Systematic evaluation of pulsed laser parameters effect on temperature distribution in dissimilar laser welding: A numerical simulation and artificial neural network

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Abstract

The heat transfer mechanism and temperature distribution in laser welding applications have a great impact on the quality of the weld bead geometry, mechanical properties and the resultant microstructure characterizations of the welding process. In this study, the effects of pulsed laser welding parameters including the frequency and pulse width on the melt velocity field and temperature distribution in dissimilar laser welding of stainless steel 420 (S.S 420) and stainless steel 304 (S.S 304) was investigated. A comprehensive comparison was conducted through the numerical simulation and artificial neural network (ANN). The results of numerical simulation indicated that buoyancy force and Marangoni stress are the most important factors in the formation of the flow of liquid metal. Also, increasing the pulse width from 8 to 12 ms due to increasing the pulse energy, the temperature in the center of the melt pool increased about 250 °C. This leads to increasing the convective heat transfer in the molten pool and heat affected zone (HAZ). The temperature difference at a distance of 1 mm from the beam center at both metals at a frequency of 15 and 20 Hz is bout 58 and 75 °C, respectively. Furthermore, reducing the frequency to 5 Hz, due to diminishment of thermal energy absorption time, has clearly decreased the weld penetration depth in the workpiece. According to the ANN results, increasing both pulse duration and frequency has the significant effect on increasing melting ratio from 0.4 to 0.8 compared to the other input parameters. The ANN results confirmed that under the same input conditions, because of the differences in thermal conductivity coefficient, absorption coefficient and melting point of the two pieces, S.S 304 has experienced higher temperatures about 10% more than S.S 420. Also, among the 13 back propagation learning algorithms, the Bayesian regularization algorithm had the best performance.

Among the number of different neurons in the hidden layer, comparison was performed to prevent network overfitting. The maximum relative error of network output data and target data for S.S 304 and S.S 420 temperatures and melting ratio were 7.297, 10.16 and 11.33%, respectively.

Full Text

Preamble

Systematic Evaluation of Pulsed Laser Parameters Effect on Temperature Distribution in Dissimilar Laser Welding: A Numerical Simulation and Artificial Neural Network Study

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The heat transfer mechanism and temperature distribution in laser welding applications significantly impact weld bead geometry, mechanical properties, and resultant microstructural characteristics. This study investigates the effects of pulsed laser welding parameters—including frequency and pulse width—on melt velocity fields and temperature distribution during dissimilar laser welding of stainless steel 420 (S.S 420) and stainless steel 304 (S.S 304). A comprehensive comparison was conducted through numerical simulation and artificial neural network (ANN) modeling. Numerical simulation results indicated that buoyancy forces and Marangoni stresses are the most critical factors governing liquid metal flow. Increasing the pulse width from 8 to 12 ms increased the temperature at the melt pool center by approximately 250 °C due to higher pulse energy, which enhanced convective heat transfer in both the molten pool and heat-affected zone (HAZ). The temperature difference between the two metals at a distance of 1 mm from the beam center was about 58 °C and 75 °C at frequencies of 15 Hz and 20 Hz, respectively. Furthermore, reducing the frequency to 5 Hz clearly decreased weld penetration depth due to diminished thermal energy absorption time. According to ANN results, increasing both pulse duration and frequency had a significant effect on increasing the melting ratio from 0.4 to 0.8 compared to other input parameters. The ANN results confirmed that under identical input conditions, S.S 304 experienced temperatures approximately 10% higher than S.S 420 due to differences in thermal conductivity, absorption coefficient, and melting point. Among 13 backpropagation learning algorithms, the Bayesian regularization algorithm demonstrated the best performance. A comparison of different neuron counts in the hidden layer was performed to prevent network overfitting. The maximum relative errors between network outputs and target data for S.S 304 temperature, S.S 420 temperature, and melting ratio were 7.297%, 10.16%, and 11.33%, respectively.

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[Figure 1: see original paper]. Schematic configuration of the laser welding process.

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1. Introduction

Connecting and cutting different components is crucial in thermal industries. In recent years, various joining methods have been proposed, with laser beam welding emerging as a popular technique for processing diverse materials [1,2]. This technology has attracted significant attention from researchers and practitioners due to its high depth-to-width ratio of heat dissipation, resulting from the high beam density and concentration in the welding zone. These unique characteristics have led to widespread adoption across automotive, aerospace, marine, construction, and laboratory applications [3-5]. One important application of laser welding is joining dissimilar alloys [6], which has been extensively reported in previous studies due to the distinct material properties involved [7,8]. The fusion zone contains elements from both base metals, making it essential to investigate property changes in relation to laser parameters.

Numerical methods have been widely studied for welding quality evaluation, as they enhance accuracy and quality while reducing production costs [9-12]. Numerical simulation of stainless steel 304 (S.S 304) and stainless steel 420 (S.S 420) dissimilar welding can lead to optimal welds due to the unique properties of these alloys. Investigation of stainless steel alloys is particularly important given their excellent strength and corrosion resistance, making them suitable for industrial and medical tool manufacturing if ideal welds can be achieved.

[Figure 2: see original paper]. Uniform grid system for the calculation domain.

Numerous studies have examined dissimilar laser welding processes. Lu et al. [13] employed smoothed particle hydrodynamics (SPH) simulations to show that waveform size at the interface increases with laser energy along the welding direction, correlating this phenomenon with normal stress, horizontal welding speed, and jet velocity. Lin et al. [14] numerically investigated molten pool dimensions and temperature distribution trends during stainless steel-copper welding, revealing asymmetric heat fields and molten pools deviated toward the AISI 304 sheet, with laser power identified as the most critical parameter determining molten pool dimensions. Li et al. [15] studied microstructure and mechanical properties of stainless steel-brass joints, finding laser energy to be highly effective in controlling amplitude, wavelength, and bonding waveform, with optimal weldability achieved at a 0.2 mm flight distance. Yu et al. [16] examined brass-SS308 laser welding properties, observing asymmetric melting pools with greater brass melting due to its lower melting temperature and higher thermal conductivity. Dong et al. [17] investigated process parameter effects on melting ratio and temperature distribution in brass-S.S 308 laser welding, demonstrating that numerical methods can reduce error, cost, and time. Ding et al. [18] studied parameter effects on weld shape and temperature distribution in stainless steel-brass welding, attributing asymmetric melt pools to brass' s lower melting temperature and high heat transfer rate, which increased melt volume. Nguyen et al. [19] investigated temperature fields and fusion zone microstructure in austenitic stainless steel-copper alloy welding, finding that increased welding speed reduced both temperature and fusion zone cracking, while higher laser power shifted cracks toward the stainless steel base due to elevated steel temperatures.

Saha et al. [20] optimized S.S 316 laser welding parameters using central composite design, confirming that laser power, focal distance, and welding speed are critical for weld quality. Prabakaran et al. [21] optimized AISI 316-AISI 1018 laser welding parameters using Taguchi-based GRA numerical simulation, identifying laser power, welding speed, and focal length as key quality determinants, with post-weld heat treatment yielding optimal tensile strength. Huang et al. [22] numerically studied aluminum-steel laser welding, confirming that increased fluid flow behind the keyhole and greater depth-to-width ratios destabilize the keyhole and increase porosity. Bhatt et al. [23] examined Nd:YAG laser welding parameter effects on S.S 316 and brass, showing that increased energy and laser power enhanced penetration depth more significantly in brass alloys.

Kumar et al. [24] investigated laser beam incident angle effects on austenitic stainless steel welding, demonstrating that weld pool geometry depends on angle deviation, transitioning from hemispherical to teardrop shapes at lower impact angles. Chen et al. [25] studied laser parameter effects on stainless steel-copper welding quality, revealing strong parameter influence on HAZ dimensions and noting that copper melting reduces joint toughness. Li et al. [26] examined laser power effects on brass-stainless steel dissimilar welding, finding that welds produced below 1846 W had fewer defects and better microstructure and mechanical properties. In another study, Li et al. [27] evaluated H62 brass-S.S 316L weld quality, demonstrating superior joint performance with brass overlapping steel and no intermetallic compounds. Sasaki et al. [28] investigated brass-stainless steel welding quality, achieving good welds by shifting laser radiation position toward brass. Dong et al. [29] examined copper-brass laser welding, achieving suitable penetration welds through optimal parameters. Galun et al. [30] studied stainless steel-brass welding, finding brass-steel welds stronger than brass-brass joints and capable of withstanding deep tensile processes. Zhang et al. [31] numerically and experimentally investigated residual stress fields at different bending angles, showing that proper welding path selection can reduce residual stress by 20-40 MPa.

Geng et al. [32] performed pulsed Nd:YAG laser welding of S.S 304 and S.S 420, obtaining temperature distribution, microstructure, and mechanical properties of the welded zone, investigating pulse width and frequency effects on fusion zone temperature and copper behavior. Their results showed that laser pulse duration and frequency induced similar changes in heating and cooling cycles.

The rapid heating and cooling process alters metal microstructure and changes mechanical and physical properties. High temperatures cause thermal expansion and stress, potentially leading to weld distortion and cracking. Therefore, temperature control during laser welding is essential for ensuring desired material properties and structure [33,34]. This study aims to investigate pulsed laser welding parameter effects—specifically pulse width and frequency—on temperature and velocity distribution and molten pool dimensions using finite volume method-based numerical simulations. Additionally, ANN is employed to develop a predictive model for molten pool dimensions based on laser welding parameters. The finite volume method is more appropriate for predicting temperature at the molten pool center and melt flow behavior, while ANN can predict temperature and approximate molten pool dimensions with lower time and cost, making it suitable for industrial applications. By combining ANN and finite volume method, this research provides comprehensive understanding of thermal behavior during laser welding and develops a useful tool for process optimization.

Temperature gradients and liquid metal flow in the molten pool directly relate to welded metal quality and mechanical properties. Therefore, predicting parameters affecting heat transfer and fluid flow can improve welding quality and reduce costs. For numerical simulation of continuous laser welding, a transient finite volume model was employed. A numerical code defined the thermal model and temperature-dependent thermophysical properties. [Figure 1: see original paper] shows a schematic of the laser welding process and workpiece dimensions. To investigate various laser welding parameters and validate results, temperature time history was obtained around the beam center as shown in [Figure 1: see original paper]. Following a grid independence study, the number of uniform grid elements was determined to be 558,748, as shown in [Figure 2: see original paper]. presents the elemental composition of stainless steel 304 and 420 alloys [35,36].

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2. Numerical Simulation

2.1. Laser Welding Process Modeling

In keyhole laser welding, a plasma cloud forms at the molten pool surface, preventing partial laser beam penetration into the keyhole. This causes some heat input to be absorbed at the workpiece surface, representing inverse Bremsstrahlung absorption, while the remaining energy is absorbed via Fresnel absorption on the keyhole wall [37]. Therefore, Gaussian elliptical and cylindrical heat sources were used to model thermal energy absorption at the surface and depth, respectively. [Figure 3: see original paper] illustrates the thermal model schematic, with equations for elliptical and cylindrical heat sources presented in Eqs. (1) to (3) [38,39]. All thermal model equations were defined as source terms in the energy equation.

$$q_v(x,y,z) = \frac{6 f_1 \eta P}{\pi r^2 d (1 - e^{-3})} \exp\left(-\frac{3(x^2+y^2)}{r^2}\right) \frac{z + r_v}{d + 2r_v}$$

$$q_f(x,y,z) = \frac{6 f_2 f_f \eta P}{a_f b c \pi \sqrt{\pi}} \exp\left(-\frac{3x^2}{a_f^2}\right) \exp\left(-\frac{3y^2}{b^2}\right) \exp\left(-\frac{3z^2}{c^2}\right)$$

$$q_r(x,y,z) = \frac{6 f_2 f_r \eta P}{a_r b c \pi \sqrt{\pi}} \exp\left(-\frac{3x^2}{a_r^2}\right) \exp\left(-\frac{3y^2}{b^2}\right) \exp\left(-\frac{3z^2}{c^2}\right)$$

In these equations, q_v is the cylindrical volume heat flux, q_r and q_f are elliptical heat sources at the rear and front of the laser beam, respectively, P is laser power, f_r and f_f are elliptical heat source distribution coefficients at the rear and front of the beam, f_1 and f_2 are energy distribution coefficients for double-ellipsoidal and cylindrical heat sources, and a_f, a_r, b, c, d are heat source distribution parameters shown in [Figure 3: see original paper].

2.2. Governing Equations

In laser welding simulation, convection heat transfer occurs due to liquid metal flow in the molten pool, requiring coupling of momentum and energy equations. To distinguish melt and solid regions, liquid fraction was defined as follows. During freezing or melting, the liquid fraction ranges between 0 and 1. By incorporating liquid fraction in the momentum equation, forces caused by material phase changes can be applied [38].

Continuity equation:

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \mathbf{U}) = 0$$

Momentum equation:

$$\frac{\partial (\rho \mathbf{U})}{\partial t} + \nabla \cdot (\rho \mathbf{U}\mathbf{U}) = -\nabla p + \nabla \cdot \quad + \rho \mathbf{g} - \mathbf{K}\mathbf{U}$$

Energy equation:

$$\frac{\partial(\rho H)}{\partial t} + \nabla \cdot (\rho \mathbf{U} H) = \nabla \cdot (k \nabla T) + q$$

Where ρ, H, t, p, $\mathbf{U}$, k, $\mathbf{g}$, $\mathbf{K}$, and μ represent density, total enthalpy, time, pressure, velocity vector, thermal conductivity coefficient, gravitational acceleration, Darcy resistance coefficient, and dynamic viscosity, respectively [39-43].

The following assumptions were made for equation discretization [38-42]: - Fluid flow was considered incompressible, Newtonian, and laminar - Molten pool surface was assumed flat - Liquid metal vaporization was ignored - Initial temperature was set at 25 °C

2.3. Boundary Conditions

Surface boundary condition [44]:

$$-k\frac{\partial T}{\partial n} = -\varepsilon\sigma(T^4 - T_\infty^4) - h(T - T_\infty) + q_s$$

Where ε is emissivity coefficient, σ is Stefan-Boltzmann constant, T_∞ is ambient temperature, and h is convection heat transfer coefficient.

Shear stress due to surface tension gradient [45]:

$$\tau_x = \frac{\partial \gamma}{\partial T}\frac{\partial T}{\partial x}, \quad \tau_y = \frac{\partial \gamma}{\partial T}\frac{\partial T}{\partial y}$$

Lower and lateral surface boundary condition [44]:

$$-k\frac{\partial T}{\partial n} = -\varepsilon\sigma(T^4 - T_\infty^4) - h(T - T_\infty)$$

2.4. Thermophysical Properties

In laser welding, parameter variation with temperature is significant. Therefore, temperature-dependent thermophysical properties were defined for pulsed laser welding simulation. presents the thermophysical properties of S.S 304 and S.S 420 [46-50].

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3. Back-Propagation Artificial Neural Network (BP-ANN)

This study employed ANN with backpropagation learning to predict the effects of laser pulse width and frequency on temperature fields and melting ratio. BP neural networks are the most common type for function estimation and pattern recognition. In these networks, signals propagate from input to output (function signals) and from output to input (error signals). In multilayer BP networks, function signals are calculated based on neuron inputs and network parameters, while error signals modify network parameters to reduce error [51-53].

3.1. Network Architecture and Training Methods

The feedforward network architecture for training consists of a hidden layer with sigmoid transfer function and an output layer with linear transfer function. A hidden layer with nonlinear functions enables the network to model both linear and nonlinear relationships between input and output vectors. The tansig transfer function was applied in the hidden layer to prevent excessive output values. The tansig and purelin transfer functions are defined as [54]:

$$y_{\text{tansig}}(n) = \frac{2}{1+e^{-2n}} - 1$$

$$y_{\text{purelin}}(n) = n$$

[Figure 4: see original paper] illustrates the network architecture, where y is the transfer function, $\mathbf{x}$ is the input vector, $\mathbf{W}$ is the weight vector, and $\mathbf{b}$ is the bias vector, providing trainable constant values for each neuron.

In neural networks, average relative error between actual and network outputs for training and test datasets serves as a performance evaluation criterion [55]. Lower error values indicate better network performance for both training and test data. Mean squared error (MSE) can also evaluate network performance [56,57]. In this study, MSE in the backpropagation algorithm was used as the objective function, with network weights as variables. The relationships for average relative error and MSE are:

$$\text{Mean Relative Error} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

$$\text{Mean Squared Error} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where n, y_i, and $\hat{y}_i$ represent the number of data points, actual output, and network output, respectively [58,59].

Several backpropagation training algorithms exist. Thirteen algorithms [58-61] were evaluated to select the optimal one for minimal error. shows average relative output errors for various training algorithms. The Bayesian regularization algorithm achieved the lowest errors: 1.917%, 3.077%, and 2.268% for S.S 304 temperature, S.S 420 temperature, and melting ratio, respectively. This algorithm does not require a validation dataset, dividing data into only training and testing sets, enabling all data participation in training [62]. This approach may stop earlier convergence, reducing error per epoch. Therefore, Bayesian regularization was selected for network training.

In network architecture design, hidden layer neuron count is critical. Too few neurons cause underfitting, while too many cause overfitting, where the network memorizes training data but cannot generalize. To determine the appropriate neuron count, 3 to 8 neurons were tested. As shown in , the lowest errors were achieved with 5 neurons for temperature and 6 neurons for melting ratio in the hidden layer.

[Figure 5: see original paper] shows network training performance based on MSE, used as the objective function for weight and bias adjustment during training and testing across epochs. The minimum MSE values in the training stage were 50.87, 64.14, and 0.00078 for S.S 304 temperature, S.S 420 temperature, and melting ratio, respectively. The network could not achieve lower MSE in subsequent epochs, and training stopped at 220, 1000, and 142 epochs, respectively.

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4. Results and Discussion

4.1. Numerical Simulation

Predicting temperature distribution, velocity distribution, and molten pool dimensions significantly affects weld quality. Due to different thermal properties in dissimilar laser welding, determining appropriate laser parameter ranges is crucial for achieving proper molten pools. This section investigates pulsed laser welding parameter effects on temperature and velocity distribution and molten pool dimensions.

4.1.1. Temperature Distribution Predicting temperature distribution helps control primary microstructure [63,64]. Temperature history was obtained at various pulse durations and frequencies.

4.1.1.1. Effect of Pulse Width

Pulse width significantly affects weld quality, as proper adjustment can prevent cracking from rapid solidification [65]. presents parameters for investigating pulse width effects.

To identify pulse width effects (8 and 12 ms) on temperature distribution, temperature time history was examined at different transverse distances 25 mm from the workpiece edge ([Figure 6: see original paper]). Increasing pulse width only elevated temperatures at different times without affecting temperature alternation. The temperature difference between S.S 304 and S.S 420 varies due to their different thermal conductivity coefficients. Since S.S 304 has lower thermal conductivity than S.S 420, thermal penetration is reduced in S.S 304, resulting in higher temperatures near the laser beam compared to S.S 420. However, when the laser beam has not yet reached or has passed the 25 mm position, S.S 420 exhibits higher temperatures than S.S 304 due to its lower thermal penetration coefficient at low temperatures. [Figure 6: see original paper]e and 6f compare numerical simulation temperature history with experimental data from Geng et al. [32] at 2 mm lateral distance from the beam center, showing good agreement and validating thermophysical property definitions and the thermal model. Increasing pulse width from 8 to 12 ms raised melt pool center temperature by approximately 250 °C due to increased pulse energy.

4.1.1.2. Effect of Frequency

presents parameters for investigating frequency effects on temperature distribution, velocity distribution, and molten pool dimensions. Frequency adjustment controls heat input and thermal cycles in laser welding.

[Figure 8: see original paper] shows temperature history at 15 Hz and 20 Hz frequencies. Increasing frequency enhanced temperatures at various lateral distances and increased temperature fluctuations over time. Maximum molten pool temperature for both frequencies occurred at 4.03 s; with increasing distance from the beam center, maximum temperature occurred at later times due to heat penetration to surrounding areas. The temperature difference between the two metals at 1 mm from the beam center was approximately 58 °C and 75 °C at 15 Hz and 20 Hz, respectively.

[Figure 9: see original paper] shows temperature contours on the workpiece surface at 15 mm from the edge for both frequencies. Due to higher thermal penetration coefficient, temperature distribution is diverted toward S.S 420.

4.1.2. Velocity Distribution Surface tension at the molten pool surface drives liquid metal flow. Since surface tension varies with temperature, temperature differences across the molten pool surface create surface tension gradients, leading to Marangoni flow.

4.1.2.1. Effect of Pulse Width

Due to surface-active elements in stainless steel, surface tension decreases with increasing temperature. [Figure 10: see original paper] shows velocity vectors at the workpiece cross-section for 8 ms and 12 ms pulse widths. The higher temperature gradient in S.S 304 compared to S.S 420 diverts liquid metal flow toward the region with higher temperature gradient.

4.1.2.2. Effect of Frequency

Negative surface tension gradient drives melt from the laser beam center toward the molten pool walls. Increased shear stress from surface tension gradient enhances melt pool width. [Figure 11: see original paper] shows velocity vectors at 15 Hz and 20 Hz. Increasing frequency raised liquid metal velocity due to higher temperature gradient, enhancing convective heat transfer in the molten pool and HAZ.

4.1.3. Shape and Dimensions of the Molten Pool

Predicting weld bead dimensions under different laser parameters enables proper sheet joining. To validate finite volume method simulation results, micrographic data from Geng et al. [32] were used. lists validation parameters, with welding speed varying from 3.1 to 4.3 mm/s while other parameters remained constant. The focal position was within 1 mm of the component surface, and parameters m, c, and d in equations (1)-(3) were adjusted to simulate focal position effects.

[Figure 12: see original paper] compares molten pool dimensions and shapes between actual micrographs and numerical simulations. The simulation successfully predicted molten pool size and shape, confirming proper thermal model parameter selection. The results demonstrate that numerical simulation accurately captured laser welding physical behavior, establishing the approach as a reliable tool for predicting molten pool behavior.

4.1.3.1. Effect of Pulse Width

Increasing pulse width enhanced molten pool and HAZ dimensions due to longer heat transfer duration. [Figure 13: see original paper] shows liquid mass fraction at 8 ms and 12 ms pulse widths. Due to S.S 304’ s low thermal conductivity coefficient, heat penetration to surrounding areas is limited, resulting in larger molten pool and HAZ dimensions for S.S 304 compared to S.S 420.

4.1.3.2. Effect of Frequency

Molten pool dimensions and formation significantly affect joint quality. Due to different thermal properties of the workpieces, asymmetric temperature distribution occurs at the surface and through the workpiece thickness. Consequently, the molten pool is asymmetric in the workpiece cross-section, as shown in [Figure 14: see original paper]. Reducing frequency to 5 Hz decreased melt penetration depth due to reduced thermal energy absorption time, preventing proper molten pool formation for joining the two sheets.

4.2. Artificial Neural Network

[Figure 15: see original paper] through [Figure 17: see original paper] present ANN training and testing phase results. Correlation coefficient R was determined to assess network output closeness to actual outputs. When variables change in the same direction, correlation is positive; when they move in opposite directions, correlation is negative; and when no consistent relationship exists, correlation is zero. The correlation coefficient measured agreement between network and actual outputs. For both training and test datasets, values closer to 1 indicate better network learning and performance. According to [Figure 15: see original paper]-[Figure 17: see original paper], R values were 0.964, 0.944, and 0.924 for S.S 304 temperature, S.S 420 temperature, and melting ratio, respectively.

[Figure 18: see original paper] shows relative error between actual outputs and trained network outputs versus input parameters. Maximum errors were 7.297%, 10.16%, and 11.33% for S.S 304 temperature, S.S 420 temperature, and melting ratio, respectively, indicating proper network training performance. While the network performed best on training data, reliability requires logical outputs for desired inputs.

[Figure 19: see original paper]–[Figure 21: see original paper] show network outputs for desired inputs for S.S 304 temperature, S.S 420 temperature, and melting ratio, respectively. The proposed model demonstrates satisfactory accuracy for all three outputs. As shown in [Figure 19: see original paper] and [Figure 20: see original paper], under identical input conditions, S.S 304 experienced higher temperatures than S.S 420 due to differences in thermal conductivity, absorption coefficient, and melting point. [Figure 21: see original paper] shows that increasing laser power had the most significant effect on melting ratio compared to other input parameters.

The ANN outputs showed commendable congruity with finite volume method (FVM) simulation results. Predicted temperature histories and contours from FVM simulations agreed well with ANN results, demonstrating ANN robustness in system prediction. Beyond accuracy, ANN offers substantial computational cost reduction compared to FVM simulation and can predict extensive parameter arrays, including temperature distribution and molten pool dimensions, making it a versatile and efficient tool for modeling complex systems.

Compared to other studies, our results show similar trends regarding pulse width and frequency effects on temperature and molten pool dimensions. However, specific parameter values and effects may vary depending on welded materials and experimental conditions, necessitating careful parameter selection and adjustment for each case to achieve desired weld quality. Dissimilar laser welding has attracted considerable attention for joining materials with different thermal properties, though controlling the process and obtaining high-quality joints remains challenging.

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5. Conclusions

This study investigated pulsed laser welding parameter effects on temperature, velocity, and molten pool dimensions in dissimilar alloy joining using numerical simulation and artificial neural network modeling. Generally, the finite volume method effectively predicts temperature at the molten pool center, melt flow behavior, and thermophysical properties, while ANN can predict temperature and approximate molten pool dimensions through experimental data training at lower time and cost.

For accurate laser welding modeling, temperature-dependent thermophysical properties were defined, and elliptical-cylindrical heat sources were employed. Key findings include:

Due to dissimilar welding of two workpieces, temperature distribution was asymmetric, with S.S 304 experiencing higher temperatures than S.S 420 due to its lower thermal conductivity coefficient. Increasing pulse width from 8 to 12 ms raised molten pool temperature by approximately 300 °C. Shear stress from surface tension gradient at the molten pool surface drove liquid metal flow. Decreasing frequency reduced melt penetration depth, with 15 Hz frequency failing to create a proper molten pool for joining. A hidden layer with sigmoidal transfer function enabled nonlinear relationships between input and output vectors, improving network performance. Optimal hidden layer neuron counts were 5 for temperature and 6 for melting ratio. Minimum training phase MSE values were 50.87, 64.14, and 0.00078 for S.S 304 temperature, S.S 420 temperature, and melting ratio, respectively. Correlation coefficients R were 0.964, 0.944, and 0.924 for the three outputs, respectively.

Declaration of Competing Interest

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability

Data and materials are available and can be provided upon request.

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