



# ANFIS prediction modeling of surface roughness and cutting force of titanium alloy ground with carbon nanotube grinding wheel

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## Abstract

This study harnesses the Adaptive Neuro-Fuzzy Inference System (ANFIS) as a powerful tool for modelling key parameters specifically surface roughness, Metal Removal Rate (MRR), and Cutting forces pertinent to the machining of titanium alloy using a cutting-edge carbon nanotube (CNT)-infused grinding wheel. The investigation is rooted in a meticulously designed experimental framework employing a comprehensive L27 full factorial design, with the crafting of CNT-mixed grinding wheels tailored for the machining process. In the pursuit of accurate predictions, a first-order Sugeno-type fuzzy interference model is strategically employed for the estimation of output parameters. The ANFIS model is subsequently developed, drawing upon machining parameters derived from meticulously curated and trained datasets. Evaluation of prediction performance reveals testing errors that underscore the robustness of the model: 2.13% for surface roughness, 0.15% for MRR, and 4.24% for Tangential force. A comparative analysis of the ANFIS models further highlights their efficacy, showcasing high residual  $R^2$  values that affirm a robust fit with experimental data in the context of CNT grinding. This underscores the model's capability to encapsulate the intricate dynamics of the machining process. Importantly, the proposed model exhibits significant potential for real-time estimation of surface roughness in CNT-based grinding applications, suggesting its applicability and utility in advancing the precision and efficiency of machining operations in this technologically advanced domain.

**Keywords** Adaptive Neuro-Fuzzy Inference System (ANFIS) · CNT Grinding · Grey relational analysis · Surface roughness · Cutting Force

## 1 Introduction

Numerous techniques can be used with fuzzy logic (FL), and hybrid approaches have been created to improve result prediction accuracy. Numerous instances of FL paired with Taguchi's techniques, along with grey fuzzy reasoning grade, in multi-objective optimization of a product's form design witness the efficacy of this hybridization. Using the Taguchi approach, ANFIS has been addedly applied as a linear compliant mechanism (Chau et al. 2018a, 2018b; Li et al. 2018). As a forecasting model for an uncertain or hitherto unknown system, ANFIS, a Fuzzy-Neuro hybrid technique,

was applied. The goal is to choose the optimal set of input parameters to produce the desired result. Rules were framed based on experience, knowledge, and competence and were defined with the use of a fuzzy inference engine of the Sugeno type. Figure 1 depicts the five layers of this architecture. The first layer representing the three control factors were inputs of wheel speed (X), feed rate (Y), and DoC (Z), and the rectangular boxes represent these. Hidden layers 2 and 3 are depicted by circles with weighted residuals having fixed values.

The following steps were required in the ANFIS problem:

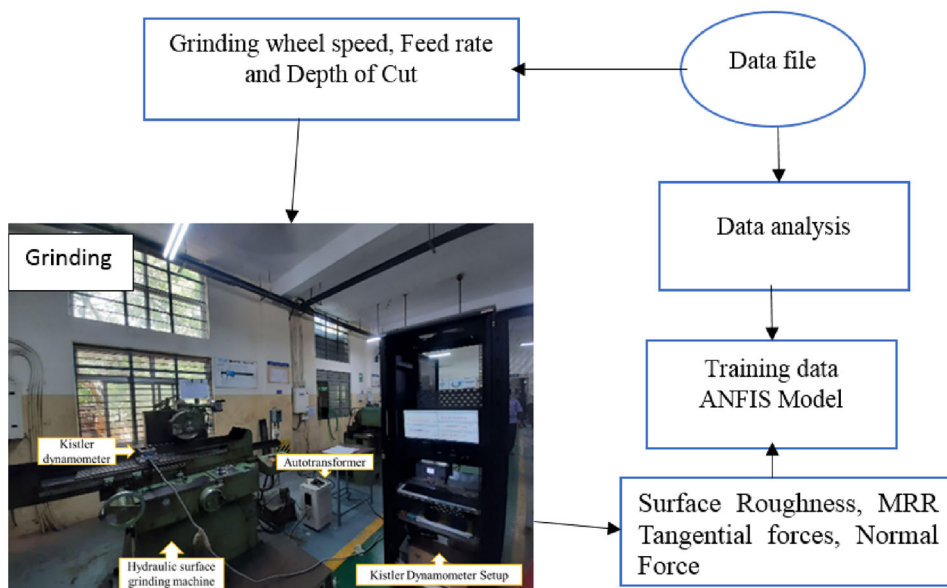
- Using a fuzzy inference engine akin to Sugeno to design the hybrid model.
- Using an authentic classification to optimize the FIS model.
- Creating training and testing data matrices involves setting up input process parameters.
- The ANFIS hybrid algorithm is executed using the training data.

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**Fig. 1** Grinding setup with CNT wheel to obtain the experimental data for Training the ANFIS model



- Using 10% of the testing data to cross-check and test the model.

The triangular membership function of the Sugeno ANFIS model, which has three input parameters, has values that are high, medium, and low. Five triangle membership functions—Very Low, Low, Medium, High, and Very High are present in the outputs. The output range was divided into five sections to produce these five levels. The Sugeno-type Fuzzy inference system was then used to frame nine fuzzy rules, yielding nine outputs with singleton membership functions. For the ANFIS results, twenty-seven validation runs were performed. The predicted values differed from the experimental results, with an extremely low average testing error of  $< 5\%$ . The remarkably low error values demonstrated the high precision and accuracy of the adaptive fuzzy inference system. This method of ANFIS-based prediction was used on MRR, surface roughness, and the tangential and normal components of the generated forces.

### 1.1 Literature survey

It is crucial to use a hybrid approach to machine learning and soft computing to boost the effectiveness of prediction models. Particularly, hybrid machine learning models have grown in favour as high-performance control systems progress. With these techniques, prediction performance and accuracy can be improved to a large extent and can be employed as components of Industry 4.0 to enhance intelligent and adaptive manufacturing (Ardabili et al. 2020). Naresh C et al. worked on the wire electro-discharge machining of Nitinol. They compared ANN with the ANFIS method to predict the surface roughness of Nitinol and its material removal rate.

Five different algorithms were compared using the same inputs to identify the sufficient number of hidden layers required and the degree of accuracy of each method. Ten layers were required for adequate accuracy, and the ANFIS model had the best accuracy (Naresh et al. 2020).

Baseri et al. have ground SPK 1.2080 D3 tool steel workpieces with a vitrified  $\text{Al}_2\text{O}_3$  grinding wheel. The grinding conditions of their experiments were held constant while the dressing depth, speed ratio and cross-feed rate were varied to find their impact on workpiece surface roughness. To identify the ideal distribution of membership functions, an Adaptive Neuro-Fuzzy Inference System using a hybrid learning method to map relationships between the input and output data was used. The ANFIS architecture employed fuzzy logic with Gaussian function and 64 rules with artificial neural networks to predict the surface roughness (Baseri and Alinejad 2011). Dambatta et al. have ground Aluminium alloy workpieces with Silicon dioxide nanoparticles dispersed in Canola vegetable oil. The coolant was delivered with Minimum Quantity Lubrication (MQL) to achieve near-dry grinding conditions. The impact of input parameters such as feed rate, depth of cut, air pressure and nanoparticle concentration on surface quality and grinding force were investigated. The specified normal force, surface quality and specific tangential force were predicted using ANFIS prediction modelling. These models showed excellent prediction accuracies of 97.4%, 98.5% and 96.6%, respectively (Dambatta et al. 2019).

DuyTrinh et al. have proposed a model to monitor and predict grinding wheel wear and surface roughness online. These experiments have been performed on Ti-6Al-4 V titanium alloy workpieces with a vitrified silicon carbide grinding wheel. Taguchi's design of experiment methods was used to

conduct the experiments by varying three levels of workpiece velocities, cutting depth, grinding wheel speeds, grit particle size and grinding wheel sizes. The measurements were carried out using a compressed air measuring head in combination with hybrid algorithms of ANFIS, Taguchi's empirical analysis and Gaussian regression. The authors found that the ANFIS-Gaussian regression combination provided the best results with a 98% confidence interval and 99.69% precision (DuyTrinh et al. 2019). Yin et al. have also worked along similar lines and used compressed air to monitor surface roughness and wheel wear online. The grinding was done on Titanium workpieces with a vitrified SiC wheel. The goal is to assess and predict how the different cutting modes, noise and forces affected the tool wear, surface roughness and noise levels. Experimenters can then decide whether to continue or repeat the experiment under better experimental settings based on the consequences of noise. Four different algorithms were considered – ANFIS, Gaussian regression, Taguchi's experimental analysis and the hybrid ANFIS-Gaussian regression. It was found that the hybrid model gave the best evaluation for online tool wear and surface roughness monitoring (Yin et al. 2019).

Roy S has experimented by turning Titanium and used ANFIS to study the accuracy of surface roughness prediction when considering the effects of tool speed, depth of cut and feed rate. Two different membership functions were considered – bell-shaped and triangular functions. As expected, the bell-shaped membership function had greater accuracy than the triangular membership function due to the higher number of points under consideration (Roy 2005). He performed similar work in vertical CNC milling. Aluminium alloy was milled with a 4-flute end milling cutter and used the same two membership functions and ANFIS to predict its surface roughness. Sixty experiments were conducted and used for 500 training cycles. The first-order Sugeno fuzzy inference system was used to frame 36 rules to predict surface roughness. The proposed method worked better than the much-practised regression modelling (Roy 2006). Grinding force is a crucial measure of grinding performance since it directly impacts the grinding machinery's functionality, the grinding tools' wear, and the machined surface's quality (Rao et al. 2018). It also affects the vibrations produced in the machine structure, workpiece-wheel interface temperature, and the service life of a grinding wheel. High-precision abrasive machining is complex, especially on hard-to-machine materials requiring high surface integrity. This surface integrity can be preserved if material removal occurs in a ductile manner instead of a brittle manner. Direct indicators of grinding efficiency, like the forces incurred, must be kept as low as possible to preserve sub-surface and surface integrity. Therefore, it becomes crucial to monitor control factors and identify those factor combinations that reduce the generated forces.

Grinding forces are a summation of friction and chip formation. However, the two cannot be identified individually, as measurements are possible only for the formation of chips. Grinding wheels cause lesser force at the beginning of the cutting run. As the wheels get loaded, the forces gradually increase. The tangential-to-normal ratio of forces can give information about the wheel's cutting capacity (Kumar et al. 2016). When measured and processed appropriately, force information can help predict even the grinding force's sliding, ploughing and cutting components. Many methods of measuring forces have been proposed to measure grinding forces over the years. Empirical and analytical modelling, simulations and experiments were improvisations, including or modifying a few parameters involved. Nevertheless, the measurement of forces continues to offer more, considering the grinding wheels' stochastic nature (Huang et al. 2018). GRA has been employed in various scenarios. It has been used in turning high strength Aluminium alloy applied in the aerospace industry. Comparisons between the performances of coated and uncoated cutting tools were studied. Power consumption, cutting time taken, material removal rate and surface roughness were a few output parameters of interest. The optimal parameter levels for depth of cut, speed, feed rate and grinding conditions were predicted using the GRA approach (Raykar et al. 2015). It has been used in fused deposition modelling for rapid tooling and intricate assemblies. The input factors considered were nozzle and bed temperatures, number of loops for the ABS feedstock, infill percentage, print speed and layer thickness. The out-of-roundness or circularity errors and surface roughness were optimised using GRA analysis (Sajan et al. 2018). Dao used a hybrid Grey-based FL approach to optimize parameters for a compliant guiding mechanism in SEM. The first natural frequency and displacement are to be optimized with the help of a hybrid GRA-FL approach (Dao 2016). Patil et al. worked on Copper Oxide (CuO) and Al<sub>2</sub>O<sub>3</sub> nanoparticles dispersed in water and supplied with compressed air as MQL. The surface roughness and grinding force ratio were the outputs to be optimised with the different outputs of lubricant types, nanoparticle size flow rate of coolant, wheel speed, feed rate and depth of cut (Patil and Patil 2016).

A perusal of the literature mentioned above and many others, it was noted that grinding still is the chosen finishing operation, even for hard-to-grind materials like Titanium. Metals that are hard to grind are usually ground with super abrasive grinding wheels with grits like CBN or diamond. However, some additives like CNTs, among many others, can enhance grinding action, which has been explored. Surface finish, material removal rates, grinding forces, interface temperatures point of view on wheel wear in the grinding process have been researched. Adaptive Neuro-Fuzzy Inference Systems were then studied for predicting outcomes, and finally,

multi-objective optimisation techniques like Grey Relational Analysis were used.

## 2 Experimental setup

The experimental setup consists of an AVRO TP-6, hydraulic surface grinding machine from Coimbatore with a table size 600 X 200 mm. With a 2HP motor for the grinding wheel and a maximum wheel speed of 2400 rpm, this machine has a maximum longitudinal travel of 650 mm and a cross travel of 225 mm, capable of 1.5–18 m/min and 0.5 – 10 mm table speeds, respectively. Wheel speeds can be varied using the input voltage manipulation on the autotransformer connected to the grinding machine.

The training dataset for the Adaptive Neuro-Fuzzy Inference System (ANFIS) procedure was formulated through the systematic combination of input parameters to derive corresponding output parameters for carbon nanotube-based grinding machining. The precision of the neural network's output calculations relies directly on the quality of the training data. The schematic representation of the grinding process for generating the training data is illustrated in Fig. 1. The utilization of the fuzzy logic toolbox facilitates the adaptation of training data for the refinement of membership functions assessment. An enlarged image of a small section of the electroplated wheel is shown in Fig. 2 (A and B). The total electroplated thickness is 3 mm, and Fig. 2 shows the specimen made for SEM analysis. Since the total thickness was very small, a composite with two mild steel layers was built to make SEM analysis feasible. SEM images were obtained for the CBN sample and a 6% CNT- CBN sample, shown in Fig. 3 A and B. The CBN grits are dark patches in the lighter Nickel matrix. In the second image, the CNT can be seen as light strands emerging from the CBN and Nickel matrix.

Once the experimental setup was ready, the experiments were conducted. Force measurements were recorded through the Kistler 9725B dynamometer, capable of measuring 3D forces. The tangential and normal forces were primarily studied as the axial forces were very small compared to the others. The dynamometer is shown in Fig. 4. The top plate has an integrated unique thermal isolation coating that makes the dynamometers mostly resistant to temperature changes.

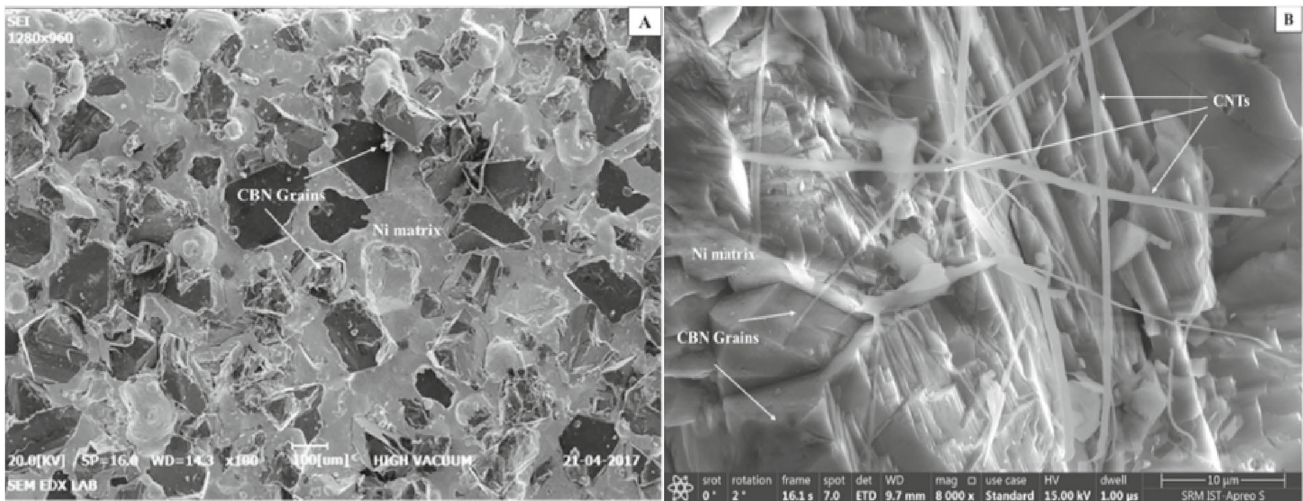
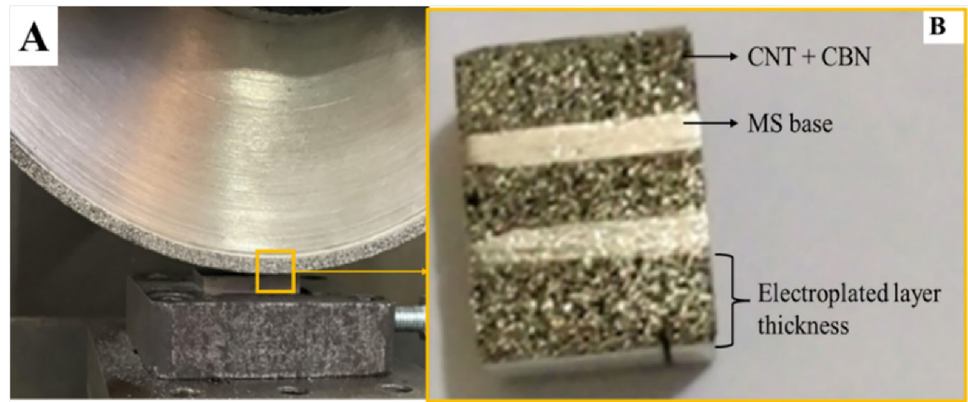
These dynamometers are made up of four three-component force sensors that are positioned between a baseplate and a top plate under heavy preload. Each sensor has three pairs of quartz plates, each responsive to shear in the x and y directions and sensitive to pressure in the z-direction. The force components are measured without any displacement. The four sensors are grounded-insulated mounted, and the dynamometer's internal connections between them enable multicomponent measurements

of forces and moments. As a result, the dynamometers are impervious to rust and shielded from splash water and cooling agents and belong to the IP67 class of protection (Kistler Group 2024). The Kistler dynamometer has accompanying software, allowing it to read the recorded forces directly as graphs. The force measurement time is plotted on the X-axis, and the forces on the Y-axis. A screenshot of the display is shown in Fig. 5. The graphs on it indicate the wheel-workpiece interactions. The area of interest can be chosen here with the cursor tool, noises can be filtered, and the average forces can be calculated with the statistical tool. Other useful documentation was also possible on this software. The axial force display was turned off since the tangential and normal forces alone were objects of interest. The forces' maximum, minimum and mean values are shown below the graph.

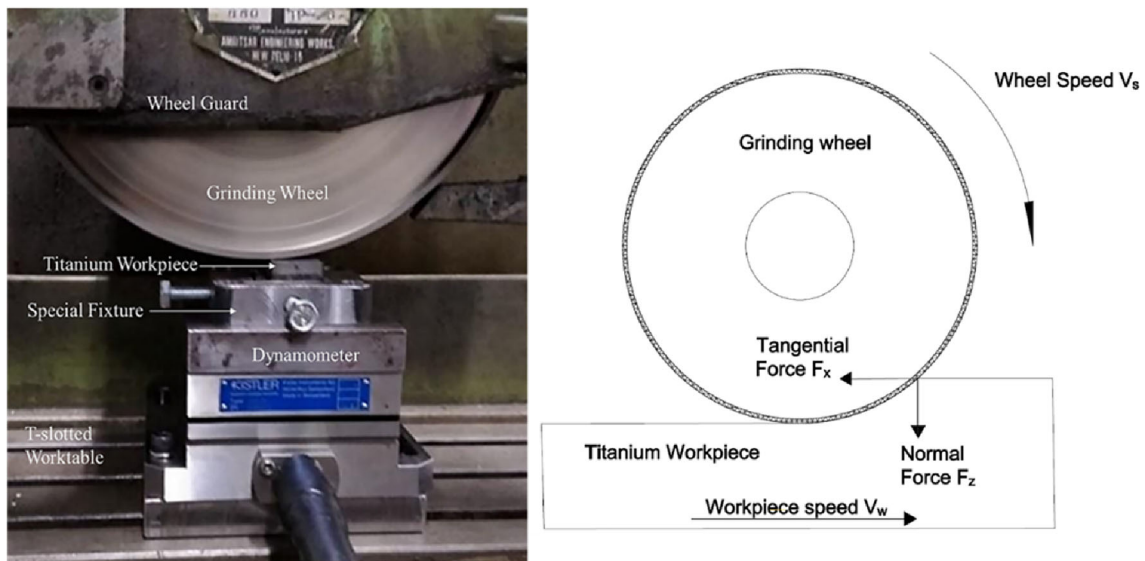
Monitoring temperature in a grinding process is important as it can lead to thermal damage on the workpiece surface. Different types of damages—rehardening, cracking, expansions and contractions with changes in stress, microstructural changes leading to variations in surface hardness and many others, can be produced based on the temperature produced at the workpiece and grinding wheel interface. Much of these damages can be avoided by grinding at lower temperatures. However, managing the heat is crucial as the damages also depend on the heating and cooling rates and the heat treatment a metal is subjected to before grinding (Marinescu et al. 2004). Many proposals have been put forward to lower interface temperatures, the simplest of which is using a coolant to remove heat and chips away. This method has been well experimented with and used in grinding varieties of steels. Other methods of applying coolants included using Minimal Quantity Lubrication (MQL) or flood cooling, applied through several nozzles, and experimented with at different angles. Some others have also worked on changing flow rates through nozzles, positions and orientation of nozzles.

Periodical redressing of the grinding wheel is another way to simplify temperature reduction as sharper grits penetrate material quicker than blunt ones, thus reducing temperature and force. Lowering the material removal rate by changing or lowering process parameters within acceptable levels is yet another way of reducing interface temperatures naturally. Other ways of reducing temperatures have been changing the shapes, sizes and even the composition of abrasive materials. A few have tried changing grit sizes, and many others have researched producing new composite materials for the grinding wheels—many combinations of super abrasives that lower thermal damage sizeably have also been studied. The performances of the new grinding wheels thus developed have been tested, and a fair amount of literature points out both the pros and cons of the wheels and the process themselves. Temperature maps have been produced through direct

**Fig. 2** Enlarged Image of Electroplated Wheel



**Fig. 3** No text of specified style in document. SEM Images of A.CBN and B. 6% CNT-CBN



**Fig. 4** Kistler Dynamometer

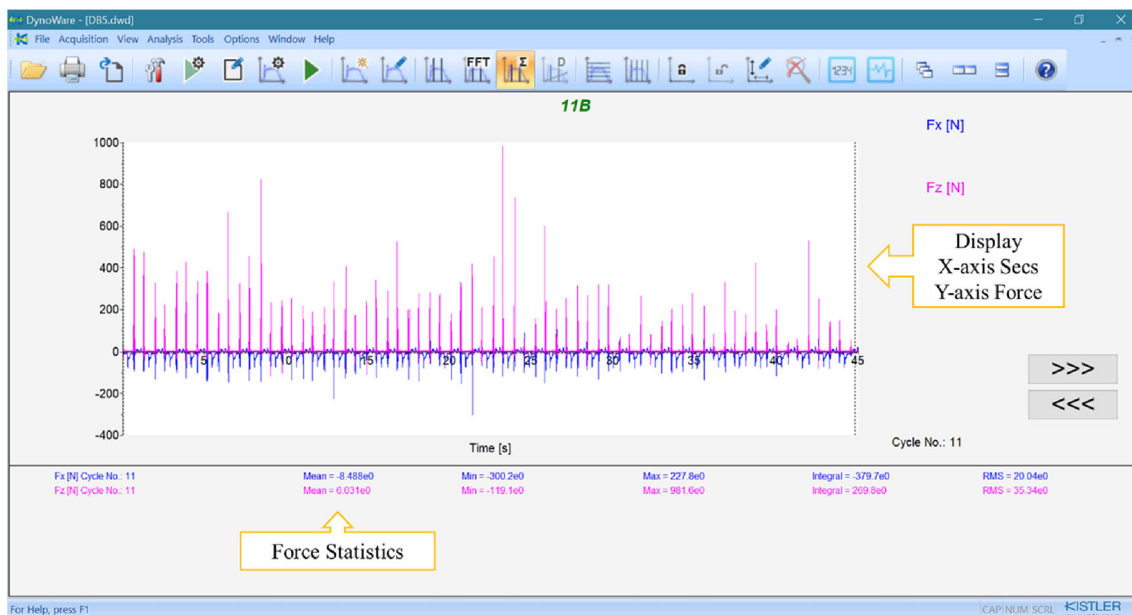


Fig. 5 Cutting Force Measurement Screenshot

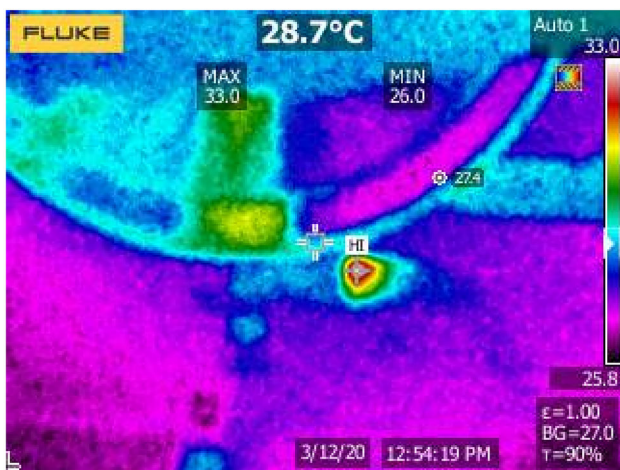


Fig. 6 Temperature measurement for CBN wheel

and indirect observations. One direct method uses a thermocouple integrated with the grinding wheel or the workpiece. The temperatures thus recorded can be fed to a computer immediately for analysis. This kind of temperature measurement rests on the measurement device's robustness.

However, this research used an indirect method with a non-contact thermometer to record the maximum and minimum temperatures at the interface. A sample of the recorded image from grinding with a CBN wheel has been shown in Fig. 6, with the maximum and minimum temperatures denoted on its colour map. This method was handy with a recording facility that allowed video and images to be captured with associated software for later retrieval. The challenge was in

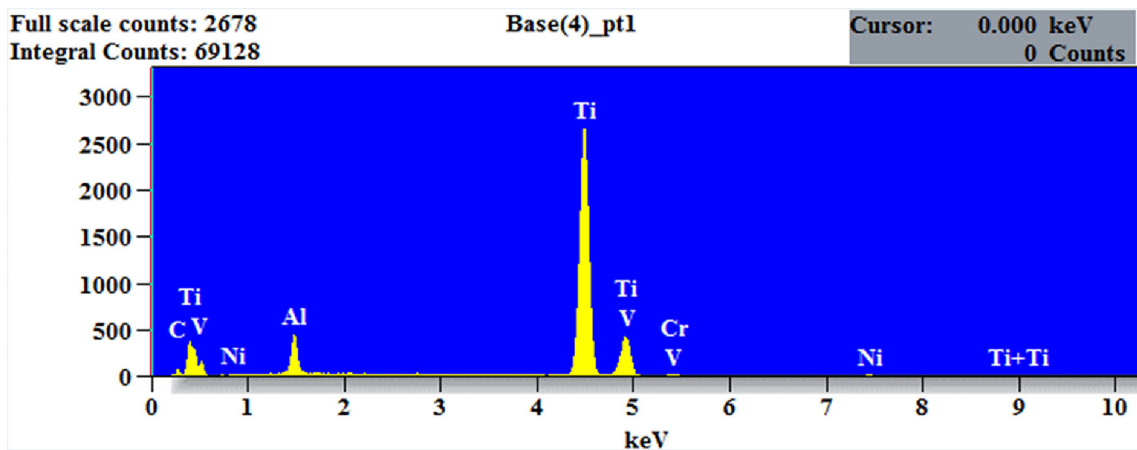
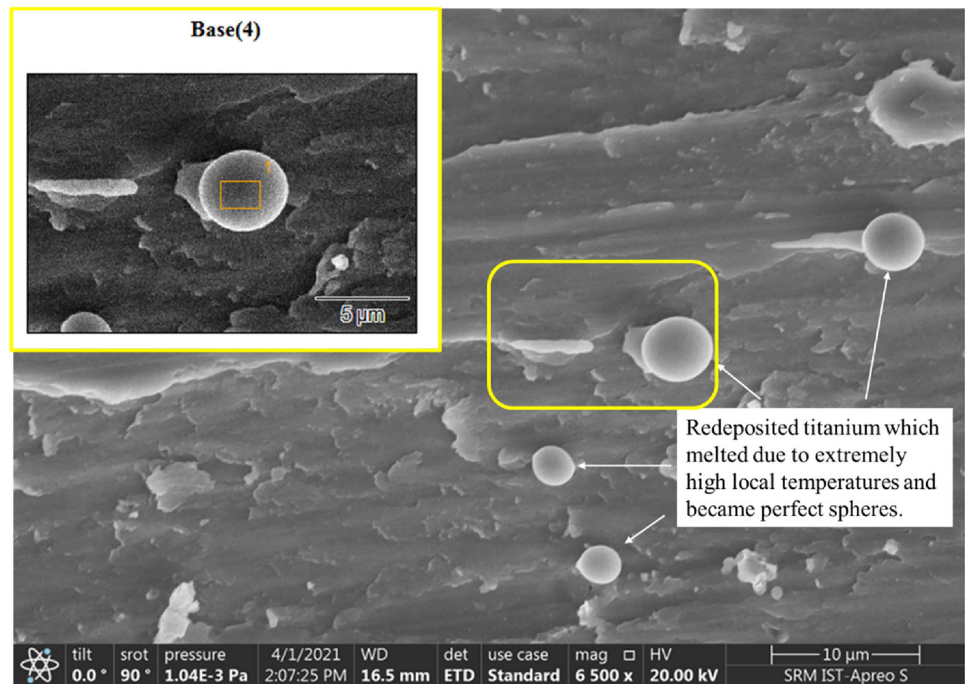
the quickness and accuracy of measurement, as the interface temperature falls very quickly once the contact between them is broken. Once the temperatures are recorded, the analyses are made. Another reason for the grinding burns is the retention of grain sharpness. Since the grains stay sharp for longer, the area or contact with the workpiece is less, and this causes a sharp rise in the local temperature of the point. This unprecedented temperature rise causes localised melting of the removed material, which in turn gets partially transferred to the workpiece, thereby causing either grinding burns or redeposition as perfect, spherical globules, as shown in Fig. 7. An Energy Dispersive X-ray Spectroscopy (EDS) allowed the globules to be identified as Titanium (Opeyemi and Justice 2012).

The EDS spectrum is shown in Fig. 8. The EDS apparatus is part of the SEM setup and helps identify elements in targeted areas. The spectrum identifies the major elements as peaks. The spectral image confirms Titanium as the spherical deposits on the workpiece surface.

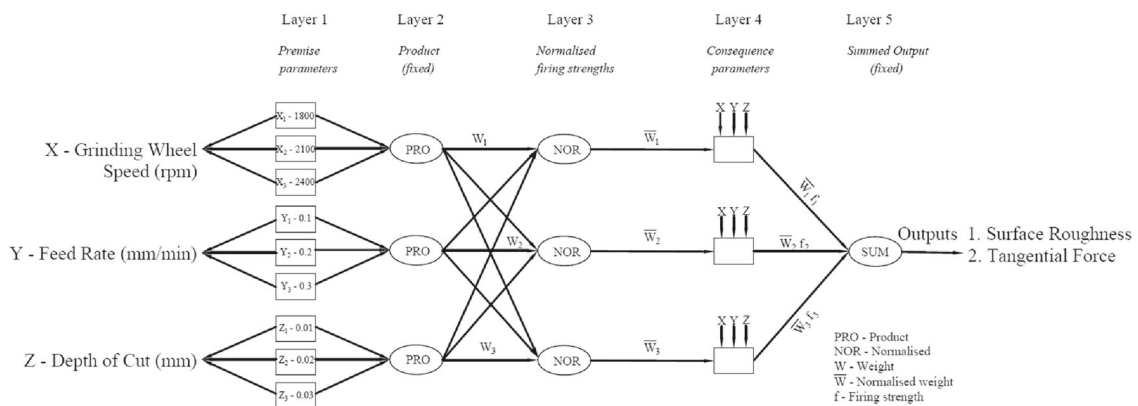
## 2.1 ANFIS: Adaptive Neuro-Fuzzy Inference System

Adaptive manufacturing is a keyword in modern factories, and it involves real-time knowledge of the many streams involved in an automated manufacturing process. With technical progress and demands for intelligent, situational controls, predicting and modelling the output becomes important when setting up such a system. The advantage of ANFIS is its ability to combine the principles of Artificial Neural Networks (ANN) and fuzzy logic in a single frame. Furthermore,

**Fig. 7** SEM image with EDS insert showing Ti redeposition



**Fig. 8** EDS Spectrum of the redeposited Material



**Fig. 9** ANFIS Schematic network

ANFIS can handle noisy data and be trained by many algorithms like Particle Swarm Optimisation (PSO) and enhanced Artificial Bees Colony (ABC) algorithm, among others. The Takagi–Sugeno fuzzy inference system, a fuzzy logic system that employs if–then rules to express the relationship between input and output variables, is the foundation upon which ANFIS is built. Five layers make up the ANFIS architecture: the input layer, the fuzzy layer, the normalisation layer, the rule layer, and the output layer, as shown in Fig. 9.

Five layers comprise the ANFIS architecture, each of which plays a particular role in the overall system (Opeyemi and Justice 2012).

- *Layer 1: Fuzzy Data:* This layer has adaptive nodes that determine the degree to which the input data is a member of each fuzzy set.
- *Layer 2: Product:* This layer has fixed nodes that compute the product of each signal received from the fuzzy layer.
- *Layer 3: Normalisation:* The product layer's input signals are normalised in the normalised layer.
- *Layer 4: De-Fuzzification:* The normalised layer's normalised signals are combined in the de-fuzzy layer to create a single output.
- *Layer 5: Total Output Layer:* To create the ANFIS's ultimate output, this layer adds the outputs from each node in the de-fuzzy layer.

A hybrid learning approach changes the parameters of the fuzzy inference system in ANFIS by combining backpropagation and least squares estimation. This process allows the algorithm to sift through many options and sort them, making them fit for use with applications like automated machine-vision systems. There are two parts to ANFIS: one is to train the system using > 70% of the images, and the other is to test the algorithm with the remaining 30% of data. The graphs obtained show the effectiveness of the process.

In grinding, surface roughness and MRR are key output factors indicative of an efficient process. These values are fed, and the ANFIS system is trained with them. Prediction and adaptive control increase with the number of instances used to train them, and this is useful when applying them to real-time control. In this research, FL and ANFIS were modelled through MATLAB.

### 3 Results and discussions

Grinding processes play a pivotal role in the precision machining of materials, and optimizing these processes is crucial for achieving desired surface quality and material removal rates. To enhance the understanding of the intricate interplay between input parameters and output responses in

titanium alloy grinding, this study employs the L27 orthogonal array experimental design. This research investigates the effects of cutting speed, feed rate, and depth of cut on key output parameters in titanium alloy grinding. The chosen output variables include cutting force, temperature, surface roughness, and material removal rate (MRR), all of which significantly influence the overall performance and quality of the grinding process. The utilization of an orthogonal array design enhances the efficiency of experimentation, enabling a comprehensive exploration of the parameter space while minimizing the number of trials as depicted in Table 1. The results and discussions of this study will shed light on the intricate dynamics of titanium alloy grinding, providing valuable insights for process optimization and quality enhancement in industries reliant on these advanced materials.

#### 3.1 ANFIS for surface roughness

The Fig. 10 A–D represents surface roughness training and testing data graphs along with the output with the Fuzzy Inference Systems (FIS) for the 6% CNT-CBN wheel. The data were trained for ten epochs, but the system was trained after the second epoch. The training data plot (A) typically shows the relationship between the input parameters (features) and the corresponding target variable, which in this case is the surface roughness. The points on the plot represent the data instances used during the training phase. These data instances are input–output pairs that the ANFIS model uses to learn and adapt its parameters. The goal of the training phase is for the ANFIS model to capture the underlying patterns and relationships within the training data, allowing it to make accurate predictions on new, unseen data. The testing data plot shows a different set of data instances that were not used during the training phase. These instances are unseen by the model, and their surface roughness values are not known to the model. The ANFIS model, after being trained on the training data, is then applied to the testing data (B) to assess its generalization ability. The model's predictions for surface roughness are compared to the actual values for these testing instances. The Fuzzy Inference System (FIS) output represents (C) the predictions made by the ANFIS model for surface roughness based on the input parameters. It reflects the model's learned relationships between cutting parameters (such as cutting speed, feed rate, and depth of cut) and the resulting surface roughness. The FIS output (D) can be compared to the actual surface roughness values from both the training and testing datasets to assess the accuracy and reliability of the ANFIS model.

A Fuzzy Rule Viewer as depicted in Fig. 11 is a tool or interface that allows users to interpret and analyze the fuzzy rules generated by a Fuzzy Inference System (FIS). In the context of surface roughness prediction using a Sugeno-type



**Table 1** Experimental readings on Ti alloy grinding

Ex No	Speed 'S' (rpm)	Feed Rate 'FR' (mm/min)	DoC (mm)	MRR (g/s)	SR ( $\mu\text{m}$ )	6% Fx (N) CNT
1	1800	0.1	0.01	0.00168	0.55870	7.2070
2	1800	0.1	0.03	0.00324	1.06460	– 5.3740
3	1800	0.1	0.03	0.00368	1.25070	– 4.3410
4	1800	0.2	0.01	0.00669	0.69690	3.1510
5	1800	0.2	0.02	0.00286	1.88190	8.5800
6	1800	0.2	0.03	0.00454	2.41780	7.1770
7	1800	0.3	0.01	0.0055	0.81830	34.9900
8	1800	0.3	0.02	0.00528	2.62300	11.4000
9	1800	0.3	0.03	0.00845	0.70970	7.9510
10	2100	0.1	0.01	0.00525	1.09960	13.2800
11	2100	0.1	0.02	0.00523	0.85670	12.4400
12	2100	0.1	0.03	0.00653	0.49860	7.6870
13	2100	0.2	0.01	0.00359	1.50910	9.9110
14	2100	0.2	0.02	0.00407	1.25870	8.5920
15	2100	0.2	0.03	0.00717	0.75960	8.4900
16	2100	0.3	0.01	0.00624	0.68970	9.3680
17	2100	0.3	0.02	0.00525	0.78570	– 13.3300
18	2100	0.3	0.03	0.00585	0.46200	– 2.3750
19	2400	0.1	0.01	0.00307	0.50800	9.6170
20	2400	0.1	0.02	0.00707	0.65530	8.8450
21	2400	0.1	0.03	0.00464	0.58760	8.1460
22	2400	0.2	0.01	0.01095	0.89870	– 4.4040
23	2400	0.2	0.02	0.00416	0.30850	7.5050
24	2400	0.2	0.03	0.00504	0.38970	8.9150
25	2400	0.3	0.01	0.00404	0.76210	8.2590
26	2400	0.3	0.02	0.00562	0.74030	10.0000
27	2400	0.3	0.03	0.00637	1.15420	28.7700

Fuzzy Inference System, the Fuzzy Rule Viewer provides insights into the linguistic rules governing the relationship between input parameters and the output surface roughness. The Fuzzy Rule Viewer displays the set of rules that have been generated by the Sugeno FIS during the training phase. Each rule consists of antecedent (input) and consequent (output) parts. The viewer often provides a visual representation of the membership functions associated with each linguistic term in the antecedent and consequent parts of the rules. These functions illustrate the degree of membership of a given input or output to a particular linguistic term. Linguistic variables represent qualitative terms (e.g., “low,” “medium,” “high”) associated with the input in yellow colour and output variables in green colour. The Fuzzy Rule Viewer may display information about the strength of each rule. Rule strength indicates the degree to which a specific rule is activated or applies to a given set of input conditions. This is

particularly important in Sugeno-type FIS, where the consequent part is a mathematical function. If required some Fuzzy Rule Viewers allow for interactive exploration and modification of rules. Users can experiment with adjusting rule parameters or linguistic terms to observe the impact on surface roughness predictions.

Now, let's create some fuzzy rules for predicting surface roughness based on these three input parameters:

- IF Cutting speed is Low AND Feed rate is Low AND Depth of the cut is Low, THEN Surface Roughness value is very low.
- IF Cutting speed is Medium AND Feed rate is Low AND Depth of cut is Medium, THEN Surface Roughness value is Medium.
- IF Cutting speed is Medium AND Feed rate is Medium AND Depth of cut is Low, THEN Surface Roughness value is High.

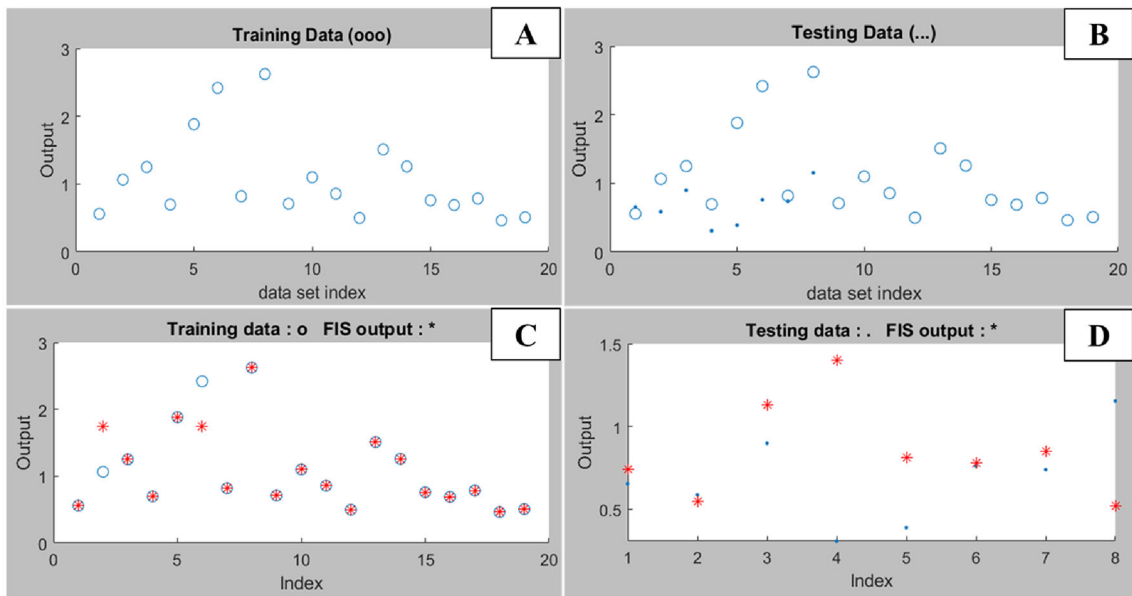
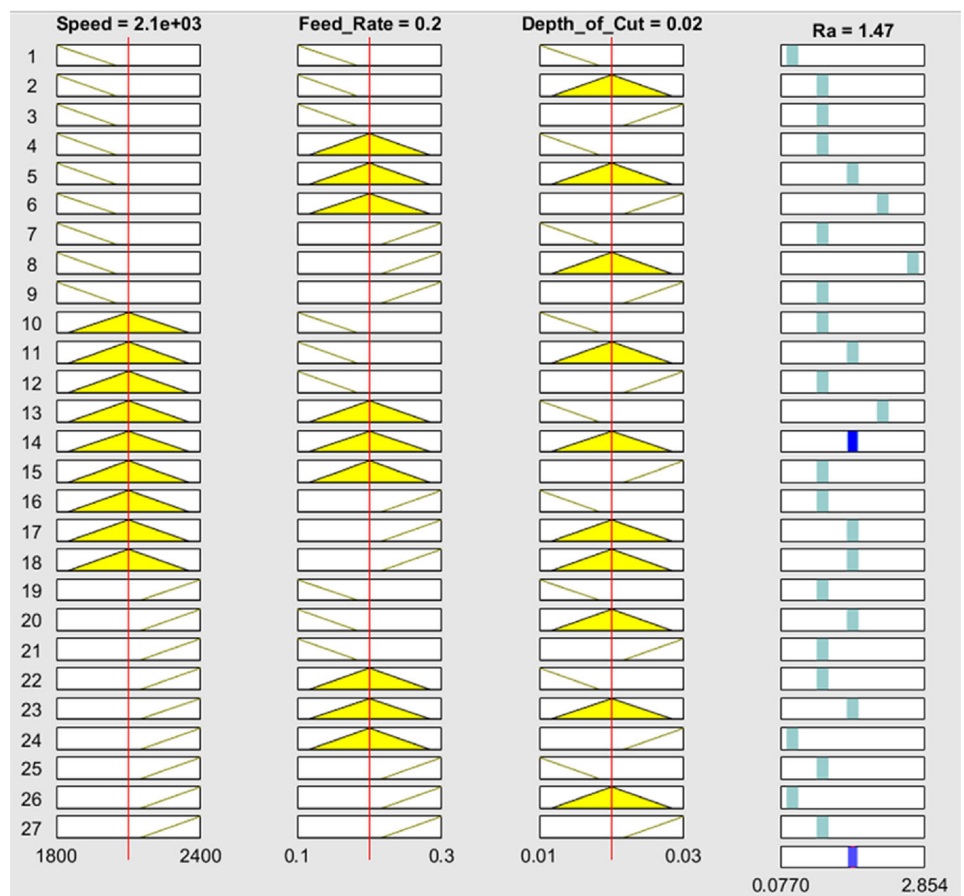
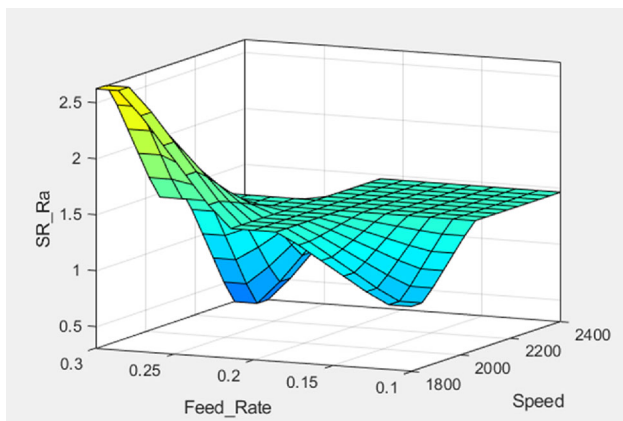


Fig. 10 Surface Roughness Training data (A) and Testing data plots (B) plots with FIS rules (C & D)

Fig. 11 Surface Roughness Rule Viewer





**Fig. 12** 3D Surface Representation of Surface Roughness ANFIS Predicted Rules

- IF Cutting speed is High AND Feed rate is Medium AND Depth of cut is High, THEN Surface Roughness value is Very High.

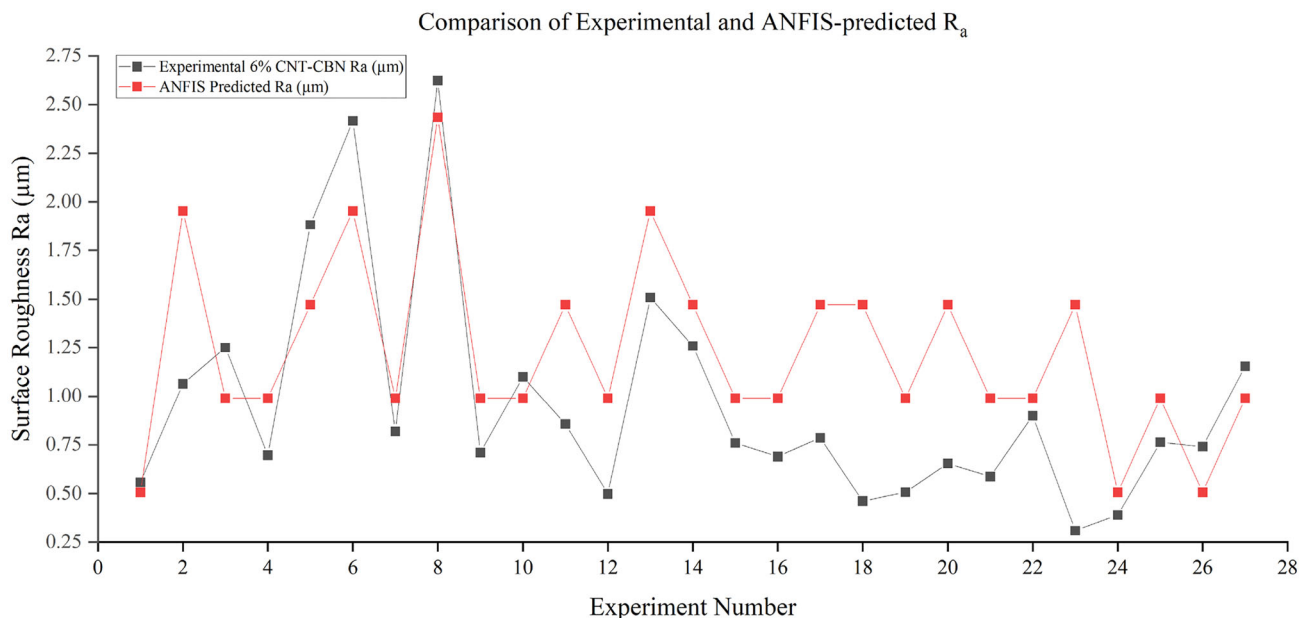
The 3D surface of the rule viewer has been shown in Fig. 12, and upon comparing the experimental and ANFIS predicted values, a difference of 2.13% was found, which an acceptable error level was. The 3D surface representation provides a graphical depiction of how changes in cutting speed and feed rate affect the predicted surface roughness according to the ANFIS model. The two input parameters, cutting speed, and feed rate are typically represented on the X and Y axes, respectively, creating a two-dimensional grid. The predicted surface roughness values are then represented

**Table 2** Model Summary of 6% CNT-CBN Wheel to Minimise Ra

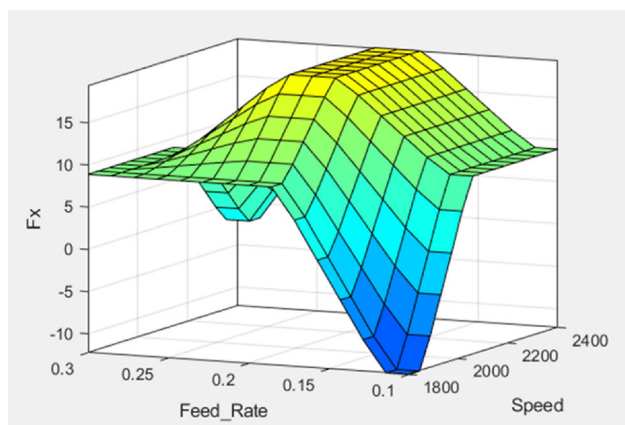
S	R-sq	R-sq (ad)	R-sq (pred)
0.020353	98.18%	97.94%	97.45%

on the Z-axis, creating a third dimension. The surface of the plot visually represents the predicted surface roughness values across the range of cutting speed and feed rate values, creating a contour-like surface that can reveal trends and patterns. Regions of the surface plot that are lower or smoother in blue colour indicate parameter combinations associated with lower surface roughness, while peaks or higher, yellow regions represent conditions leading to higher roughness.

The comparison between experimental 6% CNT CBN-based ground surface roughness and predictions from an ANFIS is a critical step in validating the model’s accuracy and utility as shown in Fig. 13. It provides insights into the model’s strengths and weaknesses, guiding further development and optimization for enhanced performance in grinding processes on titanium alloy. Employ statistical methods like Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), or R-squared ( $R^2$ ) to more than 95% quantitatively compare the predicted values from the ANFIS system with the experimental data. These values have been provided in Table 2, and these metrics provide a numerical assessment of the model’s accuracy in predicting surface roughness. The surface roughness was higher level during experiments 4 to 8 with lower cutting



**Fig. 13** Comparison of Experimental and ANFIS Predicted Surface Roughness



**Fig. 14** 3D Surface Representation of Tangential Force

speed but when the process speed was increased to the optimum level then the surface roughness values were decreased during experiments 21 to 26 and there is a significant difference between the ANFIS model and experimental data during the experiments 16 to 20. The comparative graphs for the experimental and ANFIS-predicted values are shown in Fig. 15, and the error of 2.13% was seen, which is within the acceptable limits.

### 3.2 ANFIS for tangential forces

3D Surface Representation of Tangential Force as portrayed in Fig. 14 with respect to speed and feed rate refers to a graphical representation that illustrates the relationship between two key machining parameters, cutting speed and feed rate, and the tangential cutting force experienced during a grinding process. Understanding the factors influencing cutting force in grinding is essential for optimizing machining operations. Higher cutting speeds generally lead to increased tangential cutting forces in the yellow region surface. This is because higher speeds result in more frequent interactions between abrasive grains on the grinding wheel and the workpiece material, leading to greater material removal and consequently, higher cutting forces. Higher feed rates typically result in increased cutting forces after that decrease in the blue colour region. As the grinding wheel engages more material due to a higher feed rate, the force required to remove the material also increases. Softer grinding wheels conform more readily to the workpiece, distributing the cutting forces over a larger area and potentially reducing the force per unit area. The comparative graphs for the experimental and ANFIS-predicted values are shown in Fig. 15, and the error of 4.24% was seen, which is within the acceptable limits.

### 3.3 Grey Relational Analysis (GRA)

GRA effectively investigates associations among factors for problems with differing objectives, otherwise called ‘multi-objective’ problems. Here, it has been used to analyse the effects of four responses: MRR, surface roughness, normal forces and temperature. The metal removal rate must be maximised, while all others are required to be as low as possible. GRA can convert multi-objective problems with antagonistic trends into a single objective using grey relations. The GRA is, therefore, a simultaneous optimisation approach of opposing objectives.

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the Grey Relational Analysis (GRA) were used to facilitate multi-criteria decision-making techniques, automate the grinding process, and work with expert systems and allied automation. GRA allows a person to find a workable solution when conflicting goals and multiple factors affecting the outcome of those goals are present. Developed by Deng Julong of Huazhong University, this technique helps deal with scenarios where there is neither black (no information) nor white information (complete information) but grey (partial information). In simple terms, the GRA is a technique to obtain a ‘good’ solution rather than the ‘best’ solution in cases where there are objectives with contrasting trends.

In manufacturing scenarios, the ‘grey’ areas are the interactive effects of the factors considered in the experiment. Such knowledge databases are partial or incomplete at best. They often exist only in the minds of the technician doing the job hands-on, and he works with his ‘gut instinct’ from wide and varied work experiences. Quantified prediction of any possible combination of factors is possible with GRA. A ‘Grey Correlation Degree’ statistic describes how well-correlated two variables or systems are. If all outputs have a similar trend, a higher degree of Grey correlation exists and vice-versa. In this research, the conflicting goals were to maximise MRR and minimise SR. A flowchart is shown in Fig. 16.

In this research work, the GRA was done on the 6% CNT-CBN grinding wheel. Though the 2% CNT-CBN grinding wheel gave the lowest forces, and it differed from the 6% CNT-CBN wheel’s result by a negligible margin, the 6% CNT-CBN wheel was chosen for the GRA because its MRR values were relatively close to the 7% CNT-CBN wheel. Normalisation is done for larger-the-better using Eq. 1, and for smaller-the-better using Eq. 2, the divergence sequence was then calculated by

$$Z = \frac{Y_i - \min Y_i}{\text{Max} Y_i - \text{Min} Y_i} \quad (1)$$

$$Z = \frac{\text{Max} Y_i - Y_i}{\text{Max} Y_i - \text{Min} Y_i} \quad (2)$$

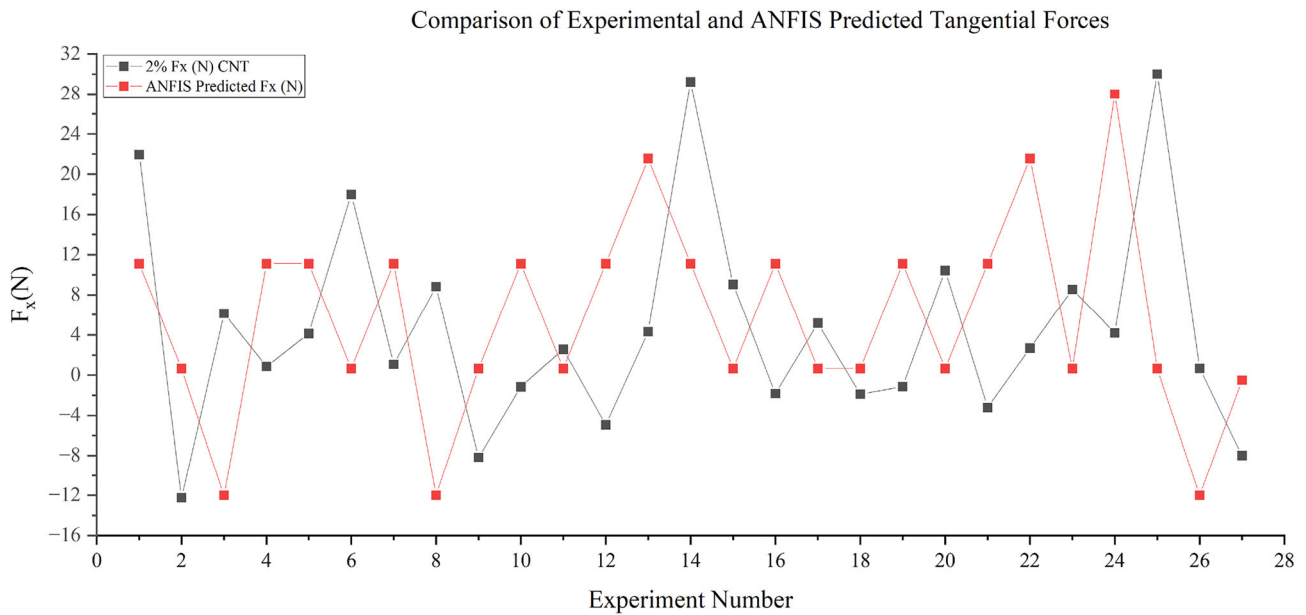


Fig. 15 Comparison of Experimental and ANFIS Predicted Tangential Forces

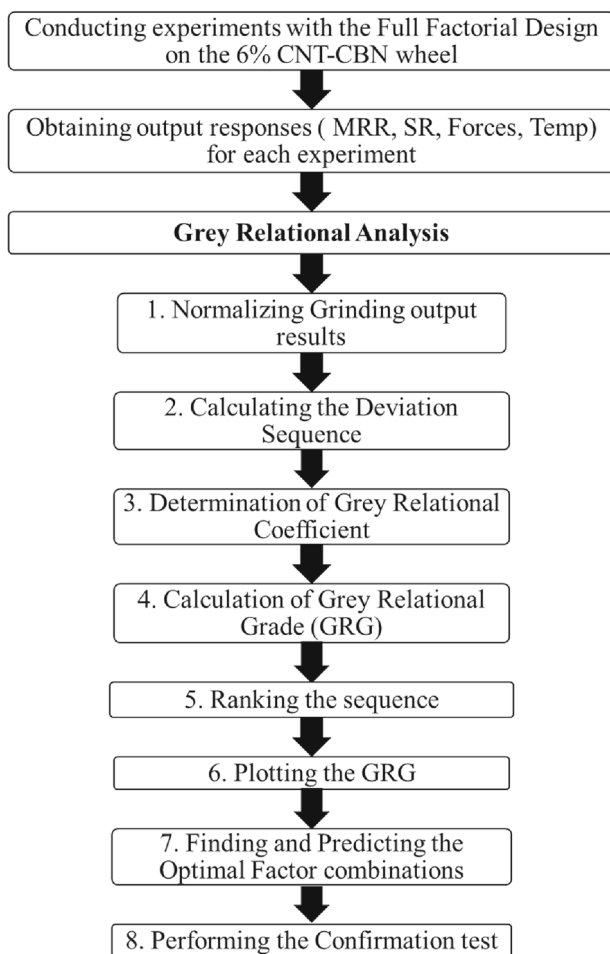


Fig. 16 Steps in Grey Relational Analysis

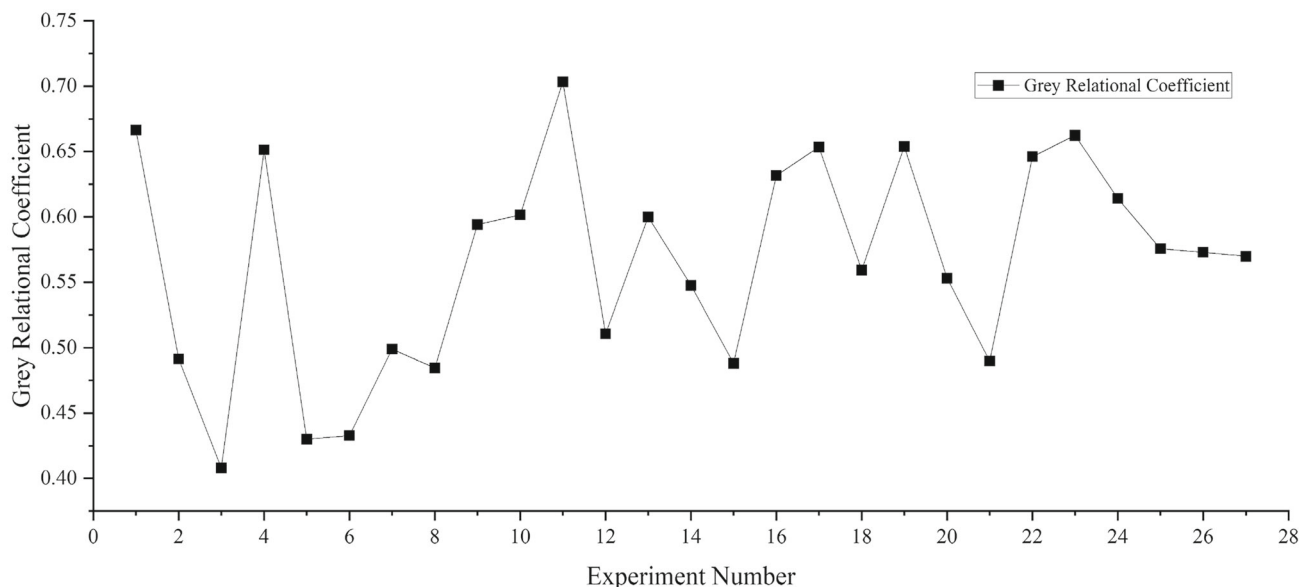
Calculation of the grey coefficient is done by subtracting the normalised sequence from 1 and then applying the formula shown in Eq. 3. This step is carried out to find the association between the normalised, actual values and ideal results. Both these steps are carried out for all four results.

$$\text{GreyCoefficient} = \frac{\Delta_{\text{Min}} + \zeta \Delta_{\text{Max}}}{\Delta_y + \zeta \Delta_{\text{Max}}} \tag{3}$$

where,  $\Delta$  = is the deviation sequence,  $\zeta$  = a distinguishing or identification coefficient and is usually held between [0, 1]. Therefore, it is mostly taken as 0.5. The Grey Relational Grade (GRG) ( $\gamma_i$ ) is then calculated using the formula as shown in Equation (4).

$$\gamma_i = \frac{1}{N} \sum \text{GreyCoefficient} \tag{4}$$

These grades are then ranked by acceding the highest rank to the factor combination with the highest GRG. The Grey Relational Coefficients have been plotted in Fig. 17. From this graph, it was seen that experiment no. 11, with a wheel speed of 2100 rpm, FR of 0.1 mm/min and a DoC of 0.02 mm, gave the best combination to optimize the overall grinding experiment. The results obtained were an MRR of 0.00523 g/s, surface roughness of 0.85670  $\mu\text{m}$ , normal force of 9.26N and a temperature of 41 °C. This combination is represented as A2B1C2, has been given the first rank among other experiments and has been highlighted in green in the tabular column.



**Fig. 17** Grey Relational Coefficients

Once the Grey relational grade (GRG) was identified for the experimentally obtained values, it was verified by predicting its values. This prediction is calculated using the formula in Equation (5) k

$$\gamma = \gamma_m + \sum (\gamma_n - \gamma_m) \quad (5)$$

where,  $\gamma$  = predicted GRG,  $\gamma_m$  = mean GRG and  $\gamma_n$  = mean GRG at the optimal level. The main effects of GRG are shown in Fig. 18, and from it, the optimal conditions can be taken as A3B3C1. The main effects plot of the S/N ratios shows the wheel speed as bearing the chief effect on the GRG, and it is to be as large as possible if the result is to perform optimally. To validate the conclusions revealed from the analysis phase which is the culminating stage in the sequence of operations of the DOE process. The experiments were conducted to authenticate using the process parameters at the optimum level.

A comparison of the initial state, experimental and predicted factor combinations are shown in Table 3. The difference in the experimental and predicted design GRG was 0.12774. Surface roughness decreased from 0.856 to 0.762  $\mu\text{m}$  and the MRR decreased from 0.00523 to 0.00404 g/s with CNT grinding. Based on the above data in Table 1, it shows clearly that surface quality characteristics can be greatly improved through this study.

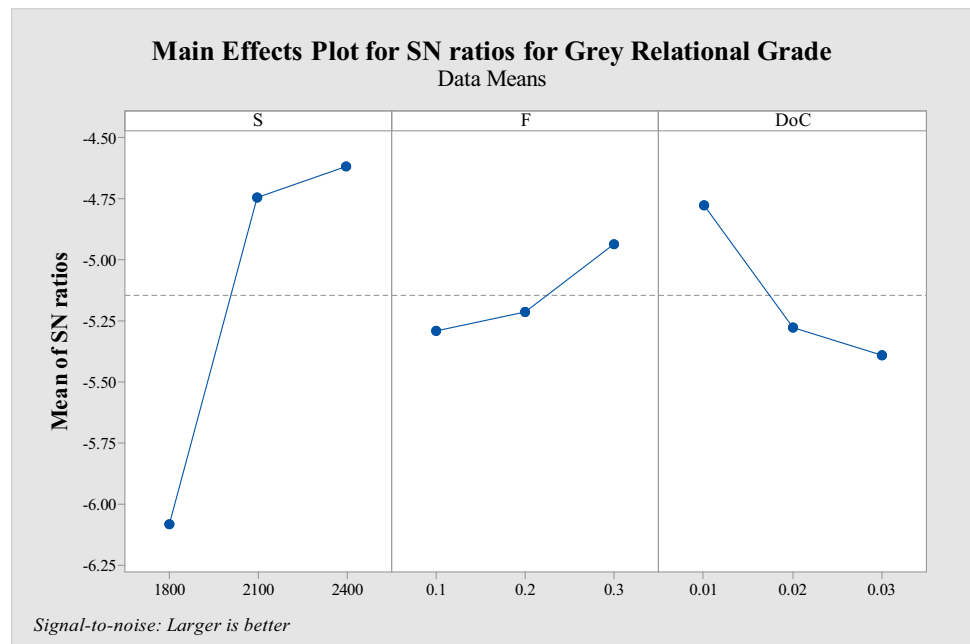
## 4 Conclusions

This study employs the Adaptive Neuro-Fuzzy Inference System (ANFIS) to model surface roughness, Metal Removal

Rate (MRR), and Cutting forces in titanium alloy machining using a carbon nanotube (CNT)-based grinding wheel and the following conclusions were obtained:

1. FL and ANFIS were used on the key results to predict the following % differences obtained for the ANFIS-predicted values: MRR—0.15%, Surface Roughness—2.13% and the Tangential Force—4.24%. These values show that the ANFIS model was good and the predictions were acceptable.
2. Multi-objective decision-making methods of GRA gave slightly differing values. The GRA inference of factor combination for optimising four outcomes of MRR, SR, Fz and temperature was A3B3C1.
3. The 6% CNT-CBN wheel provided the best surface finish at maximum speed and medium feed and depth of cut factor combination (A3B2C2). This value was a 47.36% improvement from the minimum SR caused by the CBN wheel. The least roughness values recorded were lower than the CBN wheels in every speed range, and the main effects plots showed the wheel speed bearing chief responsibility.
4. The 2% CNT-CBN wheel produced the lowest tangential and normal forces, with a difference from the CBN wheel being a massive 75.3% and 51.9%, respectively. For the tangential forces, the wheel speed-feed rate interaction was key to lowering them. Therefore, it could be summarised that an inverse proportion of wheel speed and feed rate was best for minimising the tangential forces. Therefore, it is a better solution than the commercially available CBN grinding wheel in terms of wheel life and power consumption. When normal forces were studied,

**Fig. 18** Main Effects Plots for GRG



**Table 3** Comparison of initial, experimental and predicted output GRG

Factors ↓	Initial Design	Optimal Experimental Design	Optimal Predicted Design
Setting level →	A1B1C1	A2B1C2	A3B3C1
SR (μm)	0.55870	0.85670	0.76210
S Forces (N)	7.118	9.26	9.348
Grey relational grade	0.66646	0.70339	0.57565

the wheel speed-DoC interaction was found to be the key factor combination. Higher DoCs caused a steep rise in the normal forces required to remove material from the surface.

**Consent to participate** Not applicable.

**Consent to publish** Not applicable.

**Author’s contribution** Deborah Serenade Stephen: Grinding wheel Design, manufacturing and conducted the Grinding experimental works and reported the primary results and written original manuscript. Prabhu Sethuramalingam: Planned the whole work and Multi objective optimization was done, supervised, and corrected the main manuscript text. All authors reviewed the manuscript.

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**Code availability** Not Applicable (software application or custom code).

**Declarations**

**Conflict of interests** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Ethical approval** Not applicable.

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