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Taguchi Full Factorial Design of Experiments Optimisation of Cutting Parameters for Energy Efficiency and Surface Roughness during the Dry Turning of EN19 Material

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Abstract

During metal machining, the satisfactoriness of cost-quality-time matrix convergence effectively depends on the supreme selection of cutting parameters. This study investigated the energy use minimisation and quality surface generation through optimised cutting parameters application, as sustainability enhancement during dry turning of EN19 material. Cutting parameter optimisation is a serious challenge confronting the machining industry as they strive to achieve low energy use and better component quality generation from their operations. The utility material, EN19, is a medium-carbon low alloy steel which typically gets applied in the manufacturing of multiple profiled cylindrical machine tool, rail locomotives and motor vehicle component parts, inter alia. Taguchi Full Factorial experimental plan was used to organise the empirical experiments. ANOVA and the main effects plot signal-to-noise ratio optimisation analysis were utilised in the study to establish the influence of process parameters on the response parameters—surface roughness and energy use. The aim was to investigate and determine the correlation of the machining strategy parameters with the outcome of low energy use and quality surface texture of the components as the cutting parameters were varied, and optimised for minimum surface roughness and energy use. Results of the extensive experimental study, produced optimum cutting speed, rake angle variation and feed rate which respectively influence the response parameters positively for energy use minimisation and improved surface quality. Validation experiments confirmed model findings.

Keywords

Machining, Energy Use, ANOVA, Sustainable Manufacturing, Machining Strategy

1. Introduction

Energy consumption is the main concern of the manufacturing industries [1]. Machining is one of the most fundamental energy consuming manufacturing operations which is broadly used in the production of discrete products such as components made of EN19 alloy steel. Surface roughness, of machined components, has a huge influence on finishing costs and the perceived quality of machined products, notably as considered from a sustainability point of view.

According to Pervaiz [2], during manufacturing operations, energy consumption forms one of the key parameters which play an important role towards determining the economic and environmental burden of the process. Yet machining consumes significant energy during the manufacturing process. Thus, the ever increasing cost of energy coupled with the steepening global competition against the increasing demand by customers for more efficient and cheaper products has placed tremendous pressure on the manufacturing enterprises to radically improve machining energy use efficiency and surface quality generation capabilities, in order to magnify the competitiveness and profitability of the business. Hence, an analysis and understanding of machining systems and optimisation of the machining parameters for energy use at process level and surface quality generation, before the actual cutting begins, has become very important in the metal machining business.

Sustainability generally relates to the feasibility of continuing with a defined pattern of behaviour for an indefinite duration of existence, [3] [4] [5]. The role played by manufacturing is indispensable within the global economy operation. Machining forms one of the oldest major industrial manufacturing processes and is an extremely important applications operation which allows the creation of complex-shaped items for many purposes. As such machining is regarded as the most widely used important manufacturing process for shaping a variety of components [6], especially in the manufacture of discrete mechanical industrial workpieces and components such as EN19 cylindrical components required for the rail and the automobile industries. Estimates project that 15% of the value of all mechanical components manufactured, globally, comes from machining operation [7]. Machining allows the forming of intricate-shaped items and the generation of desired surface finish quality of precision components. In the same vein, machining involves a number of sustainability factors and has potentially significant environmental impacts noting that as a manufacturing process it involves controlled application of energy to convert raw materials into finished goods.

EN19, also known as 708M40 709M40/AISI 4140 is a high quality alloy steel [8]. It is a high strength utility engineering material commonly used for high load bearing applications in the automotive, oil and gas industries for making gears, shafts, high tensile strength studs and bolts, rifle barrels, propeller shaft joints, pins, breech mechanisms for small arm parts, induction hardened track pins, spindles and rods, inter alia parts. It is a material which possesses high tensile strength, good ductility, good wear and shock resistance, and is characterized as a difficult-to-machine material, which can also be machined to highly precise dimensional tolerances. Its application properties can be further enhanced by post machining operations such as heat treatment e.g. induction hardening. Mechanical machining of EN19 material components, is widely used in manufacturing industries and represents significant demand for energy [9] [10]. Energy consumption rate and surface roughness present two essential machinability performance evaluation metrics considered and which require close attention, by the machining based manufacturing industries. The importance of these factors is amplified by the need for the machining industries, of EN19 material, to manufacture low cost high quality components in short periods of time during which production rate and material removal rate are significant considerations [11]. Sustaining the quality consistency, of machined components, during turning operation is a key challenge faced by the discrete cylindrical EN19 parts machining businesses [12], especially, when this has to be realised energy efficiently. Thus, it is vital to optimise, for the quality of surface roughness and the energy use rate, the cutting process. The machining parameter optimisation is vital in causing minimisation of the EN19 components manufacturing cost with achievement of appropriate surface roughness. Earlier research findings, on the machining of Ti6Al4V, established that higher machining rates and material removal rates are associated with lower energy use [13]. Whilst the findings by Tayisepi, *et al.*, [14], on the same material, established that the component surface quality deteriorates as the cutting speed and feed rate increased. In this highly competitive global business environment infested with constraining challenges, fulfilling the prerequisites of elevated productivity, achieving sustainably good surface quality, of the machined EN19 components, cost effectively and energy efficiently, whilst also preserving resources of the machining process forms a difficult-to-balance matrix. These features have become measurement metrics of the quality superiority in machining manufactured components lately.

Published literature exists on optimisation and machinability improvement of other materials using varied sustainability cutting strategies. For example, Duflou, *et al.*, (2012) [15] and Dawood, [16] discussed different techniques and strategies for the sustainable machining manufacturing of, particularly, Ti-alloys. Special reference was made to the selection of optimum cutting conditions intent on minimising energy use, implementation of advanced lubrication and/or cooling techniques and the application of advanced hybrid cutting strategies, cutting tool geometry optimisation and these factors material effect on the machining process. Gupta and Laubscher [17] wrote on the schemes which augment the improvement of titanium alloys machining sustainability which, among others include: adoption of hybrid machining methods, use of advanced cooling and lubrication strategies, optimising machining parameters and selection of appropriate tool material and geometries. They delineated key drivers which buttress the realisation of the sustainable machining of titanium alloys which include—attaining resource efficiency through minimising tool failure, ensuring lower power and energy consumption, reduction of consumption of cutting fluids and water, reduction of waste, part quality improvement and minimisation of environmental pollution. Papakostas, *et al.*, [18] researching on perspective on manufacturing strategy, recommended corresponding techniques and manufacturing strategies to provide the methods to attain the key drivers which target to strengthen the achievement of the three sustainability pillars. Not much literature, however, is published on the optimum and sustainability machining of EN19 steel materials, particularly with respect to the machining planning stage determination of suitable cutting parameters for minimising energy use and generation of good quality surface on the workpiece exterior from the lathe turning process.

Surface roughness, a surface integrity component, is an important quality feature of machined EN19 material components. Surface roughness, attributably, influences the mechanical and physical performance characteristics of machined components, as the post machining functionality of processed parts is essentially influenced by the surface finish quality produced during the cutting process [19]. According to Deiab, *et al.* [20] the effectiveness metrics of a machining process, among other factors, can be read through improved component surface quality and energy use efficiency. Therefore, the selection of a suitable cutting parameter combination, which prompts energy use conservation, presents an appropriate strategy to adopt—during machining—in order for the cutting to be sustainable.

This research, presents results of the experimental study of the cutting parameter optimisation process, for energy efficient machining and improved surface quality generation, during the outside turning of EN19 material. The intention of the study is to aid the machining industry of EN19 material by establishing the optimum cutting parameters for obtaining the good surface quality desired at minimum energy use.

Analysis of Variance (ANOVA) and Signal to Noise (S/N) Ratio

In a design of experiments research plan the Analysis of Variance (ANOVA) is used to test the significance of the influence of input process parameters, from a series of experimental results, on the response parameters. ANOVA determination can be used to test the significant differences between means, with the variance being used to determine whether the means are different. Analysis of variance tests the hypothesis that the means of two or more populations are equal, wherein, the null hypothesis postulate that all population means (factor levels) are equal whilst the alternative hypothesis states that atleast one is different. The importance of one or more factors is assessed by comparing the response variable means at different factor levels [21]. Vital significant process variables which impact and control the process, out of the many parameters, are used to develop the mathematical model required to represent the process. ANOVA tests can be one-way or two-way. One-way ANOVA tests the quality of population means when classification is by one variable (factor) which usually have three or more levels. The level represents the treatment applied. Examination of differences among means using multiple comparisons is possible with the one-way procedure. A one-way ANOVA with two levels is equivalent to a t-test [22]. When classification of treatment of the population means is by two variables (factors) then a two-way ANOVA is used to perform the quality testing. In a two-way ANOVA the data must be balanced, *i.e.* all cells must have the same number of observations and the factors must be fixed. The input factors in this study were cutting speed, tool rake angle and feed rate, in the 95% confidence interval. Thus, significant factors will have a p value of 0.05 or less in the tested range.

Signal-to-noise (S/N) ratio—expresses the ratio of the mean (signal) to the standard deviation (noise). This is the statistical measure of performance used to select the best control levels that best survive the noise factors with minimum variation effect on the process outcome. Control factors which reduce the inconsistency in the process are established through a measure of robustness which is attained through minimising the effect of the uncontrolled (noise) factors. Noise factors cannot be controlled during processing, but during the planning [23]. Higher S/N ratio values pin point control factor settings that minimise the effects of the noise factors. The S/N ratio measures how the response varies relative to the target or nominal value under different noise conditions. Generally the three categories of performance characteristics used to analyse the S/N ratio are nominal-is-best, larger-the-better and the smaller-the-better [23]. Whereas there are several different possible S/N ratios the main standard ones which were also considered for this research were [24]: (a) Biggest-is-Best quality characteristic given by equation Equation (1), thus:

$$SN_B = 10\log\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right] \tag{1}$$

where y_i is the value of the i^{th} quality characteristic and n is the number of experiment tests.

The nominal is best characteristic equation is presented in Equation (2)

$$SN_T = 10\log\left[\frac{y^{-2}}{S^2}\right] \tag{2}$$

The characteristic given by, Equation (3), is the smallest is best factor of quality

$$SN_S = 10\log\left[\frac{1}{n}\sum_{i=1}^{n} y_i^2\right] \quad (3)$$

S/N ratio data analysis should determine the best optimum setting of the operating parameters (cutting speed, tool rake angle and feed rate) in order to attain the desired machined component quality at minimum energy expenditure and desired surface quality. The optimum operating conditions are obtained by selecting the parameters that gives the maximum values of the S/N ratio. This is done by using the main effects plots of the S/N ratios [22]. In this study the quality of performance is maximised by minimising the surface roughness and (energy use) requirement of the machining process. Thus the smallest is best characteristic is used.

2. Methodology, Materials and Equipment

Multi-level full factorial design was utilised as the experiment planning scheme. A total set of 48 experiment runs—constituted of combinations of 3 factors—were carried out.

The aim of the experiments was to study the relationship of cutting parameters with respect to the output of energy consumption minimisation and surface quality improvement of machined EN19 components as well as being to determine the energy and surface quality optimising cutting parameters during the outside turning of cylindrical EN19 components. Turning experiments were carried out using the Cazeneuve 360 HB Precision Lathe machine, shown in **Figure 1**. The lathe machine features include the following: maximum spindle speed of 3000 rpm from least value of 50 rpm; maximum swing of 200 mm; maximum power of the main motor, 5.15 kW and spindle bore of 40 mm.

Figure 1. Cazeneuve 360 HB-X precision lathe machine.

The EN19 alloy specimens material was supplied in tensile condition as a solid round bar (Ø = 40 mm × 150 mm long). The experimental work piece chemical and mechanical properties—as provided on the material certificate—are, respectively, shown in Table 1 and Table 2.

The experimental procedure involved variation of cutting speed in four levels, four levels variation of feed rate and three levels variation of the cutting tool rake angle whilst the depth of cut was kept constant and the cooling mode was dry machining.

The cutting conditions are shown in Table 3.

The focus of this research study was the energy transformation stage at the machining process level and the surface roughness trends of the machined component. Electrical energy is supplied to the lathe machine, and is converted into mechanical energy (kinetic) which is used to separate the material during cutting at the different cutting speeds and feed rates using coated solid carbide tipped tools with 3 levels of rake angle. Some of the energy is used to power the machine functional unit modules (as constant power) as well as to supply lubrication and cooling at the cutting tool work piece interface. At process level, during cutting, the kinetic energy is transformed into various energy outputs. Coated carbide tipped tool mounted in a Sandvik tool holder (DCLNL 2525 M12) was used for the external diameter turning of EN19 solid material round billet specimens under dry machining condition. The cutting conditions were varied during the experimental process with cutting speed, v_c = 100 - 250 m/min in steps of 50 m/min, feed rate, f_n = 0.1 - 0.4 mm/rev in steps of 0.1 mm/rev and rake angle, $\alpha = 0^{\circ}$, 5° and 10°. A constant depth of cut of 0.5 mm was utilised. In

Table 1. Chemical composition the specimen material (weight %).

Element	Mn	Si	C	Cr	P	Ni	S	Mo
Composition %	0.86	0.220	0.414	1.3	0.016	0.031	0.014	0.32

Table 2. Mechanical properties of the specimen material.

Condition	Tensile, Mpa	Yield, Mpa	Elongation %	Izod impact	Hardness Brinell
T	940	680	13	54	280

Table 3. Machining parameters and conditions of the turning experiments.

Parameter	Condition	Units
Cutting Speed (v_c)	100, 150, 200 and 250	M/min.
Feed/rev (f_n)	0.1 - 0.4 in 0.1 mm steps	Mm/rev
Tool Rakeangle	0°, 5° and 10°	Degrees
Depthof Cut (DoC)	0.5 constant	mm
Coolant	Drymachining.	

order to conform with the ISO Standard 3685 - 1977 (E), for single point turning tools, a wear criterion of V_B = 300 μm [14] was used for all the machining experiments. Surface roughness (Ra) was measured using a T500 Hommel surface roughness tester. An average of 3 surface roughness measurements at 3 different spots on the machined shaft was recorded.

The power requirements of a machining production operation can be obtained by measuring the power input to the machine tool drive during a cutting operation and then subtracting the idle (tare) power [25]. The energy expended by a machining process may be estimated by direct measurement—wherein the current, voltage and power factor, during machining, are directly measured. This approach, although being expensive and requires close monitoring, produces accurate data on the exact power consumed. Deriving from the analysis of this base data, prediction and optimisation models of energy consumption and surface roughness can be developed. Else the power can be measured indirectly through estimating it from the forces and velocities data (Muataz, *et al.*, 2011). In this study, the direct energy measurement method was used. Power measurements were carried out using the Digital Lutron 3 Phase Power Analyser DW-6092. The experimental set-up is shown in **Figure 2**.

In this experimental study, Average surface (Ra) value—which is one of the most important machinability criteria—was measured by using Mitutoyo's Surftest surface roughness tester within sampling length 2.5 mm. Ra expresses the average deviation of a surface from the mean height [24]. It is a measure of the irregularities on the surface and is one of the characteristics of the surface texture, besides waviness and lay.

3. Results and Discussions

Table 4 presents the summary of the experiment results. Ensuing is the analysis of the results in detail.

The analysis of variance (ANOVA), of surface roughness, results are presented

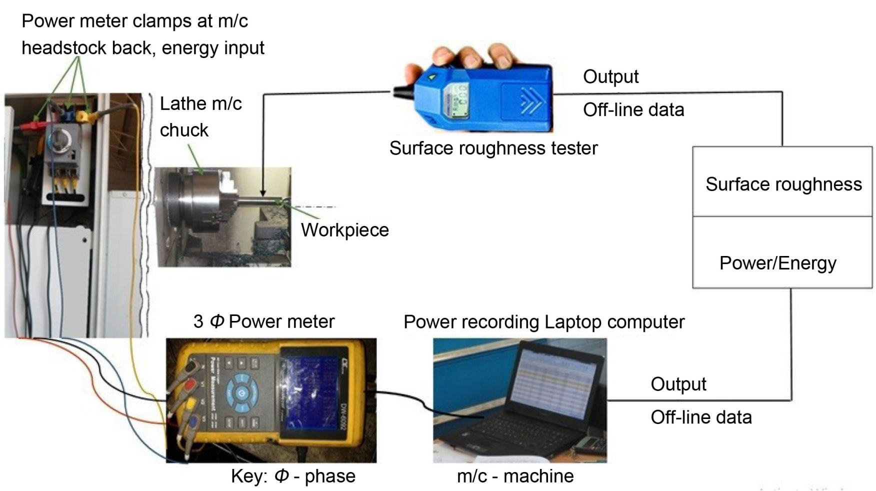

Figure 2. The machining process experimental setup.

Table 4. Summary of the experiment results.

Cutting speed, V_c	Feed rate, f_n	Rake angle	Surface Ra (μm)	Av Power (kW)	Energy (Joules)	Cutting speed, V_c (m/min)	Feedrate, f_n (mm/rev)	Rake angle (Deg)	Surface Ra (μm)	Av Power (kW)	Energy (Joules)
100	0.2	5	10.0	0.3	144.4	100	0.1	10	11.6	0.2	299.4
100	0.1	5	13.7	−0.1	317.2	150	0.4	0	20.0	1.1	86.0
200	0.2	0	10.0	0.8	108.7	200	0.4	0	16.7	1.3	67.1
100	0.4	0	15.0	0.8	146.5	200	0.2	5	10.0	0.9	115.4
100	0.4	5	15.0	0.6	100.4	100	0.3	10	15.0	0.6	112.7
250	0.3	0	10.0	0.9	75.8	150	0.3	5	12.3	0.9	99.3
150	0.3	10	12.3	0.9	101.2	250	0.2	10	10.0	1.2	117.8
150	0.1	10	10.0	0.0	260.2	200	0.3	5	16.7	0.8	102.3
100	0.3	0	30.0	0.2	170.0	250	0.3	10	20.0	1.4	83.1
200	0.4	10	17.0	1.8	79.4	150	0.2	10	11.7	0.7	139.2
150	0.1	0	13.0	0.2	304.5	200	0.4	5	15.0	1.5	72.3
100	0.1	0	15.0	0.4	347.2	200	0.1	5	10.5	0.5	232.0
250	0.4	5	13.3	1.5	58.9	200	0.3	0	10.0	1.0	104.2
250	0.4	10	10.0	1.9	68.1	250	0.3	5	15.0	1.4	83.6
250	0.1	10	8.5	0.3	165.8	100	0.4	10	20.0	0.8	89.7
250	0.2	0	10.0	0.8	105.4	250	0.4	0	15.0	1.6	66.6
150	0.2	5	5.0	0.4	120.5	100	0.2	10	12.0	0.5	149.8
150	0.4	10	15.0	0.8	94.4	100	0.3	5	11.7	0.4	99.3
100	0.2	0	10.0	0.4	242.5	200	0.1	0	11.6	0.5	258.2
150	0.3	0	12.3	0.1	72.0	250	0.1	0	10.0	0.8	193.4
250	0.1	5	9.2	0.7	180.0	250	0.2	5	12.3	0.8	110.6
200	0.1	10	9.6	0.5	188.6	150	0.4	5	15.0	0.8	77.3
150	0.1	5	12.5	0.5	295.4	200	0.3	10	15.0	1.2	94.6
200	0.2	10	15.0	0.8	145.6	150	0.2	0	15.0	0.6	121.4

in **Table 5**. The ANOVA results show that the three variable input parameters—feed rate, rake angle and cutting speed have positive effect on the measured response parameter, surface roughness—Ra. The three input parameters have significant influence on surface roughness. The ANOVA results p-values of 0.0209 for cutting speed, 0.0025 for feed rate and 0.0402 for rake angle show that all the factors have significant influence on surface roughness as they are all less than 0.05. The order of factor significance on the response parameter—surface roughnes—show that feed rate, followed by cutting speed and lastly rake angle, are in that order dominant parameters respectively influencing the surface roughness.

The signal-to-noise ratios main effects plot results for surface roughness is presented in **Figure 3**. The plot was premised on the surface quality characteristic of equation Equation (3) that smallest is the best. The Taguchi analysis of surface roughness, resulting from the main effects plots of the signal-to-noise ratio, show that the optimum cutting parameter combination returning optimum surface roughness response is 100 m/minute cutting speed, 0.4 mm/rev

Table 5. Analysis of variance for surface roughness, Ra.

Source	DF	SS	MS	F	P
Cutting speed, v_c	3	55.74	18.58	1.58	0.0209
Feedrate, f_n	3	215.68	71.89	6.12	0.0025
Rake angle	2	21.94	10.97	0.93	0.0402
Error	39	458.23	11.75	-	-
Total	47	751.59	-	-	-

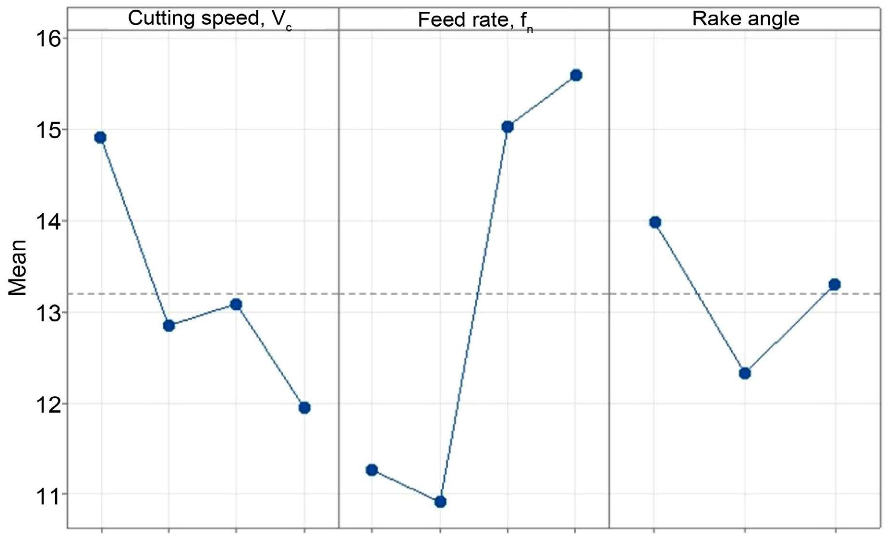

Figure 3. Surface roughness signal-to-noise ratio main effect plot.

and 0 degree rake angle.

The mathematical model explaining the relationship of surface roughness, Ra, with the variable input parameters was approximated from regression analysis, and the result is presented in Equation (4):

$$R_a = 12.31 - 0.01732 \text{ Cutting speed, } v_c + 17.06 \text{ Feed rate, } f_n - 0.068 \text{ Rake angle} \quad (4)$$

The model summary for surface roughness is presented in Table 6 and the residual plot histogram and normal probability plot, given in Figure 4, showing most of the data points around the mean line which shows near normal distribution. This confirms effective representativeness of the data being modelled by the model.

At 95% confidence level, the ANOVA results of average power in Table 7 show that the three variable cutting parameters—cutting speed, feed rate and rake angle—had significant positive influence on average machining power given that their p-values are less than the threshold value of 0.05. Thus, the input factors have significant influence on the response parameter, average machining power. It is apparent, however, that the effect of rake angle (at p-value of 0.273) is less influential, on the response parameter, than that of both cutting speed and feed rate whose p-value both is 0.000.

The Taguchi analysis of the average machining power—main effects plot for the signal-to-noise ratios of average machining power—results presented in

Table 6. Surface roughness regression model summary.

S	R-sq	R-sq (adj)
3.42775	39.03%	26.53%

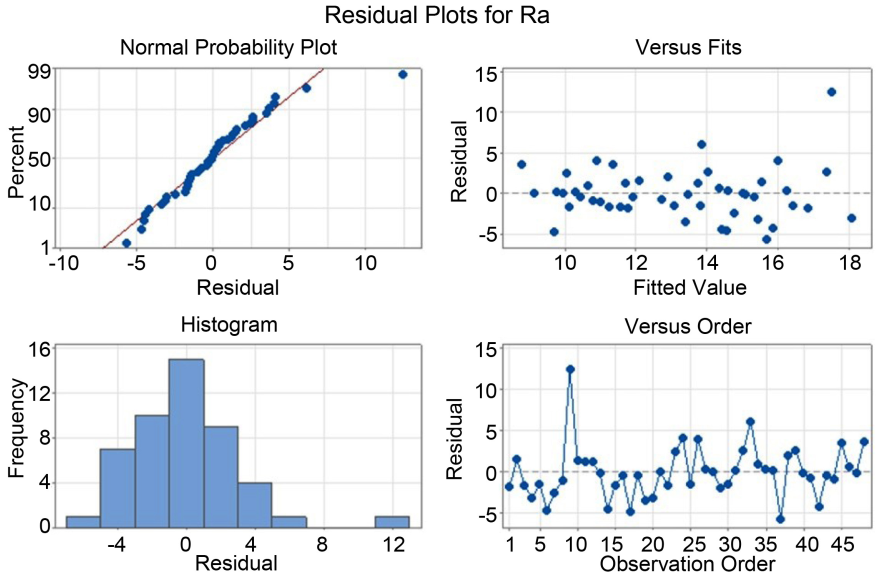

Figure 4. Surface roughness residual plots.

Figure 5, shows that power use optimisation is achievable by operating at a cutting speed of 250 m/min, feed rate of 0.4 mm/rev and rake angle of 10 degrees. Thus, efficient operation improvement would need that feed rate be addressed first before cutting speed and rake angle are respectively successfully addressed.

The mathematical relationship of the input variables (cutting speed, feed rate and cutting tool rake angle) to the response parameter (average cutting power) is expressed in the regression equation in Equation (6). The strong representativeness of the data by the fitted regression line is indicated by the coefficient of determination (r^2) of 80.45% shown in the model summary of the average machining power (**Table 8**) confirm the strong representativeness of the fitted regression model by the data.

$$\text{Av Power} = -0.794 + 0.004813 v_c + 2.624 f_n + 0.01249\,\text{Rake angle} \tag{5}$$

Further confirmation and validation of the regression model as an authentic representation, of the data considered, is presented in the residual plot of the average machining power model (**Figure 6**) in which more than 80% of the points are shown to be about the mean line in the normal probability plot and appearing to be in near normal distribution in the histogram.

Machining energy was also one of the response parameters assessed. Machining energy was determined from considering the applied power and the time length taken in executing a machining operation. The machining energy analysis of variance result is presented in **Table 9**. The machining energy ANOVA result trend is similar to the average cutting power result where in all the input variable

Table 7. ANOVA for average power.

Source	DF	SS	MS	F	P
Cutting speed, v_c	3	3.5970	1.19900	24.03	0.000
Feedrate, f_n	3	4.2771	1.42570	28.57	0.000
Rake angle	2	0.1340	0.06699	1.34	0.273
Error	39	1.9461	0.04990	-	-
Total	47	9.9542	-	-	-

Table 8. Average power regression model summary.

S	R-sq	R-sq (adj)
0.223384	80.45%	76.44%

Table 9. Analysis of variance for machining energy.

Source	DF	SS	MS	F	P
Cutting speed, v_c	3	36,965	12321.8	16.57	0.000
Feedrate, f_n	3	211,472	70490.6	94.81	0.000
Rake angle	2	3057	1528.6	2.06	0.142
Error	39	28,997	743.5	-	-
Total	47	280,491	-	-	-

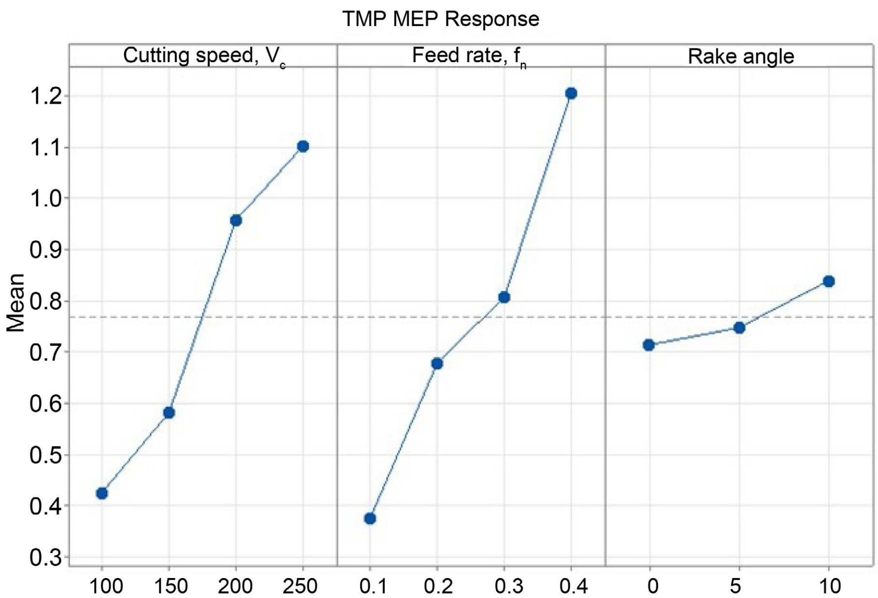

Figure 5. Signal-to-noise ratio main effect plot for average power.

cutting parameters (cutting speed and feed rate) have positive influence on the response parameter, machining energy whilst the cutting tool rake angle is insignificantly influential on the response parameter. The ANOVA p-values, of first two input parameters, were less than 0.05, showing that the influence of

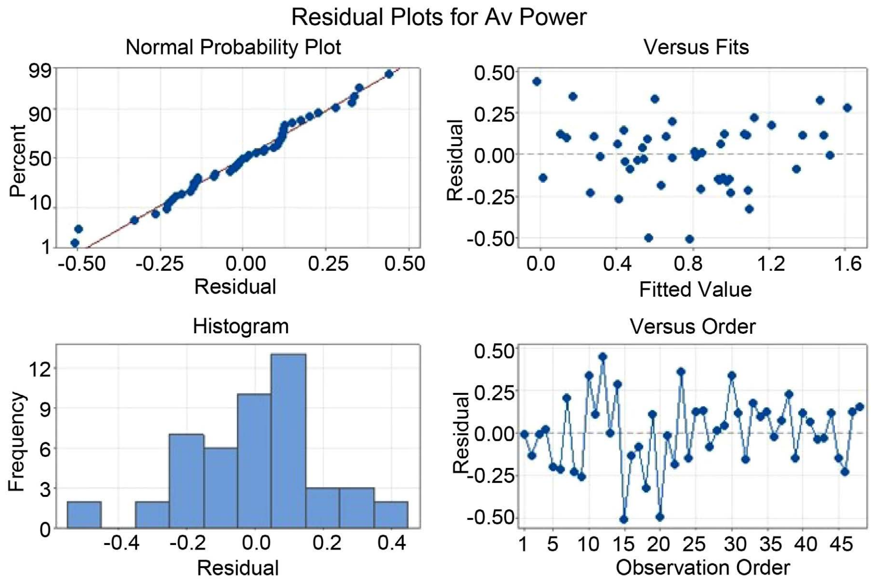

Figure 6. Residual plots of the average cutting power.

cutting speed and feed rate, on the response parameter, is more dominant than cutting tool rake angle with a p-value of 0.142 whilst the former both have p-values of 0.000.

The Taguchi analysis, main effects plot of the S/N ratio of the machining energy, results is presented in **Figure 7**. The results show that the optimum cutting energy is attainable by setting the input variables at the following conditions: cutting speed at 100 m/min, feed rate at 0.1 mm/rev and rake angle at 0 degrees.

The regression equation in 6 models the machining energy with respect to the input variable parameters. The coefficient of determination, (R^2) of 89.66%, in the model summary in **Table 10**, confirms the firm representativeness of the data by the fitted regression model. The coefficient of determination confirms the significance of how effectively the regression model (equation Equation (7)) approximates the real data points projecting the relationship between the predictor variables and the response parameter, machining energy. An R^2 of zero means that the independent variables cannot predict the dependent variable.

$$\text{Energy} = 373.4 - 0.4889 v_c - 544.0 f_n - 1.75\,\text{Rake angle} \tag{6}$$

The machining energy residual plots—normal probability plot and the near normal distribution histogram, in **Figure 8**, further expound the strong representativeness of the data by the fitted regression model.

Optimum Conditions & Confirmation Experiments Summary

According to Rajpure, *et al.* [26], the last stage in an experimental study is to conduct confirmation experiments in order to validate the authenticity of determined optimum conditions. Thus, in this study the set of established optimum conditions for surface roughness, average power and machining energy were respectively set, on the machine tool as the operating conditions, the response

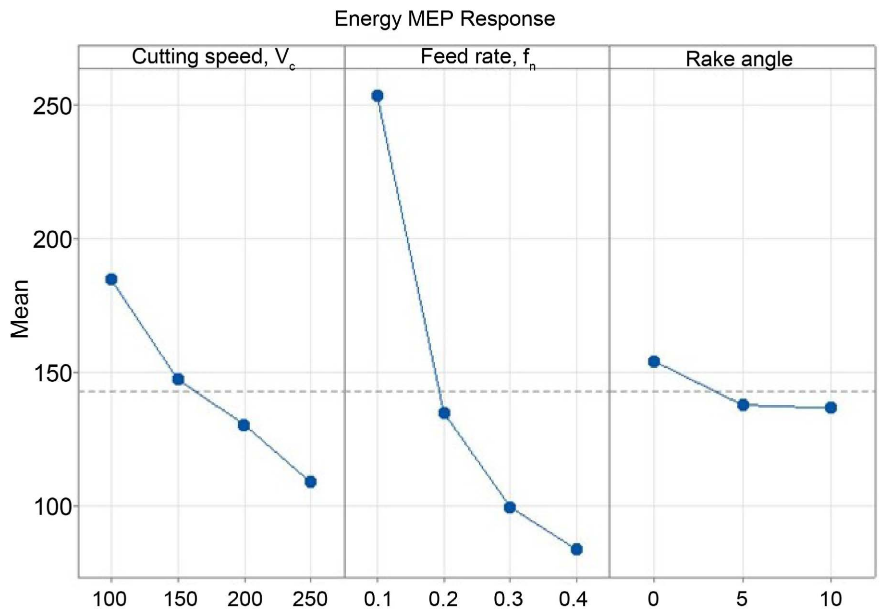

Figure 7. Signal-to-noise ratio main effect machining energy.

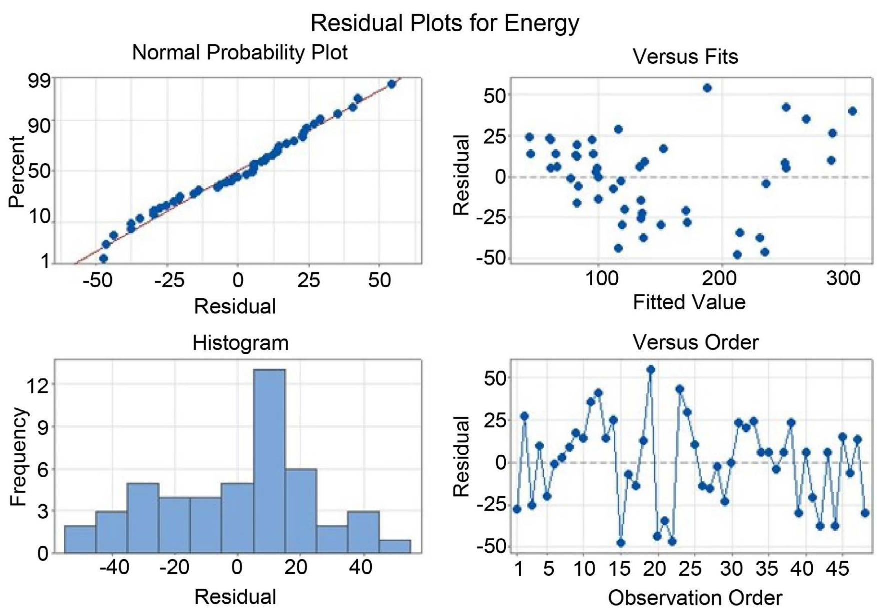

Figure 8. Machining energy residual plots.

Table 10. Machining energy regression model summary.

S	R-sq	R-sq (adj)
27.2674	89.66%	87.54%

parameters were measured and the results compared with the experiment model outcomes in order to see if there is significant or acceptable variation between the model prediction and the physical machining outcomes. The optimum and validation results summary for this study are presented in **Table 11** cluster.

Table 11. Optimum and validation experiment results cluster; (a) Surface roughness. (b) Average cutting power; (c) Machining energy.

(a)					
Model predicted input variable parameters			Response parameter optimum		Variation %
Cutting speed	Feedrate	Rake angle	Model optimum	Experiment Optimum	
100 m/min	0.4 mm/rev	0 degrees	17.42 μm	15.95 μm	8.4

(b)					
Model predicted input variable parameters			Response parameter optimum		Variation %
Cutting speed	Feedrate	Rake angle	Model optimum	Experiment Optimum	
250 m/min	0.4 mm/rev	10 degrees	1.46 kW	1.52 kW	4.11

(c)					
Model predicted input variable parameters			Response parameter optimum		Variation %
Cutting speed	Feedrate	Rake angle	Model optimum	Experiment Optimum	
100 m/min	0.1 mm/rev	0 degrees	232 J	243 J	4.7

4. Conclusion

The study utilised the design of experiments full factorial experiments design to plan the empirical experiments in the process of optimising machining parameters for minimising energy use and achieving minimum surface roughness. ANOVA was utilised to establish the most dominating variable input cutting parameter which impact on the response parameters. The S/N ratio has been used to establish the optimum process parameters which enhance energy use minimisation whilst simultaneously achieving good surface quality. Research results were analysed and conclusions were reached that feed rate is the most dominant factor, followed by cutting speed whilst cutting tool rake angle had limited effect, in influencing surface roughness, energy use and power utilisation. Optimum cutting conditions were respectively determined for producing desirable minimum surface roughness at minimum energy and power use. Regression models were generated for the three response parameters as functions of the variable input parameters. Future work entails the development of the adaptive control system for the automatic management of the determined optimum machining strategy.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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