Engineering and Applied Science Research 2025;52(3):282-295 Research Article

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, Khon Kaen University, Thailand

Optimization of aluminum matrix composite production in a friction stir process with MgO nanoparticle reinforcement using ANN-GRA modeling

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Received 28 October 2024
Revised 6 March 2025
Accepted 13 March 2025

Abstract

This research focuses on enhancing the performance of magnesium oxide (MgO) particle-reinforced aluminum matrix composites (AMCs) using friction stir processing (FSP). The study addresses the limitations of traditional methods, such as response surface methodology (RSM), which often cannot accurately capture the nonlinear relationships between critical parameters. A hybrid model that integrates artificial neural network (ANN) and grey relational analysis (GRA) approaches is developed to improve prediction accuracy and optimize mechanical properties, particularly tensile strength and hardness. MgO particles offer significant advantages by refining the grain structure, enhancing hardness, and improving tensile strength due to their large surface area and thermal stability, thereby increasing the durability and wear resistance of the composites. The ANN model effectively analyzes complex nonlinear relationships, while the GRA technique identifies optimal production parameters. The results demonstrate that the ANN-GRA model outperforms RSM, showing lower mean squared error values and more accurate predictions closely aligned with experimental outcomes. The novelty of this research lies in integration of ANN and GRA to simultaneously optimize multiple FSP parameters, addressing a research gap in composite material improvement. This approach significantly enhances the mechanical properties of the composites while minimizing material and energy use during the production process. The findings of this study hold substantial implications for the aerospace and automotive industries, which require lightweight materials with superior properties. Additionally, this research serves as a foundation for future applications of hybrid machine learning techniques to efficiently and sustainably optimize composite material production.

Keywords: Aluminum Matrix Composites (AMCs), Friction Stir Processing (FSP), Artificial Neural Network (ANN), Grey Relational Analysis (GRA), Mechanical Properties Optimization

1. Introduction

Aluminum matrix composites (AMCs) have garnered significant attention due to their exceptional combination of lightweight properties, high strength, and superior corrosion resistance. They are important in the automotive and aerospace industries as well as in electrical manufacturing [1-3]. These composites exhibit enhanced performance in structural applications where weight reduction and mechanical integrity are essential. However, achieving optimal mechanical properties in AMCs necessitates innovative processing techniques that refine their microstructure and enhance their durability. Among these techniques, friction stir processing (FSP) has emerged as a transformative method owing to its homogenized reinforcement phases, refined grain structures, improved overall strength, and composite toughness [4-6]. Nevertheless, the effectiveness of FSP is highly sensitive to process parameters, including rotational speed, traverse speed, and the volume fraction of reinforcing particles. When these parameters are improperly controlled, suboptimal mechanical properties result. This necessitates development of advanced approaches for process optimization.

Incorporation of nanoparticle reinforcements has further expanded the potential of AMCs. Specifically, magnesium oxide (MgO) nanoparticles can significantly enhance the wear resistance, tensile strength, and stiffness of aluminum-based composites due to their high hardness, thermal stability, and fine dispersion potential [1, 7-9]. This observation aligns with recent studies indicating that Mg-based and hybrid reinforcements contribute to superior wear and strength characteristics [2]. However, successful integration of MgO nanoparticles into the aluminum matrix via FSP presents notable challenges, such as achieving uniform dispersion while maintaining structural integrity throughout the process [10]. The inherent complexity of the multi-variable interactions in the FSP process, further compounded by non-linear relationships between input parameters and mechanical properties, poses significant hurdles for optimization [3, 6]. Traditional optimization techniques, such as the Taguchi method and response surface methodology (RSM), have provided useful insights for process improvement [3]. However, these methods often fail when applied to highly non-linear and complex data sets, limiting their effectiveness in multi-response optimization.

Recent advancements in machine learning, especially in artificial neural networks (ANNs), have demonstrated significant promise in modeling and predicting complex process outcomes. This is due to their capacity to capture intricate, non-linear dependencies [4].

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doi: 10.14456/easr.2025.25

Nevertheless, few studies have explored the integration of ANNs with grey relational analysis (GRA) for comprehensive multi-response optimization of AMCs reinforced with MgO nanoparticles [5]. Combining GRA with machine learning approaches, such as ANNs and grey-fuzzy methods, has shown substantial improvements in multi-response optimization [6-8]. Despite this, the ANN-GRA hybrid approach remains an underexplored yet promising avenue for addressing the challenges of process parameter control and performance enhancement in FSP. The current study aims to address this research gap by developing a robust ANN model capable of predicting the mechanical properties of MgO-reinforced AMCs produced through FSP. Key objectives include optimizing FSP parameters using an ANN-GRA framework to achieve simultaneous improvements in strength and stiffness. Additionally, the study seeks to compare the predictive accuracy and optimization efficiency of the ANN-GRA method with traditional approaches [7]. This research proposes a novel methodology that enhances the precision of multi-response optimization and enables a comprehensive improvement in mechanical properties by integrating deep learning-based predictions with grey relational analysis. The study findings have significant implications for the automotive and aerospace industries, where enhanced material performance is critical for development of lightweight, high-strength structural components.

2. Literature review

2.1 Aluminum Matrix Composites (AMCs) reinforced with nanoparticles

Aluminum matrix composites (AMCs) reinforced with nanoparticles have garnered significant attention. This is due to their exceptional mechanical properties, wear resistance, and lightweight characteristics. Substantial progress has been made in improving fabrication techniques, reinforcement materials, and mechanical performance, broadening their applications across various industries. The synthesis methods used in AMC production are crucial in determining their final properties. Recent studies highlight the effectiveness of mechanical milling for achieving uniform nanoparticle dispersion and enhancing mechanical strength. For example, Kumar et al. [11] emphasized that fabrication routes directly influence the microstructure and overall performance of AMCs, while Elsayd et al. [12] demonstrated that optimizing milling times significantly improves nanoparticle distribution and composite strength.

The choice of reinforcement materials also plays a pivotal role in the performance of AMCs. Graphene and carbide nanoparticles, known for their exceptional tensile strength and thermal conductivity, have become popular reinforcement options. Alam et al. [13] reported significant improvements in mechanical strength with these reinforcements, while Barot et al. [14] underscored the cost-effectiveness and compatibility of silicon carbide (SiC) and alumina (Al_2O_3) nanoparticles with aluminum matrices. Additionally, high-entropy alloy nanoparticles have been studied for their ability to enhance bonding strength at the matrix-reinforcement interface. Liu and Zheng [15] showed that they limit crack propagation and improve composite reliability. Hybrid reinforcement strategies have also shown great potential. Research by Sha et al. [16] revealed that incorporating SiC nanoparticles and carbon fibers within the matrix improved stiffness and load-bearing capacity. This combination of ceramic and carbon-based reinforcements is especially promising for aerospace and automotive applications requiring multifunctional properties.

Despite these advancements, challenges remain in scaling up the production of nanoparticle-reinforced AMCs, particularly in maintaining microstructural consistency. Uniform nanoparticle dispersion and preventing agglomeration during synthesis are persistent obstacles. Al-Salihi et al. [17] emphasized the importance of optimizing processing routes to balance strength and ductility. Additionally, Sharma et al. [18] findings on boron carbide (B_4C) reinforcement highlighted notable improvements in hardness, reinforcing its potential for wear-resistant applications. Addressing these challenges is critical for the widespread adoption of AMCs in industrial applications. Future research should prioritize scalable and reliable manufacturing processes to ensure uniformity and maintain the superior properties that make these composites valuable in advanced engineering fields.

2.2 Friction Stir Processing (FSP) for composite fabrication

Friction stir processing (FSP) is an effective technique for fabricating composite materials, particularly for surface strengthening. This solid-state process refines microstructure and enhances mechanical properties by optimizing key parameters. Butola et al. [19] highlighted FSP's adaptability in creating metal matrix composites under controlled thermal and mechanical conditions, demonstrating its potential in both ex-situ and in-situ surface composites. This adaptability reinforces FSP’s use for composite fabrication.

Recent studies have explored the relationship between FSP process parameters and composite properties. Rathee et al. [20] analyzed how tool geometry, rotational speed, and traverse rate influence material flow and reinforcement dispersion, crucial for achieving composite homogeneity. Gangil et al. [21] focused on in-situ composites, such as aluminum-oxide and aluminum-transition metal systems, which exhibit exceptional mechanical performance due to uniform reinforcement distribution. Hybrid composites have also garnered attention—Rana et al. [22] reported enhanced wear resistance in Al7075/B_4C composites, while Du et al. [23] demonstrated improved strength and ductility in aluminum matrices reinforced with alumina (Al_2O_3) and carbon nanotubes (CNTs).

However, challenges remain, particularly in processing high-melting-point materials. Sharma et al. [24] noted tool wear and defect formation during fabrication, emphasizing the need for optimized tool materials and geometries. Sahraeinejad et al. [25] proposed novel tool designs to improve reinforcement dispersion and reduce defects, highlighting the importance of continuous innovation.

FSP's potential extends to the fabrication of bulk composites. Arora et al. [26] emphasized its sustainability and energy efficiency, making it suitable for green manufacturing. Adi and Malik [27] discussed the scalability of FSP for bulk composite production with superior mechanical properties. These studies illustrate that FSP is effective for surface modification and transformative in composite engineering. With ongoing advancements in tool design, reinforcement materials, and process optimization, FSP will likely play a significant role in future material science and engineering developments.

2.3 Hybrid machine learning models for material property prediction and optimization

Recent advancements in hybrid machine learning (ML) models have shown significant potential in predicting and optimizing material properties across various domains, including polymers, composites, and concrete structures. Champa-Bujaico et al. [28] demonstrated that integrating experimental data with ML-based regression models allows for accurate prediction and iterative optimization of mechanical properties in hybrid polymer nanocomposites, significantly enhancing their performance. Similarly, Miao et al. [29] applied hybrid ML algorithms to predict the mechanical behavior of low-carbon recycled aggregate concrete, illustrating the superior predictive accuracy of data-driven models over traditional empirical methods.

Integration of hybrid models, which merge physical modeling with data-driven approaches, has expanded material property prediction capabilities. Stergiou et al. [30] reviewed the use of optimization algorithms, such as Particle Swarm Optimization (PSO) and the Grey Wolf Optimizer (GWO), within support vector regression (SVR) frameworks, improving predictions for complex building materials. Okafor et al. [31] emphasized that ML-aided design of reinforced composites enables the identification of optimal material factor combinations, resulting in more efficient material systems. Peng and Unluer [32] reinforced this by developing PSO-SVR models capable of capturing nonlinear relationships in recycled concrete, demonstrating the robustness of hybrid approaches in handling multivariable optimization problems.

Hybrid ML models have also found applications in nanocomposite systems. Champa-Bujaico et al. [33] used optimization techniques to model epoxy-based nanocomposites, highlighting the enhanced predictive reliability of hybrid methods in polymeric materials. Hameed et al. [34] applied hybrid models to predict the compressive strength of concrete containing industrial waste, demonstrating the potential for sustainability-driven optimizations. Additionally, Shireen et al. [35] combined deep neural networks (DNN) with coarse-grained models to improve polymer structure-property correlations. Integration of evolutionary algorithms with neural networks has further advanced composite material optimization. Lu et al. [36] demonstrated a robust multi-objective hybrid approach for predicting composite properties using diverse datasets. Similarly, Mairpady et al. [37] implemented an artificial neural network-genetic algorithm (ANN-GA) hybrid to optimize HDPE nanobiocomposite properties that outperformed traditional response surface methodologies. Collectively, these studies underscore the versatility and precision of hybrid ML models in advancing material design, optimization, and performance prediction, driving sustainable innovations in material science.

2.4 Multi-Response optimization techniques in composite material production

Recent research on multi-response optimization techniques in composite material production has demonstrated significant progress in enhancing mechanical, thermal, and wear properties through data-driven and experimental approaches. Rajeswari and Punna [38] applied response surface methodology (RSM)-based grey relational analysis (GRA) with an advanced optimization algorithm to improve the mechanical properties of multi-walled carbon nanotube (MWCNT)-reinforced glass and fiber-reinforced polymer (GFRP) composites. This highlighted the enhanced strength and durability provided by carbon nanotube (CNT) integration [38]. Similarly, Bellairu et al. [39] employed a mixture design approach for multi-response optimization of agave cantala natural fiber-reinforced polymer nanocomposites, contributing to cleaner and more sustainable composite manufacturing.

Green composites have also benefited from multi-response optimization frameworks. Akinwande et al. [40] studied metal composites derived from municipal waste and found that material agglomeration significantly affects composite strength under varying load conditions. Equbal et al. [41] demonstrated the efficacy of an artificial neural network (ANN) and genetic algorithm (GA) model in optimizing machining parameters for GFRP composites. They achieved enhanced precision and improved material removal rates [41]. Similarly, Gupta et al. [42] optimized hybrid filler composition in pultruded jute fiber-reinforced polymer composites, resulting in improved material strength and fatigue resistance.

In machining applications, Deepak and Davim [43] optimized abrasive water jet (AWJ) machining parameters for hybrid GFRP composites using a grey relational method (GRM), emphasizing the importance of process parameter control in minimizing surface defects and achieving superior finishes. Shunmugesh and Panneerselvam [44] demonstrated the integration of ANN with meta-heuristic algorithms for optimizing drilling performance in carbon fiber-reinforced polymers (CFRPs), improving hole quality and reducing delamination. Verma et al. [45] employed GRA for optimizing drilling parameters in GFRP composites to balance performance metrics such as surface roughness and tool wear, while Raveendran and Marimuthu [46] applied multi-response optimization to refine turning parameters for GFRP rods, enhancing dimensional accuracy and surface integrity. Collectively, these studies underscore the critical role of multi-response optimization in composite production, enabling manufacturers to balance competing performance criteria and improve overall product quality.

3. Materials and methods

3.1 Matrix materials

In this study, AA6061-T6 was used as the matrix material. AA6061-T6 is a versatile aluminum alloy with excellent mechanical and chemical properties, making it suitable for a wide range of industrial applications. Its high strength, corrosion resistance, and good machinability enable its use in the aerospace, automotive, construction, marine, sports equipment, and consumer goods industries. The “T6” designation refers to the tempering process, indicating that the alloy has been solution heat-treated and artificially aged to achieve optimal mechanical properties with increased strength and hardness. Its mechanical and chemical properties are shown in Tables 1 and 2, respectively.

Table 1 Chemical composition of AA6061-T6.

Materials	Element (wt%)							
	Al	Mg	Si	Fe	Cu	Zn	Ti	Mn
AA6061-T6	Bal.	0.82	0.47	0.27	0.07	0.18	0.05	0.12

Table 2 Mechanical properties of AA6061-T6.

Materials	Mechanical properties		
	F_u	F_y	HV
AA6061-T6	285	237	91

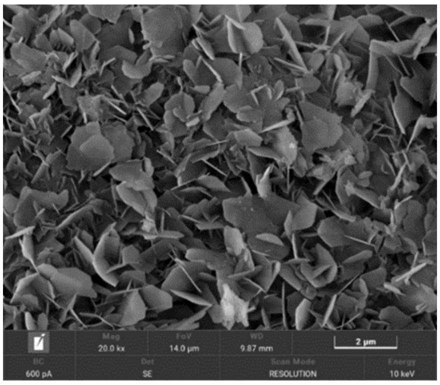


Figure 1 MgO Reinforcement materials

3.2 Reinforcement materials

In this study, the reinforcing material used is MgO, with a chemical composition consisting of 50.67 wt% Mg and 49.33 wt% O. The characteristics of MgO are illustrated in Figure 1. This SEM image of MgO particles shows its irregular and thin plate-like structures, indicating a high surface area and potential for applications in various industrial and scientific fields. The magnification and detailed observation provide a clear understanding of the MgO particle structure, which is beneficial in assessing the suitability of MgO for specific applications. The mechanical properties of MgO include a hardness of 5.5–6 Mohs, compressive strength ranging from 1,000 to 3,000 MPa, and an elastic modulus of approximately 290 GPa. This indicates its potential to withstand high compressive loads while remaining brittle. Additionally, MgO has a high melting point, 2,852 °C, and a thermal conductivity between 45 and 60 W/m·K, making it suitable for high-temperature applications.

3.3 FSP processes and investigations

Aluminum AA6061-T6 plates with a thickness of 10 mm were prepared with 150 x 200 mm (width x length) dimensions. The surfaces of these plates were drilled with straight line holes having a 2 mm diameter, with 6, 7, and 8 mm hole spacings. These holes were used for introduction of MgO reinforcement particles in volumes ranging from 320 to 456 mm³ into the pre-drilled holes of the AA6061-T6 aluminum plates. MgO nanoparticles were uniformly distributed to completely fill the holes. The FSP setup involved clamping the AA6061-T6 aluminum plates onto a CNC machine table (Model: VMC MACHINE CYCLONE-610), which ensured stable control of the operational parameters. The production parameters for the aluminum matrix composites (AMCs) were set according to Table 3, which includes tool rotational speed, tool traverse speed, and the volume of MgO. Fabrication of AMCs was done following a central composite design (CCD) matrix, providing a structured approach for varying different parameters. During the FSP process, the rotating tool traversed along the surface of the prepared aluminum plates. The tool facilitated the mixing and uniform dispersion of MgO nanoparticles within the aluminum matrix. Throughout the FSP operation, a downward force was applied by the tool onto the workpiece, combined with tool rotation and linear movement from the advancing side to the retreating side, thus creating a stir zone as depicted in Figure 2. This process ensures the effective integration and uniform distribution of the MgO nanoparticles within the aluminum base material. The fabricated AMCs were then subjected to tensile strength testing according to ASTM-E8 standards. The hardness of the stir zone was measured using a micro-Vickers hardness tester, with an indenter dwell time of 15 seconds and an applied force of 0.98 kgf, according to ASTM-E384 standards. Samples were cut and prepared to the specified dimensions shown in Figure 3.

Table 3 Experimental factors for fabrication of AMCs using the FSP process.

Parameter	Unit	(-)	Low	High	(+)
Rotation speeds (*S*)	rpm	659	800	1400	1541
Travel speeds (*F*)	mm/min	11	20	60	69
Particle valume (*P*)	mm^3	320	346	456	482

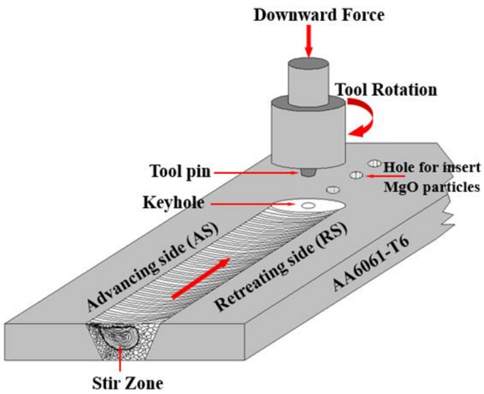


Figure 2 The tool configuration employed in the fabrication of AMC in the FSP process [7].

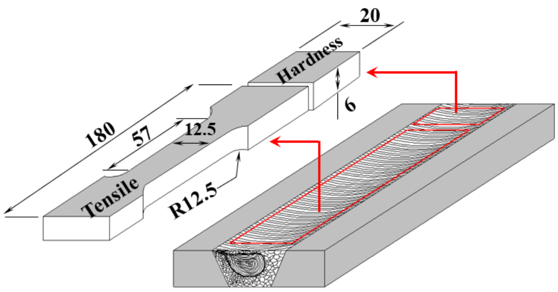


Figure 3 Specimen for tensile testing and hardness testing. Dimensions are in mm.

3.4 Pridiction and optimization

3.4.1 Artificial neural network (ANN) modeling

In this work, artificial neural network (ANN) modeling is employed to predict the outcomes of friction stir processing (FSP) in the production of aluminum matrix composites (AMCs). This material is reinforced with MgO particles using an AA6061-T6 aluminum alloy. The ANN architecture consists of three main layers. The input layer includes three neurons, which receive the welding process parameters (rotation speed, travel speed, and MgO volume). The hidden layer contains several neurons. Their quantity affects the performance of the ANN system. The output layer consists of two neurons that predict the tensile strength and hardness of the stir zone, as illustrated in Figure 4. Feed-forward backpropagation is employed to construct the ANN model, utilizing the Levenberg-Marquardt learning rule. The computed values of the neurons in the layers are determined using Equations (1)–(5), as follows [47].

Calculation of the neuron outputs in the input layer is described by Equation (1).

$$C_{Ii} = \frac{e^{a_1(I_{Ii}+b)} - e^{-a_1(I_{Ii}+b)}}{e^{a_1(I_{Ii}+b)} + e^{-a_1(I_{Ii}+b)}} \tag{1}$$

Here, C_{Ii} is the calculated output of neuron *i* in the input layer, a_1 is the constant of the transfer function in the input layer, I_{Ii} is the input to neuron *i* in the input layer, and *b* is the bias value.

Calculation of the input to the neurons in the hidden layer is given by Equation (2).

$$I_{Hk} = \sum_{i=1}^{I} C_{Ii} v_{ik} + b \tag{2}$$

where I_{Hk} is the input to neuron *k* in the hidden layer, and v_{ik} is the weight of the connection between neuron *i* in the input layer and neuron *k* in the hidden layer.

Calculation of the neuron outputs in the hidden layer is described by Equation (3).

$$C_{Hk} = \frac{e^{a_2(I_{Hk}+b)} - e^{-a_2(I_{Hk}+b)}}{e^{a_2(I_{Hk}+b)} - e^{-a_2(I_{Hk}+b)}} \tag{3}$$

Here, C_{Hk} is the calculated output of neuron *k* in the hidden layer, and a_2 is the constant of the transfer function in the hidden layer.

Calculation of the input to the neurons in the output layer is given by Equation (4).

$$I_{Oj} = \sum_{k=1}^{K} C_{Hk} w_{ki} + b \tag{4}$$

where I_{Oj} is the input to neuron *j* in the output layer, and w_{kj} is the weight of the connection between neuron *k* in the hidden layer and neuron *j* in the output layer.

Calculation of the neuron outputs in the output layer is described by Equation (5).

$$C_{Oj} = \frac{e^{a_3(I_{Oj}+b)} - e^{-a_3(I_{Oj}+b)}}{e^{a_3(I_{Oj}+b)} + e^{-a_3(I_{Oj}+b)}} \tag{5}$$

Here, C_{Oj} is the calculated output of neuron *j* in the output layer, and a_3 is the constant of the transfer function in the output layer.

The optimal ANN parameters developed for the current work include a neural network designed as a feed-forward backpropagation model. It consists of 3 neurons in the input layer, 5 neurons in the hidden layer, and 2 neurons in the output layer. The network is trained using Levenberg-Marquardt's rule, with a learning rate of 0.5 and a momentum constant of 0.4. The transfer function coefficients are 0.6 for the input neurons, 1.4 for the hidden neurons, and 0.6 for the output neurons. Additionally, the network includes a bias value of 0.0005 to adjust the output calculations.

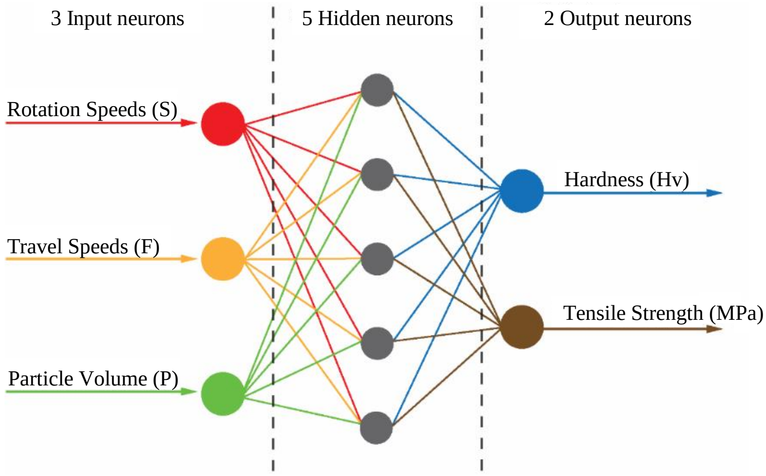


Figure 4 The optimal ANN structural system

3.4.2 Grey Relational Analysis (GRA)

Grey relational analysis (GRA) was employed to determine the optimal values of tensile strength and hardness predicted by the artificial neural network (ANN) model in the production of aluminum matrix composites reinforced with MgO nanoparticles produced via friction stir processing (FSP). The first step involved normalizing the predicted values from the ANN to a comparable scale using the "larger-the-better" criterion for both tensile strength and hardness. The normalization process was performed following Equation (6).

$$X_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{6}$$

where X_i is the normalized value, X_{min} and X_{max} are the minimum and maximum values for each response, respectively. Following normalization, the grey relational coefficient (GRC) is calculated using Equation (7).

$$\lambda_i = \frac{\Delta_{\min} - \lambda\Delta_{\max}}{\Delta_i - \lambda\Delta_{\max}} \tag{7}$$

where Δ_i is the absolute difference between the predicted value and the ideal value (1 for the "larger-the-better" criterion), $\Delta_{\min}$ and $\Delta_{\max}$ are the minimum and maximum absolute differences, respectively, and λ is the distinguishing coefficient, typically set at 0.5.

The next step is calculating the grey relational grade (GRG), which provides a comprehensive measure of the performance for each experimental trial. It is an average of the GRC values of tensile strength and hardness, using Equation (8).

$$\gamma_i = \frac{1}{n}\sum_{i=1}^{n} \lambda_i \tag{8}$$

Where γ_i is the GRG for the i^{th} trial, λ_i is the GRC for each response, and n is the number of responses (in this case, 2: tensile strength and hardness). The GRG values are then ranked, with the highest value indicating the optimal parameter setting for the FSP process. Finally, a confirmation experiment is conducted using the parameter set with the highest GRG to validate the predicted tensile strength and hardness, ensuring that the ANN model's optimization aligns with the experimental results.

4. Experimental result

Table 4 presents the design matrix and experimental results for production of aluminum matrix composites (AMCs) reinforced with MgO nanoparticles via friction stir processing (FSP). The table details the input parameters, including tool rotation speed, tool travel speed, and particle volume, as well as the corresponding output responses, which are tensile strength (Ts) and hardness (HV). The rotation speed ranged from 659 to 1541 rpm, while the travel speed varied between 11 and 69 mm/min, and the particle volume ranged from 320 to 482 mm³. The tensile strength and hardness of the produced AMC samples fluctuated based on these process parameters. These tensile strength values ranged from 258.22 to 317.34 MPa with hardness values from 110.26 to 149.35 HV. The experimental results highlight that Run 8, with a rotation speed of 1100 rpm, travel speed of 40 mm/min, and particle volume of 401 mm³, produced the highest tensile strength, 317.34 MPa. However, Run 13, with a particle volume of 482 mm³, achieved the highest hardness, 149.35 HV. These findings underscore the significance of optimizing FSP parameters to enhance the mechanical properties of AMC materials. This serves as a basis for further analysis through artificial neural network (ANN) modeling and grey relational analysis (GRA) to identify the most suitable process conditions for maximizing tensile strength and hardness.

Table 4 Design matrix and experimental results.

Std.	Run	FSP Parameters			Responses	
		S	*F*	*P*	*Ts* (Mpa)	HV
7	1	800	60	456	271.05	144.55
12	2	1100	69	401	279.72	124.75
1	3	800	20	346	284.42	114.08
2	4	1400	20	346	274.06	126.74
11	5	1100	11	401	286.14	127.33
15	6	1100	40	401	311.21	122.19
3	7	800	60	346	275.32	112.23
17	8	1100	40	401	317.34	116.45
10	9	1541	40	401	292.08	126.76
16	10	1100	40	401	316.81	128.84
8	11	1400	60	456	258.22	138.92
18	12	1100	40	401	304.45	117.56
14	13	1100	40	482	266.67	149.35
19	14	1100	40	401	309.35	121.44
5	15	800	20	456	283.18	147.64
13	16	1100	40	320	278.62	110.26
6	17	1400	20	456	275.47	136.32
4	18	1400	60	346	293.53	114.54
9	19	659	40	401	291.64	119.61

4.1 ANN and RSM model predictions

Figure 5 shows the loss curve of the 3-3-2 neural network structure, depicting the evolution of mean squared error (MSE) over six epochs for the training, validation, and test datasets. The training curve (blue) demonstrates a consistent reduction in error as the epochs increase, signifying effective learning from the data. The validation (green) and test (red) curves, however, indicate that optimal performance was achieved at epoch 1, where the best validation performance is 467.229 MSE. After this point, the validation and test errors remained relatively stable, while the training errors continued to decrease. This suggests that further training could lead to overfitting, as the validation and test errors do not improve despite continued optimization of the training data. The graph in Figure 5 highlights the importance of stopping early to prevent overfitting. This ensures that the network achieves generalization during training.

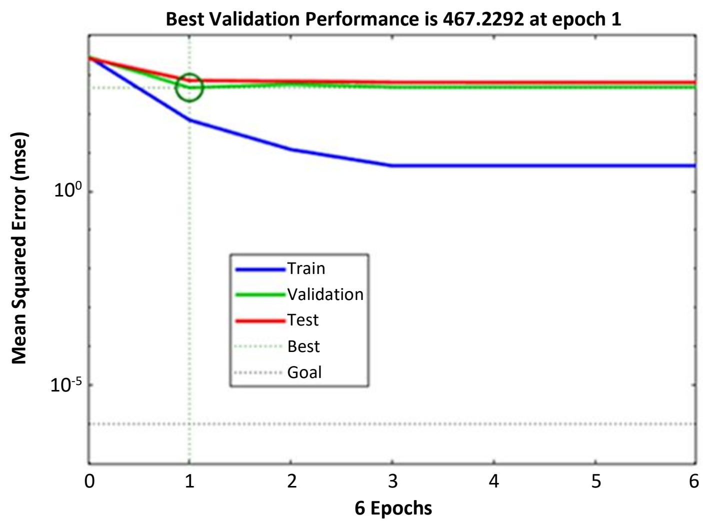


Figure 5 The loss curve of the 3-3-2 network structure

Figure 6 presents regression plots of the experimental and predicted data obtained from the artificial neural network (ANN) model, showing the correlation between the actual target values and the predicted outputs for different data subsets, (a) training, (b) validation, (c) testing, and (d) all data combined. The regression coefficients (R-values) for the training, validation, testing, and overall datasets are 0.9975, 0.9954, 0.9965, and 0.997, respectively, indicating a high level of correlation between the predicted and actual values. The plots demonstrate that the ANN model provides an accurate prediction across all data sets, with minimal deviation between the predicted and target values, as shown by a near-linear fit for each subset. This high degree of fit confirms the model's capability to effectively generalize across the training, validation, and test sets.

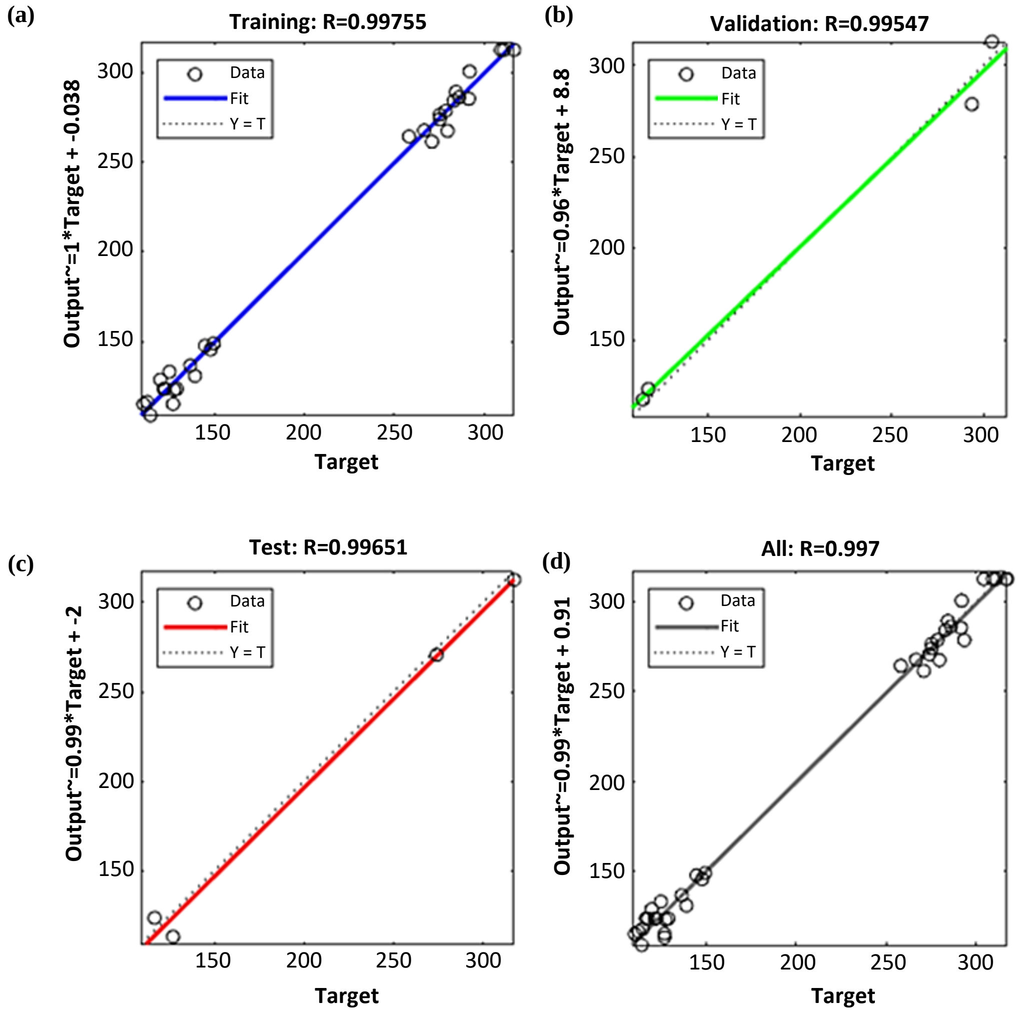


Figure 6 Experimental and prediction (ANN) the data regression plot; (a) the training set; (b) the validation set; (c) the testing set; and (d) all data.

Table 5 Experimental, ANN and RSM model.

Run	Experimental		Pre.ANN model		Pre.RSM model.	
	Ts	***Hv***	***Ts***	***Hv***	***Ts***	***Hv***
1	271.05	144.55	272.17	144.74	265.01	145.94
2	279.72	124.75	277.32	123.43	282.58	124.37
3	284.42	114.08	286.06	114.46	277.65	114.28
4	274.06	126.74	272.34	126.58	276.93	124.81
5	286.14	127.33	285.85	128.16	289.31	128.71
6	311.21	122.19	313.92	122.03	310.82	121.12
7	275.32	112.23	278.71	113.98	277.09	109.06
8	317.34	116.45	312.91	114.03	310.82	121.12
9	292.08	126.76	291.28	128.66	293.36	124.69
10	316.81	128.84	314.94	127.03	310.82	121.12
11	258.22	138.92	257.20	136.73	261.82	138.18
12	304.45	117.56	306.94	115.03	310.82	121.12
13	266.67	149.35	267.14	147.16	268.76	149.08
14	309.35	121.44	308.94	124.03	310.82	121.12
15	283.18	147.64	281.80	147.29	285.45	144.38
16	278.62	110.26	277.62	110.70	282.37	111.50
17	275.47	136.32	273.98	135.93	270.53	138.95
18	293.53	114.54	294.05	114.63	288.09	117.26
19	291.64	119.61	289.96	121.93	296.23	122.65
Mean Squared Error (MSE)			***3.02***	***2.48***	***18.23***	***8.09***

In Table 5, comparison of the experimental results, ANN model, and RSM model predictions highlight how both models perform in predicting tensile strength (Ts) and hardness (Hv) in aluminum matrix composites (AMCs). The data reveals that the ANN model outperforms RSM with significantly lower mean squared error (MSE) values for both tensile strength and hardness. The ANN model's ability to capture non-linear relationships and complex interactions between input parameters, such as rotation speeds, travel speeds, and particle volume, makes it a superior tool for predicting material properties like tensile strength and hardness. This is consistent with research findings, where ANN models have been shown to outperform traditional statistical methods like RSM in predicting material properties. For instance, studies have demonstrated that ANN can more accurately predict mechanical properties, such as tensile strength and hardness, in composites with complex reinforcement interactions [48, 49]. Moreover, while macrohardness testing can give qualitative insights into tensile strength, it often struggles with quantitative accuracy, as noted for aluminum composites reinforced with silicon carbide particles [50]. Table 5 supports the idea that ANN is a more reliable method for predicting material properties in AMCs. It accounts for complex, non-linear dependencies between input parameters and output properties that are often missed by RSM models.

In Figure 7, two comparisons are shown, one for tensile strength (a) and another for hardness (b) between the experimental results, ANN predictions, and RSM model predictions for aluminum matrix composites. In Figure 7a, both the ANN and RSM models are relatively accurate in predicting tensile strength. However, the ANN model offers slightly more precision, aligning more closely with the experimental results across most trials. This demonstrates the ANN's ability to model non-linear tensile strength relationships. This observation aligns with research findings where ANN models outperformed RSM in capturing complex interactions between input variables, such as reinforcement ratios and processing conditions, especially in aluminum matrix composites [48]. In Figure 7b, the ANN model shows a closer fit to the experimental data than the RSM model for hardness. This is consistent with previous studies where ANN models more effectively captured the influence of reinforcement volume fraction on hardness, often leading to more accurate predictions of material properties, like composite hardness and tensile strength [50].

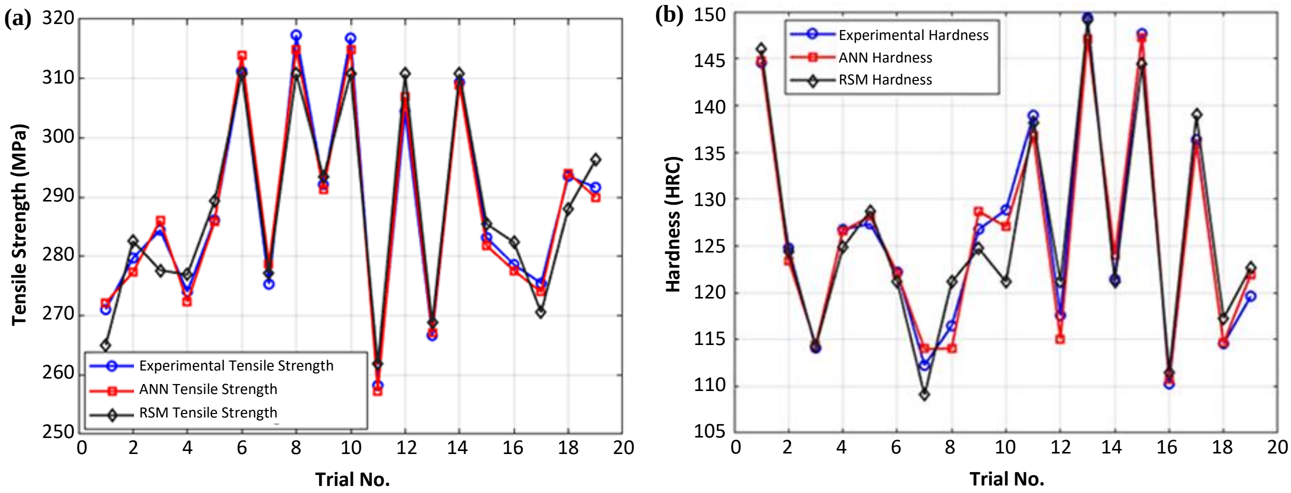


Figure 7 Experimental, RSM model estimated, and ANN predicted values of (a) tensile strength and (b) hardness.

Table 6 Normalization, GRC, GRG and Rank of tensile strength and hardness.

Run	Parameter			Normalization		GRC		GRG	Rank
	S	*F*	*P*	*Ts*	*HV*	*GRC-Ts*	*GRC-Hv*		
1	800	60	456	0.2170	0.8772	0.5609	0.8906	0.7257	7
2	1100	69	401	0.3637	0.3707	0.6111	0.6138	0.6124	15
3	800	20	346	0.4432	0.0977	0.6423	0.5257	0.5840	17
4	1400	20	346	0.2679	0.4216	0.5773	0.6335	0.6054	16
5	1100	11	401	0.4723	0.4367	0.6546	0.6397	0.6471	11
6	1100	40	401	0.8963	0.3052	0.9061	0.5900	0.7480	5
7	**800**	**60**	**346**	**0.2892**	**0.0504**	**0.5845**	**0.5129**	**0.5487**	**19**
8	1100	40	401	1.0000	0.1584	1.0000	0.5430	0.7715	3
9	1541	40	401	0.5727	0.4221	0.7006	0.6338	0.6672	10
10	**1100**	**40**	**401**	**0.9910**	**0.4753**	**0.9911**	**0.6559**	**0.8235**	**1**
11	1400	60	456	0.0000	0.7332	0.5000	0.7894	0.6447	12
12	1100	40	401	0.7820	0.1867	0.8210	0.5515	0.6862	8
13	1100	40	482	0.1429	1.0000	0.5385	1.0000	0.7692	4
14	1100	40	401	0.8649	0.2860	0.8809	0.5834	0.7322	6
15	800	20	456	0.4222	0.9563	0.6338	0.9581	0.7959	2
16	1100	40	320	0.3451	0.0000	0.6043	0.5000	0.5521	18
17	1400	20	456	0.2918	0.6667	0.5854	0.7500	0.6677	9
18	1400	60	346	0.5973	0.1095	0.7129	0.5290	0.6209	14
19	659	40	401	0.5653	0.2392	0.6970	0.5679	0.6325	13

4.2 Grey Relational Analysis (GRA) optimization

Based on Table 5, the predictions from the ANN model were more accurate than those from the RSM model. Therefore, the researchers applied the ANN predictions to optimize the results using grey relational analysis (GRA). This was done to identify the factors most affecting the tensile strength and hardness of the aluminum matrix composite (AMC). Optimization results using GRA are presented in Table 6, which shows the normalization, GRC, GRG, and rank of tensile strength and hardness. This table illustrates a comprehensive analysis of various experimental runs conducted to optimize tensile strength (Ts) and hardness (Hv) in a friction stir process experiment. The experimental parameters include rotation speed (S), travel speed (F), and particle volume (P). For each run, normalized values of tensile strength and hardness were computed, followed by calculation of the grey relational coefficients (GRCs) for both responses, tensile strength (GRC-Ts) and hardness (GRC-Hv). The grey relational grade (GRG), which aggregates these GRC values, provides an overall ranking for each experimental trial. In this table, run 10 demonstrates the highest performance with a GRG value, 0.8235, indicating the most favorable combination of input parameters for achieving both high tensile strength and hardness. Conversely, run 7, with the lowest GRG value, 0.5487, reflects suboptimal performance in terms of the desired mechanical properties.

Table 7 Grey relational analysis (GRA) and confirmation test for tensile strength and hardness.

Optimized parameter			**Responses**			**Inappropriate parameters**			**Responses**	
S	***F***	***P***		***Ts***	***Hv***	***S***	***F***	***P***	***Ts***	***Hv***
1100	40	401	**ANN**	314.94	127.03	800	60	346	278.71	113.98
			Exp.	310.27	118.76				275.32	109.56
			Error	-1.51%	-6.96%				-1.22%	-3.88%
GRG = 0.8235				GRG = 0.7886		GRG = 0.5487			GRG = 0.5347	

Table 7 presents the results of grey relational analysis (GRA) and a confirmation test for tensile strength (Ts) and hardness (Hv). The analysis is divided into two sections, optimized parameters and inappropriate parameter values. For the optimized parameters (S = 1100 rpm, F = 40 mm/min, P = 401 mm^3), the predicted values from the artificial neural network (ANN) for Ts and Hv are 314.94 MPa and 127.03 HV, respectively, which are in close agreement with the experimental values of 310.27 MPa for Ts and 118.76 HV for Hv. The percentage errors for Ts and Hv are -1.51% and -6.96%, respectively. The grey relational grade (GRG) for this set of parameters is 0.8235 for Ts and 0.7886 for Hv, indicating that these optimized parameters result in excellent mechanical properties. Conversely, for the inappropriate parameter values (S = 800 rpm, F = 60 mm/min, P = 346 mm^3), the predicted ANN values are 278.71 MPa for Ts and 113.98 HV for Hv, which closely match the experimental results of 275.32 MPa for Ts and 109.56 HV for Hv, with errors of -1.22% and -3.88%, respectively. However, the GRG values for Ts and Hv are significantly lower, at 0.5487 and 0.5347, indicating that these parameters are unsuitable for optimizing the material properties. This study demonstrates the capability of ANN to predict mechanical properties with a high degree of accuracy, closely aligning with experimental results. The optimized parameters yield significantly improved mechanical properties, confirmed by the experimental data, underscoring the efficacy of GRA in identifying optimal process parameters for this application.

Table 8 presents a comparative analysis of various methods employed to enhance the mechanical properties of aluminum matrix composites (AMCs). The study demonstrates that the proposed hybrid approach combining artificial neural network (ANN) and grey relational analysis (GRA) yields a superior tensile strength (Ts), 317.34 MPa, and a hardness value (HV) of 149.35 for AA6061-T6 reinforced with MgO nanoparticles. Notably, the ANN + CuO reinforcement method in Al6061-CuO composites achieved a tensile strength close to 310 MPa, although no hardness value was reported. In contrast, techniques such as response surface methodology (RSM) integrated with GRA, with B_4C reinforcement through friction stir processing (FSP), have shown significant improvements in tensile strength or hardness, though specific values were often omitted. Additionally, advancements through hybrid reinforcements (e.g., Al-SiC, carbon fibers, and nano-Al_2O_3) consistently indicate enhanced mechanical properties across various studies.

The present work stands out by providing a balanced and quantitative enhancement of both strength and hardness, which underscores the efficacy of using MgO nanoparticles and a data-driven optimization framework. Compared to prior research, this dual optimization not only outperforms conventional reinforcement techniques, but also highlights the benefits of integrating ANN and GRA to achieve robust property improvements in AMCs.

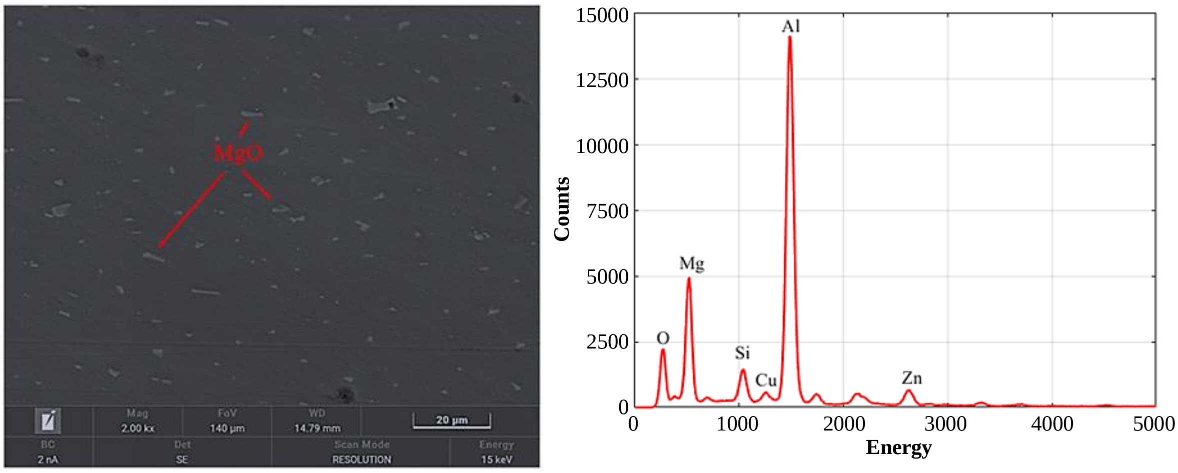
Table 8 Comparison of methods for mechanical property improvement in AMCs.

Reference	Method	Material	Ts (Mpa)	HV
This Work	ANN + GRA	AA6061-T6 + MgO nanoparticles	317.34	149.35
[1]	MgO-reinforced AMCs (review)	Magnesium Metal Matrix Composites	N/A	Improved
[2]	ANN + CuO Reinforcement	Al6061-CuO composites	~310	N/A
[6]	GRA + Grey-Fuzzy Model	Al-TiB_2 reinforced AMCs	N/A	Improved
[7]	RSM + GRA	Al-SiC composite	N/A	Increased
[16]	Hybrid Reinforcement	Al Matrix + SiC & Carbon fibers	N/A	Increased
[17]	Nano-Al_2O_3 Reinforcement	AA7075 + Al_2O_3 Nanoparticles	N/A	High
[19]	FSP (Ex-situ Composite)	Metal Matrix Composite (MMC)	N/A	Increased
[22]	FSP + B_4C Reinforcement	Al7075/B_4C composite	~310	N/A
[23]	FSP + CNT/Al_2O_3 Reinforcement	Al-Al_2O_3-CNT composite	N/A	Increased
[24]	FSP + B_4C Reinforcement	Surface Composites	300+	N/A
[26]	Bulk FSP Composite Production	Metal Matrix Composite	~280	N/A

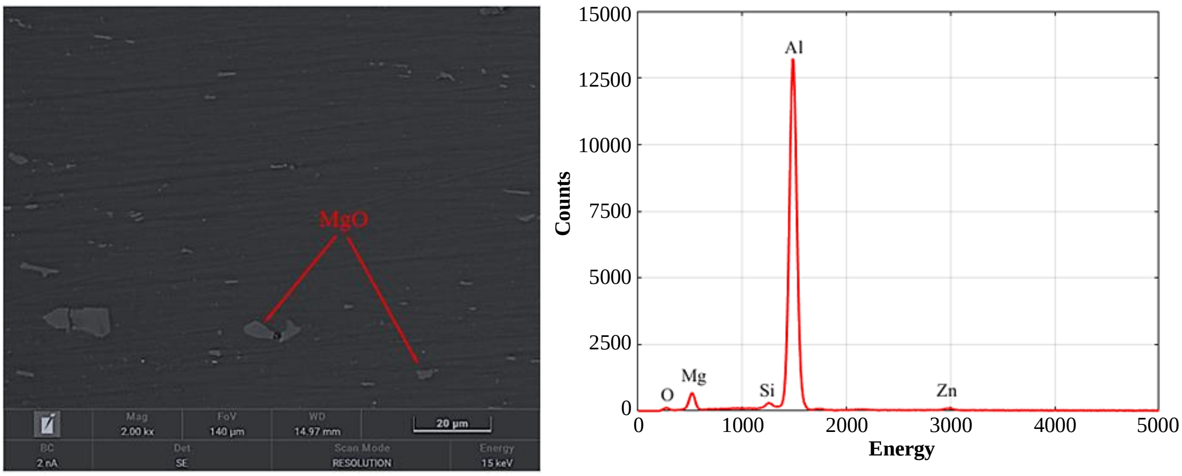
4.3 Morphology of the stirred zone

Confirmation of experimental results, presented in Table 7, compares the optimized parameters affecting the tensile strength and hardness of the stir zone. The specimens prepared with optimized parameters (1100S-40F-401P) and inappropriate parameter values (800S-60F-346P) were subjected to a morphological analysis of the stir zone. Their chemical composition was examined using

SEM/EDS techniques. The results are illustrated in Figures 8(a-b), which compare the microstructure and elemental distribution obtained through energy dispersive spectroscopy (EDS) of the specimens fabricated via friction stir processing (FSP) under two different experimental conditions, optimized and inappropriate. Figure 8(a) shows the optimized parameters (rotation speed of 1100 rpm, travel speed of 40 mm/min, and MgO particle volume of 401 mm³). MgO particles were evenly distributed within the AA6061-T6 aluminum matrix. This indicates that the MgO particles were effectively integrated into the base metal, leading to increased tensile strength and hardness. This is supported by the EDS results, which show a clear presence of Mg (magnesium) and O (oxygen), in addition to the predominant element Al (aluminum). Conversely, in Figure 8(b), which corresponds to the inappropriate parameter values (rotation speed of 800 rpm, travel speed of 60 mm/min, and MgO particle volume of 346 mm³), the MgO particles were unevenly distributed and agglomerated. This resulted in lower tensile strength and hardness, as evidenced by the reduced distribution of Mg and O in the EDS results. This comparative analysis is consistent with the data presented in Table 7, which shows that the optimized parameters (1100S-40F-401P) yield higher tensile strength and hardness than the inappropriate parameter values (800S-60F-346P). Additionally, the prediction errors from the ANN model for the optimized condition were significantly lower than those for the inappropriate condition. Therefore, optimization of process parameters in the production of composite materials has a direct impact on improving the mechanical properties of the specimens.



(a) 1100S-40F-401P



(b) 800S-60F-346P

Figure 8 Microstructure and EDS of specimens with optimized and inappropriate parameter values.

5. Discussion

Optimizing aluminum matrix composites (AMCs) reinforced with MgO nanoparticles via friction stir processing (FSP) reveals the significant advantages of employing hybrid artificial neural network (ANN) and grey relational analysis (GRA) modeling. This hybrid approach excels in predicting and optimizing tensile strength and hardness, compared to traditional methods like response surface methodology (RSM). The ANN model, with its ability to capture non-linear interactions between process parameters such as rotation speed, travel speed, and MgO particle volume, offers superior predictive performance. This flexibility in modeling complex relationships allows ANN to accurately predict outcomes that are often missed by RSM. This is further validated by high regression coefficients that indicate the model's reliability and generalization across different data sets [51, 52].

GRA also plays a crucial role in refining these predictions by identifying the most favorable combinations of process parameters that optimize both tensile strength and hardness. The GRA method simplifies the multi-response optimization process through its ranking system and the use of normalized values. This makes it an efficient tool for determining the best mechanical performance from various experimental conditions. The GRA approach ensures that optimal outcomes are achieved more effectively than traditional statistical models like RSM, which are often limited in handling complex, multi-variable interactions [52]. Combining GRA with ANN, enabled researchers to confirm that the hybrid model is accurate and robust, with low prediction errors when evaluated against experimental data.

When comparing the ANN-GRA hybrid model with traditional methods like RSM, the former offers a more precise and comprehensive approach to optimizing mechanical properties in AMCs. The mean squared error (MSE) values for both tensile strength and hardness were significantly lower with ANN predictions, showcasing its ability to model intricate non-linearities that RSM tends to oversimplify. While RSM can be effective in linear or moderately non-linear processes, its limitations become clear in more complex scenarios like AMC production. In contrast, the ANN-GRA model captures a full range of parameter interactions, leading to more precise and reliable optimization results, marking a significant advancement in material property optimization [51, 53].

6. Conclusions

This research addresses the critical need for optimizing the production of aluminum matrix composites (AMCs) reinforced with MgO nanoparticles using friction stir processing (FSP). Traditional methods, such as response surface methodology (RSM), have limitations in capturing the non-linear interactions between critical process parameters like rotation speed, travel speed, and particle volume. The complexity of optimizing these parameters to achieve enhanced mechanical properties, such as tensile strength and hardness, requires a more sophisticated approach. This study employs a hybrid model that combines artificial neural networks (ANNs) and grey relational analysis (GRA) to improve prediction accuracy and more effectively optimize the FSP process than traditional methods. The computational results of the study show that the ANN-GRA hybrid model outperforms RSM in terms of prediction accuracy. ANN's strength lies in its capability to capture complex non-linear relationships, providing more accurate predictions of tensile strength and hardness of AMCs. GRA complements this by refining the ANN predictions, enabling optimal parameter selection for the FSP process. The hybrid approach significantly reduced the mean squared errors in the predictions, confirming its robustness in multi-response optimization scenarios. The results demonstrate the method's effectiveness in identifying the best combination of process parameters, contributing to the production of AMCs with superior mechanical properties. The implications of this research are broad, particularly for industries such as aerospace, automotive, and advanced manufacturing, where material performance is crucial. This hybrid ANN-GRA model offers a powerful tool for optimizing the mechanical properties of composite materials, paving the way for more efficient and sustainable manufacturing practices. Future research could explore extending this model to other composite systems, incorporating additional parameters, or applying it in large-scale industrial settings to validate its effectiveness. The continued development of such models has the potential to further enhance the precision and efficiency of materials engineering, driving innovation in manufacturing technology.

7. Acknowledgements

I would like to express my heartfelt gratitude to my advisor, Dr. Chaiya Chomchalao, and Assistant Professor Dr. Thanatep Phatungthane for his unwavering support, invaluable guidance, and insightful advice throughout the course of my research and thesis writing. His expertise and dedication have been instrumental in the successful completion of this work. I would like to extend my sincere thanks to the Department of Industrial Technology, Faculty of Industrial Technology, Nakhon Phanom University, for providing the necessary resources, facilities, and a conducive environment for my research. The support from the department has been crucial in enabling me to pursue and complete my studies.

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