A STUDY ON FRICTION STIR WELDING OF ALUMINIUM PLATES USING AN ARTIFICIAL NEURAL NETWORK

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ABSTRACT: For attaching solid materials, friction stir welding (FSW) is a relatively novel method recently developed. Compared to fusion welding processes, it has many benefits, such as reduced distortion, porosity, shrinkage, and cracking. FSW was first used to link aluminum alloys with limited weldability, but it has since been used to join other metallic alloys and other dissimilar alloys. It is possible to fuse two plates using FSW by inserting a non-consumable rotating tool with a specifically designed pin between them and moving it along the welding line. Multiple applications in the aerospace and shipbuilding industries and the automobile sector have seen success with this approach owing to its many benefits.
Computer-aided artificial neural network (ANN) modelling may be used in material science and engineering to improve the FSW process. In the same manner, as the brain processes information, ANN is a computer processing paradigm inspired by the brain's workings. There are many nerve cells in the system. ANNs, like humans, are taught by examples and maybe both a teaching and a forecasting tool. Well-trained neural networks are excellent prediction tools and can predict results for inputs it has never seen. It may therefore be considered as an approach to automating FSW.
A wide range of variables influences the FSW process. To better understand the relationship between welded material's mechanical characteristics, such as ultimate tensile strength (UTS) and hardness, this study considers three parameters: tool rotation speed, welding speed, and axial force. An artificial neural network (ANN) is developed and then evaluated to determine the mechanical characteristics of welded materials.
KEYWORDS: Friction stir welding; Friction stir processing; Weld; Processing; Microstructure, Mechanical properties; ANN; Modeling.

INTRODUCTION:

Two well-known methodologies in their respective fields are friction stir welding (FSW) and artificial neural networks (ANN). Material science uses FSW, while computer science uses ANN. These two techniques will be combined to achieve some significant outcomes.

In the solid-state, friction stir welding (FSW) is a unique way of connecting materials. The Welding Institute (TWI) created it in 1991. It was first used to combine aluminum, but it has now been broadened to include joining alloys of all kinds, regardless of how similar or different they are. In FSW, a spinning cylindrical tool with a shoulder and pin is the primary tool. It is employed. In this step, the spinning tool's pin is driven into the sheet material, and the tool's shoulder touches the sheet's surface. When the revolving tool and the sheet come into touch with one other, heat is generated that softens the material below its melting point, resulting in a dynamically recrystallized fine grain microstructure in the treated zone.

An artificial neural network (ANN) is a network of processing elements (neurons) that shows complex behaviour, which is governed by the connections between the processing elements and the element parameter. There are a number of direct communication linkages between neurons, each with a corresponding weight. The amount of information that goes into solving a problem is represented by the weight. The activity level of each neuron is a result of the inputs it has received and describes the neuron's internal state. The activation of a neuron is communicated to multiple other neurons; however, the neuron only delivers one signal at a time.

In order to improve the process parameters and make FSW economically feasible, more research is needed since it is a unique method. Controlling the process parameters is necessary to improve the strength qualities. Predictive tools that can anticipate the mechanical characteristics of welded materials that have never been used before are another major area of research.

OBJECTIVES:

The objective of the work is given as:

(i) The ultimate tensile strength and hardness of the welded joints are affected by a variety of input factors, including tool rotation speed, welding speed, and axial force.

(ii) Train the neural network with known data and test it with sample data and analyze the results.

LITERATURE REVIEW:

For example, Friction Stir Welding (FSW), Roll Bonding (RB), and Porthole Die Extrusion (PDE) are three unrelated solid-state joining techniques studied by Buffa, et al. [1] (PDE). Temperature, strain, stress, and pressure are a few of the characteristics needed to produce a quality weld. Using a variety of tool rotational and welding speeds, FSW tests are carried out, while the data for the other two processes come from published sources. There were two outputs generated by an artificial neural network: a quantitative output demonstrating the growth of solid-state bonding and a qualitative output showing the integrity of the weld.

Using an artificial neural network, Choobiet al. [2] discovered that single-pass butt welded 304 stainless steel suffers from welding-induced angular distortion (ANN). MATLAB was used to create a neural network with many layers of feedforward and backpropagation. A series of finite element simulations over a broad variety of plate dimensions provided the input to the neural network.

Friction Stir Welding of dissimilar alloys with various parameters (AA6061 & AA7075 Al) is shown by Guo and colleagues[3]. In order to better understand how welding speed, microstructure and hardness profile, location of material, and tensile property affect the joint, we conducted an experiment. In both cases, continuous tool rotation and varying welding speeds produced the same outcomes. When AA6061 was put on an advancing plane and several vertical vortices centres produced in the nugget zone centre, the efficacy in material mixing was achieved.

Gibson, et al.[4] provide an overview of the friction stir welding (FSW) technique, which has recently been used in a variety of industries, including aerospace, automotive, and marine, and discusses the various parameters that affect it, including process parameters, material flow, tool design, joint configuration, and defects. The article addressed many process variations, including self-reacting, stationary shoulder, friction stir processing, friction stir spot welding, aided FSW, and pulsed FSW.

Friction stir welding (FSW) temperature distribution was studied by Keivani, et al. [5]. The thermal properties of copper C11000 were studied using a finite element model. The tool's mechanical response and the weld material's thermomechanical properties are both included in the model. As the tool and substance come into contact, friction generates heat.

Friction stirs welding (FSW) process parameters such as rotational speed, welding speed, and axial force play an important role in determining weld quality, as Rajkumar, et al. [6] developed an empirical relationship between base metal properties and FSW process parameters, resulting in high strength friction stir welded joints. To start with, several grades of aluminum alloys were employed as the building blocks.

[7] Elatharasan, et al.[7] used Response Surface Methodology to estimate the Ultimate Tensile Strength (UTS), Yield Strength, and displacement of friction stir welded aluminum alloys AA6061-T6 and AA7075-T6 (RSM). Axial force, tool rotation speed (TR S), feed rate, and axial force are only a few of the welding factors that have been tested to see which ones work best together.

The corrosion behaviour of friction stir treated AA 2219 aluminum alloy was studied by Surekha, et al.[8]. Corrosion behaviour is heavily influenced by rotational speed. The corrosion resistance of CuAl2 particles rises as the rotation speed increases during friction stir processing. Processed alloys are more resistant to corrosion than their unprocessed counterparts.

The mechanical and microstructural characteristics of different AA6082-AA2024 joints were studied by Cavaliere, et al.[9]. They were done at 1600 RPM at varying welding speeds (80 to 115mm/min) throughout the trials. Different alloys were positioned on the tool's advancing side to produce a variety of samples. This study used microhardness and tensile testing in order to examine the joints' mechanical characteristics. Before being subjected to mechanical testing, the materials are annealed. For all of the designed joints, the vertical force rises in direct proportion to the welding speed.

FRICTION STIR WELDING (FSW) APPROACH:

A non-consumable tool is used in the FSW welding process to join metals in solid-state. A solid-state process implies that the materials are consolidated significantly lower than their melting point.

- **OPERATING PRINCIPLE OF FSW**

1. FSW is an easy concept to grasp. A rotating, non-consumable tool with a shoulder and pin is put into the intersection of two materials and moved along that line. It is the tool's primary role to provide:
Confined heating and flow of material
Stir and movement of the material.
2. The friction between the pin and the workpiece is the primary source of heat during the first phases of the tool plunge. The tool is pushed into the work until the shoulder makes

contact with it. The greatest amount of heat is generated by the friction between the shoulder and the workpiece.
3. The non-consumable stirring tool pin's second job is to stir and move the plasticized metal from the back end in order to have a nice joint.
4. Because of the pin's constrained heating, material moves from the front to the back of the pin as the tool moves forward and rotates. Because of this, a sturdy joint is formed.
Fig. shows the advancing and retreating sides.
Spindle motion on this side of the welding tool is in the same direction as the traverse motion, making it easier to weld.
Retreating side refers to the side where the surface motion is in opposition to the traverse direction.
Because of the tool's diverse geometrical properties, the flow of material around the pin may be rather difficult. The grain is fine and equiaxed because of the strong plastic deformation of the material at high temperature. Microstructure with high mechanical qualities is characterized by fine grain size.

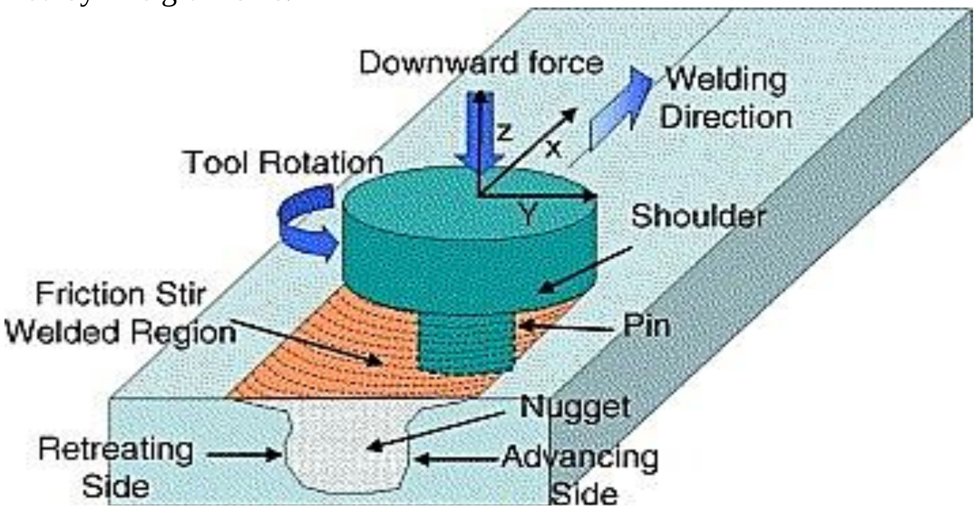

Fig.1: Schematic Diagram of FSW

ARTIFICIAL NEURAL NETWORK (ANN) APPROACH

It processes information that is influenced by the human brain's activity. It is the innovative method of processing information that is at the heart of this strategy. Countless neurons operate in unison to find a solution to a specific issue. ANN learns by mimicking human behaviour. Data categorization via the learning process is one of its intended uses. To learn in a biological network, one must adapt to the connections that are most common. This holds true for ANN as well. Due to its substantial parallelism, it processes information at a very rapid rate.

They are the most effective models for teaching and learning. Compound input-output mapping may be represented by neural networks, which are capable of estimating a wide range of complex functions. They have a natural ability to adapt to any situation, and they can do so even in a loud environment. It is possible to detect trends and patterns that are difficult to detect by either a computer system or a human person using neural networks, which have the capacity to extract the essence from complicated data. Neural networks may be regarded experts in the field of information they've been taught to analyses if they're properly trained. What-if questions can be answered by a specialist in a given fresh context.

ARTIFICIAL NEURAL NETWORKS

Mathematical models of information processing are called neural networks or neural nets. They depict relationships in a way that is quite different from turning machines or computers with pre-programmed instructions. " The methodology, like other numerical approaches, benefits substantially from the availability of computer resources, including hardware and software. This is particularly true for big problems.

A neural network is characterized by:

1. “Pattern of connection between the neuron (called its architecture)”,
2. “Its method of determining the weights on the connections (called its training or learning algorithm)”
3. “It’s activation function”.

APPLICATIONS

Neural networks are well applied for commercial applications. They are well suited for data classification or data trends. Some of applications include:

- “Sales prediction
- Control of industrial process
- Research on customer
- Validation of data
- Management of risk
- Target marketing”

Their non-linearity and robustness have made them useful in a variety of other control system fields, such as chemical plant process control.

-Autonomous cars without human operators

consumer electronics and robots

Additionally, neural networks are being used to simulate a wide range of applications that are too difficult to represent using traditional methods. Computer vision, route planning, and user modelling are all examples of these.

ARTIFICIAL NEURAL NETWORK RESULTS

The ANN is trained using the experimental data and then tested using the sample data. The training of ANN is done using MATLAB software. The training depends on many factors and the table below shows the training data.

1	Network Configuration	3-8-2
2	Number of Hidden layers	1
3	Number of Hidden neuron	8
4	Transfer Function Used	Logsig (sigmoid)
5	Number of Patterns Used for Training	70%
6	Number of Patterns Used for Testing	15%
8	Number of Epochs	1000
9	Learning Factor	0.01
10	Momentum Factor	0.9
11	Training Function	Traingdx
12	Max_fail	1000

Table 1: ANN Training Data

The training data is shown in the following table.
Tool rotational speed, Welding speed, and Axial force are all included in the 3-8-1 network architecture, which has 3 input neurons each.
There are eight neurons in the hidden layer, hence the network has a single hidden layer with a total of eight neurons.
Tensile Strength and Hardness of weld nugget are the two outputs from the output layer, which has two neurons.
Logsig is the transfer function in use here. Gradient descent approaches need a smooth, differentiable function like this.
There are 1000 Epochs in existence. Training epochs may only be increased to this limit.
An adjustable learning rate backpropagation and a steepest descent are utilised in the training function Traingdx.
Tensile Strength and Weld Nugget Density are displayed in the graphs below. This is a visual depiction of both the output parameters.

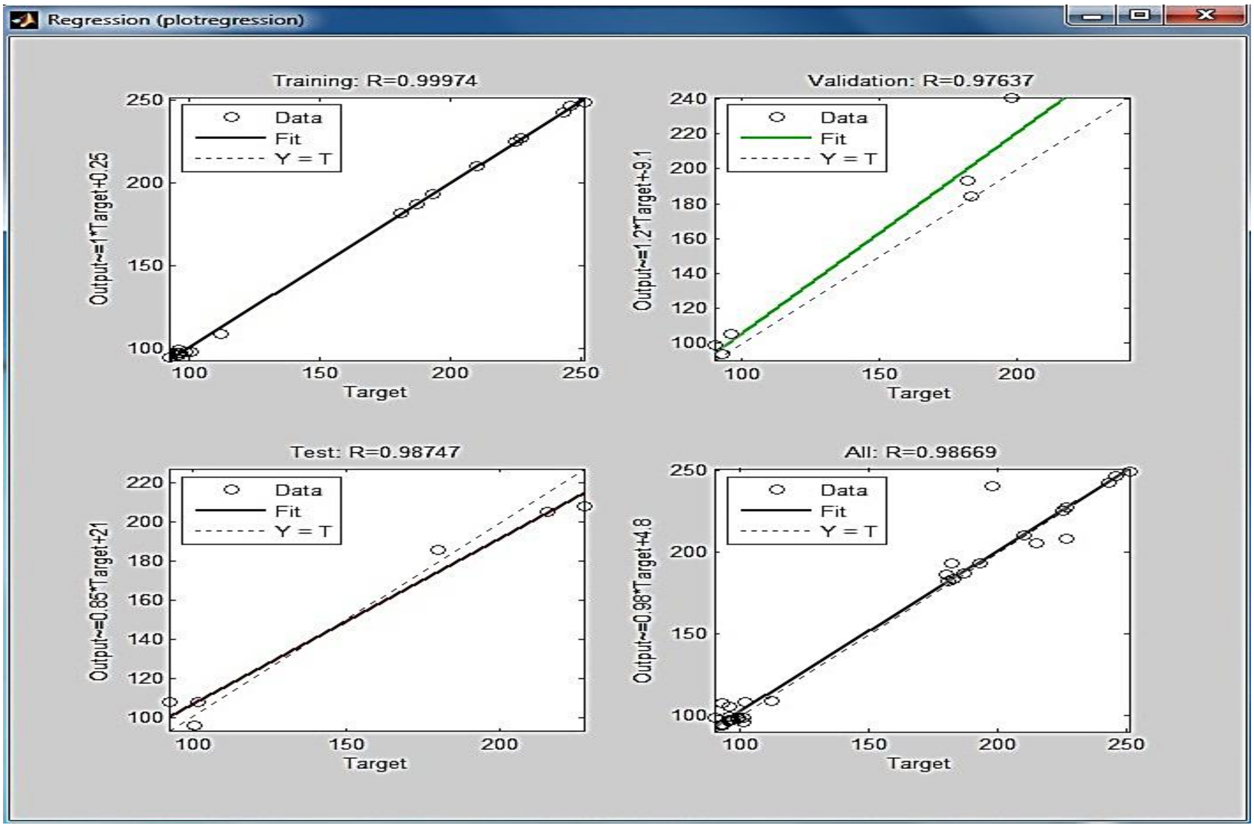

Fig.2: ANN Graphical Results

The above graphs show the plot between Output and Target data for Training set, Validation set, Test set and the combination of all three. From the results of ANN, it can be concluded that test data is very well following the training data. The results are showing that the ANN is trained well and also giving good results for validation and testing.

CONCLUSION:

FSW is a cutting-edge welding process. The FSW process is growing in scope thanks to solid state joining and the ability to combine aluminums alloys that are thought to be unwieldable by traditional welding methods.

Secondly, the FSW method relies on input and output parameters in order to produce a high-quality weld. Welding speed, tool rotational speed (TRS), and axial force are the three input factors examined in this study, whereas ultimate tensile strength and weld nugget hardness are the two output characteristics.

Response Surface Regression (RSR) is used to examine the influence of input parameters on output parameters. MINITAB 17 software is used to create the final results.

According to our findings, tool rotational speed has a bigger impact on the two output characteristics than any other input factor.4. The following is an explanation: The tool rotational speed determines the amount of heat generated in FSW. More material is stirred and mixed into a high-quality weld when the tool's rotating speed is increased. To avoid faults, it is important to keep the tool's rotational speed as high as possible. The weld nugget's tensile strength and hardness are deteriorated if the tool's rotating speed is too low or too high. Axisymmetrical force and welding speed also fall within this category.

5. ANN is a new way of thinking at the problem. Basically, it's based on how the human brain learns. Training neural networks, a term used to describe the capacity of ANNs to learn from examples. As long as the training is thorough, it will be able to produce output for inputs it has never encountered before. The ANN has three layers: input, hidden input, and output. The job of detecting the commonalities that exist in both visible and invisible occurrences is left to the hidden layer. To link the hidden and output layers, a set of weights must be applied to each.

Backpropagation learning is used to train the ANN in this study. Errors are propagated backwards from output to the hidden layer and then backwards from the hidden layer to the input layer by adjusting weights.

Seven neurons are employed in the input layer, eight in the output layer, and two in the output layer in the current work's ANN training data in a 3-8-2 arrangement. If the projected values and experimental values agree, then the neural network has been properly trained. Consequently, a well-trained neural network (ANN) may be utilised to estimate the mechanical parameters of a weld joint.

Non-linear mapping between input and output parameters is a common application for artificial neural networks (ANN). A large amount of training data is combined with an unknown underlying connection between the input and output variables to create this model.

9 A well-trained artificial neural network (ANN) may be employed as a feedback mechanism in a control system in the future. System characteristics such as weld quality assurance and defect detection may be controlled by a variety of control systems, including artificial neural networks (ANNs). An ANN can be taught to forecast potential defects before any experiments are conducted.

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