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Predictive Modeling and Optimization of Surface Roughness and Cutting Zone Temperature in Turning of Hardened Steel Using RSM, ANN, Genetic Algorithm, and Particle Swarm Optimization

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ABSTRACT
The purpose of this research is to establish a combined surface roughness and cutting zone temperature study for modeling and optimizing cutting parameters for turning operations of D3/1.2080 steel with coated carbide under cryogenic cooling and MQL conditions. Cutting speed, feed, and depth of cut are investigated as input factors, while surface roughness and cutting zone temperature are chosen as responses. The experiment has been conducted using the Box-Behnken design (BBD) with three levels and three parameters. Response surface methodology (RSM) and Artificial neural network (ANN) techniques are used for modeling to perform prediction. Where ANN outclassed RSM. Then RSM is coupled with Genetic algorithm (GA) and Particle swarm optimization (PSO). RSM-GA and RSM-PSO approaches are used for optimization. It has been discovered that combining RSM with PSO yields superior outcomes. Finally, a comparison between cryogenic cooling and MQL is done. MQL showed supremacy over cryogenic for both responses.

Keywords: *Cryogenic, MQL, prediction, RSM, ANN, optimization, GA, PSO*

INTRODUCTION

In this day and age of global competition, producers must find ways to increase efficiency while still enhancing product quality. Improving machining operations should take into account a variety of factors, including economic, environmental, and health concerns. Cutting fluids have well-known benefits in machining, but their usage is associated with health and environmental risks. Using cryogenic coolant and minimal quantities of lubricant (MQL) might be considered an acceptable approach for improved machining and a path toward green manufacturing.

The impact of cryogenic cooling and MQL was explored previously by many authors, cryogenic machining yields a lower cutting force value and better surface polish than wet and dry machining [1]. Cryogenic cooling provides better tool life and machining temperature than dry and conventional cooling machining [2]. When compared to dry cutting, cryogenic cooling with nitrogen enhances the surface integrity of AISI D6 cold work tool steel in hard turning [3]. On various materials such as super-alloys, ferrous metals, and visco-elastic polymers, cryogenic cooling proved a viable alternative to conventional cooling systems, because cryogenic results in better surface roughness, long tool life, and cutting force [4].

MQL machining beats dry and conventional machining with flood-cutting fluid supply in terms of cutting efficiency because MQL improves primarily by lowering cutting forces, surface roughness, and temperature [5]. MQL machining is more improved than dry and traditional machining with flood-cutting fluid delivery in terms of cutting performance. MQL enhanced the surface quality primarily by reducing erosion and degradation at the tooltip. MQL provides an advantage by lowering the cutting temperature, which enhances chip-tool interaction and keeps cutting edges sharp [6]. The application of MQL has no detrimental impact on the surface integrity [7].

In machining, the cutting tool also plays a vital role in the desired output. A coated carbide tool outperforms an uncoated carbide tool; the wear rate of an untreated carbide tool is much higher than that of a coated carbide tool [8]. At all cutting speeds, a coated-carbide drill excelled over an uncoated drill in terms of tool life and surface roughness of the drilled surface [9]. Coated carbide inserts beat uncoated carbide inserts in hardened steel turning [10].

Forecasting surface roughness and cutting zone temperature is crucial for adapting to changing demands in manufacturing operations. As a result, the best modeling technique for these output parameters has to be determined. Several techniques have been used, including surface response methodology (RSM) and artificial neural networks (ANN), can be utilized to achieve this objective. ANN model showed superiority in machining Titanium alloy, the experimental findings and the outcomes predicted by ANN are well agreed upon [11]. RMS is useful since it quantifies the participation of each element in the variation in responses, which enables the producer to understand better the cutting process. When using the ANN approach, the prediction of output answers is enhanced considerably [12] For prediction, Mathematical Models for surface roughness, and cutting force with RSM and ANN techniques are extremely helpful [13].

In the manufacturing world, for any kind of machining the optimum machining condition is really important for finishing quality and also avoiding economic waste. Genetic algorithm (GA) and particle swarm optimization (PSO) can assist in determining the best combination.

A surface roughness model was created utilizing RSM for steel machining with coated carbide cutting tools to discover the best cutting conditions, the surface roughness model was combined with GA [14]. GA and ANN have been combined to discover the optimal end milling cutting settings [15]. Dikshit et al. have used a genetic algorithm with RSM to optimize cutting parameters in dry-end milling [16]. Particle swarm optimization was first pioneered by Kennedy and Eberhart [17]. A multi-objective optimization employing PSO and the desirability method seeks a set of optimal cutting parameters in the turning of titanium alloy under a minimal quantity lubrication environment. It was discovered that PSO produces more accurate values than the desirability method [18].

Using regression analysis, a surface roughness model for turning was built. Both GA and PSO are used to improve machining settings, with GA producing a superior outcome [19]. The researchers used particle swarm optimization (PSO) to design, construct, and optimize a composite float depending on the performance constraints and setup requirements. The authors discovered that PSO can give a faster convergence to optimal solutions. It was explored that PSO generates more accurate answers than GA [20].

The current work explores cryogenic cooling and MQL turning through a comparison of modeling using the RSM and the ANN utilizing a three-level, three-factor Box-Behnken design (BBD). The created models were utilized to forecast surface roughness and cutting zone temperature based on the investigated cutting parameters for various cooling modes.

A comparison of ANN and RSM models has been constructed to find the optimal strategy in terms of model accuracy and capability for forecasting surface roughness and cutting zone temperature while turning steel with coated-carbide inserts. The RSM-GA and RSM-PSO approaches are used to optimize cutting parameters. A comparison of RSM-GA and RSM-PSO is performed. Similarly, it may be possible to study the efficacy of the MQL approach for environmentally friendly ecological machining.

MATERIALS AND METHODS

The experimental circumstances and cutting parameters are adjusted based on several factors such as the material to be machined, the machine tool, the cutting tool, and the cooling mode, and the experiments are conducted on a conventional Lathe Machine (CS6266B)

The workpiece is D3/1.2080 steel. The mechanical parameters of the latter are specified in Table 1. The diameter and length of the machined piece are 50.8 and 304.8 mm, respectively. The tungsten-coated carbide insert was chosen as the cutting tool. In the case of MQL machining the nozzle, the diameter was 1mm and the angle was 45 degrees.

In this study the cutting zone temperature was measured by Digital multi-meter and surface roughness was measured by Surtronic S-series surface roughness tester.

Table 1: *D3 steel's chemical make-up*

Elements	C	Si	Cr	Mn	Ni	W	V	P	s	Cu
%	2.12	.3	11.48	.40	.31	1	1	.03	.03	.25

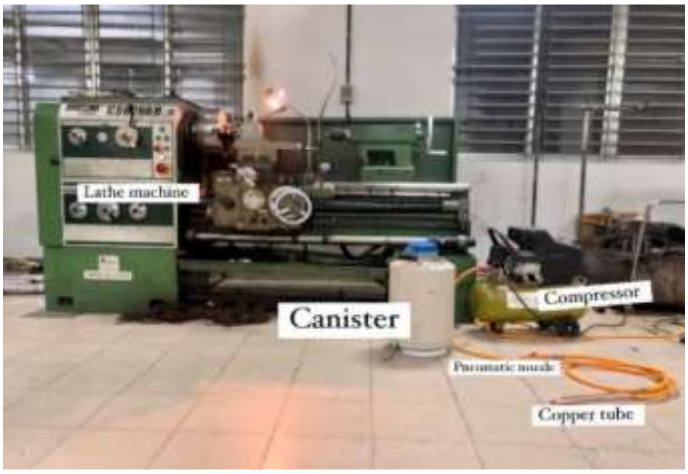
The selected machining parameters and their levels are given in Table 2.

Table 2: *Levels and Factors of machining parameters.*

SL	Variables/Factors	Levels		
		1	2	3
1	Cutting speed Vc, (m/min)	100	150	200
2	Depth of cut Ap, (mm)	0.2	0.4	0.6
3	Feed F, (mm/rev)	0.08	0.12	0.16

EXPERIMENTAL SET UP AND METHODOLOGY

In this study two different environment has been used for machining that’s why two different experimental setup is needed.



(a)

(b)

(c)

Fig. 1: *(a) Cryogenic cooling (compressed air), (b) MQL, (c) close view of material after machining.*

Here figure 1 (a) and 1 (b) shows the full experimental setup of Cryogenic cooling and MQL accordingly, and figure 1(c) shows the close view of material after machining.

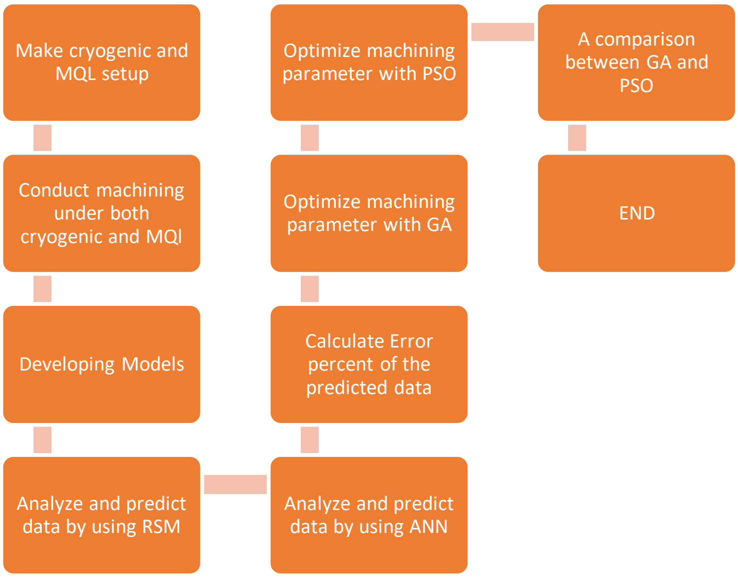


Fig. 2: *Flow chart of the working procedure of this study.*

Table 3 shows the results of combining the BBD parameters with the observed values of surface roughness and cutting zone temperature. Roughness values are the average of three measured values for each test.

Table 3: *Experimental result.*

No	Cutting Speed, Vc(m/min)	Depth of cut, Ap(mm)	Feed, F (mm/rev)	Cryogenic		MQL	
				Roughness, Ra(µm)	Temperature, T(°C)	Roughness, Ra(µm)	Temperature, T(°C)
1	150	0.4	0.12	1.4	734.938	0.84	335.856
2	150	0.2	0.16	0.9	532.391	0.72	253.331
3	150	0.4	0.12	1.2	704.905	0.87	376.28
4	200	0.2	0.12	1.1	532.391	0.56	312.505
5	100	0.4	0.16	1.2	669.349	0.74	306.639
6	100	0.6	0.12	1.3	684.656	0.87	335.856
7	100	0.4	0.08	0.7	387.727	0.38	193.017
8	100	0.2	0.12	0.8	312.505	0.47	168.572
9	200	0.4	0.16	2.4	689.73	1.49	521.537
10	200	0.4	0.08	1	669.348	0.74	306.639
11	150	0.6	0.08	1.4	601.833	0.83	575.353
12	200	0.6	0.12	2.5	817.801	1.4	622.813
13	150	0.4	0.12	1.6	734.938	0.84	335.856
14	150	0.2	0.08	0.46	312.506	0.39	162.43
15	150	0.6	0.16	2.3	769.457	1.62	601.833

RESULT AND DISCUSSION

Cooling Influence on Machining Factors

During machining, the acquired surface roughness and cutting zone temperature lead to a significant improvement when MQL cooling is used. Cryogenic machining produces comparatively poor surface quality and high temperature during turning when particular cutting parameters are used. Figure 3 depicts a graphical comparison of roughness and temperature under varied cooling settings of the experimental measures. It can also be seen that the MQL mode gives improved surface quality and reduces heating.

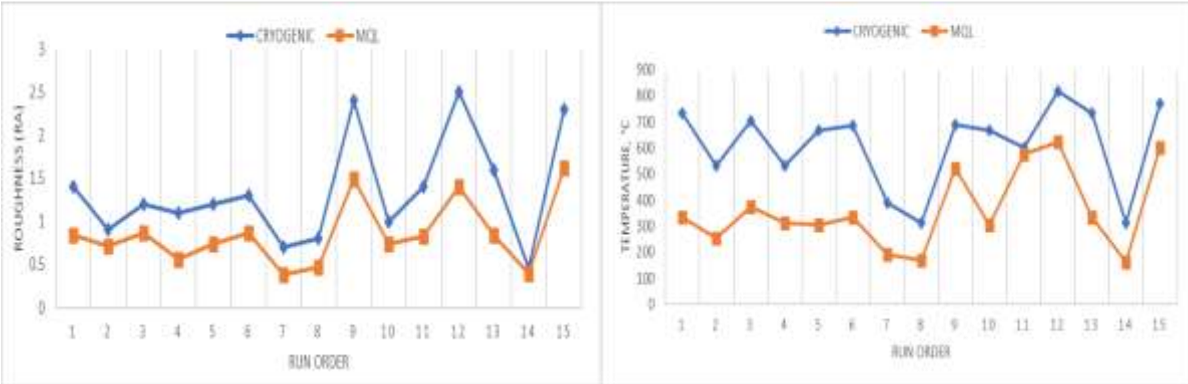


Fig. 3: *Comparison of Cryogenic and MQL experimental results.*

MQL impacts not only product quality but also respects and maintains the environment by decreasing the usage of lubricating oils, which results in lower machining costs because some turning operations require lubrication.

MODELING WITH RSM

Surface Roughness Modeling

ANOVA is a statistical approach used to determine the importance of factors or interaction factors on a certain response based on experimental data. It calculates the F-ratio or variance ratio by dividing the regression mean square by the mean square error. The F-ratio is used to quantify the importance of each parameter. In general, as the F value rises, so does the importance of the particular parameter.

Table 4: *ANOVA analysis for cryogenic cooling.*

Source	Sum of Squares	df	Mean Square	F-value	p-value	Remarks
Model	5.14	6	0.857	33.48	< 0.0001	significant
A-Vc	1.12	1	1.12	43.95	0.0002	
B-Ap	2.25	1	2.25	87.78	< 0.0001	
C-F	1.31	1	1.31	51.26	< 0.0001	
AB	0.2025	1	0.2025	7.91	0.0228	
AC	0.2025	1	0.2025	7.91	0.0228	
BC	0.0529	1	0.0529	2.07	0.1885	
Residual	0.2048	8	0.0256			
Lack of Fit	0.1248	6	0.0208	0.52	0.7737	Not significant
Pure Error	0.08	2	0.04			
Cor Total	5.35	14				

Table 5: *ANOVA analysis for MQL*

Source	Sum of Squares	df	Mean Square	F-value	p-value	Remarks
Model	1.97	6	0.3279	63.36	< 0.0001	significant
A-Vc	0.3741	1	0.3741	72.3	< 0.0001	
B-Ap	0.832	1	0.832	160.81	< 0.0001	
C-F	0.6216	1	0.6216	120.14	< 0.0001	
AB	0.0484	1	0.0484	9.35	0.0156	
AC	0.038	1	0.038	7.35	0.0266	

BC	0.0529	1	0.0529	10.22	0.0127	
Residual	0.0414	8	0.0052			
Lack of Fit	0.0408	6	0.0068	22.66	0.0429	significant
Pure Error	0.0006	2	0.0003			
Cor Total	2.01	14				

The model generated a regression equation in terms of actual factors with R^2 of 96.17 and 97.94% respectively, for surface roughness under cryogenic cooling and MQL. For both cases the difference between adjusted R^2 and predicted R^2 is less than 0.2. The regression equations are given below,

$Ra_{\text{Cryo}} = 2.01567 - 0.015000*Vc - 2.45000*Ap - 12.50000*F + 0.022500*Vc*Ap + 0.112500*Vc*F + 14.37500*Ap*F$

$Ra_{\text{MQL}} = 0.948167 - 0.00593*Vc - 1.7625*Ap - 6.09375*F + 0.011*Vc*Ap + 0.04875*Vc*F + 14.375*Ap*F$

The equation in terms of actual factors can be used to make predictions about the response for given levels of each factor

Cutting Zone Temperature Modeling

Table 6: *ANOVA analysis for cryogenic cooling*

Source	Sum of Squares	df	Mean Square	F-value	p-value	Remarks
Model	3.62E+05	9	40259.98	50.43	0.0002	significant
A-Vc	53633.53	1	53633.53	67.19	0.0004	
B-Ap	1.75E+05	1	1.75E+05	219.5	< 0.0001	
C-F	59428.5	1	59428.5	74.45	0.0003	
AB	1880.99	1	1880.99	2.36	0.1854	
AC	17061.53	1	17061.53	21.37	0.0057	
BC	682.82	1	682.82	0.8554	0.3975	
A^2	7164.05	1	7164.05	8.97	0.0302	
B^2	32653.17	1	32653.17	40.91	0.0014	
C^2	21800.8	1	21800.8	27.31	0.0034	
Residual	3991.3	5	798.26			
Lack of Fit	3390	3	1130	3.76	0.2172	Not significant
Pure Error	601.3	2	300.65			
Cor Total	3.66E+05	14				

Table 7: *ANOVA analysis for MQL*

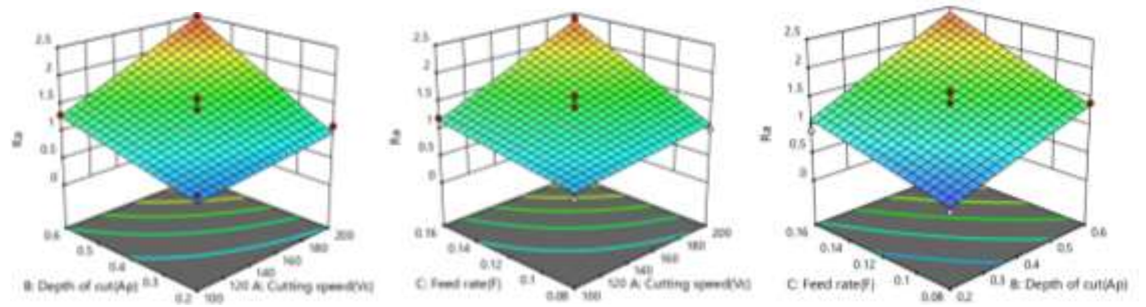
Source	Sum of Squares	df	Mean Square	F-value	p-value	Remarks
Model	2.89E+05	3	96278.7	29.35	< 0.0001	significant
A-Vc	72087.77	1	72087.77	21.97	0.0007	
B-Ap	1.92E+05	1	1.92E+05	58.49	< 0.0001	
C-F	24853.5	1	24853.5	7.58	0.0188	
Residual	36087.99	11	3280.73			
Lack of Fit	34998.57	9	3888.73	7.14	0.1288	Not significant
Pure Error	1089.42	2	544.71			
Cor Total	3.25E+05	14				

The model generated a regression equation in terms of actual factors with R2 of 98.91 and 88.89% respectively, for surface roughness under cryogenic cooling and MQL. For both cases the difference between adjusted R2 and predicted R2 is less than 0.2. The regression equations are given below,

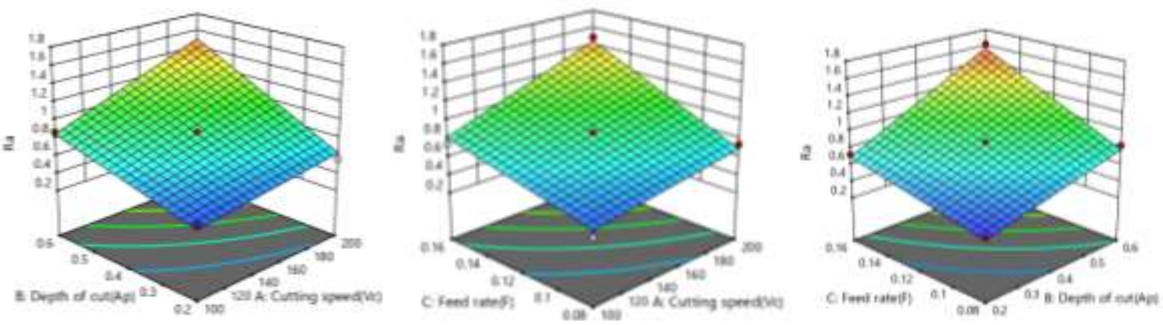
$$T_{Cryo} = -2335.7154375 + 11.70939*Vc + 3142.03469*Ap + 19232.23969*F - 2.16852*Vc*Ap - 32.65495*Vc*F - 1633.17813*Ap*F - 0.017619*Vc^2 - 2351.00594*Ap^2 - 48024.99219*F^2$$

$$T_{MQL} = -401.17738 + 1.89852*Vc + 774.38450*Ap + 1393.44156*F$$

Three-dimensional (3D) response surface plots were created to investigate the influence of the input machining settings on surface roughness and cutting zone temperature. These graphs can be used to offer an additional assessment of the link between process parameters and replication.



(a)



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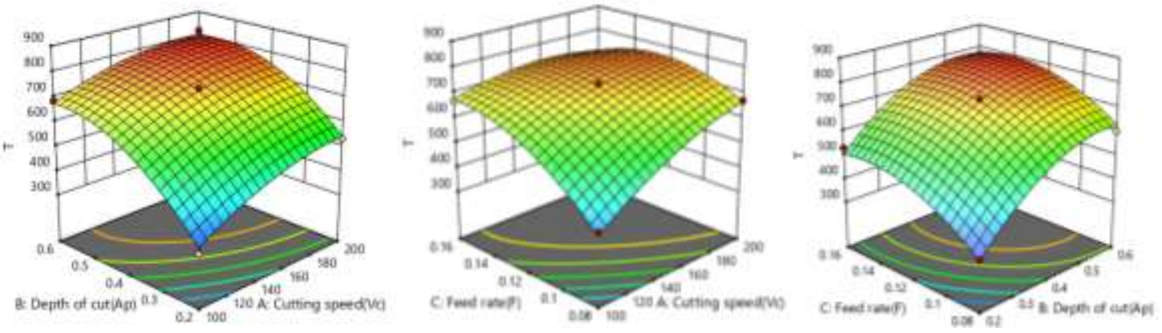

(c)

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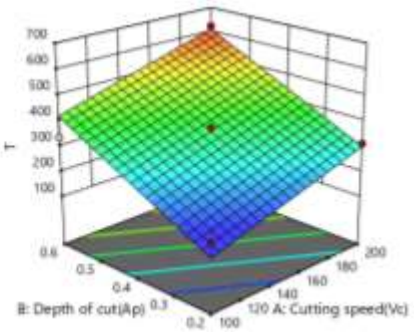


(d)

Fig. 4: *Effect of cutting factors on (a)surface roughness under cryogenic, (b)surface roughness under MQL, (c)Temperature under cryogenic, and (d) Temperature under MQL.*

Figure 4 represents the 3D surface plots that demonstrate the surface roughness and Cutting zone temperature evolution according to cutting speed and depth of cut, feed rate and cutting speed, and feed rate depth of cut. It can be shown that lubrication improves the machinability of this type of steel; moreover, MQL cooling gives a low cutting zone temperature by reducing contact friction. Figure 4 (a) and (b) shows that surface roughness increases with the increase of depth of cut. From all the 3D surface response plots it can be concluded that depth of cut and cutting speed mostly affects the responses.

Modeling with ANN

In terms of accuracy, speed, and simplicity, an artificial neural network is an AI-based simulation tool capable of nonlinear modeling of inputs and outputs more effectively than traditional methodologies. ANN may learn and implement functions similar to the human brain learning process, as well as adapt to changes by changing various weighted connections and biases that connect nodes called neurons located in different layers of ANN design. An ANN model's anatomy is composed of three layers: (a) the input layer, (b) the hidden layer, and (c) the output layer. In this study Feed-forward backdrop was used as the network type, the training function was TRAINLM, transfer function was TRANSIG. Fig. 5 depicts the topology of the chosen artificial neural network (3-10-1).

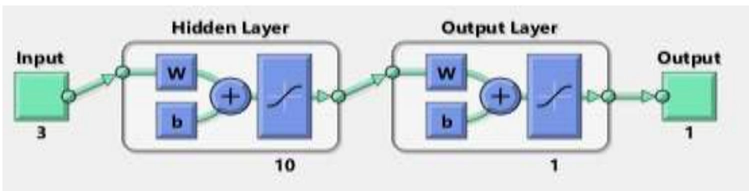
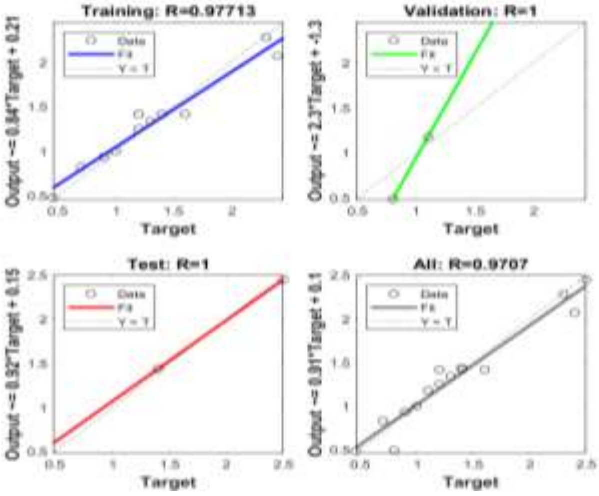
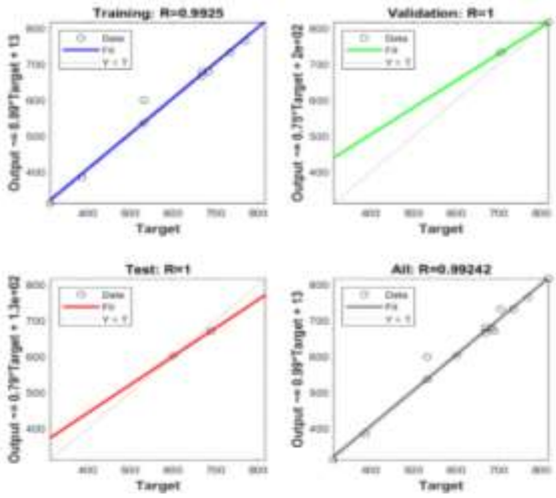


Fig. 5: *Framework for selected network.*

Here, in this network, cutting speed, depth of cut and feed rate are the three inputs. Number of neurons is ten.


Training: R=0.97713
Validation: R=1
Test: R=1
All: R=0.9707
Target
(a)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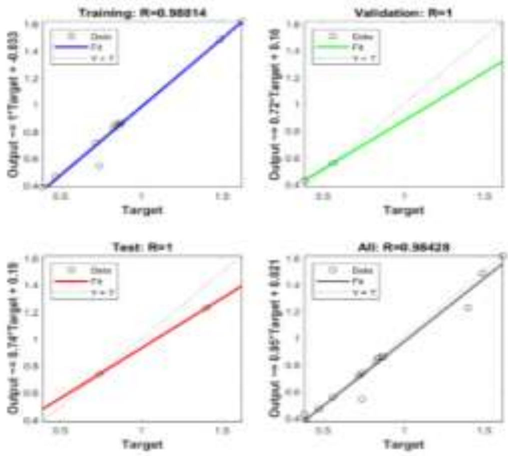
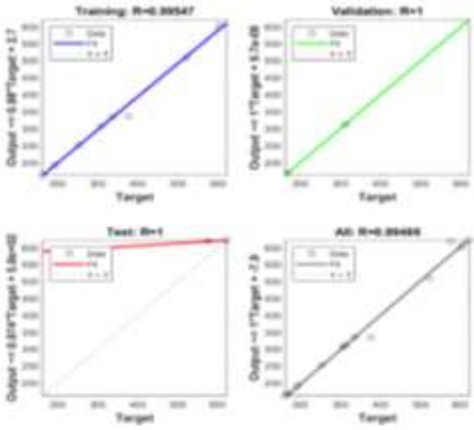
Validation: R=1
Test: R=1
All: R=0.99242
Target
(b)


Validation: R=1
Test: R=1
Target
(c)



(d)

Fig. 6: *Correlation between forecasted and experimental data using training, validation, and tests data set for (a) roughness, (b) Temperature under Cryogenic and (c) roughness, and (d) temperature under MQL.*

ANN and RSM model comparison

Table 8: *Comparison of Prediction for ANN and RSM under Cryogenic Machining*

Run	Actual	Predicted Roughness		Prediction error (%)		Actual	Predicted Temperature		Prediction Error (%)	
	Ra(μm)	RSM	ANN	RSM	ANN	T(°C)	RSM	ANN	RSM	ANN
1	1.4	1.36	1.41	2.85	0.71	734.938	724.927	733.184	1.36	0.23
2	0.9	1.1	0.93	22.22	3.33	532.391	505.307	600.4428	5.08	12.78
3	1.2	1.35	1.22	12.5	1.66	704.905	724.27	733.184	2.74	4.01
4	1.1	0.97	1.14	11.81	3.63	532.391	542.408	537.0254	1.88	0.87
5	1.2	1.16	1.25	3.33	4.16	669.349	673.658	681.561	0.64	1.82
6	1.3	1.28	1.33	1.53	2.3	684.656	674.638	680.6241	1.46	0.58
7	0.7	0.79	0.8	12.85	14.28	387.727	370.66	385.454	4.4	0.58
8	0.8	0.67	0.69	16.25	13.75	312.505	335.28	312.5058	7.28	0.00025
9	2.4	2.35	2.24	2.08	6.66	689.73	706.727	671.9241	2.46	2.58
10	1	1.09	1	9	0	669.348	665.38	668.1265	0.59	0.18
11	1.4	1.36	1.41	2.85	0.71	601.833	628.917	602.5355	4.5	0.11
12	2.5	2.48	2.45	0.8	2	817.801	795.026	817.8003	2.78	0.000085
13	1.6	1.35	1.56	15.62	2.5	734.938	724.27	733.184	1.45	0.23
14	0.46	0.53	0.47	15.21	2.17	312.506	306.798	312.5074	1.82	0.0004
15	2.3	2.4	2.28	4.34	0.86	769.457	775.164	764.899	0.74	0.59

Table 9: *Comparison of Prediction for ANN and RSM under MQL machining*

Run	Actual	Predicted Roughness		Prediction error (%)		Actual	Predicted Temperature		Prediction Error (%)	
	Ra(μm)	RSM	ANN	RSM	ANN	T(°C)	RSM	ANN	RSM	ANN
1	0.84	0.85	0.855	1.19	1.78	335.856	360.568	335.866	7.35	0.0029
2	0.72	0.69	0.72	4.16	0	253.331	261.429	253.351	3.199	0.0078
3	0.87	0.85	0.855	2.29	1.72	376.28	360.568	335.856	4.17	10.74
4	0.56	0.63	0.563	12.5	0.53	312.505	300.617	312.515	3.8	0.0031
5	0.74	0.8	0.741	8.1	0.13	306.639	321.379	306.629	4.801	0.0032
6	0.87	0.84	0.872	3.44	0.22	335.856	420.519	335.836	25.2	0.0059
7	0.38	0.45	0.41	18.42	7.89	193.017	209.904	193.015	8.74	0.00103
8	0.47	0.422	0.47	10.21	0	168.572	110.765	168.562	34.29	0.0059
9	1.49	1.44	1.491	3.35	0.06	521.537	511.232	509.7417	1.97	2.26
10	0.74	0.69	0.647	6.75	12.56	306.639	399.75	306.639	30.36	0
11	0.83	0.78	0.832	6.02	0.24	575.353	469.707	618.5866	18.36	7.51

12	1.4	1.48	1.3307	5.71	4.95	622.813	610.371	622.1024	1.99	0.11
13	0.84	0.85	0.855	1.19	1.785	335.856	360.56	335.856	7.35	0
14	0.39	0.364	0.395	6.66	1.28	162.43	149.953	162.4301	7.68	6.50E-06
15	1.62	1.57	1.624	3.08	0.246	601.833	571.182	601.833	5.095	0

From the comparison above, it is noted that under both machining conditions and for both responses ANN performed way better than RSM. It is seen from the comparison that the prediction error percentage of ANN is remarkably lower than RSM. So, it can be said that here ANN outclassed RSM.

Optimization with GA and PSO

In this study, GA and PSO were used by coupling with RSM. The goal of this study's multi-object optimization approach is to determine the optimal values of decision variables that contribute to the lowest possible Surface Roughness (Ra), Cutting Zone Temperature (T), and maximum Material Removal Rate (MRR). To formulate the optimization problem, the proposed equations were used in GA and PSO as objective functions. In the RSM-GA approach, the population size was 50, number of generations was 500. On the other hand, in the RSM-PSO approach population size was 200, the repository size was 200 and the maximum generations was 100. Both RSM-GA and RSM-PSO proposed many optimized parameter combinations. From those proposed parameter combinations, the selected and most optimal machining parameter setup is given below,

Table 10: *Optimized parameter combinations for different approaches*

Approach Name	Environment	Vc (m/min)	Ap (mm)	F (mm/rev)	Ra	T	MRR
RSM-GA	Cryogenic	159.1421	0.201621	0.080716	0.526596	343.2886	2.589877
RSM-GA	MQL	112.9789	0.202710052	0.080378993	0.360528644	82.29435	1.840837
RSM-PSO	Cryogenic	200	0.2	0.08	0.45567	431.6376	3.2
RSM-PSO	MQL	100	0.2	0.08	0.355667	55.0268448	1.6

So, it can be noted that under both MQL and Cryogenic conditions, RSM_PSO provides better optimization results than RSM_GA.

CONCLUSION

This study investigates MQL efficiency and compares the performance of both the response surface methodology (RSM) and the artificial neural network (ANN) in terms of prediction and generalization using experimental results based on the Box-Behnken design for surface roughness and cutting zone temperature under cryogenic cooling (compressed air) and MQL turning. It also contrasts the RSM-GA and RSM-PSO approaches. The following conclusions can be drawn from this research,

- The experiment result showed the supremacy of MQL over Cryogenic for both surface roughness and cutting zone temperature.
- Surface Roughness and Cutting zone temperature were predicted by RSM and ANN. The prediction of ANN had significantly less error.
- After that RSM was coupled with GA and PSO, and machining parameter optimization was performed. RSM_PSO provided the most optimal parameter under both cryogenic cooling and MQL.

FUTURE SCOPE

Although this research showed novel approaches and outstanding results, there is still some scope to carry the research further. This research suggests future researchers conduct more experiments under many different environments with more experimental runs. And for predicting and optimization use cutting-edge machine-learning approaches.

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