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ORIGINAL ARTICLE

Multi-responses optimization in dry turning of a stainless steel as a key factor in minimum energy

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Abstract

The machining of stainless steel is of interest because of its corrosion resistance and high strength. Usually, this process involves the application of cutting fluids, which negatively affect the environment, ecologic, and health impacts. Therefore, dry machining is the optimum solution, when applicable. Moreover, due to the high cost of cubic boron nitride (CBN) cutting edge, the improved performance is important for hard finish turning. Reducing energy consumption under dry condition should consider for sustainable machining. This study aims to optimize machining parameters (i.e. power consumption and surface roughness) of stainless steel 316 with CBN tool under dry conditions. A multi-responses based on response surface methodology with Box-Behnken design (BBD) was employed to optimize machining parameters. A compound desirability function was applied to determine optimum levels and contribution of parameters. A validation test was conducted to confirm results. This combination of parameters resulted in the minimum power consumption of 6.78% and decreased surface roughness by 13.89%. This method also effectively reduces the environmental effects in terms of noncutting fluid use and less energy required which is affected in sustainable of machining.

Keywords Turning machine · CBN · Multi-responses · Power consumption · Surface roughness

1 Introduction

The cutting process must be attention to sustainable of operation and product through developing approaches to eliminating or lowest environmental impact possible by using different techniques. Sustainable manufacturing is concerned about environmental, cost aspects, energy, and worker health. Machining fluid is one of the most factors influencing environmental and worker health. A common practice in machining process is using fluids, but lubrication-based oil is considered the unsustainable factor of cutting processes [1]. Moreover, the maintenance of lubrication system, power consumption, and waste/disposal of cutting fluids, which lead to growing environmental issues and increasing cost [2]. For sustainability in manufacturing, cryogenic is one of the solution [3]; it assists manufacturing processes to become environmentally toxic-free [4], and have better surface finish [5], but the installing and maintenance of the cooling system, for energy consumption, leads to an increase in manufacturing cost. Dry machining is the optimum solution, when applicable [6]. Therefore, environmentally friendly manufacturing always preferred using dry cutting strategies. Dixit et al. [6] concluded that the dry machining is an eco-friendly technique due to no air and water pollution. Schultheiss et al. [7] stated that the dry machining is a process which can be carried out without cutting fluid and thus is a more sustainable method and easier to collect the chips for waste recycling purpose. Nur et al. [8] investigated the effects of cutting parameters in turning of stainless steel machinability evaluation. Their results show that the optimum cutting parameter combination is at the feed of 0.19 mm/rev and cutting speed of 125 m/min. But, a study on the stainless steel machinability is of interest. This study also toward sustainable on stainless steel machining, the responses for this study include the energy consumption, along with surface roughness. The novelty here lies in establishing a sustainable model for selecting optimum cutting conditions for machining based on minimum energy requirements and high quality simultaneously under environment cutting conditions.

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Besides cutting fluids, machining energy has a negative impact on the environment. It is a very important part of manufacturing sustainability. Therefore, improvement of energy efficiency is one of the most interests on the world [9]. In 2010, the consumption of energy globally was 524 quadrillions Btu and is expected to increase to 630 quadrillion Btu in the next 5 years [10]. The average released emission from fuel combustion was 9084.6 million metric tons of CO_2 in China in 2015, and in the USA, 4997.5 million metric tons of CO_2 was released with by 27.4% of industry sector contribution [11]. Moreover, increase in the price of fuels and electricity increases production cost. Reducing machine energy is the concern of the industrial processes, but very limited research has been performed considering energy consumption. Usually, the energy consumption is not included in machine responses [8]. The stainless steel is extensively used in many applications [8, 12] such as automotive components (e.g. exhaust manifolds, mufflers and tailpipes, brake tubing, well covers), aerospace (e.g. bolts, nuts, screws), a component of construction, chemical production (e.g. chemical and pulp-handling photographic equipment, brandy vats, fertilizer parts, yeast tube), power plants such as jet engine part, food processing and recently in medical industry, particularly in medical instruments and medical implants, including pins, screws, and orthopedic implants like total hip and knee replacements. The machinability of stainless steel has attracted considerable interest because of its high strength and corrosion resistance. On the other hand, the steel material is considered as difficult to machine due to a high tool wear, work hardening, poor surface quality, low productivity, and high machining costs [13]. In machine performance, cutting tool should be considered in terms of quality, production rate, and cost. Cubic boron nitride (CBN) inserts are usually used on hard steel machining to achieve high accuracy of the surface. CBN tools are advanced cutting tools when machining heat-resistant alloys [14], chemical stability at high temperatures, hardness, and toughness. The cutting tool cost is around 4% of the total manufacturing cost [12]. Due to the high cost of CBN cutting edge, the performance of significant is important for hard finish turning. Some works have been done in the hard material to investigate the machine performance of CBN insert under different cutting conditions [15–17].

The optimization of cutting parameters helped toward decreasing the energy consumption and enhancement of sustainablility [18, 19]. Therefore, the selection of optimum machining parameters contributed to reducing the machining energy [20], ensuring the quality [18], and increasing the tool life and production rate. A single-parameter optimization is limited to fixing optimum cutting parameter value, and it just determined the values of a controllable parameter that produces the highest value of a particular response, such as surface finish quality. Consequently, the multi-response optimization proposed in this study is necessary to consider the trade-off for a balance of process efficiency and environmental issues, it makes optimization literature similar to a real-world design and practice, which not only one but a few objectives that must be considered simultaneously. There are several empirical multi-response optimization techniques studied, such as the Taguchi method, response surface methodology (RSM), and other statistical designs. Among them, RSM is a widely accepted multi-optimization method because it is very effective in identifying overall trends, easily applicable, and saving time and cost by reducing a number of runs. Box and collaborators developed RSM method [21]. Rao in 2014 [22] concluded in an optimization review that the RSM techniques and Taguchi methods are mostly used in optimization machining processes. One of the multi-objective approaches is desirability function which is related to the larger value the better. This approach aims to find the optimum settings of input parameters that lead to achieving the objective function of the cutting process.

Many previous studies reported the effects of cutting parameters on traditional objective optimization (i.e. surface roughness, cutting force, material removal rate, and tool wear). And, most of that research optimized based on single-objective. Usually, single-objective approaches are used to determine the optimal value of a particular response and limited to fixing optimum cutting parameters value. Additionally, steel material often machined under lubrication condition. Moreover, due to the excessive cost of CBN cutting edge, the improved performance is important for hard finish turning by selecting the desired parameter conditions. A few studies have investigated power consumption combined with other responses to machining of stainless steel material under dry condition. Therefore, due to the prohibitive cost of using cutting fluid, CBN cutting edge, and machine energy and their human/environment impacts, this study contributes to energy saving, an important consideration in sustainable multi-responses. It reports the effects of sustainable factors on sustainable cutting conditions (i.e. dry cutting). It aims to optimize machining parameters (i.e. power consumption and surface roughness) of stainless steel 316 and improve the performance of CBN tool under dry conditions. This work makes an important contribution to manufacturing for the reduction of energy and machining costs, consequently improving cutting process sustainability. This study proposes to evaluate the contribution of cutting parameters during machining turning of AISI 316 steel on the energy consumption and surface roughness under dry condition. Three cutting parameters namely cutting speed, depth of cut, and feed rate were optimized to reduce energy consumption and surface roughness during the turning of AISI316 under environment cutting conditions using multi-response optimization based on response surface methodology with Box-Behnken design (BBD). Desirability function was performed to determine the optimum values of cutting parameters to minimize power consumption and surface roughness. This study attempts to present a sustainable model for selecting optimum cutting conditions for machining on the basis of minimum energy requirements and high quality.

2 Experimental details

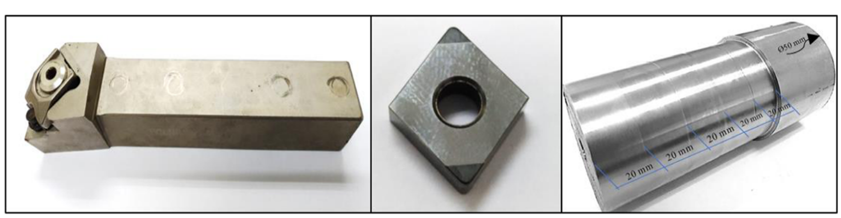
2.1 Work piece materials

The workpiece material used in this investigation is a cylindrical of stainless steel 316 with the axial length of 100 mm, the diameter of 50 mm, and the machining length of 20 mm (Fig. 1). The composition of the stainless steel 316 is tabulated in Table 1. The CBN cutting tool used for this study (Fig. 1) was designated as ISO CNMG 120408, with 80° diamond sharp and 0° relief angle. A fresh insert was used for each experiment in order to improve the reliability and ensure the accuracy of results. The tool holder details and other cutting condition are also shown in Table 1. The turning process was performed in the environment condition without cutting fluid used.

2.2 Method

The turning experiments were performed using CNC lathe ROM 240 with (100 to 4000 rpm) a spindle speed range. Power Meter KEW6300 was used to measure the power consumed at the main power, the spindle drive, and axis drive. The total machining energy can be calculated by the following components: energy of setup, energy of spindle rotation without cut, energy of cutting stage, and energy consumed during tool change. In practice, the energy consumption of setup, spindle rotation without cut, and tool change do not heavily depend on cutting parameters. For simplification, the above three energy consumption components are assumed to be constant for all runs. Therefore, the energy optimization objective which this paper focuses on is the energy during cutting; it evaluates from the energy consumed for material removal. Three voltage wires are connected from the three phases in turning machine to voltage input terminal and clamped with correct direction of clamps sensor to electric wires tidily. Then, the power consumption was recorded when the automatic cutting button was switched on until finished automatically. After connecting all wires properly and ensuring safety, the instrument turns on and the function switch on the instrument was turned in to value measurement with (Whr) unit. The value start recorded with machining start, simultaneously. Each data point was stored and transferred to a PC. Surface roughness was measured with a portable surface roughness tester (Mitutoyo Surftest SJ-301). Specifically, measuring a range of X-axis for roughness tester is 12.5 mm, measuring force (90°) is 4 mN, and measuring speed in ranges 0.25–0.5 mm/s, which are enough to indicate the surface roughness value for that cutting length. Figure 2 shows the set of experiments and analysis.

The experiments were conducted according to the Box-Behnken design (BBD) matrix and responses as shown in Table 3. BBD and central composite design (CCD) are the most popular RSM. BBD is slightly more efficient than CCD but much more efficient than the full factorial designs. The number of trials required for the development of BBD is defined as $N = 2k(k - 1) + C_0$, whereas for CCD, the number of experiments for a central composite design is $N = 2^k + 2k + C_0$, (where k is a number of factors and C_0 is the number of central points). BBD is a class of rotatable or closely rotatable second-order designs based on three-level incomplete factorial designs. It is very flexible and efficient in different experimental regions and provides considerable experimental information; it is a simple scale for transforming original variable value measurements. Three levels for all variables are studied in BBD. Each of these values is represented as a code (− 1, 0, + 1), and it is composed of two parts: the central point and the middle points of the edges. This is classified of design points called space type. Therefore, the high value of the original variable is represented by (+ 1) and the low value is represented by (− 1). The (0) value represents the average of these two values. The design of BBD and optimization by desirability function approach was performed with Design Expert V.10 to optimize the cutting parameters. In this trials, three influence cutting parameters which are cutting speed (v_c) with the three levels of (110-140-170 m/min), feed rate (fr) at (0.1-0.15-0.2 mm/rev), and depth of cut (dc) at (0.8-1.25-1.4 mm), the independent variables and their related levels and output variables are presented in Table 2. The parameter ranges were selected from the Korloy handbook [23] and based on initial experiment. Previous hard machining works [8, 24]



(a) (b) (c)

Fig. 1 **a** Tool holder. **b** CBN insert. **c** Workpiece

Table 1 Workpiece and cutting tool characteristics

Workpiece	AISI316 steel			Material	Wt.%
				C	0.078
				Si	0.337
				Mn	5.81
				Ni	3.68
	axial length	Diameter	machining length	S	0.29
				Cr	18.28
	100 mm	50 mm	20 mm	Mo	0.049
Cutting tools	CBN, 92.4 + 1 HRA			Young's modulus	Tool geometry
				47 (10^3kgf/mm^2)	CNMG 120408, 80° diamond sharp and 0° relief angle
Tool holder	BCLNR2525M12				

have used similar parameter ranges to investigate similar responses. In the present research, multi-objective based on response surface methodology (RSM) with Box-Behnken design was selected. A series of 17 experiments includes five center points which were formulated to carry out experimental work. The responses determined during the experiments were the power consumed during cutting process PW (Whr) and the average surface roughness R_a (μm). The trials were repeated three times and the average value was used in the evaluation. For measurement, the average value of surface roughness was used in the evaluation and every data recorded by power meter was repeated three times during the cutting stage to obtain accurate power measurement. To ensure the accuracy and repeatability of the data, two different methods used to verify the results, which are a standard error (SE) calculated based on predicted test and the initial value based on the optimum points. Figure 3 shows the procedure of this study.

3 Result and discussion

3.1 Evaluation of parameters effect

Experimental design and results by BBD matrix are presented in Table 3. The main and interaction effect plots for power consumption (PW, Whr) and surface roughness average (R_a, μm) with respect to all cutting parameters: Cutting speed (v_c, m/min), feed rate (*fr*, mm/rev), and depth of cut (*dc*, mm) are presented in this section.

As shown in Fig. 4, the residual versus run number plot exhibits a consistency and small variance across each

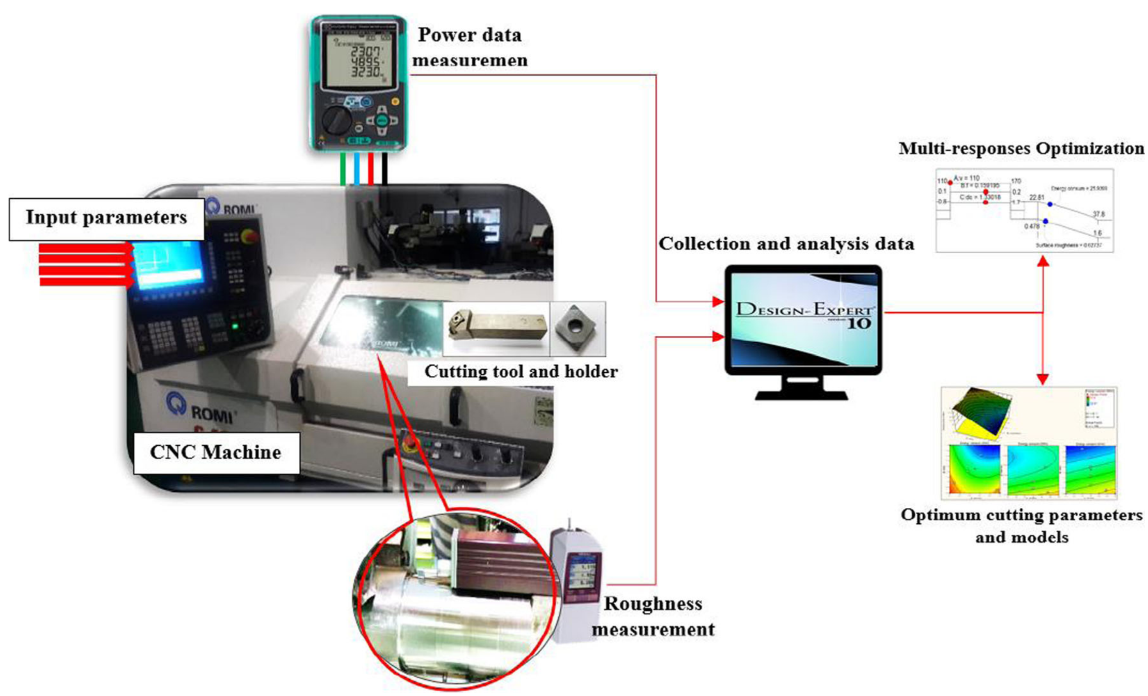


Fig. 2 Experimental and analysis setting

Table 2 Design of input and output parameters

No.	Factors	Unit	Symbol	Type	Low level	Mid-level	High level
Input parameters							
1	Cutting speed	(min/m)	A	Numerical	110	140	170
2	Feed rate	(mm/min)	B	Numerical	0.10	0.15	0.20
3	Depth of cut	(mm)	C	Numerical	0.80	1.25	1.70
Output parameters							
1	Power consumption	(Whr)					
2	Surface roughness	(μm)					
Cutting condition					Dry cutting		

treatment. There is no evidence to show the process being drifted. It is useful to determine the reliability of result and the skillfulness of an experimenter in conducting the experiments. The plot shows a random scatter residuals confined between specified domains and not exceeded it, which indicates the model accepted for validation. The residuals are randomly positioned on the up and downside of straight center line. The residuals approximately normally lie between − 2 and 2 for responses. Therefore, the errors are normally distributed.

To confirm and check for normality assumption, a normal probability plot of the residual can be plotted. In the analysis of variance, it is usually more effective to do this with residuals. If the underlying error distribution is normal, this plot will resemble a straight line. As indicated in Fig. 5, the largest residuals are not quite large as expected. No outliers are found and deviations from the linear are very minor so that the experiment provides a desirable value which can satisfy the normality assumption.

3.2 Analysis of variance (ANOVA)

Checking the normality is important in the ANOVA analysis. If the data is not normally distributed, the cause for non-normality should be determined and appropriate remedial actions should be taken. Data transformation also is known as Box-Cox power transformation, one of these remedial actions that may help to make data normal. It involves a procedure to identify an appropriate exponent (Lambda = 1) to use to transform data into a normal shape. In Fig. 6, the Lambda value indicates the power to which all data should be raised. The Box-Cox power transformation searches from Lambda − 3 to Lambda 3 until the best value if found. The lower and upper confidence levels show that the best results for normality were reached with Lambda value between − 2.6 and 2.76 for energy consumption and − 1.1 and 1.72 for surface roughness. The current value is 1 which lies between the confidence levels. Therefore, there is none recommended transformation needed which indicate that it is normally distributed. Here, the design

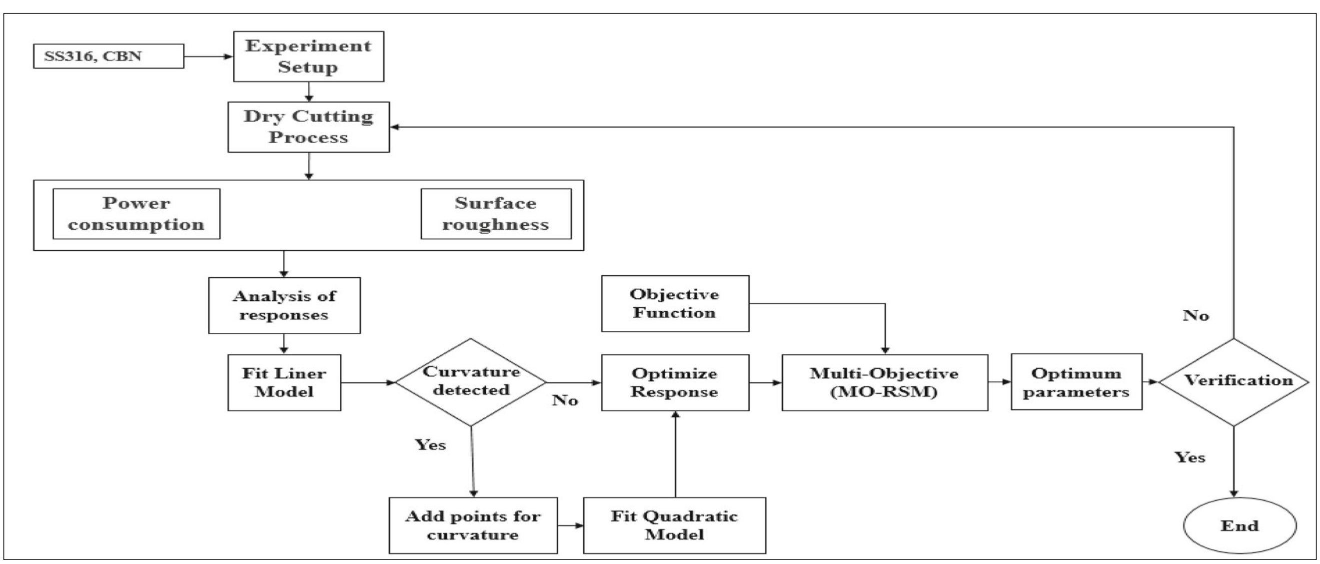


Fig. 3 Flow chart of experiments and analysis

Table 3 Results of the experiment by Box-Behnken design matrix

Std. order	Input variable			Output variable	
	A:vc (m/min)	*B:fr* (mm/rev)	*C:dc* (mm)	PW (Whr)	R_a (μm)
1	110	0.1	1.25	32.6	0.478
2	170	0.1	1.25	35.51	0.965
3	110	0.2	1.25	25.65	0.64
4	170	0.2	1.25	30.28	1.331
5	110	0.15	0.8	34.11	0.491
6	170	0.15	0.8	37.8	0.924
7	110	0.15	1.7	23.5	1.37
8	170	0.15	1.7	22.81	1.104
9	140	0.1	0.8	36.2	0.845
10	140	0.2	0.8	35.72	1.245
11	140	0.1	1.7	32.8	1.53
12	140	0.2	1.7	23.9	1.6
13	140	0.15	1.25	27.8	0.72
14	140	0.15	1.25	29.81	0.714
15	140	0.15	1.25	26.5	0.741
16	140	0.15	1.25	28.18	0.724
17	140	0.15	1.25	26.9	0.701

expert showing the best lambda are − 0.01 and 0.25 for energy and roughness, respectively.

Table 4 presents the ANOVA data on energy consumption and surface roughness. For energy, the *F*-value model indicates that the model is significant. The ANOVA table indicated that the *v*, *f*, and dc factors were significant on the basis of their *P* values. The interaction between feed and depth of cut and square of feed rate is also considered as significant. The statistical result also showed 90% of R-Square which has high significance and reliability in the estimation of energy consumption efficiency. Additionally, the difference between Pred R-Squared and Adj R-Squared was less than 0.2 that indicated that the models are satisfactory. Other important tests to check the adequacy of the models is lack of fit or

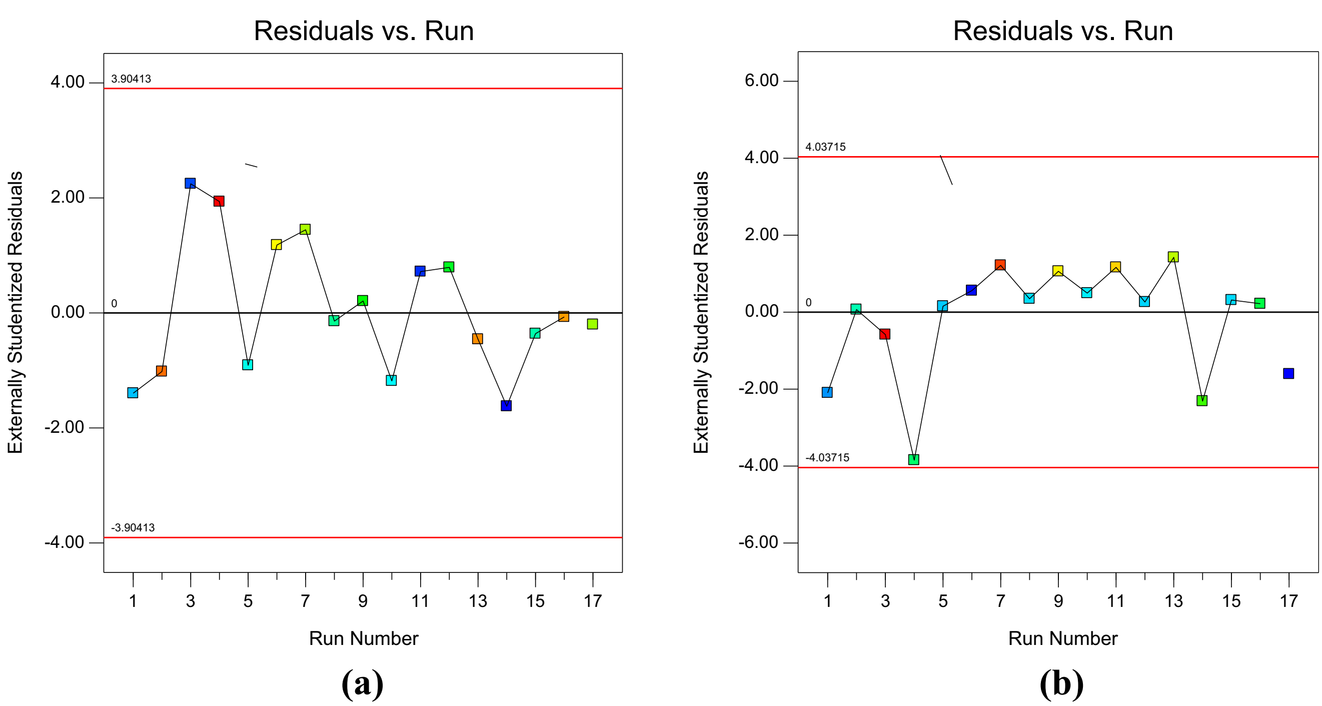


Fig. 4 Residuals vs run plot for **a** energy consumption and **b** surface roughness

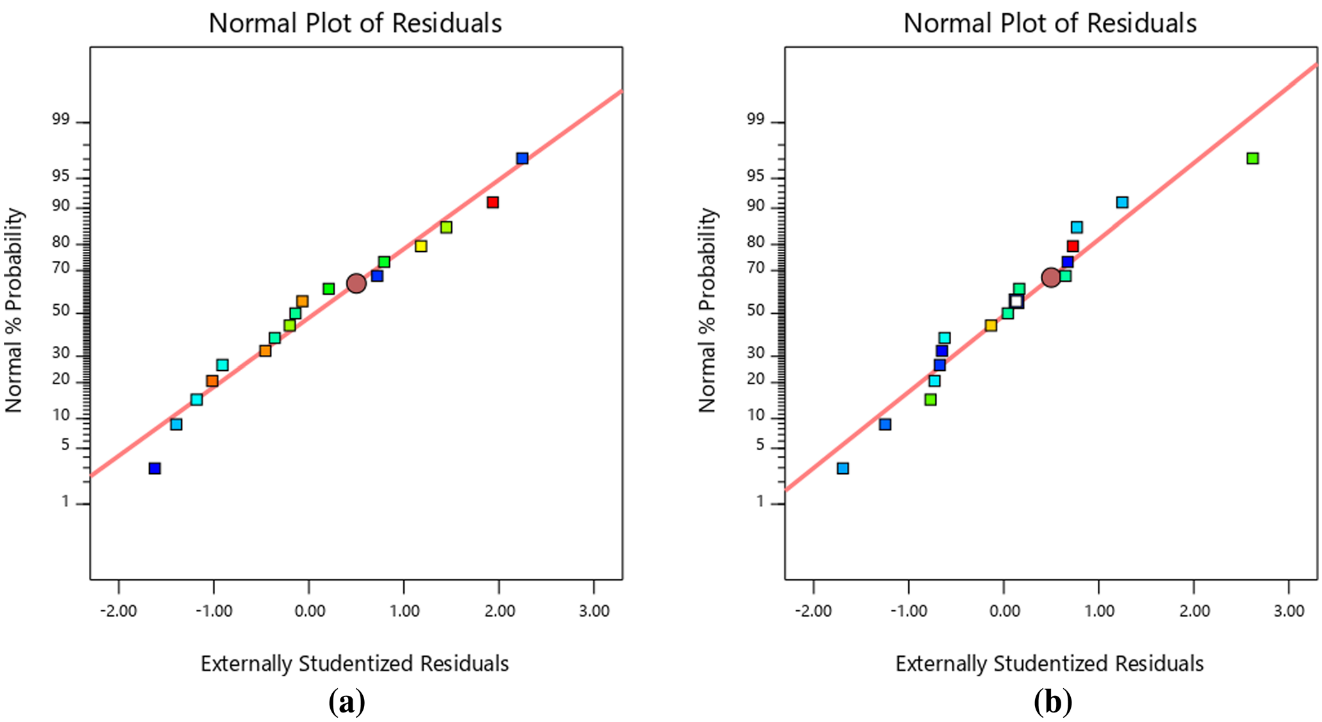


Fig. 5 Normal probability plot of residuals for **a** energy consumption and **b** surface roughness

model noise. Non-significant lack of fit indicates that the model is fit and the possibility of noise is less. For power consumption (Table 4), the lack of fit P value of $0.2042 > 0.05$ indicated that the lack of fit was not significant. The lack of fit for surface roughness, F-value of 3.15, implies that the lack of fit is not significant. Based on the model, only < 0.0002% chance existed that this extremely high F-value occurred because of noise. The feed rate and depth of cut and their square were significant parameters on surface roughness. A liner effect of cutting speed and its interaction with depth of cut was considered. A high R-Squared coefficient of 0.896 ensures a satisfactory agreement between the calculated and observed data.

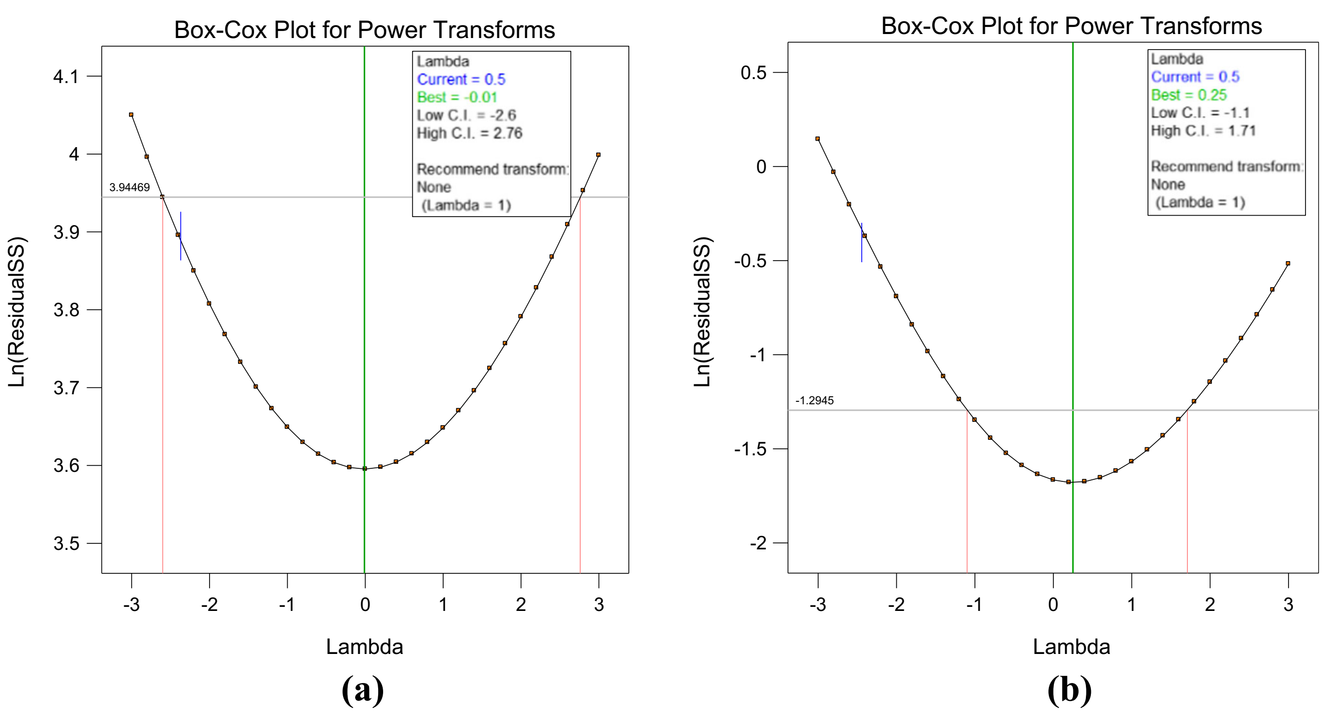


Fig. 6 Box-Cox diagram for **a** energy consumption and **b** surface roughness

Table 4 ANOVA analysis data and regression model

Responses	ANOVA value	Factors and their interaction: *model*	*v*	*f*	*dc*	*v* × *dc*	*f* × *dc*	f^2	dc^2	Lack of fit
Energy consumption	*F* value	19.94	3.76	17.29	61.79	–	5.62	11.2	–	2.43
	P value	< 0.0001	0.0001	0.0001	0.0001	–	0.003	0.0001	–	0.2042
Surface roughness	*F* value	14.42	14.50	5.98	24.74	6.80	–	9.28	23.49	3.15
	P value	< 0.0002	0.0014	0.0245	0.0006	0.0162	–	0.002	0.0007	0.062
	Regression model						R-Square		Ad-R-Square	Pr-R-Square
Energy consumption	$Sqrt(Energy) = 7.635 + 3.848E\text{-}003 \times v - 26.705 \times f + 0.291 \times dc - 8.8704 \times f \times dc + 109.48 \times f^2$						0.9006		0.8554	0.6757
Surface roughness	$Sqrt(R_a) = 0.891 + 0.012 \times v - 11.714 \times f - 0.853 \times dc - 7.0424E\text{-}003 \times v \times dc + 43.252 \times f^2 + 0.849 \times dc^2$						0.8964		0.8343	0.6240

Based on ANOVA data presented in Table 4, the mathematical functions of energy and surface roughness were developed.

Figure 7 discusses the effect of cutting parameters on the power consumption using CBN insert. The perturbation plots one of the most plots recently used that helps understand the relationships among factors and compare the effects of all the factors at a particular point in the design space. To read this plot, the greater main effect is depicted by a line with a steeper slope for long-range change. In this plot, the main effects on energy consumption were cutting speed, feed rate, and depth of cut with a different contribution. The plot for energy consumption against feed rate and depth of cut shows a negatively significant effect from high to low level, whereas the plots of cutting speed show a positively significant effect. Nevertheless, the plot of cutting speed has a lower slope compared to depth of cut and feed rate. This plot indicated that the depth of cut is highly significant among parameters. Therefore, the value of energy decreased from when depth of cut and feed change from low to high level, whereas cutting speed with low level. To explain that, the higher spindle speed value needed higher power by the motor to rotate the spindle. On the other side, high percentage contribution and parametric analysis revealed that the combination of the high feed rate and cutting depth minimized power consumption. When the values of feed and cutting depth are higher during the cutting pass, the time required to machine the workpiece decreases and the amount of removed materials increase. Therefore, a smaller quantity of energy is consumed to complete the operation. Similar researches [19, 25] concluded the low energy value consumed by low cutting speed value and high value of feed rate.

Figure 8 shows contour and 3D plots of power consumption for dry condition. Based on the perturbation plot, feed rate and depth of cut are most significant on power. Figure 8a shows the 3D square interaction plot of feed rate versus depth of cut, and the speed value is kept in middle level 140 m/min. Figure 8b shows interaction counter plot of feed rate versus depth of cut, and Fig. 8c presents relation between energy and interaction speed and feed, whereas Fig. 8d shows cutting speed versus depth of cut. From this illustration, the minimum power consumption can be reached in the region of 0.16 to 0.2 mm/rev feed rate and depth of cut at 1.6 to 1.7 mm for dry cutting, whereas from 0120 to 110 m/min for cutting speed (Fig. 8c). The liner contour plot of depth of cut versus cutting speed shows the interaction effect of the depth of cut and cutting speed on the power consumption as shown in Fig. 8d. It is seen that minimum speed value and high level of depth facilitate to reach lowest power. Therefore, the desired region to reach minimum power consumption is higher level of feed rate and depth of cut with a lower value of cutting speed.

Figure 9 shows the combined influence of cutting parameters on surface roughness; it shows that the main parameters *v*, *f*, and *dc* were positively significant on surface roughness. A steep curvature shows that the surface roughness is most sensitive to depth of cut, followed by feed rate and cutting speed. Similar

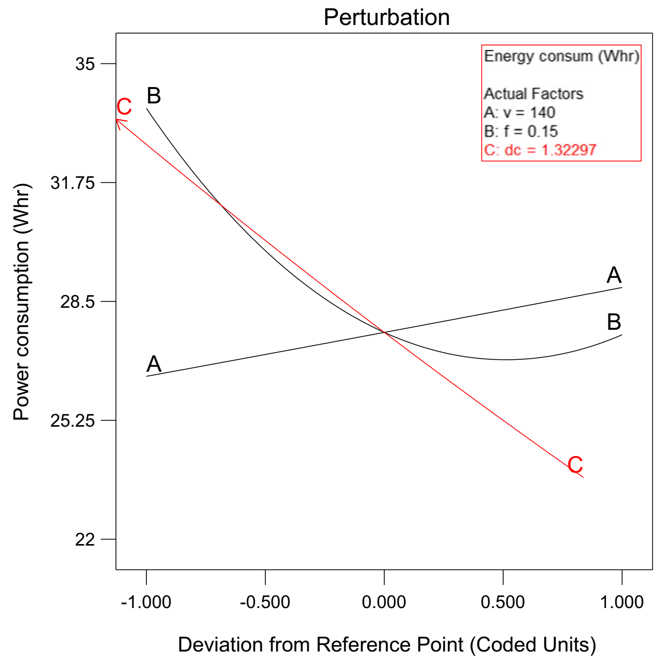


Fig. 7 Main perturbation plots of power consumption (PW) versus parameters

results were reported by Hanafi et al. [26]. The concluded work of Bagaber and Yusoff [20] showed that minimum roughness can be achieved when feed rate is the lowest.

Figure 10 shows 3D and contour plots of surface roughness. It is clearly the high quality of finish surface that can be reached when the input factors are in their lower level.

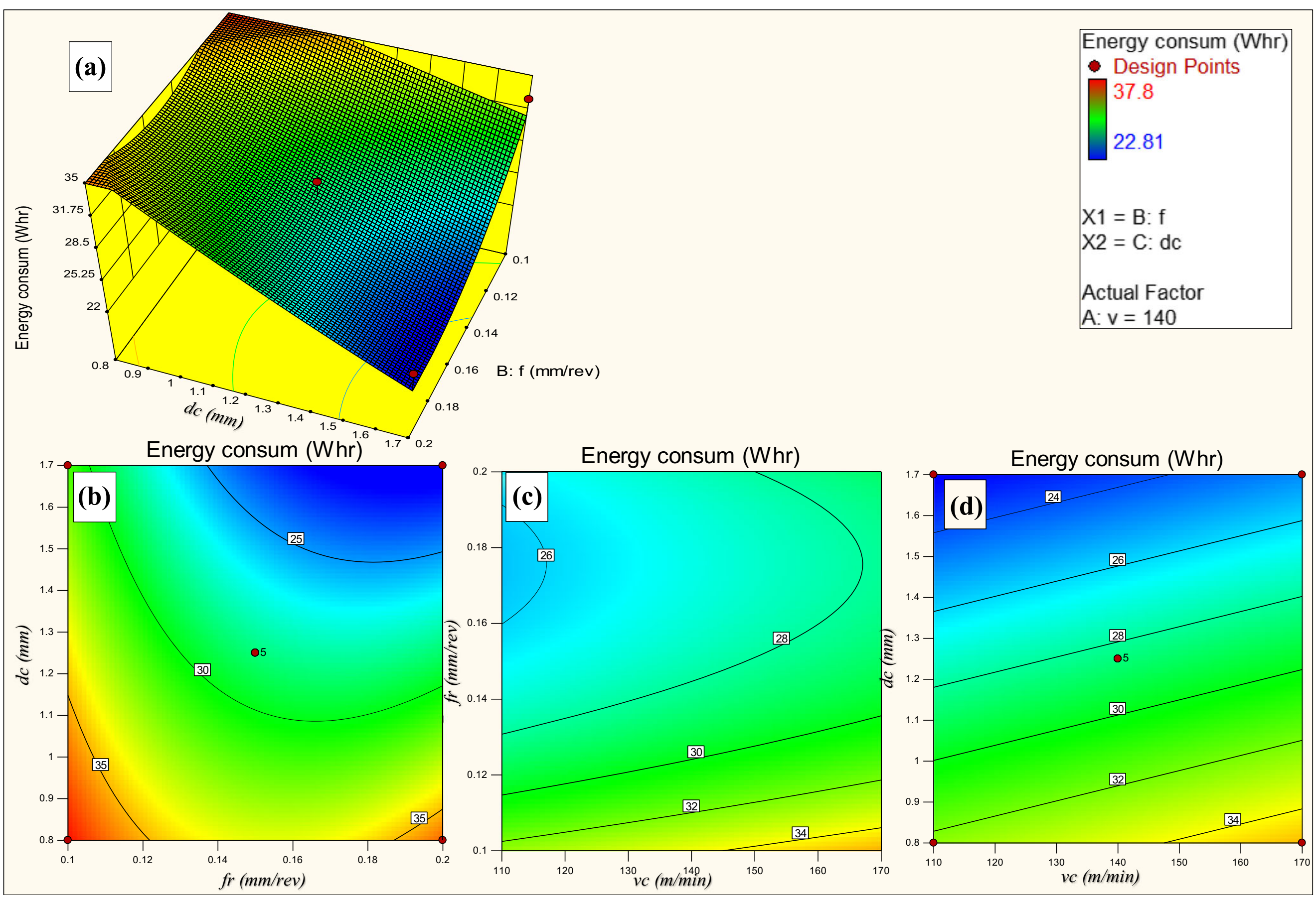


Fig. 8 Counter and 3D plots of energy consumption versus parameters

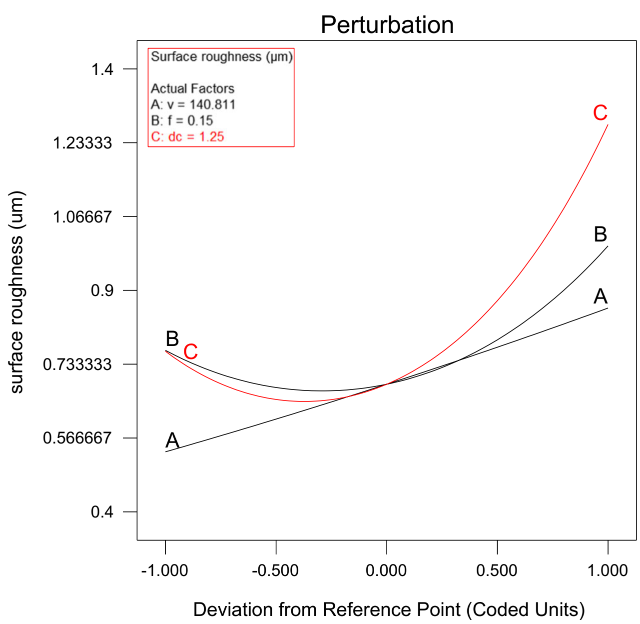


Fig. 9 The main plots of surface roughness (R_a) versus parameters

Figure 10a, b shows 3D and counter plot of square interaction effect of the depth of cut and spindle speed on the surface roughness. Figure 10a shows the 3d plot of cutting speed versus depth of cut, Fig. 10b shows correlation between power consumption and speed versus depth of cut, and fig. 10c presents interaction plot of speed and feed, whereas fig. 10d shows counter plot of feed versus cutting depth. It shows the depth of cut as the most contribution factor on the response. It is seen that low level of depth of cut and cutting speed achieved lower roughness. The best rang with smallest surface roughness are 0.12 to 0.14 mm/rev of feed rate and cutting speed less than 120 m/min (Fig. 10c), whereas for interaction effect of the depth of cut and feed rate, the values are (0.8–1.2 mm) depth of cut and (0.12–0.16 mm/rev) feed rate (Fig. 10d).

3.3 Multi-optimization of parameters

Multi-responses based on RSM were conducted to identify the optimum cutting parameters. One of the multi-objective approaches is desirability function which is related to the larger value the better. This approach aims to find the optimum settings of input parameters that lead to reduce the energy and improve quality of steel cutting process. Desirability analysis was performed on the calculated power consumption and surface roughness with desirability function. Table 5 presents the

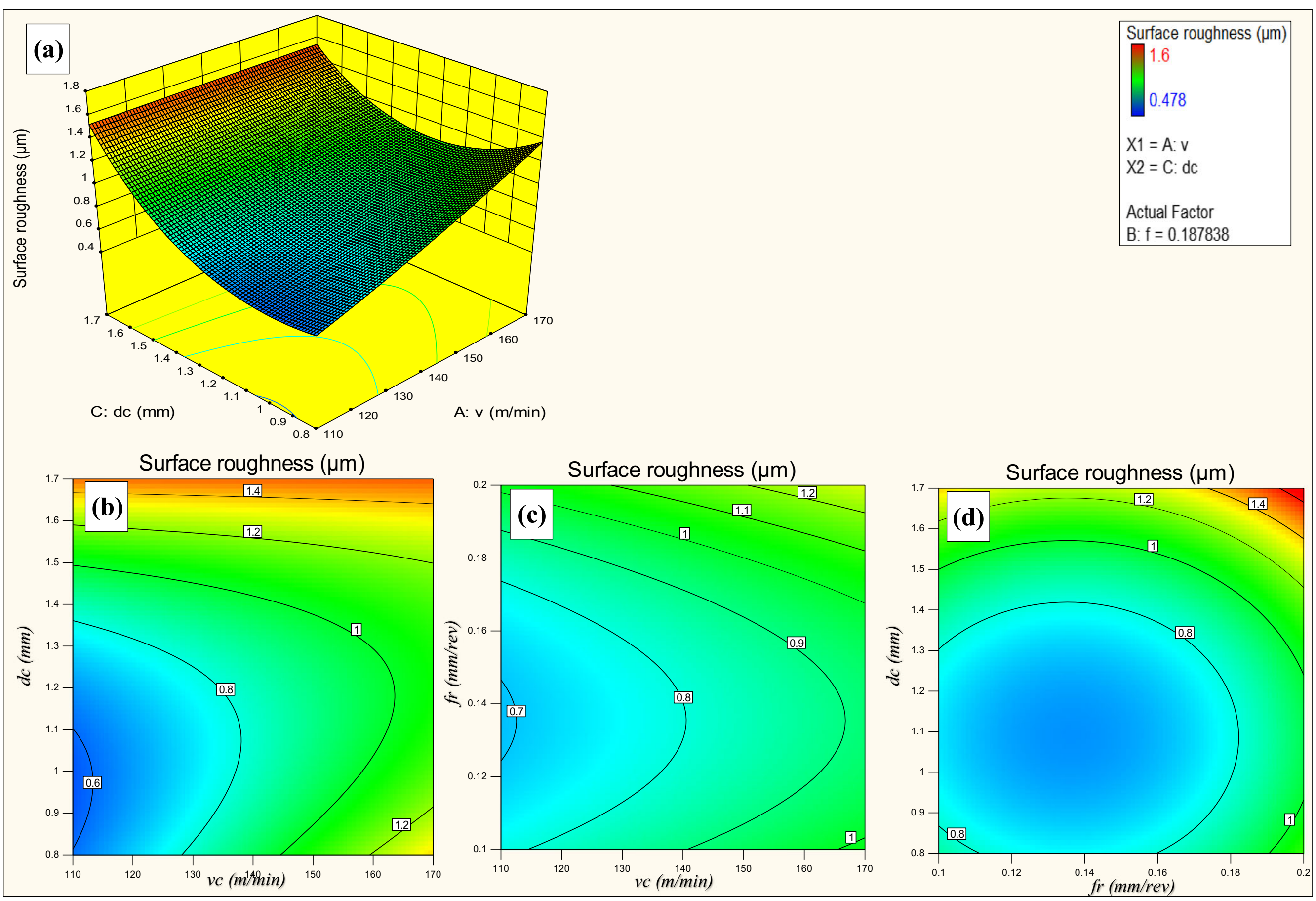


Fig. 10 Counter and 3D plots of surface roughness versus parameters

Table 5 Optimum condition for response optimization

Responses	Goal	Optimum setting			Lower	Satisfy response value	Upper	Individual desirability
		v (m/min)	*fr* (mm/rev)	*dc* (mm)				
PW (Whr)	Minimum	110	0.159	1.33	22.81	25.91	37.8	82.9%
R_a (μm)	Minimum				0.478	0.62	1.6	86.6%

criteria and constraints for multi-responses optimization. The cutting condition of input parameters was select in the range. Moreover, the objective setting was reduced power consumption and surface roughness. Table 5 shows also individual desirability value of each response.

Figure 11 shows the desirability ramp function graph for an optimum solution. The factor setting is shown in the first three straight line, and the optimal expected response values are shown in the slop down line. The desirability graph provides a graphical view of the change responses (i.e. power consumption, surface roughness) based on optimum parameter change. It shows the optimum condition of parameters that were ($v = 110$ m/min, $f = 0.159$ mm/rev, and $dc = 1.33$ mm) to reach power consumption at 25.9 Whr and 0.627 μm of surface roughness.

Table 6 shows the results of the desirability analysis. The solutions with desirability values close to 1 are the best options. Five closer results were selected of 15 total desirable values. Therefore, any of solutions 1, 2, 3, 4, or 5 can be selected. Solution 1 was selected for levels of the cutting parameters, which were 0.845 because of the high desirability value and predicted the lowest possible combined values of power consumption and surface roughness.

4 Discussion

Confirmation testing was employed to verify the obtained optimum point of parameters. Two different methods used to verify the results, which are [3] standard error (SE) calculated based on predicted test and the initial value based on the performance of CBN tool.

In order to verify the model developed by multi-objective RSM, the equation below has been employed to estimate the optimum predicted response values as follows:

$$Y_{predicted} = Y_{mean} + \sum_{i=1}^{n} (Y_i - Y_{mean})$$

where Y_{mean} is the overall mean value and Y_i is the average response at the optimum design variable level. Table 7 shows the obtained verification results, it clearly notices the good agreement between the predicted and experimental optimum results.

In the second confirmation method, the average value of center point was selected for the initial setting. The initial cutting parameters were as follows: cutting speed 140 m/min, feed rate 1.15 mm/rev, and depth of cut 1.1 mm. The responses were obtained from this average value compared with the response values obtained using the optimal parameter settings identified by the multi-responses based on RSM approach. The experimental results were provided to confirm the effectiveness of this technique. The confirmation results were obtained with the optimum parameter setting for power consumption, and surface roughness shows better than the results from the initial parameter set as shown in Table 8.

According to the analysis above, it is found that energy proportionately increases with an increase in spindle speed and decrease with an increase in both feed and depth of cut. Increases in the depth of cut and feed rate achieved minimum energy required, which is leading to decrease the time required to complete the operation machine and increases the amount of removed materials from workpiece. Moreover, the interaction analysis graphs suggested that employing lower cutting speed with a high depth of cut and feed rate can reduce power

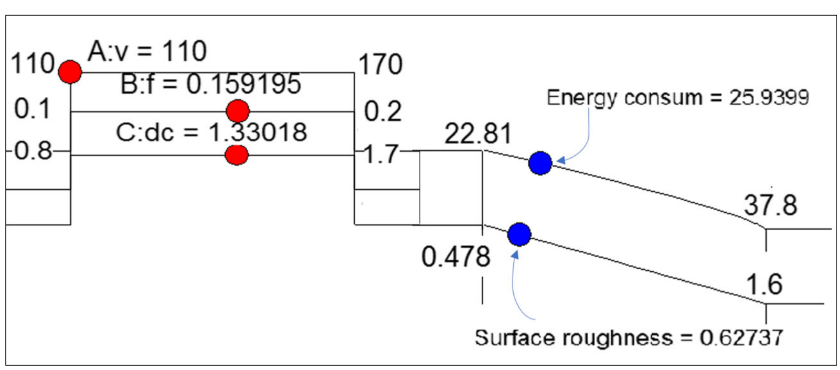


Fig. 11 Desirability ramp function graph of parameters

Table 6 Solution of optimum cutting parameters by desirability value

Solution	v	fr	dc	PW fit	R_a fit	Composite desirability
1	110.000	0.159	1.330	25.910	0.627	0.845
2	110.000	0.160	1.331	25.943	0.630	0.845
3	110.000	0.161	1.354	25.599	0.659	0.844
4	110.000	0.157	1.299	26.389	0.591	0.844
5	110.000	0.164	1.317	25.946	0.632	0.843

Table 7 Verification results based predicted test

Machining response	Experimental value	Predicted value	Error	Accuracy %
Power consumption (Whr)	28.4579	28.4296	0.0283	99.8%
Surface roughness (μm)	0.688211	0.682892	0.005319	99.2%

consumption. For surface roughness evaluation, surface roughness almost increases as cutting parameter increasing. It shows that there is positive relationship between surface roughness and the cutting parameters. Higher feed rate values lead to high temperature at the tool-chip interface which causes adhesion, and abrasion of tool defect and a high temperature occurs rapidly at workpiece which causes the high value of roughness. Due to this damage of tools, the surface roughness was influenced accordingly. For the same reasons, high depth of cut leads to high roughness which is related to continuous chip formed that affected to increase of temperature in the workpiece and tool interface which is increase friction. Moreover, surface roughness increase ranges from 0.8 to 1.2 μm when increase of speed to 170 m/min means no more effect on surface roughness compared to others parameters. The interaction relation of feed rate and depth of cut shows direct proportion high change of roughness value. Therefore, the performance of CBN cutting tool shows better with lowest value of feed and depth of cut. The similar results were reported by [26, 27]. A single-parameter optimization is limited to fixing optimum cutting parameters value, and it just determines the values of a controllable parameter that produces the highest value of a particular response, such as surface finish quality. Therefore, the multi-responses optimization proposed in this study is necessary to consider the trade-off for a balance of process efficiency and environmental issues. Accordingly, the optimum cutting condition for this study was found at 110 m/min cutting speed, feed rate at 0.159 mm/rev, and 1.33 mm of depth of cut with power consumption 25.91 Whr and less value of the surface roughness (0.62 μm) for dry condition. Considering both responses, it can be concluded that the performance of CBN insert under dry cutting condition can minimize the power consumption with acceptable quality. It is a good technique of environmental machining without fluid impact. The optimum parameters selected help to reduce the effect of issues associated with the dry machining such as tool life, cutting temperatures, and thermal damage to the workpiece.

Some previous literature's approaches have been discussed to support the significance of this study as benchmarks. Negrete [25] investigated on AISI 6061; his study aims to minimize power consumption and roughness, and he used the S/N ratio to analyze an optimum range of the cutting parameters. But, energy and surface roughness objectives were evaluated separately. In our research, the RSM with BBD design allowed to optimize the two responses (energy consumption and surface roughness) simultaneously. Khamel [28] investigated the effects of cutting parameters on performance of CBN tool by multi-response considerations during

Table 8 Results of validation of responses

Parameters	Initial value	Optimum value	Power consumption (Whr)		Surface roughness (μm)	
			Obtained from initial value	Obtained from RSM analysis (confirmation experiment)	Obtained from initial value	Obtained from RSM analysis (confirmation experiment)
Cutting speed (v)	140	110	27.8	25.913	0.72	0.620
Feed rate (f)	0.15	0.159				
Depth of cut (dc)	1.1	1.33				
Error			1.88		0.1	
% Improvement			6.78		13.89	

machining of AISI. The results show that cutting speed and feed strongly effect surface roughness. In their study, the confirmation test was based on predicted test. In the current study, two confirmation tests were applied initial condition approach and standard error test; the multi-response result showed an improvement of 13.89% for surface roughness. The research [29] aims to minimize surface roughness and power consumption using multi-objective grey analysis. Their results show an improvement of 2.65% in surface roughness and 6.59% in energy, whereas for the current study, an improvement of 13.89 and 6.78% in surface roughness and power consumption, respectively. The significant factors contributing are similar for both studies. In the previous research [8], power consumption in machining SS 316 L was evaluated by studying the effects of feed and speed, while the depth of cut was constant. The optimum combination result is at feed of 0.19 mm/rev and cutting speed of 125 m/min, but no verification test has been done. In the present study, the most significant factor in power consumption is the depth of cut.

5 Conclusions

The performance of CBN inserts study under dry cutting stainless steel on the minimum value of energy and surface roughness was evaluated. The results indicated that stainless still can be machined under a dry condition with low power consumption and roughness. The plot graphs clearly show that the minimum value of energy consumption of the cutting process was obtained at the lowest cutting speed value and at the high values of feed rate and depth of cut. The factor with the most significant influence on surface roughness was feed rate. Results of multi-responses based on RSM approach showed an improvement of power consumption under dry condition with 6.78%, whereas for surface roughness showed better with 13.89%. The CBN tools under dry cutting can be used to reduce the environmental impacts in terms of no cutting fluid use and less energy required which is affected in machining productivity and profit.

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