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ARTIFICIAL INTELLIGENCE PREDICTED MAXIMUM TEMPERATURE IN FRICTION STIR WELDING OF AA3003

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ABSTRACT

The present study highlights the influence of feed rate, rotational speed, and tool inclination angle on the evolution of the maximum temperature generated during friction stir welding (FSW) of aluminum AA3003. To predict these thermal variations, six machine learning models were developed and trained using a dataset composed of 64 experimental trials covering a wide range of process parameters. The models include an SVM, Gaussian process regression, and neural networks. The models were evaluated using standard statistical indicators (RMSE, MAE, R^2). The results demonstrate the superiority of the GPR model with a Matérn 5/2 kernel. This model achieved an excellent fit on the model development dataset (training + validation + testing), with an RMSE of less than 0.02 °C and an R^2 close to unity. On the independent external validation sets used for extrapolation assessment, the same model yielded the lowest RMSE of 1.57 °C. This model also stood out for its robustness on unprecedented configurations, with a relative error of less than 1.6%. The proposed approach demonstrates the potential of machine learning techniques to model the complex thermal phenomena of FSW accurately and represents a step towards intelligent predictive control of welding processes.

Keywords: FSW, AA3003, Maximum Temperature.

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1. INTRODUCTION

Friction stir welding (FSW) is a solid-state joining technique introduced by The Welding Institute in 1991 [1] that offers a transformative approach for assembling aluminum structures, overcoming the limitations of conventional welds, particularly for the non-heat-treatable AA3003 alloy. Indeed, FSW operates at 80% of the alloy's melting point, producing homogeneous joints with refined microstructures and minimal defects [2][3].

Temperature is a crucial factor in the FSW process because it directly impacts the microstructure and mechanical properties of welded joints. Many studies have focused on predicting and analyzing the heat generated during FSW, known as the welding temperature, especially the maximum temperature (Tmax), which depends heavily on welding parameters such as rotation speed, feed rate, tool geometry, and tool angle. Most of these studies rely on traditional methods like numerical simulation, design of experiments (DoE), and finite element analysis (FEA) to optimize FSW parameters. Schmidt and Hattel [4] and Ahmed and Ramy [5], used analytical approaches to estimate temperature by simplifying the mathematical relationships between welding parameters and temperature, though these methods are based on restrictive assumptions. Experimental designs have also identified critical parameters such as rotational speed and axial force [6–10]. Recent advancements include thermomechanical material behavior [11–13], considering temperature-dependent properties, heat generation, plastic deformation, friction, and tool geometry.

Despite the contributions of analytical, experimental, and finite element methods, the inherent complexity of FSW, characterized by highly nonlinear interactions between operating parameters and thermal responses, limits the accuracy and applicability of traditional approaches. As a result, artificial intelligence (AI) has become a promising alternative. Neural networks (RBFNN) [14], regression models (RFR, SVR) [15-16], and other machine learning techniques [17-18] have demonstrated high accuracy in predicting temperature peaks and handling FSW's complex nonlinearities.

This study aims to assess how tool rotation speed, welding speed, and inclination angle affect the maximum temperature during AA3003 welding. The main goal is to predict the maximum temperature (Tmax) during welding by evaluating and comparing the performance of six AI models: three neural networks trained with Levenberg Marquardt (LM), stepwise conjugate gradient (SCG), and Bayesian regularization (BR) backpropagation algorithms, a quadratic kernel SVM model, and two GPR models using Matern 5/2 and exponential kernels. FSW experiments are performed at different rotation speeds, welding speeds, and tool angles to gather data for training machine learning models. The predictive performance of these models is assessed by comparing their results with experimental data. Although previous studies have explored machine learning techniques such as ANN, SVM, and GPR for predicting various aspects of FSW, such as tensile strength, torque, or temperature in other aluminum alloys, the present work contributes novel insights by focusing on the thermal behavior of AA3003 alloy. Particular emphasis is placed on the influence of tool inclination angle, a parameter frequently underrepresented in modeling efforts in combination with feed rate and rotational speed.

2. EXPERIMENTAL METHOD

Two AA 3003 aluminum plates (210 × 110 × 2 mm) were joined in the rolling direction by friction stir welding. Their mechanical properties before welding were obtained from tensile tests carried out on an INSTRON tensile machine, controlled by the MTS software, as reported in Table 1.

Table. 1 Mechanical properties of the base material [19].

Microhardness (HV)	Yield Strength σ_e (MPa)	Ultimate Strength σ_U (MPa)	Rupture Strength σ_m (MPa)	Elongation A	Young's Modulus E (GPa)
51	130	160	127	5,6	60

The tool geometry chosen based on preliminary tests conducted by Chekalil and Miloudi [19] is similar to that of a conical pin, with the following dimensions: d = 5 mm, D = 6.8 mm, and length = 1.7 mm. It features a concave shoulder with a 3° angle and a diameter of 19.5 mm.

The joint configuration was obtained by fixing the plates in position using mechanical clamps. A single-pass welding procedure was followed to fabricate the joints. Temperature history is measured during FSW operation using three thermocouples on the advancing side (AS) and three on the retreating side (RS). The K-type thermocouples, capable of withstanding temperatures from − 40 °C to 1200 °C, are connected to a thermal recorder and placed on the AA 3003 plates at 10 mm, 12 mm, and 14 mm from the centerline of the weld joint.

A full factorial design of experiments (DoE) was used to investigate three key FSW parameters: rotational speed, feed rate, and tool tilt angle. The present study examines the influence of these parameters on heat input, using maximum temperature (Tmax) as the primary response. A total of 64 experimental runs were generated with Design-Expert 13 software [19].

3. PARAMETRIC STUDY

3. 1. Effects of FSW process parameters on Tmax

Predicting the maximum temperature ($Tmax$) in friction stir welding requires understanding the effects of input parameters and their interactions on $Tmax$. This section systematically analyzes these individual and combined influences to improve prediction accuracy, which is critical for preventing material melting [21].

Response surface methodology (RSM) using Design-Expert software was applied to quantify the effects of rotational speed (N), feed rate (S), and tool tilt angle (θ) on maximum temperature (Tmax) in FSW of AA3003 alloy by investigating the interaction between two factors, while keeping the third constant. Figure 1 illustrates this variation.

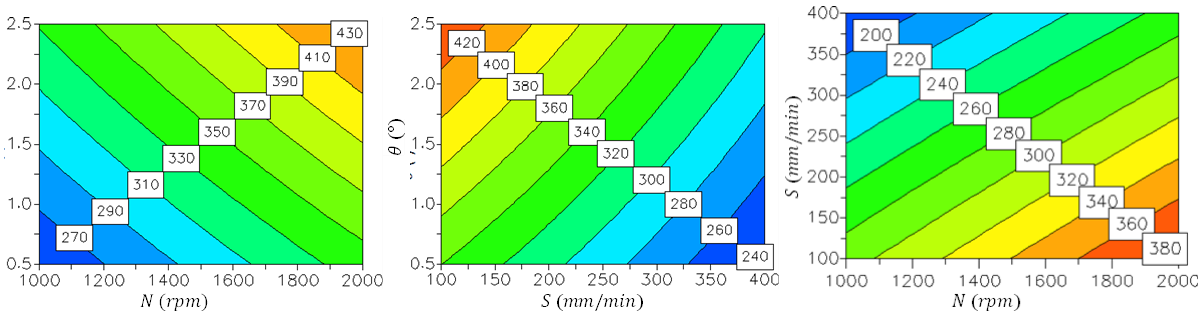

Fig.1: Variation of Tmax as a function of N, S, and θ

Analysis of the figure shows that Tmax increases markedly with higher rotational speed (N) due to greater frictional heat generated between the shoulder/pin of the tool and the surface of the workpiece. At the same time lower feed rate (S) prolongs heat exposure, and a higher tilt angle (θ) enhances shoulder contact, which also results in additional heat generation. Highest Tmax occurs at N between 1600 and 2000 rpm, θ between 2 and 2.5°, and S between 100 and 160 mm/min; lowest at N between 1000 and 1200 rpm, θ between 0.5 and 1.5°, and S between 280 and 400 mm/min, which is in agreement with [22–24] as higher heat input promotes dynamic recrystallization and grain refinement.

3. 2. Artificial intelligence models development

This step of the study compares the performance of three backpropagation-trained artificial neural networks (Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), and Bayesian Regularization (BR)) against three advanced machine learning models: Support Vector Machine (SVM) with quadratic kernel, and two Gaussian Process Regression (GPR) models with Matérn 5/2 and Exponential kernels, respectively. The goal is to determine the most accurate model for predicting the maximum measured temperature (Tmax) during friction stir welding of AA3003 aluminum alloy. Before training, all input and output data were normalized to the range [0, 1]. The selection of the three input parameters was guided by their physical influence on heat generation in FSW.

The neural networks consist of one hidden layer with sigmoid activation neurons and a linear output layer. This two-layer feed-forward architecture, available in the Neural Net Fitting tool of MATLAB R2021b, is particularly suitable for regression tasks such as modeling the complex non-linear relationships between the input parameters and the maximum welding temperature (T_{max}).

The default hyperparameters of MATLAB's Neural Network Toolbox used were: a maximum of 1000 epochs, a performance goal of 0, a minimum performance gradient of 10−7, and an initial learning rate of 0.001 when required by the training algorithm.

A structured data division was applied, combined with early stopping during neural network training, to mitigate the risk of overfitting, where the model becomes too complex and starts to fit noise instead of the actual underlying patterns, which is a common challenge with data-driven models, due to the relatively small size of the experimental dataset [25]. From the 60 experimental datasets, 70% were allocated for training, 15% for testing, and 15% for validation. Four additional independent datasets were reserved for the final external evaluation of the models.

Models were developed using a trial-and-error approach in MATLAB. Multiple network with varying

numbers of neurons in the hidden layer (ranging from 5 to 20) were systematically tested. The architecture yielding the lowest Root Mean Square Error (RMSE) across the training, testing, validation, and external evaluation sets was retained. The optimal network architecture identified was 3-10-1 (3 input neurons, 10 neurons in the hidden layer, and 1 output neuron).

This choice is supported both by empirical performance and by the commonly used heuristic formula [26] for estimating the number of hidden neurons:

$$NH \approx 0.5 \times (N_I + N_o) + p \times \sqrt{N_t}$$

where NH is the number of hidden neurons, N_I is the number of input neurons (= 3), N_o is the number of output neurons (= 1), N_t is the number of training samples, and p is an empirical parameter usually between 0 and 1 [26].

3. 3. Model's evaluation and results

The results of the various models were compared to evaluate their predictive accuracy and generalization ability in estimating the maximum welding temperature, based on process parameters. The models' performance was evaluated using three statistical indicators: the root mean square error (RMSE), the mean absolute error (MAE), and the coefficient of determination R^2, which are defined by :

architectures

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(T_{max_i} - \hat{T}_{max_i}\right)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|T_{max_i} - \hat{T}_{max_i}\right|$$

$$R^2 = 1 - \frac{\sum\left(T_{max_i} - \hat{T}_{max_i}\right)^2}{\sum\left(T_{max_i} - \bar{T}_{max_i}\right)^2}$$

Where

T_{max_i} is the experimental value, $\hat{T}_{max_i}$ is the predicted value, and $\bar{T}_{max_i}$ is the average of the observed values.

All models (ANN, SVM, GPR) showed good correlation with experimental data. The results of the statistical indicators on the entire dataset are shown in Table 2.

Table 2: Comparison of model performance.

Model	RMSE	MAE	R^2
LMV	9.3020	5.7375	0.9794
BR	7.1881	5.7009	0.9877
SCG	7.5369	5.1503	0.9865
Matern 5/2	11.2244	8.5157	0.9701
Exponential	0.0182	0.0139	0.9999

We were able to highlight the performance differences between the various models by plotting the performance trends of the machine learning models in terms of RMSE on Figure 2 for the training, validation, and test phases, as well as on the entire dataset.

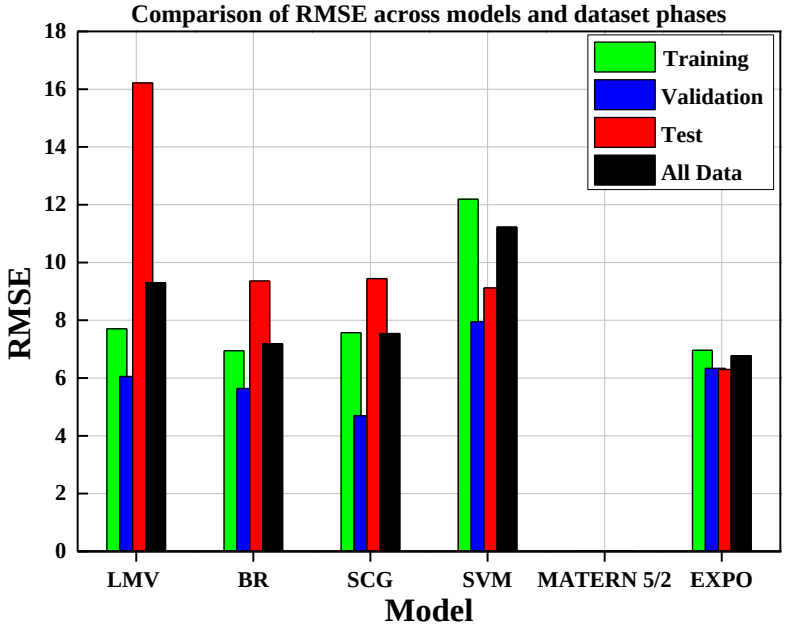

Fig.2: Comparison of RMSE across models and dataset phases

Artificial neural networks (ANNs) provide strong predictive performance for FSW temperature estimation. The Levenberg-Marquardt (LMV) model achieves good accuracy (R^2 = 0.9794), while Bayesian regularization (BR) improves generalization (R^2 = 0.9877, RMSE = 7.19 °C). The SCG model delivers the lowest MAE (5.15) with R^2 = 0.9865. Though slightly less accurate than GPR, ANNs offer a favorable trade-off between accuracy and computational efficiency for industrial use.

The quadratic SVM shows moderate performance, with higher error (RMSE = 11.22 °C), likely due to sensitivity to complex nonlinearities in the FSW process.

To evaluate model robustness and generalization, four new experimental tests (Table 3) were conducted using parameter combinations outside the training/validation sets. Predictive accuracy was evaluated by extrapolation, calculating the root mean square error (RMSE) between the measured and predicted Tmax values for each model.

Table 3. Validation of LMV, BR, SCG, SVM, and GPR models using additional experiments outside the training, testing, and validation datasets.

N°	Vr	S	θ	T_{max}	LMV	BR	SCG	GPR Matern 5/2	GPR Expo	SVM
1	1500	400	0.5	200	210.39	204.77	209.13	202.98	204.50	211.37
2	1700	400	1.5	238	241.51	236.11	235.85	238.33	237.25	244.93
3	1500	300	2	258	266.65	261.18	257.35	257.61	260.55	267.10
4	1000	400	2.5	216	220.51	218.32	219.34	216.82	217.44	230.43

RMSE	7.34	3.23	4.98	1.57	2.71	10.82

4. CONCLUSION

This study investigates the maximum measured temperature (Tmax) during friction stir welding (FSW) of AA3003 alloy as a function of rotational speed, feed rate, and tool inclination angle. The effect of process parameters was first analysed using Response Surface Methodology. Then six AI-based models were developed and compared for Tmax prediction: three ANNs (trained with Levenberg-Marquardt, Scaled Conjugate Gradient, and Bayesian Regularization), one quadratic-kernel SVM, and two GPR models (Matérn 5/2 and exponential kernels). Performance was evaluated using RMSE, MAE, R^2, and R.

Key findings on process parameters:

- Temperatures are slightly higher on the advancing side.
- Higher rotational speed and lower feed rate markedly raise Tmax.
- Tool inclination angle has a negligible influence below 1.5°, but higher angles produce a near-linear decrease in Tmax.

Among the models, the GPR with Matérn 5/2 kernel achieved the best performance (RMSE < 0.02 °C, $R^2 \approx 1$), followed by the SCG-ANN. The quadratic SVM showed the largest errors. Extrapolation tests on new parameter combinations confirmed GPR's superior robustness, with relative errors < 1.6%.

The adoption of GPR with a Matérn 5/2 kernel, validated through rigorous external testing on unseen configurations, demonstrates excellent predictive accuracy and generalization potential. This approach represents a concrete step toward data-driven predictive control of the FSW process, addressing the growing industrial need for accurate real-time temperature management to ensure weld quality and process stability

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