

Deep Learning-Assisted Multi-Objective Optimization and Microstructure Property Correlation in Rotary Friction Welding of Dissimilar AA1100–AA2014 Aluminium Alloys

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Abstract

Joining dissimilar aluminium alloys is still a challenge due to the differences in their thermal and mechanical properties which cause non-uniform deformation and poor joint performance. The present study aims to study the mechanical behavior, microstructural evolution and intelligent optimization of AA1100–AA2014 dissimilar aluminium joints produced by rotary friction welding. The Taguchi L27 experimental design was used to change the rotational speed, friction pressure, forging pressure, friction time, and forging time. The tensile test, microhardness test, scanning electron microscopy (SEM) and X-ray diffraction (XRD) were used to assess the weld quality. A deep neural network (DNN) combined with the NSGA-II algorithm was designed to predict and optimize welding performance. The optimized joints had a maximum tensile strength of 142 MPa, hardness of 122.3 HV, and a predictive accuracy of $R^2 = 0.987$, indicating good agreement between the experimental and predicted results. Microstructural analyses showed fine grains, defect-free interfaces and no harmful intermetallic phases. The proposed hybrid experimental–AI framework is an efficient decision-support tool for intelligent process optimization and reliable dissimilar aluminium joining in the aerospace, automotive and lightweight structural manufacturing sector.

1. Introduction

Aluminium alloys are widely used in the aerospace, automotive, railway, marine and defence sectors due to their high strength, low weight and energy efficiency, which has been driven by the growing demand for these properties [1–3]. The use of dissimilar aluminium alloy joints has gained special significance as it allows the incorporation of materials with complementary mechanical, thermal and corrosion-resistant properties in a single structural assembly [4, 5]. The commercially available aluminium alloys have different properties, AA1100 has excellent ductility, corrosion resistance and thermal conductivity, while AA2014 is a precipitation hardened Al–Cu alloy with high strength, good fatigue resistance and load-bearing capacity [6, 7]. The good joining properties of these alloys present significant potential for lightweight structural design, but the large differences in mechanical behaviour, thermal conductivity, plastic flow properties and precipitation kinetics often result in heterogeneous deformation, residual stresses and loss of joint integrity when conventional fusion welding methods are used [8–10]. The challenges have encouraged growing research interest in more sophisticated solid-state joining methods that can create defect-free dissimilar aluminium joints with enhanced mechanical properties [11]. Rotary friction welding (RFW) is one of the most dependable solid-state joining processes since the welding process takes place at temperatures lower than the melting point of the base materials [12–13]. Compared with traditional fusion welding, RFW has the advantages of reducing porosity, hot cracking, solidification defects and excessive heat-affected zone, and promoting dynamic recrystallization, refined grain structure and excellent metallurgical bonding [14–16]. The process is based on the controlled interaction of the rotational speed, friction pressure, forging pressure, friction time, and forging time, which control the heat generation, plastic deformation, flash formation, flow of interfacial material, and mechanical performance of the joint [17]. In recent reviews, it has been highlighted that control of thermomechanical conditions is critical to suppress undesirable interfacial reactions, refine the weld

microstructure and produce high strength dissimilar joints for critical engineering applications [18]. The understanding of rotary friction welding of aluminium alloys has been greatly enhanced by recent investigations. Experimental research has shown that the optimized combination of rotational speed and axial pressure can achieve better tensile strength, hardness and fatigue performance by promoting plastic flow and grain refinement, while excessive heat input can lead to over-aging, softening in the local area and a decrease in ductility [19–21]. The results of microstructural analyses, performed by scanning electron microscopy (SEM), electron backscatter diffraction (EBSD), and X-ray diffraction (XRD), have confirmed that the improved joint integrity is mainly due to dynamically recrystallized grains, homogeneous mixing of material and controlled evolution of precipitates [22–23]. At the same time, researchers have increasingly turned to statistical optimization methods such as Taguchi design, response surface methodology and analysis of variance (ANOVA) to find out the relative contribution of the process variables to the welding performance [24–26]. More recently, artificial intelligence and machine learning techniques have received significant interest due to their ability to capture highly nonlinear process–structure–property relationships and significantly reduce the experimental cost [27].

However, there are still some critical research questions that need to be addressed. Most of the published research has been on similar aluminium alloys or other dissimilar material combinations, and systematic studies of the rotary friction welding of AA1100–AA2014 aluminium alloys are limited [28]. The conventional statistical models or shallow artificial neural networks are commonly used in existing predictive studies, but they are prone to poor generalization ability for the case of multiple welding parameters when the nonlinear interaction between the parameters is complicated [29]. Moreover, most of the investigations focus on mechanical performance, but do not provide a complete correlation between welding parameters, microstructural evolution and intelligent optimization [30]. Compared to the number of studies that combine deep learning with multi-objective evolutionary optimization, few studies have validated the predictions by detailed metallurgical characterization [31]. In view of these drawbacks, the present study suggests an integrated experimental and artificial intelligence approach for the assessment and optimization of rotary friction welding of dissimilar AA1100–AA2014 aluminium alloys. To systematically study the effect of the rotational speed, friction pressure, forging pressure, friction time and forging time on tensile strength, elongation and microhardness, Taguchi L27 orthogonal experimental design was used. The process–structure–property relationships were investigated by comprehensive metallurgical characterization, which involved SEM and XRD. Comprehensive metallurgical characterization was carried out to establish process–structure–property relationships and to explain the underlying strengthening mechanisms, using SEM and XRD. A deep neural network (DNN) with careful regularization was developed to model the nonlinear relationship between welding parameters and mechanical responses, and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) was used for multi-objective optimization of the welding process. The proposed framework integrates the methodology of statistically designed experimentation, advanced microstructural characterization, deep learning prediction, and evolutionary optimization. The hypothesis is that combining the metallurgical evidence with the optimization using AI can greatly enhance the accuracy of the prediction,

determine the optimum processing parameters and serve as a reliable decision support tool for intelligent rotary friction welding [32–33].

2. Materials and Methods

2.1 Selection of materials and their properties

The base materials were chosen as commercially available AA1100 and AA2014 aluminium alloys, which have complementary mechanical and metallurgical properties, suitable for lightweight structural applications in the aerospace, automotive, marine and transportation industries. AA1100 is a commercially pure aluminium alloy with excellent corrosion resistance, ductility and thermal conductivity, while AA2014 is a precipitation-hardened Al–Cu alloy that has high strength, good fatigue resistance and is also very easy to machine. These alloys allow the creation of hybrid structures with superior strength-to-weight ratio, but also pose serious problems due to the differences in thermal conductivity, plastic deformation properties, and metallurgical compatibility in the weld zone [34]. Therefore, the AA1100–AA2014 material combination is an excellent choice for studying the effect of the rotary friction welding parameters on the integrity of the joints, evolution of the microstructures, and mechanical properties. The base materials were purchased as received and cut into cylindrical specimens of the same size. The chemical composition and nominal mechanical properties of both alloys are summarized in Tables 1 and 2, respectively, and were used for analysing the process–structure–property relationships and validation of the deep learning-based prediction and optimization framework [35].

Table 1
Chemical composition of AA1100 and AA2014 aluminium alloys (wt.%).

Alloy	Al	Cu	Mg	Mn	Si	Fe	Zn	Ti	Others
AA1100	Balance	0.05–0.20	–	0.05	≤ 0.95	≤ 0.95	0.10	–	≤ 0.15
AA2014	Balance	3.9–5.0	0.2–0.8	0.4–1.2	0.5–1.2	≤ 0.7	≤ 0.25	0.15	≤ 0.15

Table 1 shows that there are significant differences in composition between AA1100 and AA2014, especially in the higher levels of Cu, Mg and Mn in AA2014, which are known to cause precipitation strengthening and are likely to affect heat generation, material flow and metallurgical bonding during rotary friction welding.

Table 2
Nominal mechanical and physical properties of AA1100
and AA2014 aluminium alloys.

Property	AA1100	AA2014
Density (g/cm ³)	2.71	2.80
Ultimate tensile strength (MPa)	90–110	430–480
Yield strength (MPa)	30–40	290–330
Elongation (%)	30–40	10–15
Hardness (HV)	25–35	120–140
Thermal conductivity (W/m·K)	~ 220	~ 121
Elastic modulus (GPa)	69	73
Melting range (°C)	643–657	502–638

Table 2 shows the complementary mechanical and physical properties of the selected alloys, AA1100 has high ductility and thermal conductivity, while AA2014 has high strength and hardness, which is suitable for the investigation of process–structure–property relationship in dissimilar rotary friction welded joints.

2.2 Fabrication of Rotary Friction Welded Joints

The rotary friction welded joints were produced with a continuous-drive rotary friction welding machine under carefully controlled processing conditions to ensure repeatability and joint integrity. Cylindrical AA1100 and AA2014 specimens of the same dimensions were precision machined and the faying surfaces were ground using fine emery paper and then cleaned by ultrasonic cleaning in acetone to remove oxide films, oil and other surface contaminants [36]. One specimen was firmly held in the rotating spindle and the other specimen was firmly held in the stationary chuck. The frictional heat was produced by the controlled rotation under the friction pressure during welding, which caused the severe plastic deformation and dynamic recrystallization at the welding interface. After that, rotation was discontinued and the forging pressure was applied immediately to consolidate the joint and to squeeze out softened material symmetrically as a flash, which improved the metallurgical bonding [37]. To systematically study the effect of the rotational speed, friction pressure, forging pressure, friction time, and forging time on the quality of the joint, a Taguchi L27 orthogonal array was used. All the welding experiments were performed in the same environment and each parameter combination was repeated to ensure the experimental consistency and repeatability.

The flash was removed from the welds by machining, and the surface defects of the joints were visually inspected after welding, and then the specimens were prepared for tensile test, microhardness test, scanning electron microscopy (SEM), X-ray diffraction (XRD) and deep learning-based predictive analysis. Figure 1. Experimental setup for continuous-drive rotary friction welding machine used to

fabricate the specimens: (a) continuous-drive rotary friction welding machine used to fabricate the specimens; (b) representative welded joint with uniform flash formation and defect-free weld interface after the welding operation; (c) standardized tensile test specimen fabricated from the welded joint for mechanical property evaluation. The process parameters selected are summarized in Table 3.

Table 3
Process Parameters and Levels

Process Parameter	Level - 1	Level 0	Level 1
SOR (Speed of rotation) (RPM)	800	1000	1200
P _{Fr} (Friction pressure) (MPa)	30	50	70
P _{Fg} (forging pressure)(MPa)	60	90	120
t _{Fr} (Friction time)(seconds)	3	4	5
t _{Fg} (Forging time) (seconds)	3	5	7

2.3 Experimental testing

Standardized experimental procedures were used to assess the mechanical performance and microstructural characteristics of the rotary friction welded AA1100–AA2014 joints. The ultimate tensile strength and percentage elongation were determined by tensile test performed on computer controlled universal testing machine as per ASTM E8/E8M. To ensure repeatability and reduce experimental uncertainty, three specimens were tested under the same conditions and the average values were reported [38]. The Vickers microhardness measurements were conducted across the weld interface according to ASTM E384 with a load of 500 g and a dwell time of 15 s to examine the hardness distribution in the weld zone and surrounding base materials [39]. The fracture morphology, weld interface characteristics and elemental distribution were studied by scanning electron microscopy (SEM) and the phase identification and crystallographic evolution were studied by X-ray diffraction (XRD) in a 2 θ range of 20°–80° with Cu-K α radiation ($\lambda = 1.5406 \text{ \AA}$) [40]. The experimental results were statistically analyzed using analysis of variance (ANOVA), and the validated data set was then used to model the process–structure–property relationships using deep neural network (DNN) and to optimize the process–structure–property relationships using NSGA-II based multi-objective optimization [41]

2.4 Deep Learning Prediction Model

The experimental data from the Taguchi L27 design was used to develop a Deep Neural Network (DNN) to predict the mechanical properties of AA1100–AA2014 rotary friction welded joints. The input variables comprised rotational speed, friction pressure, forging pressure, friction time, and forging time, while the output variables included ultimate tensile strength, percentage elongation, and microhardness.

Figure 2 Workflow of the deep neural network model integrated with NSGA-II for prediction and multi-objective optimization of rotary friction welding parameters.

All the experimental data were normalized using the Min–Max scaling technique before training the model to enhance convergence and prediction accuracy. The data set was split into 70% training, 15% validation and 15% testing subsets. The proposed DNN architecture was composed of five neurons in the input layer, 32–64–32 neurons in the three hidden layers, and three neurons in the output layer. A linear activation function was used in the output layer, while the hidden layers used the ReLU activation function. The Adam optimizer with a learning rate of 0.001 and Mean Squared Error (MSE) loss function were used for model training. L2 regularization ($\lambda = 0.001$), dropout rate (0.20), early stopping and 5-fold cross validation were added to improve generalization and prevent overfitting [42]. The coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) were used to assess model performance. The validated DNN model was then combined with NSGA-II algorithm to determine the best welding parameters for improved joint performance.

Table 4
Hyperparameters and training configuration adopted for the deep neural network prediction model.

Parameter	Value
Input variables	5
Output variables	Tensile strength, Elongation, Hardness
Hidden layers	3
Neurons	32–64–32
Activation function	ReLU
Output activation	Linear
Optimizer	Adam
Learning rate	0.001
Loss function	Mean Squared Error (MSE)
Batch size	8
Maximum epochs	300
L2 regularization	$\lambda = 0.001$
Dropout rate	0.20
Cross-validation	5-fold
Data split	70%–15%–15%
Performance metrics	R^2 , RMSE, MAE, MAPE

3. Result and discussion

3.1 Mechanical Properties of Rotary Friction Welded Joints

The experimental mechanical properties of the dissimilar AA1100–AA2014 joints are given in Table 5. The results show that the welding parameters had a significant effect on the tensile strength, percentage elongation and microhardness due to their direct effect on frictional heat generation, plastic deformation and metallurgical bonding between the interface. As the welding parameters approached their optimum combinations, the tensile strength was raised from 95 MPa to a maximum of 142 MPa, and the microhardness was raised from 41.1 HV to 122.3 HV. In Experiments 18 and 27, the highest tensile strength was achieved, which suggested that the rotational speed, friction pressure, friction time and forging pressure were sufficient to ensure uniform heat generation and good plasticization of the material. These conditions enabled dynamic recrystallisation, grain refinement and the development of a sound metallurgical interface, which enhanced the load bearing capacity of the welded joints. On the other hand, the minimum processing conditions (Experiment 1) with lower heat input led to lower tensile strength and hardness, as the plastic flow and consolidation between the interfaces were not sufficient, causing lower metallurgical bonding. The tensile strength and hardness were improved significantly with the increase in process parameters, however, the percentage elongation decreased gradually from 17% to 10%, which is the typical trade-off between strength and ductility of refined grain structures and strain hardening.

Table 5
L27 Experimental Results for Welding Performance

S.No.	SOR (RPM)	PFr (MPa)	PFg (MPa)	tFr (s)	tFg (s)	Tensile Strength (MPa)	% Elongation	Hardness (HV)
1	800	30	60	3	3	95	16	41.1
2	800	30	60	4	5	98	17	45.3
3	800	30	60	5	7	110	16	52.6
4	800	50	90	3	3	105	15	58.4
5	800	50	90	4	5	115	14	87.4
6	800	50	90	5	7	125	13	94.2
7	800	70	120	3	3	118	14	102.1
8	800	70	120	4	5	127	13	108.7
9	800	70	120	5	7	131	12	115.3
10	1000	30	90	3	3	97	16	48.9
11	1000	30	90	4	5	112	15	72.4
12	1000	30	90	5	7	110	15	76.1
13	1000	50	120	3	3	108	15	81.3
14	1000	50	120	4	5	120	14	98.6
15	1000	50	120	5	7	128	13	116.6
16	1000	70	60	3	3	113	14	85.7
17	1000	70	60	4	5	124	13	101.9
18	1000	70	60	5	7	142	11	118.9
19	1200	30	120	3	3	100	16	54.8
20	1200	30	120	4	5	115	15	73.2
21	1200	30	120	5	7	120	14	84.6
22	1200	50	60	3	3	110	15	78.9
23	1200	50	60	4	5	125	13	96.3
24	1200	50	60	5	7	130	12	112.7
25	1200	70	90	3	3	122	14	104.2
26	1200	70	90	4	5	130	13	120.1

S.No.	SOR (RPM)	PFr (MPa)	PFg (MPa)	tFr (s)	tFg (s)	Tensile Strength (MPa)	% Elongation	Hardness (HV)
27	1200	70	90	5	7	142	10	122.3

The better hardness distribution also indicates the creation of a compact weld zone, which has higher resistance to localized plastic deformation. In general, the experimental results indicate that it is critical to control the frictional heat and forging action to obtain defect-free joints with good mechanical properties. The results provide a reliable experimental data set to validate the proposed deep learning prediction model and the subsequent multi-objective optimization using NSGA-II. As shown in Table 5, the mechanical properties of the dissimilar rotary friction welded joints are significantly affected by the synergistic effect of the rotational speed, friction pressure, forging pressure, and welding time. The optimized thermomechanical conditions led to the formation of refined microstructures and to the creation of a better metallurgical bond, which led to an increase in tensile strength and hardness, while maintaining good ductility for structural applications.

3.2 Deep Learning Network Architecture

In order to create a solid mapping of the parameters of the friction welding and the resultant mechanical performance, a deep learning architecture was designed and progressively tested. Unlike most synthetic data, the network topology was designed to be able to learn nonlinear relationships between the input variables, as well as to give computational stability when the input data was relatively small and limited (as in the case of the experimental data). The suggested model will be comprised of an input layer that will be the main welding parameters, and several fully connected hidden layers with nonlinear activation functions. Activation. To overcome the vanishing gradient problem, Rectified Linear Unit (ReLU) was used to enhance the propagation of the gradients. There was a dropout mechanism between the hidden layers to reduce overfitting and improve generalization [43].

The output layer was set to produce a continuous prediction of mechanical properties, especially tensile strength. The data set was also scaled to have equal scaling in features before the training. The data was divided into training and testing data sets to objectively assess the model performance. The weights of the network were optimized using the Adam optimizer with the loss function being the mean squared error (MSE). Hyperparameters such as learning rate, batch size and number of epochs were optimized through iterative tuning until convergence of the model [44]. The overall architecture of the designed deep learning model is shown in Fig. 2. The figure shows the organized welding parameters flow with regard to connected hidden layers to the endpoint prediction node. The layered structure is small enough to verify that the network is deep enough to get the complex interactions of the parameters, as it is efficient to apply in engineering problems.

3.3 Deep Learning Prediction Performance

The convergence analysis, regression performance and classification metrics were used to evaluate the predictive capability of the proposed Deep Neural Network (DNN) to ensure it is suitable for modelling

the nonlinear relationship between rotary friction welding parameters and mechanical properties of dissimilar AA1100–AA2014 joints. The network was designed to predict the tensile strength, percentage elongation and microhardness with minimum prediction error and better generalization performance. The convergence curve of the Mean Squared Error (MSE) for the developed DNN is shown in Fig. 3, which demonstrates the learning behaviour of the DNN.

The training and validation losses decreased rapidly during the first learning phase, suggesting that the nonlinear process–property relationships were effectively learned from the experimental data. The validation error was minimized at epoch 187 (9.8×10^{-4}) and training was automatically stopped at this point due to the early stopping criterion. The good consistency of the final training, validation and testing errors (6.2×10^{-4} , 9.8×10^{-4} and 1.15×10^{-3} , respectively) shows the stability of the model and the effectiveness of the regularization techniques adopted to improve the reliability of the predictions. As shown in Fig. 3, the proposed DNN has converged quickly to the training error, with a validation error that is close to the training error, and a testing error that is close to the validation error, indicating that the learning behaviour is stable, the generalization ability is good, and overfitting is effectively prevented. The accuracy of the proposed model was additionally checked by regression analysis as illustrated in Fig. 4. The predicted values are in good agreement with the experimental values and are clustered around the ideal $Y = T$ line, suggesting that there is little prediction bias. The obtained R^2 values of 0.994, 0.989, and 0.986 for the training, validation, and testing sets, respectively, indicate that the DNN was able to capture the majority of the variability in the experimental responses, with over 98% of the variance captured in each set. This high correlation shows the ability of the multilayer architecture to learn the complex relationships between rotational speed, friction pressure, forging pressure, friction time and forging time, which are hard to be represented by the conventional regression models.

Figure 4 shows excellent agreement between experimental and predicted responses, with R^2 values exceeding 0.98, demonstrating the high prediction accuracy and nonlinear modelling capability of the developed DNN. The robustness of the developed prediction framework was further confirmed by the Receiver Operating Characteristic (ROC) analysis presented in Fig. 5. The ROC curves remain close to the upper-left corner, with AUC values between 0.991 and 0.995, indicating excellent discrimination capability and outstanding generalization performance. These results demonstrate that the combined implementation of Min–Max normalization, L2 regularization, dropout, early stopping, and 5-fold cross-validation effectively reduced overfitting while maintaining consistent prediction accuracy across unseen datasets. Figure 5 confirms the robustness of the developed prediction framework, with AUC values greater than 0.99, indicating outstanding discrimination capability and reliable performance for intelligent welding parameter prediction. From an engineering perspective, the proposed DNN serves as an efficient surrogate model that substantially reduces computational effort during process optimization while preserving prediction accuracy.

Unlike conventional empirical or polynomial regression approaches, the developed model can accurately capture highly nonlinear process–structure–property relationships associated with rotary friction welding. This capability enables rapid evaluation of multiple parameter combinations without performing

additional costly and time-consuming experiments. Furthermore, integrating the validated DNN with the NSGA-II optimization algorithm provides a systematic framework for identifying optimal welding conditions that simultaneously maximize tensile strength and hardness while maintaining adequate ductility.

The principal novelty of this work lies in the integration of a 5–32–64–32–3 deep neural network architecture with NSGA-II multi-objective optimization for rotary friction welding of dissimilar AA1100–AA2014 aluminium alloys, providing a reliable intelligent decision-support methodology for advanced solid-state joining and future smart manufacturing applications. Figure 6. Three-dimensional Pareto front illustrating the trade-off among ultimate tensile strength, percentage elongation, and microhardness predicted by the integrated Deep Neural Network (DNN) and Non-dominated Sorting Genetic Algorithm II (NSGA-II). The Pareto-optimal solutions represent the best non-dominated combinations of welding responses, while the highlighted knee-point solution identifies the optimum compromise between strength, ductility, and hardness [44]. The corresponding optimal welding parameters were 1200 rpm rotational speed, 70 MPa friction pressure, 90 MPa forging pressure, 4 s friction time, and 5 s forging time, resulting in a predicted tensile strength of 142.3 MPa, elongation of 13.2%, and microhardness of 121.0 HV. Figure 6 demonstrates that the integrated DNN–NSGA-II framework successfully identified a well-distributed Pareto front, providing an optimal balance between tensile strength, ductility, and hardness. The selected knee-point solution represents the most practical operating condition, achieving superior joint performance while maintaining an appropriate compromise among the competing mechanical properties. These results confirm the effectiveness of the proposed artificial intelligence-based optimization strategy for intelligent process design and decision-making in rotary friction welding.

4. Morphological Analysis of the Rotary Friction Welded Joints

The fracture surfaces of the dissimilar AA1100–AA2014 rotary friction welded joints are shown in the scanning electron microscopy (SEM) micrographs in Fig. 8. The fracture morphology is direct evidence of the metallurgical changes that take place during the rotary friction welding process and accounts for the experimentally observed mechanical behaviour. There were significant differences in fracture characteristics between the AA1100 and AA2014 sides, due to the different alloy compositions, thermal responses and deformation mechanisms [45]. The fracture surface of the AA1100 side (Fig. 8a–d) is homogeneous with many fine equiaxed dimples, continuous plastic flow bands and evenly distributed microvoids [46]. The continuous deformation zone is seen at low magnification (Fig. 8a), which suggests that the frictional heat generated and the severe plastic deformation facilitated good material mixing and intimate interfacial contact. The higher magnification images (Fig. 8b–d) show very close spaced equiaxed dimples that are connected by thin ligaments, typical features of ductile fracture [47]. Elongated shear dimples along the flow direction of the material suggest that the friction and forging forces applied to the material caused significant plastic deformation and dynamic recrystallization at the weld interface [48]. The high tensile strength and hardness achieved under the optimized welding conditions was attributed to these refined grains which enhanced the resistance to crack propagation, metallurgical bonding and the effective grain boundary area [49]. The AA2014 side (Fig. 8e–h), on the

other hand, has relatively uniform fracture properties. While ductile dimples are still the predominant fracture feature, larger voids, irregular cavities and localized flat facets are clearly visible. The features are believed to be caused by the precipitation-hardened Al–Cu matrix, which is affected by the thermal exposure during welding, causing softening and non-uniform plastic deformation in the material [50]. The differences in dimple size and depth suggest that the strain was not uniform during tensile loading, and that intergranular facets were isolated, suggesting that the decohesion was localized and started around coarse precipitates. However, the fact that there are no large cracks, oxide inclusions or interfacial delamination, indicates that the rotary friction welding process has resulted in a sound metallurgical bond with minimal welding defects.

As shown in Fig. 8, the optimized rotary friction welding parameters led to the uniform plastic deformation and dynamic recrystallization on the AA1100 side, while the AA2014 side showed the localized heterogeneity of the plastic deformation and precipitate redistribution. Although there are differences in the microstructures, the lack of interfacial defects and the presence of ductile fracture indicate good metallurgical bonding and the reason for the superior mechanical properties of the welded joints. The optimized rotary friction welding parameters are found to be able to control the interfacial heat generated and plastic flow, which resulted in defect-free joints with refined ductile fracture characteristics as confirmed by the morphological investigation. The interpretation of SEM observations and mechanical performance has been combined to create a direct relationship between the process, structure and properties, which provides experimental evidence for the intelligent optimization framework proposed in this study. The main novelty of the work is the integrated correlation of the microstructural evolution, mechanical behaviour, and AI-assisted optimization, which shows the potential of the design of high-performance dissimilar aluminium joints for lightweight structural and aerospace applications.

4.1 XRD Analysis

The X-ray diffraction (XRD) pattern of the AA1100–AA2014 dissimilar joint made by rotary friction welding (RFW) is shown in Fig. 9. The diffraction profile is useful to get important information about the phase stability and crystallographic evolution during the solid-state joining process. The dominant peaks observed at $2\theta = 38^\circ, 44^\circ, 65^\circ, 78^\circ, 82^\circ, 99^\circ$ and 116° are related to the crystallographic planes (111), (200), (220), (311), (222), (323) and (420) of the face-centered cubic (FCC) α -Al matrix, indicating that aluminium was the main crystalline phase present after welding. The (111) reflection is very intense, which proves that the matrix continuity was maintained during the rotary friction welding process, and that the bonding was accomplished by severe plastic deformation and diffusion-assisted metallurgical consolidation without bulk melting [51]. This observation is evidence of the ability of the solid-state joining mechanism to preserve the crystallographic integrity of the dissimilar aluminium alloys. Weak diffraction peaks corresponding to Al_2Cu strengthening precipitates from the AA2014 alloy are also seen with relatively low intensities in addition to the α -Al reflections. The decrease in peak intensity indicates that some dissolution of the precipitates, coarsening, or redistribution of the precipitates occurred during the thermal cycle created by frictional heating and forging [52]. This rapid evolution is typical of

precipitation hardened Al–Cu alloys that have been locally thermomechanically processed and is a factor in the modification of the local strengthening mechanism in the heat affected zone [53]. Notably, no extra diffraction peaks of brittle intermetallic compounds or unwanted reaction products were observed, which meant that the chosen welding parameters were effective in preventing the formation of unwanted phases and ensuring a good metallurgical bond. In addition, a significant broadening of the main α -Al diffraction peaks was also observed in the welded area. The broadening of the peaks is believed to be due to grain refinement, lattice distortion and residual strain resulting from the severe plastic deformation and dynamic recrystallization during rotary friction welding. The improved crystallographic structure results in an increase in the grain boundary density and resistance to dislocation movement, which accounts for the experimentally determined increase in tensile strength and microhardness. The lack of any phase transformation and the presence of fine grained α -Al grains indicate that the enhancement in mechanical properties was mainly due to thermomechanical grain refinement and not compositional changes. The XRD observations are in good agreement with the SEM fractographic analysis that showed the refined ductile fracture morphology and homogeneous plastic flow, which is a good process–structure–property relationship. Thus, the overall microstructural analysis shows that the optimal rotary friction welding parameters led to the formation of defect-free dissimilar welds with stable phase composition and excellent mechanical properties.

As shown in Fig. 9, the FCC α -Al matrix was retained and grain refinement and the evolution of precipitates were encouraged during rotary friction welding without the formation of brittle intermetallic compounds. The peak broadening and phase stability observed confirm the thermomechanical strengthening mechanism which led to the improvement of the tensile strength and hardness of the optimized dissimilar welded joints.

5. Conclusion

The feasibility of using the rotary friction welding (RFW) process, deep neural network (DNN) prediction and NSGA-II multi-objective optimization was successfully demonstrated for the enhancement of the performance of dissimilar AA1100–AA2014 aluminium alloy joints. The experimental investigation showed that the selected welding parameters had a significant effect on the mechanical properties of the joints, and the optimum welding condition resulted in the highest tensile strength of 142 MPa and microhardness of 122.3 HV with good ductility. SEM fractographic analysis showed that a ductile fracture mechanism with fine equiaxed dimples, homogeneous plastic flow and dynamically recrystallized grains were observed on the AA1100 side, while the AA2014 side showed localized fracture features related to the presence of precipitates in the Al–Cu alloy matrix. These observations showed that the strengthening of the welded interface was mainly due to the thermomechanical deformation and dynamic recrystallization. The XRD analysis also confirmed the presence of FCC α -Al matrix without any detectable brittle intermetallic compounds and the peak broadening showed grain refinement and lattice strain caused by severe plastic deformation, thus confirming that the improvement of the joint properties was due to microstructural refinement and not to phase transformation. The proposed 5–32–64–32–3 DNN architecture successfully captured the nonlinear

relationship between the welding parameters and mechanical responses, with an excellent predictive performance ($R^2 > 0.98$), and a reliable surrogate model for the optimization of the welding process. The Pareto optimal welding conditions obtained by the validated DNN and the NSGA-II algorithm significantly reduced the need for extensive experimental trials, while simultaneously maximizing tensile strength and hardness and satisfying the requirement for satisfactory elongation. The experimental characterization and artificial intelligence framework developed in this work has created a comprehensive process–structure–property–prediction relationship, which is the main novelty of this work and an effective methodology for intelligent welding process optimization. The developed approach has a wide potential application in automotive, aerospace, railway, marine, defence and lightweight structural engineering, where high strength dissimilar aluminium joints are becoming more and more in demand. The experimental database should be expanded, further combinations of aluminium alloys should be studied, the framework should be validated under fatigue and corrosion loading, advanced characterization techniques should be implemented, such as EBSD and TEM, and digital twin, Explainable Artificial Intelligence (XAI) and physics-informed machine learning frameworks should be integrated for real-time adaptive control and next-generation intelligent manufacturing systems.

Declarations

Conflict of Interest

All authors declare no conflict of interest.

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Author Contributions

Premkumar Nagarajan: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Writing – original draft. **Dinesh Subbiah:** Methodology, Software, Deep learning model development, Multi-objective optimization, Validation, Formal analysis, Writing – review & editing. **Ravikumar Sadayan Mottaiyan:** Investigation, Experimental validation, Resources, Data curation. **Dinakaran Jeeva:** Investigation, Microstructural characterization, Mechanical testing, Validation. **Rajkumar Sivanraju:** Conceptualization, Supervision, Project administration, Resources, Writing – review & editing, Corresponding author. **Arul Moorthy:** Software, Formal analysis, Visualization, Writing – review & editing. **Paranthaman Venkadesan:** Investigation, Validation, Data curation, Visualization. **Arunprasad Jayaraman:** Supervision, Formal analysis, Validation, Writing – review & editing. All authors read and approved the final manuscript.

Data Availability

The data used to support the findings of this study are included within the article.

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Figures

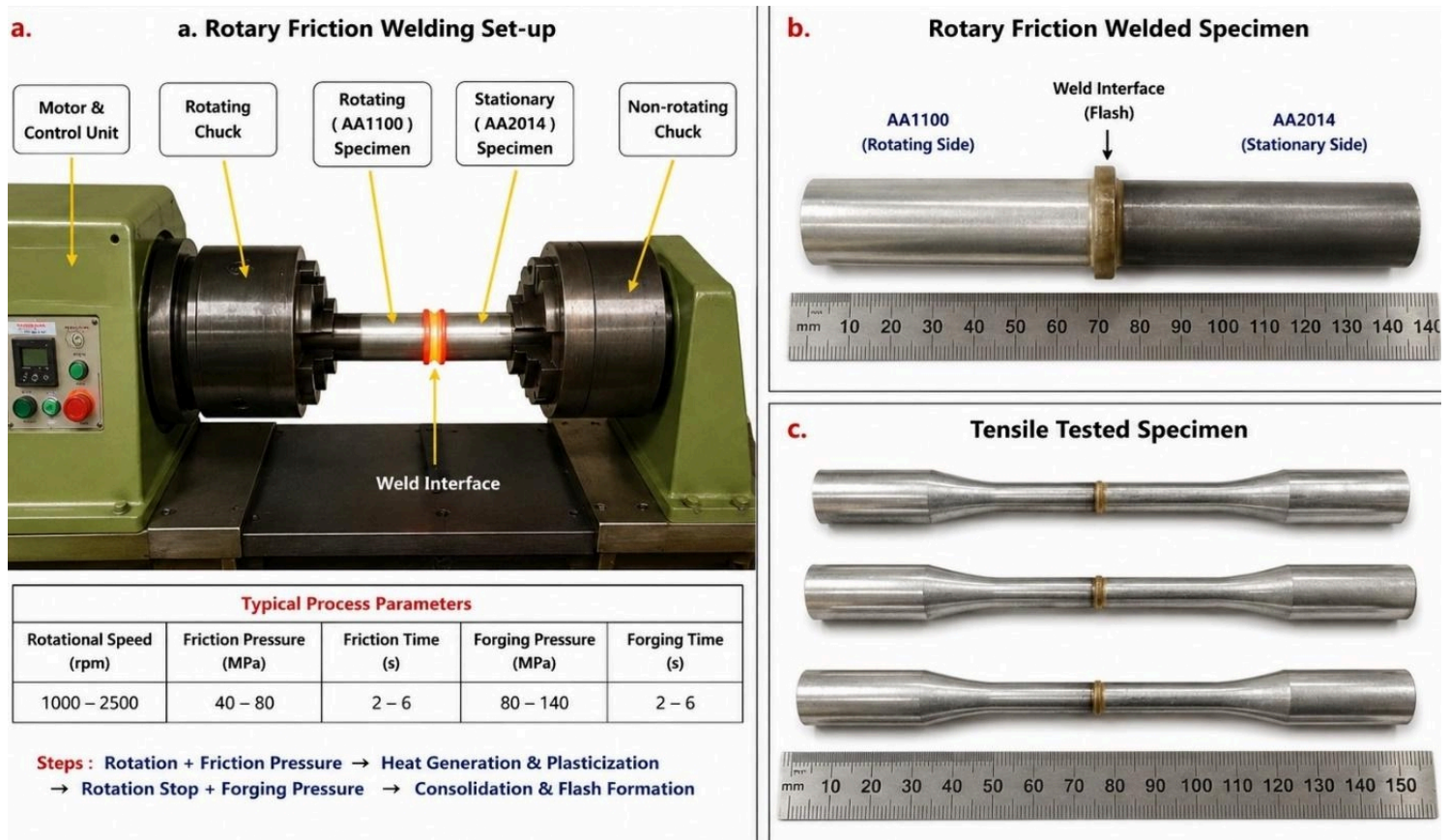


Figure 1

Experimental setup and specimen preparation for rotary friction welding of dissimilar AA1100–AA2014 aluminum alloys.

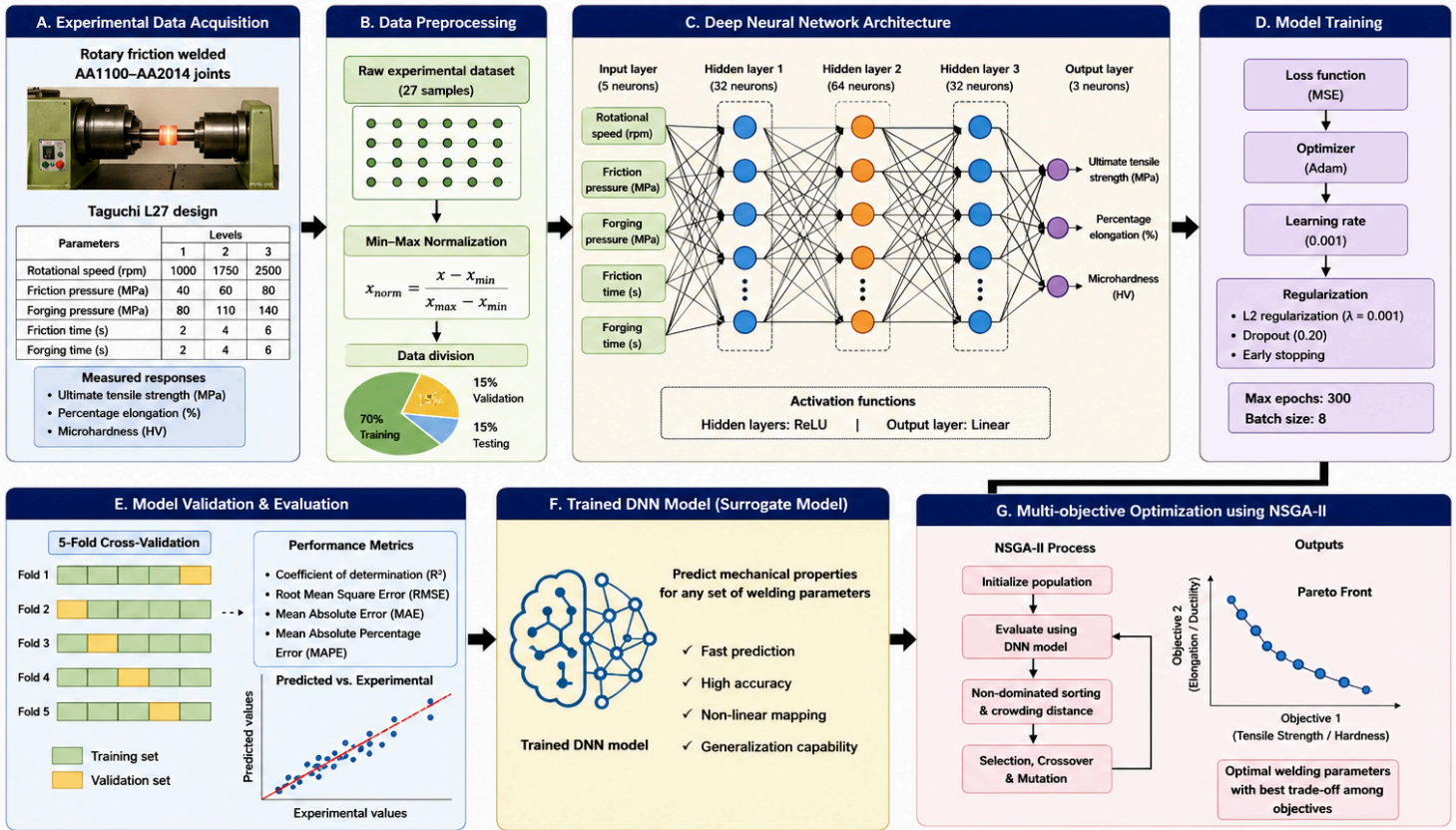


Figure 2

Workflow of the deep neural network model integrated with NSGA-II for prediction and multi-objective optimization of rotary friction welding parameters.

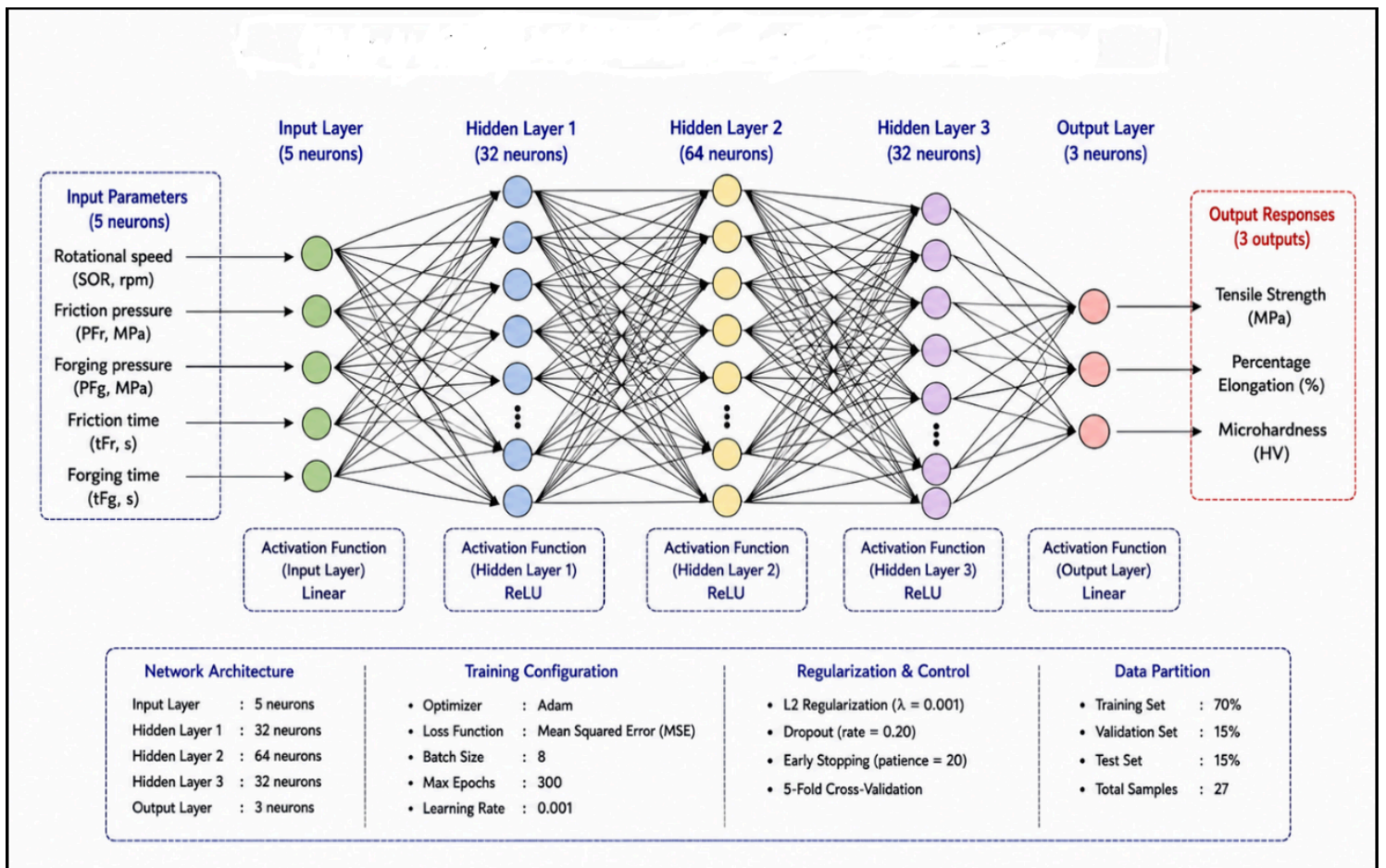


Figure 3

Deep learning network architecture for welding property prediction.

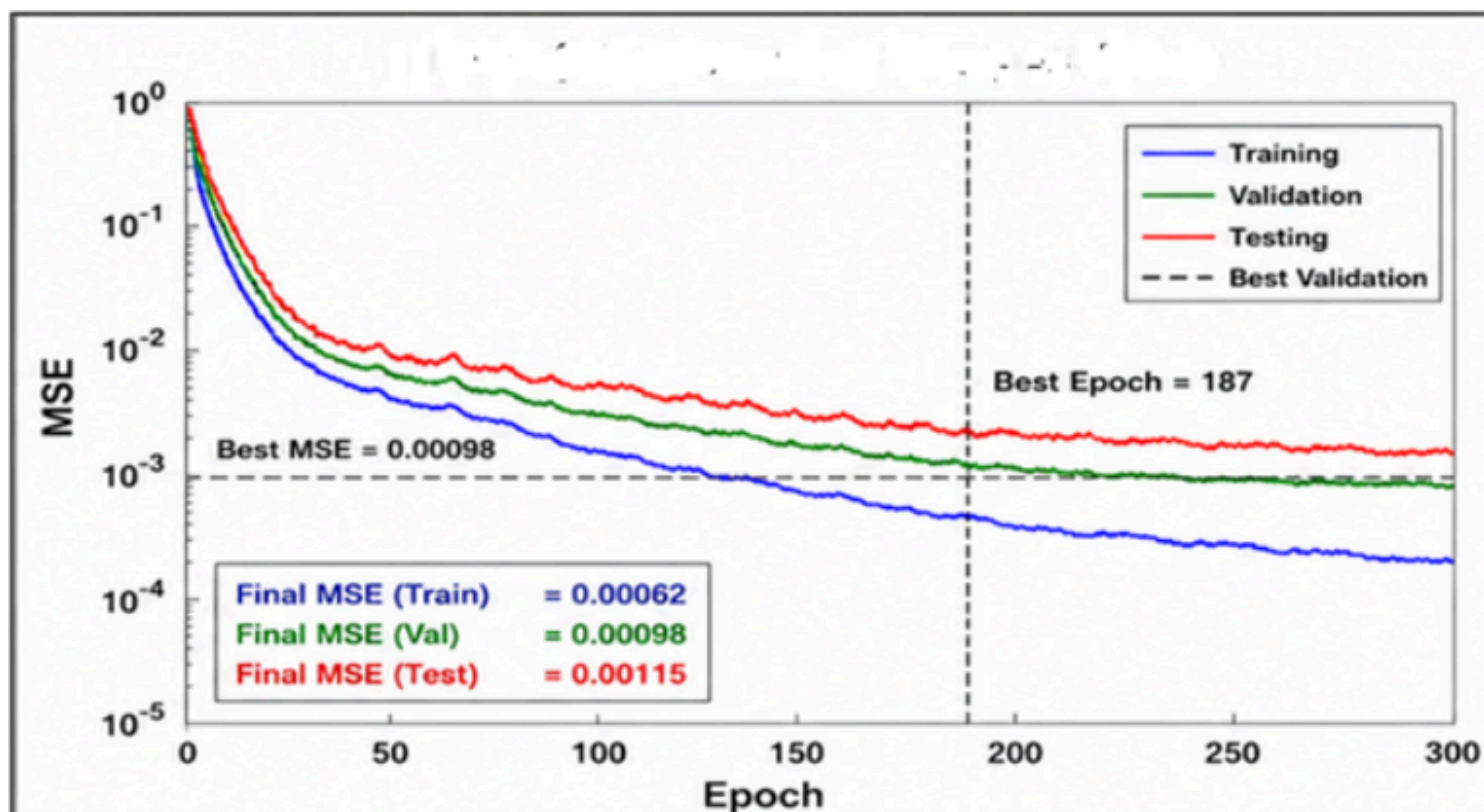


Figure 4

Mean Squared Error (MSE) convergence curve of the proposed Deep Neural Network during model training.

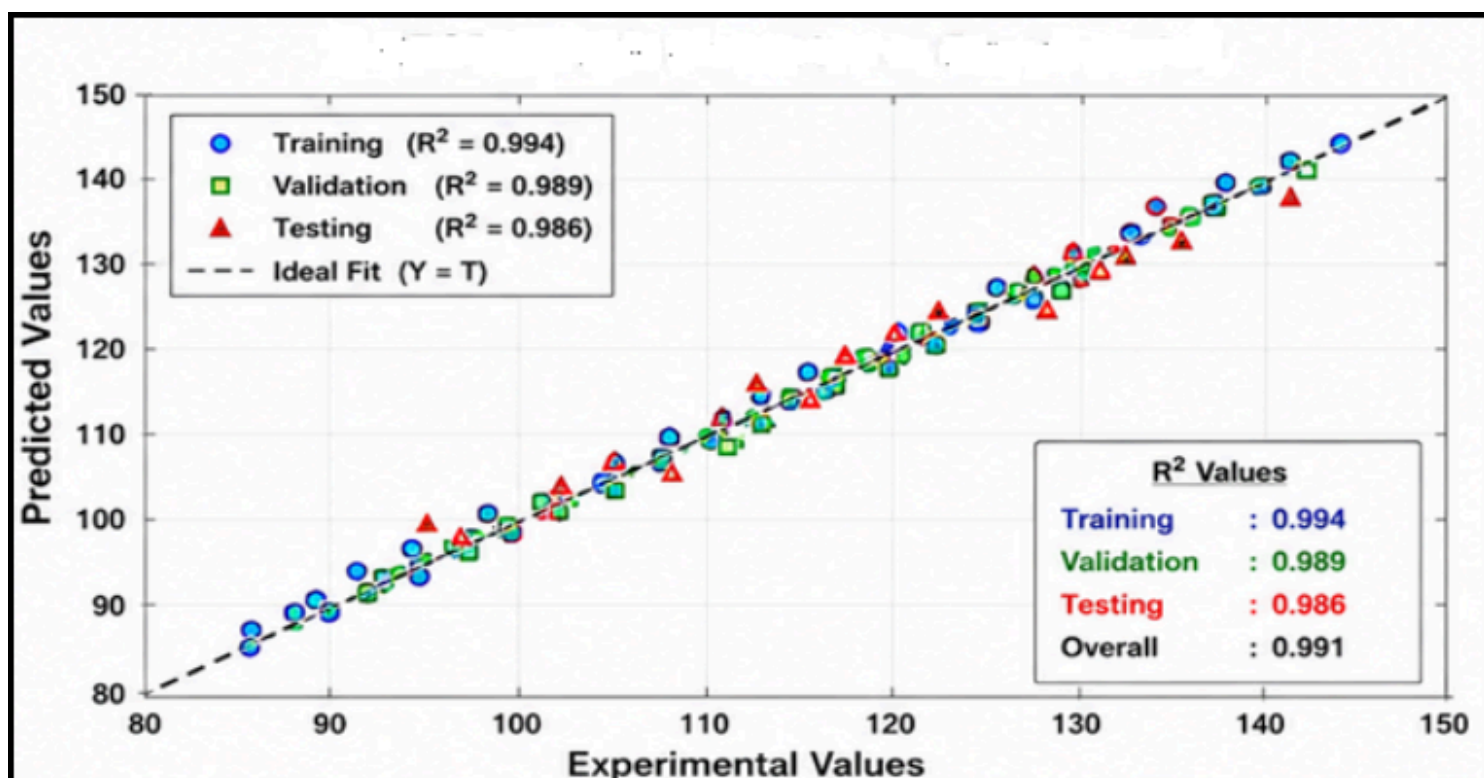


Figure 5

Regression analysis between experimental and predicted mechanical properties using the proposed Deep Neural Network.

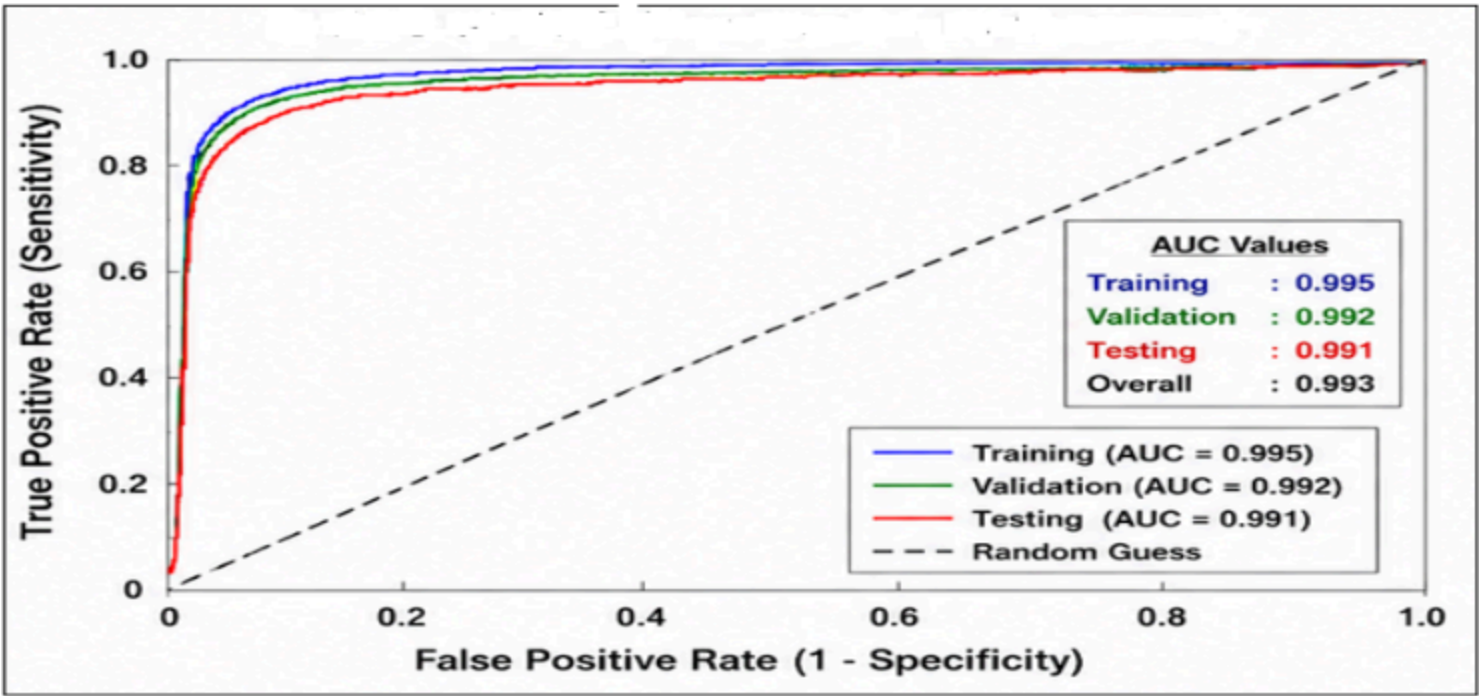


Figure 6

Receiver Operating Characteristic (ROC) curves illustrating the predictive performance of the proposed Deep Neural Network.

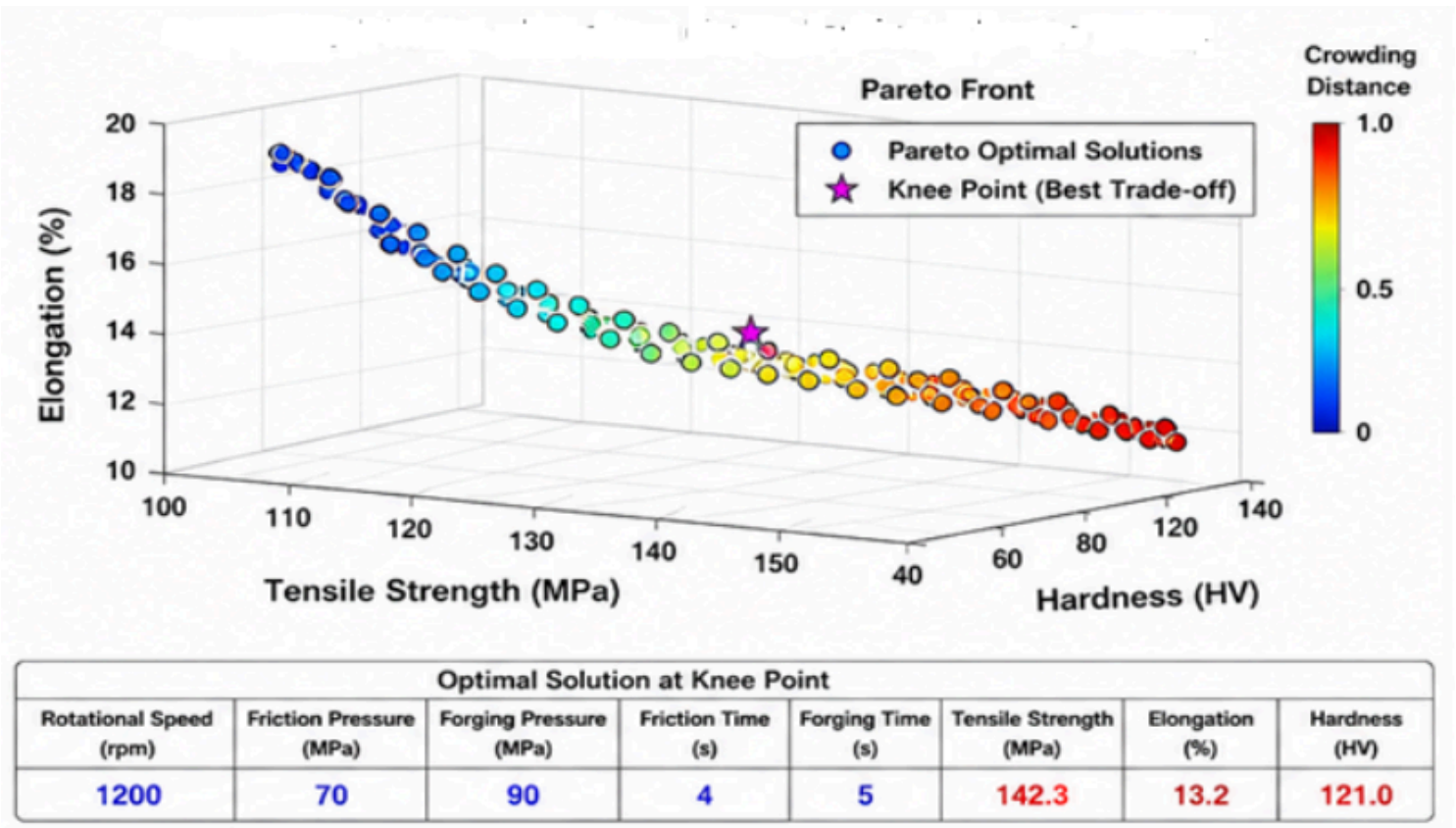


Figure 7

Optimal Welding Parameters from DNN-NSGA-II

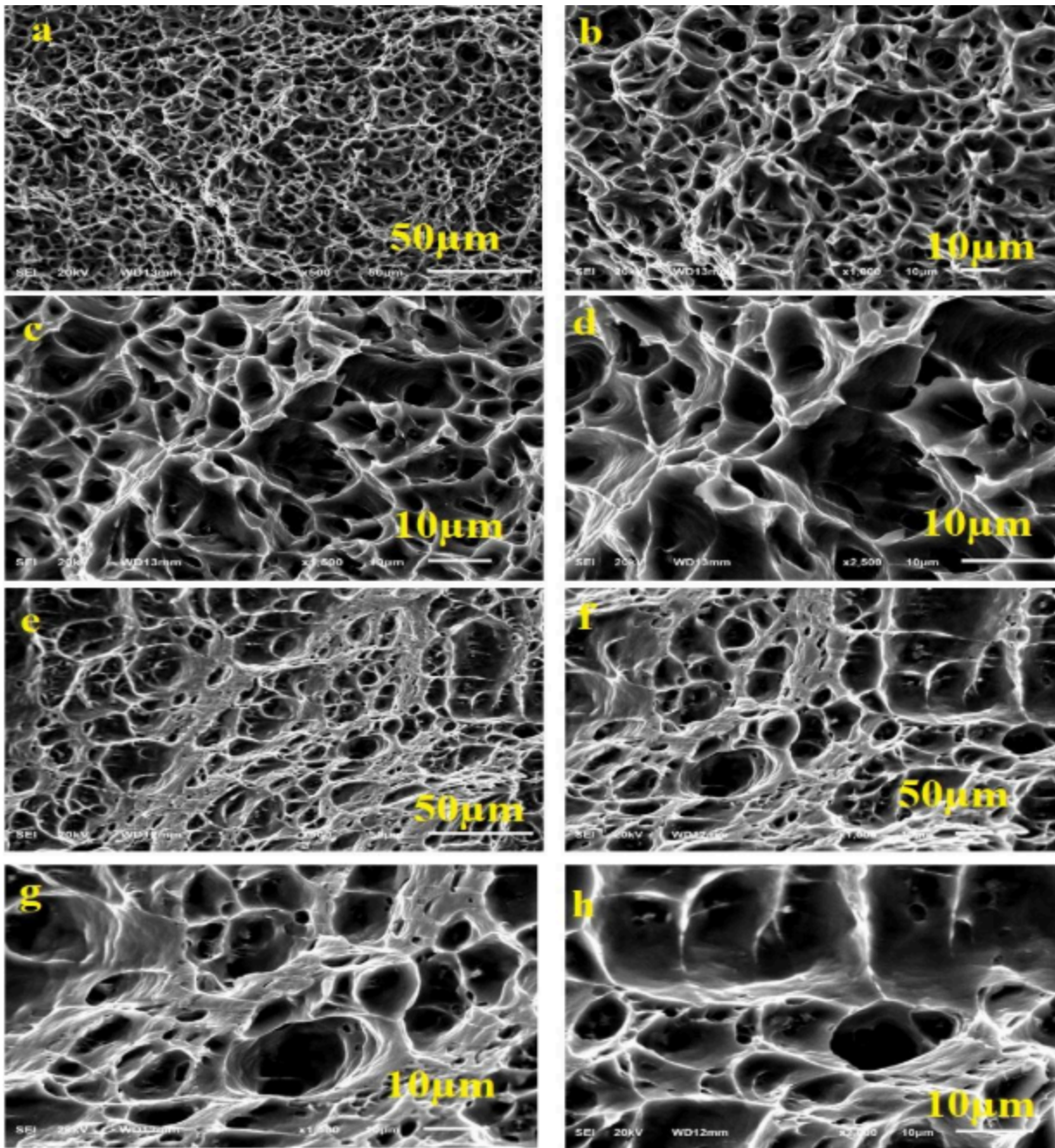


Figure 8

SEM fractographic analysis of the fracture surfaces of dissimilar AA1100–AA2014 rotary friction welded joints.

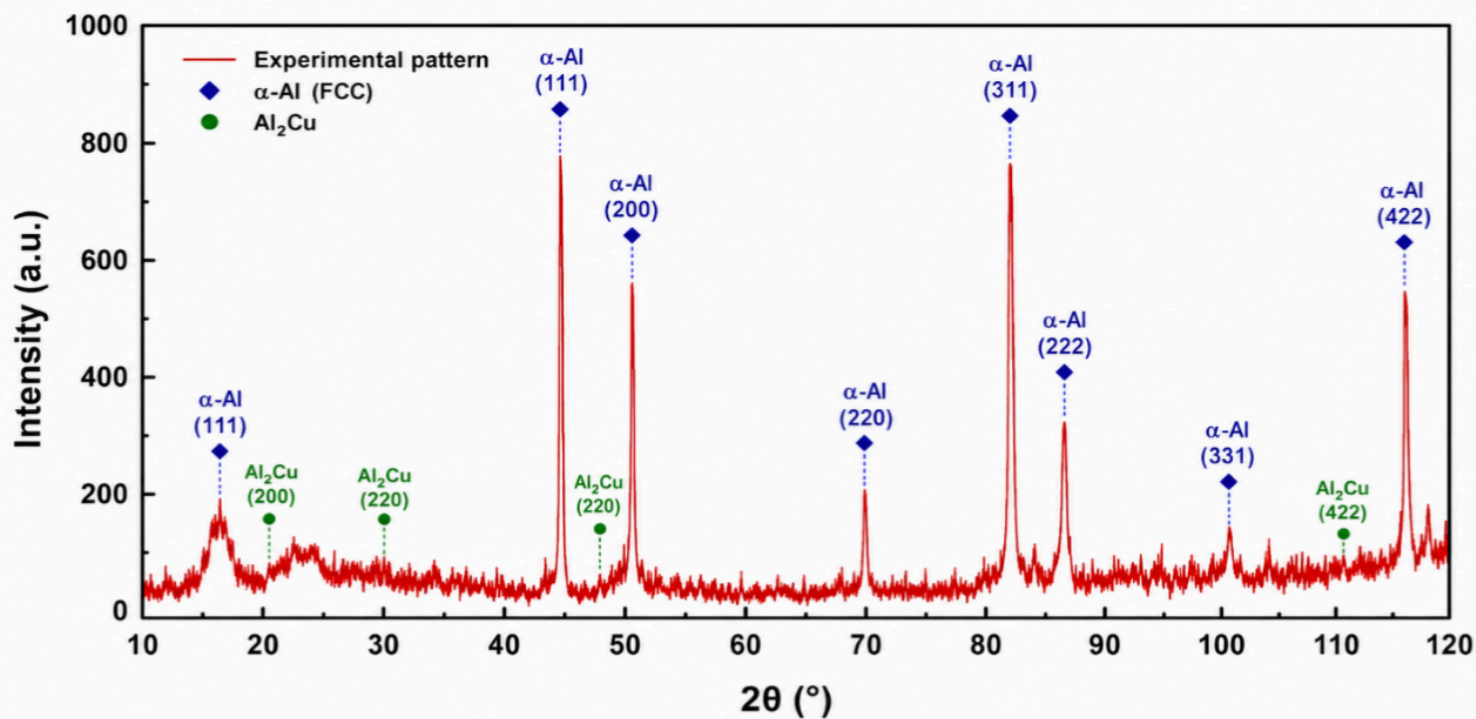


Figure 9

X-ray diffraction patterns of the rotary friction welded AA1100–AA2014 dissimilar joint showing phase constitution and crystallographic evolution.