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Research Article

Optimization of Surface Quality and Power Consumption in Machining Hardened AISI 4340 Steel

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Hard turning has become an attractive method of machining for most manufacturers in the last few years due to its low cost and superior surface quality compared to grinding. In this experimental study, the machinability of hardened steel under dry machining on a CNC lathe is undertaken to optimize the cutting parameters for minimum surface roughness and energy consumption with the cutting speed (320, 450, and 575), tool type (coated and uncoated), and feed rate (0.1, 0.18, and 0.26) as the input parameters. The Taguchi method, based on the L_{18} orthogonal array, the variance analysis, the signal-to-noise ratios, and the response surface methodology have been used to optimize surface roughness (R_a) and cutting power (C_p). Optimum cutting parameters and levels were determined, and the relationship between cutting parameters and output variables was analyzed with the aid of two-dimensional and three-dimensional graphics. The results show that the most effective parameter on the surface roughness was the tool type (78%), while the most effective parameter on energy consumption was the cutting speed (90%). The combination of low feed rate and high cutting speed is necessary for minimizing the surface roughness. Besides, the impact of two-factor interactions of the feed rate-cutting speed and depth of cut-cutting speed appears to be substantial. The linear regression models were validated using confirmation tests. Finally, regression coefficients were determined as a mathematical model, and it was observed that this estimated model yielded results that were very similar to those achieved via real experiment (correlation values: 97.64% for surface roughness and 98.72% for energy consumption).

1. Introduction

In the modern times, steels are the highest used material for the manufacturing of mechanical parts around the world due to their excellent mechanical properties [1]. Manufacturing industries are currently faced with multiple challenges like CO2 emissions, productivity, quality surface finish, wear resistance, energy utilization among others as they strive to produce critical mechanical components and products using hardened steel. Hard turning which has been an important research topic in both the industry and academia is the phenomenon of machining at extremely high cutting speeds. It is an exceedingly difficult and delicate procedure since a better surface quality is achieved minus a grinding operation [2]. Hard machining offers a range of benefits including greater process flexibility [3], reduced number of steps and a shorter processing time [4], and reduction of production costs and saving of resources [5]. Issues like elevated cutting temperature, increased cutting force, material softening, poor surface quality, premature tool failure, and accelerated tool wear hinder effective deployment of the material which thus needs to be checked. Due to these factors, the energy consumed for hardened steel machining is more significant than that required to cut normalized or nonhardened materials. Hence, there is the necessity to craft ways and methods that will ensure energy efficiency and surface quality during the machining of the hardened steels.

As reported by [6], energy savings in machining can be classified into two: machine improvements and parameter optimization. Advanced energy-saving devices have been conjured with a promise of making some energy-efficient improvements. These devices come at a very high cost, in both acquisitions and installation. There is a second approach to ensuring energy efficiency using optimized parameters, which both is inexpensive and requires less effort [7]. Saving time, energy, and scrap can be achieved by optimizing the input parameters in machining [8]. This method can be considered positive and be deployed in the improvement of energy efficiency in machining.

There has been an increased uptake of studies in parameter optimization to ensure energy efficiency without compromising productivity. This optimization has been applied in turning, drilling, and milling [9–14]. While studying the optimization of process parameters on surface roughness using Taguchi robust design principles, Deepak and Rajendra concluded that the most influential parameters on the surface roughness were the feed rate followed by cutting speed and depth of cut [15]. An increase in feed rate and depth of cut is found to increase the surface roughness too [16]. While machining EN 24 grade steel, [17] used design of experiments (DoE) and analysis of variance (ANOVA) to analyze the effects of the parameters on the surface roughness and concluded that feed rate was the most influencing factor. In examining the surface roughness of AISI 1045 using RSA and GA, [18] concluded that surface roughness decreases with an increase in depth of cut and spindle speed. While using a multilayer regression analysis and GRA in milling AISI 1045, [19] determined the optimum cutting conditions as feed per tooth $f_z = 0.25$ mm/tooth, cutting speed $v_c = 392.6$ m/min, and machined length $l = 5$ mm and feed per tooth $f_z = 0.125$ mm/tooth, cutting speed $v_c = 392.6$ m/min, and machined length $l = 5$ mm for a fast manufacturing and resource conservation cases, respectively. In a CNC face milling of grade-H steel, [20] optimized a set of machining parameters to obtain minimum cutting power where artificial neural network (ANN) with the Edgeworth–Pareto method was used. Employing multi-objective optimization based on ratio analysis (MOORA), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), and technique for order of preference by similarity to ideal solution (TOPSIS) during AISI304 steel turning with minimum quantity lubrication, [21] found that the use of hybrid nanofluid (alumina–graphene) reduces response parameters by approximately 13% in forces, 31% in surface roughness, and 14% in temperature, as compared to alumina nanofluid. They further analyzed the response parameters using ANOVA where they concluded that the depth of cut and feed rate had a significant impact on the responses.

The effects of cutting tool materials and geometry on the energy efficiency of drilling and turning processes were investigated by [22]. Venkatesan opined that feed rate hugely affects surface roughness, and he suggested that on top of optimal process parameters (high speed, depth of cut, and low feed rate) the point angle was the most predominant factor in milling [23]. Moreover, [24] recommended potential solutions to reduce energy consumption in drilling and turning. Using genetic programming to predict tool flank wear, [25] applied the particle swarm optimization algorithm in turning operation of hardened AISI D2 where surface roughness was estimated by neural networks. They concluded that a higher efficiency was achieved by the intelligent optimization methodology than conventional techniques with constant optimized cutting parameters. In turning ASI 52100 hardened steel, Serra et al. used full factorial, multiple linear regression (MLR) analysis, and ANOVA to design, develop, and optimize cutting parameters where the empirical models obtained were used to determine the optimal machining parameters based on weighting factors and genetic algorithm (GA) optimization method [26]. Mustafa investigated the effect of cutting speed, feed rate, and depth of cut on surface roughness experimentally in the turning of AISI 409 (ferritic chromium stainless steel). He used Taguchi L_{27} orthogonal array and the signal/noise (S/N) ratios. He concluded that the most important parameters affecting the surface roughness were feed rate, depth of cut, and cutting speed, respectively [27].

Altering various parameters, such as cutting speeds, feed rates, the nose radius, edge radius, rake angle, and relief angle, have contributed to variations in cutting power and energy efficiency. Therefore, a practical approach optimizing cutting parameters in terms of energy efficiency can contribute significantly to energy reduction, and this is, therefore, an essential area of research. While turning EN 10503 steel, [28] successfully deployed Taguchi combination method and MOORA techniques to tackle the multi-objective optimization problem where insert nose radius, cutting velocity, feed rate, and depth of cut were considered. The evaluated parameters were the surface roughness, the cutting force amplitudes in X, Y, Z directions, and the material removal rate. They determined the optimal values as 1.2 mm, 76.82 m/min, 0.194 mm/rev, and 0.15 mm for insert nose radius, cutting velocity, feed rate, and cutting depth, respectively. Corresponding to these optimal values of the input parameters, the surface roughness, cutting force amplitudes in X, Y, Z directions, and material removal rate were 0.675 μm, 124.969 N, 40.545 N, 164.206 N, and 38.130 mm^3/s, respectively.

For consumers, product quality is very essential and one of the most prominent indicators for quality is the surface quality which also exerts a massive influence on the service life and reliability of manufactured objects. Other factors of a machined part, like fatigue strength, corrosion resistance, wear behavior, and the overall appearance of the product, depend on the surface quality [29–31]. A rough surface usually wears more quickly and has an elevated friction coefficient than a smoother surface does. Thus, decreasing the roughness of a surface will increase manufacturing costs [32]. In their experimental investigation of the effects of cutting speed and feed rate on tool wear, surface roughness, and cutting forces in turning of AISI 4340 hardened steel using cBN–TiN-coated carbide inserts and PCBN compact inserts, More et al. concluded that the wear of the former is less than that of the later due to the lubricity of a TiN capping layer on the coating [33]. During the examination of the tool wear mechanisms and surface integrity in the hard-speed turning of AISI D2 cold work tool steel, [34] showed that at high cutting speeds, the stress was minimal, thus concluding that it is possible to optimize cutting parameters for favorable residual stress levels. In their study, [35] concluded that a better surface finish could be achieved using a large tool nose radius on finish turning of AISI 52100 bearing steel. They used alumina titanium-carbide tools, which generated deeper white layers. While studying the influence of machining parameters and tool nose radius on surface quality of AA7075/15 wt.% SiC (20–40 μm) composites using tungsten carbide inserts, [36] employed response surface method (RSM) while considering both a single and multiple objective optimizations of turning parameters. A minimum surface roughness was obtained at a nose radius of 1.2 mm and 0.4 mm, respectively. During the turning of Ti–6Al-4V (ELI) to examine the impact of cutting speed, feed, depth of cut, and tool nose radius on surface roughness, cutting temperature, and cutting force, [37] developed mathematical models using RSM while assessing each parameter's contribution by ANOVA. Using PVD-TiN-coated (Al2O3–TiCN) mixed ceramic tool inserts in hard turning of hardened AISI grade die steel D3, [38] carried out modeling and optimization of parameters to quantify their contributions. Experiments were based on Taguchi's L_{18} orthogonal array design of experiments.

In a display of the advances made in the machining field including theoretical and experimental aspects, the correlations between process parameters and surface integrity were shown and analyzed by [39] for turning, milling, EDM, and grinding processes. The authors described the development of predictive models for the correlation of the surface integrity to the functional performance of machined components to the set parameters of the surface integrity. While trying to reduce energy consumption and improve the cutting quality and production rate, Su et al. applied grey relational analysis and response surface methodology (RSM) to turn AISI 304 austenitic stainless steel. They determined the optimal turning parameters as ($a_p = 2.2$ mm, $f = 0.15$ mm/rev, and $v = 90$ m/s) which decreased the surface roughness by 66.90%, material removal rate (MRR) increased 8.82%, and specific energy consumption (SEC) decreased 81.46% simultaneously [40]. An endeavor has been made to predict and optimize surface roughness and the power consumed in terms of cutting speed, feed rate, and cutting tool type in the machining of hardened steel.

According to the literature reviewed, the primary difficulty that most manufacturing companies face, particularly in the metal-cutting industry, is the requirement to improve manufacturing quality while lowering production costs. This attribute is paramount to the sectors that utilize the steels since the power consumed during machining provides an array of knowledge into the material workability. A variety of factors not limited to the cutting parameters, tool material, coating technologies, lubricants, tool geometry, etc., do affect both the product quality and the production cost since the energy consumption during operation is greater than the energy required to meet the demands of the machine. Manufacturing organizations have been utilizing the trial-and-error method for a long time to try to achieve a balance. This method consumes a lot of time and resources, thus defeating the overall goal of attempting in the first place. In this context, the objective of this study is to correlate cutting parameters with surface roughness and cutting power during the machining of hardened steel using the Taguchi method. ANOVA is used to determine the contribution of each machining parameter to surface roughness and cutting power. The development of a second-order model is adopted to predict the technological parameters (*Ra* and *Pc*). The final goal of this work is to optimize cutting conditions using the desirability function.

2. Materials and Methods

2.1. Materials. This research was carried out at the High-Speed Machining Laboratory, NUAA, Nanjing, China. The machining was carried out using a CNC lathe machine fitted with a 22-kW spindle power and a maximum spindle speed of 5000 rpm. Both the axial and radial run-outs were checked on the machine and were within the acceptable limit of error. Ten (10) pieces of 300 mm length and 50 mm diameter from a single bar (L/D ratio is 6 : 1) of hardened and tempered high carbon steel with a hardness of 69 HRC were used. Both the chemical compositions and mechanical properties of the material are given in Table 1. This material has been chosen due to its extensive industrial and engineering applications like extrusion and die forging, engine mounting, gears, and bearings. Notable material properties are excellent fatigue and torsional strength, toughness, high resistance to abrasion, and impact [41]. The experimental setup is shown in Figure 1.

Two types of carbide tool inserts (PVD-coated and uncoated) from Sandvik Coromant with a specification of SNMG120408 with a -6° rake angle, 75° principle cutting edge angle, -6° inclination angle, and a nose radius of 0.8 mm rigidly mounted on a right-hand style tool holder (MTFNR2525M22C) were selected due to their low cost, high wear resistance, and impact shock resistance properties. A new insert was used for each experiment. The experimental conditions are shown in Table 2. The machining was done under dry-cutting conditions.

One of the prime indices for defining the surface quality is the average arithmetic value of the surface roughness (*Ra*). A Mahr Perthometer M1 Concept (Germany) shown in Figure 2 was used to measure the workpiece's Ra over a sampling length of 8 mm at a stylus speed of 0.5 mm/s with a cut-off length of 0.8 mm. Nine measurements were made at uniformly distributed surfaces along the circumference for each machined surface at the end of every machining cycle, and an average value was reported for an accurate reading.

A custom-made energy measurement system-dubbed "smart meter" was used to measure the cutting power consumed during machining. The energy values presented in this study only account for the machining duration.

2.2. Experimental Design. It is an uphill task to utilize the traditional experimental design due to its complexities since it will require a huge number of experiments to be carried out, thus soaring the costs and consuming a lot of time. As a result, the variation causing factors must be determined and verified under laboratory conditions [42, 43]. These studies are considered under the scope of offline quality

Table 1: The composition and properties of AISI 4340 steel.

Composition		Properties	
Element	Content (%)	Physical properties	
Fe	95.195–96.33	Properties	Metric
Ni	1.65–2.00	Density	7.85 g/cm^3
Cr	0.700–0.900	Melting point	1427°C
Mn	0.600–0.800		
C	0.370–0.430	Mechanical properties	
Mo	0.200–0.300	Tensile strength	745 MPa
Si	0.150–0.300	Yield strength	470 MPa
S	0.0400	Elastic modulus	190–210 Gpa
P	0.0350	Poisson's ratio	0.27–0.30

improvement [44]. The Taguchi method is used in the industry to decrease the product development period for the design and production, which also decreases the costs, thus increasing the profit of the organization. The Taguchi method is applied in the determination of the loss function which is converted to a signal-to-noise (S/N) ratio. The S/N ratio is defined as the desired signal ratio for the undesired random noise value and shows the quality characteristics of the experimental data [45]. The experiments are planned, and tests run according to L18's mixed orthogonal array. The variables and their levels are shown in Table 3. The aim is to achieve minimum values for surface roughness and the power consumed. There are three different functions used which are known as the objective function and also defined as S/N ratio: "the-larger-the-better," "the-smaller-the-better," and "the-nominal-the-best."

2.2.1. S/N Ratio Analysis. The S/N ratio is the ratio of the mean to the standard deviation (M.S.D). It is used to determine the quality characteristic deviating from the desired value. As described by [46], the S/N ratio is given by

$$\eta = -10\ \log(\text{M.S.D}). \tag{1}$$

For optimal cutting performance, "the-lower-the-better" quality characteristics for surface roughness and energy must be considered. The M.S.D. for a "the-lower-the-better" quality characteristic of surface roughness and energy efficiency can be given by the following equations, as discussed by [46], respectively.

$$\text{M.S.D}_{sr} = \frac{1}{j}\sum_{i=1}^{j} S_i^2, \tag{2}$$

$$\text{M.S.D}_{ee} = \frac{1}{j}\sum_{i=1}^{j} E_i^2, \tag{3}$$

where j is the number of experiments, and S_i and E_i are the observed data values for surface roughness and consumed power, respectively, for the ith test. The estimated S/N ratio ($\acute{\eta}$) at the optimal level of the design parameters can be calculated by equation (4), as discussed by [46], and is used to predict and verify the quality characteristic at the optimal level.

$$\acute{\eta} = \eta_j + \sum_{i=1}^{p}\left(\eta_i - \eta_j\right). \tag{4}$$

Here, η_j is the total mean S/N ratio, η_i is the mean S/N ratio at the optimal level, and p is the number of the main design parameters affecting the quality characteristic.

2.2.2. Analysis of Variance. The analysis of variance (ANOVA) is applied to experimental results to determine in percentage the contribution of each factor and whether a factor requires control or not. The ANOVA test establishes the relative significance of the individual factors and their interaction effects. The total sum of the squared deviations SST was computed by equation (5), as discussed by [46].

$$\text{SS}_T = \sum_{i=1}^{k}\left(\eta_i - \eta_j\right)^2. \tag{5}$$

3. Results and Discussion

The experimental data presented herein were analyzed, and results interpreted via statistical analysis. Signal-to-noise (S/N) ratios with the analysis of variance (ANOVA) method were utilized according to the L18 orthogonal array. Given in Table 4 are the experimental results and S/N ratios calculated according to Taguchi's "the-smaller-the-better" quality characteristics.

3.1. S/N Ratio Analysis. Surface roughness (R_a) and cutting power (C_p) were measured via the experimental design for each combination of the control factors. The optimization of the measured control factors was provided by signal-to-noise (S/N) ratios. For quality improvement of the product and lowering production costs, the lowest values of surface roughness and cutting power are essential. After machining, the average values of R_a and C_p were calculated by equations (2) and (3) to be 1.1 μm and 589 kW, respectively. Similarly, the average values of the S/N ratio for surface roughness and cutting power were calculated to be 2.2 dB and 55 dB, respectively.

The results of the experimental tests are supported by graphs depicting the impact of control parameters on *Ra* values obtained using the Taguchi method (Figure 3) and on *Cp* values (Figure 4). The values closest to the vertical on the main effects plot for S/N ratios are the most effective parameters. The most effective parameter for surface roughness was found to be cutting speed. The S/N responses for each control factor and their ranks are presented in Table 5.

Figures 5-6 show 3D surface plots depicting the relationship between the cutting parameters and the considered output variables.

From the 3D surface plots in Figure 5, it is evident that surface roughness value increases with the increase of cutting speed. The same phenomenon is evident with an increase of the feed rate though the magnitude is not very pronounced as observed by [47]. Therefore, low feed is

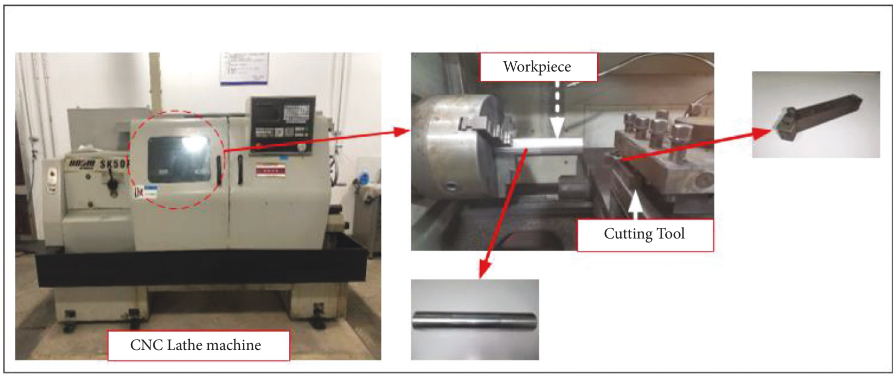


Figure 1: Experimental setup.

Table 2: Summary of experimental conditions.

Machine tool	CNC lathe
Work material	AISI 4340 steel
Hardness, HRC	69
Dimensions	300 × 50 mm
Cutting tool	Carbide inserts

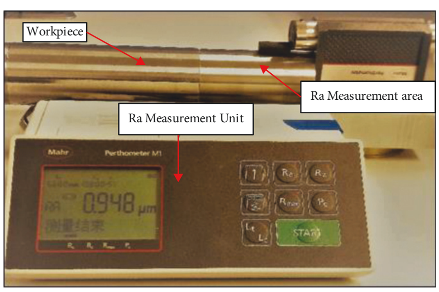


Figure 2: Surface roughness measurement setup.

Table 3: Input variables and levels.

Symbol	Variable	Levels	1	2	3
V_c	Cutting speed, m/min	3	320	450	575
F	Feed rate, mm/rev	3	0.1	0.18	0.26
T	Tool type	2	Coated	Uncoated	—

advantageous for good surface quality as long as the speed is reasonably high. The increased cutting speed increases the average surface roughness for the uncoated cutting tool, while there is a marginal change for the coated tool. This behavior tallies with results presented by [48, 49]. This is because the rapid deformation of the uncoated tools brings about an increase in surface roughness due to the material's deformation hardening property. Olsson et al. in their study also noted this behavior [50]. The cutting tool type demonstrated a significant change in the overall values of surface roughness. For the coated tools, there is an improved wear resistance due to a low thermal conductivity resulting in improved surface quality. Comparatively less irregular surface while machining with coated tools has been found than uncoated tools just as determined by [51]. The poor surface quality is partly attributed to the abrupt increase in the chip volume due to the increased cutting speed that translates into high cutting forces as observed by [52] in their study.

From the 3D plots in Figure 6, it is seen that the cutting power value increases tremendously with an increase in the cutting speed. This increase is not discriminatory since it depicts the same trend for both the coated and uncoated cutting inserts. The feed rate and the tool type have a slight significance over the cutting power.

Surface roughness and cutting power increase with cutting speed. This phenomenon is attributed to the thermal and mechanical load increase as a result of an increase in the cutting speed. This increase raises the temperatures in the cutting area, thus speeding up the deformation of the cutting tool. This phenomenon is rampant in uncoated cutting tools.

From the plots and contours presented, it was observed that the feed rate was the most effective parameter in the increase of surface roughness. Since the surface roughness is a function of feed rate, an increasing feed rate caused a significant increase in the R_a values. Likewise, an increase in feed rate increased cutting power.

3.2. Analysis of Variance (ANOVA). The analysis of variance (ANOVA) used was to analyze the effects of the cutting speeds, the cutting tool types, and the feed rates on R_a and C_p. The F, P, and DoF values shown in the ANOVA table (Table 6) are the variance ratio, significant factor, and the degrees of freedom, respectively. These analyses were performed at a confidence level of 95% ($\alpha = 0.05$ significance level), thus showing that values with P values less than 0.05 represent significant results. Marked in bold in the ANOVA table are the significant P values. The percentage value of each parameter contribution is shown in the last column of Table 6. This percentage indicates the degree of influence on the process performance. According to the ANOVA in Table 6, the most influential parameter was the feed rate for surface roughness. Likewise, the cutting speed was the most effective parameter for cutting power.

Table 6 shows that the most effective parameter for surface roughness is the cutting with 70.53%, followed by feed rate (9.828%), while the tool type has a minor contribution of 4.73%. It is clear that the cutting speed is the

Table 4: The results of experiments and S/N ratio values.

Exp. no.	Control factors: Tool type	Control factors: Cutting speed	Control factors: Feed rate	Surface roughness, R_a (um)	S/N ratio for R_a (dB)	Cutting power, C_p (kW)	S/N ratio for C_p (dB)
1.	1	320	0.1	1.9008	15.8635	400	−52.0412
2.	1	320	0.18	1.2460	1.1698	416	−52.3819
3.	1	320	0.26	1.2484	−0.3072	450	−53.0643
4.	1	450	0.1	1.1564	−1.2215	615	−55.7775
5.	1	450	0.18	0.9371	−1.4229	620	−55.8478
6.	1	450	0.26	1.2001	−2.8353	640	−56.1236
7.	1	575	0.1	0.8501	−4.0770	722	−57.1707
8.	1	575	0.18	0.9792	−5.4739	765	−57.6732
9.	1	575	0.26	1.2236	−8.8245	788	−57.9305
10.	2	320	0.1	0.4162	−2.7976	385	−51.7092
11.	2	320	0.18	0.6624	−1.2742	395	−51.9319
12.	2	320	0.26	1.2525	−0.6443	421	−52.4856
13.	2	450	0.1	0.3642	−1.4008	580	−55.2686
14.	2	450	0.18	1.1123	−2.3785	594	−55.4757
15.	2	450	0.26	1.8492	−2.7661	602	−55.5919
16.	2	575	0.1	0.5494	−5.2822	691	−56.7896
17.	2	575	0.18	0.6016	−8.3361	751	−56.2716
18.	2	575	0.26	2.5646	−8.3361	771	−56.5345

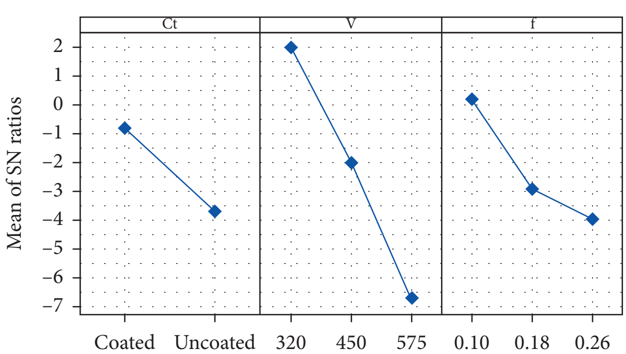


Figure 3: Effect of process parameters on average S/N ratio for R_a.

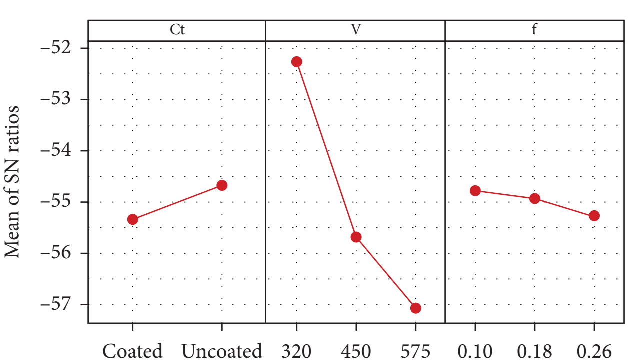


Figure 4: Effect of process parameters on average S/N ratio for C_p.

main parameter theoretically, and this observation is corroborated by [53–56]. As for the cutting power, the most effective parameters were cutting speed (93.61) and tool type (3.32%). Feed rate had a negligible effect compared to others. This observation was in tandem with the study carried out by [57]. The observed percent error was at 14.91% for R_a and 0.94% for C_p.

Table 5: S/N response table for R_a and C_p factor.

Levels	Surface roughness (R_a) A	Surface roughness (R_a) B	Surface roughness (R_a) C	Cutting power (C_p) A	Cutting power (C_p) B	Cutting power (C_p) C
Level 1	−0.7921	2.0017	0.1807	−55.33	−52.27	−54.79
Level 2	−3.6907	−2.0042	−2.9526	−54.67	−55.68	−54.93
Level 3		−6.7216	−3.9522		−57.06	−55.29
Delta	2.8985	8.7233	4.1330	0.66	4.79	0.50
Rank	3	1	2	2	1	3

3.3. Regression Analysis of R_a and C_p. To model and analyze a relationship between a dependent variable and one or more independent variables, regression analysis is utilized. The surface roughness (R_a) and cutting power (C_p) are the dependent variables, whereas the cutting tool type (C_t), cutting speed (V_c), and feed rate (f) are the independent variables. Using the outcomes from the experimental values in MINITAB 18, the mathematical regression RA's linear and quadratic models, predictive equations were developed with backward elimination method for the considered parameters, were obtained, and are given below.

$$R_a = -1.718 + 0.279Ct + 0.004958V + 3.07f, \quad (6)$$

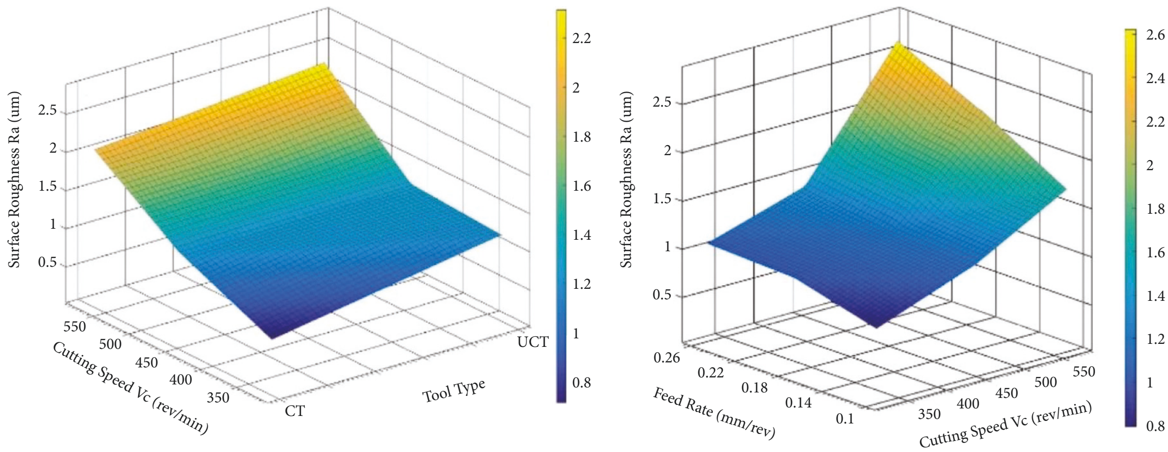
R-sq = 85.09% R-sq (adj) = 78.87%,

$$C_p = 81.2 - 47.3Ct + 1.1924V + 186f, \quad (7)$$

R-sq = 97.87% R-sq (adj) = 96.98%

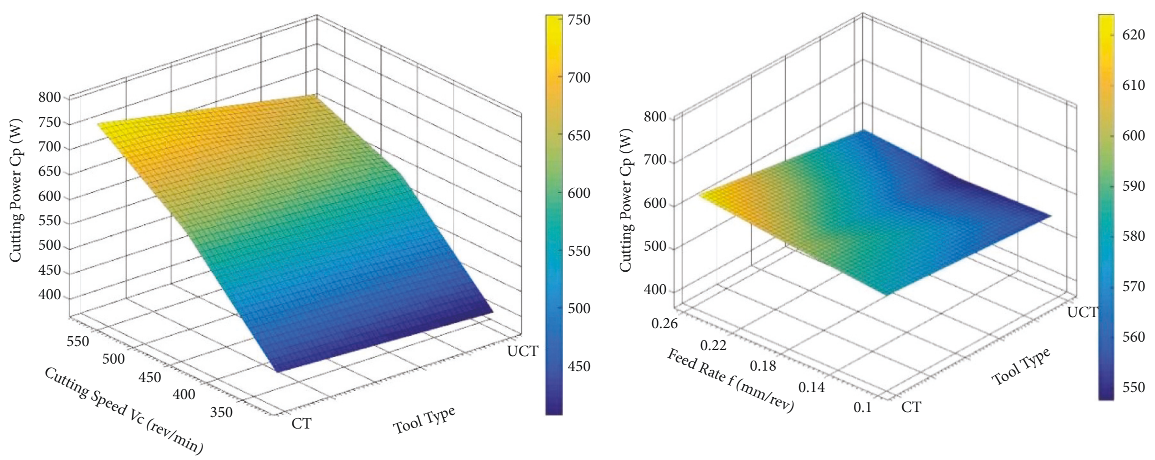
The obtained R^2 values by a linear regression model for R_a and C_p equations were found to be 85.09% and 97.87%, respectively.

The quadratic regression predictive equations for the surface roughness and cutting power are given below:



(a) (b)

Figure 5: Effect of the cutting parameters on surface roughness.



(a) (b)

Figure 6: Effect of the cutting parameters on cutting power.

Table 6: Surface roughness and cutting power ANOVA results.

Variance source	Degrees of freedom (DoF)	Sum of squares (SS)	Mean squares (MS)	F ratio	P-value	Contribution rate (%)
R_a						
Tool type	1	0.3511	0.35112	3.81	0.075	4.73
Cutting speed	2	5.2347	2.61737	28.38	≤0.001	70.53
Feed rate	2	0.7286	0.36430	3.95	0.048	9.82
Error	12	1.1069	0.09224			14.92
Total	17	7.4213				100
C_p						
Tool type	1	10082	10082	18.69	≤0.001	3.32
Cutting speed	2	284648	142324	263.88	≤0.001	93.61
Feed rate	2	2861	1431	2.65	0.111	0.94
Error	12	6472	539			2.13
Total	17	304064				100

Table 7: Mean response table for R_a and C_p factors.

Levels	Control factors					
	Surface roughness (R_a)			Cutting power (C_p)		
	Tool type	Cutting speed	Feed rate	Tool type	Cutting speed	Feed rate
Level 1	1.3361	0.9477	1.2172	601.8	411.2	565.5
Level 2	1.6154	1.2633	1.5023	554.4	608.5	573.5
Level 3		2.2163	1.7078		714.7	595.3
Delta	0.2793	1.2687	0.4907	47.3	303.5	29.8
Rank	3	1	2	2	1	3

Table 8: Predicted values and confirmation test results by the Taguchi method and regression equations.

Level	Taguchi			Linear regression			Quadratic regression		
	Exp	Pred	% Error	Exp	Pred.	% Error	Exp	Pred.	% Error
R_a (um)									
Optimum	0.56	0.52	7.14	0.56	0.46	17.85	0.56	0.63	12.50
Random	0.72	0.65	9.72	0.72	0.73	1.38	0.72	0.73	1.38
C_p (kW)									
Optimum	415.2	408.6	1.59	415.2	386.57	6.89	415.2	473.73	13.91
Random	401.4	418.3	4.21	401.4	448.74	11.79	401.4	454.03	13.2

$$R_{aq} = -0.105 + 0.000002V^2 - 3.9f^2 + 0.000799CtV - 0.77Ctf + 0.01250Vf. \quad (8)$$

R-Sq = 82.56%R-Sq (adj) = 75.30%

$$C_{pq} = 318.2 + 0.001301V^2 + 679f^2 - 0.045CtV - 159Ctf + 0.41Vf. \quad (9)$$

R-Sq = 92.93% R-Sq (adj) = 88.99%

The obtained R^2 values by the quadratic regression model of the equations derived for R_a and C_p were found to be 82.56% and 92.93%, respectively. Hence, we can observe that the quadratic regression model obtained more intensive predicted values when compared to the linear regression model. As a result, we may conclude that the quadratic regression model has performed better in approximating both surface roughness and cutting power.

3.4. Optimum Parameter Estimation. Optimum levels are determined as the lowest values of the considered output parameters. When using the Taguchi method, optimization is verified by confirmation experiments [58]. The following equations (equations (10) and (11)) are applied in the estimation of the optimum surface roughness and cutting power. The optimum input parameter levels and values are shown in Table 7, and the average optimum output values for each cutting parameter are in bold fonts.

$$Ra_{\text{opt}} = (A_1 - T_{Ra}) + (B_1 - T_{Ra}) + (C_1 - T_{Ra}) + T_{Ra}, \quad (10)$$

$$Cp_{\text{opt}} = (A_2 - T_{cp}) + (B_1 - T_{cp}) + (C_1 - T_{cp}) + T_{cp}, \quad (11)$$

where (A1B1C1) and (A2B1C1) denote the optimum level mean values of R_a and C_p, respectively (Table 4), while T_{Ra} and T_{Cp} are the mean values of all the R_a and C_p determined as stated in Table 7.

The observed optimum levels and values for surface roughness are tool type (level 1), cutting speed (level 1), and most importantly feed rate (level 1). From the published literature, the lowest surface roughness values were obtained at high cutting speeds [48, 55]. As for the cutting power, the optimum cutting parameters were determined to be tool type (level 2), cutting speed (level 1), and feed rate (level 1).

It is paramount to establish if some of the objectives of the study have been met or not. Therefore, equations (10) and (11) are used to evaluate if the system achieved its optimization demands.

$$\mathrm{CL}_i = \sqrt{F_{0.05}(1, \nu_e)V_e\left(\frac{1}{\eta_{\text{eff}}} + \frac{1}{r}\right)}, \qquad \eta_{\text{eff}} = \frac{N}{1 + \nu_T}, \quad (12)$$

where ν_e is the error degree of freedom, V_e is the error variance, η_{eff} is the repeating number of experiments, r is the number of confirmation experiments, N is the total number of the experiments, and ν_T is the variable's degree of freedom.

The response confidence intervals were calculated as $\mathrm{CL}_{Ra} = \pm 0.024$ and $\mathrm{CL}_{Cp} = \pm 0.041$. The estimated average optimal surface roughness and cutting power with the confidence interval at 95% confidence are given by solutions to the following inequalities:

$$\left[Ra_{\text{opt}} - Cl_{Ra}\right] < Ra_{\text{exp}} < \left[Ra_{\text{opt}} + Cl_{Ra}\right], \qquad \left[Cp_{\text{opt}} - Cl_{Cp}\right] < Cp_{\text{exp}} < \left[Cp_{\text{opt}} + Cl_{Cp}\right]. \quad (13)$$

The Ra_{exp} and Cp_{exp} values that were obtained from the study were within the confidence interval limits. Thus, we can comfortably conclude that by the use of that Taguchi method and at a significance level of 5%, parameter optimization was realized.

3.5. Confirmation Tests. In the Taguchi method, confirmatory experiments are carried out to verify the optimization after the determination of the variable levels that will give the optimal results. Confirmation experiment tests of the control factors were made for both the Taguchi method and regression equations at both the optimum and random levels. The comparison of the test results and the predicted values obtained by using the Taguchi method and regression equations (equations (2)–(5)) is given in Table 8. The results from the predictive and the experimental processes are very close to each other.

For reliable statistical analyses, error values must be less than 20% [59]. Therefore, the results obtained from the confirmation tests reflect successful optimization since the percentage error is within the allowed limits.

4. Conclusion

In this study, hard turning of hardened AISI 4340 steel was done under a dry machining environment to determine the optimal variable levels for the minimization of both the surface roughness and the energy consumed. The experimental design was based on Taguchi L_{18} orthogonal array where the surface roughness and energy consumed were determined. The statistical methods of signal-to-noise (S/N) ratio and the analysis of variance (ANOVA) are used to determine the relationship between input parameters (tool type, cutting speed, feed rate) and output variables (surface roughness, energy consumption) and the effect of the parameters on surface roughness and energy consumed, respectively. To test the validity of the optimization, confirmation experiments were undertaken and the following conclusions were drawn:

(i) During machining, the surface roughness increased for both types of cutting tool used.

(ii) Optimum values for the minimization of the cutting power and surface roughness were determined. These conditions were observed at (A2B1C1) and (A1B1C1) for C_p and R_a, respectively, leading to conclusions that coated tools exhibited much better performance for both responses and therefore are recommended for the machining of hardened steel.

(iii) Analysis of variance revealed the influence of input parameters on the response parameters. The ANOVA results determined the most important parameter effective on R_a and C_p to be the cutting speed, at 70.53% and 93.61%, respectively.

(iv) Taguchi's "smaller-the-better" objective function was adequate to ascertain the influence exerted by the control factors. This methodology has revealed that the tool type (coated or uncoated) has the most significant influence on R_a at 78%, and the cutting speed is the parameter with the enormous impact on C_p at 90%.

(v) There is absolutely a high correlation coefficient between measured and predicted values for C_p and R_a as exhibited by the estimated statistical parameters "S," R-sq., and R-sq. (adj) for C_p and R_a, thus implying that the developed models can be used in the machining of hardened steel since they give sufficient values that are within the allowed ranges.

(vi) Results from the confirmation test measured values were found to be within the permitted confidence interval of 95% showing that the Taguchi method was quite effective in the optimization of machining parameters. Measured values were within the permitted confidence levels, as demonstrated by the confirmation test results.

The results from this study have demonstrated the reliability of the Taguchi method in the evaluation of minimizing the cutting power and surface roughness in the machining of hardened steel. The optimum values achieved can be used in the future for both academic research and industrial applications like the aerospace, automotive, and marine industries where other factors like cutting tool geometry, machining environment, nose radius, lubricants, etc., would be considered. The environment can be protected adequately with proper energy savings. Energy consumption should be minimized to save energy. In this vein, machining time can be shortened by selecting the cutting parameter values to optimum levels to reduce energy consumption. In addition to low energy consumption, the material must be processed with a good surface quality.

Nomenclature

ANOVA: Analysis of variance
BU: Built-up edge
CI: Confidence interval
C_p: Cutting power
CNC: Computer numerical control
DoC: Depth of cut
DoF: Degree of freedom
EC: Energy consumption
f: Feed rate
f_z: Feed per tooth
n_{eff}: Effective number of replications
R: Number of confirmation experiment replications
R_a: Surface roughness
V_c: Cutting speed
V_e: Error variance.

Data Availability

All data generated or analyzed during this study are included in this article.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Dennis Ochengo: conceptualization; investigation; and writing–original draft; Li Liang: funding acquisition; supervision; and validation; Zhao Wei: funding acquisition; resources; and review and editing; Ning He: funding acquisition and supervision.

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