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# Inverse prediction of Friction Stir Welding parameters using Artificial Neural Networks

Kudzanayi Chiteka*, N. Yuvaraj, Vipin
Department of Mechanical Engineering, Delhi Technological University, Delhi, India

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**Abstract**

Friction Stir Welding has become an invaluable joining process in aerospace and automotive industry. It is often required that the independent input parameters (traverse speed, pin diameter, rotational speed etc.) in Friction Stir Welding (FSW) be predicted from response values such as tensile strength and hardness. This will enable the use of input parameters that gives the desired results. If this is attained, near optimal results can be achieved without use of many resources. It also allows the selection of the closest input parameters available on the machine. Artificial Neural Networks (ANN) have been successfully applied in determining the input parameters in Friction Stir Welded materials when given the tensile strength. This procedure is however problematic at times since there may be several combinations of input parameters that gives the same result.In this research ANNs were used to predict the input parameters required to give a tensile strength of 300, 340, and 345 MPa of an aluminium alloy AA6082-T6. The predicted speeds were rotational speeds of 532.7 rpm at a traverse speed of 11.8 mm/min to obtain a tensile strength of 300 MPa. For tensile strength of 340 and 345 MPa, 437.1 rpm at a traverse speed of 13.6 mm/min were predicted as the input parameters.

## 1. Introduction

FSW is a developing joining process that combines the effect of forging and extrusion to form a joint. It is a solid state joining process [1, 2] as such the materials do not melt but are plasticised. In this process a shouldered tool with a pin profile is rotated between the two materials to be joined [3].The frictional resistance generates heat and soften the materials and thus the materials through the effect of the shoulder and axial force are forced to join [4, 5]. This joining process was initially meant for aluminium and magnesium alloys but it has been extended to other materials like copper, steels as well as platinum [5, 6].

FSW can allow precise external process control and is also characterised with high repeatability as such it can create homogeneous welds. Very little preparation is required on the work materials. The greatest advantage associated with this joining process is that it can join dissimilar alloys which were deemed unweldable by other methods [5].

**Corresponding Author,**
**E-mail address:** tavakudzira@gmail.com


Pin rotation speed and the welding speed are among the most important factors in FSW. Pin length which determines the welding depth also has a contribution in determining the resulting weld [5].

Three distinct regions can be found and these regions are known as the heat affected zone (HAZ), thermo-mechanically affected zone (TMAZ) and the stir zone (SZ) [7].

The use of FSW is particularly necessitated by the need for advanced aircraft design [8] as well as other applications in shipping, construction and automobile design.AA6082 alloy is normally used in automotive and other highly stressed applications which include trusses, bridges, cranes etc.

ANNs are computational models composed of neurons that can solve complex problems in real life situations. They try to mimic the way the brain functions in problem solving [9]. ANNs can be used in situations where the relationship between variables is complex to define mathematically. They have the capability to "learn" thus they are capable of predicting the outcome based on past "learned" experience. Yousif et al. (2008) [10] used ANNs to predict the tensile properties of a Friction Stir Welded aluminium alloy. They used welding speed and

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rotational speed as the input into the ANN and successfully predicted the tensile behaviour and hardness with high accuracy. In their research, Levenberg – Marquardt algorithm which showed better performance than gradient descent was used for training.

Okuyucu et al. (2007) [11] also used ANN to predict the tensile strength of aluminium alloys joined by FSW and got convincing results.Welding speed as well as rotational speed were also used as the input parameters into the network. Back-propagation algorithm was used. This algorithm was improved by making use of the scaled conjugate gradient and Levenberg-Marquardt algorithms.

Nagesh and Datta (2002) [12] used ANNs to predict weld bead geometry and penetration in shielded metal arc welding. Back-propagation neural networks were used to associate the welding process variables with the features of the bead geometry and penetration. Their results from the experiments carried out showed a small errorpercentage difference between the estimated and experimental values.

## 2. Experimental Procedure

### 2.1 Welding and Testing Procedure

Aluminium alloy AA6082-T6 with a tensile strength of 340MPa was used in the experimentation. Its dimensions were 150 x 100 x 6 mm. Welding was carried out on a vertical milling machine using rotational speeds of 630, 1000 and 1600 rpm and welding speeds of 10, 16 and 25 mm/min. These speeds were chosen based on availability on the milling machine used.A total of nine (3 x 3) experiments were done. The chemical composition of AA6082-T6 is as shown in table 1.

**Table: 1. Chemical composition of AA6082**

| Element | % Present |
|---|---|
| Si | 0.7-1.3 |
| Fe | 0.0-0.5 |
| Cu | 0.0-0.1 |
| Mn | 0.4-1.0 |
| Mg | 0.6-1.2 |
| Zn | 0.0-0.2 |
| Ti | 0.0-0.1 |
| Al | Remaining |

Tool material used was H13. The tool had the following dimensions; 18mm shoulder diameter, 6mm pin diameter, 5.8mm pin length and a left hand thread of 1mm pitch. For tensile tests, samples were cut using Wire Electric Discharge Machining (WEDM) in a direction perpendicular to the welding direction. For each work sample, three tensile test samples were taken. The results were averaged for each particular set of input parameters i.e. for each combination of rpm and welding speed.

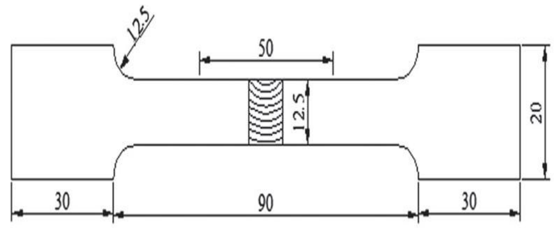


**Fig: 1.** Tensile test sample

The tensile properties of the FSWed specimens were examined using computer controlled universal testing machine (Tinius Olsen H50KS) at a constant cross head speed of 1mm/min in room temperature. The tensile specimens prepared on the middle of the FSW stir zone by wire EDM as per ASTMstandard. Fig.1shows the size and configuration of the tensile specimen

### 2.2 ANN procedure

A feed-forward back propagation ANN architecture with two layers was made. It had one input, one hidden layer with ten neurons and two outputs. The input was the tensile strength and the outputs were the rotational speed (Rs) and Traverse speed (Ts). The training algorithm used was Levenberg-Marquardt.

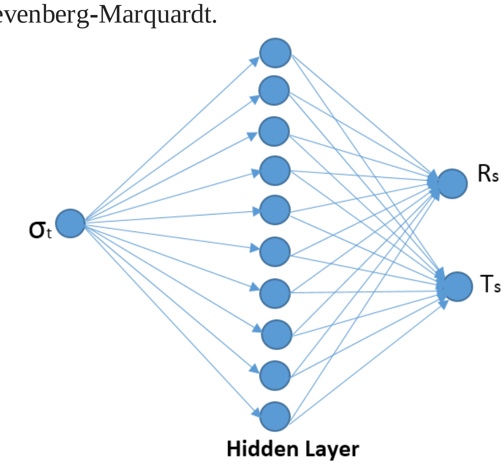


**Fig: 2.** ANN architecture in inverse prediction

The results taken from the experimentation were fed into the neural network for training. There was no testing of the ANN using known data because the concept of inverse prediction is a bit complex in nature. There are several input combinations that can give rise to the same output. The predicted output, however, could still be validated through experimentation.

## 3. Results and Discussion

Experiments were done according to the values given in table2. Tensile strength ($\sigma_t$) decreased significantly with increase in rotational speeds.

Three desired tensile strength ($\sigma_{req}$) values were established arbitrarily for prediction of the input values. They were put into the ANN and the predicted values were obtained. These values were not readily available on the milling machine used so the nearest available values were selected as shown in table4with available rotational speed and traverse speed denoted by $R_{s(Av)}$ and $T_{s(Av)}$ respectively. The available values from which the selection was made are given in table3.These were the speed values present on the milling machine gear box available for selection.

**Table: 2.** Input parameters and the resulting Tensile strength

| | $R_{s(rpm)}$ | $T_{s(mm/min)}$ | $\sigma_{t\ (MPa)}$ |
|---|---|---|---|
| 1 | 630 | 10 | 296.96 |
| 2 | | 16 | 260.25 |
| 3 | | 25 | 255.34 |
| 4 | 1000 | 10 | 257.51 |
| 5 | | 16 | 190.00 |
| 6 | | 25 | 211.88 |
| 7 | 1600 | 10 | 195.55 |
| 8 | | 16 | 140.56 |
| 9 | | 25 | 129.89 |

**Table: 3.** Speeds available on the machine

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $R_{s\ (rpm)}$ | 25 | 40 | 63 | 100 | 160 | 250 | 400 | 630 | 1000 | 1600 |
| $T_s$ (mm/min) | 10 | 16 | 25 | 40 | 63 | 100 | 160 | 250 | 400 | 630 |

**Table: 4.** Predicted and available speeds

| | $\sigma_{req}$ | $R_{s(ANN)}$ | $T_{s(ANN)}$ | $R_{s(Av)}$ | $T_{s(Av)}$ |
|---|---|---|---|---|---|
| 1 | 300 | 532.7507 | 11.8268 | 630 | 10 |
| 2 | 340 | 437.1815 | 13.6182 | 400 | 16 |
| 3 | 345 | 437.1348 | 13.6191 | 400 | 16 |

$\boldsymbol{\sigma_{req}}$- Required tensile strength, $\mathbf{R_{s(ANN)}}$ - rpm predicted by ANN, $\mathbf{T_{s(ANN)}}$- welding speed predicted by ANN, $\mathbf{R_{s(Av)}}$-available rpm on the machine, $\mathbf{T_{s(Av)}}$-available welding speed on the milling machine.

The selected input parameters were used to join two work samples and the results were astonishingly convincing. There was some difference but this could easily be attributed to the difference in predicted values and the actual values used in the experiments.

**Table: 3.** Experimental Testing of predicted values

| | $\sigma_{req}$ | $\sigma_{exp}$ | $R_{s(Av)}$ | $T_{s(Av)}$ |
|---|---|---|---|---|
| 1 | 350 | 331.23 | 630 | 10 |
| 2 | 372<br>375 | 340.31 | 400 | 16 |

$\boldsymbol{\sigma_{req}}$- required strength, $\boldsymbol{\sigma_{exp}}$- strength obtained from experiment.

## 4. Conclusion

ANNs can predict the independent FSW input parameters given the desired response values and it is possible to get the desired result as long the predicted parameters are available on the machine. However, since the ANNs can predict any values, there is need to integrate the machine characteristics so as to develop a method that predicts values close to those available on the machine. This is however not a problem if advanced machines with infinite variable gearboxes are used. If an effective and more accurate method is developed, the number of experiments in FSW to obtain desired tensile strength and even hardness values could be reduced significantly.

If the parameters predicted can be made available on the machine, tensile strengths close to or just above the UTS of the material can be obtained.

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