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Modeling Mechanical Properties of FSW Thick Pure Copper Plates and Optimizing It Utilizing Artificial Intelligence Techniques

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Abstract

Friction stir welding (FSW) is an innovative solid state joining technique and has been employed in aerospace, rail, automotive and marine industries for joining aluminum, magnesium, zinc and copper alloys. In this process, parameters play a major role in deciding the weld quality these parameters. Using predictive modelling for mechanical properties of FSW not only reduce experiments but also is created standard model for predict outcomes. Therefore, this paper is undertaken to develop a model to predict the microstructure and mechanical properties of FSW. The proposed model is based on Ring Probabilistic logic Neural Network (RPLNN) and optimize it utilizing Genetic Algorithms (GA). The simulation results show that performance of the RPLNN algorithm with utilizing Genetic Algorithm optimizing technique compared to real data is reliable to deal with function approximation problems, and it is capable of achieving a solution in few convergence time steps with powerful and reliable results.

Keywords: Friction stir welding; Artificial intelligence; Modeling; Optimization; Ring probabilistic logic; Neural networks; Genetic algorithms

Introduction

Special properties of copper such as high electrical and thermal conductivities, good combinations of strength and ductility, and excellent resistance to corrosion have made it an excellent applicant to be utilized in industrial areas. On the other hand, high thermal conductivity of copper causes the need for higher heat input during conventional fusion welding, which results in large distortion, solidification cracking, and high oxidation rate. Fortunately, friction stir welding (FSW) which requires lower heat input for joining of the copper and copper alloys can overcome this problem [1,2].

Friction stir welding (FSW) as a solid-state welding process, which was invented in 1991 has been used for joining of different types of metals and alloys successfully [3,4]. Friction stir processing (FSP) is a new metal working method for producing surface composites, which is based on the concept of FSW [5]. During FSP, the stirred material undergoes severe plastic deformation. The material flow associated with stirring and severe plastic deformation can be used for bulk alloy modification by mixing in a second element. This mixing is followed by the precipitation of a second phase, distribution of fine particles of the second element, increased density of defects, and so forth. As a result, the stirred zone becomes a metal matrix composite with an improved hardness and wear resistance.

During recent years, some investigators have studied the fabrication of different types of surface composites using FSP technique, and have studied their microstructure, mechanical, and wear properties [6]. Although numerous investigations have been done on FSW of aluminum alloys, efforts in the FSW of the copper and copper alloys are somewhat limited [7]. Recently, some researchers have studied the microstructural and mechanical properties of the friction stir welded copper plates with different thicknesses of 1 mm, 2 mm [8], 3 mm [9]. For instance, Galvao et al. [10] have studied the effect of tool geometry, rotational, and traverse speeds on the microstructure and mechanical properties of the 1-mm-thick copper plates. They showed that for the same rotational and traverse speeds, finer grains, higher hardness, and enhanced strength can be achieved in the stir zone (SZ) of the joints, using a scrolled tool. Furthermore, Liu et al. [11] achieved a defect free 3-mm-thick copper joint under a low heat input condition of 400 rpm and 100 mm/min, which resulted in a fine-grained structure in the SZ. In addition, Jabbari [12] has established a thermal model to simulate the FSW of 4-mm-thick pure copper plates in the constant traverse speed of 25 mm/min and five different rotational speeds. He demonstrated that the highest hardness, maximum tensile strength, and minimum elongation could be obtained at rotational speed of 900 rpm.

Even though some investigators explored mathematical models in the case of some aluminum alloys, a research into the establishing mathematical relationships between the FSW parameters, grain size, and hardness of friction stir-welded AA 7020 aluminum alloy joints is lacking [7]. In addition, the effect of FSW parameters on grain size and hardness of the joints has not been studied more. Therefore, the aim of this study is to apply Ring Probabilistic Logic Neural Networks (RPLNN) to model and establish the functional relationships between FSW parameters, i.e., rotational speed, traverse speed and tool axial force, and responses of average grain size (Dav) and hardness (HV) of the friction stir-welded thick pure copper and optimize it utilizing the Genetic Algorithms (GA).

Experiment Work

Identifying important parameters

From the literature and the previous work [3,13] done among many independently controllable primary and secondary process parameters

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affecting the tensile strength, the primary process parameters such as rotational speed (N), welding speed (S), and axial force (F), were selected as process parameters for this study. The rotational speed (N), welding speed (S), and axial force (F) are the primary parameters contributing to the heat input and subsequently influencing the tensile strength variations in the friction stir welded thick pure copper plates.

Design of experiments

A large number of trial runs were carried out using pure copper plates of 10 mm thicknesses as based. These plates were annealed at 700°C for 1 h before FSW. FSW was conducted at a constant rotational speed of 700 rpm and different traverse speeds of 50 mm/min, 100 mm/min, 150 mm/min, and 200 mm/min. Each of the welds are named in the text by a code which contains W and rotational speed divided by 100 and V, the traverse speed divided by 10. For example, a joint welded at 700 rpm and 50 mm/min is identified as W7V5. A FSW tool made of H13 steel with a shoulder (30 mm diameter) and a square pin (9 mm equivalent diameter and 9.7 mm length) was used, as shown in Figure 1.

The slope angle of the tool relative to normal direction of the work piece surface was set at 2.5°C. Subsequent to visual inspection of the joint surfaces; the microstructures of the joints were analyzed using an optical microscope (OM). Accordingly, the metallographic specimens were cut from the joints transverse to the welding direction, then polished and etched with a solution of 20 mL nitric acid and 10 mL acetic acid. Clemex image analysis software was used for calculation of average grain size and grain size distribution in the SZ of the different joints. This software distinguishes different grains via a range of color contrast and then computes related diameter D_{eq} of each grain from its area using the following equation:

$$D_{eq} = 1.2247\sqrt{\frac{4A}{\pi}}$$

Where A is area (μm²). The microstructure of the W7V15 joint was also characterized by transmission electron microscope (TEM). For the TEM specimen preparation, specimen was thin polished and then double-jet electro-polished using a solution of $HPO_4/CH_4O/H_2O$=1:1:2 in volume. The Vickers hardness profiles of the joints along the centerline on the traverse cross section of the different joints were achieved using a 100 g load for 10 s. In addition, five tensile specimens were prepared per joint (Figure 2a) according to the ASTM:E8M standard and tensile tests were conducted at a crosshead speed of 1 mm/min. Furthermore, the fractography of the tensile specimens was done by scanning electron microscope (SEM). Additionally, type K thermocouples were placed at the bottom of the plates exactly on the joint line, for recoding the temperatures during FSW (Figure 2b) [3].

Design of function free model

Artificial intelligence and cognitive modeling try to simulate some properties of natural Neural Networks. While similar in their techniques, the former has the aim of solving particular tasks, while the latter aims to build mathematical models of biological neural systems. In the artificial intelligence field, artificial neural networks have been applied successfully to speech recognition, image analysis and adaptive control, in order to construct software agents or autonomous robots. Most of the currently employed artificial neural networks for artificial intelligence are based on statistical estimation, optimization and control theory. The cognitive modeling field involves the physical or mathematical modeling of the behavior of neural systems; ranging from the individual neural level through the neural cluster level to the complete organism [14,15].

In this section we introduce the Ring Probabilistic logic Neural Network (RPLNN) by employing the concept of Probabilistic Logic Neuron (PLN) as powerful artificial intelligence technique that has been frequently used in pattern recognition problems [16,17].

RPLNN are made up of interconnecting artificial neurons. RPLNN may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system.

The tasks to which RPLNN can be applied tend to fall within the following broad categories:

Function approximation, or regression analysis, including time series prediction and modeling.

Classification, including pattern and sequence recognition, novelty detection and sequential decision making.

Data processing, including filtering, clustering, blind signal separation and compression. Application areas include system identification and control (vehicle control, process control), game-playing and decision making (chess, racing), pattern recognition (radar systems), sequence recognition (gesture, speech), medical diagnosis, financial applications, data mining (or knowledge discovery in databases, "KDD"), visualization and e-mail spam filtering.

A PLN consist of a node and a truth table, inputs is given as 0 or 1 and the output is in the form of 0 or 1. These numbers go to a decoding

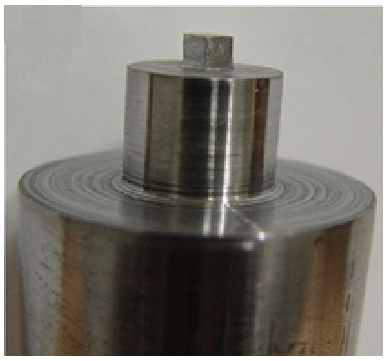

Figure 1: The picture of the used FSW tool in this study.

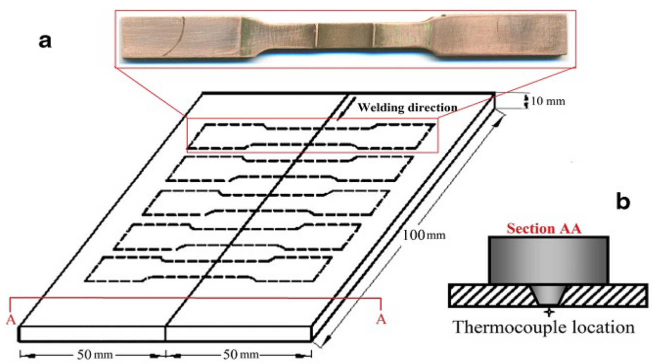

Figure 2: (a) Tensile test specimen and (b) thermocouple location.

function, if the answer is desired the truth table will be saved otherwise random value will be replaced and the operation will start from the beginning. In other word, PLN optimization technique is trained and learned based on pure random search. Figure 3 shows schematic of PLN. This random search algorithm is known as A-Learning rule. In pattern reorganization PLN networks can be used by using A-learning rule algorithm [18].

The steps taken for A-learning rule can be summarized as below:

1. Encode an initial population.
2. For each Gen in each individual assign a PLN with random inputs and outputs
3. Calculate the fitness function for each individual.
4. If the calculated fitness function is equal to the desired value, save the value of inputs and outputs.
5. If the fitness function is not equal to the desired value, reset the inputs and outputs values and calculate the fitness function again and train the network for *m* times, where m is a positive non-zero integer (we assume *m*=10).
6. If the calculated fitness function is equal to the desired value, save the value of inputs and outputs.
7. If the calculated fitness function is not equal to the desired value, go to calculation for nest individual.
8. Repeat these steps until all random values will be changed to fixed values.

PLN networks can be formed in different structures and there is no exact pattern to select which architecture should be used (Figure 4).

The structure shown in following Figure 5 is used as one layer RPLNN structure case to generate function approximation based model to model the data obtained in tests, which described in previous section. Function approximation using RPLNN is a completely novel technique to model different systems, and it has an advantage of simplicity in calculations and obtaining better results in less time over other computational techniques [19].

Implementing optimization

A genetic algorithm emulates biological evolution to solve optimization problems [20]. It is formed by a set of individual elements

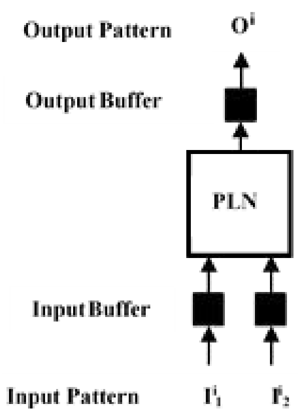

Figure 3: Probabilistic logic neuron (PLN).

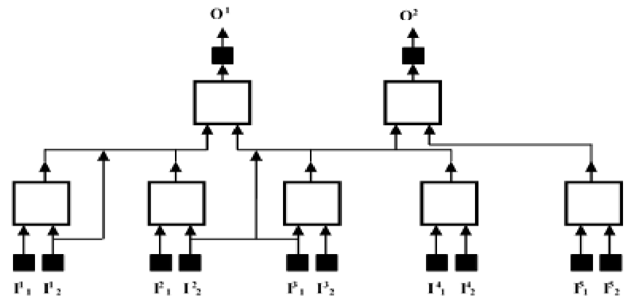

Figure 4: Example of structure of PLN network.

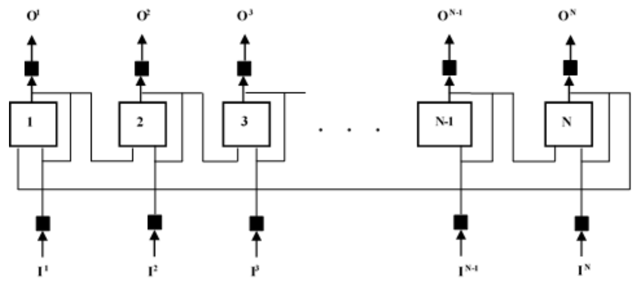

Figure 5: The ring probabilistic logic neuron (RPLN).

(the population) and a set of biological inspired operators that can change these individuals. According to evolutionary theory, only the individuals that are the more suited in the population are likely to survive and to generate offspring, thus transmitting their biological heredity to new generations.

In computing terms, genetic algorithms map strings of numbers to each potential solution. Each solution becomes an individual in the population, and each string becomes a representation of an individual. There should be a way to derive each individual from its string representation. The genetic algorithm then manipulates the most promising strings in its search for an improved solution. The algorithm operates through a simple cycle [21]:

1) Creation of a population of strings.

2) Evaluation of each string.

3) Selection of the best strings.

4) Genetic manipulation to create a new population of strings.

At the first stage, a population of possible solutions is created as a start point. Each individual in this population is encoded into a string (the chromosome) to be manipulated by the genetic operators. In the next stage, the individuals are evaluated, first the individual is created from its string description (its chromosome) and its performance in relation to the target response is evaluated. This determines how fit this individual is in relation to the others in the population. Based on each individual's fitness, a selection mechanism chooses the best pairs for the genetic manipulation process. The selection policy is responsible to assure the survival of the fittest individuals. The manipulation process applies the genetic operators to produce a new population of individuals, the offspring, by manipulating the genetic information possessed by the pairs chosen to reproduce. This information is stored in the strings (chromosomes) that describe the individuals. Two operators are used: Crossover and mutation. The offspring generated by this process take the place of the older population and the cycle is repeated until a desired level of fitness in attained or a determined number of cycles are reached.

The objective function is used to provide a measure of how individuals have performed in the problem domain. In the case of a minimization problem, the fit individuals will have the lowest numerical value of the associated objective function. This raw measure of fitness is usually only used as an intermediate stage in determining the relative performance of individuals in a GA. Another function, the fitness function, is normally used to transform the objective function value into a measure of relative fitness, thus:

$F(x)=g(f(x))$

Where f is the objective function, g transforms the value of the objective function to a non-negative number and F is the resulting relative fitness. This mapping is always necessary when the objective function is to be minimized as the lower objective function values correspond to fitter individuals [20].

In many cases, the fitness function value corresponds to the number of offspring that an individual can expect to produce in the next generation. Normally, in the genetic algorithm, error has an important role in expressing fitness function [21].

For our purpose we defined fitness function as a function of error:

$$Fitness\ Function = \frac{1}{1+E}$$

$E=mean|e_k|$

$|e_k|=(RPLNN\ model\ output)-(Experimental\ data)$

Results and Discussion

As seen in Figure 6 the test results show that ultimate tensile strength (UTS) of the joints increases with increasing the traverse speed up to a maximum value and then decreases.

Figure 7 shows the test result for changes of elongation (EL) of the joints with changing the traverse speed. EL of the joints decreases continuously with increase of the traverse speed.

As mentioned before in this paper RPLNN algorithm is chosen to deal with modeling the mechanical properties of FSW thick copper plates from the point of view of the changing Elongation and ultimate tensile strength due to changing the travers speed (TS). The RPLNN model is trained using the data obtained during the laboratory, as seen in Figure 8 simulation results show that the error of the generated RPLNN model for UTS-TS and EL-TS after 100 training iterations respectively converges to 2.5 and 1.2.

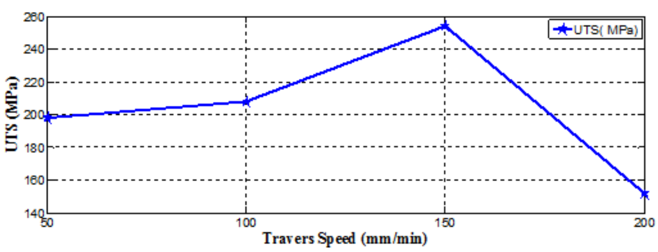

Figure 6: Test results for ultimate tensile strength.

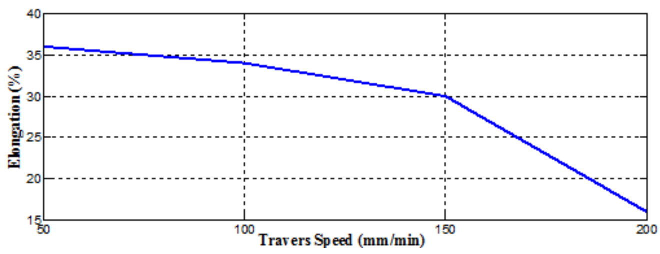

Figure 7: Test result for elongation.

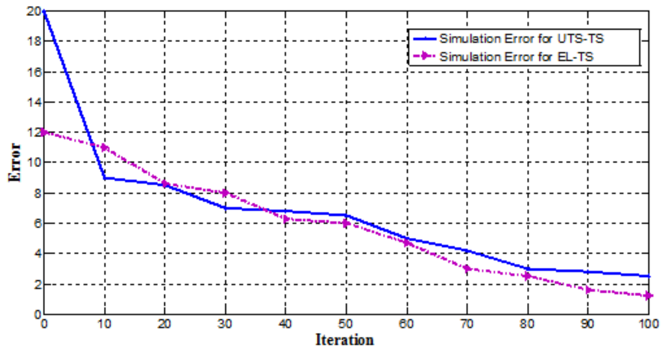

Figure 8: Simulation error for UTS and EL.

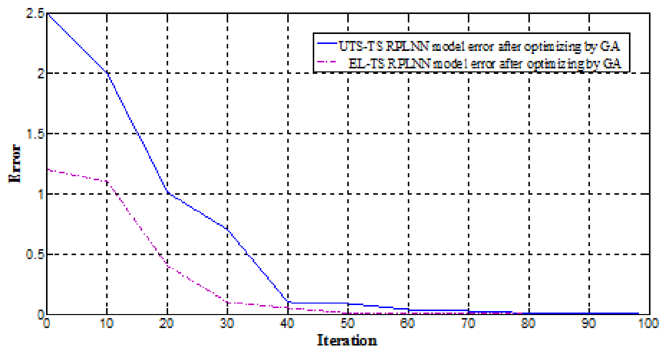

Figure 9: UTL and EL RPLNN model error after optimizing by GA.

The ultimate goal of the modeling is to generate a model reflecting the reality, so as mentioned before Genetic Algorithms is used here to optimize the RPLNN models to reduce the difference between of the output of the models and real data to generate reliable models. As seen in Figure 9 by utilizing GA as optimization technique, the error of the RPLNN models of UTS-TS and EL-TS respectively are reduced to 0.003 and 0.001, which with compare to the amounts of EL and UTS are very small and neglect able.

Summary and Future Work

In this paper, changing ultimate tensile strength and elongation of the joints due to changing the speed of traverse as mechanical properties of FSW thick copper plate is modeled by RPLNN architecture and the model optimized using genetic algorithms as evolutionary artificial intelligence optimization technique. The results show that the generated model is reliable and can predict output with neglect able error.

As future work, different mechanical properties can be modeled using different artificial intelligent techniques and different optimization techniques can be used to optimize the models.

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