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Sustainable machining of AISI4140 steel: a Taguchi-ANN perspective on eco-friendly metal cutting parameters

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Abstract

This work explores environmentally conscious machining practices for AISI4140 steel through Taguchi analysis. The study employs a design of experiments (DOE) approach, focusing on cutting speed, depth of cut, and coolant type as parameters. Taguchi's L9 orthogonal array facilitates systematic experimentation, and the results are analyzed using MINITAB 17 software. Signal-to-noise ratios (SNR) are utilized to establish optimum operating conditions, evaluate individual parameter influences, and create linear regression models. The experiments reveal neem oil with graphene coolant as an eco-friendly solution, addressing health and environmental concerns. Main effects plots visually represent the impact of parameters on machining quality. Additionally, regression and artificial neural network (ANN) models are compared for surface roughness prediction, with ANN showing superior performance. The findings advocate for optimized cutting conditions, emphasizing material conservation, enhanced productivity, and eco-friendly practices in AISI4140 steel machining. This research contributes valuable insights for industries seeking sustainable machining solutions.

Keywords Optimization, Milling parameters, AISI4140 steel, Taguchi analysis, Metal cutting

Introduction

Nanofluids represent a novel category of fluids in which nanometer-sized materials such as nanoparticles, nanofibers, nanotubes, nanorods, nanosheets, and droplets are dispersed within the base fluids (Anthony Xavior and Adithan 2009). These fluids are essentially nanoscale colloidal suspensions that incorporate solid nanomaterials. Given their two-phase composition involving a solid phase and a liquid phase, addressing the pertinent challenges associated with two-phase systems becomes crucial (Kuram et al. 2010). Of particular significance in the realm of nano-cutting fluids, the issue of nanofluid stability arises, posing a considerable obstacle in achieving the desired stability of these fluids (Zhang et al. 2012).

In recent years, nanofluids have gained significant prominence, finding diverse applications across various domains and playing a crucial role in numerous aspects of life. While a considerable body of research articles in this field predominantly focuses on experimental and theoretical studies related to the thermo-physical properties and convective heat transfer of nanofluids (Lawal et al. 2015; Ademoh et al. 2016), there is a noticeable trend towards exploring novel application avenues for these fluids, particularly in the context of their heat transfer properties (Onuoha et al. 1330). The diminutive size of nanoparticles, often measuring less than 100 nm, endows them with the capacity to engage with liquids at a molecular level, imparting superior heat conduction abilities compared to conventional heat transfer fluids that incorporate larger particles. Notably, metallic nanofluids have emerged as a viable means to preserve enhanced

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thermo-physical properties, including thermal conductivity, thermal diffusivity, viscosity, and convective heat transfer coefficients, in comparison to base fluids such as oil or water. This surge in the importance of nanofluids is evident across various fields, with notable applications extending to solar collector systems and solar thermal storage (Nizamuddin et al. 1045; Mir and Wani 2018; Gunjal and Patil 2018). The unique characteristics of nanofluids position them as valuable contributors to advancements in heat transfer technology, opening up new possibilities for more efficient and sustainable systems in diverse industrial and scientific domains.

Nanofluids exhibit improved stability and rheological properties, enhanced thermal conductivity, and minimal pressure drop penalties when compared to suspensions containing larger millimeter- or micrometer-sized particles (Lenin et al. 2021). This novel composite fluid bears considerable significance, yet there remains a dearth of research and information surrounding issues such as nanofluid preparation and stability. Accurate prediction of nanofluid thermal conductivity under industrial conditions and the viscosity of nanofluids in conjunction with heat transfer processes hold critical importance (Agrawal and Patil 2018). Given the ongoing industrial advancements and the demand for innovative processes to enhance production, comprehensive studies are indispensable across diverse domains. Manufacturers consistently strive for increased efficiency and profits, aiming to minimize production time, costs, energy consumption, and resource utilization while simultaneously improving performance (Onuoha et al. 2016; Agu et al. 2019). This pursuit involves cutting fluids, which play a pivotal role in achieving these goals.

The role of cutting fluids is paramount, as they prevent direct metal-to-metal contact, thereby mitigating internal friction (Syafiq et al. 2020). In metalworking operations, the introduction of a lubricant between surfaces reduces the frictional resistance. Lubricants form a protective film that separates the sliding surfaces, leading to reduced friction and wear (Osayi et al. 2021). Additionally, cutting fluids possess the capacity to cool the workpiece, the cutting tool, and the chip. They also aid in the removal of the generated chips during the cutting process. Cutting fluids prevents rewelding and corrosion, reduce machine energy consumption, and extend tool life (Khan Aug. 2009). During metal cutting operations, cutting fluids serve a threefold purpose: they cool the workpiece and cutting tool surfaces, remove chips from the cutting zone, and lubricate the tool-workpiece interface (Lenin et al. 2021). While cutting fluids have been recognized for their positive contributions to tool economy, tolerance maintenance, and surface preservation, their application also raises concerns about human health and environmental impact, both during usage and disposal. Moreover, cutting fluid costs constitute a significant portion (16–20%) of production expenses in the manufacturing industry. Therefore, it is imperative to exercise caution and avoid excessive use of these fluids, particularly flood lubrication, to ensure efficient resource management. The field of machining and metal cutting processes has seen substantial advancements over the years, with ongoing research and practical innovations aimed at enhancing cutting tool performance, surface quality, and overall machining efficiency. One critical element in machining operations is the selection and use of cutting fluids, which are essential for extending tool life, controlling temperature, reducing friction, and improving surface finish. This introduction summarizes key research papers that delve into the impact of cutting fluids on various machining parameters and outcomes, contributing to a deeper understanding of their role in machining processes.

Research investigations, exemplified by the works of Xavior and Adithan (Anthony Xavior and Adithan 2009), have explored the impact of cutting fluids on distinct materials, with a specific focus on processes like turning AISI 304 austenitic stainless steel. Their research underscores the critical role of evaluating tool wear and surface roughness to gauge the efficacy of cutting fluids in machining operations. Likewise, Kuram et al.'s study (Kuram et al. 2010) has employed optimization methodologies such as Taguchi and ANOVA to refine cutting fluids and machining parameters, specifically in the context of milling operations. These studies collectively contribute valuable insights into the nuanced relationship between cutting fluids, material behavior, and machining performance.

Recent research has prominently featured the exploration of sustainable and environmentally friendly alternatives in machining fluids. Zhang et al. (Zhang et al. 2012) conducted an assessment of the performance of a bio-based cutting fluid, evaluating multiple machining characteristics and highlighting the growing interest in sustainable machining practices. Lawal et al. (Lawal et al. 2015) delved into the use of vegetable and mineral oil-in-water emulsion cutting fluids in the turning of AISI 4340 steel, concentrating on aspects such as tool wear, surface quality, and performance optimization. In addition to material-specific studies, researchers have scrutinized the influence of cutting fluid properties on machining outcomes. Onuoha et al. (Onuoha et al. 1330) specifically investigated the impact of emulsifier concentration on the properties of oleochemical (chemical compounds derived from natural fats and oils) oil-based cutting fluids, underscoring the pivotal role of fluid formulation. Ademoh et al. (Ademoh et al. 2016) explored the potential of neem seed oil as an alternative cutting fluid, emphasizing the ongoing quest for sustainable alternatives in machining operations. The optimization of cutting parameters in conjunction with fluid selection represents another crucial facet of machining research. Mir et al. (Mir and Wani 2018) examined the effect of cutting fluids on surface roughness during the turning of AISI 1330 alloy steel using the Taguchi method, highlighting the significance of parameter optimization. Furthermore, Khan (Khan Aug. 2009) conducted investigations into the effects of minimum quantity lubrication on turning AISI 9310 alloy steel, employing a vegetable oil-based cutting fluid in the pursuit of efficient machining practices. These studies collectively contribute to the broader understanding of sustainable machining practices and the optimization of machining parameters for improved performance.

The investigation of unconventional and natural fluids for their machining capabilities has extended to diverse sources. Agu et al. (Agu et al. 2019) conducted a study evaluating the impact of blended cutting fluids during the turning of die steel D2. This research contributes to the expanding body of knowledge on alternative fluids in machining applications. Similarly, the study by Osayi et al. (Osayi et al. 2021) centered on the performance evaluation of a cutting fluid derived from rubber seed oil in the turning of mild steel, highlighting the exploration of a variety of fluid sources in the pursuit of effective machining solutions.

The progress in machining techniques has spurred investigations into novel fluid applications. Syafiq et al. (Syafiq et al. 2020) conducted an experimental evaluation of SiO_2 nano-cutting fluids in CNC turning of aluminum alloy AL319, employing the minimum quantity lubrication (MQL) technique. This study reflects the integration of nanotechnology into machining processes, showcasing the pursuit of innovative approaches to enhance machining efficiency. Moreover, the performance of cutting fluids concerning specific materials has been a subject of exploration. Agu et al. (Agu et al. 2019) undertook the optimization of machining parameters in the turning of AISI 304L, employing various oil-based cutting fluids. Their focus on surface roughness and material removal rate underscores the importance of tailoring cutting fluid applications to specific materials, demonstrating a targeted approach to improving machining outcomes.

The presented work contributes to a comprehensive understanding of the influence of cutting fluids on various machining parameters and outcomes. From the assessment of conventional fluids to the exploration of sustainable and nanotechnology-enhanced options, these studies shed light on the complexities and potentials of cutting fluid applications in modern machining practices. As the field continues to evolve, research efforts in this area will contribute to the development of more efficient and environmentally friendly machining techniques.

Experimental work

Test method

AISI4140 steel (EN19) alloy with a thickness of 20 mm is used as a workpiece material. Machine specifications, material properties, and constant parameters are mentioned in Table 1. Machining operations were performed on an AISI4140 (EN19) steel block measuring 100 mm × 100 mm × 20 mm using a Bharat Fritz Werner Limited machine. The cutting inserts employed were APMT1604 ZCCCT YBG205/202 Grade with a rhombic shape, sharp and honed cutting edges, and 11° relief angle. The experimental parameters were organized using the Taguchi L9 orthogonal array (OA) design, facilitating efficient experimentation with three parameters and three levels. The chosen parameters were cutting speed (355, 500, 710) in rpm, depth of cut (0.5, 1, 1.5) in mm, respectively, and coolant type (neem oil with graphene, normal coolant, dry). Different coolants were employed, namely neem oil with graphene nanoparticle, dry (no coolant), and SERVOCUT S soluble cutting oil. Machining outcomes were evaluated using a "MITUTOYO" SJ301 model surface roughness tester, considering three quality characteristics for each experiment. The study aimed to establish the optimum operating conditions through signal-to-noise ratio (SNR) analysis, evaluate the influence of individual parameters using ANOVA, and develop linear regression models for two characteristics over the three parameters. The cutting tool moves across the normal to the surface of the workpiece. The tool followed a straight (linear) trajectory. The amount of

Table 1 Machine specifications and material properties

Workpiece material and dimensions	AISI4140 (EN19) steel block (100 mm × 100 mm × 20 mm)
Cutting inserts	APMT1604 ZCCCT YBG205/202 Grade
Working insert tool geometry	Shape: 80° rhombic, sharp, and honed cutting edge and 11° relief angle
Environments and coolants used	Neem oil with graphene nanoparticle, dry (no coolant), SERVOCUT S soluble cutting oil
Surface roughness tester	"MITUTOYO" make SJ301 model

material removed by each tooth of the cutter in one revolution is determined by the feed per tooth. The feed per tooth used in this research is 40 mm/min. This comprehensive experimental setup employed (Fig. 1) industry-standard tools and methodologies to ensure reliable and meaningful results.

Taguchi and design of experiments

Taguchi method

The design of experiments (DOE) is a systematic approach employed to investigate conditions where a response is subject to variation based on one or more independent parameters. This method involves meticulously defining and exploring all conceivable situations within a test that encompasses multiple factors. The key elements of DOE include planning the experiment to ensure suitable data for analysis, as well as determining and establishing optimal conditions while evaluating the impact of individual factors. Both DOE and the statistical analysis components play integral roles in addressing any experimental problem. Understanding the crucial factors that demand special attention, whether for control or optimization of system performance, is imperative. In the present study, Taguchi's L9 orthogonal array is employed, featuring three parameters each with three levels. For every experiment conducted, three distinct quality characteristics are measured. The culmination of these experiments is subjected to thorough analysis to ascertain the optimal operating conditions through signal-to-noise ratio (SNR) analysis. Simultaneously, the influence of individual parameters is assessed using statistical tools such as analysis of variance (ANOVA) and linear regression analysis. These analytical techniques help discern the most dominant parameters, providing valuable insights into the intricacies of the experimental system. The findings derived from this study contribute to a comprehensive understanding of the system's behavior and guide decisions aimed at enhancing performance or maintaining control in a diverse array of scenarios.

Following the principles of the orthogonal array, a series of experiments were conducted, yielding outcomes for various combinations. The analysis of the measured results was carried out using the commercial software MINITAB 17, a tool widely employed in design of experiments (DOE) applications. To assess the qualities under consideration, the experimental data were converted into signal-to-noise ratios (SNR). This conversion allows for a comprehensive examination of the impact of control factors, such as load, sliding speed, and distance, on the wear rate. The SNR responses were employed to scrutinize and understand the influence of these control factors on the wear rate. The response tables generated from these analyses provide a ranking of process parameters based on SNR derived from wear rate observations. This ranking facilitates the identification of critical factors and their relative significance in the experimental setup. In order to further refine the analysis, experimental observations were subjected to transformation into SNR. This transformation involved the calculation of logarithmic functions, converting the observed loss function into a more manageable and informative format. This approach enhances the precision and clarity of the findings, contributing to a more nuanced understanding of the experimental outcomes.

$$\text{Higher is better characteristic : SNR } (\eta) = -10\log 1/n[\Sigma y2] \quad (1)$$

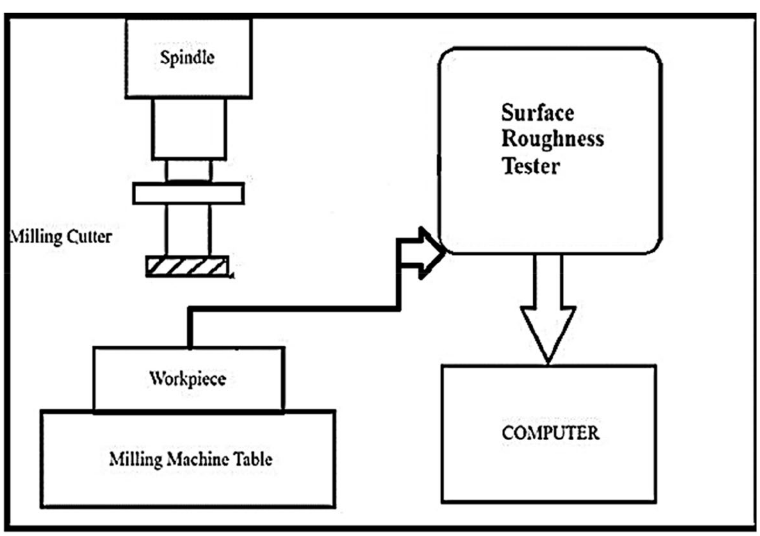

Fig. 1 Experimental milling setup

Table 2 Factors and their levels wear test

Sr. No	Input parameters	Levels		
1	Cutting speed (rpm)	355	500	710
2	Depth of cut (mm)	0.5	1	1.5
3	Coolant type	Neem oil with graphene (1)	Normal coolant (2)	Dry (3)

Table 3 Taguchi's L9 orthogonal array design

Experiment No	Parameters and their levels			
	Cutting speed (rpm)	Depth of cut (mm)	Coolant type	Surface roughness
1	355	0.5	1	2.9
2	355	1	2	3.3
3	355	1.5	3	4.8
4	500	0.5	2	2.9
5	500	1	3	3.2
6	500	1.5	1	2.3
7	710	0.5	3	4.8
8	710	1	1	1.9
9	710	1.5	2	3.1

$$\text{Lower is better characteristic : SNR } (\eta) = -10\log 1/\text{n}[\Sigma \text{y}2] \quad (2)$$

where "n" is the number of observations and "y" is the observed data.

Process parameters levels

The experimental design was conducted utilizing the principles of design of experiments (DOE) through Taguchi analysis. Table 2 delineates the parameters considered for the study along with their corresponding levels. In Table 3, the Taguchi orthogonal L9 (3^2) array is presented, outlining the configuration for a set of 9 experiments. These arrays are systematically designed to ensure a comprehensive exploration of the parameter space, allowing for a robust analysis of the factors under investigation (Fig. 2).

The selection of the range for each controllable parameter was determined through preliminary experiments, as detailed in Table 2. To streamline the experimental process and minimize costs, we employed the Taguchi L9 orthogonal array (OA) design. This design choice is effective in reducing both effort and the overall expense associated with experimentation. For evaluating the surface roughness, a "MITUTOYO" SJ301 model surface roughness tester was utilized in accordance with ISO 4287–1997 norms. The arithmetic mean surface roughness (Ra) of the machined surface was calculated using Eq. (3), which defines Ra as the arithmetic mean of the absolute deviations in the roughness profile from the center line over the total length. To ensure precision, the Ra value was determined based on the average of five measurements taken from each machined surface. Additionally, a cut-off length of 4 mm was used for each Ra value. The results of the uncertainty analysis for the surface roughness measurements are presented in Table 3.

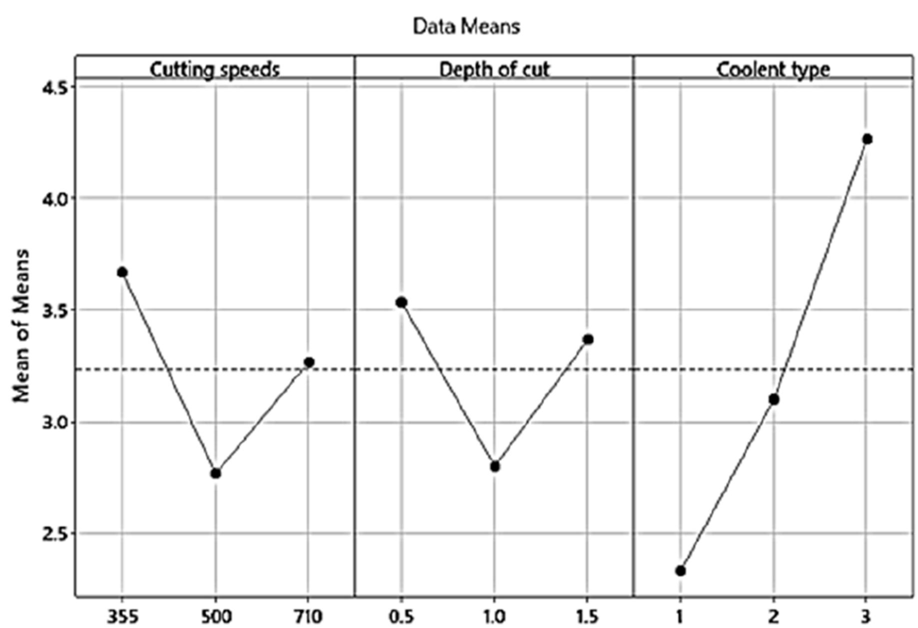

Fig. 2 Main effect plot for means

SNR and ANOVA

In every experimental trial, an evaluation of surface roughness is conducted, with the concurrent determination of the signal-to-noise ratio. The surface roughness is designated as the response variable, while the process parameters include cutting speed, depth of cut, and coolant type. Adhering to the principles of the Taguchi method, a decision is made to adopt the "smaller is better" criterion for the ratio assessment. The objective in this context is to enhance the surface roughness, positioning it as a minimized parameter. Mathematically, this is expressed as follows:

$$S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad (3)$$

The investigation into signal-to-noise ratios has yielded valuable insights, revealing that the delta value is notably higher in the coolant type. This observation signifies the coolant type as the predominant influencing factor in the milling process. Following closely in influence are the cutting speed and depth of cut. The utilization of rank analysis aids in discerning the hierarchical impact of different factors on the machining process. Notably, the coolant type holds the top rank (rank 1), highlighting its paramount influence. Subsequently, cutting speeds and depth of cut secure ranks 2 and 3, respectively. This ranking structure facilitates the identification of the most influential factors in the milling process. Moreover, the obtained data, as presented in Table 4, establishes a consistent pattern, with coolant type, cutting speeds, and depth of cut maintaining their respective ranks. Further insights are revealed in Table 5, which displays the responses in terms of means (predicted values). This comprehensive analysis provides a clear understanding of the relative importance of different factors in the context of the hydroforming process.

Results and discussion

The investigation into surface roughness relies on the utilization of the L9 (3^2) orthogonal array, as delineated in Table 1, to serve as the foundational framework for the analysis. In this study, the influential factors under consideration encompass cutting speed, depth of cut, and coolant type. The response parameters being scrutinized are surface roughness generated during the machining process. The primary objective of the experimental design is to discern the key parameters and their interactions that significantly influence surface roughness. The orchestrated tests have been systematically devised using the orthogonal array methodology. The overarching aim is to establish a coherent relationship elucidating the impacts of cutting speed, depth of cut, and coolant type on the surface roughness test, ultimately striving to identify the optimal conditions that yield the lowest surface roughness.

Table 4 Response for signal-to-noise ratios (smaller is better)

Level	Cutting speeds (rpm)	Depth of cut (mm)	Coolant type
1	−11.081	−10.707	−7.224
2	−8.733	−8.683	−9.815
3	−9.676	−10.100	−12.451
Delta	2.348	2.024	5.227
Rank	2	3	1

Table 5 Response for means (predicted values)

Level	Cutting speeds (rpm)	Depth of cut (mm)	Coolant type
1	3.667	3.533	2.333
2	2.767	2.800	3.100
3	3.267	3.367	4.267
Delta	0.900	0.733	1.933
Rank	2	3	1

Influence on surface roughness

The wear rate is predominantly influenced by the type of coolant, with statistical significance observed in the SNR for control parameters. Figures 3 and 4 depict the impact of process factors on surface roughness and SNR means. Through an analysis of test results using the SNR, optimal conditions leading to enhanced surface roughness have been identified.

ANOVA for signal o noise (S/R) ratio

ANOVA, or analysis of variance, serves as a valuable tool for interpreting and analyzing the variances among group means within experimental data. This statistical method facilitates informed decision-making by assessing the significance of different factors. In the context of the present experiment, the factors under consideration include cutting speed, depth of cut, and coolant type, with the response variable being the signal-to-noise ratio (SNR) (refer to Fig. 4). Table 6 presents the results obtained through ANOVA, offering insights into the contributions of each factor to the variability in the SNR. Notably, the percentage contribution analysis reveals that coolant type stands out with the highest impact, registering a substantial 12.71 according to the *F*-test score. On the other end of the spectrum, the

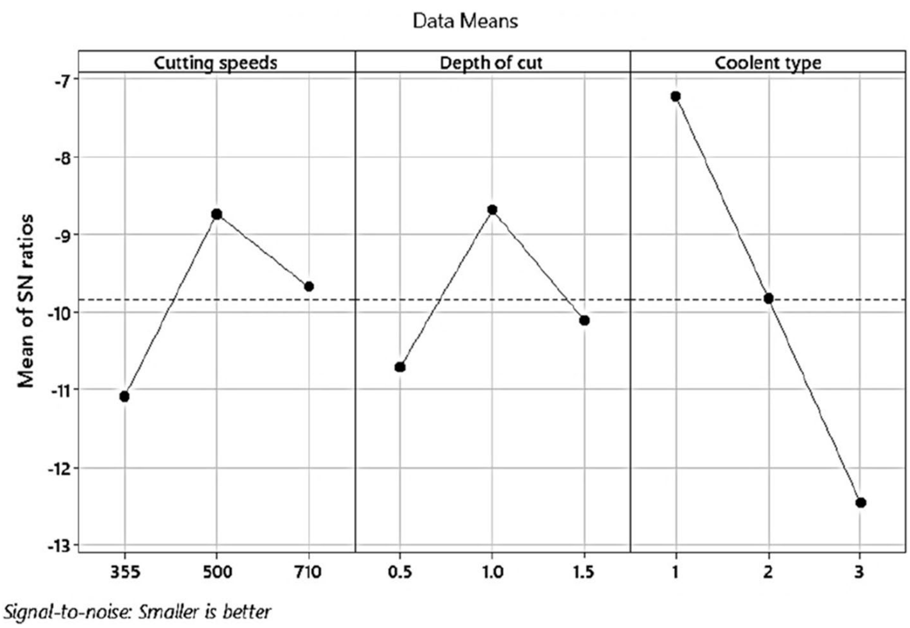

Fig. 3 Main effect plot for SNR

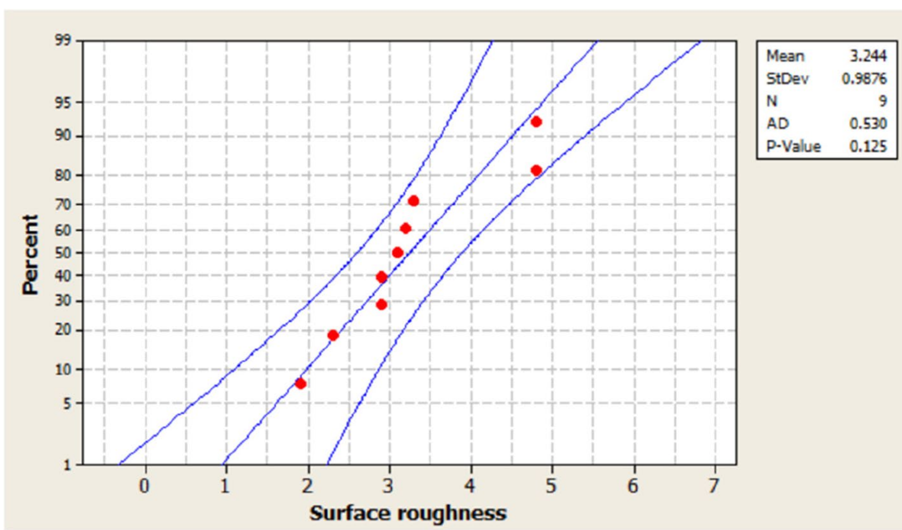

Fig. 4 Standard deviation plot

Table 6 Analysis of variance (ANOVA) for SNR (analysis of variance)

Source	DF	Adj SS	Adj MS	*F*-value	*P*-value
Regression	3	5.79511	1.93170	4.38	0.073
Cutting speeds	1	0.14678	0.14678	0.33	0.589
Depth of cut	1	0.04167	0.04167	0.09	0.771
Coolant type	1	5.60667	5.60667	12.71	0.016
Error	5	2.20489	0.44098		
Total	8	8.00000			

depth of cut exhibits the lowest contribution, amounting to a modest 0.09 as per the *F*-test score. From the model summary in Table 7, it observed that the value of R-sq is 72.44% which indicates this model can be considered to predict the optimal process parameter combination. Equation (4) encapsulates the optimal conditions derived from regression analysis, delineating the parameters that yield improved surface roughness. This equation represents the culmination of the experimental findings, pinpointing the specific values of cutting speed, depth of cut, and coolant type that

Table 7 Model summary

S	R-sq	R-sq(adj)	R-sq (pred)
0.664062	72.44%	55.90%	0.00%

result in an enhanced SNR. Through this comprehensive approach, the study not only identifies the most influential factors affecting surface roughness but also provides a practical framework for achieving optimal outcomes in machining processes.

Effect on surface roughness due to cutting speeds, depth of cut, and coolant type

The primary effect plot of means serves as a visual encapsulation of the distinct impact of cutting speed, depth of cut, and coolant type on the performance of machining. This graphical representation effectively communicates the contribution of each factor, providing a lucid overview of their influence on crucial parameters such as surface roughness. The succinct yet comprehensive nature of this representation plays a pivotal role in understanding the key drivers that shape the outcomes of the Taguchi analysis within the realm of environmentally conscious machining of AISI4140 steel. The Taguchi analysis was meticulously conducted for surface roughness, with Figs. 2 and 3 presenting the results. These figures specifically highlight the impact of various machining parameters on surface roughness. Notably, in Fig. 3, coolant type emerged as the most influential factor in determining surface roughness. The relationship between depth of cut and surface roughness was found to be non-linear in the current study, adding a nuanced dimension to the understanding of these machining dynamics. Furthermore, the main effect plot of signal-to-noise ratios (SNR) offers a concise and visually informative representation of how cutting speed, depth of cut, and coolant type collectively influence machining quality. Through the evaluation of SNR and surface roughness, this plot elucidates the optimal settings for machining parameters. It stands as an indispensable tool in the Taguchi analysis, providing valuable insights into the factors that significantly impact the overall performance and efficiency of AISI4140 steel machining processes.

Regression model for surface roughness for cutting speeds, depth of cut, and coolant type

The regression model (Eq. 4) for surface roughness against cutting speeds, depth of cut, and coolant type provides a quantitative framework to predict surface quality. It delineates the intricate relationship between machining parameters and surface roughness, enabling precise optimization. This model, a key outcome of Taguchi analysis, offers a systematic approach to enhance machining efficiency for AISI4140 steel. By elucidating the impact of each variable, it facilitates informed decisions for achieving superior surface finishes in metal cutting operations. Examining the residual plot, illustrated in Fig. 5, provides insights into the suitability of a linear model for the given data. The vertical dispersion of data points around the zero-centered horizontal line serves as an indicator of the appropriateness of the linear model. When the residuals exhibit a random and uniform spread around this line, it suggests a favorable fit of the linear model to the data, as exemplified in Fig. 6. Notably, the absence of significant deviations between the residual line and the component line signifies a linear relationship between the predictor and the dependent variable.

$$\text{Surface Roughness} = 1.92 - 0.00088\ \text{Cutting speeds} - 0.167\ \text{Depth of cut} + 0.967\ \text{Coolant type} \tag{4}$$

For a more specific context, Fig. 7 displays the resultant residual plots concerning surface roughness. These visual representations offer a comprehensive view of the relationship between the predictor and the dependent variable, aiding in the assessment of the linear model's adequacy for the dataset at hand. Regression analysis was employed to discern the connection between the response variable Ra and the input factors. Equation (4) delineates the association between Ra and the parameters of cutting speed, depth of cut, and the type of coolant used in the process.

Contour plot of cutting speeds and surface roughness versus depth of cut

Contour plots serve as a valuable tool for examining the interplay between a response variable and two control variables, providing a visual representation of discrete contours for predicted response variables. In Fig. 8, these contour plots elucidate the relationship between process parameters and the surface roughness value. Upon closer inspection of Fig. 8a, it becomes evident that an elevated cutting speed corresponds to a heightened surface roughness value. Conversely, the plot reveals that lower surface roughness can be achieved at higher levels of cutting speed and depth of cut. This observation underscores the inverse correlation between cutting speed and surface roughness, indicating that a high cutting speed tends to result in increased surface roughness. Furthermore, Fig. 8b

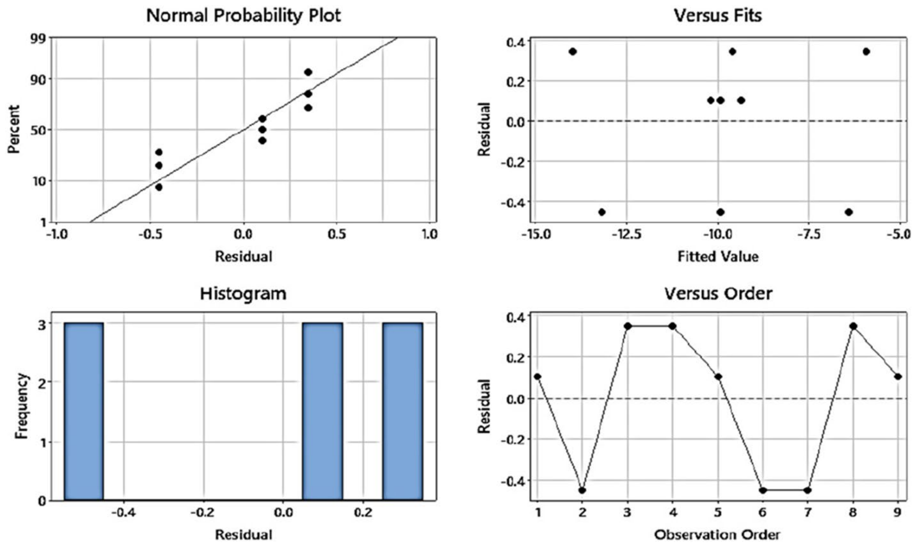

Fig. 5 Residual plots for SNR

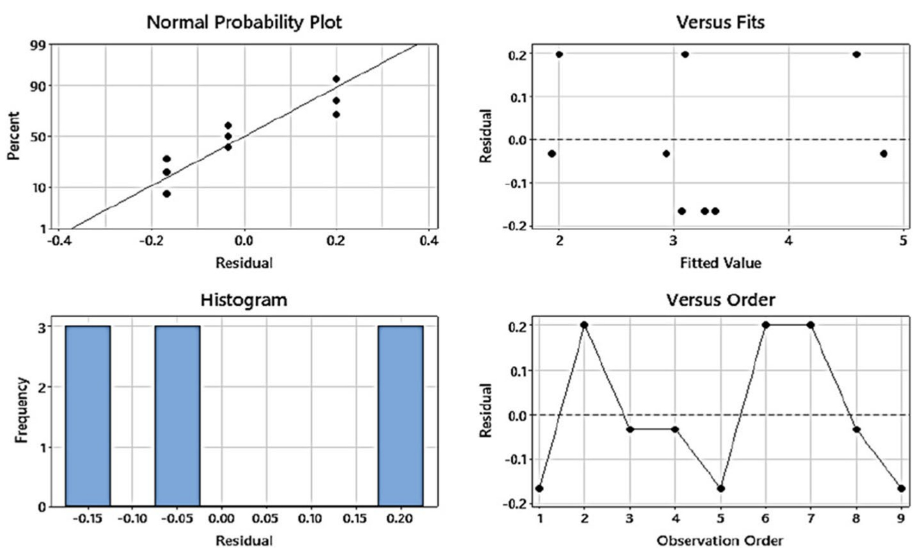

Fig. 6 Residual plots for means

underscores the impact of neem oil with graphene cutting fluid on the surface roughness value, demonstrating a significant reduction compared to other cooling environments. This suggests that the specified cutting fluid condition plays a crucial role in minimizing surface roughness during the machining process. The utilization of neem oil with graphene cutting fluid emerges as an effective strategy for achieving superior surface quality in comparison to alternative cooling conditions, as illustrated in the contour plot.

Multi-layer ANN structure

A MATLAB-generated surface roughness graphs offer a nuanced perspective on the machined surface quality across various datasets, providing a comprehensive evaluation of the efficacy of the machining process. Each set of data—training, validation, and test—along with the overall trend, contributes unique insights into the impact of cutting parameters on surface finish. The MATLAB-generated surface roughness graphs are invaluable tools to optimize machining parameters. Identification of

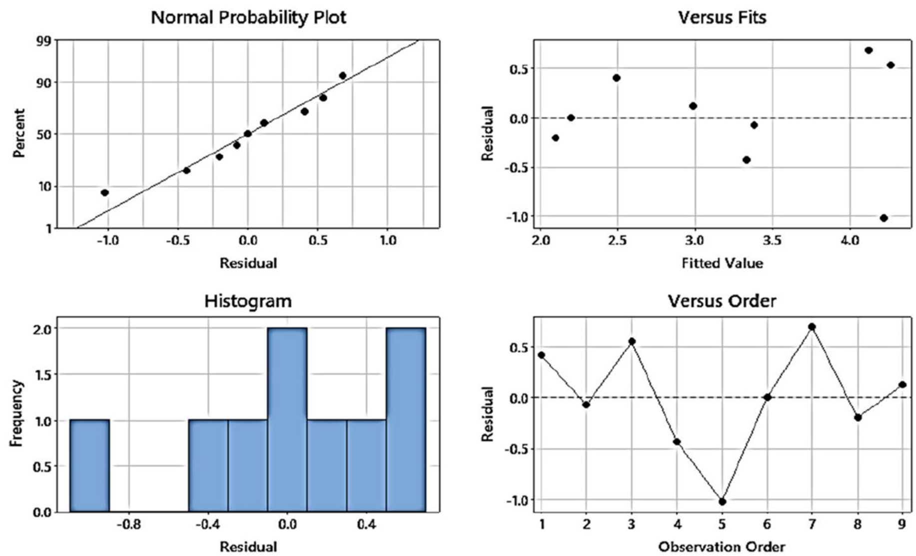

Fig. 7 Residual plots for surface roughness

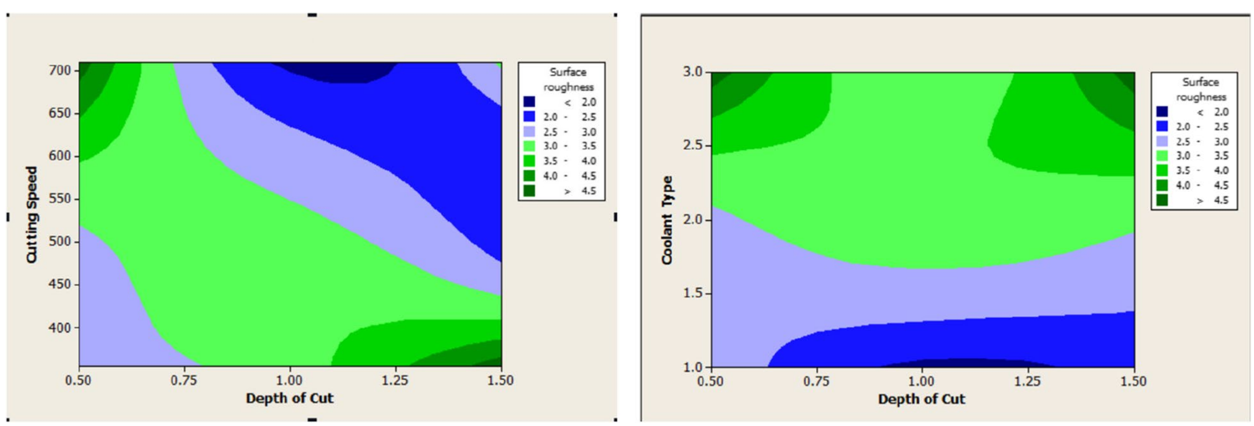

Fig. 8 Contour plot for surface roughness for **a** cutting speed, depth of cut and **b** coolant type, DOC

optimal cutting speeds, depths of cut, and coolant types becomes evident through the trends observed in the graphs. Researchers and practitioners can leverage this information to strike a balance between material removal rates and achieving the desired surface finish. By comparing the predicted surface roughness with the actual outcomes, the graphs instill confidence in the predictive model. A close alignment between predicted and actual values underscores the model's accuracy and applicability in guiding machining operations for superior surface quality. In summary, the surface roughness graphs derived in MATLAB ANN analysis as shown in Fig. 9 serve as dynamic visual aids, guiding the understanding, validation, and optimization of machining processes. Their role in enhancing the predictive capacity of models and facilitating real-world machining improvements is pivotal for advancing precision manufacturing methodologies. Regression *R*-values measure the correlation between outputs and targets. An *R*-value of 1 means a close relationship, and 0 a random relationship. Mean squared error is the average squared difference between outputs and targets. Lower values are better. Zero means no error.

MATLAB surface roughness histogram

MATLAB-generated surface roughness histogram (Fig. 10) provides a concise and insightful representation of the distribution of surface roughness values, offering a statistical overview of the machining outcomes. This histogram serves as a robust tool for understanding the

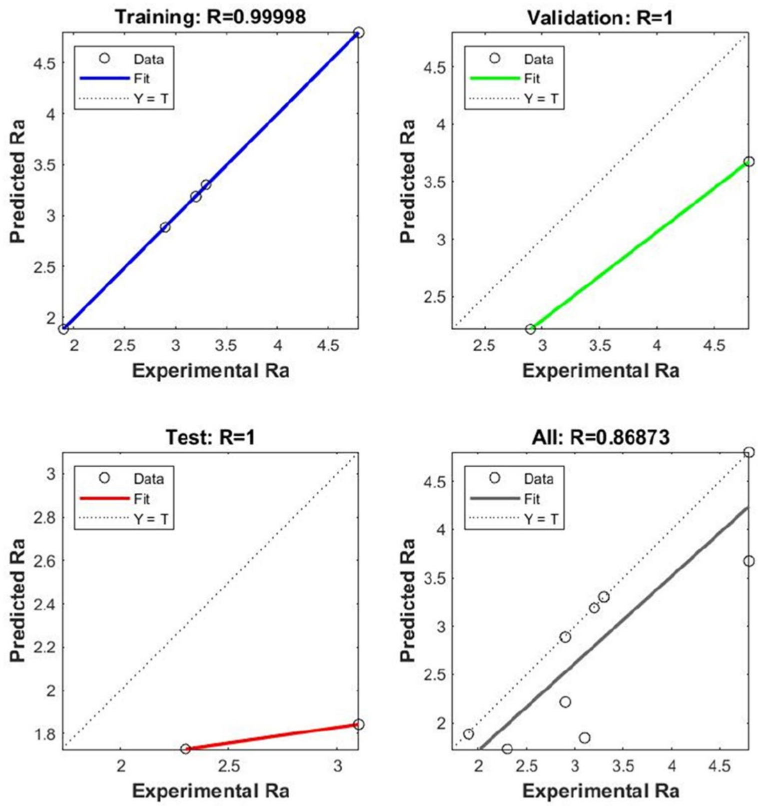

Fig. 9 ANN regression plots for training dataset, validation dataset, test dataset, and overall dataset

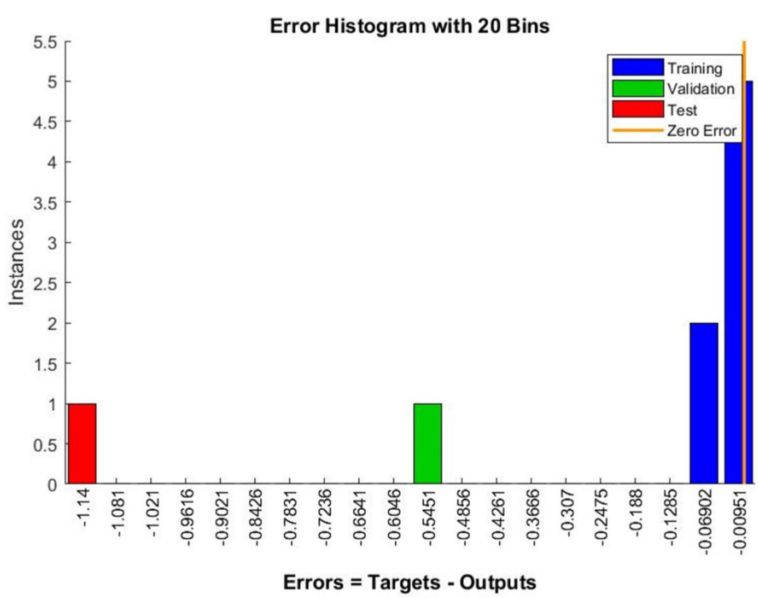

Fig. 10 MATLAB surface roughness histogram

variability in surface finish and elucidating key characteristics of the machined components. MATLAB-generated surface roughness histogram serves as a guide for optimization efforts. Identifying the desired range of surface finish values and correlating them with specific machining parameters becomes intuitive through this histogram. Researchers can leverage this information to fine-tune cutting speeds, depths of cut, and coolant types to achieve the optimal balance between material removal rates and surface quality. In summary, the MATLAB surface roughness histogram is a pivotal analytical tool that goes beyond raw data, providing a visual and quantitative foundation for understanding, optimizing, and controlling surface finish in machining processes. Its integration into the research framework contributes significantly to the comprehensive analysis of machining outcomes.

Model comparison

The prediction results of the modified regression model are compared with ANN to elevate precision in surface roughness prediction for turning AISI4140 steel. The predictive capabilities of modified regression models and ANN structures are undertaken in the context of surface roughness (Ra) estimation during the milling process of AISI4140 steel. The study employs carbide inserts and explores how these models contribute to precision machining practices by integrating cutting parameters (depth of cut, cutting fluid, spindle speed) as inputs with Ra as the output. The determination of a single hidden layer's suitable number of neurons involved a trial-and-error approach, ensuring optimal network architecture. Training employed the Levenberg–Marquardt (LM) learning algorithm with a tangent sigmoid function. A comprehensive dataset of 9 sets, with 50% utilized for training, 25% for validation, and the remaining 25% for testing, underscored the diversity and robustness of the models. Remarkable accuracy was achieved, with overall R^2 value of 86.86% (Table 8). Comparing prediction results with modified regression models, the ANN structures demonstrated superior performance, surpassing 85% accuracy in terms of R^2 values for training. Both models exhibited robust predictive capabilities, establishing their efficacy for real-time process control and contributing significantly to the precision machining of AISI4140 steel with carbide inserts. This analysis sheds light on the potential of ANN structures to elevate surface roughness predictions in turning operations.

This comparison highlights the ANN's superior performance in predicting surface roughness compared to the regression model's prediction of the SNR, emphasizing its potential for enhancing precision in machining operations, particularly in predicting surface quality in turning AISI4140 steel.

Conclusion

The primary aim of this study was to investigate the impact of cutting fluids on diverse machining parameters and their resultant effects. The focus was specifically on improving the parameters related to surface roughness during face milling of EN19 through Taguchi analysis. The conclusions drawn from the study provide valuable insights into optimizing machining processes for enhanced surface finish. In the pursuit of simultaneously optimizing multiple responses, it was revealed that cutting fluid played a pivotal role, emerging as the most influential factor, closely followed by speed and depth of cut. The intricate balance between these factors was found to significantly impact the surface roughness in EN19 face milling. To further enhance the predictive capabilities in this context, the study introduced regression and ANN models. These models were designed to capture the complex relationships between the machining parameters and surface roughness. However, it is important to note that these models exhibited varying degrees of fitness. In order to identify the most suitable model for accurate Ra estimation, a thorough analysis of the estimated results and associated error investigations was carried out. This meticulous approach ensures the selection of the most reliable model for predicting surface roughness in the machining of EN19. By scrutinizing the estimated results and errors, the study aimed to provide a robust framework for choosing the optimal model, thereby enhancing the precision and reliability of surface roughness predictions in the machining process.

The research proposes the utilization of an ANN as a predictive tool to evaluate established regression models. This ANN undergoes training and testing with a combination of cutting and response parameters. Remarkably high R^2 values, reaching 99.998%, signify a robust association and an excellent fit. Comparative analysis reveals

Table 8 Comparison table between the regression model and ANN

Model	Statistical method	Factors considered	Response variable	Performance metric	Accuracy (%)
Regression model	Ordinary least squares (OLS)	Cutting speed, depth of cut, coolant type	Signal-to-noise ratio (SNR)	R-squared (R^2)	**72.44**
Artificial neural network (ANN)	Levenberg–Marquardt algorithm	Depth of cut, cutting fluid, spindle speed	Surface roughness (Ra)	R-squared (R^2)	**86.86**

that the ANN models exhibit superior predictive capabilities when contrasted with traditional regression models, as evidenced by improved R^2 values.

To validate the efficacy of the developed ANN models, independent data is employed, affirming their effectiveness in estimating in-process Ra. Notably, the modified regression model achieves Ra estimations exceeding 90%, while the ANN demonstrates even more accurate estimations, surpassing 98% based on R^2 values. This leads to the conclusion that the ANN serves as a superior predictive tool for the in-process monitoring of Ra for both types of inserts. The findings underscore the potential of such predictions for real-time control of the manufacturing process, ensuring the attainment of the desired Ra.

This paper presents a comprehensive analysis using regression and artificial neural network (ANN) models to predict surface roughness (Ra) during the turning process of EN19 steel. The proposed ANN tool demonstrates superior predictive capabilities compared to traditional regression models, as validated with independent data. The results confirm the reliability of the developed ANN models for accurate in-process Ra estimation, providing valuable contributions to precision machining practices.

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Declarations

Competing interests
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