ISSN: 0974-2115
www.jchps.com Journal of Chemical and Pharmaceutical Sciences

Failure Potency Forecast of Tensile Coupon Using Acoustic Emission Felicity Ratio with Artificial Neural Networks

Mahil Loo Christopher C[1*] and Sasikumar T[2]
[1]Department of mechanical engineering, Sathyabama University
Chennai, India
[2]Department of Mechanical Engineering, Lord Jegannath College of Engineering & Technology
Kanyakumari District, India.
***Corresponding author: E.Mail: mahil_be@rediffmail.com**

ABSTRACT

Acoustic emission gives the significant information about the fracture observance of composite ingredients. In this study, AE activity was recorded during a tensile test in the specimens made of Aluminum 6061and silicon carbide, the specimens were weighted in a load governed tension, in a step loading mode. The benefit of AE guidelines is discussed in, for the characterization of the fracture mechanisms and to predict the ultimate failure of the material. Acoustic emission parameters like Hits, energy, duration, rise time are used to determine the crack growth of the material several cycles before the ultimate failure of the composite materials. The proposed methodology to identify the damage of composite metals is an initial step of predicting fracture considering hits and felicity ratio. The ultimate strength of the specimen is predicted by artificial neural network using Back propagation with Leavenberg-Marquardt Algorithm. Network structured with 70-46-1 along with amplitude and felicity ratio at 1dB period of time as an input and failure strength as output was able to describe a possible failure strength within 4.49 % of error tolerance.

Keywords: Hits; felicity ratio; Artificial neural network-Back propagation algorithm

1. INTRODUCTION

Acoustic emission (AE) was used to supervise the structural conditions of materials and structures. The sensors are used to manifest the acoustic emission activity to show the fracture, more signals express that whether the material is a weaker are stronger with the observation of low signal and stronger signals. Many sensors are used to detect the acoustic emission signals, the waves generated from different areas in the material gives attention to take necessary steps to repair the material. There are many quality parameters to caliper the acoustic emission from the signals. During tensile testing, the events are characterized by considering the duration of signals crossing the threshold. It can be said that all these measurements based on the threshold setting which is selected to avoid the other disturbance created in the atmosphere, surroundings and other various noises, but at the same the setting of threshold should be in such a way that it should allow the sensor to record the acoustic emission (AE) which are created during cracks occurred in the material. Disengagement during applying external force on the fiber reinforced concrete and the matrix cracking. Mainly in the area of composites and alloys, specifically the cumulative of acoustic emission hits is used to compare the strength of the single fiber fragmentation test and the total life period of a metal specimen with various V shape indentations undergoing various testing. Acoustic expulsion parameters allied rise time, count, Energy, Duration as shown in Fig 1. Are well mutually related to find the cracks created in metal specimen, for aluminum amplitude is compared with the cumulative of the parameters to determine the cracks.

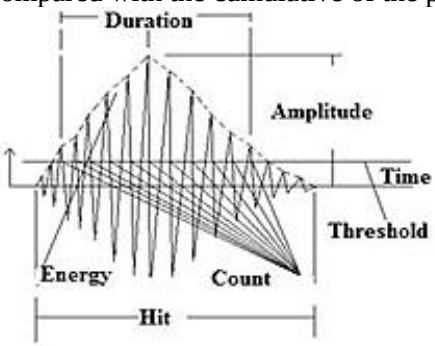

Figure.1.Characteristics of AE events

In this study, aluminum reinforced with silicon carbide was undergone to tensile testing by cyclic loading for 60 % of loading and remaining load applied for the ultimate failure of the specimen. The main focus of this paper will be on the acoustic emission hits created for each successive load that is recorded by the sensors which inform about the damage of the specimen. Felicity ratio (FR) is also discussed as one of the phenomenon to find the characteristic of the material. When a material is loaded it emit stress waves and again when it is unloaded, emission should not be created for the next reloading till the previous load level exceeds. FR is used as index of damage in composite materials. The ratio of FR is defined as and the ratio between a load of the previous maximum and the load at which they hit emits before. Kaiser Effect is a good indicator of the damage. If the ratio is lower the damage

is greater, at the same if the FR=1 there is no damage in the specimen. Felicity ratio is also used to qualify the damage of the materials. This paper focuses variant improvement of artificial neural network (ANN) for predicting the crack-up of metal specimens. This network deals with many input and output variables which are calculated through a training process where a pair of inputs are correlated to the network and the cause are assessed with the already known values. The errors in the artificial neural network are changed by modifying the network parameters. In common artificial neural network are practiced using supervised or unsupervised teaching models. The trained networks are used to find the output that is found from the input values which are not entered in the training data. After the construction and validation of the ANN models for the collected data, these models will predict the ultimate failure of the material.

2. EXPERIMENTAL PROCEDURE

A. **Materials and mechanical testing:** Among metallic matrices, aluminum based matrices produce high specific strength and stiffness, high- temperature performance, and low thermal expansion. The material utilized in the present study is of pure silicon carbide of 200 mesh grains and aluminum 6061.SIC reinforced aluminum metal matrix composites were prepared by stirring casting process were melted in the separate furnace for 1050° C to reach the liquid state. After adding of liquid SIC with the molten metal it is stirred at 500 RPM for 10 minutes, and then the composite was poured into the wooden mold to solidify. Finally, it was manufactured according to ASTM B557-14 sub size specification by using a vertical milling machine for a term of 100 mm and a width of 6 mm. Tensile testing was done in a universal testing machine by holding the specimen as shown in Fig. 2 between the two crosshead, A pair of R15 (150 KHz, resonant) sensors were used, AE transducers are attached on both the sides of the specimen by using silicone vacuum grease and adhesive tape to avoid slipping. The samples were stacked in a load controlled tension in a stage stacking mode. The cross head is operated at a speed of 0.25mm/s. Loading was applied to the specimen at a rate of 0.5 kN and again, it is unloaded by releasing the grips of the crosshead and returning it back to the initial position The load was incremented for 0.5 kN for each consecutive step. The loading consisted of triangular shape with Loading and unloading for 60% and the remaining load was applied to the ultimate failure of the metal. Simultaneously the emission occurred on the specimen during the loading is supervised with a physical Acoustic corporation (PAC) AE system. The procurement edge was set to maintain a strategic distance from the foundation clamor, while the obtained signs were enhanced by the preamplifier.

B. Artificial neural network: The Artificial Neural Networks are equivalently rough electronic models in light of the neural structure of the mind. Presently, recommendation in organic examination is promising an essential comprehension of the regular deduction instrument. This examination demonstrates that brains stock data as examples of these patterns are very troublesome and allow us the ambitious to notice sole faces from many different angles.

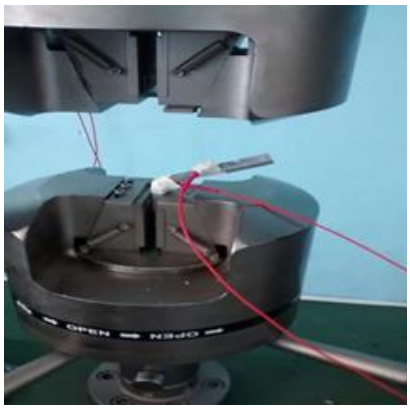

Figure.2.Photography of the Testing setup

This procedure of putting away data as examples, using those examples, and afterward taking care of issues incorporates another field of figuring. This field, as specified some time recently, does not use notable programming, but rather includes the generation of thickly parallel systems and the preparation of those systems to take care of accurate issues. ANN is made out of number of neurons which frame the underlying preparing unit. Every neuron is moreover subsidiary to different neurons by connections. All neuron gather various inputs which are changed by weights. The synaptic weights would either fortify or debilitate the sign which is prepared also. A limit esteem, called inclination which conveyance the yield. The activity of neural system is constant by a structure of neurons, association qualities, and the sort of adjusting actualized at components. On examination extend, the yield being anticipated is an insistent variable, while in relapse issues the yield is a critical variable. The Neural system utilizes restrictive cases, similar to an arrangement of inputs or data yield sets, and significant preparing instrument to more than once modify the quantity of neurons and weights of neuron linkage to perform the coveted capacity. Regulated learning, wherein the info and yield examples are contributing. An educator is reenacted to be available amid the

learning process, when a relationship is made between system's yield and genuine expected yield, in order to decide the blunder. Unsupervised realizing the objective yield is not presented to the system. The framework learns without anyone else by changing of the basic components in info designs. Reinforce taking in, an instructor, however practical does not display the ordinary answer, but rather just outline if the computed yield is right or mistaken.

An ANN lives various connected manufactured preparing neurons called hubs, joined together in layers shaping a system. An ANN is schematically represented in Fig 3. The quantity of hubs in the information and yield layers is forced by the way on the issue to be illuminated and the quantity of info and yield variables expected to portray the issue. The quantity of concealed layers and the nodes inside of each shrouded layer is normally an experimentation process.

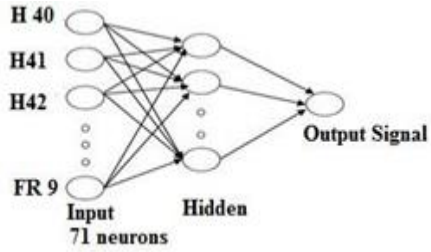

Figure.3.ANN Network with Layers

C. Training of Artificial Neural network: The ANN was prepared abundantly to reduce the presence of Mean square error between the actual outputs and the desired outputs. For training, a Mean square error of $7x10^{-8}$, an upper limit gradient of $1x10^{-10}$ and a maximum iteration (epoch) of 500 were pre-owned. The initial weights and biases are trained with back propagation algorithm which compares the error values at the output layer, allowing the incoming weights of these layers to update. Feed forward multilayer algorithm has been broadly utilized as a learning calculation as a part of the back propagation calculation Calculating the weights of the hidden layer in multilayer perceptron in a powerful way that result in a minimum output error. At the yielding layer, the screw up is measured to find the difference amidst veritable and needed yields. The back spread estimation instrument is a mazy exploratory mechanical assembly. In any case executing of the preparation, comparisons are set up in the cycle process. Therefore, it is effectively implementable on the computer. Mat lab 10 was utilized to plan and testing of manufactured neural models. Every node has the weight associated with all hubs in the following layer. And all nodes execute as an expansion of its inputs, going the outcomes through an exchange capacity. Hyperbolic digression capacity was utilized as a part of the center layer the info layer has 70 preparing components. Each of them is partnered to an info component that crashed from the recurrence range. The quantity of hubs in the center layer taking into account the info and execution of the system. A learning rate of α=0.9 was utilized everywhere throughout the energy learning guideline. One hub was given to the yielding layer. Quantities of nodes in the center were picked in light of the experimentation strategy. To diminish the run time stand out concealed layer was analyzed. By taking the information from the mean square mistake the quantity of nodes in the concealed layer, chose was 46.A mean square blunder for various quantities of shrouded handling components at different ages was researched. Taking into account the quality these examinations, a system with handling components in the concealed layer were thought to be the base standard deviation mistake in like manner a high quality. Henceforth, the ideal chose a standard 70-46-1 for examination.

3. RESULTS

A. **Failure load prediction:** Out of fourteen quantities of the malleable examples, ten specimens were chosen for gathering 1. Their AE information gathered up to its 60% of the disappointment burden was utilized as a part of the preparation stage to prepare the neural system. The staying four examples were chosen for gathering 2. These examples were utilized for testing the system. AE information gathered and its comparing disappointment burden was used for expectation. Adequacy values in every dB interim (40 to 100 dB) were put away. Those qualities and felicity proportion qualities were made as a numerical exhibit (lattice), which was advantageous as an info for the system. The disappointment heap of every specimen appeared in Table. I additionally masterminded similarly, and it was given as they focused on yield for the system. The neural system model was created in the MATLAB-10 workspace, and it was prepared with ten example information. Here 70 neurons in the info layer and one and only neuron (disappointment load) in the yielding layer. In the middle of a single center, the layer was balanced and streamlined with 40 neurons. The learning coefficient and energy were 0.01 and 0.9 individually. Because of the quantity of the info neurons was more, Levanberg - Marguart calculation was utilized as learning tenet. Hyperbolic digression exchange capacity was utilized as a part of the center layer. The upgraded neural system was tried with the staying four example information. Recorded Failure loads

Table.1. Failure prediction for 70-40-1 structure

Specimen no	Failure load (kN)	Specimen no	Failure load (kN)
1	5.07	8	6.00
2	5.47	9	5.71
3	5.12	10	5.47
4	5.33	11	5.65
5	5.26	12	5.14
6	5.18	13	5.74
7	5.28	14	5.43

Specimen no	Hits &FR Data		
	Actual load (kN)	Predicted load (kN)	% Error
2	**5.47**	**5.66**	**-3.4**
3	**5.12**	**5.20**	**-1.56**
7	**5.28**	**5.79**	**-9.65**
6	**5.18**	**5.39**	**-4.05**

Failure Disappointment load expectation mistake of example number 7 was found outside the satisfactory blunder edge of 5 percent. Above said another three example's disappointment burden are inside of the reach at which the system was prepared represented in table 2. It demonstrates the lack of ability of the system to anticipate the disappointment load, which was outside the preparation range. In this way, the system was prepared with some additionally preparing sets. It was seen that changing the information set with the new preparing stage structure of 70-46-1 gave much decrease in its mistake edge as shown in Table 3. The consequence of a calibrating system execution of 84 emphases appeared in Fig 4. The correlation consequence of both the genuine and anticipated burden result in a more pessimistic scenario blunder of 3.83 % appears in Fig 5. In this way, the system has demonstrated its potential inside of the scope of target disappointment loads given in the preparation stage.

Table.2.Failure prediction for 70-46-1 structure

Specimen no	Actual load (kN)	Hits & FR Data	
		Predicted load (kN)	% Error
2	5.47	5.29	3.290676
3	5.12	5.35	-4.49219
14	5.33	5.28	2.762431
6	5.18	5.28	-1.9305

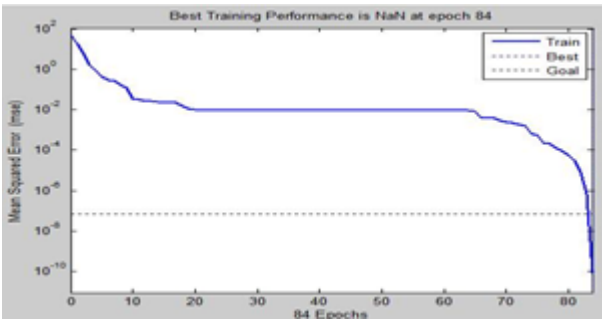

Figure.4.Network performance of Amplitude and FR data

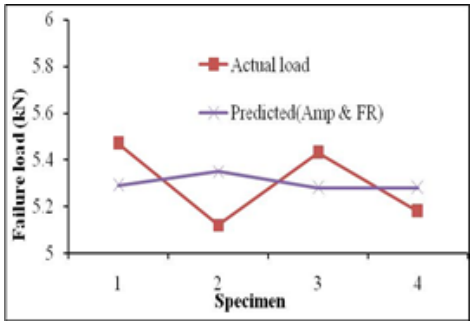

Figure.5.Result chart of Actual and Predicted load

4. CONCLUSION

The exploratory work in this paper exhibited that a back spread neural system can be utilized to foresee a definitive quality in the aluminum fortified silicon carbide pliable example by utilizing sufficiency and FR information as the data values with their referred to the extreme qualities as the yield esteem. Just the Hits of 60% of the acoustic emission of the normal disappointment quality of ten examples were utilized as a part of data preparing vectors. The shrouded layer of the neural system could concentrate and guide the elements of the plentifulness information to the known disappointment quality of the example tried. The strategy allowed a more pessimistic scenario extreme disappointment expectation mistake of 4.49 %. In mix of hits and felicity proportion information has anticipated the disappointing quality of example in a less error edge.

5. REFERENCES

Aggelis DG, Shiotani T, Momoki S, Hirama A, Acoustic emission and ultrasound for damage characterization of concrete elements, ACI Mat. Jour., 106 (6), 2009, 509–514.

Aggelis G, Aggelis DG, Barkoula NM, Matikas TE, Paipetis AS, Acoustic emission monitoring of degradation of cross ply laminates, Acoust. Soc. Am., 127(6), 2010, 246–251.

Anastassopoulos AA, Philippidis TP, Clustering methodology for evaluation of acoustic emission from composites, Journ. of Acou. Emis.Vol.13 (1/2), 1995, 11–22.

Ativitavas N, Pothisiri T, Fowler TJ, Identification of fiber reinforced plastics failure mechanisms from acoustic

emission data using neural networks, J Compos Mater, 40(3), 2006, 193-226.

Grosse C, Reinhardt H, Dahm T, Localization and classification of fracture types in concrete with quantitative acoustic emission measurement techniques, NDT & E Int., 30 (4), 1997, 223– 230.

Ohno K, Ohtsu M, Crack classification in concrete based on acoustic emission, Const. & Buil. Mat., 24, 2010, 2339–2346.

Ohtsu M, Tomoda Y, Phenomenological model of corrosion process in reinforced concrete identified by acoustic emission, ACI Mat. Jour, 105 (2), 2008, 194–199.

Rajendraboopathy S, Sasikumar T, Usha KM, Vasudev ES, Artificial neural network a tool for predicting failure strength of composite tensile coupons using acoustic emission technique", Int. Jour. for Adv. Manuf. Tech., 44, 2009, 399–404.

Roberts TM, Talebzadeh M, Fatigue life prediction based on crack propagation and acoustic emission count rates, Journ. of Const. St.Res,Vol. 59, 2003, 679–694.

Rousset G, Martin E, Lamon J, In situ fibre strength determination in metal matrix composites, Comp. Sc. & Tech., 69, 2009, 2580–2586.

Sasikumar T, Rajendraboopathy S, Usha KM, Vasudev ES, Artificial Neural Network Prediction of Ultimate Strength of Unidirectional T-300/914 Tensile Specimens Using Acoustic Emission Response, J Nondestruct Eval, 27, 2008, 127-133.

Tyagi CS, A comparative study of SVM classifiers and artificial neural networks application for rolling element bearing fault diagnosis using wavelet transform preprocessing, Wor. Acad. of Sci.. Eng. & Tech, 43, 2008, 309-317.

Walker JL, EvK Hill, Back propagation neural network for predicting ultimate strength of unidirectional graphite/epoxy tensile specimens, Adv. Perform mater, 3, 1996, 75–83.

Yun HD, Choi WC, Seo SY, Acoustic emission activities and damage evaluation of reinforced concrete beams strengthened with CFRP sheets", NDT & E Int., 43(7), 2010, 615–628.