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Multi-Objective Optimization of Machining Parameters for Sustainable Turning of AISI 630 Stainless Steel using Taguchi-Based Desirability Function Analysis

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Abstract. Dry machining has a good association with ecological and economic control. Even though dry machining is environment-friendly, it produces poor surface quality with excessive tool wear due to a vast amount of heat generation at the machining interface. This paper aims to determine the optimum machining parameters for enhanced machining performance. The turning process was performed under a dry environment on AISI 630 steel by varying the machining parameters. The experimental run for three factors, each at three levels, was framed with the help of Taguchi's technique. Machining responses such as tool-work interface temperature, surface roughness, and material removal rate were measured online and offline with corresponding measuring devices. A temperature measuring system was developed indigenously to measure temperature. The effect of machining parameters on machining response, determination of optimum machining parameters for individual machining response, the influence of machining parameters on machining responses, and mathematical model for individual machining response were discussed. Taguchi-Desirability Function Analysis was employed to determine the optimum machining parameters for enhancing the machining performance. Enhanced machining performance was obtained at the optimum parameters of 800 rpm, 0.12 mm/rev, and 0.70 mm.

Keywords: Dry machining, AISI 630, Steel, Optimization, Taguchi, Desirability Function Analysis, Temperature

Introduction

Stainless steel is often used in many engineering applications for its properties such as high strength, hardness, and corrosion resistance [1,2]. One of the most widely used materials in the stainless-steel group is AISI 630 steel. It is often known as a difficult-to-machine material by its composition and properties [3]. In addition, AISI 630 steel has superior corrosion resistance compared to 304 and 316L steel. It is used to make fasteners, reactor components, missile fittings, jet engine parts [4], safety valves, studs, nuts [5], sailboat propeller shafts [6] and implantation [7]. However, the machining of such material requires higher cutting force, resulting in higher friction at the machining interface, thus generating considerable heat. Its lower thermal conductivity nature retains the generated heat at the machining interface. It affects the quality of the machined surface and tool life, resulting in lower productivity and high production cost [8,9]. These problems are mitigated by selecting suitable cutting fluid and cooling techniques.

The flood cooling system uses plenty of cutting fluid to reduce the cutting temperature and friction. Generally, the cutting fluid used in the machining industry is a conventional fluid, i.e., a mineral oil that contains chemical components harming the environment and workers' health. It also might cause damage to the workpiece surface due to chemical reactions. The quality of the fluid degrades rapidly and gets contaminated due to bacterial growth [10,11]. Further, the disposal of conventional cutting fluid is a difficult task that severely impacts the environment. Contamination of soil and water, environmental pollution, health issues for workers, and high-cost disposal processes are the limitations of conventional cutting fluids [12]. In addition, the cost of the cutting fluid during machining under a conventional environment account for approximately 8 to 16% of the total manufacturing cost [13]. Approximately 1.2 million workers have been affected by cutting fluids that are too toxic and hazardous to the environment [14].

The adverse effect of the conventional cutting fluid can be minimized by using it at a minimum level, and it can be avoided by introducing alternate cutting fluids. The primary factor in sustainable manufacturing is the process parameters, the tool's geometry and material, the workpiece's material and geometry, and the cooling method [15]. Recently, many researchers and practitioners are showing keen interest in implementing alternatives to conventional cutting fluid, which would reduce the quantity of the cutting fluid. Thereby, reduction in environmental effects and machining costs can be reduced. Some alternatives, such as dry machining, minimum quantity lubrication, cryogenic cooling, nanofluids, and vegetable oils, are better alternatives for conventional cutting fluids [16,17].

The gaseous cutting fluid is a substance that is used as a cooled-pressurized liquid, and it contains air, nitrogen, argon, helium, and carbon dioxide. The commonly used gas-based cutting fluid is air [18]. Gas-based cutting fluid has higher corrosion resistance and cooling ability, which can be performed and utilized even at elevated temperatures. Sivaiah and Chakradhar investigated the machining performance of turning 17-4 PH stainless steel under various machining environments such as flood, MQL, cryogenic, and dry. Compared to other machining environments, reductions in temperature, surface roughness and tool wear were observed under cryogenic machining [19]. However, it cannot be used as a lubricant at the tool-work interface because of its poor viscosity. Poor viscous cutting fluid is not conducive to better lubrication, therein leading to poor surface roughness [20,21]. Moreover, the utilization of cryogenic cooling systems is a threat to ecology, and their installation requires high capital and operational cost [22].

Minimum Quantity Lubrication (MQL) is in demand in various industries due to its environment-friendly nature. The essential functions of cutting fluid are obtained significantly through MQL machining. MQL system also provides superior cooling and better lubrication. It produces tiny oil droplets with excellent flowability and penetrability [23,24]. It is an efficient technique adopted for better performance, as it uses a small quantity of cutting fluid. It also reduces the issues associated with excessive use of coolant [25]. MQL machining method utilises cutting fluid in the form of mist in the machining zone. The generated mist can float in the air and would be inhaled by the worker. Thus, it leads to lung disease, respiratory issues, and the oesophagus, stomach, pancreas, prostate, colon, and rectal cancer [18].

Dry machining nullifies the cutting fluid usage, thus eliminating the polluted environment. Compared to conventional machining, dry machining makes the environment green and pollution free. It appeals to more fabulous eco-friendly, and cost-effective environments than wet and MQL machining [26]. Selvam and Sivaram (2018) experimented to investigate the surface roughness during the turning of AISI 4340 steel under dry, near-dry, and flood environments. It was noted that the highest surface quality of the machined workpiece was achieved by flood machining. It was also found that flood and near-dry machining outperformed dry machining by improving the surface roughness, with contributions of 13% and 4.11%, respectively [27].

Ali Khan (2019) studied the effect of machining parameters and cryogenic environment during the turning of Titanium alloy, and machining responses were compared with dry and flood machining. Cryogenic machining reduced the tool wear, surface roughness, and energy consumption by 4%, 9% and 10%, respectively than dry machining [28]. Recently, Khan et al. (2020, 2022) studied the effect of flood, cryogenic and dry environments on Titanium alloy. The machining responses were enhanced by cryogenic and flood machining compared to dry machining. Despite this, they have used a dual nozzle to supply the LN_2 with a flow rate of 4 L/min and 6 L/min for flood machining. This leads to the disappearance of cost-effective machining [29, 30].

It has been observed from the literature that only some alternate machining environments have been implemented, and only tenuous improvements in machining performance have been obtained compared to dry machining. Further, an alternate machining method would deteriorate the environment by utilizing the cutting fluid. In this view, machining parameter optimization would improve the dry machining performance. Very few researchers have investigated the machining of AISI 630 steel so far. Furthermore, it has been observed that more studies are needed in machining the chosen material. In the present study, multi-response optimization was performed using Taguchi-based desirability function analysis to enhance machining performance.

1. Materials and Methods

All the experiments were conducted to measure the machining responses under a dry environment using Kirloskar make Turnmaster-35 model centre lathe with variable speed and feed drive. The stainless-steel grade of AISI 630 was chosen as a workpiece material for the current study. It was used in the form of a cylindrical shape with dimensions of 50 mm diameter and 150 mm length. A pictorial view of the workpiece with dimensions is shown in Figure 1. The cutting tool insert and holder were chosen based on the workpiece hardness and machining conditions. In addition, the cutting tool insert was chosen based on its utility in the machining industry and availability on the market. Ceratizit makes coated carbide inserts used as a cutting tool and has an ISO designation CNMG 120408EN-M70 with a nose radius of 0.8 mm. A new cutting edge was used for each level of process parameters and it is mounted on a tool holder with ISO designation PCLNR 2020 K12 WIDIA. The cutting tool insert and tool holder are shown in Figure 2.

Fig. 1. - Workpiece material used during the experiment

Fig. 2. - Pictorial view of tool insert and tool holder

2. Measuring devices for machining responses

The machining responses, such as tool-work interface temperature, surface roughness and material removal rate, were measured with appropriate measuring equipment. The machining responses were measured online and offline during and after turning under variable machining parameters. All the mechanical works are converted into thermal energy during the machining process. A considerable amount of heat is generated in the machining zone. It affects productivity, surface quality, workpiece dimensions, tool wear and other machining responses. Due to this, investigations of measuring tool-work interface temperature are of utmost importance.

Temperature was measured using a K-type thermocouple, and it is positioned in the modified tool insert. A pictorial view of the modified tool inserts and thermocouple is shown in Figure 3. An electric spark discharge machine made a hole in the tool insert with a 1.5 mm diameter and 3.76 mm depth. The hole was positioned 1 mm from the cutting edge and 1 mm below the rack surface. Thermocouple was inserted in the tool insert where the hole was made. The criteria for selecting thermocouples were the measuring temperature range and accuracy; availability in the market and cost were also considered.

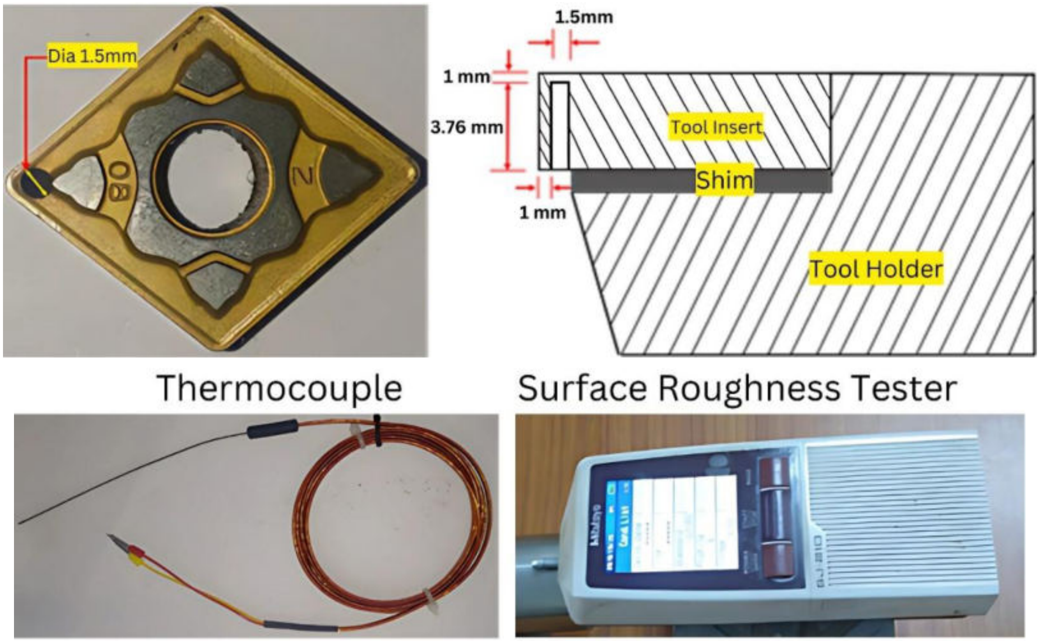

Fig.3. - Pictorial view of modified tool insert and thermocouple

Tool-work interface temperature was measured using an in-house developed temperature measuring system (TMS). A thermocouple, amplifier, UNO Arduino, and personal computer are the components utilised to develop TMS. The components are connected, as shown in Figure 4. The processor was programmed with code for measuring the temperature, which assisted the TMS in simultaneously measuring the temperature and machining time.

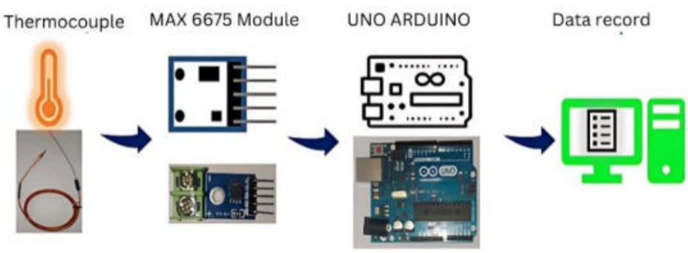

Fig. 4. - Temperature measuring system

The quality of the product is identified with the value of surface roughness. The surface roughness of the machined parts was measured offline using Mitutoyo make SJ-210 model after the turning process. Surface roughness was measured around the machined workpiece at different locations, and the average value was taken into account. The material removal rate identifies the productivity of the machining process. It was determined using the conventional method. The measurement of the material removal rate is done offline. The weight of the workpiece was measured using a weighing machine before and after the machining at each level of machining parameters. The material removal rate is defined as the ratio of the difference between the weight of the workpiece before and after the turning process to the time taken. Equation (1) represents the material removal rate at each level of machining parameters:

$$MRR = \frac{W_i - W_f}{t}(g/min) \quad (1)$$

where W_i, W_f and t are represented as the weight of the workpiece before and after the machining and time of cutting, respectively.

3. Taguchi's technique

Taguchi's technique is an excellent tool for optimizing the parameters of any machining process. Depending on the type of procedure, the approach is typically conducted utilizing L_9, L_{18}, or L_{27} orthogonal array system. Primarily, L_9 orthogonal array was used to carry out the experimental design in most situations where the process was built with three machining parameters. The design of the experiment under the general full factorial method sets a total of twenty-seven experiments for three factors at three different levels. As the number of experimental runs increases, so does the cost and effort require. The experiment design is more economical when setting it up using the Taguchi technique because it reduces the experimental setup substantially compared to the conventional experimental design approach.

This study performed the turning process on AISI 630 stainless steel in a dry environment. Taguchi L_9 orthogonal array design was selected for designing the experiments. The experiments were conducted by varying the machining parameters such as cutting velocity, feed rate and depth of cut. Each machining parameter varied at three levels. Nine experiments were employed to determine the optimum machining parameters for enhanced turning performance in terms of lower temperature and surface roughness (Ra) and higher material removal rate (MRR). The machining parameters at different levels are presented in Table 1.

Table 1. Machining parameters and their levels for the turning process

Symbol	Machining parameters	Level 1	Level 2	Level 3
v	Cutting speed (rpm)	700	800	900
f	Feed rate (mm/rev)	0.06	0.12	0.18
a_p	Depth of cut (mm)	0.35	0.70	1.05

The Signal to Noise (S/N) ratio is the mean and standard deviation ratio. The process is considered good in any machining process when the temperature and surface roughness are smaller and the material removal rate is larger. The mean S/N ratio for tool-work interface temperature and surface roughness was calculated using the 'lower the better' response, and 'larger the better' was used for the material removal rate:

$$\text{S/N ratio}_{\text{smaller the better}} = -10\log\frac{1}{n}\sum R^2 \quad (2)$$

$$\text{S/N ratio}_{\text{Larger the better}} = -10\log\frac{1}{n}\sum \frac{1}{R^2} \quad (3)$$

where n - number of observed data;

R - observed data for each response

The value of the S/N ratio for the temperature and Ra was calculated using Equation (2). Equation (3) calculates the S/N ratio for the MRR. Minitab 19.1 is the statistical analysis tool utilized for performing the Taguchi technique.

4. Desirability Function Analysis

Desirability Function Analysis (DFA) is a multi-criteria decision-making statistical tool. It is used to determine the optimum input parameters for the output responses. DFA is a well-known technique adopted in the industry to simultaneously determine the optimum independent variable. The objective of the current study is to estimate the best among the given set of experiments with optimal multi-responses. The responses have conflicting criteria, such as smaller, nominal, or better. DFA is implemented to avoid such conflicting criteria.

Harrington was the one who first introduced DFA in 1967. Further, the modification has been extended by Derringer and Suich. It is implemented to estimate the machining responses of many researchers in different machining processes, namely EDM, end milling, and tuning. In this methodology, a set of experiments is undesirable if any of the output responses falls outside the desired boundary. The objective is to identify the optimum machining parameters that produce the highest desirable index value for the responses. The desirability value lies between zero to one. The value near 1 indicates that the response is within the desirable and ideal limits. The value near zero represents the response being outside the desired limit and considered undesirable.

In the present study, tool-work interface temperature, Ra and MRR are considered performance characteristics of the turning process. Machining performance is enhanced by reducing the temperature and Ra and increasing the MRR. All the machining responses are normalized using the desirability function. Therefore, the 'smaller the better' desirability function is applied for temperature and Ra, whereas the 'larger the better' is used for MRR. Individual desirability values for the machining response to be maximized are estimated using Equation (4). Individual desirability values for minimizing machining response are estimated using Equation (5):

$$d_{i\,(larger\ the\ better)} = \left(\frac{y_i - y_{min}}{y_{max} - y_{min}}\right)^r \tag{4}$$

$$d_{i\,(smaller\ the\ better)} = \left(\frac{y_{max} - y_i}{y_{max} - y_{min}}\right)^r \tag{5}$$

$$Composite\ desirability\ (CD) = \left[d_1^{r_1} \times d_2^{r_2} \times d_3^{r_3} \times \ldots\right]^{\frac{1}{w}} \tag{6}$$

where d_i - individual desirability value;

y_i - current value of the machining response;

y_{min} - minimum value of the machining response;

y_{max} - maximum value of the machining response;

r - weightage to the individual machining response, w = number of machining responses

The composite desirability value for all sets of experiments is calculated using Equation (6). It is estimated as the geometric mean of the individual desirability values of the machining responses. The maximum composite desirability value indicates optimal machining parameters for multiple machining responses.

Table 2. Experimental plan and machining responses under dry turning

S. No	Machining Parameters			Machining responses		
	v (rpm)	*f* (mm/rev)	a_p (mm)	T (°C)	Ra (μm)	MRR (g/min)
1	700	0.06	0.35	140.50	0.454	16.056
2	700	0.12	0.7	196.25	0.936	72.000
3	700	0.18	1.05	244.25	2.114	132.300
4	800	0.06	0.7	210.25	0.963	49.524
5	800	0.12	1.05	274.25	1.634	100.800
6	800	0.18	0.35	192.00	1.268	77.143
7	900	0.06	1.05	293.50	1.726	56.786
8	900	0.12	0.35	215.25	1.099	49.286
9	900	0.18	0.7	236.75	2.076	113.400

Machining responses for enhanced machining performance during AISI 630 stainless steel turning are investigated under a dry environment. The machining responses are measured online and offline. The tool-work interface temperature is measured during the turning process (online). Surface roughness and material removal rate are measured after turning (offline). The machining parameters for the process and its resultant machining responses are presented in Table 2.

5. Results and discussion

Machining responses depend on several factors, such as cutting tool and workpiece material, machining environment, and parameters. Among all of these, the machining parameter is the one that can be controlled during the turning process. The effect of cutting speed, feed rate, and depth of cut on tool-work interface temperature is shown in Figure 4. It is observed that the tool-work interface temperature increased with the increase in the levels of all machining parameters. The rotary movement of the workpiece resists the cutting tool's linear movement, which results in heat generation at the machining zone. Friction between the tool and workpiece is further increased when the cutting speed, feed rate, and depth of cut is increased. Hence the temperature at the interface increased. In the current study, tool-work interface temperature was increased when the cutting speed, feed rate and depth of cut increased, respectively.

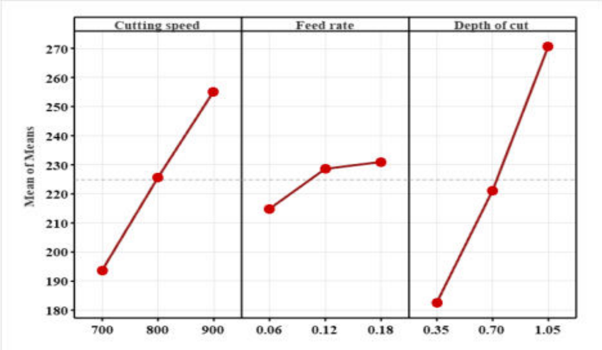

Fig. 4. - Effect of machining parameters on tool-work interface temperature

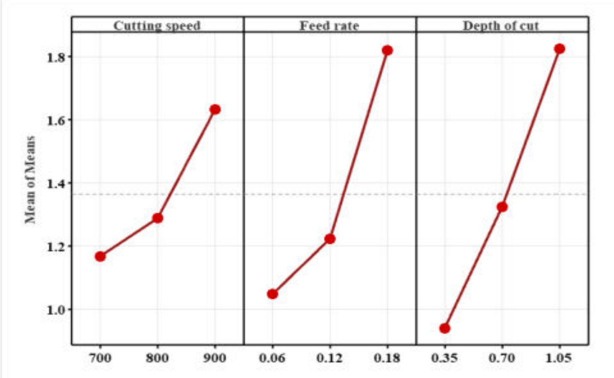

Fig. 5. - Effect of machining parameters on surface roughness

Surface roughness is the common term used in the manufacturing industry to measure the quality of the machined surface. In this study, the surface roughness of the machined workpiece was measured by varying machining parameters. Variations in surface roughness by cutting velocity, feed rate, and depth of cut are depicted in Figure 5. It was noticed that the surface roughness of the workpiece increased with increasing cutting speed. An increment in the cutting speed increases the friction between the tool and workpiece, thus resulting generation of higher tool-work interface temperature. The surface of the workpiece becomes softer due to higher temperature at the machining interface and, consequently, more adhesion of workpiece particles on the tool flank faces. This results in more tool marks on the workpiece, leading to a poor surface finish. Therefore, higher surface roughness was obtained.

It was also observed that the surface roughness value was found to increase in trend as the feed rate and depth of cut are increased, respectively. Higher cutting force and generation of heat at the machining interface caused tool marks on the machined workpiece when increasing the feed rate [31]. Surface roughness is also increased due to a built-up edge (BUE) on the cutting tool. Movement of the cutting tool is resisted by the workpiece when the depth of the cut is increased, resulting in a more BUE formation. Thus, the machined workpiece's surface roughness increased as the cut depth increased. The trends obtained from this study for surface roughness at different turning parameters concurred with the machining theory [19,32].

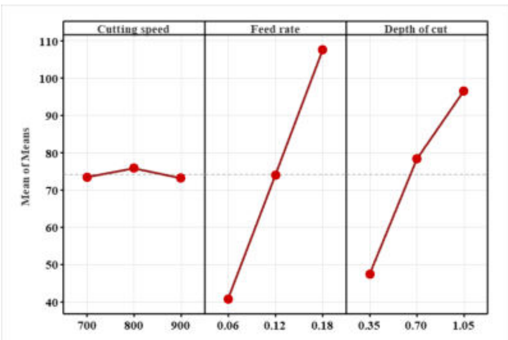

Fig. 6. - Effect of machining parameters on material removal rate

The material removal rate is the key control parameter for machining time and productivity. Higher productivity at lower machining time is achieved with higher material removal rate. The effect of cutting speed, feed rate and depth of cut on the material removal rate is shown in Figure 6. The material removal rate was found to increase when the levels of all the machining parameters increased. It is well-known that material removal rate is a function of machining parameters (MRR = *f (cutting speed, feed rate, depth of cut)*). Thus, higher MRR was obtained by increasing the machining parameters. Higher material removal rate is possible when the chip reduction coefficient is lower [31,33]. This can be achieved when increasing the machining parameters.

6. **Identification of optimum machining parameters for individual machining responses**

In any machining process, improved performance is obtained at optimum parameters. Prediction of optimum machining parameters is necessary for any machining process. Minitab 19.1 was employed to examine the machining responses, and the results of the mean S/N ratio at all levels of machining parameters were tabulated and presented. A higher value of the S/N ratio denotes the minimum changes in the difference between the expected and measured output of the process. A higher S/N ratio for the responses at each level of machining parameters is highlighted. Also, the rank for the machining parameters was awarded based on the difference between the maximum and minimum value of the S/N ratio. The rank preference was given for the machining parameters having a higher difference in the S/N ratio value. A higher mean S/N ratio for the machining parameters represents a better machining response. Based on that, the levels of machining parameters are chosen to obtain improved machining performance.

Table 3. Mean S/N ratio for tool-work interface temperature

Symbol	Machining parameters	Mean S/N ratio			Delta	Rank
		Level 1	Level 2	Level 3		
v	Cutting speed (rpm)	-45.52	-46.96	-48.07	2.55	2
f	Feed rate (mm/rev)	-46.25	-47.09	-47.20	0.95	3
d	Depth of cut (mm)	-45.09	-46.83	-48.62	3.53	1

The results of the mean S/N ratio for the tool-work interface temperature at all levels of process parameters are presented in Table 3. It is observed that the value of delta was decreased in the order of depth of cut, cutting speed, and feed rate, respectively. The depth of cut is considered the predominant parameter for the temperature. A graphical representation of the means of S/N ratio for the tool-work interface temperature at various levels of machining parameters is shown in Figure 7. It is clearly seen that the maximum S/N ratio was found at the cutting speed of 700 rpm, feed rate of 0.06 mm/rev, and depth of cut of 0.35 mm. Hence, the levels of machining parameters $v_1 - f_1 - d_1$ were chosen as the predicted optimum machining parameter at which lower tool-work interface temperature was obtained.

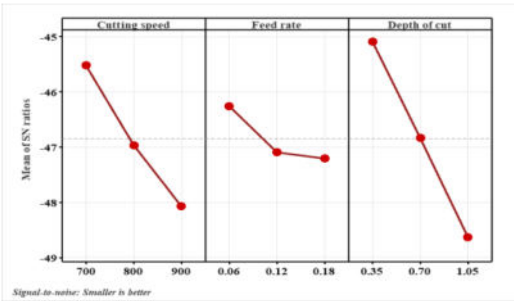

Fig.7. - Mean of S/N ratio of tool-work interface temperature

The results of the mean S/N ratio for the surface roughness at all levels of machining parameters are presented in Table 4. It was observed that the value of delta is decreased in the order of depth of cut, feed rate, and cutting speed, respectively. The depth of cut was considered the most predominant machining parameter for surface roughness. The means of the S/N ratio for surface roughness at various levels of machining parameters is shown graphically in Figure 8. It is seen that a cutting speed of 700 rpm, feed rate of 0.06 mm/rev, and depth of cut of 0.35 mm is found as the level of machining parameters where the maximum S/N ratio was obtained. Hence, $v_1 - f_1 - d_1$ was chosen as levels of machining parameters and considered as the predicted optimum machining parameter, which provided lower surface roughness.

Table 4. Mean S/N ratio for surface roughness

Symbol	Machining parameters	Mean S/N ratio			Delta	Rank
		Level 1	Level 2	Level 3		
v	Cutting speed (rpm)	0.3104	-2.0000	-3.9684	4.2789	3
f	Feed rate (mm/rev)	0.8152	-1.5035	-4.9697	5.7849	2
d	Depth of cut (mm)	1.3255	-1.8142	-5.1693	6.4948	1

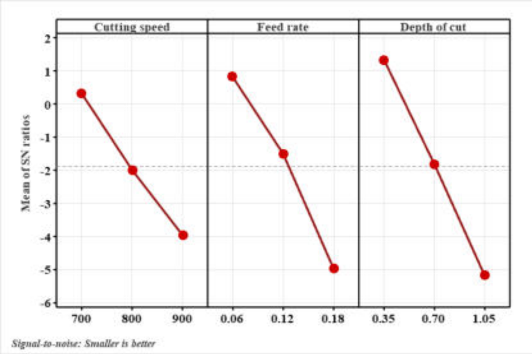

Fig. 8. - Mean of S/N ratio of surface roughness

Table 5. Mean of S/N ratio for material removal rate

Symbol	Machining parameters	Mean S/N ratio			Delta	Rank
		Level 1	Level 2	Level 3		
v	Cutting speed (rpm)	34.56	37.24	36.68	2.67	3
f	Feed rate (mm/rev)	31.03	37.02	40.42	9.39	1
d	Depth of cut (mm)	31.90	37.38	39.20	7.29	2

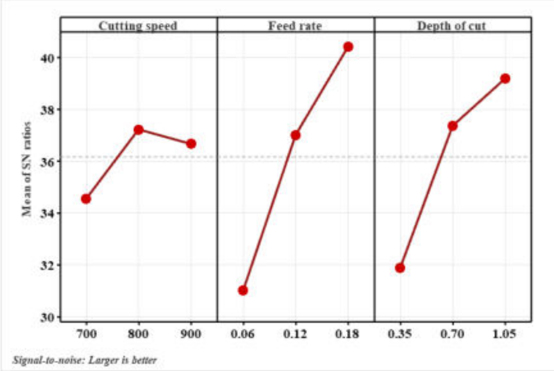

Fig. 9. - Mean of S/N ratio of material removal rate

The response table of the means of the S/N ratio for the material removal rate at all levels of machining parameters is presented in Table 5. It was found that the value of delta decreased in the order of feed rate, depth of cut, and cutting speed, respectively. The feed rate was the most predominant machining parameter, which gives a more significant delta value for the material removal rate. The means of the S/N ratio for the material removal rate for machining parameters are represented graphically in Figure 9. It is seen that the maximum S/N ratio was found at 800 rpm, 0.18 mm/rev, 1.05 mm, and it was considered as the level of machining parameters for MRR. Therefore, the levels of machining parameter $v_2 - f_3 - d_3$ were chosen as the predicted optimum machining parameter to obtain a higher material removal rate.

7. Analysis of Variance

Analysis of Variance (ANOVA) is one of the statistical tools. Sir Ronald A Fisher is a British biologist who first introduced the ANOVA. It determines the most dominating independent variables on the dependent variable. It comprises the sum of squares, means squares and percentage contribution-related calculations. Identification of the dominant parameter is an essential task because it alters the machining performance of any machining process. The most dominant machining parameters on the machining are evaluated with the help of the ANOVA technique. The number of levels minus one (n-1) is the formula adopted to determine the degrees of freedom of all the machining parameters. The sum of the square was obtained when adding the square value of the difference between the machining response's mean value and the current response's value ($\sum (y_{mean} - y_{current})^2$). The mean sum of the square was arrived at when taking the ratio between the sum of the square and the degrees of freedom.

The results obtained from the ANOVA for tool-work interface temperature, surface roughness and material removal rate are shown in Table 6. Among all the machining parameters, depth of cut and feed rate was found to be the most dominating parameter on the tool work interface temperature, surface roughness, and material removal rate, respectively. Depth of cut was involved in the control of temperature and surface roughness, with the highest contribution of 61.72% and 44.08%, respectively. Feed rate was involved in the control of MRR, with the highest contribution of 56.73%. In addition, cutting speed and feed rate also considerably affect temperature and surface roughness, with contributions of 32.24% and 35.42%, respectively. Hence, it is confirmed from the ANOVA results that the depth of cut and feed rate was considered as the machining parameters which highly influence the machining responses during the turning of AISI 630 steel.

Table 6. ANOVA response table for the machining responses

Machining parameters	DoF	Sum of squares	Mean square	p-value	% contribution
Tool-work interface temperature					
Cutting speed (rpm)	2	9.7706	4.8853	0.021	32.24
Feed rate (mm/rev)	2	1.6208	0.8104	0.113	5.35
Depth of cut (mm)	2	18.7045	9.3522	0.011	61.72
Residual Error	2	0.2072	0.1036		0.68
Total	8	30.3031			100.00
Surface roughness					
Cutting speed (rpm)	2	27.521	13.761	0.065	19.17
Feed rate (mm/rev)	2	50.855	25.428	0.036	35.42
Depth of cut (mm)	2	63.297	31.649	0.029	44.08
Residual Error	2	1.917	0.9583		1.34
Total	8	143.591			100.00
Material removal rate					
Cutting speed (rpm)	2	11.929	5.965	0.301	4.99
Feed rate (mm/rev)	2	135.67	67.835	0.036	56.73
Depth of cut (mm)	2	86.419	43.21	0.056	36.13
Residual Error	2	5.139	2.569		2.15
Total	8	239.158			100.00

8. **Regression model**

The dependent variable and independent variables form the structure of the mathematical model. In a mathematical model, the independent variables evaluate the dependent variable. A mathematical model for the response was developed with the help of linear regression analysis in Minitab 19.1. The predictive mathematical model for the temperature, surface roughness and material removal rate developed by regression analysis is represented as a series of Equation 7, 8, and 9 respectively:

$$\mathrm{T} = -125.6 + 0.3075 * v + 135.4 * f + 125.83 * d \tag{7}$$

$R^2 = 0.9912$; R^2 (adj.) = 0.9859

$$\mathrm{Ra} = -2.155 + 0.002328 * v + 6.43 * f + 1.263 * d \tag{8}$$

$R^2 = 0.9472$; R^2 (adj.) = 0. 9155

$$\mathrm{MRR} = -40.6 - 0.0015 * v + 556.9 * f + 70.19 * d \tag{9}$$

R^2 = 0. 9785; R^2 (adj.) = 0. 9656

The accuracy of the predictive mathematical model was verified by the coefficient of determination R^2. The range of R^2 values varies from 0 to 1. The independent and dependent variables are a good fit when the R2 value is close to unity. Equation (7) represents the predicted mathematical model for tool-work interface temperature. The R^2 and adjusted R^2 values were obtained as 0.9912 and 0.9859, respectively. Equation 8 represents the predicted mathematical model for surface roughness. R^2 and adjusted R^2 values are found as 0.9472 and 0.9155, respectively. Material removal rate at any level of machining parameters is determined using Equation 9. The R^2 and adjusted R^2 values for the material removal were found as 0.9758 and 0.9656, respectively. The obtained R^2 value for all three machining responses is close to the unit, and the variables fit well.

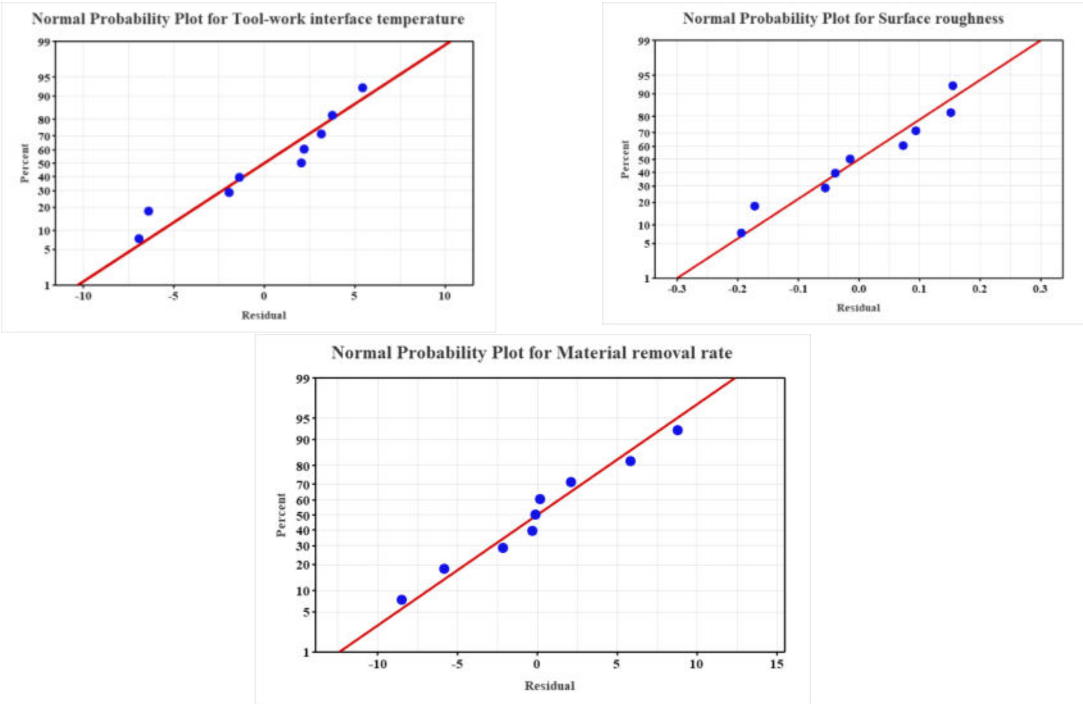

Fig. 10. - Residual plot for all the machining responses

The implication of the coefficients in the predicted model was verified by using a residual plot. The straight-line residual plot represents the residue errors in the predicted model following normal distribution, and the coefficients are significant. The residual plots for tool-work interface temperature, surface roughness and material removal rate are depicted in Figure 10. It is noticed from the plot that residuals are accumulated near the straight line in the plot for surface roughness. Hence, the coefficients in the mathematical model are valid for corresponding process parameters.

9. Confirmation test

A confirmation test has to be performed to examine the predicted model. The results of all the machining responses obtained during the confirmation test are given in Table 7.

Table 7. Confirmation test results

Run	TWIT (°C)		Ra (μm)		MRR (g/s)		Error (%)		
	Exp.	Reg.	Exp.	Reg.	Exp.	Reg.	TWIT	Ra	MRR
3	244.25	246.144	2.114	1.958	132.3	132.292	-0.775	7.372	0.006
5	274.25	268.770	1.634	1.805	100.8	98.728	1.998	-10.474	2.056
6	192.00	188.813	1.268	1.307	77.143	83.009	1.660	-3.064	-7.603
8	215.25	211.439	1.099	1.154	49.286	49.445	1.771	-4.991	-0.322

The test was conducted by choosing the response randomly from the design of the experiments. It is seen from Table 10 that variation in the percentage of residual error among the experimental and predicted model was observed within 10%. Hence, machining responses obtained from experiments had good agreement with the results determined by the predicted model.

10. Determination of optimum machining parameter

Each level of machining parameter and its response sets up the desired objective for the machining process. The desired objective (enhanced machining performance) of the process is achieved through optimization. The objective is obtained in a specific range by setting the machining parameters from low to high. Lower tool-work interface temperature, surface roughness, and higher material removal rate are the quality characteristics that enhance machining performance. It is necessary to combine all three machining responses for better performance. Taguchi-desirability function analysis (DFA) determines the optimum machining parameters for multiple responses.

Table 8. Composite desirability values for experimental run

Run	Machining responses			Individual desirability			Composite Desirability	Rank
	T	Ra	MRR	T	Ra	MRR		
1	140.50	0.454	16.056	1.0000	1.0000	0.0000	0.0000	7
2	196.25	0.936	72.000	0.8599	0.8921	0.7839	0.8440	1
3	244.25	2.114	132.300	0.6856	0.0000	1.0000	0.0000	7
4	210.25	0.963	49.524	0.8166	0.8852	0.6606	0.7816	3
5	274.25	1.634	100.800	0.5014	0.6615	0.9001	0.6684	5
6	192.00	1.268	77.143	0.8723	0.7989	0.8071	0.8255	2
7	293.50	1.726	56.786	0.0000	0.6163	0.7052	0.0000	7
8	215.25	1.099	49.286	0.7999	0.8489	0.6590	0.7649	4
9	256.75	2.076	113.400	0.6219	0.2843	0.9426	0.5503	6

Minimum tool-work interface temperature and surface roughness were obtained at $v_1 - f_1 - d_1$, whereas the maximum material removal rate was at $v_2 - f_3 - d_3$. The levels of machining parameters satisfy the requirement for temperature and surface roughness but do not meet for material removal rate. Hence, Taguchi-DFA was implemented to optimize the machining parameter, improving the machining performance. Machining responses for all experimental design and their corresponding desirability values, followed by composite desirability values, is presented in Table 8.

Table 9. Response values for mean composite desirability

Symbol	Machining parameters	Mean composite Desirability			Delta	Rank
		Level 1	Level 2	Level 3		
v	Cutting speed (rpm)	0.2813	0.7585	0.4384	0.4771	3
f	Feed rate (mm/rev)	0.2605	0.7591	0.4586	0.4986	2
d	Depth of cut (mm)	0.5301	0.7253	0.2228	0.5025	1

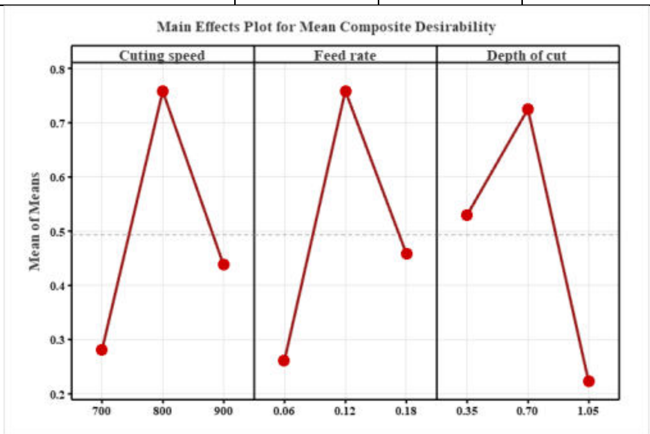

Fig. 11. - Mean composite desirability values for optimum machining parameters

The highest composite desirability was found in experiment 2, with a value of 0.844. The corresponding individual desirability values for temperature, surface roughness and material removal rate were obtained as 0.8599, 0.8921 and 0.7839, respectively. Experiment 2 was considered the optimum machining parameter, enhancing the machining performance. Further, it was verified by employing the Taguchi technique. Means of composite desirability values were determined for all the experimental runs and presented in Table 9. The effect of the machining parameter on mean composite desirability is illustrated in Figure 11. It is clearly seen that the highest mean desirability value for cutting speed, feed rate and depth of cut was observed at parameter levels 2, 2 and 2, respectively. Hence, the optimum machining parameter for simultaneous optimization of multiple machining responses in the current study was obtained as $v_2 - f_2 - d_2$, i.e., 800 rpm, 0.12 mm/rev and 0.7 mm.

Conclusions

The study experimentally investigated temperature, surface roughness, and material removal rate by varying the machining parameters in turning AISI 630 steel in a dry environment. The optimum machining parameter was determined using Taguchi-based desirability function analysis to enhance the machining performance. The following conclusions are drawn based on the statistical analysis carried out for experimental results:

- Depth of cut was found as the most influencing parameter on the tool-work interface temperature and surface roughness. Depth of cut influenced the temperature and surface roughness with contributions of 61.72% and 44.08%, respectively.
- Feed rate was observed as the most influencing parameter on the material removal rate, contributing to 56.73%.
- Individual optimum machining parameter for tool-work interface temperature and surface roughness was identified as $v_1 - f_1 - d_1$, whereas $v_2 - f_3 - d_3$ was noted for material removal rate.
- Mathematical models were developed for tool-work interface temperature, surface roughness, and material removal rate. All models were found to be significant, with the value of R^2 as 0.9912, 0.9472, and 0.9758, respectively.
- Taguchi-Desirability Function Analysis confirmed the optimum machining parameter as 800 rpm, 0.12 mm/rev, and 0.7 mm ($v_2 - f_2 - d_2$) at a desirability value of 0.844.

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