-hydraulic (UTM) Universal Testing Machine with the help of split disk test fixtures to ensure uniform distribution of loads on the ring and fixing AE sensors on the specimen at discrete locations. A series of 24 carbon/epoxy rings were monitored with an acoustic emission (AE) system, while loading them up to failure. AE signals emitted due to different failure modes in tensile specimens were recorded. Amplitude, duration, energy, counts, etc., were the effective parameters to classify the different failure modes in composites, viz., matrix crazing, fiber cut, and delamination, with several subcategories such as matrix splitting, fiber/matrix debonding, fiber pullout, etc. A Multi-layer Back propagation neural network was generated to predict the failure load of tensile specimens. The network was trained with the amplitude distribution data of AE collected up to 50%, 60%, and 70% of failure loads, respectively along with their slope of cumulative amplitude distribution plot. 10 specimens were in the training set with their corresponding failure loads. The trained network was able to predict failure loads of remaining 14 specimens within the acceptable error tolerance. The results were compared, and we found that the network trained with 60% data having better prediction performance.**

***Index Terms* - Carbon/epoxy rings, Acoustic emission (AE), Strength, Artificial neural networks, Tensile testing.**

I. INTRODUCTION

The carbon epoxy composite materials have been widely used in aerospace industry as structural materials due to their advantages, like high strength-to-weight ratio, good corrosion resistance characteristics and fast on-site installation. These weight savings in turn contribute to greater payload capability. With the increased use of composites, continuing research in assessment and quality control of composites must be an ongoing process. The major types of damage mechanism of composites are matrix crazing, fiber breakage, and delamination. As far as the structural integrity is concerned, there is a question of whether or not the proof loading lowers the actual failure load of composite hardware. For metals, assuming the absence of macroscopic flaws, as long as the stress is kept below the proportional limit or yield point, there is little in the way of plastic deformation and, therefore, no noticeable degradation in the structural integrity. This, however, does not hold true for fiber/matrix composites because fibers are the primary load-bearing constituents in composites; the structural integrity begins to degrade as soon as the fibers begin to break. The only way to avoid such an unintentional structural degradation is to reduce the proof test load. One such application is carbon epoxy filament wound rocket motor casings of solid propulsion systems for aerospace and missile structures where the weight saving contributes to greater payload and range capabilities. Non-destructive testing has helped to improve the quality thereby structural integrity and the performance of composite structures.

Acoustic Emission technique is a fast-developing non-destructive testing tool ideally suited for the integrity evaluation of composite hardware during proof load testing. AE is defined as “the class of phenomena where by transient elastic waves are generated by the rapid release of energy from localized sources within a material, or the transient waves so generated”. AE signals, once generated, will be detected by the AE sensors, which are attached to the material, and sent to the AE data acquisition system for recording and processing. A typical AE signal, Fig. 1, is a complex, damped, sinusoidal voltage vs time plot. Some of the characteristics, such as amplitude, duration, energy, events, and counts, are the key parameters for material characterization and structural integrity evaluation. Very long back itself amplitude distribution has been utilized for analyzing the failure mechanism in composite materials. Predicting ultimate failure load of composite specimens using AE data was proved earlier by Walker and Hill.

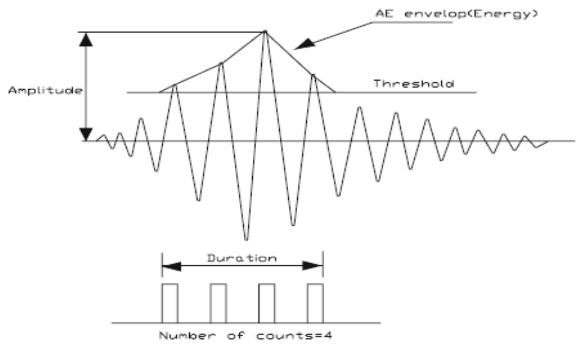


Fig. 1 Typical AE signal and characteristics

Artificial neural network (ANN) is an information processing system that has certain characteristics similar to biological neural networks. A neural network consists of a large number of simple processing elements called neurons or nodes. Each of these neurons is connected to other neurons by communication links, each with associated weightage. The weightage represent information that is used by the network to solve a problem. A hidden layer neuron has many input paths and combines values of the input paths by a simple summation. The summed input is then modified by a transfer function and passed directly to the output path of the processing element, as shown in Fig. 2. The output path of the processing element can then be connected to input paths of other nodes through connection weightings. Since each connection has a corresponding weighting, these weightings prior to being summed modify the signals on the input lines to a process element. The processing elements are usually organized into groups called layers. Typically, a network consists of an input layer, where data are presented to the network; one or more hidden layers for processing; and one output layer to get the results from the network. It has been demonstrated that AE data could be used along with neural network for predicting ultimate strength of graphite epoxy tensile specimens and weld strength of aluminium–lithium specimens by researchers Walker and Hill, respectively.

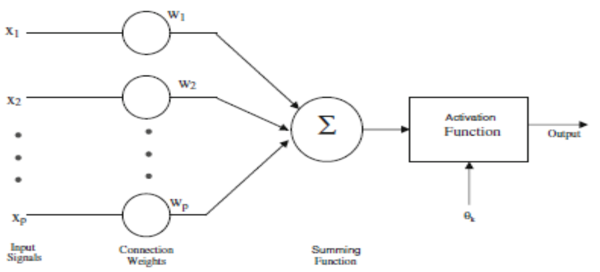


Fig. 2 Artificial neuron model

II. EXPERIMENTAL SETUP AND PROCEDURE

AE data sets were generated by loading 24 carbon/epoxy unidirectional tensile specimens at a rate of 1mm/min to failure. BiSS 300 KN capacity UTM was used to do the tensile test. While loading, AE activity was monitored with a Physical Acoustic Corporation (PAC) DiSP AE system. A pair of R15 sensors (150 KHz, resonant) and preamplifiers with 20 dB gain were used. AE transducers were mounted in position using adhesive tapes. In order to acquire emissions from complete volume, the sensors were mounted on alternate sides of the specimen, as shown in Fig. 4.

Fig. 3 Actual Specimens manufactured and tested

Fig. 4 Specimen with sensors

Fig. 5 Specimen mounted on UTM

AE signal transmission between specimen and sensor was ensured through appropriate couplant (silicone vacuum grease). A threshold setting of 35 dB was adopted for the test after estimating background noise. Hsu-Nielson 0.5 mm diameter, 2H pencil break was conducted before each test for ensuring proper working of AE channels. Only AE amplitude frequency data collected up to 50%, 60% and 70% of failure load along with the slope of cumulative amplitude distribution plot of 10 specimens were supplied as input to the Backpropagation ANN models. Input data of 14 remaining specimens were used as the test phase for the ultimate strength prediction in MATLAB Workspace. Failure load prediction was obtained using MATLAB neural network toolbox. Walker has taken only the matrix crazing signals (23 to 45 dB) for his weibull analysis and neural network prediction at 25% level. This research has contemplated that accurate prediction could be possible with high-amplitude hits recorded during loading because a significant number of fiber breakage and matrix splitting events, which produce high-amplitude signals, are adversely affecting the failure load of the specimen.

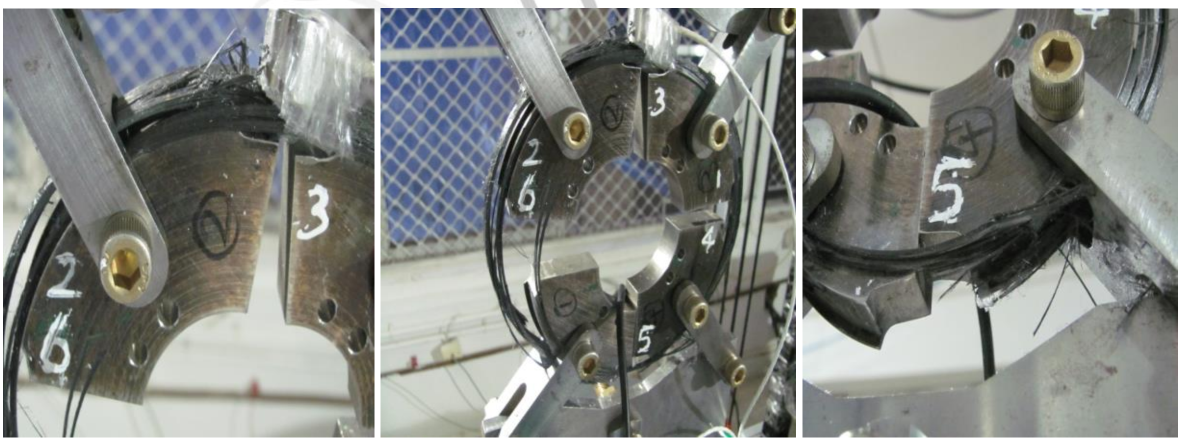


Fig. 6 Failure of specimen

III. FAILURE MECHANISMS ANALYSIS

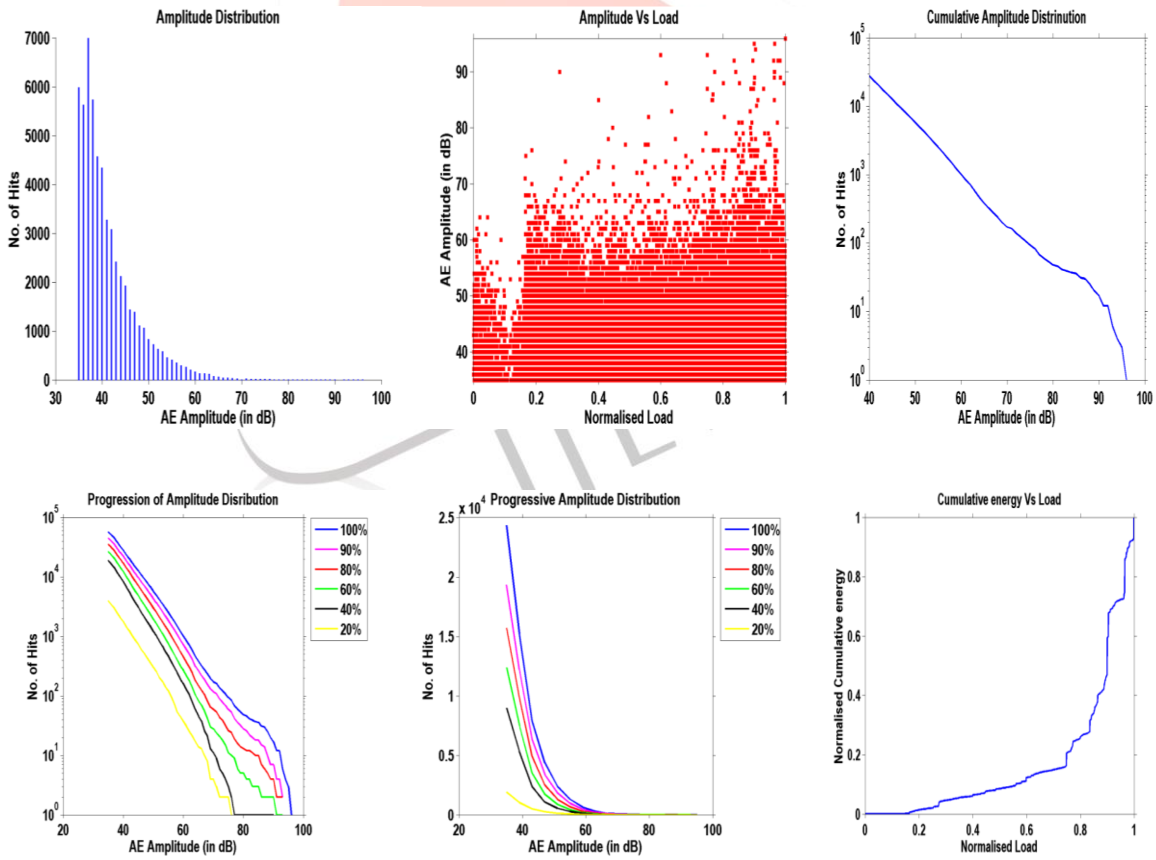
As mentioned previously, the three primary failure modes for most composites are matrix crazing, fiber breakage, and delamination. Unlike in pressure vessels and flexural tests, considerable delamination was not expected in unidirectional tensile test, but matrix splitting can occur. Each of these failure modes has specific magnitudes for various AE characteristics, which makes AE useful in identifying these failure mechanisms. A typical matrix crazing signal is of long duration with low amplitude and low energy. Matrix crazing occurs throughout the testing cycle and is usually the least damaging of the mechanisms. Matrix splitting occurs when matrix cracking occurs along the fibers. This mechanism can bring down the failure load as much as the fiber failure. Duration of this failure is long; energy and amplitude are also lesser than fiber breakage. Another failure mode, fiber breakage, is typically the most damaging mechanism since the fibers are the main load-bearing constituents of the structure. Fiber breaks have the highest amplitudes and energy in the three primary failure mechanisms. These are all consolidated in Table 1.

Table 1 Characteristics of failure modes

AE Parameters	**Failure Modes**		
	Matrix Crazing	***Matrix Splitting***	***Fiber Breakage***
Amplitude	Low	Medium	High
Duration	Long	Long	Short
Energy	Less	More	More

Although all the characteristics are useful in providing information on AE, the research herein used only amplitude (in the form of frequency in each dB from 35 to 100) and the slope of cumulative amplitude distribution plot for failure load prediction. Here, event frequencies at 5-dB intervals are provided as input for the neural network. Statistical methods are also capable of predicting the failure strength of specimens; however, neural network prediction accuracy was found to be better.

A series of plots were generated between different AE parameters to illustrate, evaluate and assess the possible correlation between these parameters and failure load. The AE data acquired during the tests has been post processed with Matlab software and AE correlation plots were generated to identify the failure mechanisms. The load is normalized for ease of comparison of the data for different specimens.



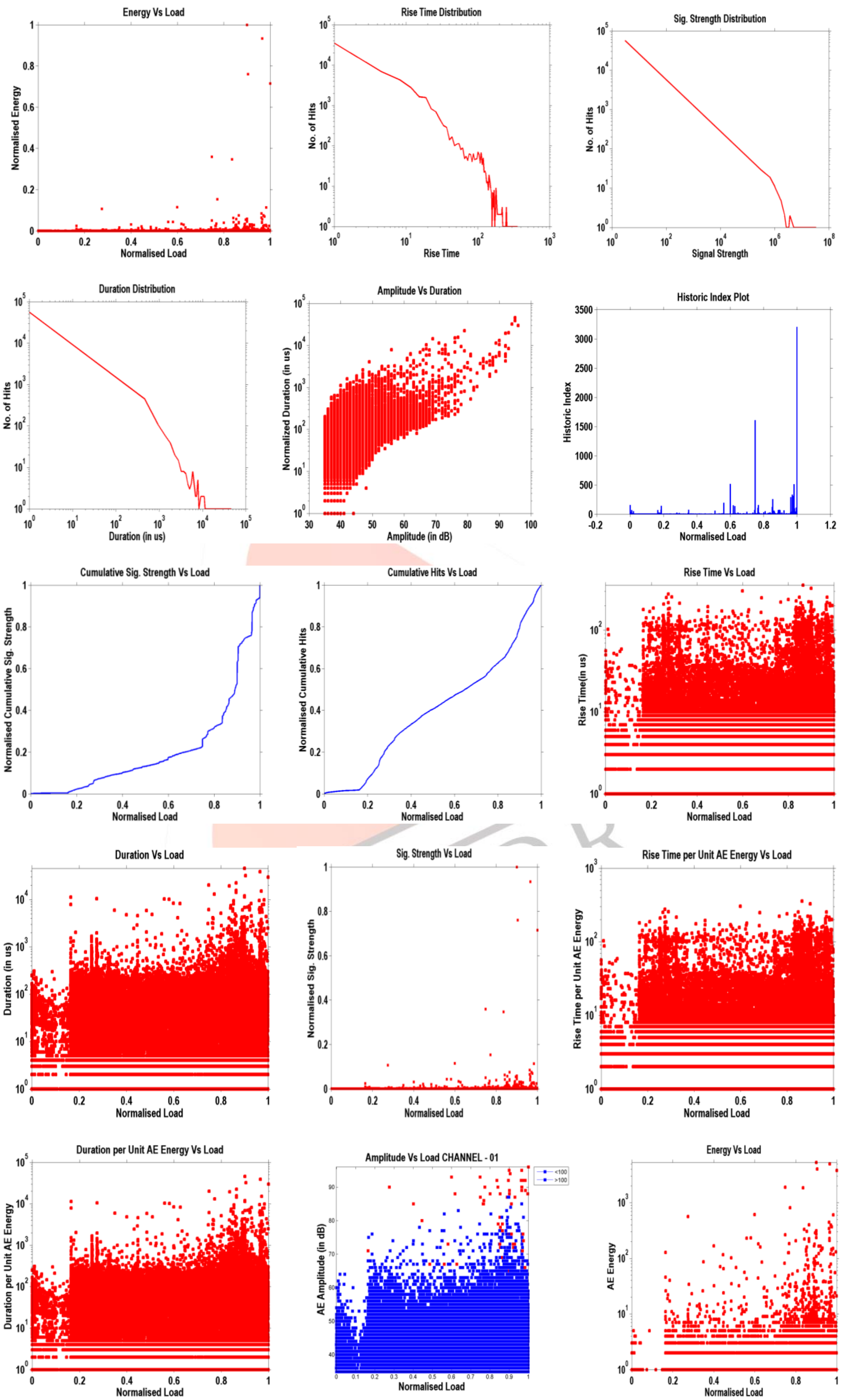


Fig. 7 Acoustic Emission correlation plots

Researchers have reported that the slope of the cumulative amplitude distribution curve indicates the dominant failure mechanism and the presence of two dominant failure modes give rise to bilinear nature to the cumulative amplitude distribution plot. The curves of all the specimens exhibit a linear trend up to around 70% of the breaking load beyond which bi-linearity (2 distinct slopes) is noticed. The number of slopes in the plot indicates number of failure modes that the sample experienced. Hence it can be concluded that, matrix cracking has been dominant until 70% of the load and beyond this fiber breakage initiates.

IV. RESULTS AND DISCUSSIONS

AE data were collected during loading until failure of each specimen. AE hits recorded while testing of each specimen at different loading levels. Data acquired till failure are used for post-test analysis. After analysis, three parameters chosen for further studies are amplitude, duration, and energy. Multiple linear regression analysis performed by Fatzinger and Hill using percentage of hits associated with each failure mechanisms has provided a failure load (I beams) prediction error of 36%, but an optimized ANN with amplitude frequency provided only 9.5% error. From this research work, it was concluded that amplitude frequency along with ANN proved to be better than all other AE parameters. Hence, here, the same approach was also adopted.

Twenty four tensile specimens were grouped into two sets called training and testing sets. The training set contains 10 specimens inclusive of best and worst failure loads recorded; the fourteen remaining specimens were in the test set. AE hits recording up to 50%, 60% and 70% of load were taken for failure load prediction. Amplitude frequencies at 5 dB interval (35 to 99 dB) along with the slope of cumulative amplitude distribution plot are given as the input vector. The sorted Input training data for ANN up to 50%, 60% and 70% of load are listed in below tables.

Table 2 Input training data for ANN up to 50% of load

Spec. no.	**35-39**	**40-44**	**45-49**	**50-54**	**55-59**	**60-64**	**65-69**	**70-74**	**75-79**	**80-84**	**85-89**	**90-94**	**95-99**	**Slope**
2	12677	6355	2401	976	396	147	42	11	4	1	1	1	0	0.08665
03	11888	6876	3374	1393	613	236	105	29	12	2	2	1	0	0.08214
04	11895	5861	2370	993	408	179	54	22	9	3	1	0	0	0.08489
05	19220	11382	5362	2349	1067	480	127	31	12	4	7	7	0	0.07379
06	19662	12385	5653	1906	731	331	115	15	7	5	1	0	0	0.09195
07	16691	9565	4008	1648	672	252	80	20	16	1	2	0	0	0.08750
08	21975	15036	7593	3005	1118	459	185	53	13	3	6	1	0	0.08627
09	18754	10857	4380	1672	759	311	100	25	6	6	2	0	0	0.08598
10	14398	6741	2579	996	418	136	42	14	4	3	1	0	0	0.08630
11	20594	14994	7988	3118	1069	393	160	45	13	5	0	0	0	0.09433
12	20877	15510	8758	3792	1585	603	211	76	17	11	3	2	0	0.08366
13	15770	9177	3464	1316	544	211	62	15	8	1	1	0	0	0.09266
14	14762	8032	3116	1143	417	143	38	6	4	3	0	0	0	0.09394
15	22312	14064	6549	2499	1058	434	176	45	18	5	3	1	0	0.08648
16	16876	10416	4415	1498	661	272	90	24	6	3	1	0	0	0.09237
17	19091	13606	7547	3004	1145	485	217	82	24	10	5	0	0	0.08310
18	16807	10373	5245	2002	692	327	111	30	6	3	1	0	0	0.09349
19	21252	13205	6450	2723	1131	475	155	55	13	5	3	0	0	0.08852
20	16007	9047	4144	1710	727	265	90	24	6	3	1	0	0	0.08998
21	9108	5099	2128	889	352	165	47	18	8	2	0	0	0	0.08826
22	20048	12199	5922	2515	1066	430	154	37	19	1	0	0	0	0.09507
23	21877	13730	6680	2823	1270	586	232	76	22	10	3	5	0	0.07798
24	16211	11098	7417	6816	1389	326	105	35	10	2	0	0	0	0.10093
25	18878	12891	7170	3152	1108	468	172	50	12	5	1	0	0	0.09303

Table 3 Input training data for ANN up to 60% of load

Spec. no.	**35-39**	**40-44**	**45-49**	**50-54**	**55-59**	**60-64**	**65-69**	**70-74**	**75-79**	**80-84**	**85-89**	**90-94**	**95-99**	**Slope**
02	14495	7436	2891	1201	483	186	55	17	6	2	1	2	0	0.08127
03	14426	8361	4143	1759	771	301	134	38	15	2	4	1	0	0.08058
04	13268	6567	2733	1175	486	206	62	24	9	3	2	0	0	0.08379
05	22173	13478	6460	2976	1369	619	194	58	17	6	9	8	0	0.07342
06	22728	14269	6606	2360	908	404	149	21	14	8	1	0	0	0.09115
07	19081	10884	4659	1929	785	299	93	22	17	1	2	0	0	0.08905
08	25533	17585	9115	3707	1460	603	244	69	19	5	7	1	0	0.08587
09	21265	12441	5161	2017	931	394	132	45	10	9	3	1	0	0.08227
10	15878	7633	3007	1160	503	180	54	18	8	6	1	1	0	0.08287
11	22599	16513	8977	3562	1254	468	192	49	20	8	0	0	0	0.08901
12	23818	17505	9964	4429	1904	742	273	96	21	12	3	2	0	0.08476

13	18557	10775	4200	1674	678	277	84	22	9	2	1	0	0	0.09296
14	16213	8911	3499	1347	504	186	50	16	7	3	1	0	0	0.09000
15	24348	15277	7197	2762	1189	477	193	55	24	6	4	1	0	0.08606
16	18786	11601	5000	1780	758	319	105	32	6	3	1	0	0	0.09340
17	21347	15265	8438	3390	1336	589	262	99	26	12	5	0	0	0.08358
18	19058	11834	5952	2323	820	370	128	36	9	3	1	0	0	0.09413
19	24143	15235	7631	3275	1370	597	205	68	18	7	4	1	0	0.08600
20	19446	11427	5339	2295	975	368	132	40	11	3	1	0	0	0.09182
21	11176	6387	2870	1241	516	234	77	27	16	5	1	0	0	0.08324
22	23515	14343	6982	3056	1343	551	188	46	23	1	1	1	0	0.09085
23	25279	15926	7821	3306	1455	681	261	83	23	13	3	5	0	0.09446
24	17927	12176	7921	7044	1507	364	125	42	13	2	0	0	0	0.09941
25	20900	14184	7903	3493	1252	528	191	57	15	6	2	0	0	0.09127

Table 4 Input training data for ANN up to 70% of load

Spec. no.	**35-39**	**40-44**	**45-49**	**50-54**	**55-59**	**60-64**	**65-69**	**70-74**	**75-79**	**80-84**	**85-89**	**90-94**	**95-99**	**Slope**
02	16168	8490	3423	1422	583	222	66	26	8	3	2	2	0	0.08028
03	16806	9941	4922	2111	932	380	157	48	20	6	5	1	0	0.07985
04	14413	8267	3748	1691	767	319	126	44	20	15	5	2	0	0.07384
05	25086	15549	7572	3621	1719	821	259	90	27	10	10	10	0	0.07263
06	26715	17088	8219	3177	1276	555	216	45	25	11	4	1	0	0.08393
07	22353	13043	5794	2545	1050	380	129	35	20	3	7	1	0	0.08281
08	29024	20014	10645	4542	1870	786	315	94	30	8	10	1	0	0.08360
09	23629	13955	5976	2394	1085	454	164	64	14	10	5	1	0	0.08175
10	18002	8938	3735	1469	650	236	77	25	13	9	2	1	0	0.08056
11	24517	17836	9775	3893	1411	531	215	57	23	12	2	0	0	0.08737
12	27298	19926	11409	5171	2254	903	337	125	34	16	5	2	0	0.08354
13	20882	12074	4806	1946	762	315	98	29	10	4	1	0	0	0.09173
14	17323	9545	3783	1477	584	204	57	21	10	4	1	0	0	0.08978
15	26252	16491	7861	3009	1290	527	215	63	28	7	5	2	0	0.08207
16	20566	12715	5570	2056	857	377	124	48	8	5	1	1	0	0.08795
17	24069	17082	9478	3930	1622	728	310	117	29	15	5	1	0	0.08388
18	21819	13826	7020	2791	1012	448	160	43	12	6	2	0	0	0.09057
19	27333	17482	8946	3908	1699	729	251	84	24	9	4	1	0	0.08669
20	22892	13745	6556	2919	1289	518	182	59	16	5	1	2	0	0.08596
21	13009	7569	3469	1513	649	286	104	34	20	8	4	1	0	0.07917
22	25826	15810	7709	3400	1516	607	211	57	28	3	1	1	0	0.09009
23	28575	18103	9007	3898	1724	787	316	93	28	15	4	5	0	0.07977
24	20305	13440	8581	7346	1634	411	145	50	15	3	1	0	0	0.09734
25	22825	15492	8604	3806	1404	583	211	66	17	9	2	1	0	0.08847

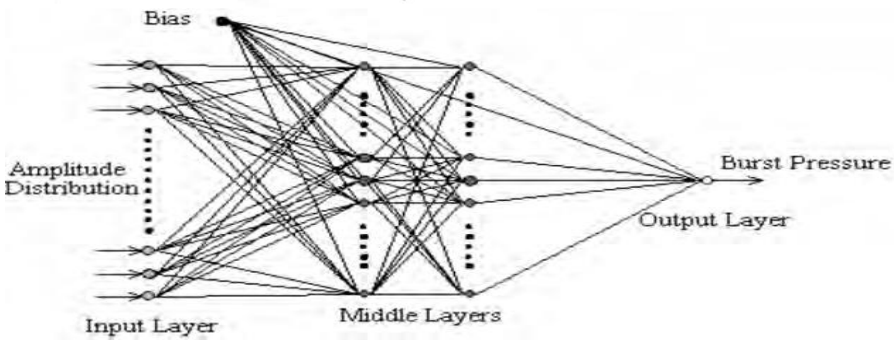


Fig. 8 Neural network for failure load prediction

A network was constructed with 14 input neurons and only one output (failure load) neuron. The network was trained with different combinations of middle-layer neurons to get the targeted output. Two hidden layers with nodes 12 and 2 were used. Lots of trial and error methods were adopted to arrive at network parameters such as number of nodes in hidden layer, changes in learning rate etc. The better error convergence was obtained at the network architecture 14-12-2-1. TRAINLM (Levenberg-Marguart algorithm) and TANSIG were used as the training function and transfer function and 0.01 and 0.9 are the learning coefficient and momentum, respectively. Then, the network was given only the inputs of testing set specimens and their failure loads were predicted by the network. Output results of the network are given in Table 5.

Table 5 Failure load predicted by neural network

Specimen number	Actual Failure Load (KN)	Predicted Failure Load at 50%	% Error	Predicted Failure Load at 60%	% Error	Predicted Failure Load at 70%	% Error
02	53.52113	59.34089	-10.87	57.91185	-8.20	56.56209	-5.68
03	63.17223	66.48543	-5.24	64.80163	-2.57	62.27266	1.42
04	70.64911	67.04457	5.10	64.81387	8.25	70.24814	0.56
05	60.60697	61.42602	-1.35	60.63214	0.04	65.57476	-8.19
06	70.89085	67.47309	4.82	64.54994	8.94	64.45373	9.08
07	55.73695	57.09275	-2.43	56.02518	0.51	54.06207	3.00
08	61.45385	57.91388	5.76	60.64532	1.31	62.19231	-1.20
09	65.00436	65.84595	-1.29	66.15129	-1.76	62.63021	3.65
10	71.21047	63.56004	10.74	63.85792	10.32	63.70435	10.54
11	57.13214	61.28516	-7.26	61.22613	-7.16	62.65157	-9.66
12	64.86225	58.88264	9.21	61.25320	5.56	62.15584	4.17
13	56.2265	60.92924	-8.36	59.61136	-6.02	61.32826	-9.07
14	59.14672	65.27514	-10.36	60.18119	-1.74	59.84777	-1.18
15	67.86856	63.43045	6.53	60.73196	10.51	63.44271	6.52
16	65.08395	66.01878	-1.43	62.56368	3.87	61.76968	5.09
17	61.68812	62.00516	-0.51	61.62639	0.1	62.14812	-0.74
18	65.52305	66.25188	-1.11	62.89332	4.01	61.98645	5.39
19	58.39666	60.10650	-2.92	60.76220	-4.05	62.15031	-6.42
20	62.5226	66.98498	-7.13	61.94031	0.93	61.82509	1.11
21	67.55335	67.59579	-0.06	66.22098	1.97	63.17561	6.48
22	65.97717	59.18384	10.29	59.17492	10.30	62.00115	6.02
23	61.11546	58.70644	3.94	61.45301	-0.55	62.32882	-1.98
24	62.87532	66.25727	-5.37	61.20161	2.66	60.26458	4.15
25	62.73173	62.91969	-0.29	61.44307	2.05	62.11194	0.98

The network trained with 50% of AE data has obtained Error convergence at 8th epoch and the Best validation performance is 8.9592 at epoch 1 and the maximum prediction error is 10.87%. The network trained with 60% of AE data has obtained Error convergence at 13th epoch and the Best validation performance is 20.1039 at epoch 7 and the maximum prediction error is 10.51%. The network trained with 70% of AE data has obtained Error convergence at 7th epoch and the Best validation performance is 15.1578 at epoch 1and the maximum prediction error is 10.54%. Error convergence plots are shown in Fig. 9.

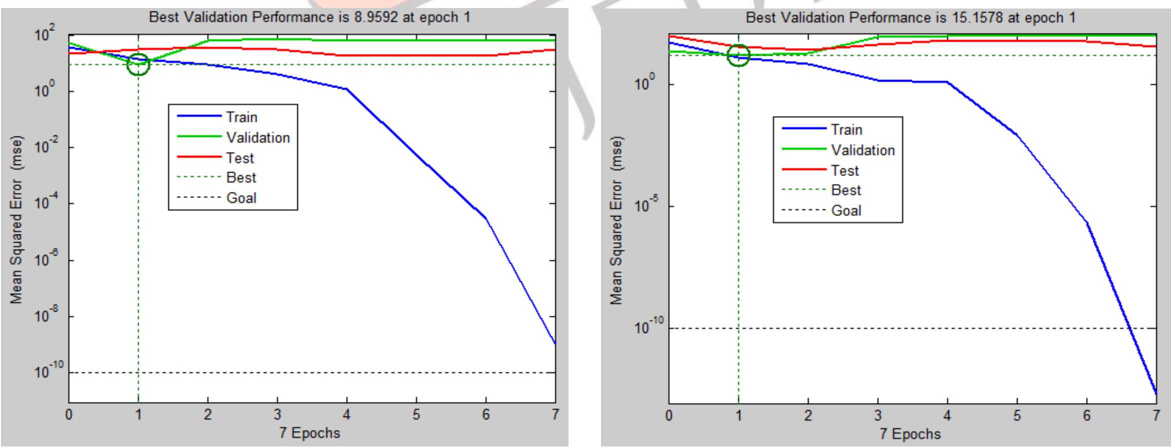
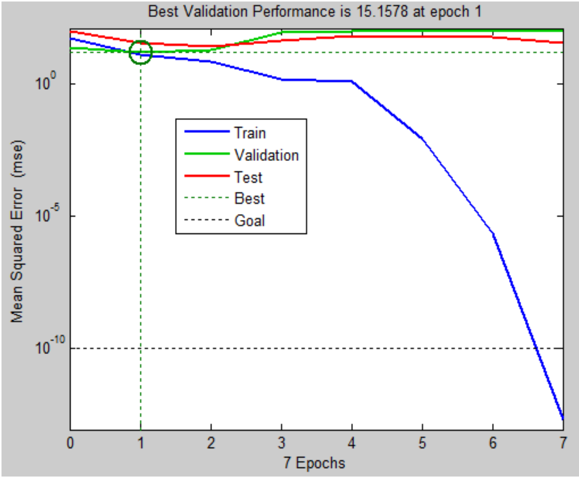
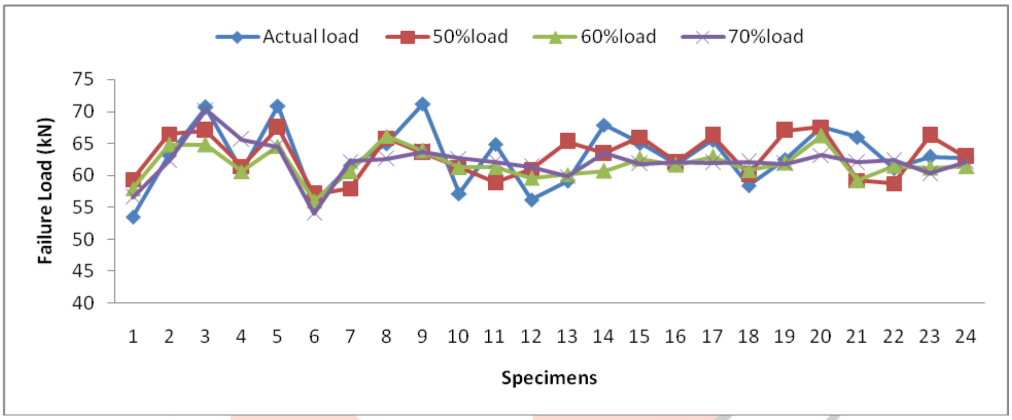


Fig. 9 Error convergence plot at 50%, 60% and 70% of AE data

Fig. 10 Results plot with actual failure loads





Prediction results of three networks were compared with the actual failure loads, and they were plotted in Figure 10. This comparison spelled out that the increase in accuracy of the neural network depends on the increase of data quantity. However, an increase in the load of composite hardware above a particular limit will adversely affect the structural integrity, as discussed in the introduction of this manuscript.

Therefore, the failure load prediction was restricted with a maximum of 70% loading level. The maximum prediction error at 50% loading level was 10.87% and 10.54% at 70% loading level where the damage accumulation gets started. Hence, the maximum error tolerance of 10.51% obtained at 60% loading level was found sufficiently nearer to the actual failure load of the specimen.

V. CONCLUSION

This work predicted the ultimate strength of carbon/epoxy composites using online acoustic emission (AE) monitoring and artificial neural networks (ANN) under uniaxial tension. Failure load prediction was carried out for 24 specimens by means of ANN using amplitude distribution data obtained up to 50%, 60% and 70% of the actual failure load. Amplitude frequency at 5 dB interval (35 to 99 dB) along with the slope of cumulative amplitude distribution plot was given as the input vector and their known ultimate strength as the output data. Two hidden layers with nodes 12 and 2 are used. The better error convergence was obtained at the network architecture 14-12-2-1. This technique permitted the ultimate tensile strength with an acceptable error tolerance of 10.5 percent. AE combined with neural network (NN) is an effective method to predict failure load.

This project demonstrates the capability of a backpropagation neural network to predict the ultimate strength of carbon/ epoxy tensile specimens. An increase in performance of the network with a higher quantity of AE data was proved very clearly by the comparison done between the results of three networks developed. In order to avoid the structural integrity degradation during proof testing, the failure loads of tensile coupons were predicted with 60% and the lower level itself. At 70% of failure load the damage accumulation get started. So that it may be possible to proof test the composite hardware, more sophisticated methods than those that are currently being tested need to be developed (70% to 80% of failure load), and their failure loads could be predicted.

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