

Entire-Process Simulation of Friction Stir Welding — Part 2: Implementation of Neural Networks

This research provides additional information about the structure-parameter-property relationships of friction stir welded aluminum alloy joints

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Abstract

To further understand the structure-parameter-property relationships of friction stir welded aluminum alloy joints, a nested neural network was proposed to map the macro- and microstructural response. The uncoupled effect of each primitive parameter on the joint performance was depicted. Reducing heat input and keeping an adequate load-bearing area of the welding nugget zone were proven to be the sufficient and necessary conditions to obtain high load-bearing performance. The entire-process simulation strategy showed great potential for prediction and optimization of the macro- and microstructural response of complex and large components.

Keywords

- Friction Stir Welding
- Aluminum Alloys
- Numerical Analysis
- Weld Process Simulation
- Mechanical Properties

Introduction

Friction stir welding (FSW), which features high-flow nonlinearity induced by severe plastic deformation, remains a great challenge when mapping mechanical and microstructural responses with various parameters (Ref. 1). Data-driven learning is beneficial to establishing the weight tables among different datasets of parametric variables (Refs. 2–4). In

machine learning methods, the primitive datasets can be obtained in peer-reviewed literature and experimental results as well as in the numerical simulation in Part 1 of this paper (Ref. 5), avoiding the unacceptable cost for massive experimental results (Ref. 6). In this way, we can have the opportunity to realize a high-throughput numerical model and complete the quantitative control and optimization.

In this paper, we propose the entire-process simulation strategy based on neural networks to map the macro- and microstructural response. The nested neural network using numerical results from both the computational fluid dynamics (CFD) method and the relevant microstructural revolution model were trained to understand the structure-parameter-property relationships of Al-Cu-Li alloys. The effectiveness of the integrated strategy was tested using the experimental results. One should note that although this strategy is applicable for the AA2195 alloy, it equally has the potential to be utilized for other FSW techniques and materials.

Methodology

The implementation of the nested neural network is schematically represented in Fig. 1. This model was composed of two parts. The first part was a generator of field data output. Two types of data were used as input. The quantifiable data was processed using the normalization method, such as welding parameters, diameters, length, the pitch of the thread, and the number of milling facets. The unquantifiable data was processed by a one-hot method, such as thread type. This part of the neural network was mainly composed of full connect and transposed convolution layers. The applied activation function was leaky ReLU (Equation 1) and ReLU (Equation 2). The loss function and optimizer used were mean squared error and ADAM (Equations 3 and 4).

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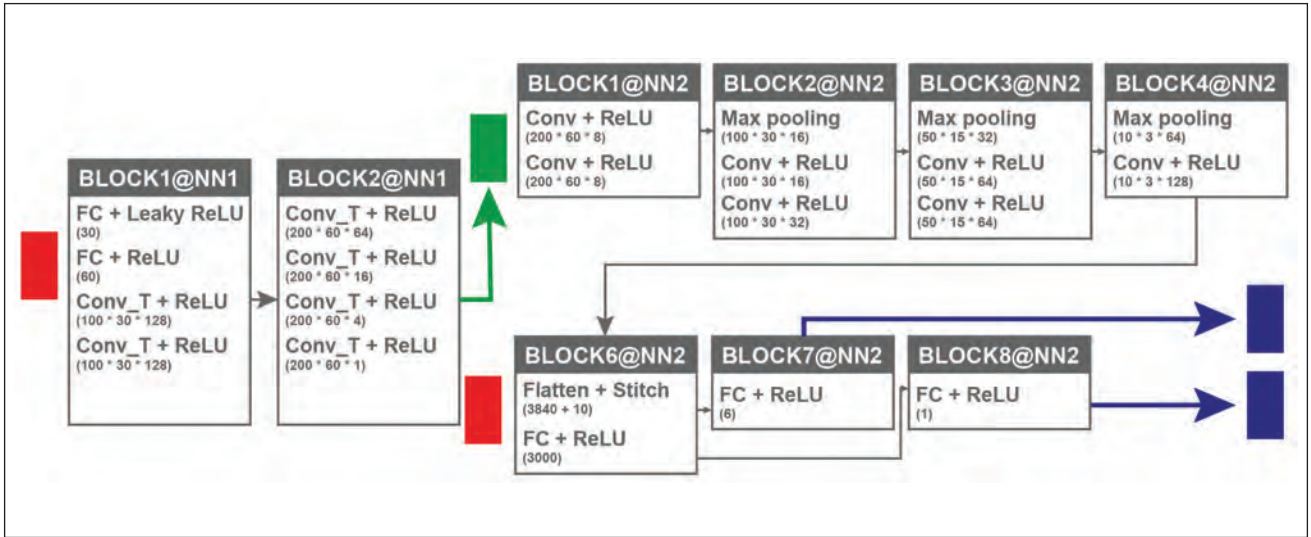


Fig. 1 — A nested neural network model.

$$y_i = \begin{cases} x_i & x_i \geq 0 \\ \frac{x_i}{5} & x_i < 0 \end{cases} \quad (1)$$

$$y_i = \begin{cases} x_i & x_i \geq 0 \\ 0 & x_i < 0 \end{cases} \quad (2)$$

$$g_t = \nabla_{\theta} J(\theta_{t-1}) \quad (3)$$

$$\theta_{t+1} = \theta_t - \alpha \cdot g_t / \sqrt{\sum_{i=1}^t g_t^2} \quad (4)$$

where g_t represents the gradient of the t time step (a vector, including the partial derivative corresponding to each parameter), and g_t^2 represents the gradient squared at the t time step.

The output data were three field outputs, which had the same shape as the CFD results. The evaluation criterion R-squared was given as follows:

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (\bar{y} - y_i)^2} \quad (5)$$

The second part of the neural network is a predictor of local and global strength. All the inputs of the first part were also used as input in this part. Moreover, the output from the first part was also used as another input data. This neural network part was mainly composed of convolution, max pooling, and full connection layers. The applied activation function was ReLU. The loss function and optimizer used were mean squared error and RMSprop, respectively (Equations 3 and 6). The evaluation criterion had the same form as Equation 5. The output was a global tensile strength and six local strengths. When the training of the model was completed, the two neural networks were spliced to form the final model. A simple neural network with only full connection layers and ReLU activation were also trained for contrast, as shown in Fig. 2.

$$\theta_t = \theta_{t-1} - \alpha \cdot g_t / (10^{-8} + \sqrt{v_t}) \quad (6)$$

Eighteen datasets from our experiments and 122 extra datasets from experiments in other peer-reviewed literature (Refs. 7–24) were used as test sets. A total of 6400 CFD datasets and microstructural models validated by thermo-couple temperature tests were used as the train sets and development sets with the ratio of 8:2. The authors adjusted the input corresponding to different sheet thicknesses in peer-reviewed papers, including length and diameter, by proportional scaling to standardize the data. The microstructural models were conducted based on the CFD results. The actual coordinates of each point were taken from the surface near the outlet surface of the domain. The temperature and strain rate cycle were obtained by retrospectively tracing the streamline. TensorFlow conducted all the training and validating processes.

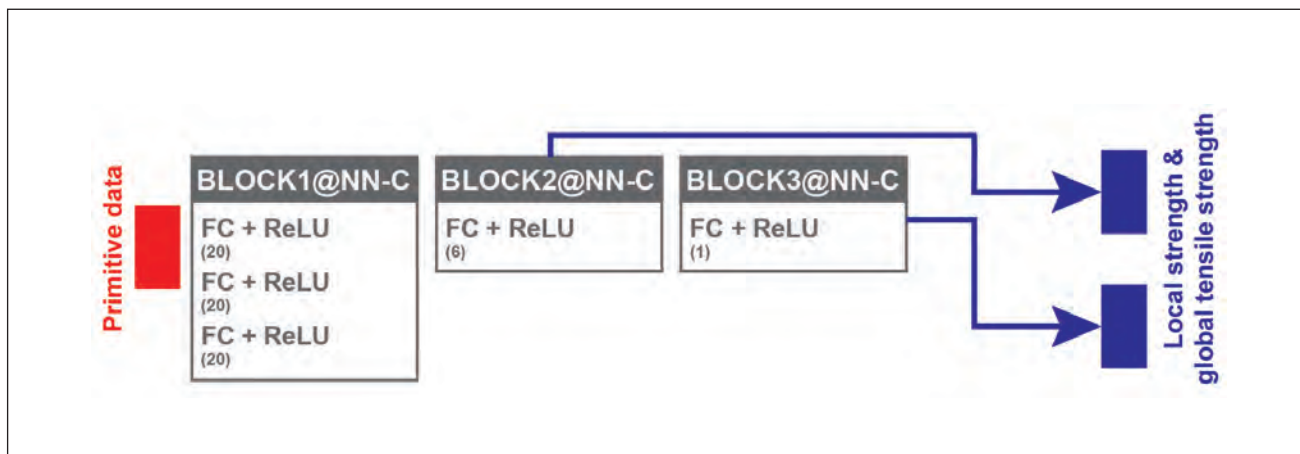


Fig. 2 — Simple neural network model for comparison.

Results and Discussion

To obtain a satisfactory neural network model, great effort was needed to provide sufficient training samples in experiments and numerical simulations. The primitive input variables included 12 types, as shown in Appendix I. The output variables were composed of global tensile strength and local strength, where the local strength was obtained by linearly converting the microhardness in experiments. A simple method is to directly use these primitive datasets to establish the relationship through a simple backpropagation neural network. However, this simple method has proven to be unreliable (Ref. 2). This unreliability is mainly due to the following issues: FSW involves complex material nonlinearity, geometric nonlinearity, and boundary nonlinearity (Refs. 25–27). These facts and the essence of severe plastic deformation resulted in the depth of simple neural networks not providing much information. For such complex system engineering, the authors applied the CFD simulation and microstructural model as an effective upgrade in the complexity of the model, which was provided in Part 1 of this paper (Ref. 5). This strategy converts the information contained in the numerical model into the neural network model. Therefore, a nested neural network was proposed. The primitive dataset was first converted into the required field output through a generator network and trained by the results from the CFD simulation. Thus, we could embed the information in the quasi-steady temperature field and strain rate field in the welding process into the neural network model, improving the rationality of massive parameters in the generator network. The corresponding field dataset was then combined with the primitive data. The prediction of global and local strength was obtained by a predictor neural network. A modified Kampmann-Wagner model, dynamic recrystallization model, and strengthening model provided the technical information required.

Based on the previously mentioned systematic numerical model, we obtained the detailed evolution and relevant datasets of the friction stir welded joints. We trained this data through the nested neural network method illustrated in Part 1 (Ref. 5). Figure 3 depicts the curves of the R-squared

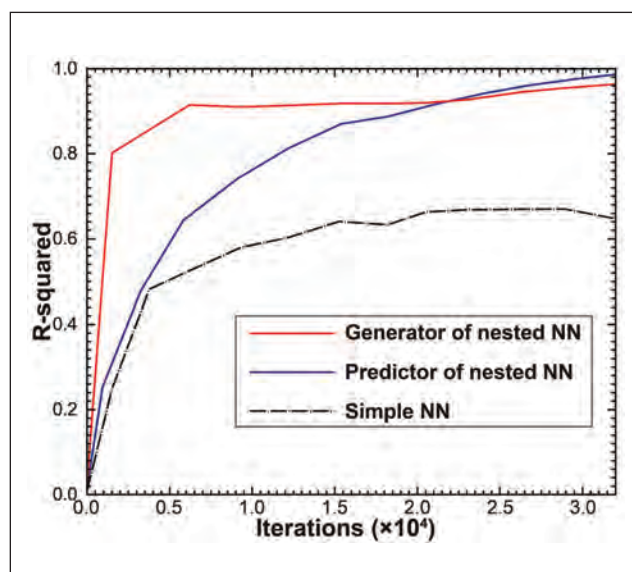


Fig. 3 — The evolution of evaluation criterion R-squared during training of the nested neural network. NN refers to the neural network.

during the training of the nested model and a simple model for contrast in the increased iterations. The final R-squared of our generator model was about 0.967, while the R-squared of the predictor model was about 0.983. One should note that we did not pursue a lower error to avoid the occurrence of overfitting. Finally, we spliced the generator and the predictor to form the final model. The input of this model included only the primitive datasets, while the output was local and global mechanical properties. Only the global tensile strength was used for the evaluation by test datasets. The final R-squared based on the experimental result for tests was 0.951, which can effectively predict the load-bearing capacity of the joints. In contrast, the simple neural network illustrated in Part 1 (Ref. 5) could not obtain satisfactory results. The R-squared curve fluctuated violently during training. This is because the primitive data cannot directly bear such high information density, including several field datasets. By splitting the neural

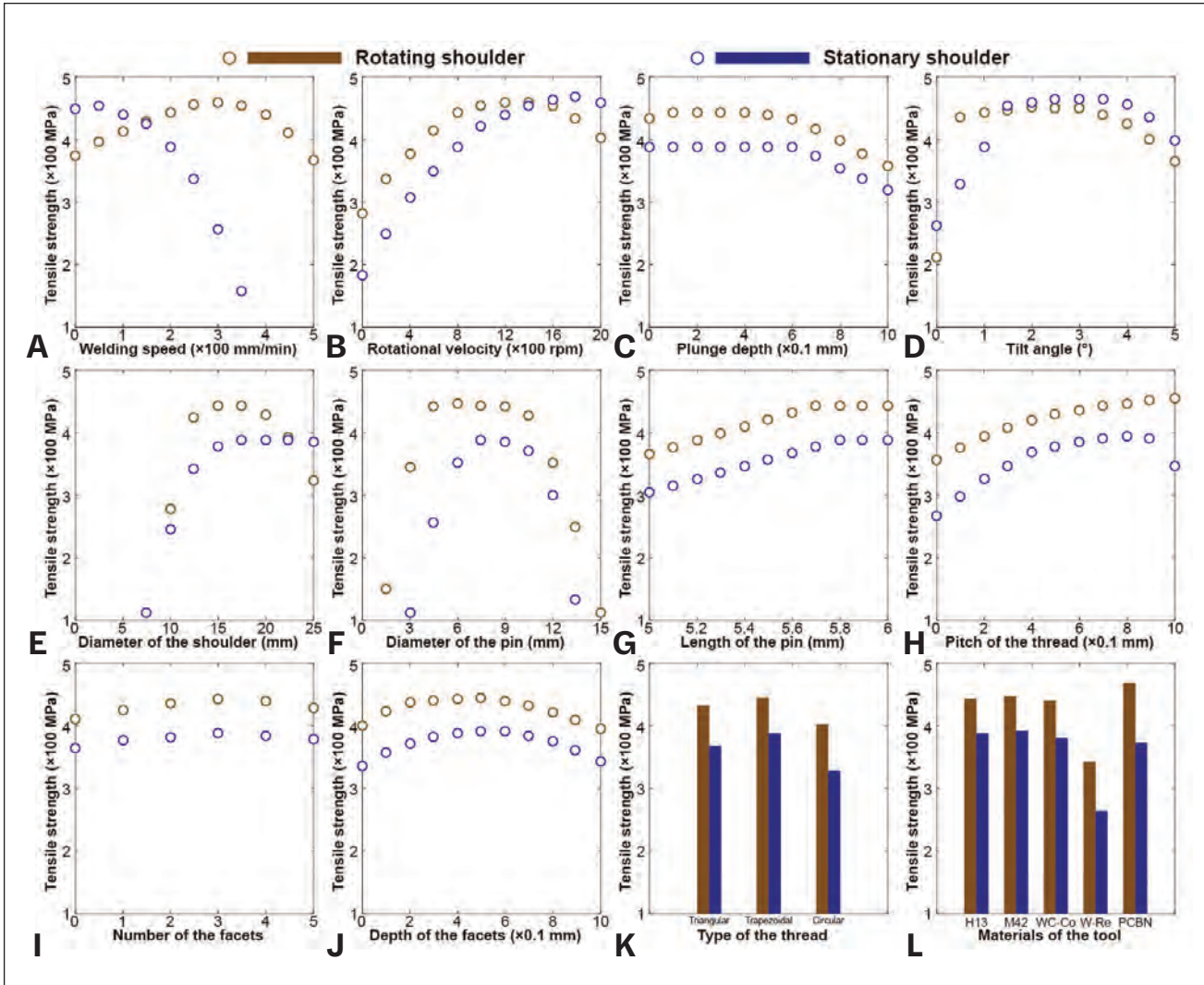


Fig. 4 – Curves of the effect of primitive parameters on joint performances in uncoupled mode: A – Welding speed; B – rotational velocity; C – plunge depth; D – tilt angle; E – diameter of the shoulder; F – diameter of the pin; G – length of the pin; H – pitch of the thread; I – numbers of facets; J – depth of the facets; K – type of the thread; L – material of the welding tool. Default combination of parameters: 200 mm/min, 800 rpm, 0.1 mm, 1 deg, 16 mm, 8 mm, 8 mm, 5.8 mm, 0.75 mm, 3, 0.4 mm, trapezoidal, and H13, respectively.

network into two parts and supplementing the numerical simulation results, we indirectly introduced the field data that affected the mechanical performance into the model. The nested neural network model, including a generator and a predictor, had been independently trained to improve the reliability and accuracy of the model significantly.

Figure 4 shows the comparison of the joint performance based on the typical parameters generated by the model. Each input parameter, except the non- or rotating shoulder, was drawn in a single figure while this excepted parameter was depicted in each figure. The rotation velocity and welding speed were undoubtedly the most critical factors affecting the mechanical properties of the joints. Turning points were observed in both the figures, which meant a compromise between low heat input and no welding defects. There were conditional influences on the load-bearing capacity for plunge depth and tilt angle. When the induced welding

thinning was much larger than the load-bearing area of the welding nugget zone (WNZ), it decreased significantly, so the load-bearing area of the WNZ was lower than that of the heat-affected zone (HAZ), and the global tensile strength started to decline. In addition, the tilt angle also had effects on the suppression of welding defects. Zero or a much too small tilt angle tended to induce welding defects, which reduced the performance of the joints. Moreover, for various welding tools, their impacts on joint performance were mainly reflected in regulating heat input and changing material flow behavior. These behaviors were difficult to analyze through existing theories. Our prediction achieved the dissecting of valuable information. There was a turning point in the prediction of each parameter to provide design references for obtaining optimal local combinations of welding parameters. The nested neural network was built with a built-in generator and predictor, rather than a simple full connect

neural network using only primitive parameters. This allowed our model to obtain more intrinsic information about the impact of various parameters on the load-bearing capacity of the joints. This combined strategy made the model have better generalization performances and provided a potential for the transfer application.

Conclusions

A nested neural network, including a generator and a predictor, can accurately predict the tensile strength of the joint. The final R-squared based on the experimental result for tests was 0.951. The nested neural network is better than the simple neural network with low information density at forecasting the tensile performance of the welded joints. The introduction of the intermediate field data effectively improves the generalization performances.

The primitive parameters affect the mechanical performances of the joints via changing the thermal cycle and the velocity gradient around the welding tools. Reducing heat input decreases the critical nucleation size of the precipitations, increases the nucleation rate, and obtains more efficient precipitation strengthening. It also reduces the coarsening tendency of grains with or without recrystallization, which avoids the loss of grain boundary strengthening. The strain rate representing the velocity gradient improves the joint performances by increasing the diffusion rate, increasing the nucleation rate, and suppressing the grain coarsening.

Reducing heat input as much as possible and remaining an adequate load-bearing area of the WNZ under the premise of no welding defects are sufficient and necessary conditions to obtain high performance of the joints. The strategy can be accessed based on the selection of welding parameter combinations and tailored to the geometric design of the welding tool to improve the material flow. Threads and milling facets on a welding pin can increase the strain rate, but they also increased the tendencies of welding defects. Increasing the diameter of the welding tool enhances material flow but also increases the heat input. Therefore, a compromise needs to be realized to obtain the ideal joint performances.

This strategy reveals the macro-micro dynamic evolution during the whole FSW process. Combining classic numerical simulation and machine learning provides an efficient and accurate prediction of the joint load-bearing characteristics. Since the reliability of the neural network can continue to increase with more datasets from both experiments and simulation, this combined strategy has a promising potential for development. In addition, this strategy is not only suitable for friction stir welded aluminum alloys but can also effectively achieve general transfer learning and application for more welded materials.

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Appendix I: Standardization and Normalization of Raw Inputs

The methods of standardization and normalization of raw inputs are listed in Table A1.

Table A1 — Standardization and Normalization of Raw Inputs		
Input	Method	Value
Diameter of the shoulder	Standardization	Input = Raw value/ (1 mm)
Diameter of the pin	Standardization	Input = Raw value/ (1 mm)
Length of the pin	Standardization	Input = Raw value/ (1 mm)
Pitch of the thread	Standardization	Input = Raw value/ (0.1 mm)
Numbers of the facets	Standardization	Input = Raw value
Depth of the facets	Standardization	Input = Raw value/ (0.1 mm)
Welding speed	Standardization	Input = Raw value/ (100 mm/min)
Rotational velocity	Standardization	Input = Raw value/ (100 rpm) ^a
Plunge depth	Standardization	Input = Raw value/ (0.1 mm)
Tilt angle	Standardization	Input = Raw value/ (1 deg)
Non- or rotational shoulder	One-hot method	Stationary shoulder (0) Rotational shoulder (1)
Type of the thread	One-hot method	Triangular (1, 0, 0) Trapezoidal (0, 1, 0) Circular (0, 0, 1)
Material of the tool	One-hot method	H13 (1, 0, 0, 0, 0) M42 (0, 1, 0, 0, 0) WC-Co (0, 0, 1, 0, 0) W-Re (0, 0, 0, 1, 0) PCBN (0, 0, 0, 0, 1)

^a In the case of the rotating shoulder, this value is the rotational velocity of both the shoulder and pin, while in the case of the stationary shoulder, this value is the rotational velocity of the pin only.

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