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PREDICTION OF MACHINING PARAMETERS FOR MINIMIZING ENERGY CONSUMPTION AND OPTIMIZING CUTTING CONDITIONS IN TURNING OPERATIONS OF THICK MILD STEEL PLATES

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ABSTRACT
The safety issue of nuclear power generation has affected the whole world, leading to active movements to reduce dependence on nuclear power generation and increase use of renewable energy such as wind power and solar power. However, the technology of renewable energy generation is still in the developing stage; accordingly, the energy supply is far behind nuclear power and thermal power. Therefore, energy saving is the most important issue for many industries; needless to say, for the manufacturing industry and the machine tool industry. This experimental study applies Response Surface Methodology to optimize CNC turning operations of thick mild steel plates EN8, seeking to minimize power consumption while enhancing cutting performance through systematic analysis of spindle speed, feed rate, and depth of cut.

Keywords: cutting parameters; energy consumption; surface roughness; response surface methodology (RSM); Central Composite Design (CCD)

INTRODUCTION
The manufacturing sector, whose major operations consist of metal cutting processes, represents one of the largest consumers of energy in the world. Over the years, metal cutting operations have only been analysed based on technological and economic considerations without extending such to environmental dimension [1-2]. The environmental impact of manufacturing processes can be enhanced by minimizing the energy consumption. The optimization of machining parameters with minimal energy consumption will not only lead to the use of lower power rated electric motors, drives and auxiliary equipment, but also energy saving during machining, build-up to machining, post machining and idling condition [3].
As a cornerstone of manufacturing operations, turning enables precise material removal to achieve components with desired dimensional specifications and geometric configurations. Turning is one of the essential machining processes in the manufacturing industry to remove material to get the final size and shape of the component, thereby essential for achieving and maintaining stringent quality standard [4-5]. It is a metal removal process used to create rotational parts by cutting away unwanted material from the work piece with single point non-rotary cutting tool. The cutting tool feeds into the rotating work piece and removes unwanted material in the form of chips to create the required shape and size of the work piece. The tool's axes of movement maybe literally a straight line, or along some form of curves or angles, but they are essentially linear [3-4]. Turning operation is aimed at reducing the diameter of work piece to the required size, to obtain material removal rate (Fig. 1).

Turning is a fundamental metal-cutting operation in manufacturing industries, essential for achieving and maintaining stringent quality standards during the production of hard metal components.

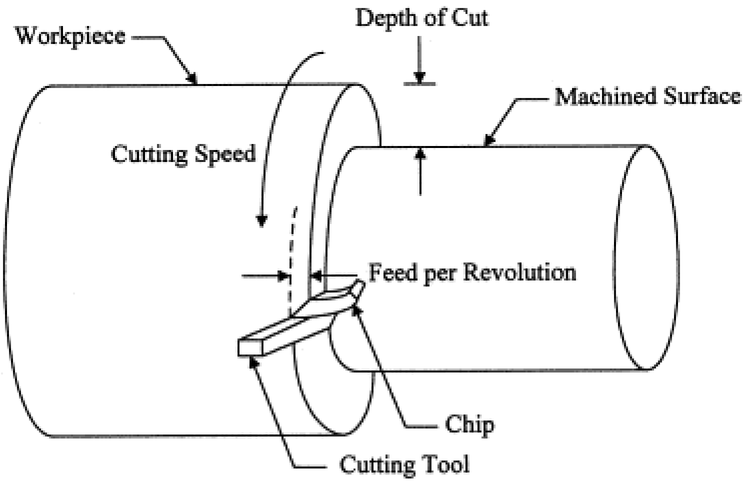

Fig. 1. Cutting parameters in cutting operation.

The optimization of cutting parameters has traditionally centered on three fundamental objectives: maintaining surface integrity, maximizing machining efficiency, and controlling cutting forces [6-9]. The efficiency of production processes is determined by Material Removal Rate (MRR) and machining time, with surface roughness (Ra) serving as a crucial quality metric that requires minimization to prevent friction-related failures between mating parts. Established research has confirmed that the optimization of cutting parameters fundamentally affects machining outcomes, including cut quality, production capacity, and energy consumption levels [10-12].

The safety issue of nuclear power generation has affected the whole world, leading to active movements to reduce dependence on nuclear power generation and increase use of renewable energy such as wind power and solar power. However, the technology of renewable energy generation is still in the developing stage; accordingly, the energy supply is far behind nuclear power and thermal power. Therefore, energy saving is the most important issue for many industries; needless to say, for the manufacturing industry and the machine tool industry. Machine tool manufacturers have recently released various machines aiming for energy saving. Also, various effects have been reported in the recent study papers.

The power demands of machines vary across different operational states, leading to fluctuating energy requirements even for identical processes. This characteristic allows for the development of specialized energy conservation strategies tailored to specific operational assessments and management requirements [13-15]. On the other hand, most of the manufacturing lines consisting of multiple machines at manufacturing sites, especially, for automobile parts are operated for 24hours, consuming massive amount of electricity.

Emerging market economies demonstrate a strong link between industrial expansion and escalating energy requirements, as economic growth drives new energy demand challenges. This trend is reflected in global statistics, where energy consumption has risen by more than 30% since 1990, with forecasts predicting an annual increase in global energy demand of 1.6% between 2009 and 2035 (Fig 2).

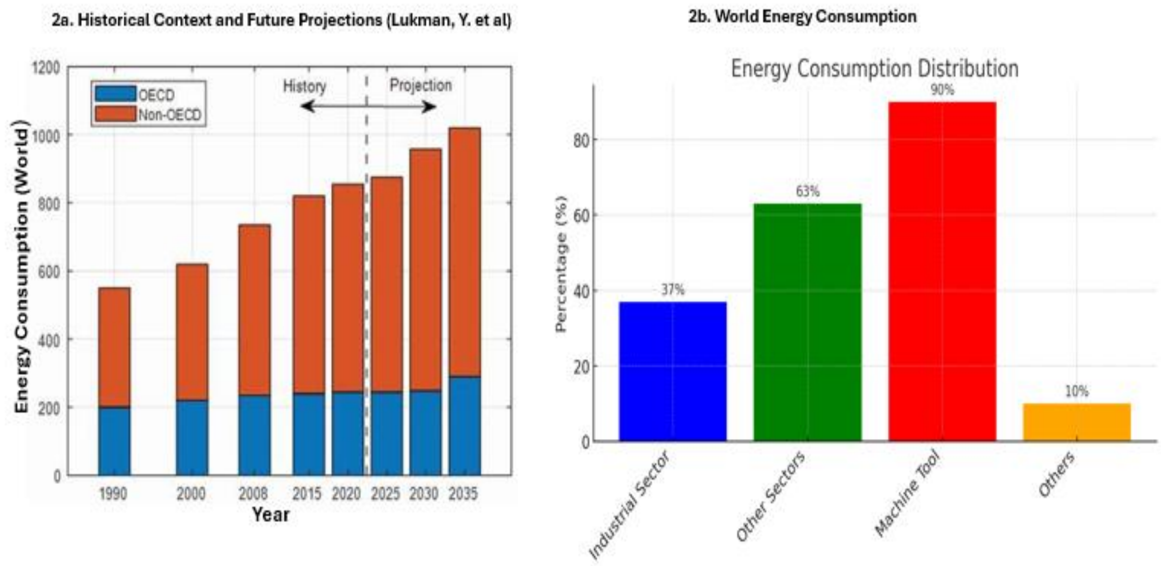

Fig. 2. Analysis of Global Energy Usage

Therefore, suppressing the energy supply in these manufacturing lines is significantly effective for energy saving. Although reducing machining time and securing the operation rate are emphasized in these machining lines, the energy consumption is not emphasized. Recently, researchers have reported various effects as analyzed in table one below.

Ref	Authors	Aim	Observations
16	Fatima Z. et al.	Focuses on establishing a predictive model and optimizing energy consumption for facing and turning operations on two types of steel, namely, AISI 1038 and AISI 4142, using two different cutting tools.	The results of this study show that the selection method used in GA significantly affects convergence toward the optimal solution, while the choice of cutting tool has a considerable impact on energy usage.
17	Lakshmanan, S. et al	Focuses on the validation of nano-coated tool insert with various controlled cutting parameters under different coolants in the turning Ti-alloy.	The results show the AlCrN nano-coated insert under cryogenic (LN2) coolant was better compared to other conditions.
18	Shailendra P. et al	Reviews the recent advancement made for improving the energy efficiency of machining processes.	There results show amongst other findings that employing AI shows promising energy efficiency improvements of around 20%

19	Tzeng C. et al.	Investigated the optimization of CNC turning operation parameters for SKD11 (JIS) using the Grey relational analysis method	The depth of cut was identified to be the most influence on the roughness average and the cutting speed was the most influential factor to the roughness maximum and the roundness.
20	Asilturk I. et al.	Determined multi-objective optimal cutting conditions and mathematic models for surface roughness (Ra and Rz) on a CNC turning	They concluded that, Both Taguchi and response surface statistical analyses indicated that the main effect of the feed rate is the most significant factor on the workpiece surface roughness
21	Aggarwal A. et al.	finds an experimental investigation into the effects of cutting speed, feed rate, debt of cut, nose radius and cutting environment	Taguchi's technique as well as3D surface plots of RSM revealed that cryogenic environment is the most significant factor in minimizing power consumption followed by cutting speed and depth of cut.
22	Ahilan C. et al	Proposed the development of neural network models for prediction of machining parameters in CNC turning process.	performance of neural network model trained with particle swarm optimization model was superior in terms of computational speed and accuracy
23	Asiltrurk I. et al.	use the artificial neural network and multiple regression method for modelling and prediction of surface roughness in turning operations of AISI 1040 steel	The feed rate is the dominant factor affecting the surface roughness, followed by cutting of depth and cutting speed.
24	Routara B.C. et al.	conducted the experiment for optimization of cutting condition in CNC turning for minimum surface roughness using RSM	The concluded that surface roughness parameters Ra, Rq, Rsm, are decreases with increase in depth of cut and spindle speed but increases with increases in feed.
25	Ganeshan H. et al.	determined the optimal machining parameters for continuous profile machining with a set of practical constraints, cutting force, power and dimensional accuracy and surface finish.	The most affecting machining parameters were considered as cutting speed, feed, and depth of cut. Physical constraints were speed, feed, and depth of cut, power limitation, surface roughness, temperature, and cutting force.

Table 1. Past Research Findings

EXPERIMENTAL SET UP

Machining Details

A DIY CNC lathe (Fig.3) was selected to accomplish the experimentation work and gather the data. Different skills and education level workers were chosen for absorbing variation in the process modelling.

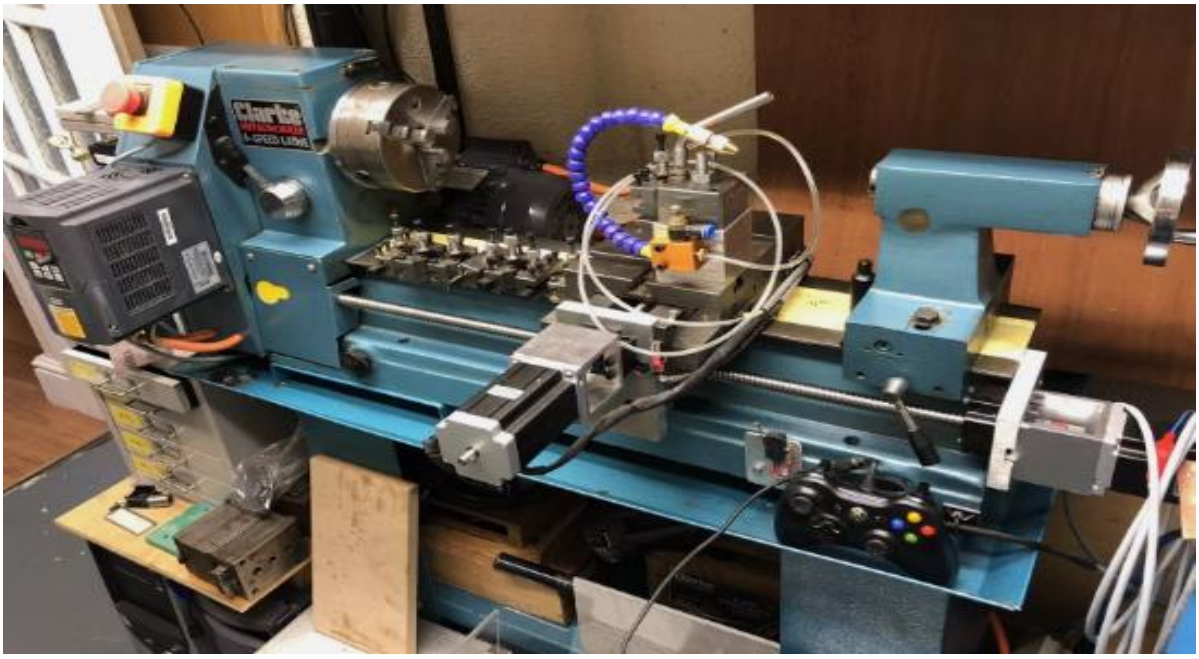

Figure 3. Pictorial view of DIY CNC lathe

The CNC lathe is designed for precision machining and automated cutting operations, making it ideal for applications such as hobby machining, small batch production, prototyping, and CNC learning. It can perform various turning operations, including facing, threading, drilling, and contouring, with improved accuracy and repeatability compared to manual operation. It features a bed length of approximately 400-600 mm and a swing over bed of around 200-300 mm, making it suitable for machining small to medium-sized parts. The spindle operates at variable speeds ranging from 100 to 2500 RPM, driven by a motor that has been adapted for CNC control. The machine utilizes stepper or servo motors for precise movement of the cutting tool, controlled by a GRBL, Mach3, or LinuxCNC system.

Materials Selection

AISI 1040 carbon steel commonly known as EN-8 (Fig. 4.) was selected for the case study because of its wide engineering applications. Three types of tools namely Brazed ceramic tool, Insert with Titanium Nitride (TiN) Coating and Insert with Titanium Aluminum Nitride (TiAlN) coating, which are most used in machining industry were selected for study purpose.

Elements	C	Mn	Si	Cr	Mo
Wt.(%)	0.399	0.643	0.175	0.013	0.002

Table 2. Chemical Composition of AISI 1040 carbon steel

Fig. 4. Experimental Samples

Response Surface Methodology

In this study, all variables are quantifiable hence we decided to use Response Surface Methodology which is a statistical technique to analyze several independent variables influencing the response. Response Surface Methodology (RSM) is a set of techniques used in the empirical study of relationships between one or more responses and a group of variables.

The primary objectives of this methodology are to optimize responses or elucidate underlying mechanisms. Response Surface Methodology (RSM) becomes particularly valuable when studying relationships between assessable input factors and responses, especially in scenarios with limited data points. This approach employs a sequential experimentation strategy that efficiently explores the input factor space through an initial first-order experiment followed by a second-order experiment. The RSM demonstrates notable advantages through its generation of second-order linear regression models, which yield significantly improved predictive capabilities over conventional first-order linear models [26]. The second-order experiment evaluation utilizes fitted second-order regression models based on central composite designs to estimate response surface relationships effectively. For systematic experimental analysis, Central Composite Design (CCD) methodology was implemented, with Table 3. presenting the specific cutting parameter values utilized in the experimental matrix.

				Levels				
S. No.	Parameter	Symbol	Range	-1.75	-1	0	1	1.75
1	Cutting Speed (rpm)	A	740 to 1080	740	825	910	995	1080
2	Depth of Cut (mm)	B	0.2 to 1.0	0.2	0.4	0.6	0.8	1
3	Feed (mm/rev)	C	0.05 to 0.25	0.05	0.1	0.15	0.2	0.25

Table 3. Machining Parameter and their respective levels

DATA COLLECTION

The acquired data from the turning operations were collected for onward processing with RSM design (using a second order linear model). Table 4 and Table 5 shows the predicted values using RSM model in turning AISI 1040 carbon steel and the experimental observations using the experimental coded values. Data were collected with MarSurf PS 10 (for surface roughness) and Keysight 34461A (for voltage, current, and resistance).

Exp. No.	Cutting Speed (rpm)	Depth of Cut (mm)	Feed (mm/rev)	Machine Time (Secs)
1	940	0.2	0.05	24

2	940	0.4	0.15	27
3	850	0.2	0.2	25
4	1000	0.4	0.15	26
5	980	0.4	0.1	30
6	740	0.6	0.1	34
7	940	0.2	0.15	26
8	850	0.8	0.2	28
9	850	0.6	0.2	27
10	980	0.6	0.2	26
11	940	0.8	0.15	23
12	980	0.4	0.05	22
13	980	0.4	0.1	21
14	980	0.8	0.15	27
15	940	0.6	0.2	28
16	1000	1	0.25	25
17	980	0.8	0.15	21
18	980	0.8	0.15	20
19	1000	0.8	0.1	19
20	1080	0.6	0.2	26

Table 4. shows the predicted values using RSM model

MATHEMATICAL MODEL

Next is to input in the observed experimental data into a mathematical model using regression analysis. This is a multi-variable engineering problem; hence it can be solved using a second order equation such as,

$$Y = N\beta 0 + \beta 1x1 + \beta 2x2 + \beta 3x1^2 + \beta 4x2^2 + \beta 5x1x2 + \ldots + \beta nxn \text{ ------------------------ } \mathbf{(1)}$$

Where, Y = Response, β = Correlation Coefficient, and N = Regression Constant

Equations (2) and (3) express the mathematical relationships for Surface Roughness and Machining Time that were established through this experimental work.

Surface Roughness $= 2.0657 + 4.9876x\ 10\text{-}4 \times N - 5.8796 \times f + 1.6887 \times d + 2.88 \times 10^{-3} \times N \times f - 1.26 \times 10^{-3} \times N \times d + 5.75 \times f \times d$ ------------------------- **(2)**

Machining time $= 122.33898 - 0.06760 \times N - 377.24348 \times f + 5.53017 \times d + 0.12500 \times N \times f - 2.50000 \times 10^{-3} \times N \times d - 5.00000 \times f \times d + 7.61213 \times 10^{-6} \times N^2 + 359.60891 \times f2 - 0.96525 \times d^2$ --- **(3)**

Where, N = Spindle Speed, f = Feed, and d = Depth of Cut

Exp. No.	Cutting Speed (rpm)	Depth of Cut (mm)	Feed (mm/rev)	Surface Roughness
1	0	0	-1	2.32
2	-1	0	1	2.18
3	-1	1	1	1.18
4	0	1	0	0.68
5	0	-1	0	2.47
6	-1.75	1	0	2.38

7	0	1	-1	2.12
8	0	-1	1	2.2
9	1	-1.75	0	2.18
10	1.75	0	0	2.33
11	1	0	0	2.42
12	0	0	1	2.05
13	1	0	-1.75	1.9
14	1	1	1	2.18
15	0	1.75	1	2.22
16	0	1	0	0.8
17	0	0	0	2.18
18	-1	0	1.75	1.18
19	-1	0	1	0.89
20	1	1	0	0.78

Table 5. Experimental observations in coded form

ANALYSIS OF VARIANCE

To determine the relative impact of cutting depth, feed rate, and speed on surface roughness, Analysis of Variance (ANOVA) was performed at a 95% confidence level, with results documented in Table 6 & Table 7. Surface roughness, machining time, and Material Removal Rate (MRR) are validated for the significant effect of cutting speed, depth of cut and feed and power consumption. Results shows that all the parameters possess significant influence on the surface roughness, machine time and MRR.

The established model provides reliable guidance for navigating and optimizing within the defined design space as the respective R^2 values for Surface roughness, machining time, and Material Removal Rate are greater than 0.8.

Table 6. ANOVA for Surface Roughness

Source	Sum of Square	DOF	Mean Square	F value	P-value Prob>F	
Model	8.68	9	0.964444444	1.4183	0.00013	Significant
A - Cutting Speed	1.57	1	1.57	2.30882	0.0002	
B - Depth of Cut	0.04256	1	0.04256	0.06259	0.0345	
C - Feed Rate	6.25	1	6.25	9.19118	0.6576	
AB	3.6677	1	3.6677	5.39368	0.4565	
AC	0.5641	1	0.5641	0.82956	0.0053	
BC	0.4356	1	0.4356	0.64059	0.2435	
Residual	0.68	10	0.068			
Lack of Fit	2.26	5	0.452			
Pure Error	0.13	5	0.026			

Table 7. ANOVA for Machining Time

Source	Sum of Square	DOF	Mean Square	F value	P-value Prob>F	
Model	32.3456	9	3.593955556	8.55704	0.0001	Significant

A - Cutting Speed	6.2222	1	6.2222	14.8148	0.00012
B - Depth of Cut	1.8843	1	1.8843	4.48643	0.0246
C - Feed Rate	13.5644	1	13.5644	32.2962	0.7234
AB	9.3433	1	9.3433	22.246	0.6897
AC	2.3425	1	2.3425	5.57738	0.0653
BC	1.9888	1	1.9888	4.73524	0.0786
Residual	0.42	10	0.042		
Lack of Fit	1.86	5	0.372		
Pure Error	0	5	0		

RESULTS

The ANOVA analysis results indicate that feed has a significant correlation with cutting force and surface roughness, while cutting velocity shows a strong association with power consumption. This finding highlights the importance of including power consumption in turning operations, as it represents a critical aspect of sustainable manufacturing practices alongside other machining response variables.

Figure 5 presents a three-dimensional surface, which can alternatively be displayed as a response surface contour for easier interpretation. There is a direct relationship between uncut chip thickness and feed's influence on cutting force, with cutting force naturally increasing as feed levels rise. Research on turning hardened steel confirms that cutting force serves as the primary force acting on the tool's rake face. Cutting speed shows negligible effect on cutting force because uncut chip thickness dimensions remain independent of cutting speed. This observation aligns with previous studies on different workpiece materials [27-29].

Figure 6 displays both the response surface contour and the corresponding 3D surface. When operating within the selected cutting parameters, the resulting surface roughness primarily fell within the finish turning range of 0.5–1.75 mm [29-31], particularly when feed was maintained at 0.2 or below. The mild steel workpiece behaved as expected, exhibiting increased surface roughness with higher feed rates. Figure 7 illustrates the response surface contour alongside the 3D surface representation of the empirical equation developed for power consumption as an actual factor.

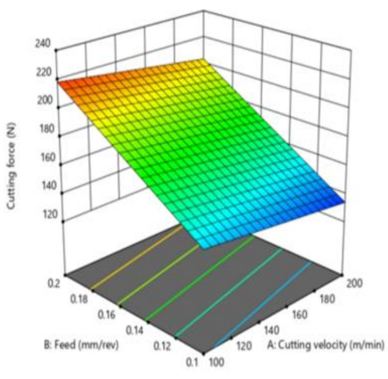

Fig. 5. RS graphs for power consumption.

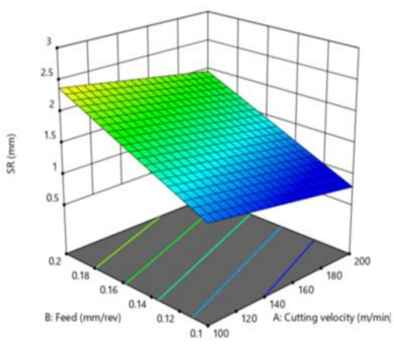

Fig. 6. RS graphs for power consumption.

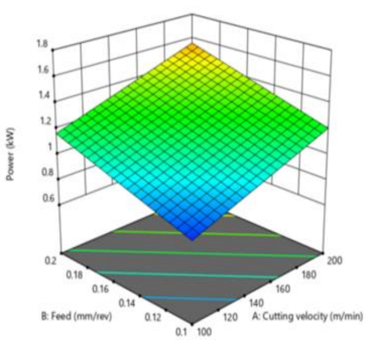

Fig. 7. RS graphs for power consumption.

CONCLUSION

This research employed a central composite design methodology to examine how turning parameters affect surface roughness. The findings reveal that feed rate has the most significant impact on surface roughness, with roughness increasing dramatically as feed rate rises. Conversely, higher cutting speeds resulted in decreased surface roughness, while depth of cut demonstrated minimal influence. The study successfully identified optimal cutting parameters to achieve minimum surface roughness. The close correlation between predicted and measured values validates the accuracy of the developed model for surface roughness when machining EN 8 materials.

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