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ANFIS modeling of turning Al7075 hybrid nanocomposites under compressed air cooling

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ABSTRACT

Introduction. Hybrid metal matrix composites (*HMMCs*) are increasingly used in the aviation and automotive industries due to their low density, high stiffness, and exceptional specific strength. Among aluminum *MMCs*, *Al7075*-based composites are gaining wider acceptance. Continuous research and development in this field focuses on improving the durability and performance of these advanced materials. **Purpose of the work.** Machinability of *Al7075* is a significant challenge because the abrasive reinforcement phase causes rapid tool deterioration, increased machining forces, and a poor surface finish. Moreover, the industrial focus on green manufacturing has led to a shift from traditional coolant-based machining to sustainable alternatives. In this context, researchers have optimized machining performance using advanced technological advancements and techniques. However, limited work is reported on modeling the machining performance of *Al7075* nanocomposites during turning under compressed air cooling. **Methods of investigation.** Manufacturers can gain a better understanding of increasing the effectiveness of turning processes for *Al7075* nanocomposites by creating a comprehensive model. Therefore, this work models the machining performance of hybrid *Al7075* nanocomposites during turning under compressed air-cooling conditions with an artificial neuro-fuzzy inference system (*ANFIS*) to predict tool wear (***TW***), surface roughness (***Ra***), and cutting force (***Fc***) as a function of process parameters. **Results and discussion.** In this work, an *ANFIS* model was developed to predict the machining performance considering the effect of process parameters such as cutting speed, feed rate, and depth of cut for different *Al7075*-based nanocomposites. These nanocomposites were prepared using silicon carbide (30–50 nm) and graphene (5–10 nm) nanoparticles as reinforcements by the stir casting process. Reinforcement materials affect the mechanical and physical properties of composites. For engineering applications, *SiC* and graphene are preferred reinforcements with distinctive features. *ANFIS* models were developed to predict ***Ra***, F_c, and ***TW*** based on the experimental results. The *Sugino* method was used to represent fuzzy rules and membership functions, as it utilizes weighted averages in the defuzzification process and offers better processing efficiency. The *MATLAB ANFIS* toolbox was used to design and tune fuzzy inference systems. The developed *ANFIS* model predicts machining responses effectively and offers a practical approach for optimizing process parameters with high reliability. The results of this research show good agreement between the experimental results and the predicted *ANFIS* outcomes, with an average prediction error below 8%. Specifically, the *ANFIS* model yielded errors of 5.1% for ***Ra***, 13.45% for F_c, and 7.92% for ***TW***. The model exhibited excellent agreement with experimental data, demonstrating high prediction accuracy and generalization capability. 3-D graphs are plotted for a better understanding of the effect of process parameters on F_c, ***Ra***, and ***TW*** for different nanocomposites. The findings affirm the efficacy of compressed air cooling in improving machinability while minimizing environmental impact. Furthermore, the developed ANFIS model serves as a reliable tool for optimizing turning parameters for Al7075 composites, supporting the advancement of green manufacturing strategies. This research warrants further investigation into the application of *ANFIS* in machining processes, specifically exploring various metal matrix composite types and rigorously assessing the long-term effects of compressed air cooling on both environmental sustainability and tool life.

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Introduction

Hybrid metal matrix composites (*HMMCs*) are increasingly found in the aviation and automotive industries because of their extraordinary properties, including low density, high stiffness, outstanding specific strength, and a low coefficient of thermal expansion. The growing demand for advanced materials in the aerospace, automotive, and defense sectors has driven the widespread adoption of aluminum metal matrix composites (*MMCs*), particularly *Al7075*, due to its excellent specific strength and corrosion resistance [1].

However, the machinability of *Al7075* composites presents a significant challenge due to their abrasive reinforcement phase, which accelerates tool wear, increases cutting forces, and degrades surface finish. Concurrently, the industrial shift towards green manufacturing has emphasized a move away from traditional coolant-based machining to sustainable alternatives. One such method is compressed air cooling, which not only reduces the environmental impact but also improves chip removal and provides localized cooling at the tool-workpiece interface.

Intelligent modeling techniques have proven highly effective in addressing the nonlinear and multi-parametric nature of the turning process under compressed air cooling. Traditional flood cooling relies heavily on mineral-based fluids, which have adverse effects on the environment, operator health, and operational costs due to fluid disposal. Consequently, alternative methods such as minimum quantity lubrication (*MQL*), nanofluids, cryogenic cooling, and compressed air techniques have gained significant demand in machining. These sustainable alternatives address not only environmental concerns but also key machinability aspects, including tool wear, cutting force, and surface finish [2, 3].

Studies have shown that turning *Al7075* under *MQL* with a coolant chilled to −20°C significantly improves surface finish and reduces cutting force compared to other cutting environments [4]. Furthermore, research indicates that tool nose radius has a more substantial influence on surface finish than most other process parameters. In recent decades, manufacturing has heavily relied on empirical data from previous studies. To achieve superior machining outcomes, the application of advanced cutting techniques combined with scientifically validated approaches, such as artificial intelligence (*AI*), is essential. Precise modeling is critical for obtaining desired results in machining processes. Owing to their fuzzy logic rules, self-learning capability, and ability to process complex, non-linear data, soft computing techniques are now extensively employed for modeling [5].

The literature suggests that the adaptive neuro-fuzzy inference system (*ANFIS*) often outperforms other computational methods in estimating machining responses [6, 7]. Comparative studies indicate that while gene expression programming (*GEP*) may surpass artificial neural networks (*ANN*) in specific applications, *ANFIS* frequently yields more accurate predictions. Furthermore, both *ANN* and *ANFIS* have been demonstrated to provide superior results compared to response surface methodology (*RSM*) in several investigations [8–12]. The application of optimization approaches is crucial for enhancing surface quality and advancing machining technology [13]. For instance, genetic algorithms (*GA*) have been successfully applied to optimize the milling of *Al7075-T6*, with the developed models proving adequate for predicting cutting forces [14]. Similarly, studies utilizing ANN to forecast the tribological properties of $Al7075$-Al_2O_3 composites have reported close agreement between experimental data and model predictions [15].

Researchers have also modeled machining responses using nanofluids under minimum quantity lubrication (*NFMQL*) [16, 17]. Among various modeling techniques, *ANFIS* has been widely adopted in most studies due to its superior capability in capturing the complex, non-linear dependencies among machining parameters [18–21]. However, a significant research gap remains: few investigations have considered the effect of varying the weight percentage of nanoparticles within the *Al7075* matrix on machinability. Furthermore, *ANFIS* modeling of the machining performance for hybrid *Al7075* nanocomposites under compressed air cooling conditions is virtually unreported. To address this gap, the present work develops an *ANFIS* model to predict the machining performance of hybrid *Al7075* nanocomposites, with a specific focus on quantifying the influence of nanoparticle weight percentage and cutting parameters on key output responses.

Accordingly, in the present study, nine distinct *Al7075*-based nanocomposites were fabricated with varying weight percentages of silicon carbide (*SiC*) and graphene reinforcements. For each nanocomposite specimen, nine turning experiments were conducted under compressed air cooling. An adaptive neuro-fuzzy inference system (*ANFIS*) model was developed to predict cutting force, flank wear, and surface roughness, accounting for the influences of both turning parameters and nanocomposite composition. Finally, additional validation trials were performed to verify the predictive accuracy of the developed *ANFIS* model.

Methods

This section details the experimental methodology employed to develop adaptive neuro-fuzzy inference system (*ANFIS*) models for predicting surface roughness (***Ra***), cutting force (F_c), and tool wear (***TW***) during the turning of *Al7075* nanocomposites. The experimental setup, including the machining configuration and conditions, is described, followed by a comprehensive explanation of the *ANFIS* model development process.

The workpieces were cylindrical bars (300 mm in length and 30 mm in diameter) made from *Al7075*-based nanocomposites. Turning was performed using a *CNMG120408MS* carbide insert mounted on a *PCBNR2525M12 ISO*-coded tool holder. All cutting experiments were conducted on a precision *CNC* lathe to ensure consistent tool positioning and geometry throughout the operation. The machining setup is illustrated in Fig. 1. The chemical composition of the base *Al7075* alloy is provided in Fig. 2, while Table 1 summarizes the specifications of the different composite specimens fabricated via the stir casting process.

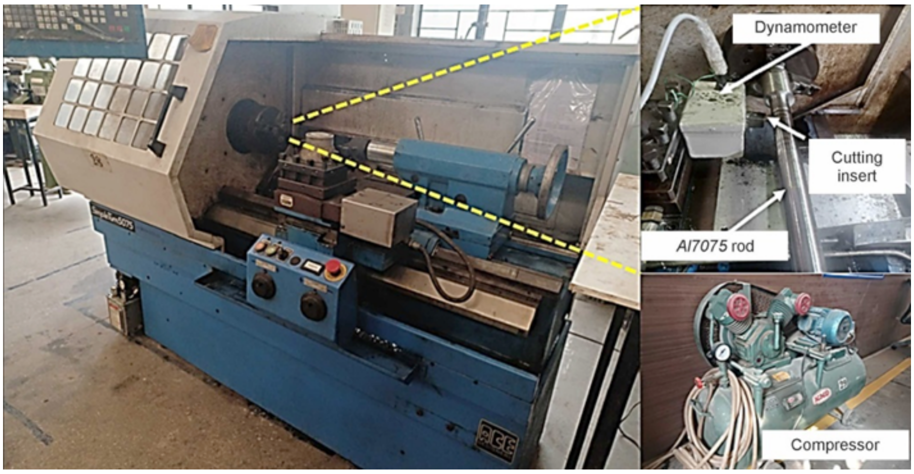

Fig. 1. Appearance and components of the lathe setup

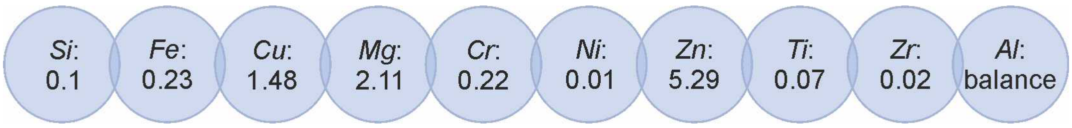

Fig. 2. Elemental composition of *Al7075* alloy

The input parameters were selected based on a comprehensive analysis of the literature, preliminary experimental trials, the operational limits of the machine tool, and technical specifications from the tooling manufacturer. The finalized parameter ranges were chosen to optimize machining performance and extend tool life. A full factorial design of experiments was employed, resulting in a total of 81 turning trials conducted across the nine distinct composite specimens, as summarized in Fig. 3.

The trials involved varying the cutting speed (***V***) from 100 to 200 m/min, the feed rate (***f***) from 0.1 to 0.3 mm/rev, and the depth of cut (***d***) from 0.2 to 0.8 mm. For each machining experiment, the output responses – surface roughness (***Ra***), cutting force (F_c), and tool wear (***TW***) – were recorded. The cutting force (F_c) was measured using a pre-calibrated dynamometer. Tool wear (***TW***), specifically flank wear (***FW***), was measured after each pass using a *Dino-Lite* digital microscope. Surface roughness (***Ra***) was measured using

Table 1

_Al7075_ aluminum alloy nanocomposites with different types of reinforcement

Specimen	Types of reinforcement
S1	Unreinforced *Al7075*
S2	*Al7075* + 0.5 % *SiC* + 0.1 % graphene
S3	*Al7075* + 0.5 % *SiC* + 0.2 % graphene
S4	*Al7075* + 0.5 % *SiC* + 0.3 % graphene
S5	*Al7075* + 0.5 % graphene + 1 % *SiC*
S6	*Al7075* + 0.5 % graphene + 2 % *SiC*
S7	*Al7075* + 0.5 % graphene + 3 % *SiC*
S8	*Al7075* + 1 % graphene + 2 % *SiC*
S9	*Al7075* + 1 % graphene + 4 % *SiC*

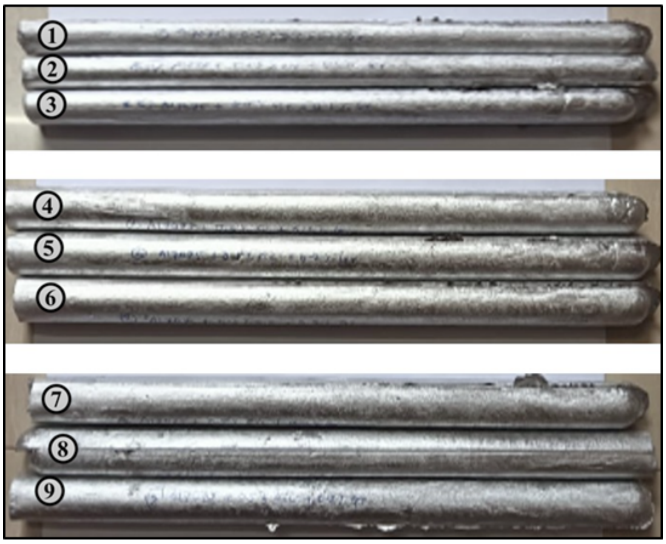

Fig. 3. Nine samples of various composite materials

a surface profilometer. Tool wear was monitored in accordance with *ISO 3685:1993* standards, with the tool life failure criterion defined as either 0.2 mm of average flank wear or the occurrence of catastrophic tool failure.

Adaptive neuro-fuzzy inference system (ANFIS)

The adaptive neuro-fuzzy inference system (*ANFIS*) is ideally suited for modeling complex systems characterized by uncertainty and imprecise information, while maintaining model transparency and interpretability. This machine learning technique synergistically combines the intuitive reasoning of fuzzy logic with the learning capabilities of artificial neural networks. The *ANFIS* approach constructs an adaptive network that maps inputs to outputs by integrating fuzzy inference mechanisms with neural learning rules. The *ANFIS* architecture comprises five distinct layers, each consisting of interconnected nodes, as illustrated in Fig. 4 [8]. Input data is processed sequentially through these layers, with each stage executing a specific function within the overall inference mechanism.

The first layer, the fuzzification layer, converts crisp input values into fuzzy membership grades using predefined membership functions. In the subsequent product layer, the firing strength of each fuzzy rule is computed by multiplying the incoming membership grades. The third layer, the normalization layer, calculates the relative contribution of each rule by dividing its firing strength by the sum of all firing strengths, thereby ensuring that the total influence of all rules is unity. The normalized firing strengths are then processed in the defuzzification layer, where each is used to weight a linear function to generate

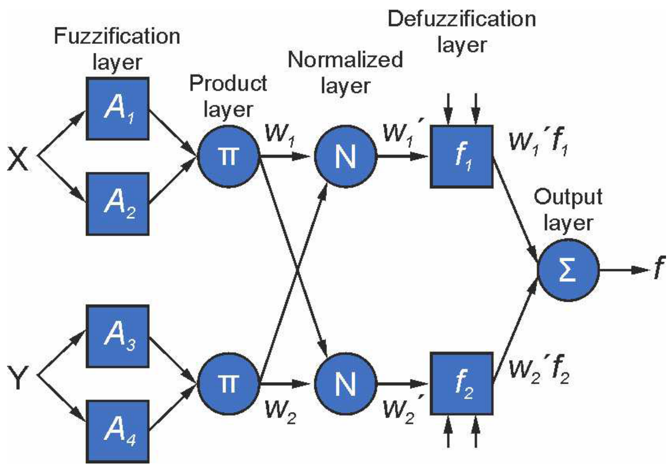

Fig. 4. General structure of *ANFIS*

the output of individual rules. Finally, the output layer aggregates all the weighted rule outputs to produce a single, crisp value representing the system's final prediction.

Results and Discussion

This section presents the development and analysis of adaptive neuro-fuzzy inference system (*ANFIS*) models for predicting the turning performance of *Al7075*-based nanocomposites under compressed air cooling. The models were constructed to evaluate the influence of key process parameters and varying nanocomposite compositions on surface roughness (***Ra***), cutting force ($\boldsymbol{F_c}$), and tool wear (***TW***). Experimental data were gathered, and distinct *ANFIS* models were established for each output response. The model's decision-making logic is encapsulated in its fuzzy rules and membership functions, the parameters of which were optimized through a data-driven learning process.

The *Sugeno* fuzzy inference method was selected for this study due to its computational efficiency and straightforward implementation, as it utilizes weighted averages during the defuzzification process. A principal advantage of the *Sugeno* method is its ability to represent complex nonlinear systems through a set of linear equations. The *ANFIS* modeling was conducted using the *MATLAB* environment, which provides a dedicated toolbox offering a user-friendly interface for designing, training, and tuning fuzzy inference systems, making it accessible for researchers in artificial intelligence.

The procedure for creating the *ANFIS* models in *MATLAB* is illustrated in Fig. 5. Since the *ANFIS* architecture is designed for single-output systems, three separate models were developed and analyzed independently to predict surface roughness (***Ra***), cutting force ($\boldsymbol{F_c}$), and tool wear (***TW***). Each model utilized cutting speed (***V***), feed rate (***f***), and depth of cut (***d***) as input variables. The initial step in constructing each *ANFIS* model involved defining the input-output variables, their respective value ranges, and partitioning the relevant experimental data for model training and testing.

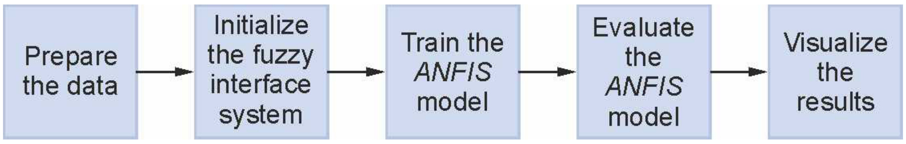

Fig. 5. Stages of *ANFIS* modeling

The initial fuzzy inference system (*FIS*) was generated using the grid partitioning method available in the *MATLAB ANFIS* toolbox. Grid partitioning was selected as it simplifies the rule base and enhances the interpretability of the resulting *FIS* model. Triangular membership functions were chosen for the input variables, while constant membership functions were assigned to the outputs. The model was then trained using a hybrid optimization algorithm to fine-tune its parameters, including the membership function shapes and rule weights. The training was conducted over 10 epochs. The specific hyperparameters configured for the *ANFIS* models predicting ***Ra***, $\boldsymbol{F_c}$, and ***TW*** are detailed in Fig. 6.

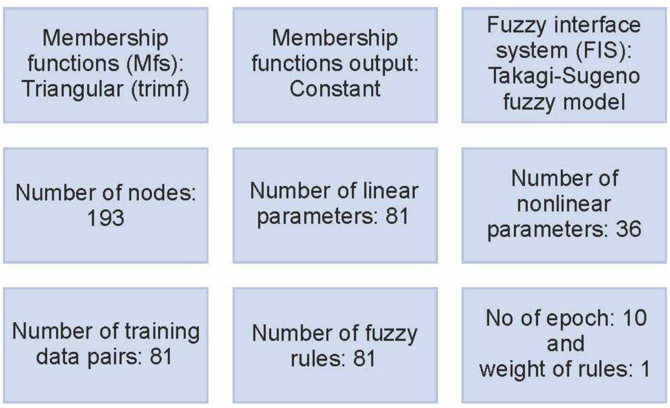

Fig. 6. ANFIS model parameters

Fuzzy inference system *(FIS)* training was terminated once the predefined target epoch was reached and the minimum root mean squared error (*RMSE*) for the developed model was achieved. Specifically, the *RMSE* values for the *ANFIS* models predicting ***Ra***, F_c and ***TW*** were found to be 1.56637, 1.56637, and 3.31021, respectively, when utilizing triangular membership functions (*MFs*). In this study, a total of eighty-one fuzzy rules were employed for each model. The *ANFIS* structures developed for predicting ***Ra***, F_c and ***TW*** are illustrated in Fig. 7.

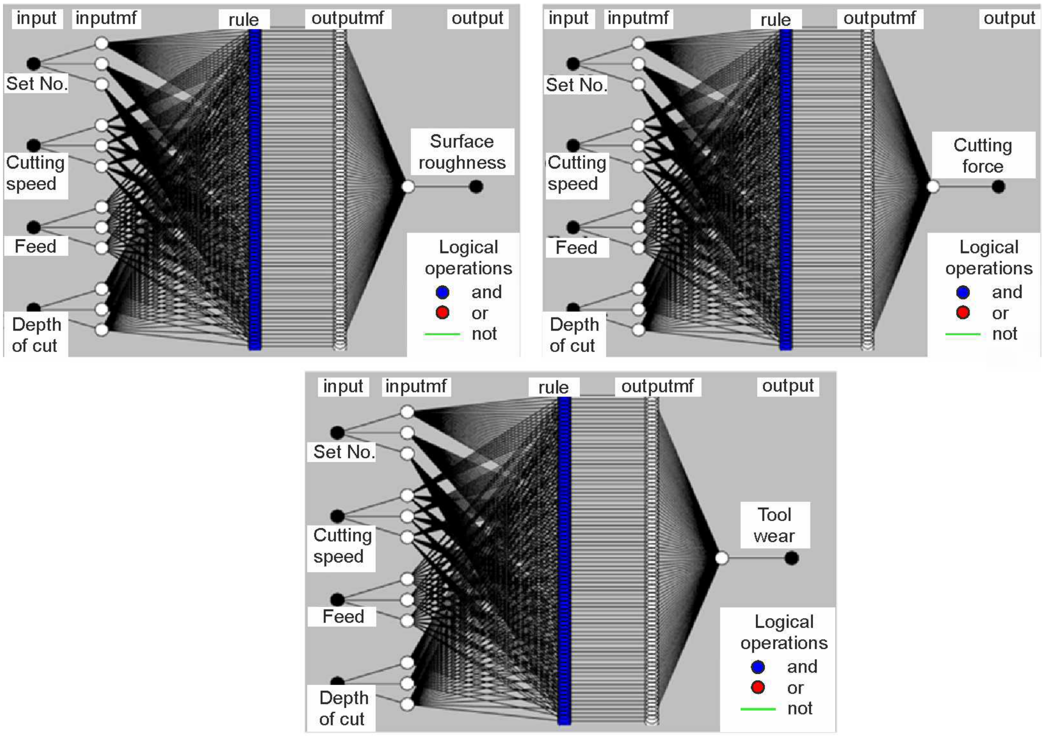

Fig. 7. Developed *ANFIS* model structure

Following model development, the prediction errors for both the training and testing datasets were evaluated for ***Ra***, F_c and ***TW***. Fig. 8 illustrates the correlation between the *FIS* outputs and the experimental data for training and testing, achieved using the triangular membership function configuration. The resulting training and testing errors were 0.057 and 0.086 for surface roughness (***Ra***), 1.55 and 0.82 for cutting force (F_c), and 3.310 and 4.15 for tool wear (***TW***), respectively.

To better understand the concurrent influence of process parameters on the responses, three-dimensional surface plots for ***Ra***, F_c and ***TW*** were generated, as shown in Figs. 9–11. These plots facilitate a more intuitive analysis of machining performance by providing visual clarity on the effects of input parameters. Each plot illustrates the variation of an output response with two input parameters, while the third parameter was held constant at its central value (V_c = 150 m/min, f = 0.2 mm/rev, d = 0.5 mm).

Analysis of the surface plots in Figs. 9–11 indicates that a lower surface roughness (***Ra***) is achieved by employing a higher cutting speed (V) in combination with moderate to low feed rate (f) and depth of cut (d) settings. Similarly, cutting force (F_c) is minimized by using a higher cutting speed with lower feed and depth of cut. Tool wear (***TW***) is also reduced at higher cutting speeds, even when maintaining feed rate and depth of cut settings.

To validate the *ANFIS*-predicted results, additional turning experiments were conducted using parameter combinations not included in the original training dataset. A comparison between the experimental results and the *ANFIS* predictions is presented in Table 2. These validation trials allowed for a detailed assessment of model performance across an expanded range of input variables. The experimental values for ***Ra***, F_c and ***TW*** represent averages from three separate trials to minimize the influence of outliers.

The *ANFIS* model demonstrated reliable predictive accuracy, with an average prediction error below 8 % across all responses, showing strong agreement with the experimental data. Specifically, the model

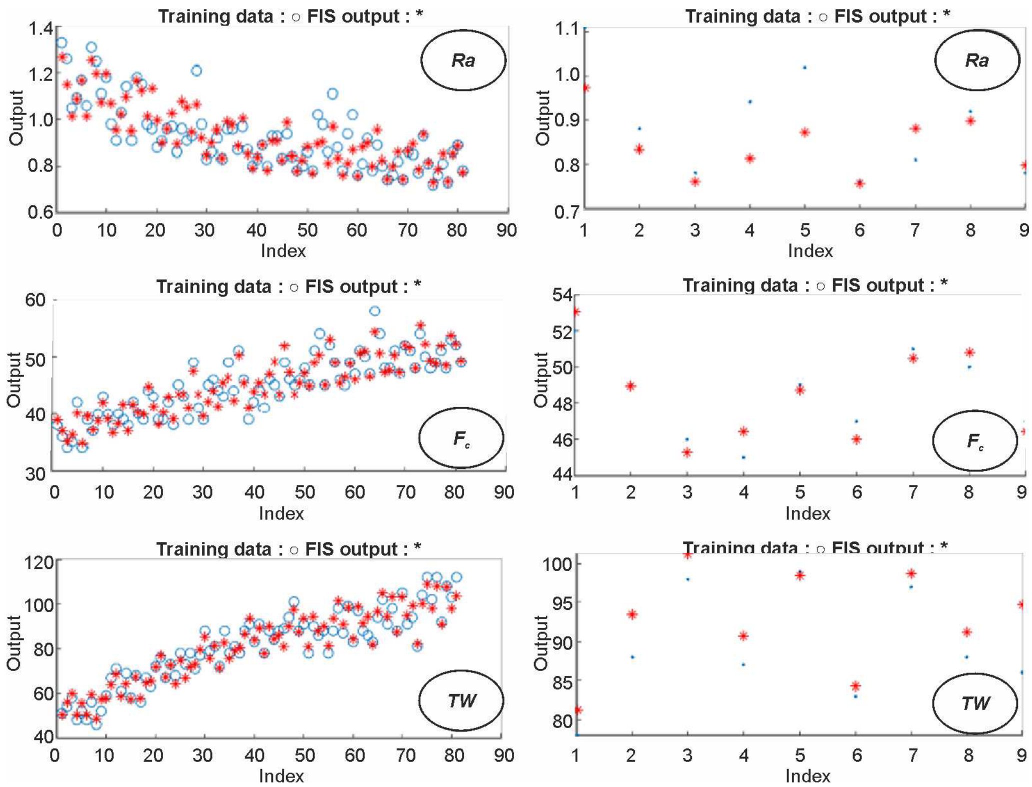

Рис. 8. Mapping test and training data using *FIS* output

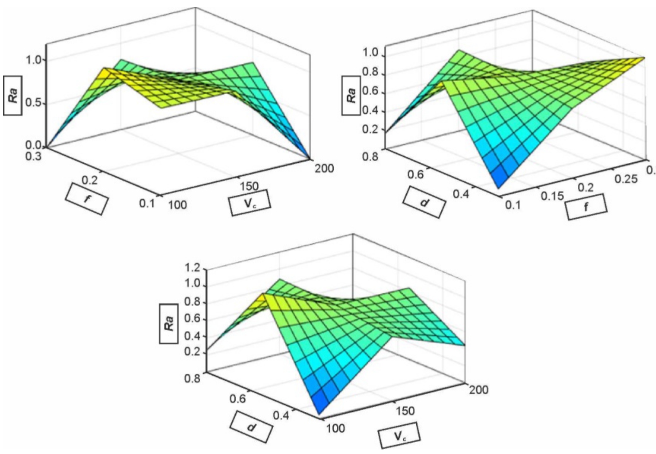

Fig. 9. Dependence of ***Ra*** on process parameters

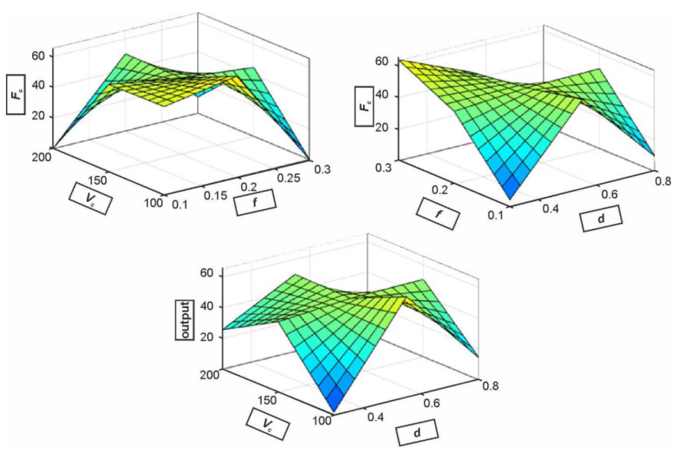

Fig. 10. Dependence of $\boldsymbol{F_c}$ on process parameters

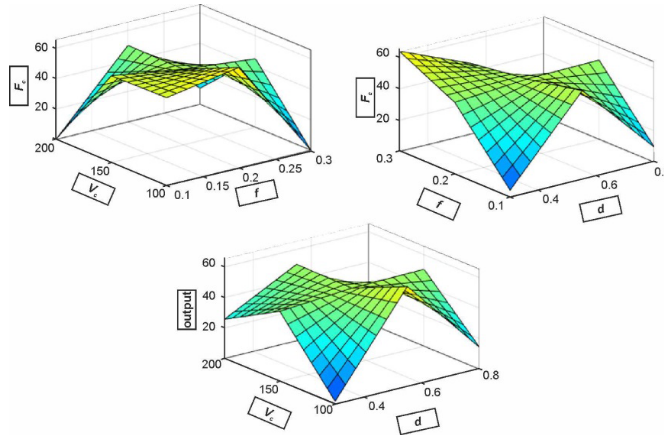

Fig. 11. Dependence *of* ***TW*** on process parameters

Table 2

Validation experiments

V (m/min), f (mm/rev), d (mm)	*Ra* (µm)		*Fc* (N)		*TW* (µm)	
	Expt.	ANFIS	Expt.	ANFIS	Expt.	ANFIS
110; 0.12; 0.4	0.854	0.843	51.39	55.7	83.47	87.5
130; 0.17; 0.45	0.875	0.835	55.92	63.1	86.19	91.7
165; 0.23; 0.65	0.836	0.841	58.38	49.7	94.88	103.7
180; 0.27; 0.75	0.812	0.896	48.33	57.7	112.32	122.7
200; 0.15; 0.35	0.701	0.759	39.89	44.6	94.95	104.3

yielded errors of 5.1% for surface roughness (***Ra***), 13.45% for cutting force ($\boldsymbol{F_c}$), and 7.92% for tool wear (***TW***). These results confirm the potential of *ANFIS* as a robust and effective tool for predicting machining performance in the turning of *Al7075* metal matrix composites.

Conclusion

This study successfully demonstrates the application of an adaptive neuro-fuzzy inference system (*ANFIS*) for modeling the turning performance of *Al7075* hybrid nanocomposites under compressed air cooling. The key findings are summarized as follows:

– Compressed air cooling is confirmed as a viable and environmentally sustainable alternative to conventional flood cooling, effectively enhancing machinability in the turning of *Al7075* nanocomposites.

– The developed *ANFIS* model provides a highly reliable and practical methodology for predicting key machining outputs enabling the optimization of process parameters.

– The ANFIS model exhibited strong predictive accuracy with the average prediction error remaining below 9%, with errors of 5.1% for ***Ra***, 13.45% for $\boldsymbol{F_c}$, and 7.92% for ***TW***, demonstrating a high degree of alignment with experimental validation data.

– This research establishes a framework that integrates sustainable cooling technology with intelligent modeling, presenting a significant advancement for green machining strategies in the manufacturing of metal matrix composites.

Furthermore, the study underscores that the specific composition of the nanocomposite (i.e., reinforcement percentage and type) is a critical input variable for accurately modeling machining performance, a key insight for industrial application.

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Conflicts of Interest

The authors declare no conflict of interest.