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Application of Neural Network Techniques in Friction Stir Welding Process

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Abstract: Artificial Neural Network (ANN) is a brain modelling technique by providing a new approach to computing. It introduces a less technical way to develop machine solutions. This research paper discusses the use of Artificial Neural Network (ANN) concept in Friction Stir Welding research, for example it is used in the investigation of tool parameters, for the evaluation of feedback forces which is provided by Friction Stir Welding process. Previous research also shows that ANN finds application in developing the correlation between the Friction Stir Welding parameters of the light alloy plates and mechanical properties. This method was also used for predicting average grain size in Friction Stir Welding processes.
Keywords: Friction Stir Welding; AI Technique, Artificial Neural Network; Mathematical Modelling

I. INTRODUCTION

Artificial Neural Network (ANN) can be considered as a mathematical model of a human brain. This elemental inspired method marks the next generation advancement in the computing field. The composition of Artificial Neural Network (ANN) consists of a large number of simple processing elements or basic units called *neurons*. Each neuron applies an activation function to its net input to determine its output signal. Every neuron is connected to other neurons by means of directed communication links, each with an associated weight [1].

Each neuron has an internal state called its activation level, which is a function of the inputs it has received. This can be compared with a bottle with a liquid. If we have a bottle and if we fill in the bottle with a liquid, and if we have an alarm to caution us when the level of the liquid is up to the neck of the bottle, then activation level also does the same thing as that of the alarming signal we receive. As and when the neuron receives the signal, it gets added up and when the cumulative signal reaches the activation level the neuron sends an output. Till then it keeps receiving the input. So activation level can be considered as a threshold value for us to understand.

The technique is particularly suited to problems that involve the manipulation of multiple parameters and non-linear interpolation, and as a consequence are therefore not easily amenable to conventional theoretical and mathematical approaches. Neural networks have therefore seen growing application in materials property (mechanical and physical) determination, particularly the more difficult to analyse complex multiphase and composite materials, which are growing in popularity [2].

Friction Stir is a solid state joining process developed by The Welding Institute (TWI) in the UK in 1991. This method is used for joining the alloys of aluminium, magnesium, copper, titanium and as well as steel plates [3-8]. Artificial Neural Network (ANN) plays an important role in Friction Stir Welding (FSW) Research. It is basically used to develop the applications of Friction Stir Welding (FSW) and reduce the cost of experiments.

Tansel *et al* [9] represented the characteristics of Friction Stir Welding process by using Artificial Neural Network (ANN). Dehabadi *et al* [10] predicted the Vickers micro hardness of AA6061 Friction Stir Welded sheets by using Artificial Neural Network (ANN). Shojaeefard *et al* [11] performed Artificial Neural Network (ANN) analysis to model the correlation between the tool parameters (pin and shoulder diameter) and heat-affected zone, thermal, and strain value in the weld zone. Fratini *et al* [12] linked Artificial Neural Network to a finite element model (FEM) and predicted the average grain size values of butt, lap and T friction stir welded joints. Jayaraman *et al* [13] by Artificial Neural Network modelling predicted the tensile strength of A356 alloy which is a high strength Aluminium-Silicon cast alloy used in food, chemical, marine, electrical and automotive industries. This research paper mostly discusses these five papers, using them as an exemplar only to highlight the importance and use of Artificial Neural Network (ANN) in Friction Stir Welding (FSW) process.

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II. HOW DO ARTIFICIAL NEURAL NETWORK WORKS?

This is a large and complex topic because there are many different types of artificial neural network models. The most common model, which has become the foundation for most of the others, is the 3-layer fully-connected back propagation (BP) model:

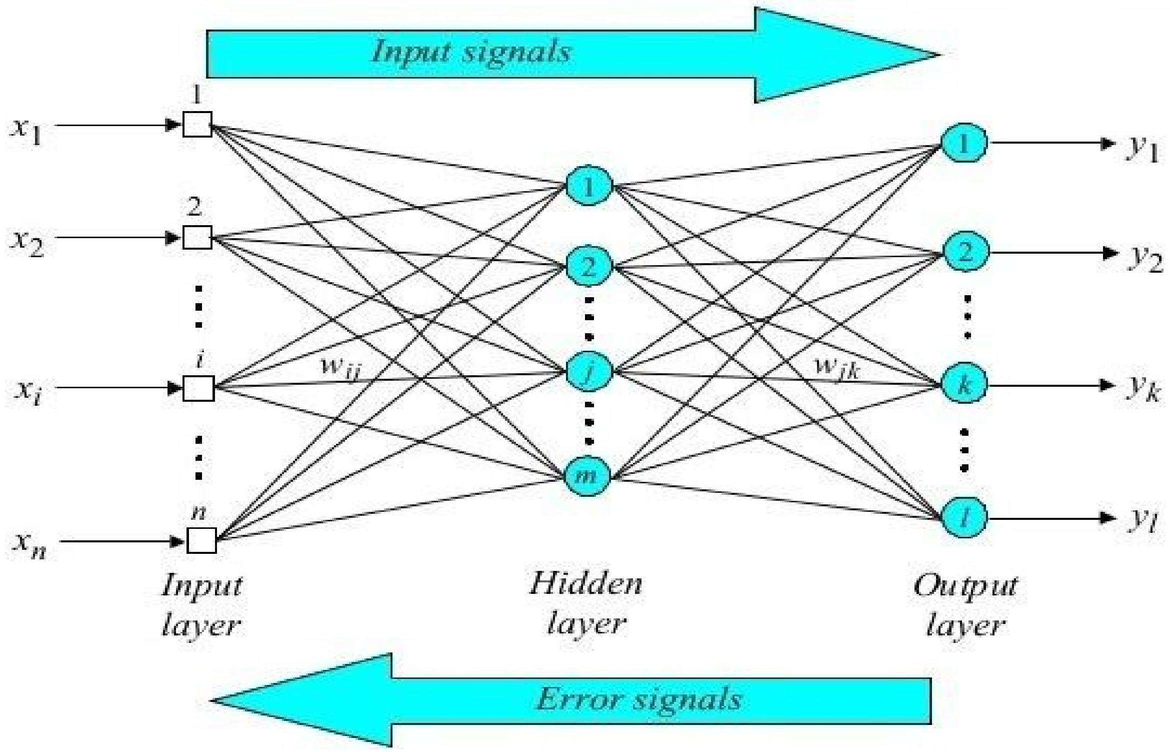

Figure 1: 3 layered fully connected back propagation model

A. Network Design

The basic idea is that you have three layers of "nodes." The "nodes" are intended to be analogous to neurons in a neural network of the brain, but the similarity is only metaphorical (real neurons don't work this way, but the analogy is not unreasonable). The nodes have values of 0.0 to 1.0, where 0 represents fully inactive "off" and 1 represents fully active "on" with many values in between. The three layers are an input layer, an output layer, and a "hidden" layer in the middle (hidden means neither input nor output, so not exposed to the outside world). The nodes are linked by connections which have a "weight" ("w" in the figure) that are analogous to synapses in the brain. Signal values propagate from the inputs, through the connection weights to the hidden nodes, and then onward through more connection weights to the output nodes. The number of the neurons at the first and the last layer are equal to the inputs and outputs of the ANN. The user determines the number of neurons at the intermediate layer (hidden layer) with trial and error. In most of the BP applications, each neuron is connected to all the neurons of the following layer.
In the beginning, the network will of course get the wrong answer because it knows nothing. This is where the "training" and "back propagation" comes in. The error values are propagated backward through the network using some complicated math that tells the algorithm how to modify each connection weight so that the network will get closer to the correct answer next time.

III. USE OF ARTIFICIAL NEURAL NETWORK (ANN) IN FRICTION STIR WELDING (FSW) PROCESS

Tansel *et al* [9] used genetically optimized neural network systems (GONNS) to estimate the optimal operating condition of the friction stir welding (FSW) process. He introduced the genetically optimized neural network system (GONNS) by using Artificial Neural Network (ANN) and Genetic Algorithm (GA) together. He represented Friction Stir Welding (FSW) process in five artificial neural networks (ANN) as shown in the Figure 2. The genetically optimized neural network is shown in the Figure 3. Artificial Neural Network (ANN) is first trained by the genetically optimized neural network systems (GONNS) with experimental data. . It was observed that the inputs of the five ANNs were the same (tool rotation and welding feed rate). The estimation errors of the ANNs were better than average 0.5%. GA estimated the optimal FSW conditions to minimize or maximize one of the stir welding characteristics, while the others were kept at the desired ranges.

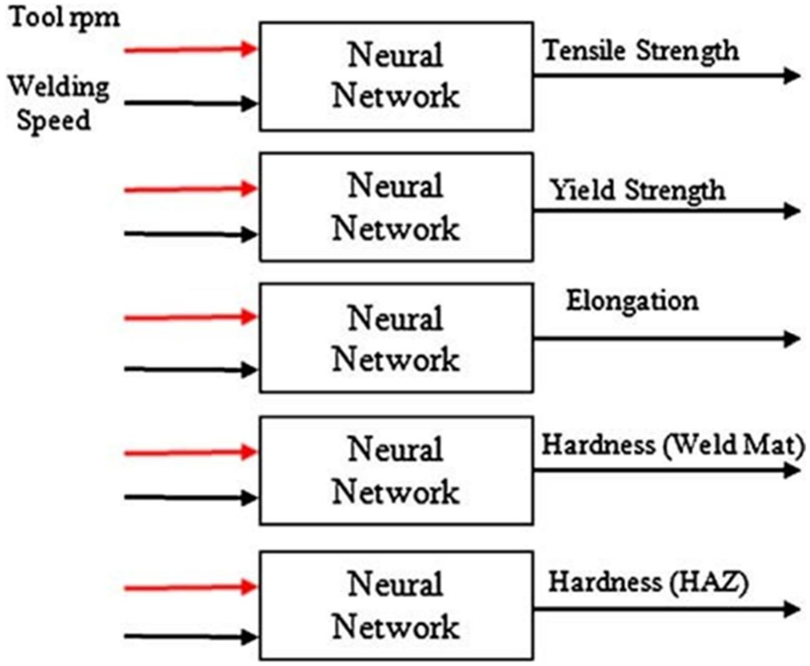

Figure 2: Five artificial neural networks for representation of the friction stir welding operation

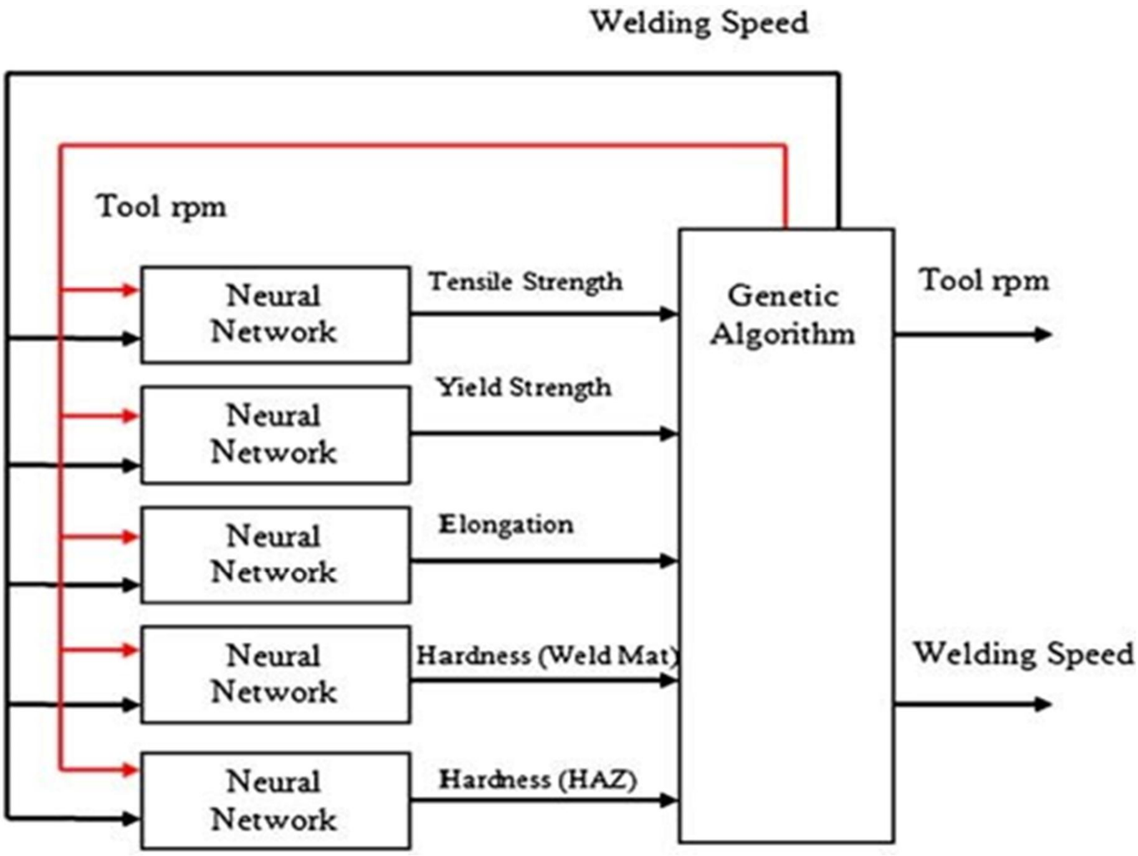

Figure 3: Genetically optimized neural network structure

Dehabadi *et al* [10] used tow Artificial Neural Network (ANN) to study the effects of thread and conical shoulder of each pin profile on the micro hardness of welded zone of AA6061 plates as shown in the Figure 4.

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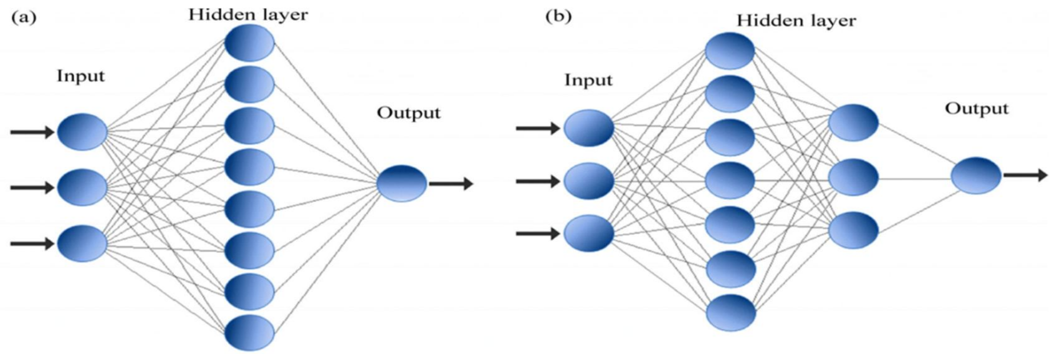

Figure 4: Schematic of neural networks in this work for predicting Vickers micro hardness in triangle (a) and tapered cylindrical (b) pin profile tools.

It was observed that the Mean absolute percentage error (MAPE) for train and test data sets did not exceed 5.4% and 7.48%, respectively. MSE values for both networks were less than 10, which indicated appropriate trained models as shown in the Figure 5.

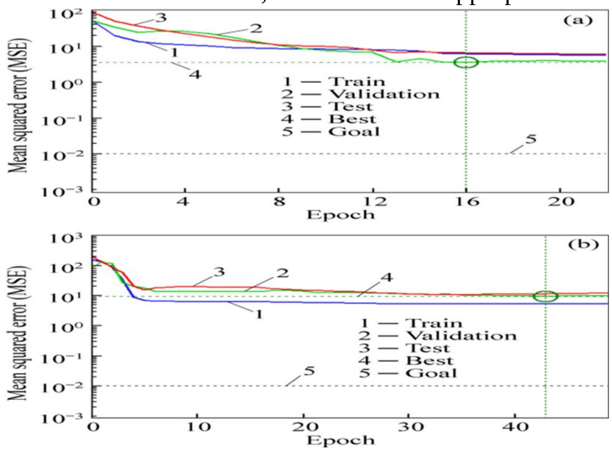

Figure 5: MSE for ANN models for triangle pin profile (a) and tapered cylindrical pin profile (b) tools

Shojaeefard *et al* [11] numerically modelled a different tool pin and shoulder diameter for a Friction Stir Welding (FSW) process. He used Feed-forward neural network with back-propagation algorithm to understand the correlation between tool dimensions and peak temperature, maximum strain, and HAZ area as shown in the Figure 6.

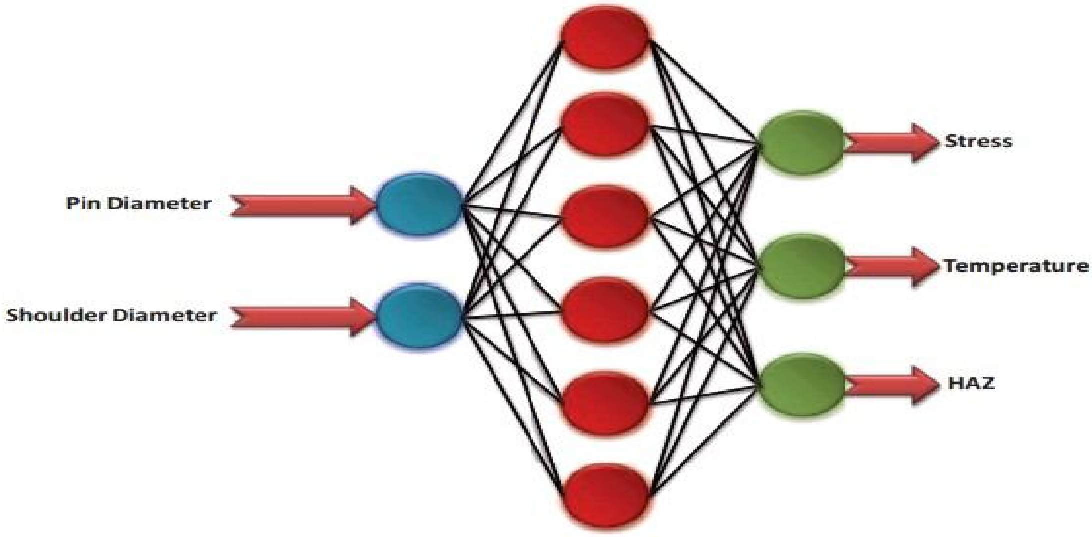

Figure 6: Three layer neural network

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It can be observed that the neural network having an input layer with two neurons for each input factor (pin diameter, shoulder diameter) and an output layer with three neurons (maximum strain, maximum temperature, and HAZ area) was used. In order to get the best network architecture evaluation of several architectures were performed and trained using the experimental data. Based on this analysis, the optimal architecture was selected as 2–6–2 NN, and both activation functions in hidden layer and output layer were ‘‘logsig.’’

Fratini *et al* [12] in his research showed the capability of the AI technique in conjunction with the FE tool to predict the final microstructure of the Friction Stir Welded Joints. He designed the network architecture which was composed of five layers as shown in Figure 7. From the Figure 7 it is clearly seen that the neural network consisted of an input layer, three hidden layers and finally the output layer. Input layer was composed of four neurons which represented the local values of the equivalent plastic strain, the strain rate, temperature and the Zener Holloman parameter in a transverse section. The introduced three hidden layers have three, five and four neurons, respectively, and finally in the output layer one neuron is present corresponding to the output variable (D), namely the local value of the final average grain size. Each layer is fully connected to the next and according to the back propagation rule, the weights (wij) of the connections linking neurons belonging to two consecutive layers are adjusted in the learning stage with the aim to minimize the error between the desired output and the calculated one.

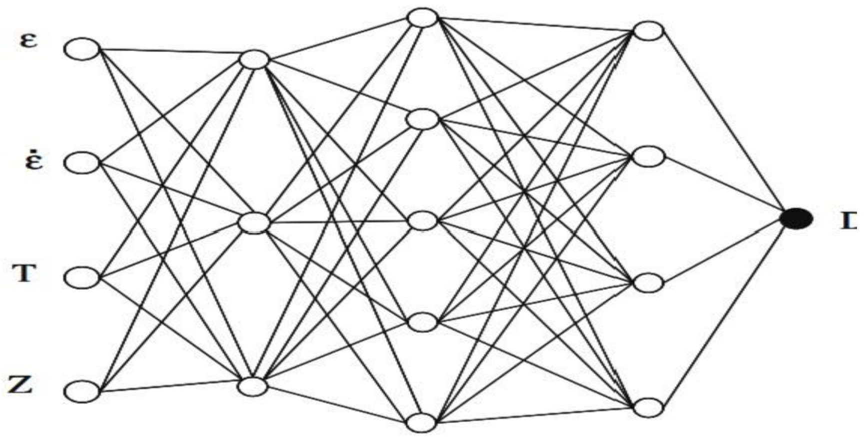

Figure 7: The utilized Neural Network architecture

Jayaraman *et al* [13] pedicted the tensile Strength of Friction Stir Welded A356 Cast Aluminium Alloy by using Response Surface Methodology (RSM) and Artificial Neural Network (ANN). He used the topology architecture of feed-forward three-layered back propagation neural network as shown in the Figure 8. He noted that the performance of Artificial Neural Network (ANNs) is better than the other techniques, especially RSM when highly non-linear behaviour 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 larger number of experiments are used to develop a model.

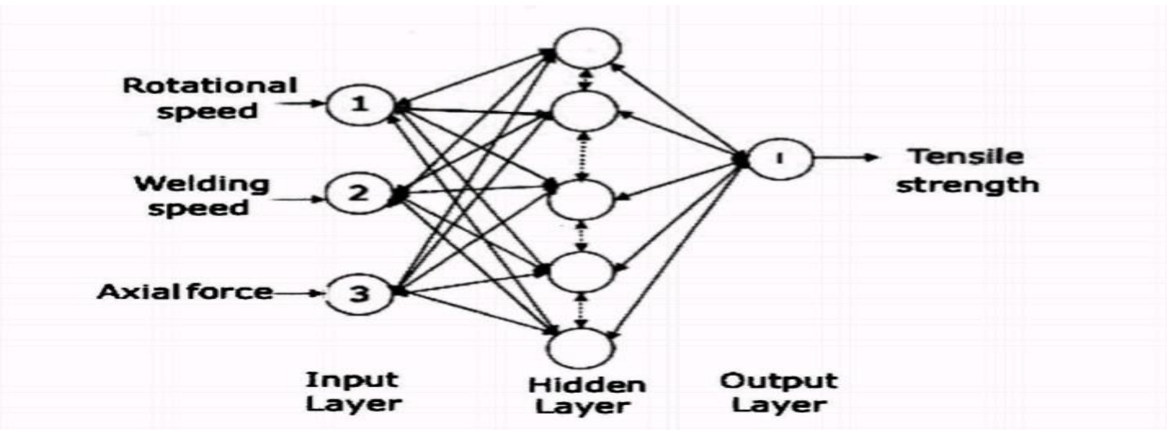

Figure 8: Used Artificial Neural Network Architecture

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Maleki *et al* [14] used ANN as an efficient approach for modeling the mechanical properties of Friction Stir Welded 7075-T6 Aluminum alloy. ANN devloped was based on Back propogation algorithm. Rotational speed of tool, welding speed, axial force, shoulder diameter, pin diameter and tool hardness are regarded as inputs of the ANNs. Yield strength, tensile strength, notch-tensile strength and hardness of welding zone are gathered as outputs of neural networks as shown in the Figure 9.

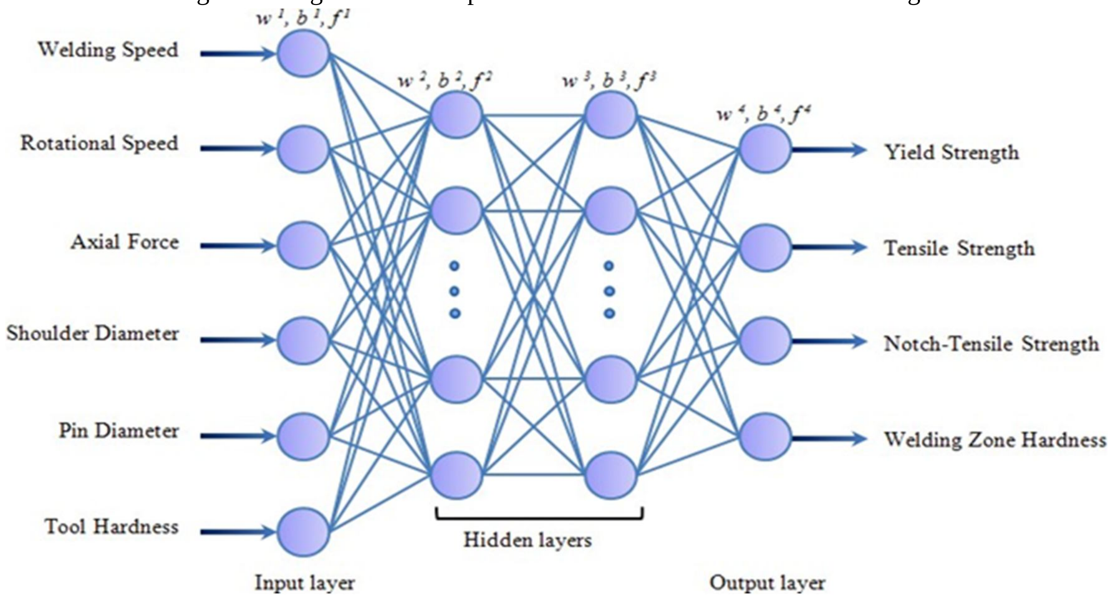

Figure 9: ANN devloped for predicting mechanical properties of FSWed 7075-T6 alloys

The least mean relative error (MRE) was obtained for the hardness of welding zone, yield strength, tensile strength and notch-tensile strength.

Khoursid *et al* [15] used the topology architecture of feed-forward three- layered back propagation neural network as illustrated in Figure 10 below for predicting the ultimate tensile strength, percentage of elongation and hardness of 6061 aluminum alloy.

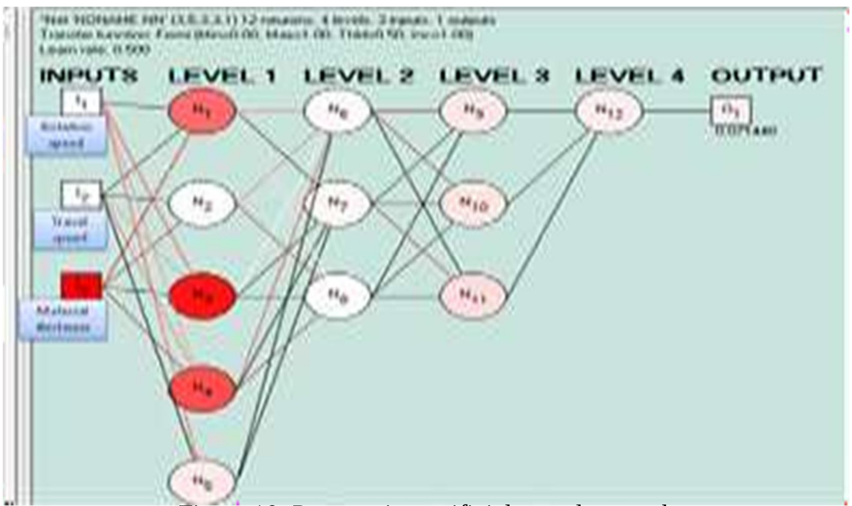

Figure 10: Propagation artificial neural network

Equation is calculated as On = F(ΣIk * Wkn).On is the neuron's output, n is the number of the neuron, Ik are the neurons inputs, k is the number of inputs, Wkn are the neurons weights. F is the Fermi function 1/(1+Exp(-4*(x-0.5))).

Software (pythia) was used for training the network model for tensile strength, the percentage of elongation and hardness prediction. The neural network described in this paper, after successful training, will be used to predict the tensile strength of friction stir welded joints of 6061 aluminum alloy within the trained range. The results obtained after training and testing On artificial neural networks are shown in the Fig.(11-13).

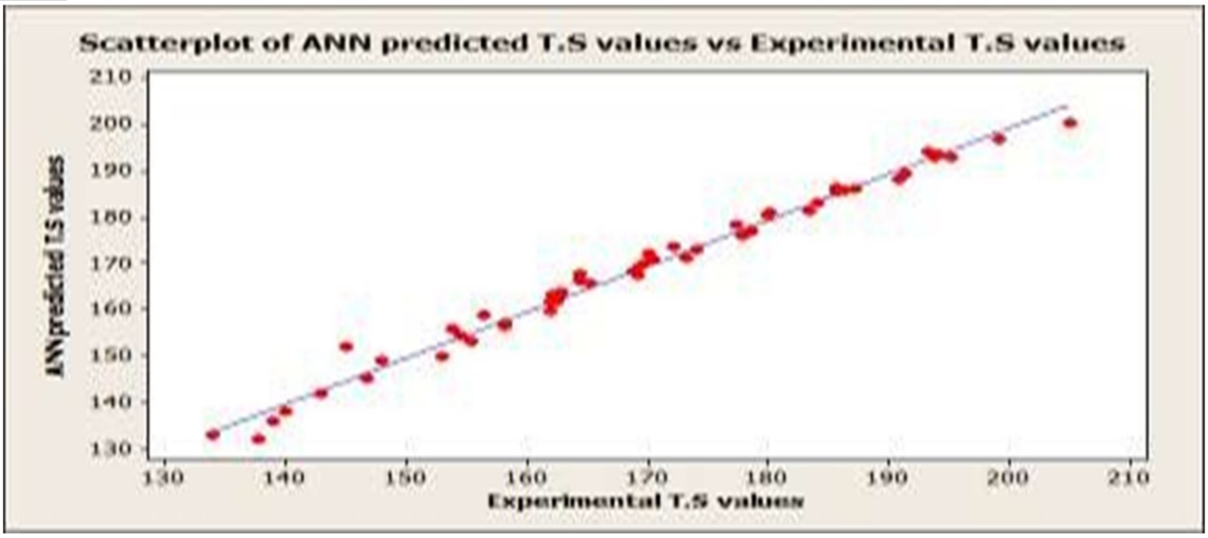

Figure 11: Relation between experimental tensile strength and predicted tensile strength

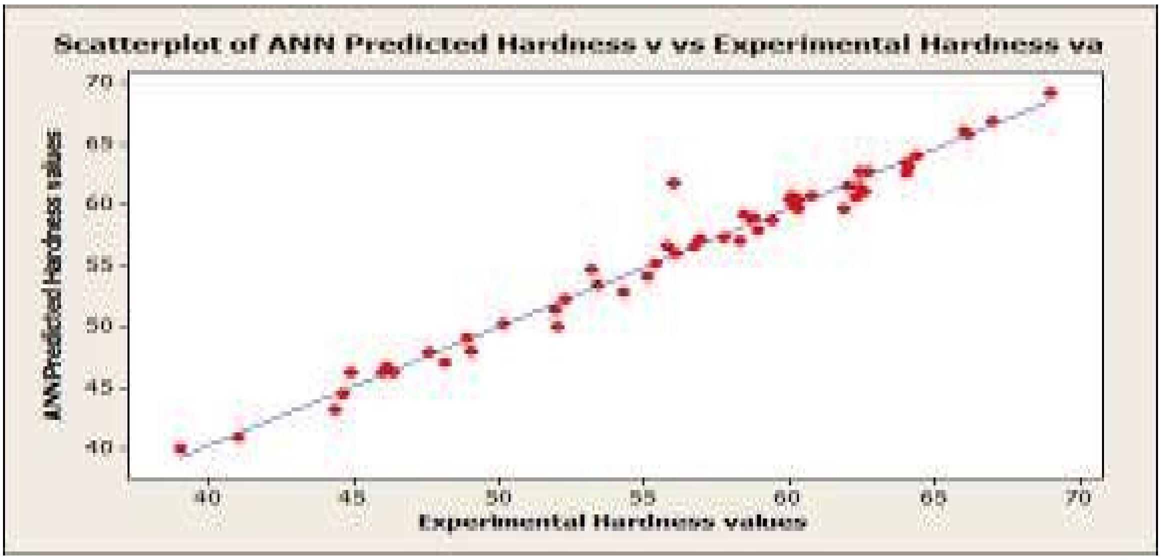

Figure 12: Relation between experimental elongation% and predicted elongation%

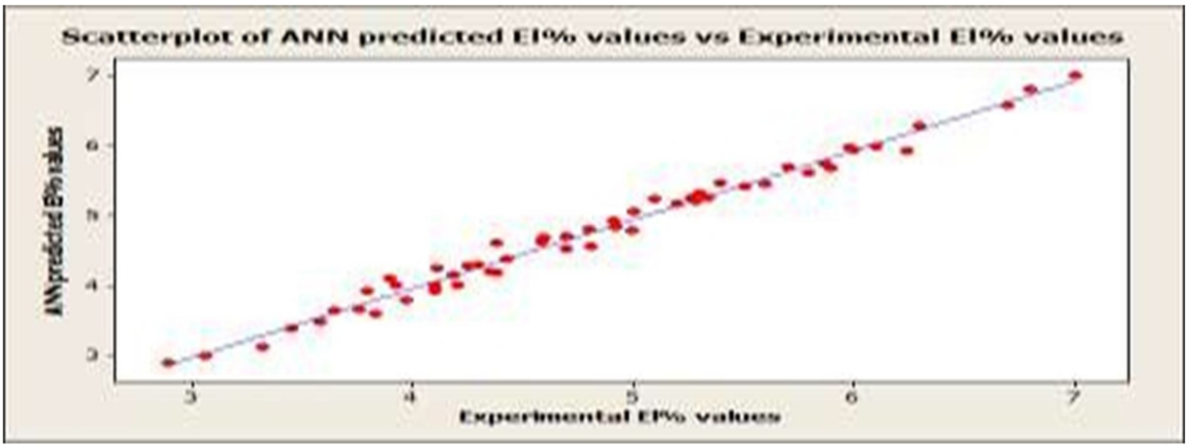

Figure 13: Relation between experimental hardness and predicted hardness

The ANN model proved to be successful in terms of agreement with experimental results ratio 96.5%.

H. Okuyucu et al. [16] developed an artificial neural network (ANN) model for the analysis and simulation of the correlation between the friction stir welding (FSW) parameters of aluminium (Al) plates and mechanical properties. The input parameters of the model consist of weld speed and tool rotation speed (TRS). The outputs of the ANN model include property parameters namely: tensile strength, yield strength, elongation, hardness of weld metal and hardness of heat effected zone (HAZ). Good performance of the ANN model was achieved. The model can be used to calculate mechanical properties of welded Al plates as functions of weld & tool rotation speeds. The combined influence of weld speed and TRS on the mechanical properties of welded Al plates was simulated. A comparison was made between measured and calculated data. The calculated results were in good agreement with measured data. The aim of the paper was to show the possibility of the use of neural networks for the calculation of the mechanical properties of welded Al plates using FSW method. Results showed that, the networks can be used as an alternative in these systems.

L Fratini and G Buffa [17] studied the continuous dynamic re-crystallisation phenomena occurring in the FSW of Al alloys. A good agreement with the experimental results was obtained using the ANN model. In regard to ANNs, it noted that ANNs perform better than the other techniques, especially RSM when highly non-linear behaviour 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 larger number of experiments are used to develop a model.

IV. CONCLUSIONS

A. The Artificial Neural Network (ANN) model provides little information about the design factors and their contribution to the response if further analysis has not been done. Generation of ANN model requires a large number of iterative calculations.

B. Artificial Neural Network (ANN) method can be used to economize material and time by considering the accurate results and acceptable errors.

C. This method can be used to model the mechanical procedures. By usin g mathematical modelling methods like ANN can save time, material and costs and results are optimized in designs.

D. GONN's performance is a viable option for modelling the friction stir welding process and searching for the optimal solutions.

E. A good correlation can be observed between the predicted data obtained from the Artificial Neural Network (ANN) and FEM models.

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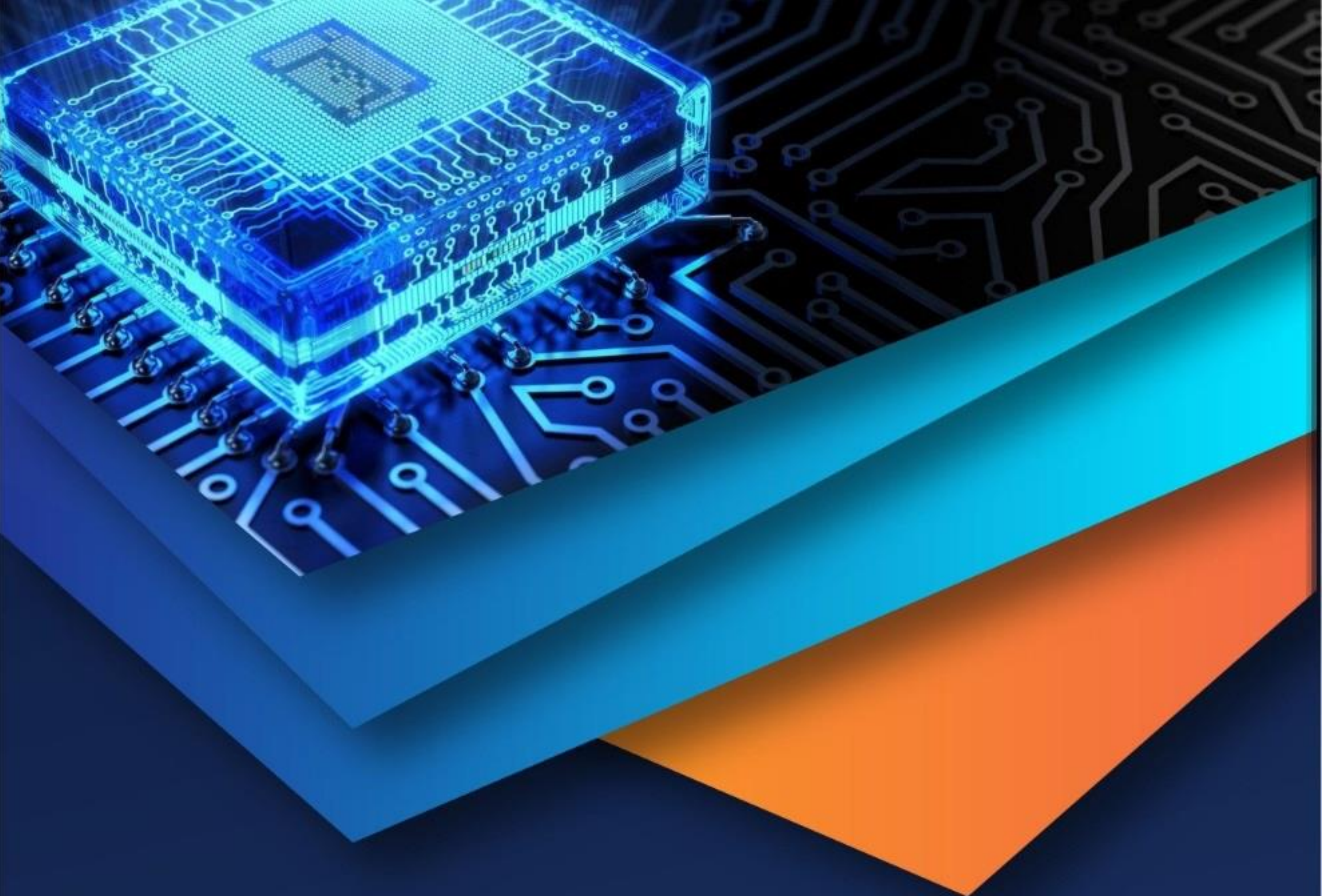

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