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Research Article

Turning SKD 11 Hardened Steel: An Experimental Study of Surface Roughness and Material Removal Rate Using Taguchi Method

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Heat-treated steel is widely used in industrial applications due to its high strength and other desirable mechanical qualities. Grinding, which requires a lot of power and is expensive, is typically used to harden machining. In recent times, hard machining has emerged as a viable alternative to grind in select applications. In this investigation, turning operations with a carbide insert (CNMA 120408-KR3215) were carried out on SKD 11 (53 HRC) hardened steel. A total of nine machining tests were completed using the L_9 orthogonal array. The response variables considered in this study were surface roughness (Ra) and material removal rate (MRR). The analysis of the signal to noise ratio reveals that the optimal combination of cutting process parameters for achieving a desired surface roughness consists of a cutting speed of 119 m/min, a feed rate of 0.11 mm/rev, and a depth of cut of 0.2 mm. The contribution of each process parameter to the machining performance of the carbide tool-work piece combination is determined through the use of ANOVA. Depth of cut has the greatest impact (57.33%) to MRR, while feed rate has the highest contribution (82.15%) to Ra. Moreover, desirability function analysis (DFA) was conducted to optimize the multiple responses. DFA suggested that, to attain a satisfactory response to the output parameters, higher range of cutting speed, depth of cut, and lower range of feed rate are appreciable; therefore, the analytical findings suggest that a cutting speed of 189 m/min, feed rate of 0.11 mm/rev, and a depth of cut of 0.5 mm can induce a favorable Ra of 0.971 μm and MRR of 10.248 cm^3/min. In hard machining, cutting speed has a bigger influence on surface finish than feed rate.

1. Introduction

In recent years, industrial sectors have been seeing the rise of novel materials such as alloys and super alloys due to the exceptional material qualities they possess; high-strength steel is frequently utilized in the fabrication of products for the aviation, aerospace, and high-tech equipment industries [1–4]. However, the advent and extensive utilization of high-strength, heat-resistant, and difficult-to-cut materials has posed challenges to manufacturing operations [5, 6]. The development of hard cutting techniques has been driven by the increasing demand for enhanced productivity, ability to respond to complicated parts, elimination of cutting fluids, achievement of excellent surface quality, and the reduction of production costs [7]. The issue of climate change has garnered significant interest from researchers and manufacturers worldwide, particularly in relation to the potential alternative option it offers for many conventional final grinding procedures. The machining of workpieces in these procedures involves the direct utilization of cutting edges that are geometrically specified, with the typical hardness value falling within the range of 45–70 HRC [8, 9].

Turning hardened steel presents a number of challenges, the most significant of which is the accomplishment of superior quality of the product. This may be measured in terms of dimensional accuracy, surface polish, and a high output rate and price [10, 11]. In addition, to guarantee a high level of precision and an excellent surface finish on machined products, choosing the right cutting inserts is always a challenge. Numerous cutting tool advancements have made it possible to execute hard turning on hardened steels using CBN, ceramic, coated carbide, and coated ceramic inserts [12–16]. Due to their high melting point, excellent hardness, and resistance to wear, these inserts are able to withstand the high cutting temperature and cutting speed without failing. Polycrystalline cubic boron nitride (PCBN) and coated mixed ceramic tools have enabled industries and researchers to conduct dry turning operations for hard materials ranging from 50 to 65 HRC to achieve the required quality of machined parts [17–19]. While these advanced cutting tools exhibit high precision cutting capabilities, the manufacturing cost has correspondingly increased [20]. In the field of hard turning, researchers are currently focused on the primary goal of reducing machining costs and enhancing productivity through the reduction of tool wear rates. As a result, there is a growing emphasis on the implementation of environmentally conscious lubrication systems in the context of hard turning [21, 22]. Several researchers have indicated that new cutting fluid techniques such as minimum quantity lubrication (MQL), high pressure cutting fluid application, and spray impingement cooling are considered to be more advanced compared to traditional methods like flooded cooling and dry surroundings [22–25]. The lack of lubricant/coolant during high-speed turning of heat-treated steel results in a chip disposal issue. This issue leads to increased friction at the tool-chip and tool-work interfaces, thus causing faster attrition and tool wear [26]. While a plentiful supply of coolant proved beneficial in reducing friction, it also resulted in increased machining costs and gave rise to certain adverse health effects for individuals [27, 28].

The development of surface roughness and material removal rate is influenced not only by the cutting inserts but also by various uncontrollable factors [29, 30]. Previous studies have demonstrated a strong correlation between the cutting parameters of the machining process and both the surface finish quality and the amount of material removed from machine workpieces [31, 32]. The cutting parameters encompass several factors such as the cutting speed, feed rate, depth of cut, tool geometry, and the material properties of both the tool and the workpiece [33]. Moreover, the diverse permutations of these factors might result in highly distinctive outcomes with regards to the quality of the machined surface and the pace at which the material is removed. The outcomes are influenced by the objective of the machining process and the specific cutting tool employed. Nevertheless, it poses a significant challenge to ascertain the most ideal combination that effectively decreases the roughness value while simultaneously maximizing the rate of material removal [34, 35]. Asilturk and Neseli [36] conducted a study to identify the optimal machining parameters for achieving improved surface roughness in the dry turning process of AISI 304 steel. They utilized a coated carbide insert and employed a response surface methodology to develop a mathematical model for predicting the desired outcome. Their findings indicated that the feed rate was the most influential factor in achieving the desired surface roughness. The study conducted by Tamizharasan and Senthilkumar aimed to investigate the impact of different cutting tool geometries on surface roughness and material removal rate (MRR). The researchers employed Taguchi's technique and analysis of variance (ANOVA) to assess the data [37]. In another study, Kopac et al. conducted an investigation to identify the most favorable parameters for achieving the desired surface roughness during the turning process of C15 E4 steel [38]. They achieved this by manipulating several factors, including the cutting speed, tool and workpiece material, depth of cut, and number of cuts. Additionally, they utilized coated inserts in their experimental setup. Srithar et al. examined how machining parameters impact surface quality when turning AISI D2 tool steel with a polycrystalline cubic boron nitride insert. The workpiece was heat-treated to 64 HRC. The study found that feed rate significantly impacts surface roughness. As feed rate and cutting depth rise, surface roughness increases. Cutting speed significantly impacts surface quality. Increasing cutting speed reduces surface roughness [39].

The investigation of surface roughness and material removal rate in the turning process can be accomplished by employing appropriate models that establish a relationship between the process parameters and the resulting outcome [40–43]. Inconel 718 dry turning characteristics were statistically modeled and optimized by Ramanujam et al. [44]. Turning experiments were conducted at varying degrees of cutting parameters using Taguchi's L_9 orthogonal array to examine performance indicators such cutting force, surface roughness, and tool wear. The efficacy of Taguchi's optimization method was demonstrated by conducting confirmation experiments on the optimal cutting settings. In another work, to determine its machinability, Dutta and Reddy turned a newly created aluminum-manganese (AM) series Mg alloy [45]. In order to optimize the feed, speed, and depth of cut (DOC) of the turning process, the Taguchi method using a L_9 array has been implemented. According to the derived statistical parameters, DOC has the greatest impact on cutting force, whereas feed has the most impact on roughness. Using an experimental, modeling, and optimization approach, Kumar et al. performed the turning of JIS S45C hardened structural steel with a multilayered (TiN-TiCN-Al_2O_3-TiN) CVD-coated carbide insert. They discovered that in the machining of medium carbon low alloy steel, to improve the cutting performance of multifaceted-coated carbide tool to a greater extent [46]. Nalbant et al. utilized the Taguchi technique to discover the best cutting settings for surface roughness in turning AISI 1030 carbon steel. Three cutting parameters insert radius, feed rate, and depth of cut optimized surface roughness [47]. They found that insert radius and feed rate are the key adjustable elements that affect surface roughness. Furthermore, Taylor et al. explored the optimization of a turning process for hardened steel by utilizing the design of experiments (DOE) approach with an orthogonal array to predict the surface roughness [48]. In addition to this, they make use of the analysis of variance (ANOVA) to discover which parameters had the most significant impact on the turning process.

Furthermore, in 2012, Tonk and Ratol determined the parametric effects for turning EN31 alloy steel by applying Taguchi's robust design technique and found that feed rate and depth of cut affect thrust force and feed force, respectively [49]. Taguchi method employs highly fractionated factorial designs in addition to orthogonal arrays. This makes it easier for the experimenter to study the whole experimental region of interest, and in addition to that, the Taguchi technique leads to a lower total number of runs compared to traditional methods of experiment design [50]. In addition to this, it is of the utmost importance to save expenses without compromising the quality of the output. The measurement of surface roughness, which is a key property of surface quality, is often used in the process of evaluating the quality of the surface that has been machined [51]. Kumbhar and Waghmare [52] utilized the Taguchi technique to evaluate the influence of PVD TiAlN/TiN-coated carbide inserts on tool life and surface roughness in hardened EN31 alloy steel during dry turning. They studied machining parameter performance using L_9 orthogonal array, signal-to-noise ratio, and ANOVA and found that feed rate greatly affects surface roughness and tool life. Utilizing advanced optimization algorithms, which assist manufacturers in making informed decisions in the presence of multiple objectives that need to be satisfied, is one way to improve the application of hard-turning technology [8, 53, 54].

The findings of previous studies clearly demonstrate that the selection of machining parameters in hard turning significantly affects both surface roughness and material removal rate. Furthermore, the machining process of hardened steel using a conventional tool such as carbide exhibits significant limitations. To overcome this limitation throughout the duration of this study, the researchers conducted a series of turning experiments utilizing a normal lathe machine. The primary objective was to ascertain the optimal cutting parameters that yield the highest quality cut while employing a carbide tool for the purpose of cutting SKD11 under dry conditions to reduce cost. SKD 11 alloy steel is classified as a tool steel with high carbon and chromium content. Following the process of heat treatment, SKD 11 alloy steel exhibits numerous notable characteristics, including commendable wear resistance, elevated hardness, and enhanced strength. SKD 11 steel is frequently employed as a material for stamping dies, plastic molds, and cold-work dies due to its favorable mechanical qualities. Nevertheless, the material has challenges in terms of workability, particularly following heat treatment. Hence, it holds great significance to conduct research on the efficient cutting techniques employed for SKD 11 steel.

2. Materials and Methods

2.1. Workpiece Material. In the interest of research hardened steel according to the specifications of the Japanese standard SKD 11 (JIS-G4404) was used into a workpiece with a cylindrical shape, measuring 59 millimeters in diameter and 400 millimeters in length. A noncoated carbide tool was employed to eliminate a coating of rust and scales from the surface of the workpiece before commencing the machining process, with the objective of achieving a workpiece diameter to length ratio of 1 : 4 [43]. Tables 1 and 2 provide a comprehensive breakdown of the chemical constituents comprising SKD 11, as well as its corresponding physical properties. The initial hardness of the workpiece was measured to be 20 HRC. Subsequently, a bulk hardening and tempering procedure was employed, resulting in an increase in the workpiece's hardness to 53 ± 1 HRC. This method not only enhanced the toughness of the workpiece but also mitigated its brittleness [57].

The hardening procedures were conducted within the confines of the heat treatment laboratory at the Bangladesh Industrial and Technical Assistance Center (BITAC), as depicted in Figure 1. The CNMA 120408-KR 3215 carbide inserts were employed as the cutting tool for conducting all of the experiments. The photographs depicting the chosen cutting tool can be observed in Figure 2. Carbide tools are widely regarded as the most readily accessible cutting tools within the category of hard cutting tools. In recent times carbide tools are gradually being substituted by ceramic and CBN tools in high-speed cutting scenarios due to their inferior performance. However, carbide tools still possess satisfactory wear resistance and strength, making them suitable for machining SK 11 Material [58, 59]. In addition, carbide tools possess a high degree of accessibility and benefit from a well-established manufacturing process, resulting in a comparatively lower cost when compared to alternative cutting tools. Carbide tools are deemed to be a highly favorable selection for the present investigation.

2.2. Methods

2.2.1. Taguchi Approach. The conventional methodologies for experimental design are excessively intricate and challenging to implement. Moreover, as the quantity of machining parameters escalates, a substantial quantity of trials must be executed. The Taguchi method is a systematic approach utilized for the purpose of experimental design. Utilizing orthogonal arrays offers significant benefits in reducing the number of required tests and mitigating the influence of uncontrollable factors. The utilization of the Taguchi technique offers several notable advantages. First, it leads to a notable reduction in the duration required for conducting experiments. Additionally, it results in a significant decrease in the financial resources expended. Lastly, it facilitates the efficient identification of pertinent factors within a compressed timeframe [60, 61]. In order to satisfy this prerequisite, Taguchi employs a conventional orthogonal array for construction purposes. Furthermore, the selection of the signal-to-noise ratio, also referred to as the S/N ratio, is the preferred quality characteristic. The signal-to-noise ratio (S/N ratio) is utilized as a quantifiable measure in lieu of the standard deviation due to the inverse relationship between the mean and standard deviation.

Indeed, it is worth noting that the target mean value has the potential to undergo changes during the course of process development. The utilization of signal-to-noise ratio principles has demonstrated potential advantages in various applications, including the enhancement of measurement

Table 1: Chemical composition of hardened steel SKD 11 [55].

Chemical composition (wt. %)										
C	Si	Mn	Ni	Cr	Mo	W	V	Cu	P	S
1.4–1.6	0.4	0.6	0.5	11–13	0.8–1.2	0.2–0.5	≤0.25	≤0.25	≤0.03	≤0.03

Table 2: Physical properties of hardened steel SKD 11 [56].

Physical properties	Value
Specific weight (kg/m^3)	4800
Poisson's coefficient	0.3
Melting temperature (°C)	1733
Thermal expansion coefficient (10^{-6}/k)	11
Specific heat (j/kg °C)	461
Thermal conductivity (W/m·K)	20.5

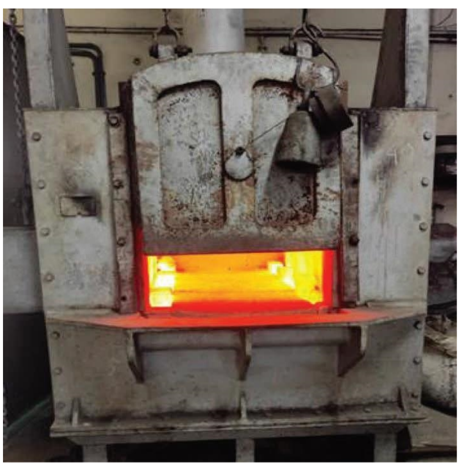

Figure 1: Hardening of material.

Figure 2: CNMA 120408-KR 3215 carbide insert.

accuracy and the reduction of variability to improve overall quality. The characteristics of the signal-to-noise ratio (S/N ratio) can be categorized into three distinct groups according to the mathematical equations.

(i) Nominal the best,

$$\frac{S}{N} = 10\log\frac{\overline{y}}{S_y^2}. \quad (1)$$

(ii) Smaller the better,

$$\frac{S}{N} = -10\log\frac{1}{n}\left(\sum y^2\right). \quad (2)$$

(iii) Larger the better,

$$\frac{S}{N} = -\log\frac{1}{n}\left(\sum\frac{1}{y^2}\right). \quad (3)$$

2.2.2. Analysis of Variance (ANOVA). ANOVA is a significant statistical technique that is utilized to assess the impact of a specific input parameter in a series of tests carried out for the machining process. Additionally, it can be employed to evaluate the outcomes of these experiments [62]. Additionally, this approach can be employed to enhance the machining parameters for turning operations with the aim of achieving optimal outcomes (source). The construction of this expression is designed in a manner that symbolically represents the concept that any function with a high number of dimensions can be broken down into a subset of terms derived from the expansion.

$$f(x) = f_0 + \sum_{i=1}^{p} f_i(x_i) + \sum_{i=1}^{p}\sum_{j=i+1}^{p} f_{i,j}\left(x_i, x_j\right) + f_{1,2,\cdots,p^{(x)}}, \quad (4)$$

where p stands for the number of inputs, f_0 is a constant (bias term), and the other terms on the right-hand side represent the univariate, bivariate, trivariate, etc., functional combinations of the input parameters. When carrying out an analysis of variance (ANOVA), it is important to take into account both the degrees of freedom and each sum of squares [63]. The measurement of the error variance is of utmost significance in ANOVA research involving tests with known errors. Obtained data are used to estimate F value. In an experiment, the amount of variation that can be attributed to each significant factor or interaction is expressed as a percentage contribution. This percentage contribution reflects the relative strength of a factor or interaction to reduce variance. A significant part is played both by the factors themselves and by the interactions between them.

2.2.3. Desirability Function Analysis. According to Myers et al., objective functions (D) with a value (di) ranging from 0 to 1 are what they refer to as desirability functions [64]. With a response surface equation, numerical optimization by desirability function is carried out for the machining responses. The objective of the optimization method is to arrive at the optimal factor settings that result in the maximization of material removal rate and minimization of surface roughness. The function of desirability is given by equation (5), where n is the total number of responses. In this situation, each factor and response are given the same amount of weight. The factors are rated as having a 3 out of 5 importance rating.

$$D = \left(d_1\, x\, d_2\, x, \ldots, x\, d_n\right)^{(1/n)} = \left(\prod_{i=1}^{n} d_i\right)^{(1/n)},$$
$$D = \left(d_1^{r_1}\, x\, d_2^{r_2}\, x, \ldots, x\, d_n^{r_n}\right)^{(1/n)} = \left(\prod_{i=1}^{n} d_i^{r_i}\right)^{1/\Sigma r_i}. \quad (5)$$

2.3. Material Removal Rate. During turning operation, the material removal rate (MRR) refers to the volume of material that is removed per unit time. The material is removed in the form of a ring-shaped layer at the rate of one layer for every revolution of the work piece. Material removal rate is one of the most essential variables that determine the machining process, and it is usually preferable to have a greater rate when doing operations. The equation allows for the determination of the material removal rate in mm^3/s.

$$\mathrm{MRR} = \frac{\pi/4D_0^2L - \pi/4D_i^2L}{L/\mathrm{fN}}, \quad (6)$$

where D_0 and D_i represent the initial and final diameter of the workpiece in mm, respectively. L is the length of the workpiece to be turned in mm, and f and N represent the feed rate in mm/rev and spindle speed in rpm, respectively.

3. Experimentation

All of the turning activities are carried out on a Gap Bed Lathe Machine, which, as shown in Figure 3, is capable of reaching a maximum speed of 1600 revolutions per minute and possesses a spindle power of 7.5 kilowatts. A roughness tester of the stylus type was employed in order to assess the surface roughness of each individual run that was acquired from the experiment depicted in Figure 4. The parameter ranges for the degree of cutting, as well as the starting values for those ranges, were chosen from the manufacturer's handbook based on what was recommended for the material that was being examined [65, 66]. Table 3 provides an overview of various cutting settings together with the degrees of operation that correspond to them. The Taguchi approach and the L_9 orthogonal array were applied in order to cut down on the overall number of tests that needed to be performed. The results of the design of experiments (DOE) that was carried out are detailed in Table 4. There were three different sets of controls utilized during the course of the tests.

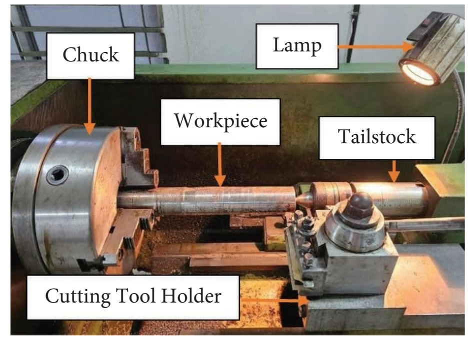

Figure 3: Experimental setup.

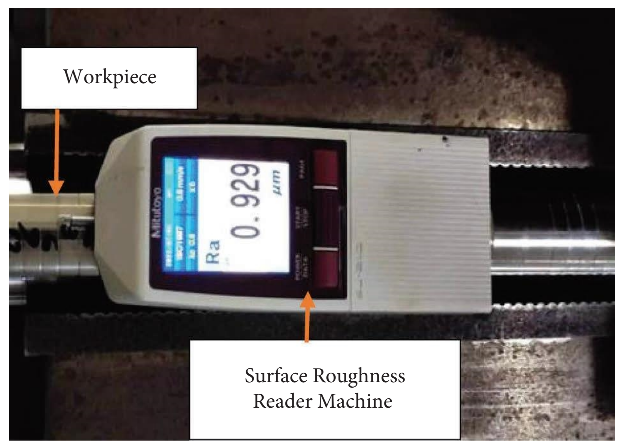

Figure 4: Stylus-type roughness tester.

Table 3: Selected process parameters with different operating levels.

Input parameters	Levels		
	Level 1	Level 2	Level 3
Cutting speed (m/min)	119	151	189
Feed rate (mm/rev)	0.11	0.17	0.20
Depth of cut (mm)	0.2	0.4	0.5

4. Result and Discussion

Finding the ideal settings for the turning parameters (spindle speed, feed rate, and depth of cut) is this research's primary goal. These numbers are targeted to maximize material removal rate and provide a surface with the least amount of roughness possible. Table 5 displays the design of experiments (DOE) that was conducted, including the experimental data for the surface roughness levels and the calculated signal-to-noise ratio. The signal-to-noise ratio (SNR) holds significant importance within the Taguchi technique for the analysis of experimental data because of its efficacy to provide valuable guidance in the selection of the optimal level by minimizing variation around the average value [67]. Moreover, it enables an objective comparison between two sets of experimental data by evaluating the deviation of the average from the target. Based on the principles of the Taguchi Method, quite a few researchers

Table 4: Experimental design using L_9 orthogonal array.

Experiment no.	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)
1	119	0.11	0.2
2	119	0.17	0.4
3	119	0.20	0.5
4	151	0.11	0.4
5	151	0.17	0.5
6	151	0.20	0.2
7	189	0.11	0.5
8	189	0.17	0.2
9	189	0.20	0.4

Table 5: The results of the experiments with S/N ratio values.

Test no.	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	R_a (μm)	MRR (cm^3/min)	S/N ratios R_a	S/N ratios MRR
1	119	0.11	0.2	0.541	2.5821	5.33605	8.2395
2	119	0.17	0.4	1.157	7.9812	−1.26667	18.0414
3	119	0.20	0.5	1.516	11.7370	−3.61398	21.3911
4	151	0.11	0.4	0.691	6.5578	3.21044	16.3352
5	151	0.17	0.5	1.428	12.6684	−3.09456	22.0544
6	151	0.20	0.2	1.415	5.9616	−3.01513	15.5073
7	189	0.11	0.5	1.043	10.2465	−0.36569	20.2115
8	189	0.17	0.2	1.223	6.3342	−1.74853	16.0338
9	189	0.20	0.4	1.527	14.9040	−3.67678	23.4661

recommended that the signal-to-noise (S/N) ratio be maximized for this study to heighten the cutting conditions for optimal outcomes [67, 68].

Figure 5 plot of the S/N ratio illustrates that there is less fluctuation for changes in the depth of cut, whereas there is greater variation for changes in the cutting speed. For surface roughness, it is clearly showing that the optimal level for turning is at the first level of cutting speed, feed rate, and depth of cut. Specifically, this means that the cutting speed at 119 m/min, feed rate at 0.11 mm/rev, and the depth of cut at 0.2 mm are the optimum values of cutting parameters for lowest surface roughens, which is in slight contrast with the results found by Karim et al. [69]. However, Figure 6 plot for the S/N ratio indicates that there is less variance for changes in cutting speed, whereas there is greater variation for changes in feed. In 2011, Akkus conducted a study on hard turning of AISI 4140 grade steed and found that feed rate is the most significant factor for reducing the surface roughness [70].

In addition, when it comes to MRR, the variation in the depth of cut is much more significant than the differences in cutting speed and feed. Similarly, for material removal rate, the optimal level of turning are all at third level. That is, cutting speed at 189 m/min, feed rate at 0.2 mm/rev and depth of cut at 0.5 mm will provide the highest value of MRR. Manikanda with his colleagues performed experimental investigation on EN31 steel by using a diamond shape carbide insert and found that depth of cut is the most promising factor for maximize the MRR followed by feed rate and cutting speed [71].

S/N ratio indicates the importance of each input parameter on the desired outputs. As a higher S/N ratio indicates closer to a higher quality, a bigger S/N ratio is preferable for both the cases. The responses for signal-to-noise ratios obtained from the two sets of data are presented in Tables 6 and 7. Tables 6 and 7 demonstrate that, feed rate ranked 1, trailed by depth of cut which is rank 2 affected the surface roughness significantly, whereas in accordance with the S/N ratio, depth of cut is ranked 1, followed by feed rate at rank 2 to ensure higher amount of material removal.

The analysis of variance (ANOVA) is a statistical method employed to assess the influence of individual parameters within a given process. The acquired data are assessed using the Minitab-19 software and are presented in Tables 8 and 9. The calculation of the mean square involves dividing the sum of squares by the number of degrees of freedom. Similarly, the F ratio is determined by dividing the mean square by the mean square of the experimental error.

According to the results of the analysis of variance (ANOVA) conducted on surface roughness (as presented in Table 8), the F value is determined to be 126.86. Additionally, the contribution of feed rate to the observed variance is found to be 82.15%, followed by depth of cut with 9.16%. The parameter's F value of 8.41 suggests that the cutting speed has a relatively smaller impact on the minimal surface roughness, which can be justified by its lower contribution percentage. The impact of these factors has statistical significance with a p value less than 0.05. These findings indicate that feed rate has a greater influence on achieving low surface roughness, which can be observed in the findings of multiple researchers [72, 73]. Additionally, the R^2 value of the model for surface roughness is 96.76%, suggesting a higher level of reliability and credibility for the model. The first test yielded a minimum surface roughness value of $R_a = 0.541$ m. According to the data presented in Table 8, the F value of 41.02 suggests that the depth of cut is the most influential factor in determining the material removal rate, accounting for 57.33% of the overall contribution. In

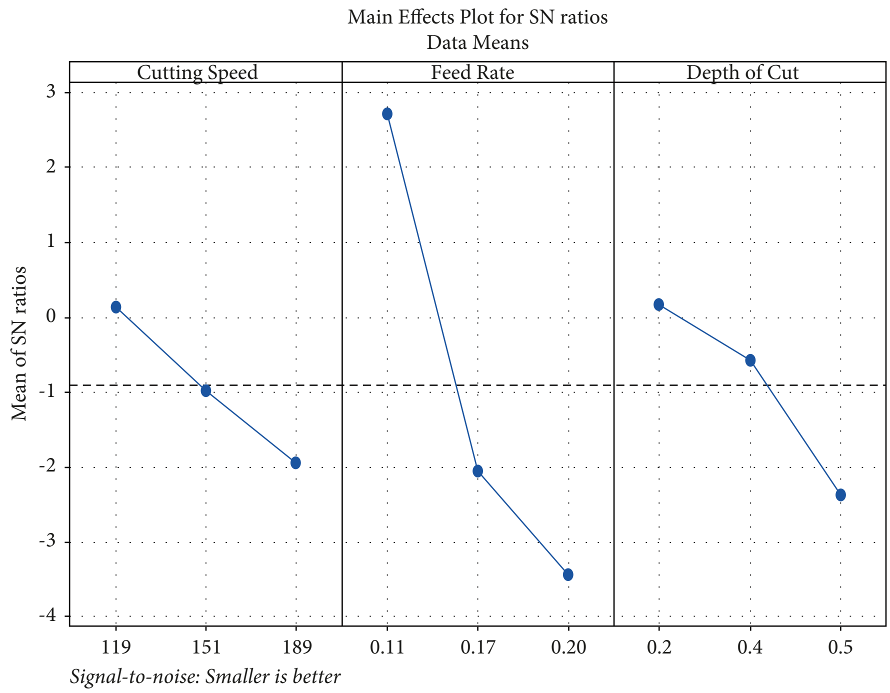

Figure 5: Main effects plot for surface roughness.

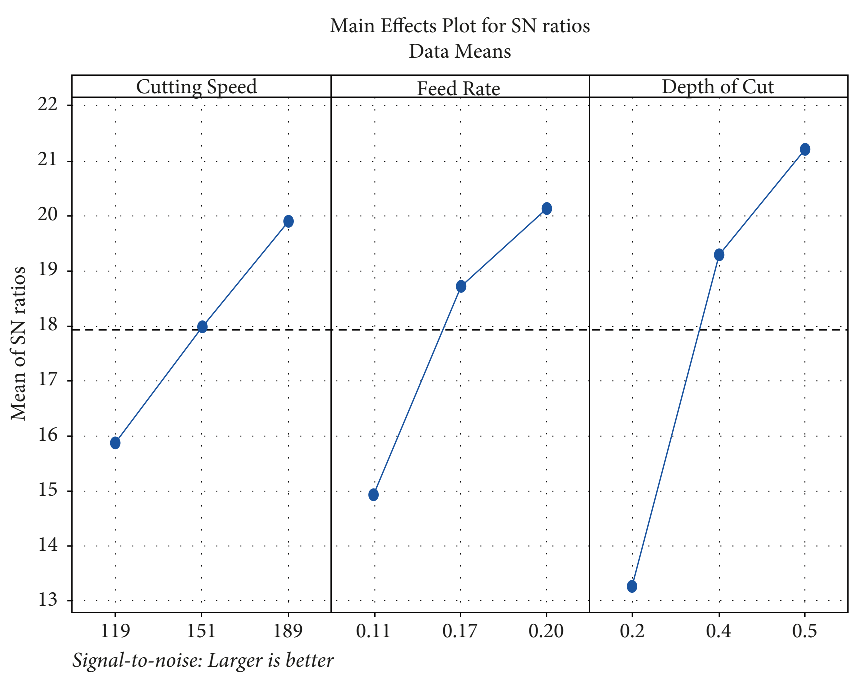

Figure 6: Main effects plot for material removal rate.

contrast, for material removal rate, feed rate is moderately significant to induce a favorable rate of material removal. This result is consistent with the earlier research conducted by various researchers [68, 69]. The R^2 value of 93.01% obtained for the MMR model provides evidence of its statistical significance. The Taguchi technique lacks the capability to evaluate or ascertain the impact of individual process parameters on the overall process. The analysis of variance (ANOVA) is a statistical method employed to assess the influence of individual parameters within a given process. The acquired data are assessed using the Minitab-19 software and are presented in Tables 8 and 9. The calculation of the mean square involves dividing the sum of squares by the number of degrees of freedom. Similarly, the F ratio is determined by dividing the mean square by the mean square of the experimental error.

Table 6: Response table for signal-to-noise ratios for surface roughness (smaller is better).

Level	Cutting speed	Feed rate	Depth of cut
1	0.1518	2.7269	0.1908
2	−0.9664	−2.0366	−0.5777
3	−1.9303	−3.4353	−2.3581
Delta	2.0821	6.1622	2.5489
Rank	**3**	**1**	**2**

Table 7: Response table for signal-to-noise ratios for material removal rate (larger is better).

Level	Cutting speed	Feed rate	Depth of cut
1	15.89	14.93	13.26
2	17.97	18.71	19.28
3	19.90	20.12	21.22
Delta	4.01	5.19	7.96
Rank	**3**	**2**	**1**

Table 8: Analysis of variance (ANOVA) for surface roughness.

Source	DF	Seq SS	Contribution (%)	Adj SS	Adj MS	*F* value	*p* value
Regression	3	0.98497	96.76	0.98497	0.328323	49.81	0.001
Cutting speed	1	0.05543	5.45	0.05543	0.05543	8.41	0.034
Feed rate	1	0.83627	82.15	0.83627	0.83627	126.86	0.000
Depth of cut	1	0.09326	9.16	0.09326	0.09326	14.15	0.013
Error	5	0.03296	3.24	0.03296	0.006592		
Total	8	1.01793	100.00				

Model summary: $S = 0.08119$, $R^2 = 96.76\%$, R^2 (adj) $= 94.82\%$, R^2 (pred) $= 89.84\%$.

Table 9: Analysis of variance (ANOVA) for material removal rate.

Source	DF	Seq SS	Contribution (%)	Adj SS	Adj MS	*F* value	*p* value
Regression	3	112.947	93.01	112.947	37.649	22.18	0.003
Cutting speed	1	14.311	11.79	14.311	14.311	8.43	0.034
Feed rate	1	29.013	23.89	29.013	29.013	17.09	0.009
Depth of cut	1	69.622	57.33	69.622	69.622	41.02	0.001
Error	5	8.486	6.99	8.486	1.697		
Total	8	121.433	100.00				

Model summary: $S = 1.30278$, $R^2 = 93.01\%$, R^2 (adj) $= 88.82\%$, R^2 (pred) $= 67.64\%$.

$$\begin{gathered}\text{Regression Eq. for MMR,}\\ \text{MRR} = -13.83 + 0.00834\ \text{Cutting Speed} + 48.0\ \text{feed rate} + 22.30\ \text{depth of cut.}\end{gathered} \tag{7}$$

The experimental design lacked the inclusion of a specific condition necessary for determining the maximum rate of material removal. The experiment was conducted under optimal machining conditions, revealing that the maximum rate of material removal reached 18.63 cm^3/min. In addition, the predictive value of material removal rate was calculated using regression equation (7) in order to determine the percentage of error between the actual and predicted MRR. The analysis revealed a discrepancy of 3.37% between the observed values, with the predictive value for material removal rate estimated at 15.26 cm^3/min. This range of deviation is well validated by multiple previous investigations conducted by researchers on a close to similar cutting environment [26, 69].

4.1. Optimization Using DFA. Finding the independent variable conditions that result in ideal or nearly ideal values for the response variables is the goal of multi-response optimization. The main goal of this analysis of the desirability function was to minimize surface roughness and maximize material removal rate. Table 10 displays the defined factor ranges for the primary optimization. Table 11 illustrates an overview of the optimization to achieve the primary goal of optimizing the response parameter. The selection of the ideal factor level and the desirability of each solution in the multiresponse optimization process are therefore depicted in Table 10. Because of the greatest desirability value being 0.903, the best parameters should be set

Table 10: Goals and factor range for optimization of surface roughness and material removal rate.

Factor	Goal	Limit		Weight		Importance
		Low	High	Low	High	
V_c	Is in range	119	189	1	1	3
S_o	Is in range	0.11	0.2	1	1	3
t	Is in range	0.2	0.5	1	1	3
R_a	Minimize	0.541	1.527	1	1	3
MRR	Maximize	2.5821	14.904	1	1	3

Table 11: Summary of the values obtained from optimization.

No.	V_c	S_o	t	R_a	MRR	Desirability	
1	189.000	0.11	0.5	0.971	10.248	0.903	Selected
2	187.657	0.11	0.5	0.968	10.184	0.902	
3	185.808	0.11	0.5	0.963	10.092	0.902	
4	142.926	0.11	0.5	0.845	8.064	0.892	
5	139.704	0.11	0.5	0.836	7.912	0.891	
6	143.559	0.123	0.5	0.950	8.930	0.890	
7	134.183	0.117	0.5	0.882	8.107	0.888	

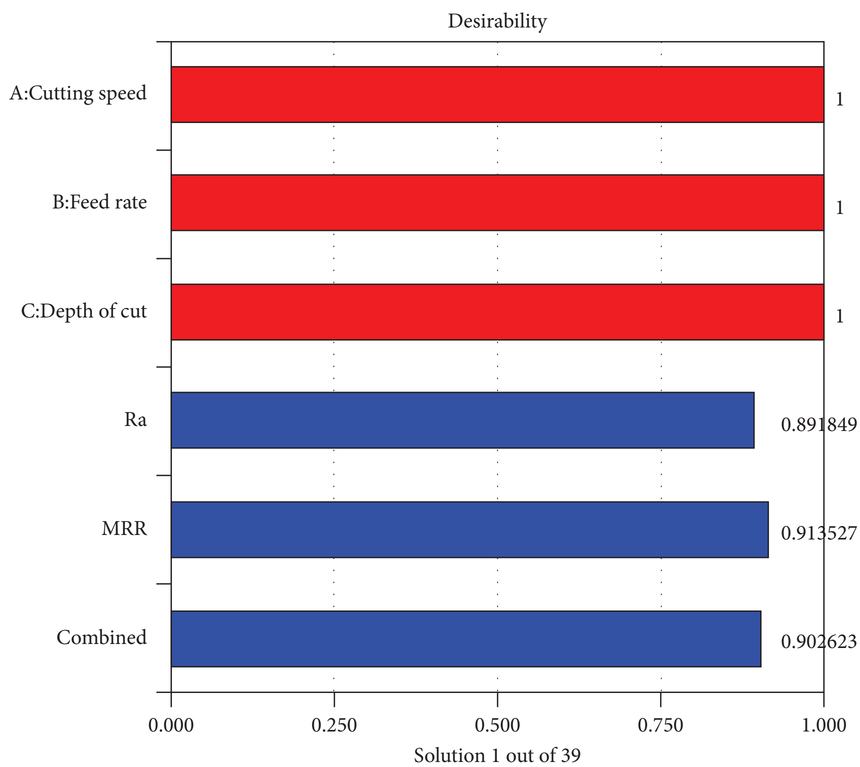

Figure 7: Desirability chart for optimum solution.

at $V_c = 189$ m/min, $S_o = 0.11$ mm/rev, and $t = 0.5$ mm. At this level, the minimum surface roughness and maximum material removal rate of material removal are 0.971 μm and 10.248 cm^3/min, respectively. Figure 7 shows how desirable the controllable and response parameters are separately and collectively. It shows that whereas surface roughness and material removal rate have desirability values of 0.8918 and 0.914, respectively, cutting speed, feed rate, and depth of cut have a desirability value of 1. After taking into account all of the trade-off factors, the final combined desirability is 0.903.

5. Conclusion

The study provides a simultaneous optimization of cutting speed, feed rate and depth of cut by incorporating Taguchi L_9 orthogonal array and ANOVA methods. Furthermore, the study also presents the significance of each input parameter through statistical analysis.

(1) Taguchi analysis L_9 shows that the optimum level of input parameters for minimum surface roughness are as follows: 630 rpm for cutting speed, 0.11 mm/rev for feed rate, and 0.2 mm for depth of cut and the cutting speed at 1000 rpm, feed rate at 0.20 mm/rev, and depth of cut at 0.5 mm are the optimal values for maximum MRR. On the contrary, DFA showed the optimum surface roughness and material removal rate, with a combination of 0.5 mm for the depth of cut, 189 m/min for cutting speed, and a 0.11 mm/rev for feed rate. Moreover, the highest perceived value of 0.903 could be attained amongst the 39 solutions while setting the mentioned parameters.

(2) By incorporating ANOVA analysis, contribution for each of the input parameters for both surface roughness and MRR are found as follows: For surface roughness, the relevance of feed rate (82.15%) and depth of cut (9.16%) are statistically significantly more important than those of spindle speed (which is demonstrated to have less of an impact on surface roughness). On the other hand, the material removal rate is affected by the depth of cut, feed rate, and spindle RPM to varying degrees (57.33%, 23.89%, and 11.79%, respectively).

(3) Validation was performed on the analysis that was established by ANOVA for surface finish and MRR. It yielded an average error of 3.24% and 6.99%, respectively. This demonstrates that the model's prediction is obviously at a level that is acceptable since it has a greater R^2 value, which is the measure of how adequate the model is.

5.1. Theoretical and Practical Implications of the Research. This study has multiple implications from both perspectives (theoretical and practical). The research focuses on optimization of SKD 11 steel machining based on multiple parameters. Furthermore, the study combines the use of Taguchi L_9 and ANOVA which appears to be valid from the error calculations. Moreover, the research also gives insight on tool conditions from dry machining of SKD 11. These insights can work as a guideline for future researchers who are working with similar hardened materials. On another note, the finding of this study will help manufacturing industries to improve production rate by optimizing spindle speed, feed rate and depth of cut for dry machining of hardened materials. The proposed method will help engineers to identify the significant parameters with ease and optimize them accordingly which in turn will allow small to medium industries in underdeveloped countries to use hardened materials for production without the requirement of heavy equipment's such as CNC lathe or advanced manufacturing systems such as Laser systems or electrochemical systems. The study shows an interesting outlier: Although feed rate is the most significant factor for minimum surface roughness, in case of MRR, depth of cut is the most important. When compared, feed rate provides 58.26% more significance in case of surface roughness.

5.2. Future Research Direction. This study, like all others, has limitations that future researchers can attempt to overcome. For instance, since optimizing the machining parameters in response to a greater number of output performance criteria will result in improved control over the machining process. Subsequent investigations may concentrate on integrating Taguchi-PCA in order to further improve the parameters. Researchers can acquire valuable insights into techniques to improve tool life by including more experimental trials to examine the impact of factors on different types of tool wear. To gain a more thorough understanding of the machined surface and the longevity of the machined component, the study could be extended to include residual stress, microhardness, or surface texture in addition to surface roughness. More research might be conducted to investigate the sustainability aspects of the machining process by examining energy consumption and carbon footprints related to turning SKD 11 hardened steel, this could lead to the discovery of new pathways for the application of environmentally friendly machining processes. Comparative research with other widely used materials in related applications could be performed before using it for large-scale applications to determine the machinability of various materials for a given application.

Data Availability

The data used to support the findings of this study are included in the manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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