A Review on the Fabrication of Surface Composites via Friction Stir Processing and Its Modeling Using ANN

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Abstract Friction Stir Processing (FSP) is a surface modification and surface composite fabrication technique that was first theorized and demonstrated in 2002. Since then, it has grown exponentially in the industry due to its efficiency, ease of usability and various other advantages over conventional surface modification and fabrication processes. Artificial Neural Networks provide a computational model that can handle complex relationships between the various determinants involved in FSP and the effect they have on the final output. ANN has been used extensively to predict the impact of various FSP determinants and hence model the most efficient values of these determinants for various base metals. This paper has tried to encapsulate the plethora of research done on the optimization of FSP determinants using ANN architecture.

Keywords FSP · MMCs · ANN

1 Introduction

Most metal matrix composites, reinforced with ceramic phases or another desired metal, exhibit a higher elastic modulus, higher strength, higher Vickers hardness and better resistance to fatigue, creep and wear than the base metal. This makes them suitable for the aerospace and automobile industries. Since the ceramic reinforcement materials introduced in the base metal matrix are non-deformable and brittle, one of the drawbacks of such composites, especially in the case of such ceramic additives, is the loss of crucial properties of the base material—ductility and toughness. Thus, the composites formed have a limited application. The solution for this is sought from the

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R. M. Singari et al. (eds.), *Advances in Manufacturing and Industrial Engineering*, Lecture Notes in Mechanical Engineering,
https://doi.org/10.1007/978-981-15-8542-5_1

fact that for a majority of applications, the surface properties of the composite play a major role. Following this, Friction Stir Processing (FSP) was ideated and pioneered by Mishra et al. [1] in 2002. This technology stems from Friction Stir Welding (FSW) that was actualized back in 1991. It was derived from the process of using friction to weld joints even in aluminium, titanium and various other alloys. FSP is generally utilized for lightweight and flexible metals like aluminium and magnesium, but only after the base metal has experienced FSP to acquire certain desirable properties and make up for their absence of strength and hardness. Chaudhary et al. [2] studied the consequences of using FSP on different alloys like Mg_4Y_3Nd(WE43), Mg–$ZrSiO_4$–N_2O_3, Al–Si hypoeutectic A356 alloy, 5210 steel (WC-12% CO coated). The difference in the properties of friction stir processed alloys were observed as the processing was executed at different angles and speeds. A variety of ingenious materials may be used as reinforcement while preparing friction stir processed composites. The effects and properties of reinforcing materials such as Silicon Carbide, Graphite, Fly ash, Rice husk ash and boron halide were examined in detail by Butola et al. [3] for the preparation of surface composites using FSP. Properties like corrosion behaviour, tensile strength, hardness, wear-resistance and so forth were studied rigorously and summarized.

There exist several surface modification techniques like Laser Surface Engineering [4], high-energy electron beam irradiation [5], high-energy laser melt treatment [6], plasma spraying [7], stir casting [8], etc. The above-described techniques for the formation of surface composites rely on liquid-phase processing at high temperatures. Because of the nature of the processing, it is inescapable that an interfacial reaction occurs between the reinforcement and the metal matrix. Some other impeding phases may also be formed. The aforementioned problems may be mitigated by carrying out the processing at a temperature below the melting point of the substrate.

Artificial neural network is an innovative prediction model that utilizes existing data to train an intuitive network of neurons so that accurate complex predictions can be made. Okuyucu et al. [9] pioneered the use of ANN in friction stir welding. An ANN model was created for the simulation and analysis of the interrelationship of FSW determinants and the mechanical properties of the aluminium plates. Similarly, ANN models considering various FSP determinants were developed and implemented on friction stir processed alloys of aluminium and magnesium.

2 Principle and Effect of Parameters of FSP

Friction Stir Processing involves the heating and plasticization of the substrate and reinforcement material due to the friction created by the tool (with or without the protruding mandrel). FSP can be carried out on a conventional FSW machine [10]. During FSP, a non-consumable tool turns at a high RPM and gradually slides into the workpiece while applying a power pivotally until the shoulder of the instrument interacts with the outside of the workpiece, which brings about erosion. The rotating

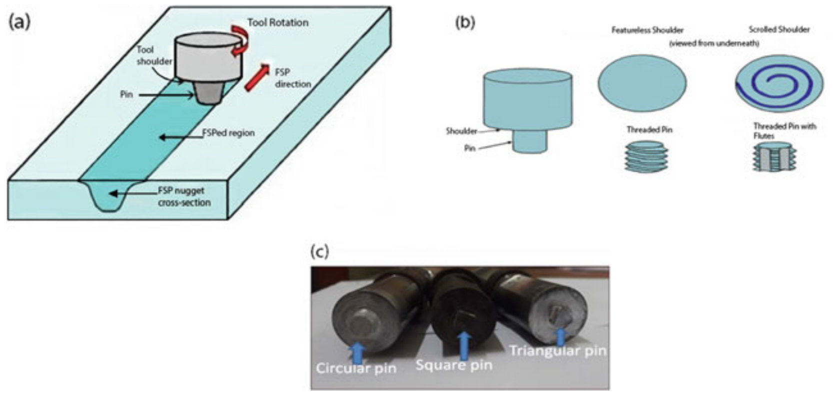

Fig. 1 FSP for frictional modification of surface layers, **a** process diagram, **b** tool design [2], **c** a variety of mandrel designs of tools for FSP [11]

tool then moves along the workpiece in the desired direction of FSP. A substantial amount of heat is engendered due to traction between the shoulder of the tool and the workpiece. The plasticized and heated material is forced along the modification line and underneath the back-up rim to the end of the tool, where it's compacted and blended because of severe deformation before it cools. FSP is a versatile method that can be used for manufacturing, modification as well as fabrication of materials with special properties (Fig. 1).

Moreover, FSP is an eco-friendly process as the heat energy required is generated through friction [12]. This leads to the formation of a dynamically recrystallized fine grain structure. Friction stir processed areas can be generated to the depths of 0.5–50 mm, with a progressive evolution from a fine-grained, thermodynamically worked microstructure to the elementary original microstructure [13]. The processing region in FSP, like FSW, is usually categorized into a thermo-mechanically affected zone (TMAZ), a stir zone (SZ), heat-affected zone (HAZ) and base metal zone(BM) [14, 15]. The SZ undergoes acute plastic deformation and primarily consists of homogeneously refined grains which are equiaxial and whose dimensions are contracted monumentally in comparison to the principal metal. During recrystallization, the formation of grains is promoted by the particle-stimulated nucleation when particles of the reinforcement material are introduced to the metal matrix. During the dynamic recrystallization process, the uniform dispersion of fine particles can inhibit grain growth. This is in accordance with the Zener–Holloman mechanism. This occurs due to the pinning action on the grain boundaries leading to a substantial amelioration of the microstructure [16]. The factors affecting the FSP modified substrate are tool traversal speed, tilt angle of tool, RPM, tool plunge depth and dimensions of the tool [12].

2.1 Impact of Process Determinants

The most important determinants are the RPM and the speed of traversal of the tool. This is because they directly affect the addition of heat and the flow of the plasticized material during FSP. This drastically influences the microstructure and hence, the mechanical properties of the processed material. A higher speed of rotation, coupled with a lower speed of traversal, leads to more heat being generated in the processing region, which in itself becomes larger. This leads to a better-refined microstructure and an increase in the hardness [17–20]. A lower speed of traversal also helps to control unusual grain growth [21]. Moreover, a higher speed of rotation of the tool or lower speed of traversal ensures that a higher augmentation of heat and more plastic deformation is achieved. This becomes significant for the mixture of reinforced particles and the base metal matrix.

Multi-pass FSP has been proven to better the material properties by aiding the plastic deformation of processed materials. Increasing the number of passes and reversing the direction of rotation of the tool with every subsequent pass ensures that the composites manufactured by multi-pass FSP have a progressively uniform phase dispersion and strengthening because of thoroughly propagated in situ reactions as compared to single-pass FSP [22]. The procedure may be designed accordingly by selecting the percentage of overlap viz. 5, 10, 25, 50, 75% and thus desirable dimensions of the modified surface may be obtained [12].

2.2 Impact of Tool (Pin) Geometry

Tools used to stir the material in FSP may be with or without a mandrel and are usually non-consumable [23]. A stir tool is usually used with the mandrel and the mandrel-less tools are used for either modifying the surface of the material or processing of reinforcement material into the native metal during the fabrication of composites. The tool size and the geometry of the tool pin significantly affect the amount of heat produced as well as the flow of the material during processing. A large shoulder diameter of the tool results in the frictional heat being more concentrated. Subsequently, the particles in the second phase are refined better and thus the microstructure is also more stable. Thus, the influence of pin profile is crucial and this results in the temperature being the lowest when a conical pin is plunged into the material. Three different pin profiles were studied by Butola et al. [11] by observing their effect on SiC, RHA and B_4C-reinforced composites with AA7075 as the native metal. The coda showed that in the stir zone, which had also decreased in size, the most homogeneous distribution of reinforcement particles was seen in the case of a square mandrel.

2.3 Fabrication of Surface Composites

Many methods have been explored by various researchers to fabricate composites containing reinforcement particles. High modulus of elasticity, high strength, etc. are some of the inherent properties possessed by metal matrix composites. Surface composites may be fabricated from these to enhance the surface properties of these composites. The main challenge affecting this has been the introduction of these particles in the base metal during FSP. Apart from casting [24], a number of other methods were also tried. The SiC powder was mixed with methanol to form a paste, which was, in turn, applied evenly onto the surface of the workpiece before FSP. But, the particles slipped easily and were splashed out of the surface due to the rotation of the tool. This leads to an irregular distribution of the reinforced phases and inefficient use of material [1]. Some other ways to incorporate the reinforced particles in the matrix include making grooves on the surface of the base metal plates and adding the particles in it. To prevent splashing, the grooves are pre-processed with a pin-less tool using FSP [25, 26]. Similarly, blind holes may be drilled into the surface of the workpiece [27]. In both of these cases, final processing via FSP ensures that the particles are uniformly dispersed in the metal matrix and the homogeneity in the dispersion of the strengthening phases vastly improves the properties of the surface composite hence formed.

Liquid-phase techniques like laser cladding and plasma spraying are often used for this purpose. Butola et al. [8] used stir casting for the introduction of natural fibres like bagasse, banana and jute to form metal matrix composites and studied their effect on the mechanical properties of the base metal. In another study, Butola et al. [28] used stir casting and ball milling to fabricate and refine MMCs and study the effect of Groundnut Shell Ash (GSA), Rice Husk Ash (RHA) and ash-forms of some other natural fibres as reinforcement. Due to the formation of a liquid-phase in the above-mentioned techniques, the deleterious reactions mentioned at the beginning of the research may happen. Using FSP for the same will ensure that a finely distributed phase of strengthening particles may be obtained while keeping the SZ in a solid-state. This effectively prevents the formation of detrimental phases and any unwanted interfacial reactions. The commonly added reinforcement materials in FSP include SiC, B_4C, GNPs and Al_2O_3.

3 Artificial Neural Networks

Artificial neural network, popularly known as ANN, is a biology-inspired architecture of nodes (neurons) that are extensively interconnected [29]. It is a complex learning model that trains on a set of data, analyzes and learns the pattern followed in it and then predicts the result of a similar dataset. It processes the information in the datasets using a connectionist approach and multiple functions are run on it simultaneously. Synapses link neurons and a weight factor is associated with each of

Table 1 The inputs and outputs used by some previous works [31]

Inputs	Outputs	References
Welding speed (WS) Rotational speed (RPM)	Yield strength (YS), Length variation	[9]
WS, RPM	Tensile shear force, Hardness	[32]
WS, RPM	Tensile strength (TS), YS, Elongation	[33]
WS, RPM, Axial force (F)	TS	[34]
WS, RPM, Tool shoulder diameter	TS	[29]

them. ANNs are data processing models that mirror the role of the biological matrix, made out of neurons and are utilized to understand convoluted capacities in different applications by determining the nonlinear relationship between the involved, influential determinants and the output(s) obtained. The model has three layers viz. input, hidden and output layers. The input layer comprises of all the input factors. Data, via the input layer, is then processed through one or more hidden layers and the corresponding output vector is calculated in the final layer. One of the most popular learning algorithms is the backpropagation algorithm [30]. One of the primary hurdles while constructing an ANN model is to choose an appropriate network framework, which includes the activation function and the number of neurons in the hidden layer. Largely, tentation is used for the same. Since its introduction, ANN has been used by various researchers to study the effect of various determinants on a process under scrutiny. Friction Stir Processing is one such process. Since the advent of this processing method, the variables that control the resultant surface composite formed, have been closely studied. Since there is no explicit correlation for estimating target determinants based on the input factors, usually target determinants are modeled by a three-layer perceptron ANN using data obtained from mechanical and microstructural experiments (Table 1).

Neural architecture with the following [35]:

- Input has **r** determinants
- Output has **s** determinants
- **p**—inputs
- **w**—weight matrix
- **b**—bias vectors
- **f**—transfer function in neurons
- **a**—transfer functions in outputs.

Training of a neuron is carried out by multiplying the input vector with a vector of weights, followed by the addition of a bias vector. The result of this processing is then fed into the hidden layer. The sum of all the inputs is then fed into a transfer function. The output thus obtained is the output of the neural network. This output is then compared with the corresponding experimental values obtained. Due to the difference in the expected and practical values, an error vector is generated. In case this error value exceeds the acceptable error limit, the output is propagated back

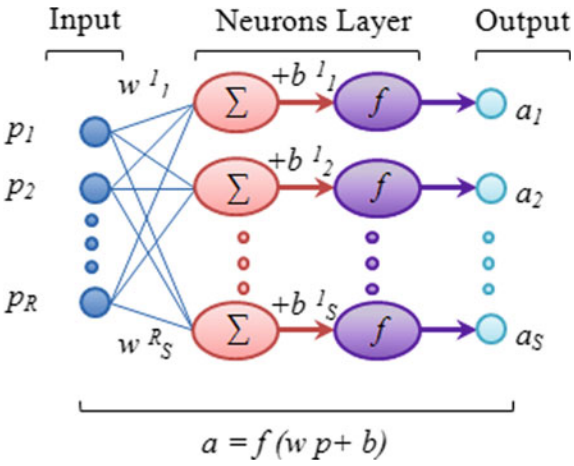

Fig. 2 Tangent sigmoid (Tansig) transfer function [31]

through the network and appropriate corrections in the weights and biases are made till the desirable values are attained.

Logarithmic sigmoid (Logsig) transfer function:

$$\psi(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

Linear transfer function (Fig. 2):

$$\chi(x) = \mathrm{linear}(x) \tag{2}$$

3.1 Training of ANN

The dataset that is available is usually split into two parts, usually in a 3:1 ratio [36]. The bigger of the two datasets are used to train the ANN, while the other one acts as the testing dataset. The final outputs obtained are compared with the expected values, error calculated and in case the error exceeds the permitted limit, the output is sent back through the network and required adjustments in the weights and biases are made. The aim of the feed-forward backpropagation (BP) algorithm is to minimize the sum of the mean squared errors obtained between the calculated and practical values of output and the minimization is achieved via the gradient descent method. BP is one of the most efficient algorithms for the optimization of the weights and biases of a multi-layer supervised feed-forward network.

3.2 Implementation of ANN

There are many input factors in a neural network, changing which will, in turn, change the method of operation and the overall precision and processing speed of the network [37]. Some of these include but are not limited to the number of neurons in each hidden layer, hidden layers, the bias used and the rate of training of the network. As the count of hidden layers and nodes(neurons) in each layer are crucial in the overall functioning and performance of the ANN (act as the primary processing entity of the network), they are chosen after careful consideration. They are usually chosen by tentation because of the lack of a fixed formula to determine the same. Increasing them does not always lead to better performance in terms of the speed and accuracy of the network. In fact, it increases the complexity of the network, which in turn, tends to slow down the network after a certain limit. An unstable network may be obtained if the rate of training is increased or decreased beyond a certain limit. All the input and output determinants are normalized to prevent them from scattering. This means that the values of these determinants are divided by the maximum value and hence reduced to a value between 0 and 1. This decreases the scattering of the determinants.

3.3 Performance Evaluation of ANN

A lot of statistical models are at one's disposal to determine the performance of any neural network [26]. The most common ones include the Pearson coefficient of correlation (PCC) and mean relative error (MRE). Their equations are as follows:

Where,

$$\mathrm{PCC} = \frac{\sum_{i=1}^{n}\left(f_{\mathrm{EXP},i} - F_{\mathrm{EXP}}\right)\left(f_{\mathrm{ANN},i} - F_{\mathrm{ANN}}\right)}{\sqrt{\sum_{i=1}^{n}\left(\left(f_{\mathrm{EXP},i} - F_{\mathrm{EXP}}\right)^2\left(f_{\mathrm{ANN},i} - F_{\mathrm{ANN}}\right)^2\right)}} \tag{3}$$

$$\mathrm{MRE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|f_{\mathrm{ANN},i} - f_{\mathrm{EXP},i}\right| \times 100}{f_{\mathrm{EXP},i}} \tag{4}$$

$$F_{\mathrm{EXP}} = \frac{1}{n}\sum_{i=1}^{n} f_{\mathrm{EXP},i},\ F_{\mathrm{ANN}} = \frac{1}{n}\sum_{i=1}^{n} f_{\mathrm{ANN},i},$$

$$f_{\mathrm{EXP}} = \text{Experimental},\ f_{\mathrm{ANN}} = \text{Predicted} \tag{5}$$

The methodology of constructing an optimum ANN architecture is as follows:

1. Start
2. Normalization of data (inputs and outputs)
3. Feeding the normalized data to the hidden layer of the ANN

4. Determining the optimum values of the determinants involved
5. Executing the training algorithm of the network
6. Obtaining the Pearson coefficient
7. If PCC is atleast 0.99, continue. If it is less than that, go back to the optimization step (step 4)
8. Till the convergence of experimental and predicted data is not obtained, the processing is to be continued
9. Weights and biases vectors are obtained
10. Analysis is done based on the function used in the model
11. Final error is calculated
12. End.

4 Summary

Friction Stir Processing has a wide variety of applications which include, but are not restricted to, surface modification and fabrication. There are numerous ways to incorporate reinforcement material into the surface of the base metal and these have been optimized over time. Friction Stir Processing can be used for achieving superplasticity, producing alloys that possess special properties, improving the fatigue strength of welded joints, etc. ANN has been used extensively and successfully to figure out the most efficient parameter values for FSP by various researchers.

5 Future Scope

Friction Stir Processing has rapidly made a niche for itself in the industry. As it is a surface modification and fabrication technique that overrides the drawbacks of the existing technologies by a mile, the acceptance of this technique has exponentially grown. Moreover, the fact that FSP can be implemented on existing CNC milling machines, it is being adapted quickly far and wide through the industry. In addition to this, the varied applications of FSP, combined with its arsenal of advantages and easy adaptability, have made FSP very promising. Since artificial neural networks are also increasingly being used all through the world, the ease of determination of the relationship between the various determinants and variables associated with FSP in a mathematical way, which can accurately predict the impact of every parameter on the resultant MMC, has not only drastically reduced the cost of experimentation and research but also made it far more accessible than before.

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