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Research Article

Sub Zero Cryo Treatment for WC-Co Inserts and its Performance Study during Milling EN8 Steel

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Abstract
The research study investigates the application of cryogenic treatment as a green manufacturing strategy to enhance the performance of cutting tools in the dry milling of EN8 medium-carbon steel. Titanium Aluminium Nitritae (TiAlN)-coated Tungsten Carbide-Cobalt (WC–Co) inserts were cryogenically treated at −196 °C for varying soaking durations (6, 18, and 30 hours) and evaluated for their mechanical and tribological properties. The results showed significant improvements in hardness, with microhardness testing revealing increases of 0.63%, 15.32%, and 9.46% for the 6-, 18-, and 30-hour treatments, respectively. Microscopy observations indicated the formation of η-carbide, which contributed to enhanced tool performance. Dry milling experiments were conducted using an L8 orthogonal array design to evaluate the effects of cryogenic treatment on tool wear, surface roughness, and material removal rate (MRR). The results demonstrated that cryogenic treatment reduced wear, improved surface finish, and increased MRR, with the 18-hour treated tool exhibiting superior performance. Specifically, it achieved approximately a 35.9% reduction in surface roughness, a 55.56% reduction in tool wear, and a 20.5% increase in MRR compared to the untreated tool. Single-response optimization using Taguchi's Signal-to-Noise ratio and predictive modeling with Artificial Neural Networks (ANN) identified the optimal cutting conditions for individual responses. Multi-response optimization using the DEAR (Data Envelopment Analysis-based Ranking) method integrated with Taguchi's Multi-Response Performance Index (MRPI) determined the optimal cutting parameters to be a cutting speed of 750 rpm, a feed rate of 0.15 mm/rev, and a depth of cut of 0.50 mm. This study establishes the effectiveness of cryogenic treatment as a green manufacturing strategy for extending tool life and improving machining productivity in industrial applications.

Keywords: Artificial Neural Network, Cryogenic treatment, Data Envelopment Analysis-based Ranking, Eta-carbide, Taguchi analysis

1 Introduction

Machining without coolant or dry machining is the greatest option for reducing health and environmental dangers. Dry machining has several advantages: there will be no emissions into the atmosphere, water, or land; no workplace dangers; and high cost savings due to the lack of fluid maintenance and disposal requirements. Dry machining, by removing the cutting fluid entirely, has drawn a lot of interest from researchers and processing sectors in the development of safe and clean surroundings. However, in dry cutting, excessive heat generation and increased friction contribute to high cutting tool wear and a built-up edge that affects the machined surface finish. Dry cutting maintains the workpiece geometrical accuracy, workpiece surface integrity and tool life in an efficient manner [1]. Cutting fluids account for 16–20% of total production costs, not including the cost of coolant spray equipment, cutting fluid disposal, and their harmful effects on the environment and the operator. As a result, for environmental safety and waste reduction, dry machining is becoming increasingly popular in the industry [2], [3].

EN8 is a typical through-hardening medium carbon steel grade that can be machined in any condition. EN8 steel can be used to make products such as general-purpose axles and shafts, gears, bolts, and studs. EN8 material may be subjected to high loads during Computer Numeric Control (CNC) turning of components such as shafts. EN8 material may be subjected to considerable heat generation under these machining circumstances. During initial conditions, EN8 can experience up to 50-55 Hardness Rockwell C (HRC), resulting in modules with improved wear resistance. EN8 exhibits a homogeneous metallurgical structure and good machining characteristics in its heat-treated condition [4], [5]. Many surface roughness optimization models have recently been examined with processing factors, which aid in simulating and optimizing the cutting process. Various researchers have determined surface roughness during dry machining operations of steel. El-Tamimi et al. used carbide cutting tools to examine AISI 420 stainless steel under a variety of machining conditions. Mean effect and interaction plots were used to identify the most significant influences[6].

TiAlN coatings are still widely utilized in industry, owing to their exceptional wear resistance at high machining speeds, high mechanical characteristics, thermally stable, and high resistance to corrosion even at extreme machining temperatures. TiAlN-based coatings mixed with Ru, Mo, and Ta are now being studied because they showed great promising performance regarding mechanical qualities and improvement in wear behavior. With advancements in deposition using technology, contemporary studies appear to be focusing on the analysis of TiAlN-based nanocomposite coatings, as the tiny layers improve the coatings' favorable qualities for machining applications dramatically. At high cutting temperatures, TiAlN coatings are well known for their high oxidation and wear resistance [7], [8]. There are lots of coating deposition methods. Physical vapor deposition (PVD) coatings can be placed on steel substrates and cemented carbide tools without compromising their characteristics. Furthermore, unlike the cathodic arc evaporation CVD method, the PVD technique does not use any hazardous precursors and is more energy efficient, consuming significantly less energy[9-11].

The rough WC particles are sintered into a metal matrix to create sintered carbide cutting tools. As a result, a better composite material is developed. Because of their higher hardness, capacity to manufacture complex shapes and higher abrasion resistance, they are frequently chosen over other cutting tool materials [12]. There is a faster wear that occurs during machining of hard materials at higher temperatures in the cutting material zone. The cryogenic treatment is defined as the temperature applied much below room temperature and used to extend the carbide cutting tools' lifetime [13-15].

This heat treatment ensures a more stable structure for the carbides in the metal matrix. Also, it alters the crystal structure of the cobalt phase in the metal matrix, improving resistance to cutting at various loads. In the metal matrix, the increase in η-phase can be linked to the increased hardness of WC cutting tools. Comparatively, the η-phase in the metal matrix is harder than other phases, which has a negative impact on the material's toughness. As a result, in order to obtain optimal conditions, it requires adjusting small changes in the η-phase of the matrix. Furthermore, the cryogenic heat treatment regulates the internal stresses that arise during the manufacture of tungsten carbide cutting tools [16-18]. Cryogenic heat treatment involves gradually cooling the samples at temperatures ranging from - 80 °C to - 196 °C at 2 °C/min, maintaining them at these temperatures for a duration (18 to 36 hours), and then gradually bringing them back to room temperature [19-21]. Cryogenic treatment can improve the qualities of cutting tools, such as hardness, toughness and resistance to abrasion by homogenizing the carbide particle distribution [13].

Cryogenic treatment improves carbide tool cutting performance by reducing cutting forces and wear of the tool, extending tool life, and maintaining the workpiece material's surface integrity in a better way [22], [23]. When milling of C45 steel, cryogenic treatment enhances the mechanical properties of carbide tools, results in good tool life and lowers the cutting force compared to non-treated carbide tools [24], [25].

Multiple performance measurements, such as surface roughness, tool wear and rate of material removal, are part of the machining operation. The selection of process parameters is heavily influenced by these numerous responses. As a result, the traditional strategy for optimizing single responses does not appear to be appropriate for machining processes that measure multiple responses. Multi-response optimization is required to solve this problem and improve machining effectiveness[26-28]. Therefore, for optimizing the process parameters, multiple response optimization techniques such as Grey relational analysis (GRA) and weight assignment method, and Data Envelopment Analysis-based Ranking (DEAR) analysis were used[29], [30]. The machining characteristics of metal matrix composites are analyzed using analysis of variance (ANOVA). The work aimed to find the relationship between feed rate, cutting speed, depth of cut and surface finish of the workpiece. ANOVA is a technique for allocating output variability to different inputs. The analysis of variance is used to determine which machining parameters have a major impact on the characteristic performance[31].

Surface roughness is the measure of the quality of the surface and one of the most requested client specifications in machining process. Optimal cutting parameters (depth of cut, feed and speed) are essential for efficient use of the machine tool. As a result, an appropriate optimization approach for finding optimum cutting parameter values for minimizing surface roughness is required. From the data obtained, an ANN model was developed using Matlab software employing a back-propagation feed-forward network to measure the surface roughness. The experimental data and ANN results indicate no significant variations, indicating that ANN can be employed confidently. ANN is both reliable and has higher accuracy at determining value[32]. Despite the fact that numerous optimization methodologies are utilized to optimize input process parameters, a more efficient and simpler MCDM technique still has a greater level of expectation.[33]

In this regard, the DEAR method has proven to be effective and the results are comparable to those achieved from other optimization techniques. This technique was used by several authors to optimize multiple responses during milling[34-36]. As the use of the Taguchi-DEAR approach to optimize the machining input process parameters of EN8 steel has yet to be investigated, this study filled the gap by analyzing the subject using a cryogenically treated TiAlN-coated tungsten carbide insert.

EN8 medium carbon steel is highly used for making shafts, gears, bolts, studs and is also used in automotive and general engineering sectors. Tungsten tools are often used to machine the referenced material. Furthermore, research studies show that coating materials like AlTiN, TiAlN and TiN, have demonstrated significant machining performance. Also, the cryogenic treatment improves carbide tool cutting performance by reducing wear of the tool and cutting forces, extending tool lifetime.

The following results were analyzed in this study:

1. The effectiveness of cryogenically treated TiAlN-coated cutting inserts in the machining of EN8 steel is explored experimentally in this study.
2. Furthermore, the research study included the use of a simplified optimization tool, the Taguchi-DEAR technique, to efficiently achieve optimum machining process parameters (cutting speed, feed rate and depth of cut).
3. It also included the use of Taguchi and ANN techniques to predict the optimized machining process parameters effectively for individual output responses (tool wear, surface roughness and material removal rate).

The focus of this research is to find an effective cryogenically treated cutting insert for the dry machining of EN8 steel in milling operations. This paper's main purpose is to help the users of EN8 steel to determine the ideal process conditions for their applications.

2 Materials and Methods

The experimental methodology has been depicted in Figure 1.

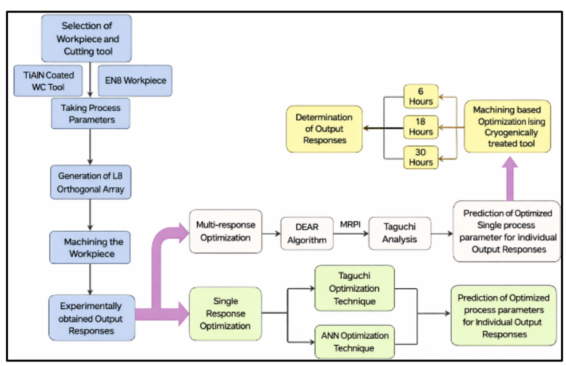

Figure 1: Methodology of experimental work.

2.1 *Selection of work-piece material and input process parameters*

The workpiece used in this research is EN 8, a medium-carbon, low-alloy steel known for its high strength and excellent machinability under various cutting conditions. EN 8 is predominantly used in automobile manufacturing and machine tool parts. Table 1 presents the chemical composition of EN 8 steel, while Table 2 outlines its mechanical properties. In selecting the feed rate and cutting speed, the workpiece material is a primary consideration. The milling process is performed on a workpiece measuring 60 mm in length and 32 mm in diameter under dry conditions. The cutting speeds chosen for this study are 500 rpm and 750 rpm. The depth of cut is set at 0.50 mm and 0.75 mm, while the feed rates are 0.10 mm/rev and 0.15 mm/rev.

Table 1: Chemical elemental composition of EN8 Steel in wt%.

C	Si	Mn	S	P
0.44	0.40	1.0	0.05	0.5

Table 2: Mechanical properties of EN8 steel.

Maximum stress (N/mm^2)	Yield stress (N/mm^2)	Proof stress (0.2%) (N/mm^2)	Elongation	Impact strength (Joules)	Hardness value (HB)
700 - 850	465	450	16%	28	201 - 255

2.2 *Selection of output responses*

Surface roughness (SR), flank wear, and material removal rate (MRR) are critical machining factors for assessing machining quality. In our research study, these parameters were selected as output measures. Surface roughness is defined as the average of the surface depths and heights across the machined surface, representing the irregularities inherent in the machining process. It is typically measured as "Ra" (Roughness Average), which is used to evaluate compliance with various industry standards. Tool wear refers to the degradation occurring on the flank face of the cutting tool, caused by friction between the machined workpiece surface and the flank face of the tool. This wear leads to a loss of cutting edge, impacting dimensional accuracy. Material removal rate (MRR) is defined as the amount of material removed by the cutting tool from the workpiece per unit time during machining. MRR can be calculated based on the weight difference of the workpiece before and after machining or by measuring the volume of material removed. Tool wear was assessed using a profile projector, while the average centerline surface roughness of the machined workpiece was measured with a Mitutoyo surface roughness tester. MRR was determined from the difference in weight of the workpiece before and after machining, measured using a precision weighing balance and divided by the machining time. To minimize experimental errors, the averages of three measurements were taken for wear rate, surface roughness and material removal rate.

2.3 *Orthogonal array*

This research study investigates three machining input parameters: cutting speed, depth of cut, and feed rate, each at two input levels. To evaluate how these parameters influence the mean and variance of overall performance, an L8 orthogonal array (OA) was generated using Taguchi's design of experiments methodology. The L8 orthogonal array was created with the assistance of Minitab software. Table 3 presents the selection of process variables for the L8 orthogonal array.

Table 3: L8 orthogonal array.

S.No	Cutting Speed (rpm)	Depth of cut (mm)	Feed rate (mm/rev)
1	500	0.5	0.1
2	750	0.5	0.1
3	500	0.75	0.1
4	750	0.75	0.1
5	500	0.5	0.15
6	750	0.5	0.15
7	500	0.75	0.15
8	750	0.75	0.15

2.4 *ANN technique*

Artificial neural network (ANN) is one of the most used computer analysis methods which is in use. Artificial neural networks are also known as artificial neural systems, neural nets, connectionist systems, and parallel distributed processing. The main feature of ANNs that set them apart from other approaches is their ability to store the data, process and interpret data, as well as consider events that have never been seen before. ANNs are referred to as a directed graph that has a set of connections between the nodes and a set of nodes (vertices). Every node has a purpose, such as simple calculation and each connection transports data or signals between nodes. Every connection between two nodes is given a weight or connection strength number. The weight indicates how much the signal will be reduced or distorted by the connection. ANNs are made up of neural cells that are grouped together. This aggregation usually takes place in layers and it is not random. The input, hidden, and output layers are the three main layers of artificial neural networks. The data coming from the external world is transferred into the hidden layer by neurons in the input layer. Unlike the other layers, the data in the input layer is not processed. The data from neurons in the input layer, bias, summation and activation functions are used to produce the outputs in the hidden layer. The net input of the cell is calculated by the summation function.

2.5 Taguchi analysis

Taguchi analysis is one of the most significant processes used by researchers. Between these desired and experimental trials, the difference can be calculated, and a loss function was created. The signal-to-noise (S/N) ratio was calculated using this loss function. In the analysis of the S/N ratio, there are three categories of performance characteristics. The nominal-the-better (NB), lower-the-better (LB), and higher-the-better (HB) are the three options. The S/N ratio was calculated for each level of process parameters using the S/N analysis using equations (1) and (2). Lower flank wear in the milling process indicates longer tool life and improved performance. Lower surface roughness suggests improved tool performance and longevity. To determine which parameters were significant, a statistical ANOVA was used. The best process combination is determined via ANOVA analysis and S/N ratio. The optimal process parameters obtained from the parameter design were verified using a confirmation experiment.

The formula for the greater-the-better signal-to-noise (S/N) ratio using base 10 log is:

$$\mathrm{S/N\ ratio} = -10\log(\Sigma(1/\mathrm{Y}^2)/\mathrm{n}) \quad (1)$$

where n is the number of responses for the factor level combination
Y is the response for the specified level combination.
The lesser-is-better signal-to-noise (S/N) ratio using base 10 log is:

$$\mathrm{S/N} = -10\log(\Sigma(\mathrm{Y}^2)/\mathrm{n}) \quad (2)$$

where n is the number of responses for the factor level combination
Y is the response for the specified factor level combination.

2.6 *DEAR algorithm*

In the DEAR Algorithm, a collection of original replies is mapped into a ratio so that the best acceptable level can be discovered based on this ratio. Using the MRPI approach, these values are utilized to find optimum combinations of process parameters. In the DEAR Algorithm, the following rules are applied.

Firstly, the weights(w) for each response of all experiments are evaluated. The ratio between the response at any trial and the summation of all responses is called the weight of response. Weights are computed through the equations (3), (4) and (5) as shown below,

$$\mathrm{WTw} = (1/\mathrm{Tw})/(\sum 1/\mathrm{Tw}) \quad (3)$$

$$\mathrm{WSR} = (1/\mathrm{SR})/(\sum 1/\mathrm{SR}) \quad (4)$$

$$\mathrm{WMRR} = \mathrm{MRR}/\sum \mathrm{MRR} \quad (5)$$

Secondly, the observed data is multiplied by its own weight to transfer the data of response into weighted data as shown in equations (6), (7), and (8).

$$\mathrm{T} = \mathrm{WTw} * \mathrm{Tw} \quad (6)$$

$$\mathrm{S} = \mathrm{WSR} * \mathrm{SR} \quad (7)$$

$$\mathrm{M} = \mathrm{WMRR} * \mathrm{MRR} \quad (8)$$

Thirdly, (MRPI) is calculated as the ratio of the "greater-the-better" metric (MRR) to the sum of the "lesser-the-better" metrics (TW and SR), as expressed in Equation (9).

$$\mathrm{MRPI} = \mathrm{M} / (\mathrm{T} + \mathrm{S}) \quad (9)$$

3 Results and Discussion

3.1 *Hardness of the cryogenically treated tool*

The Vickers hardness tester was used to calculate the micro-hardness of coated carbide cutting tools. The average hardness of the untreated tool was measured as 17.41 GPa, whereas the 6, 18 and 30 hours cryogenic treated tools were measured as 17.52, 20.56 and 19.23 GPa, respectively. It has been portrayed in Figure 2. The 6, 18 and 30 hours cryogenic-treated tools possess micro-hardness of 0.63, 15.32 and 9.46% higher than that of the untreated tool. The cryogenic treatment enhances the mechanical properties of the carbide tools more than untreated ones. The hardness of tungsten carbide cutting tools is increased by cryogenic treatment due to an increase in the metal matrix η-phase of tungsten carbide tools [23-25].

Figure 3 shows the procedure used for cryogenic treatment. The TiAlN-coated cutting tools were cryogenically treated for 6, 18, and 30 hours at a temperature of -196 °C. Cryogenic treatment speeds are 2 °C/min for cooling and heating. By using the muffled furnace, the cutting tools were tempered at 200 °C for 2 hours after cryogenic treatment, bringing them to the ambient temperature of 20 °C.

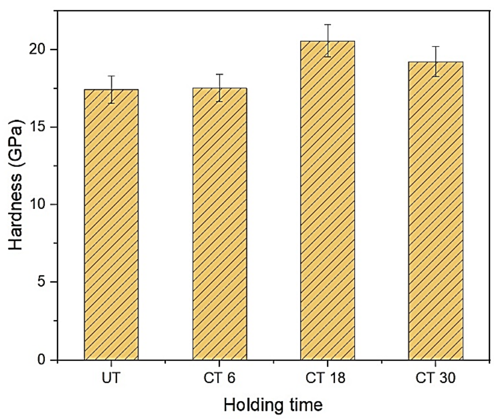

Figure 2: Average vickers hardness values of samples.

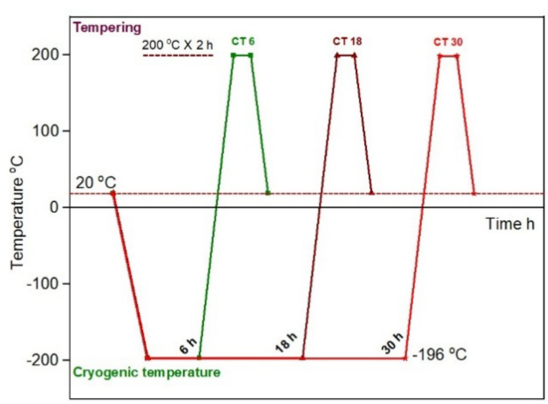

Figure 3: Cryogenic treatment procedure.

3.2 *Dry machining of EN8 steel using untreated cutting inserts*

The dry milling processes were carried out on EN8 medium carbon steel using the L8 Orthogonal Array. Table 4 represents the experimental results for all 8 experiments. The output responses, like surface roughness and insert wear, were measured through a portable surface roughness tester and profile projector, respectively.

Table 4: Experimentally determined output responses.

S.No	Cutting Speed (rpm)	Depth of cut (mm)	Feed rate (mm /rev)	Surface Roughness (µm)	Tool wear (mm)	Material Removal rate (mm^3/s)
1	500	0.5	0.1	2.674	0.0289	0.0123
2	750	0.5	0.1	2.709	0.0336	0.025
3	500	0.75	0.1	2.713	0.0310	0.014
4	750	0.75	0.1	2.745	0.0352	0.019
5	500	0.5	0.15	2.721	0.0279	0.035
6	750	0.5	0.15	2.745	0.0336	0.045
7	500	0.75	0.15	2.768	0.0275	0.027
8	750	0.75	0.15	2.781	0.0342	0.039

3.3 *Single response optimization of individual responses*

Taguchi's analysis was used to examine every individual output parameters like as surface roughness, material removal rate, and tool wear. The optimized parameters were measured using 'lesser the better' characteristics for surface roughness and tool wear, and 'greater the better' characteristics for material removal rate.

3.3.1 Effect of process parameters on surface roughness

Figure 4 represents the main effect plot graph for the means of surface roughness. It is observed that the decrease in spindle speed, feed rate and depth of cut lowers the surface roughness. Table 5 represents the analysis of variance for surface roughness. The P value for each parameter is less than 0.05, indicating that the parameter has an acceptable level of physical significance. The feed rate has the greatest impact on surface roughness, followed by the depth of cut and the cutting speed.

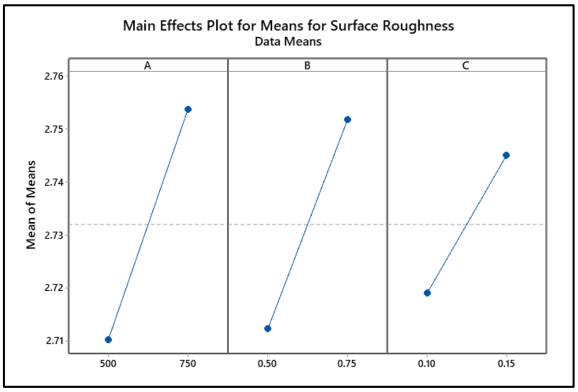

Figure 4: Plot for means of surface roughness.

Table 5: ANOVA for surface roughness.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	0.008257	0.002752	71.96	0.001
Cutting Speed	1	0.001352	0.001352	35.35	0.004
Depth of cut	1	0.003120	0.003120	81.58	0.001
Feed rate	1	0.003784	0.003784	98.94	0.001
Error	4	0.000153	0.000038		
Total	7	0.008410			

Figure 5 represents the regression plot between target and network output for surface roughness. A higher R value nearer to 1 on the regression figure indicates that the significant training model fits the output data better. Both the R values for validation and testing are 1. The training regression coefficient was found to be 0.99988. The R value for combined training, testing, and validation performance is 0.99962, indicating that less trained error with better output values fits better with the model. It demonstrates that the developed ANN model could predict surface roughness during the milling process.

In Table 6, the percentage of error for predicted values with experimental values obtained from both the Taguchi and artificial neural network optimization techniques is analysed. From the observation, the first set of input parameters gives the better result for surface roughness as it has lesser values of 2.678 and 2.672, which were obtained from Taguchi and ANN process, respectively. Finally, it gives the optimum input parameters for surface roughness that are spindle speed: 500 rpm, Depth of cut: 0.50 mm and feed rate: 0.10 mm/rev.

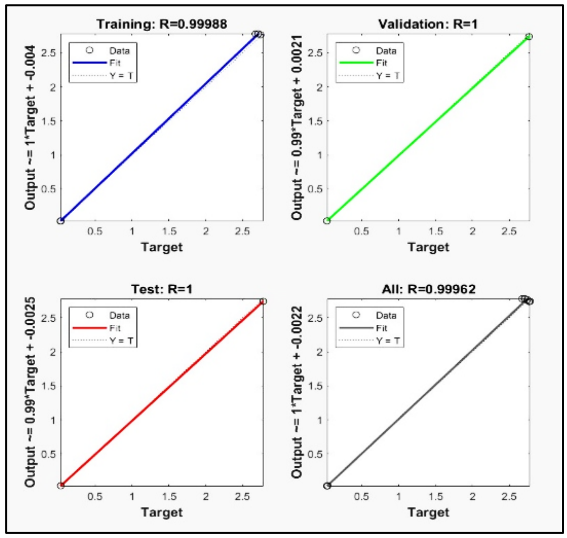

Figure 5: Regression plot for surface roughness.

Table 6: Error analysis for surface roughness.

S.No	Experimental values	Taguchi		ANN	
		Predicted values	Error %	Predicted values	Error %
1	2.674	2.678	0.131	2.672	0.082
2	2.709	2.704	0.203	2.707	0.081
3	2.713	2.717	0.147	2.711	0.081
4	2.745	2.743	0.073	2.743	0.080
5	2.721	2.721	0.000	2.719	0.081
6	2.745	2.747	0.073	2.743	0.080
7	2.768	2.761	0.271	2.766	0.079
8	2.781	2.787	0.198	2.779	0.079

3.3.2 Effect of process parameters on tool wear

Figure 6 represents the main effect plot graph for the means of tool wear. It is observed that the decrease in feed rate and depth of cut lowers the tool wear,

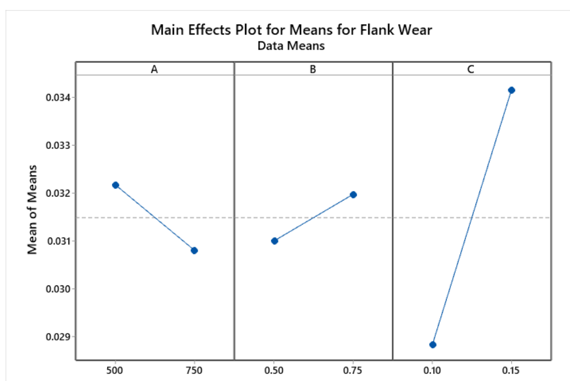

Figure 6: Plot for means of tool wear.

whereas the decrease in cutting speed causes the tool wear to increase. Table 7 represents the analysis of variance for tool wear. P-value for each parameter is less than 0.05, indicating that the parameter has an acceptable level of physical significance. It is observed that cutting speed has the highest significance on tool wear.

Figure 7 represents the regression plot between target and network output for flank wear. The higher R value, closer to 1 on the regression figure, indicates that the significant training model fits the output data better. Both the R values for validation and testing are 1. The training regression coefficient was found to be 0.99989. The R value for the entire training, testing, and validation performance is 0.9998, indicating that less trained error with better output values fits better with the model. It demonstrates that the developed ANN model may predict tool wear throughout the milling operation.

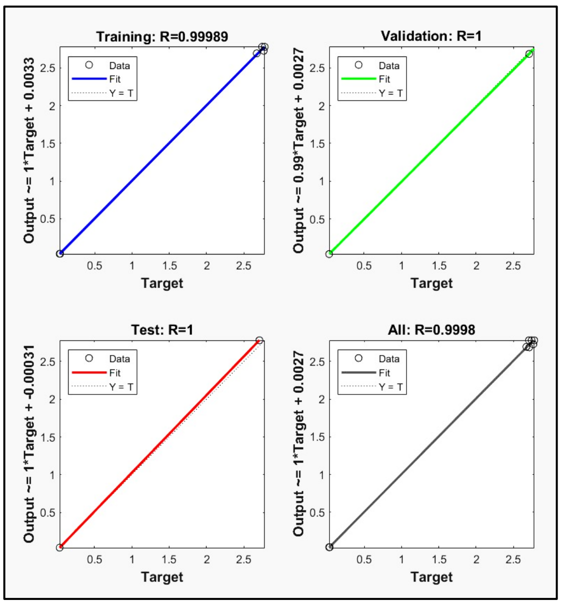

Figure 7: Regression plot for tool wear

The percentage of error for predicted values with experimental values obtained from both Taguchi and artificial neural network optimization techniques is listed in Table 8. From the observation, the seventh set of input parameters gives the better result for tool wear, as it has the lowest values of 0.027 and 0.030 was obtained from the Taguchi and ANN optimization process, respectively. Finally, it gives the optimum input parameters for tool wear: cutting speed: 500 rpm, Depth of cut: 0.75 mm and feed rate: 0.15 mm/rev.

Table 7: ANOVA for tool wear.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	0.000062	0.000021	24.65	0.005
Cutting Speed	1	0.000057	0.000057	67.21	0.001
Depth of cut	1	0.000002	0.000002	2.25	0.208
Feed rate	1	0.000004	0.000004	4.48	0.102
Error	4	0.000003	0.000001		
Total	7	0.000066			

Table 8: Error analysis for tool wear.

Respective set of parameters	Experimental values	Taguchi		ANN	
		Predicted values	Error %	Predicted values	Error %
1	0.0289	0.029	0.104	0.032	-9.343
2	0.0336	0.034	-1.548	0.036	-8.036
3	0.0310	0.030	3.726	0.034	-8.710
4	0.0352	0.035	0.298	0.038	-7.670
5	0.0279	0.028	1.452	0.031	-9.677
6	0.0336	0.033	2.545	0.036	-8.036
7	0.0275	0.027	-3.527	0.030	-9.818
8	0.0342	0.034	1.404	0.037	-7.895

3.3.3 Effect of process parameters on material removal rate

Figure 8 represents the main effect plot graph for the means of MRR, it is observed that the increase in feed rate and cutting speed increases the tool wear, whereas an increase in depth of cut causes the MRR to decrease. Table 9 represents the Analysis of variance for MRR. The P value for

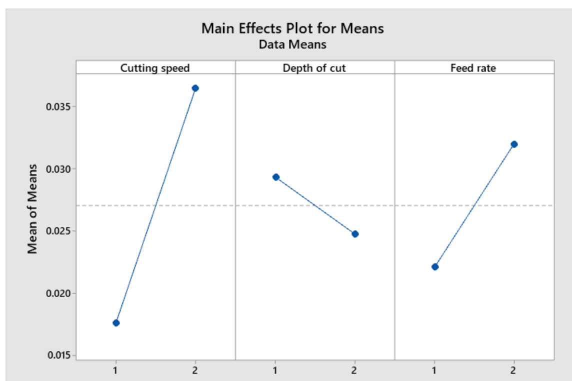

Figure 8: Plot for means of MRR

Table 9: ANOVA for MRR

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	0.000955	0.000318	42.60	0.002
Cutting Speed	1	0.000197	0.000197	26.36	0.007
Depth of cut	1	0.000042	0.000042	5.60	0.077
Feed rate	1	0.000716	0.000716	95.84	0.001
Error	4	0.000030	0.000007		
Total	7	0.000985			

each parameter is less than 0.05, indicating that the parameter has an acceptable level of physical significance. It can be seen that the feed rate has the greatest impact on MRR.

Figure 9 represents the regression plot between target and network output for MRR. The higher R value, closer to 1 on the regression figure, indicates that the significant training model fits the output data better. Both the R values for validation and testing are 1. The training regression coefficient was found to be 0.99991. The R value for combined training, testing, and validation performance is 0.99981, indicating that less trained error with better output values fits better with the model. It demonstrates that the specified ANN model could predict MRR during the milling process.

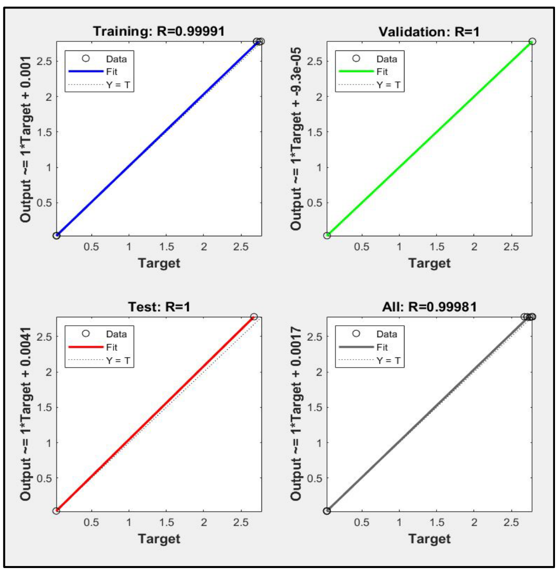

Figure 9: Regression plot for MRR

In Table 10, we analysed the percentage of error for predicted values with experimental values obtained from both the Taguchi and artificial neural network optimization techniques. From the observation, the sixth set of input parameters gives the better result for MRR, as it has higher values of 0.044 and 0.047 obtained from Taguchi and ANN optimization processes, respectively. Finally, it gives the optimum input process parameters for MRR: cutting speed: 750 rpm, Depth of cut: 0.50 mm and feed rate: 0.15 mm/rev.

Table 10: Error analysis for MRR

Respective set of parameters	Experimental values	Taguchi		ANN	
		Predicted values	Error %	Predicted values	Error %
1	0.012	0.015	-0.224	0.014	-0.138
2	0.025	0.025	-0.002	0.027	-0.068
3	0.014	0.010	0.252	0.016	-0.121
4	0.019	0.020	-0.078	0.021	-0.089
5	0.035	0.034	0.029	0.037	-0.049
6	0.045	0.044	0.023	0.047	-0.038
7	0.027	0.029	-0.089	0.029	-0.063
8	0.039	0.039	-0.010	0.041	-0.044

3.4 *Multi-criteria decision-making using Taguchi-dear analysis*

DEAR methodology is used to obtain the optimal process parameters for all three output responses by evaluating the combined impact of every input process parameter on multiple outputs. The DEAR method was used to determine MRPI. The Taguchi-DEAR technique was used to estimate the MRPI of each experiment for various input variable configurations. The computed MRPI for all input parameters at all phases is shown in Table 11.

The input parameters were analysed by summing up all of the MRPI values for each process variable. The maximum level of any of the process parameters, which reflects the prime input level, was used to calculate output measures in any such process [29], [33].

The main effects plot graph is used to evaluate the impact of the input process parameters on performance output measures in any process. The cutting speed was found to have a stronger influence on the measurement of output performance. For our research, we used Minitab software to create the main effect plots. It was revealed from the main effects that the cutting speed has a greater impact on the surface roughness, tool wear and material removal rate while machining the EN 8 steel by TiAlN-coated insert tool. Equation (10) was used to predict the MRPI. The calculated MRPI was found to

Table 11: Calculation of MRPI

SI. No	MRR	TWR	SR	1/TWR	1/SR	MRR	TWR	SR	MRPI
1	0.012	0.0289	2.67	34.6	0.3739	0.0568	0.1350	0.1276	**0.00203**
2	0.025	0.0336	2.70	29.7	0.36914	0.11558	0.116149	0.1260	**0.00837**
3	0.014	0.031	2.71	32.2	0.368596	0.064725	0.125891	0.1258	**0.00262**
4	0.019	0.0352	2.74	28.4	0.364299	0.087841	0.11087	0.1243	**0.00483**
5	0.035	0.0279	2.7	35.8	0.367512	0.161812	0.139879	0.1254	**0.0164**
6	0.045	0.0336	2.74	29.7	0.364299	0.208044	0.116149	0.1243	**0.02711**
7	0.027	0.0275	2.76	36.3	0.361272	0.124827	0.141913	0.1233	**0.00976**
8	0.039	0.0342	2.78	29.2	0.359583	0.180305	0.114111	0.1227	**0.02036**

be the greatest when linked to the average of all MRPI values acquired from experimental values.

$$\text{MRPI} = -3.70 + 0.01265\ \text{cutting speed} + 7.87\ \text{feed rate} + 8.13\ \text{depth of cut} \tag{10}$$

Figure 10 represents the plot graph for S/N ratios of MRPI. It gives the optimum input parameters such as cutting speed: 750 rpm, depth of cut: 0.50 mm and feed rate: 0.15 mm/rev.

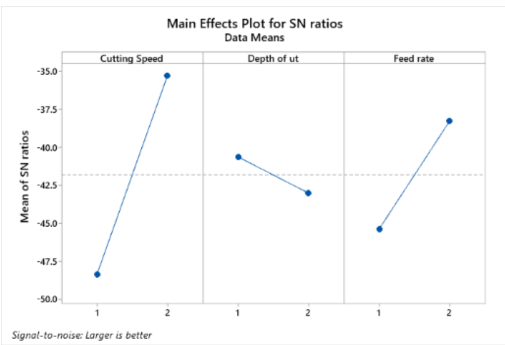

Figure 10: S/N ratio plot for MRPI

3.5 *Machining of cryogenically treated tools based on validation using Taguchi-DEAR analysis*

The optimized parameters obtained from the DEAR algorithm, which are cutting speed of 750 rpm, depth of cut of 0.50 mm and feed rate of 0.15 mm/rev. These parameters are used to machine EN8 steel by a cryogenically treated insert at time intervals of 6,18 and 30 hours, respectively. Cryogenic treatment improves carbide tool cutting performance by reducing cutting forces and wear of the tool, extending tool life, and maintaining the workpiece material's surface integrity in a better way. Cryogenic treatment can also improve the qualities of carbide cutting tools, such as hardness, toughness and resistance to abrasion by homogenizing the carbide particle distribution [19], [20].

The output responses were shown in Table 12. From the observations, the 6 and 30 hours treated tools possess surface roughness of 3.17% and 13.08% higher than that of the untreated tool, respectively. But the 18-hour treated tool possess 35.90% less than comparing to untreated ones. The results of tool wear show that the 6-hour and 18-hour treated tools consist of 6.67% and 55.56% less than that of untreated ones. But the 30-hour tool possess 15.48% higher than untreated ones. The values of MRR show that the 18-hour treated tool possess 20.5% higher values than the untreated ones. It is known that the machining parameters like surface roughness and tool wear are smaller is better, but for MRR, larger is better. According to this condition, 18 hours treated tool have lower SR and TW values and higher MRR values compared to other treated tools and untreated ones.

Table 12: Output responses of cryogenically treated tools.

TiAlN-coated inserts (Based on Cryogenic intervals)	Inserts Hardness (GPa)	Surface Roughness (Ra) µm	Average Tool Wear (mm)	Material Removal Rate (mm^3/s)
6 hours	17.52	2.832	0.0315	0.218
18 hours	20.56	2.020	0.0216	0.325
30 hours	19.23	3.104	0.0388	0.201

4 Conclusion

The performance of EN8 steel machining using cryogenically treated TiAlN-coated WC–Co inserts at soaking durations of 6, 18, and 30 hours was investigated. The results indicate that the 6, 18, and 30-hour treatments improved microhardness by 0.63%, 15.32%, and 9.46%, respectively, compared to the untreated tool, with the 18-hour treatment yielding the highest hardness of 20.56 GPa. Multi-response optimization using the Taguchi–DEAR approach identified the optimal machining parameters as 750 rpm cutting speed, 0.15 mm/rev feed rate, and 0.50 mm depth of cut.

Under these optimal conditions, the cryogenically treated tool (18 h) exhibited significant performance improvements over the untreated tool, including a 35.9% reduction in surface roughness, 55.56% reduction in tool wear, and a 20.5% increase in material removal rate (MRR). These results confirm that the 18-hour cryogenic treatment provides the best balance between hardness and machining performance, thereby enhancing tool life and productivity in dry milling of EN8 steel

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Author Contributions

M.P.C.: conceptualization, investigation, reviewing and editing; S.R.K.: investigation, methodology, writing-original draft; S.V.P.: research design, data analysis; R.R.: conceptualization, data curation, writing-reviewing and editing, funding acquisition, project administration. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

We acknowledge the use of Quilbot for grammar correction and language refinement. All technical content, analysis, interpretations and conclusions presented in this paper are solely the responsibility of the authors.

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