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Acoustic Emissions Signal Parameter selection for training Artificial Neural Network

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***Abstract* - Selection of right parameters of acoustic emissions to train back-propagation multi-layer perceptron (MLP) neural network(ANN) is paramount for developing a model that can accurately predict impending failures in the materials. In our previous article titled "Failure prediction using Acoustic emissions and Artificial Neural Networks", the ANN model was detailed to have been trained using amplitude-hit distribution data, along with augmented parameters such as Weibull distribution parameters along with the energy rate and hit rates. The trained ANN model developed using these parameters is identified to have predicted the impending failure in maraging steel specimens at proof loads as low as 50% with 4.5% prediction error. Identifying appropriate signal parameters for training requires extensive experimentation and data analysis. In this article we detail the assessment of other signal parameters that were reviewed for Artificial Neural Network model's training.**

Keywords—Acoustic Emissions, Artificial Neural Networks, Material failure prediction, Non-destructive techniques, Neural Network training

I. INTRODUCTION

Rocket The use of maraging steel for rocket motor casings has gained prevalence due to its unique mechanical properties of dimensional stability during age hardening, superior fracture toughness and machinability with minimum distortion[1]. However, this material suffers from premature brittle fracture at stress levels lower than the designed levels due to presence of imperfections like voids in the crystal structure and defects introduced at the time of fabrication. Therefore, a fracture-based design approach along with heavy emphasis on quality control can allow for use of these materials in critical mechanical structures. To this end, our previous article illustrates how non-destructive techniques like acoustic emissions and artificial neural networks can be used to accurately predict the impending failure in materials with high accuracy in prediction error[2]. The type of failure mechanism or the defect in the specimen is characterized by the kind of AE signal and its signal parameters. For an accurate prediction of impending failure, the neural network is required to be trained with relevant data for generating prediction equations that can classify the defect appropriately. As reported in our previous paper [2], AE amplitude distribution data is shown to contain specific information related to an accurate identification of failure mechanisms in materials [3]. Various failure mechanisms are reported to have characteristic humps or bands in amplitude distribution with distinctive differences between failure mechanisms for plastic deformation and crack propagation. Although signal parameter data such as amplitude/hit data is considered to accurately predict the impending failure and was reported to have 8.1% prediction accuracy, the neural network was found to have better accuracy when trained with certain augmented inputs such as data from other signal parameters such as AE energy rate, AE count rate, AE activity and AE hit rate. This article's objective is to detail the data analysis of AE's other signal parameters to develop the required augmented input to improve the accuracy of model's predictive abilities.

II. EXPERIMENTAL SETUP

The experimental setup is as detailed in our previous article[2]. To summarize, the tensile testing acoustic emission signal data is collected from 17 maraging steel specimens varying in presence and/or type of defect. The data is then routed through a PAC AEWin system and MISTRAS signal acquisition and analysis software to pre-amplify, filter, and process the data into outputs containing the required AE signal features that are footprint of the defects in the specimen.

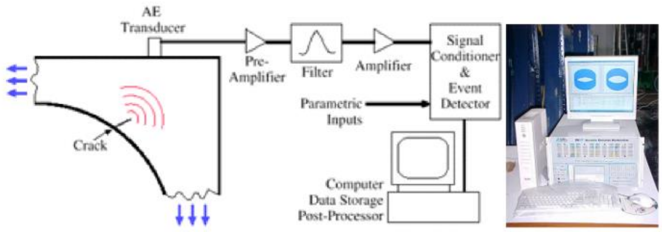

Figure 1 Schematic Block Diagram of AE-Win System

III. RESULTS AND DISCUSSION

The tensile test data from Walter-Bai hydraulic tester is presented in Table 1[2]. It can be inferred that the presence and/or type of defect in the sample resulted in a difference of 21% in the peak loads. Table 1 details the data from 17 test samples that were subjected to tensile loading up to failure using the test setup discussed in section 3. The behavior of the specimen, based on the underlying defect, can be characterized by the acoustic emission activity with straining of the material[4]. The AE signal parametric data such as amplitude, counts, energy rise time, duration provide information related to failure mechanism such as plastic or brittle failure[3]. And AE rate graphs like hit rate, energy rate, count rate and AE

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amplitude distribution data can be used for an accurate prediction of material failure[5].

Table 1 Test Sample defect type, failure mode and Peak Load

Specimen	*Type of Defect*	*Type of failure observed*	*Failure Load in KN*
Specimen 10	Weld Defect	Defect failure	70.57
Specimen 05	G-Notch	Notch failure	74.79
Specimen 23	70% G-Notch	Notch failure	72.47
Specimen 22	70% G-Notch	Notch failure	75.30
Specimen 03	50% G-Notch	Notch failure	79.13
Specimen 20	50% G-Notch	Notch failure	79.14
Specimen 06	F-Notch	Notch failure	79.47
Specimen 17	F-Notch	Notch failure	80.91
Specimen 14	E-Notch	HAZ failure	84.85
Specimen 24	None	Weldment failure	79.84
Specimen 07	None	Weldment failure	80.27
Specimen 01	None	Weldment failure	80.56
Specimen 13	None	Weldment failure	80.81
Specimen 11	None	Weldment failure	75.80
Specimen 04	None	Weldment failure	81.43
Specimen 18	None	HAZ failure	81.54
Specimen 08	None	HAZ failure	82.79

A. *Neural Network Program AE Signal Parametric data analysis*

In the sections below, each of the data type is analyzed for its ability to train the neutral network model for accurately predicting the material failure different characteristics of failure mechanism or defect of the specimen correspond to different kinds of AE signals and their signal parameters. The neural network program is required to be adequately trained with relevant data for allowing it to generate prediction equations for an accurate defect classification and predict impending failure.

1) *Cumulative AE Activity*

Figure 2 represents cumulative AE activity vs strain interposed with stress-strain graph, with all of the four (4) graphs indicating sudden spurt of activity with changing stress-strain graph's linearity. This sudden growth in AE activity can be corelated with the start of yield of material[6]. It can also be noted that the highest AE activity is observed in defect free sample while the lowest in HAZ failure sample. While this data is adequate to indicate the onset of yield in the material but not suitable for predicting the material failure as the AE activity slope is fixed and due to the presence of noise data.

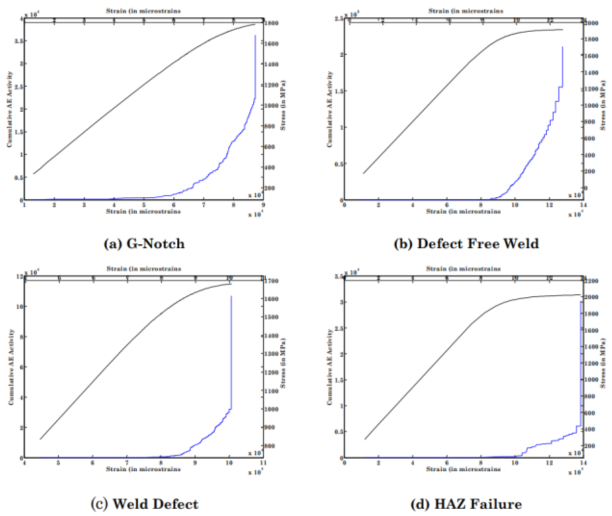

Figure 2 Cumulative AE Activity and Stress-strain comparative plot

2) *AE Hit Rate*

The AE hit rate vs. strain data when plotted with stress-strain data yields information related to onset of impending failure as indicated in Figure 3. The highest hit rate was observed in defect free sample and the lowest in HAZ failure sample. The instantaneous hit rate data is identified as suitable for being an augmented input to the neural network program for better prediction.

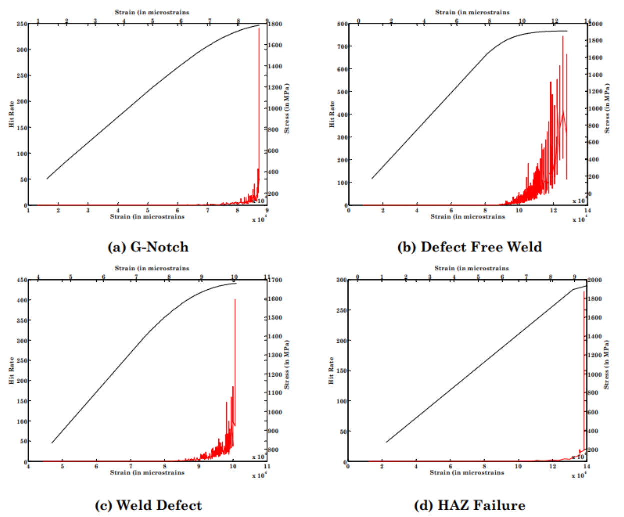

Figure 3 AE Hit Rate and Stress-Strain comparative plot

3) *AE Energy Rate*

Similar to the trends observed with cumulative AE activity and hit rate, AE energy rate is observed to be highest in the defect free sample, while the lowest was in HAZ failure sample (see Figure 4). A clear change in linearity of the energy rate graphs is an effective indicator of impending failure. Therefore, instantaneous energy rates could be used as augmented input to the neural networks program for better prediction.

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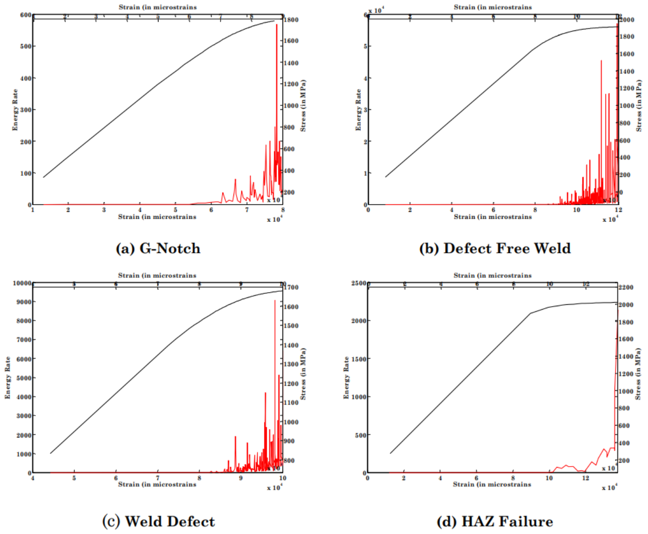

Figure 4 AE Energy Rate and Stress-Strain comparative plot

4) AE Count Rate

Similar to the AE energy rate, the change in linearity of AE count rate slope at around 90-120 counts per second is an effective indicator of change in slope of stress-strain curve and thus an impending failure. Also, the highest count rate is observed in defect free sample and lowest in HAZ failure sample similar to the trends observed with other data. Hence, the instantaneous count rates could also be used as an augmented input to the neural networks program for better prediction of impending material failure.

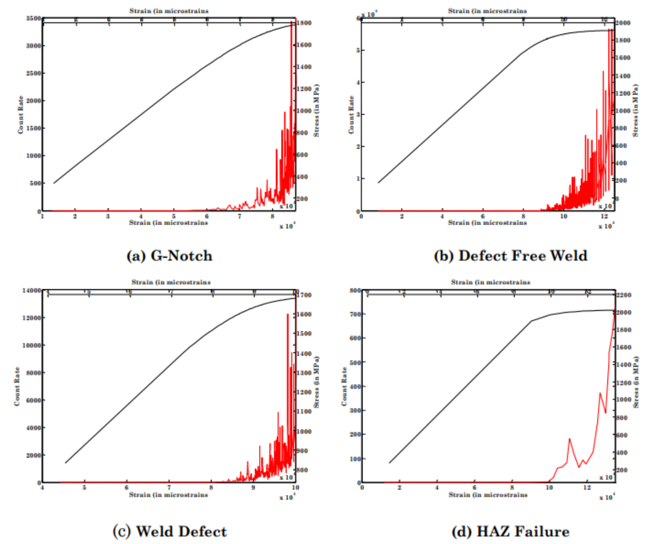

Figure 5 AE Count Rate and Stress-Strain comparative plot

5) AE Amplitude Distribution

AE distribution data is considered to contain vital information related to defect growth, microstructural changes, grip noises etc. As seen in Figure 6, the emissions are highest for defect free sample and lowest for the sample with HAZ failure. Figure 6 also indicates that all types of samples have characteristics of increase in emissions at the onset of yielding or plastic deformation. Therefore, this data type is considered to possess vital information regarding the behavior of material under stress loading.

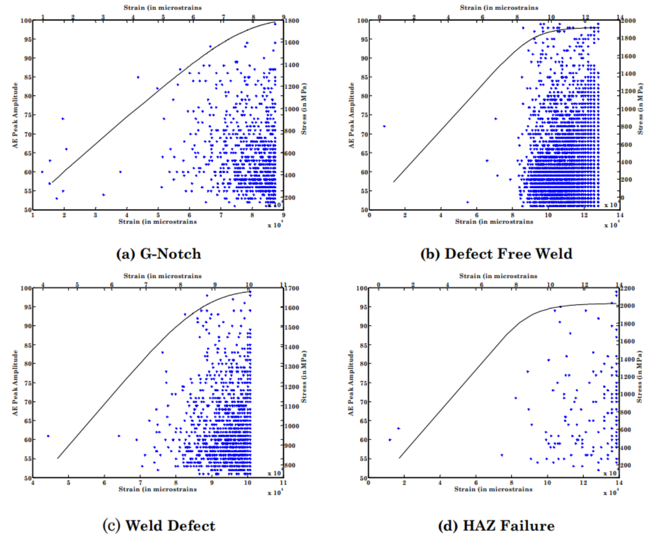

Figure 6 AE Amplitude Distribution and Stress-Strain comparative plot

6) AE Counts

Figure 7 represents AE counts vs strain interposed over stress-strain graph and is considered to have critical information regarding sample behavior under stress similar to amplitude distribution and count distribution data. However, it was identified that it couldn't be effectively used in failure prediction due to the presence of a high number of low count hits related to noise. Also, high variation in the AE count values impacted effective training of neural network. Therefore, this data was used for qualitative assessment of the samples under load but not used for training the neural network for failure prediction.

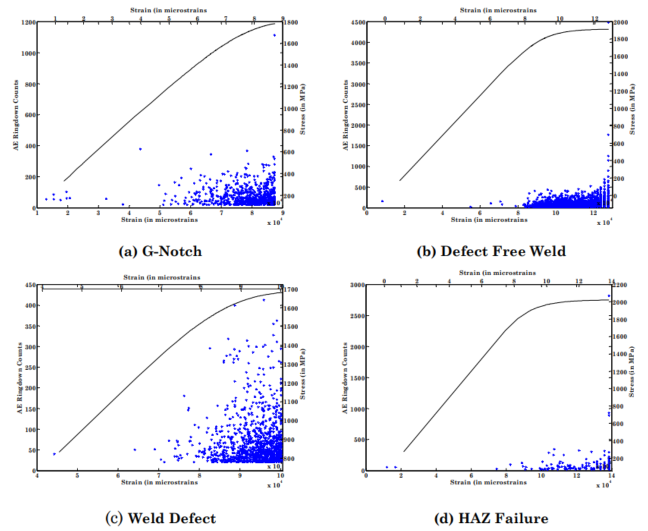

Figure 7 AE Count Distribution and Stress-Strain comparative plot

7) Amplitude-Counts correlation plots

The amplitude and counts data combination was recognized to allow for isolation of critical hits (amplitude > 60 dB and count >250) that carry critical information related to material failure process. High amplitude with low count and low amplitude with high count data does not characterize the material's failure

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process and hence the data filtration allows for plotting of significant information. Figure 8 shows combination plots of AE amplitude vs. strain interposed with stress-strain data and AE counts vs. strain data interposed with stress-strain data. As seen with other signal parameters, defect free sample has high number of critical hits (amplitude > 60 dB and counts > 250) signifying a brittle failure at a lower peak load, while HAZ failure sample has low number of critical hits representing a soft failure.

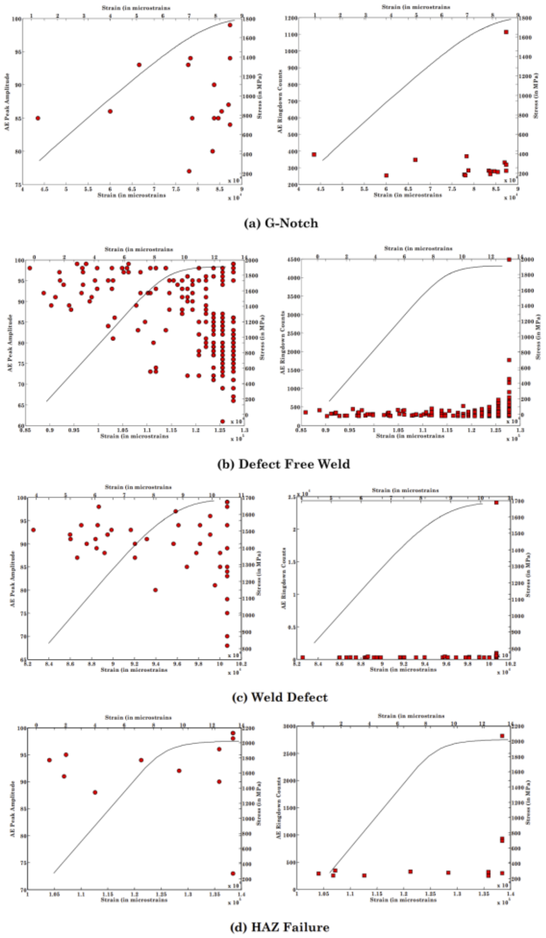

Figure 8 Filtered AE Data and Stress-Strain comparative plot

8) *Hit-amplitude distribution plots*

The overall damage state of the sample can be qualitatively assessed by using the distribution of hit amplitude data[7] and it is considered to provide most information regarding the damaged state of the test specimen. A shift of amplitude-hit data towards higher values signifies a higher quality part and conversely, a shift towards lower amplitude-hit data implies a lower quality part with stress concentration areas such as defects and voids. Figure 9 shows amplitude-hit distribution data, with defect free sample showing high hit- peak amplitude at 60 dB, and HAZ failure sample showing high hit-peak amplitude at 55 dB.

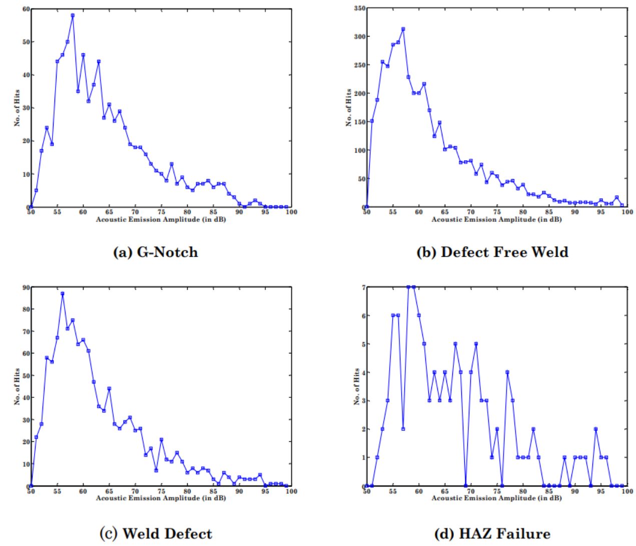

Figure 9 Actual Amplitude Distribution Plots

The hit-amplitude data when plotted using Weibull yields 3 parameters to identify shape of the distribution (A_o, θ and b). A_o represents threshold amplitude, θ represents mean of amplitude distribution which represents ductility or brittleness of the specimen, and b represents skewness of distribution towards low or high stress events with high value of b representing high quality part. Once these Weibull parameters for the amplitude-hit distribution are identified, they were used as inputs for the neural network model for failure prediction.

B. *ANN training and model's performance*

Based on the data analysis presented in the section above, two (2) neural network models were developed- one trained with just amplitude-hit distribution data, other trained with amplitude-distribution data along with augmented inputs such as AE count rate, hit rate and Weibull parameters. Of the 15 specimens (excluding 2 from the list due to slippage from grips), acoustic emission data from the testing of 7 specimens was used to train the models, while the rest 8 were used to test the trained models. The results indicated that the ANN model trained with augmented inputs such as Weibull parameters was able to reduce the impending failure prediction error from 8.1% to 4.5% at proof loads as low as 50% of peak load.

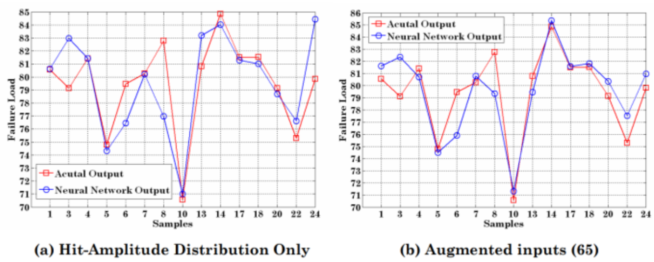

Figure 10 Failure prediction performance of ANN Models

IV. CONCLUSION

The acoustic emission data that was used to train the neural network model for failure prediction of maraging steels at low proof loads was determined to have a significant impact on the accuracy of the back-propagation multi-layer perceptron neural network. It was identified that the error in failure prediction was reduced by 45% when the neural network was trained with augmented inputs such as hit rate, energy rate, count rate and Weibull shape parameters of amplitude-hit distribution data compared to the one trained with just the amplitude-hit data. Thus, the analysis presented in this article signifies the importance of selection of right AE signal parameters for Neural network model training used to predict impending failures in materials used for critical structures such as rocket motor casings in satellites or missile systems.

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