



## PERFORMANCE OF ANN IN PREDICTING THE TENSILE AND SHEAR STRENGTH OF AL-STEEL EXPLOSIVE CLADS

\*Saravanan S and Kumararaja K

Department of Mechanical Engineering, Annamalai University, Annamalaiagar, Tamil Nadu-608002, India

### ABSTRACT

In this study, an artificial neural network (ANN) model is created to predict aluminium-stainless steel explosive clads' tensile and shear strengths. The parameters for the explosive cladding process, such as the loading ratio (mass ratio of the explosive and the flyer, 0.6-1.0), standoff distance (5-9 mm), preset angle ( $0^{\circ}$ - $10^{\circ}$ ), and groove in the base plate (V/Dovetail), were altered. The ANN algorithm was trained in Python using the tensile and shear strengths gathered from 80% of the experiments (60), trials, and prior results. The constructed model was evaluated utilizing the remaining experimental results. The ANN model successfully predicts the tensile and shear strengths with an accuracy of less than 10% deviation from the experimental result.

**Keywords:** *Explosive cladding; Artificial Neural Network; Mechanical Strength*

### 1. Introduction

The best lightweight constructions for cars and aeroplanes are frequently made from multi-material assemblies, which has attracted great interest in dissimilar metal welding [1]. It is challenging to use fusion welding techniques to join different metals that create intermetallics; hence solid-state welding techniques are looked for [2]. Explosive cladding is a solid-state welding technique that leverages plastic deformation at high strain rates to form a bond and is employed to weld dissimilar metals that have been difficult to join using conventional fusion welding techniques [3-5]. Most studies on explosive cladding concentrated on the mechanical characteristics and microstructure of the dissimilar joints [6, 7]. However, fewer studies were made on creating a prediction model for the mechanical characteristics of dissimilar joints. In industrial applications, the joint's mechanical characteristics are essential. The many explosive cladding factors, such as the loading ratio, standoff distance, preset angle, and type of mating surface, affect the clad quality, including the tensile, shear, and impact strengths, fatigue life, and dynamic response [8, 9]. Sivagurumanikandan et al. [10] utilized three factors and three levels to evaluate the laser welding of SDSS comprehensively, employed the analysis of variance and artificial neural network to examine the effects of the laser welding parameters on the mechanical property and concluded some diverse findings. Despite the technique being used for a while, the creation of prediction models corresponding to bond formation is still not thoroughly investigated. Therefore, this study used experiments and an artificial neural network to

investigate the effects of cladding parameters on Al 6061-SS304 explosive clads.

### 2. Experimental

Aluminium 6061 sheets with dimensions of 110 mm x 50 mm x 3 mm and stainless steel 304 plates with dimensions of 110 mm x 50 mm x 8 mm were used as the flyer and base plates, respectively, in an inclined explosive cladding configuration reported elsewhere [4]. Before cladding, the dovetail and V-groove were machined on the mating surface of the SS 304 plates along the transverse direction. The distance between the two plates was varied from 5 mm to 9 mm, and the positioning of the flyer plate with the base plate was varied from  $5^{\circ}$  to  $15^{\circ}$ . A corner-mounted electric detonator was used to set off the chemical explosive (density:  $1.2 \text{ g/cm}^3$ , detonation velocity: 4200 m/s), with a loading ratio, R (mass ratio between explosive and flyer), that ranged from 0.6 to 1.0. Table 1 lists the chosen influencing process variables in this study. Sixty experiments were performed by altering these parameters, detailed elsewhere [11].

Following cladding, three tensile test specimens (ASTM E8-16 sub-size standard) for each condition were made in the detonation direction and tested in a universal testing machine (UNITEK-94100). Similarly, three shear test specimens (ASTM B 898 standard) were fabricated for each condition and assessed by compressing the various explosive clads.

\*Corresponding Author - E-mail: ssvcdm@gmail.com

Table 1 Experimental conditions

| Parameters                       | Value          |
|----------------------------------|----------------|
| Loading Ratio                    | 0.6,0.8, 1.0   |
| Standoff distance (mm)           | 5,7,9          |
| Preset angle (°)                 | 5,10,15        |
| Type of Groove on the base plate | V and Dovetail |

### 3. Building a model using Artificial Neural Network

ANN is a machine learning technology that uses data and comprises big, interconnected processing units called neurons. It has three layers: an input layer that receives data, a hidden layer that processes the data, and an output layer (sends computed information). An ANN is superior to an empirical model because of these layers' ability to learn, memorize, and build a link between inputs and outputs [12]. Associated weights are adjusted through a learning process to match the actual output to provide the targeted output.

The ANN model was built using four input parameters (Table 1), two responses (tensile and shear strengths), and one thousand experimental data gathered from trial tests and previous findings. The ANN model uses a feed-forward network built on a back-propagation learning technique. Three optimization methods (RMSprop, SDG, and ADAM) were tried to train the data; the ADAM algorithm was chosen because of its high speed, capability, and resilience [13]. The training dataset includes 800 data (80% of the total data), of which 200 data (20% of the total data) are used for testing.

Neurons of the input layer receive the information from four input variables. The first hidden layer receives these data from the input layer. Rectified Linear Units (ReLU), nonlinear activation functions, are implemented in each layer to reduce error and the vanishing point [14]. In the mathematical notation shown below, ReLU is expressed [14]

$$f(x) = \max(0, x) \quad (1)$$

The second hidden layer receives the first hidden layer's preliminary output. The procedure is repeated in the second hidden layer to get the final result in the output layer. This unidirectional signal flow in a network goes from input to output. The output layer creates an error by comparing experimental data and predicted data. The Mean Absolute Error (MAE) is employed to update the weights and bias of each neuron in hidden layers. This process is repeated until the MAE is within acceptable limits [15]. The MAE is determined using [15] equation 2.

$$MAE = \frac{\sum_{j=1}^n (Y_k - y_k)}{n} \quad (2)$$

The letters  $Y_k$ ,  $y_k$ , and  $n$  represent experimental strength, predicted strength, and the total number of data, respectively.

### 4. Results and discussion

The experimental loading ratio of 0.8, standoff distance of 7 mm, preset angle of 5°, and base plate with V grooves produced the maximum tensile (392 MPa) and shear (262 MPa) strengths, whereas the lowest loading ratio of 0.6, standoff distance of 5 mm, parallel arrangement without grooves produced the lowest strength (Tensile: 344 MPa, Shear: 220 MPa). According to earlier research [16], the lowest strength is attributable to the reduced kinetic energy and the absence of grooves. On the other hand, a base plate with a "V" groove delivers the highest strength (14% higher) for the midrange of process parameters. Increased kinetic energy consumption and bonding region are the reasons for the improvement in strength when using grooved base plates.

#### 4.1. Prediction using artificial neural network

By altering the number of neurons from 04 to 1024, one thousand distinct ANN models were created for this study. The Optuna optimizer framework determines the optimum condition while changing the hidden layer's number of neurons and the optimizers (Adam, RMSprop, and SGD). By adjusting the hyperparameters, the optimal level is attained in the region of low target values (Fig. 1), proving that the Adam optimizer performs better.

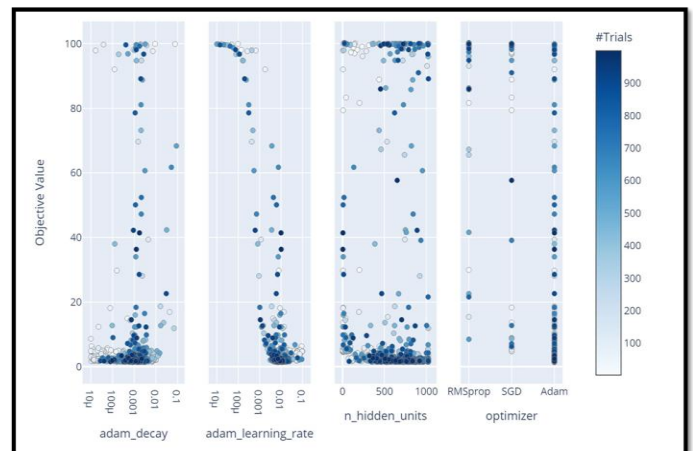


Fig. 1 Hyperparameters tuning

Chandriah and Naraganahalli employed the Adam algorithm to forecast the demand for automobile spare parts and reported superior performance [17]. Fig. 2 depicts the ideal ANN structure and the number of hidden neurons.

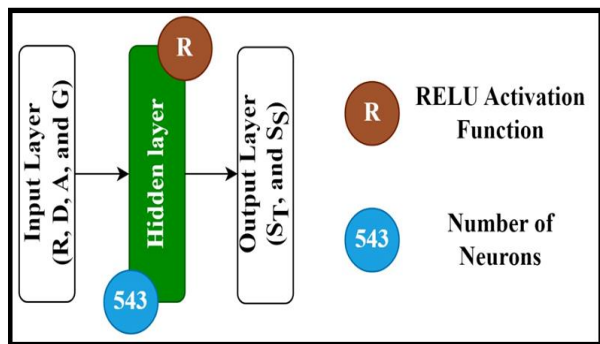


Fig. 2 Optimal ANN model

#### 4.2 Uncertainty

The 565<sup>th</sup> ANN model with 543 neurons yields the highest  $R^2$  value. The prediction performance of the best ANN is 0.9628, which means that about 96% of the experimental conditions agree with the predicted value (Fig.3: shown by the black line). Test data are used to validate the prediction accuracy of the constructed ideal ANN model. The current ANN model's prediction is compatible with the validation dataset with an MAE of 0.7861, despite the fact that this dataset was not employed in building an ideal ANN. According to the studies of Awais et al. [18], an MAE of 0.78 is an acceptable prediction. Thus, it can be concluded that the overall prediction of ANN is appropriate across the range of statistical parameters.

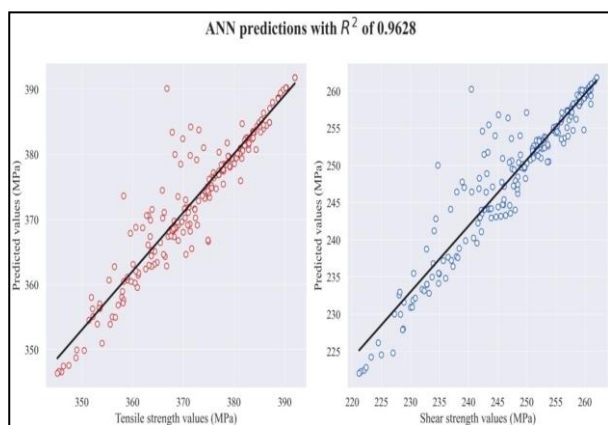


Fig. 3 Comparison of accuracy between experimental and ANN

## Conclusions

The following conclusion was made in the present work.

- i. Higher strength was obtained for Al-Steel explosive clads with V grooves on the base plate at midrange process parameter values.
- ii. The ANN model fared better in predicting the mechanical strengths of the explosive clads, with an MAE of 0.7861 and prediction accuracy of 0.9628.
- iii. With all statistical factors taken into consideration, the ANN's overall forecast is judged to be satisfactory.

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