Investigation on the Multi-Objective Optimization of Machining Parameters and Prediction for EN Series Materials

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ABSTRACT

To meet the requirements of modern Computerized Numerical Control (CNC) turning processes, it is necessary to improve efficiency, precision and surface quality while reducing negative effects such as vibration and cutting force. In an attempt to minimize vibration, surface roughness, and cutting force at the same time, this study optimizes machining settings in CNC turning of EN8. Manufacturers can find the optimal parameters by using a multi-objective optimization strategy. According to the conducted experimental validation, by reducing vibration, improving surface roughness, and minimizing cutting forces, the adjusted parameters can significantly increase productivity and quality in CNC turning operations. This research contributes to the ongoing effort to improve machining processes to meet various performance goals, for industries that rely on CNC turning.

Keywords-multi objective optimization; EN; materials; Analysis of Variance (ANOVA)

I. INTRODUCTION

In the context of contemporary manufacturing, the utilization of precision machining techniques, such as Computer Numerical Control (CNC) turning, is a vital component of the production process, facilitating the creation of superior-quality components for a diverse range of industries, including automotive and aerospace. It is of great importance to attain optimal machining conditions in order to guarantee both, product quality and durability of the tools and machinery. However, challenges, such as excessive vibrations, poor surface roughness, and high cutting forces can compromise the pursuit of enhanced efficiency, precision, and surface finish in turning. Vibrations during the machining process can compromise the integrity of the workpiece, leading to premature tool wear, reduced accuracy, and higher energy consumption. Furthermore, rough surfaces can have a detrimental impact on the functionality and appearance of machined parts, underscoring the necessity to minimize imperfections. Furthermore, high cutting forces can strain the machine's structure, leading to wear and tear as well as to a reduction in tool lifespan. Traditionally, the optimization of machining parameters in CNC turning has focused on a single objective, such as increasing productivity or reducing performance indicators, while other important factors have often been overlooked. However, in today's competitive manufacturing environment, a more holistic approach is necessary, one that takes into account multiple objectives simultaneously. This paper examines the significance of a comprehensive approach to CNC turning by investigating the Multi-Objective Optimization of Machining Parameters and Prediction (MOO-MPP) methodology, which aims to simultaneously minimize vibration, surface roughness, and cutting force. The objective is to achieve a balance between high-quality results and efficient resource utilization by optimizing various performance criteria, thereby catering to the diverse needs of modern machining industries. In order to achieve this objective, it is essential to integrate advanced optimization techniques, experimental validation, and a deep understanding of the complex relationships between machining parameters and performance metrics. The goal of this study is to present a structured framework that combines genetic algorithms, response surface methodology, and practical experimentation to determine the optimal sets of machining parameters. The following sections will explore the methodology, experimental setup, and outcomes of the MOO process, providing valuable insights into achieving comprehensive CNC turning optimization for improved product quality, reduced tool wear, and increased manufacturing efficiency.

The application of MOO methodologies has been an effective approach for identifying well-distributed Pareto optimal solutions, with a broad range of applications in diverse problem-solving contexts [1]. This paper employs metaheuristic MOO algorithms to generate Pareto optimal solutions for micro-turning and micro-milling applications. A comparative study is conducted to evaluate the performance of the Non-dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Ant Lion Optimization (MOALO), and Multi-Objective Differential Evolution (MODE) [2]. In the optimization of the machining parameters for a chatter-free milling process, the inevitable Surface Location Error (SLE), which reflects the accuracy of the machined workpiece dimensions, has been largely overlooked as a quality indicator, resulting in a reduction in optimization accuracy. This paper presents a methodology for developing a MOO model, wherein the Material Removal Rate (MRR) and SLE are regarded as the primary objectives [3]. A MOO approach was employed using the Jaya algorithm to enhance the effectiveness of machining a curve hole in P20 mold steel through sinking Electrical Discharge Machining (EDM). The experimental results demonstrated that the current and pulse on time have a significant impact on material removal and tool wear diagnostic parameters [4]. This research proposes the development of novel hybrid optimization techniques for the acquisition of optimized wire EDM machining parameters and the analysis of the performance and microstructure of a hybrid treatment alloy 20 material following its machining in wire EDM [5]. The optimization of process parameters in wire EDM of TiB_2 nano-composite ceramic was performed using a fuzzy logic analysis coupled with a Taguchi dynamic experiment [6]. This paper presents a standardized methodology for determining the process window for ductile machining of brittle materials. The methodology was applied to CaF_2 and an optimized process window for single-point diamond turning was identified [7]. A review of the use of evolutionary algorithms for the optimization of machining parameters is provided in [8]. The paper discusses the application of MOO techniques to the problem of cutting parameter selection in turning processes. The approaches deployed are differential evolution and NSGA-II [9]. In [10], a model is presented, which allows the optimization of multiple objectives simultaneously, namely the minimization of surface roughness, cutting force, and power, and the maximization of productivity, in the context of turning operations on tempered stainless steel AISI 420. This paper presents a Taguchi S/N-based optimization of machining parameters for surface roughness, tool wear, and material removal rate in hard turning under Minimum Quantity Lubrication (MQL) cutting conditions [11]. This study describes the optimization of cutting inserts and parameters for turning based on artificial neural networks and a genetic algorithm [12]. The performance of coated Cubic Boron Nitride (CBN) cutting tools in green turning of gray cast iron (EN-GJL-250) was modelled and optimized [13]. This research discusses the online prediction of the mechanical properties of hot rolled steel plate using machine learning [14]. This paper proposes a statistical approach to wire EDM that is coupled with artificial intelligence techniques and soft computing [15]. A hybrid approach combining Taguchi and NSGA-II is presented for the modeling and optimization of wire-EDM parameters for the machining of a Ni55.8Ti shape memory alloy [16]. The optimization of process parameters in the machining of Nimonic superalloy on EDM is presented, with the use of a genetic algorithm [17]. The process parameters optimization for die sinking EDM for the machining of SS316H is discussed in the context of the Taguchi L9 approach [18].

II. EXPERIMENTAL SETUP

The tests were conducted on a 30 mm diameter rod of EN 8 steel in its original state. The experiments used a multi-functional CNC machine with specific features, including a JK - L1 model, CNC retrofit control, a 3 KW motor running at 2,800 rpm, and a stepper motor controlled by Mach3 software, as shown in Figure 1. The CNC machine deployed for the experimentation work is equipped with an acceleration sensor and strain gauge in connection with the tool, tool post and compound rest schematically observed in Figure 2. The experimental setup evidenced in Figure 3, is equipped with an Arduino Uno Rev3 to measure all output parameters. The Arduino Uno is a microcontroller board that uses the ATmega328P (datasheet). It has 14 digital input/output pins (6 of which can be utilized as PWM outputs), 6 analog inputs, a 16 MHz ceramic resonator (CSTCE16M0V53-R0), a USB connector, a power connector, an ICSP header, and a reset button.

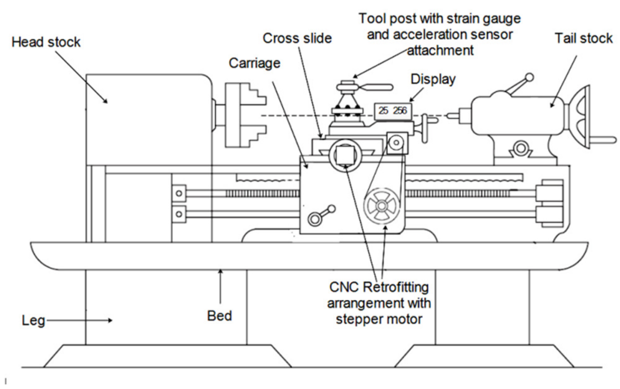

Fig. 1. Schematic diagram of experimental setup.

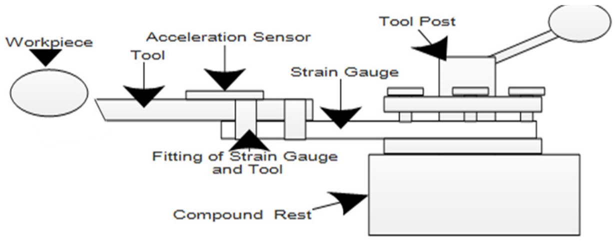

Fig. 2. Strain gauge in connection with tool, tool post and compound rest.

It includes everything necessary to support the microcontroller, and it can be connected to a computer with a USB cable or power it with an AC-to-DC adapter or battery to get started. The GY-61 ADXL335 3-axis analog accelerometer sensor measures the forces involved in machining. The GY-61 ADXL335 is a small, thin, low power, complete 3-axis accelerometer with signal conditioned voltage output. This product measures acceleration with a minimum full-scale range of ±3 g. It is capable of measuring static acceleration due to gravity in tilt sensing applications as well as dynamic acceleration caused by motion, shock, or vibration. The sensor operates from 1.8 V to 3.6 V DC (3.3 V is optimal) and typically uses 350 µA of current. However, an on-board 3.3 V regulator is ideal for use with 5 V microcontrollers such as the Arduino. Surface topography is measured by the arithmetic mean known as R_a. The R_a is determined using a HOMMEL TESTER T500 surface roughness tester and its values, for the machined surface, were calculated by averaging the surface roughness values over a 5 mm measurement length.

III. PILOT EXPERIMENTAL WORK

Based on initial observations, it can be concluded that changing certain parameters has an impact on the quality of the material. It is necessary to determine the optimal parameters that result in a satisfactory cut quality. By making a series of pilot experiments, it is possible to identify the effective range of parameter changes, as presented in Figure 4.

Fig. 3. Actual machining set-up.

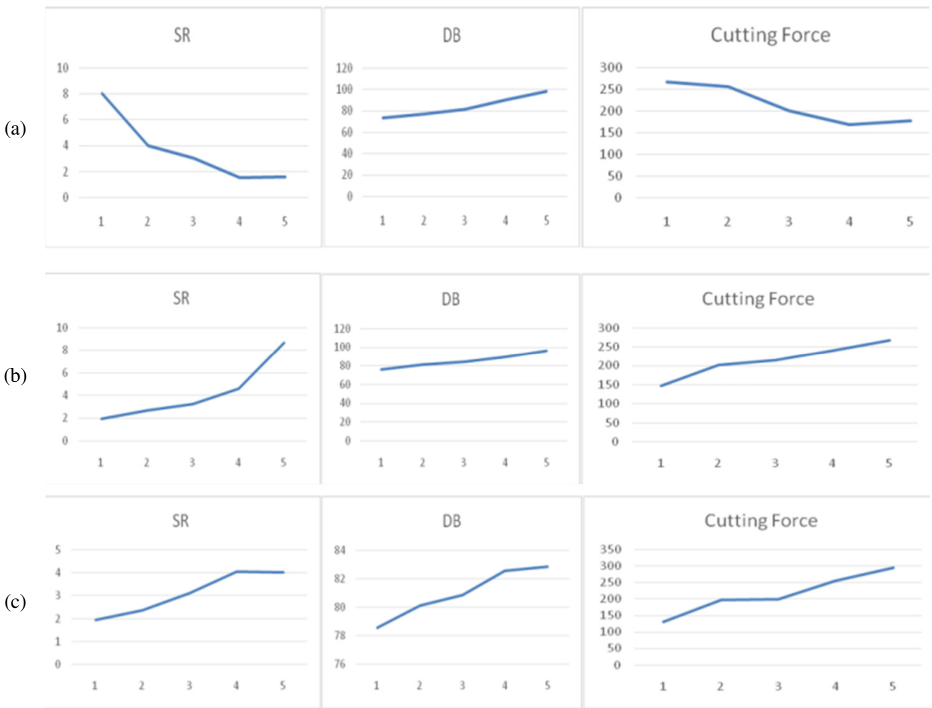

Fig. 4. (a) Output trend of first five pilot, (b) output trend of the second five pilot experiment, (c) output trend of third five pilot experiment.

This study was designed to achieve the highest possible quality of cut through the implementation of primary research methodologies. At present, industry operators employ a trial-and-error methodology, necessitating numerous manual attempts to adjust parameters and conduct experiments until the desired cut is achieved. A review of the data from multiple pilot experiments in addition with the effective range of input parameters is portrayed in Table I.

TABLE I. MACHINING PARAMETERS AND THEIR LEVELS

Factor	Symbol	Level 1	Level 2	Level 3
Cutting speed (m/min)	n	354.6	471.0	628.3
Feed rate (mm/rev)	f	0.1	0.6	0.8
Depth of cut (mm)	d	0.4	0.6	0.8

IV. EXPERIMENTAL WORK

An experimental design is a plan for conducting tests with the objective of drawing accurate conclusions about the connections between different factors and also provides the framework in which the experiment is performed. In the present study, tests were carried out on a lathe utilizing a cutting tool for En8 steel. The way data are collected has a significant impact on the outcome of any experimental inquiry. The most prevalent experimental design is the full factorial, which entails conducting trials for each potential combination of variables. A full factorial Design of Experiments (DOE), allows the measurement of the outcome of all potential factor combinations and levels. These responses are then examined in order to yield details regarding each main effect and each interaction impact. The experimental design for the three turning parameters (speed, feed rate, and depth) with three levels was structured using Taguchi's L27 orthogonal array. The influence of cutting variables, including speed, feed rate, and depth, on surface roughness was evaluated through ANOVA. A total of 27 experiments were made using a specific orthogonal array, as shown in Table II. Once the outcome has been determined, it is essential to analyze the impact of the various parameters on all three variables and ascertain the percentage contribution of each parameter through the use of mathematical calculations and the Design Expert 13 software. The Response Surface Methodology (RSM) and ANOVA methods are employed for the analysis of the experimental data, with the objective of determining the impacts and relative importance of the cutting parameters.

V. EXPERIMENTAL AND PREDICTED VALUES OF SURFACE ROUGHNESS, VIBRATION AND CUTTING FORCE

The objective of engineering experiments is to ascertain the optimal conditions for achieving the most favorable results. One method for attaining optimal performance is RSM, a collection of mathematical and statistical procedures that can be used to model and analyze problems in which the response of interest is affected by multiple factors in order to optimize the response. It constitutes a perpetual assessment of design and optimization. The response model of independent feedback can be obtained through the implementation of experimental procedures and the subsequent application of regression analysis. The point that is closest to optimal can be identified as the standard answer. RSM is primarily employed for the purposes of characterization and optimization and the independent process can be expressed in a number of different forms:

$$Y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \pm \varepsilon \qquad (1)$$

where Y is the corresponding response and x_i (i =1, 2, …, n) are the independent input parameters. The terms b_0, b_1, b_2, etc., are the second-order regression coefficients. The second term contributes to the linear effect, the third term contributes to the higher-order effects, and the fourth term contributes to the interactive effects of the input parameters. The coefficients' values are estimated using the responses collected (Y_1, Y_2, … Y_n) through the design points (n) by applying the least square technique. This equation can be rewritten in terms of the three variables:

$$Y_u = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{23}x_2x_3 \ldots \qquad (2)$$

The objective of employing RSM is to examine the response across the entire domain and identify regions of interest, where the response attains or approaches optimality. A meticulous analysis of the surface response patterns allows for the identification of a combination that yields the optimal response.

TABLE II. EXPERIMENTAL MEASUREMENT OF R_A, V AND F_C

Ex No	Speed n (m/min)	Feed f (mm/ rev)	Depth of cut, d (mm)	Surface roughness R_a (µm)	Vibration V (db)	Cutting Force F_c (N)
1	345.6	0.1	0.4	2.013	70.11	76.45
2	345.6	0.1	0.6	1.907	71.41	160.3
3	345.6	0.1	0.8	1.837	73.46	225.85
4	345.6	0.2	0.4	2.797	75.91	120.25
5	345.6	0.2	0.6	3.087	77.06	210.85
6	345.6	0.2	0.8	2.807	78.76	280.15
7	345.6	0.3	0.4	3.932	81.11	138.85
8	345.6	0.3	0.6	4.221	83.22	225.25
9	345.6	0.3	0.8	4.151	84.91	291.05
10	471.0	0.1	0.4	1.937	73.82	73.75
11	471.0	0.1	0.6	2.217	75.75	147.6
12	471.0	0.1	0.8	1.954	78.07	202.05
13	471.0	0.2	0.4	2.825	79.409	125.45
14	471.0	0.2	0.6	3.036	80.739	200.3
15	471.0	0.2	0.8	2.957	82.068	253.95
16	471.0	0.3	0.4	3.68	83.398	136.75
17	471.0	0.3	0.6	3.901	84.728	211.1
18	471.0	0.3	0.8	3.951	86.057	264.65
19	628.3	0.1	0.4	2.161	87.387	76.5
20	628.3	0.1	0.6	2.337	88.717	128.6
21	628.3	0.1	0.8	2.227	90.046	160.85
22	628.3	0.2	0.4	2.877	91.376	126.45
23	628.3	0.2	0.6	3.265	92.706	176.5
24	628.3	0.2	0.8	3.487	94.035	212.85
25	628.3	0.3	0.4	4.029	95.365	144.35
26	628.3	0.3	0.6	4.499	96.695	195.9
27	628.3	0.3	0.8	4.654	98.024	230.15

Table III presents a comparison between the predicted and experimental values of surface roughness, vibration, and cutting force, as derived from the developed mathematical model. A comparison of the predicted and measured values indicates that the predicted values of surface roughness are in close agreement with the measured values. The mean relative error between the experimental and predicted values for R_a, V, and F_c are 2.75%, 0.306%, and 1.014%, respectively.

VI. ANOVA ANALYSIS

It is of great importance to evaluate the appropriateness of the model by analyzing the observed responses for the specified input parameters. This may be achieved by verifying the regression model, model coefficient, and lack of fit value. The adequacy of the model is ensured by employing ANOVA, while a multi-output optimization technique is used to determine the optimal combination of input parameters. This is done with the aim of achieving an improved surface finish, a reduction in vibration, and a reduction in cutting force. The primary goal of data analysis is to ascertain the significant individual and interactive effects of independent variables on dependent responses. There are numerous types of regression models, including linear, quadratic, and interaction models. However, for the purposes of this study, a quadratic model was selected for all surface roughness, tool vibration, and cutting force. The results of ANOVA analysis are depicted in Table IV (Surface Roughness), Table V (Tool Vibration), and Table VI (Cutting Force), respectively.

TABLE III. EXPERIMENTAL AND PREDICTED VALUES OF R_A, V AND F_C

No.	Actual R_a	Predicted R_a	Actual V	Predicted V	Actual P	Predicted P
1	2.013	2.049	70.110	69.960	0.423	0.456
2	1.907	2.088	71.410	71.870	0.866	0.964
3	1.837	1.882	73.460	73.650	1.186	1.374
4	2.797	2.854	75.910	75.630	0.635	0.717
5	3.087	2.965	77.060	77.420	1.446	1.231
6	2.807	2.832	78.760	79.070	1.902	1.646
7	3.932	3.925	81.110	81.170	0.857	0.756
8	4.221	4.109	83.220	82.830	1.124	1.276
9	4.151	4.047	84.910	84.360	1.676	1.696
10	1.937	1.903	73.420	74.040	0.736	0.635
11	2.217	2.035	76.750	75.800	1.159	1.148
12	1.954	1.923	78.070	77.430	1.704	1.561
13	2.825	2.723	79.410	78.980	0.953	0.993
14	3.136	2.928	80.740	80.600	1.580	1.511
15	2.957	2.889	82.070	82.110	1.837	1.930
16	3.680	3.809	83.400	83.770	1.074	1.129
17	3.901	4.087	84.730	85.270	1.672	1.653
18	3.811	4.120	86.060	86.650	1.921	2.077
19	2.161	2.067	87.390	87.360	0.907	0.787
20	2.337	2.318	88.720	88.920	1.137	1.303
21	2.227	2.324	90.050	90.360	1.831	1.721
22	2.677	2.907	91.380	91.360	1.115	1.266
23	2.865	3.230	92.710	92.790	1.806	1.788
24	3.487	3.309	94.030	94.100	2.019	2.211
25	4.229	4.013	95.360	95.220	1.564	1.524
26	4.499	4.408	96.690	96.530	2.135	2.052
27	4.654	4.559	98.020	97.710	2.619	2.480

. The value R^2 for all surface roughness, tool vibration, and cutting force is greater than 90%, indicating a strong correlation between the model and the experimental data. The adjusted R^2 value for surface roughness, vibration, and cutting force is 98.25%, 99.76%, and 99.86%, respectively, which indicates a strong positive correlation. The models for surface roughness, vibration, and cutting force are statistically significant, as evidenced by p-values that are less than 0.05, which is consistent with a 95% confidence level.

TABLE IV. ANOVA FOR SURFACE ROUGHNESS

Source	Sum of squares	*df*	Mean square	*F*-value	*p*-value	% contribution
Model	20.101	9	2.2335	163.61	1.02E-14	98.859
A-n Speed	0.43059	1	0.43059	31.541	3.08E-05	2.118
B-f Feed	18.825	1	18.825	1379	1.02E-17	92.583
C-d DOC	0.18875	1	0.18875	13.827	0.0017082	0.928
AB-n×f	6.58E-06	1	6.58E-06	0.00048205	0.98274	0.000
AC-n×d	0.13328	1	0.13328	9.7628	0.006171	0.655
BC-n×d	0.12161	1	0.12161	8.9077	0.0083237	0.598
A^2-n^2	0.17242	1	0.17242	12.63	0.0024412	0.848
B^2-f^2	0.032856	1	0.032856	2.4067	0.13923	0.162
C^2-d^2	0.13142	1	0.13142	9.627	0.0064665	0.646
Residual	0.23208	17	0.013652			1.141
Total	20.333	26				100.000

R^2 = 0.98859 R^2(Adj.) = 0.9825 R^2(Pred.) = 0.9726

Table IV demonstrates that the individual effect of feed rate (f) is the most significant for surface roughness, as indicated by the highest F value (lowest P value). In addition to the feed rate, the individual effect of spindle speed (n), depth of cut (d), the second-order effect of spindle speed (n^2), depth of cut (d^2), and the interaction effect of spindle speed-depth of cut (n-d) and feed rate-depth of cut (f-d) are the most significant terms for the model, as indicated by p-values less than 0.05. The interaction effect of spindle speed and feed rate (n-f) is not deemed significant, as the p-values of the terms fall below the 0.05 threshold.

TABLE V. ANOVA FOR VIBRATION

Source	Sum of squares	*df*	Mean square	*F*-value	*p*-value	% contribution
Model	1,639.5	9	182.17	1,195.8	5.22E-22	99.842
A-n Speed	1,064.2	1	1,064.2	6985.4	1.14E-23	64.807
B-f Feed	392.74	1	392.74	2578	5.25E-20	23.917
C-d DOC	41.709	1	41.709	273.78	6.46E-12	2.540
AB-n×f	8.5218	1	8.5218	55.939	9.01E-07	0.519
AC-n×d	0.3544	1	0.3544	2.3263	0.14559	0.022
BC-n×d	0.10849	1	0.10849	0.71215	0.41045	0.007
A^2-n^2	81.807	1	81.807	537	2.66E-14	4.982
B^2-f^2	0.063311	1	0.063311	0.41559	0.52775	0.004
C^2-d^2	0.029634	1	0.029634	0.19452	0.66474	0.002
Residual	2.5898	17	0.15234			0.158
Total	1,642.1	26				100.000

R^2 = 0.99842 R^2(Adj.) = 0.9976 R^2(Pred.) = 0.9961

ANOVA analysis for tool vibration is manifested in Table V, where the single effect of spindle speed (n) has the highest significance in the tool vibration model as it has the lowest p-value. Apart from this, feed rate (f), depth of cut (d), second order term of spindle speed (n^2), second order effect of depth of cut (d^2), and interaction effect of spindle speed-feed (n-f) are significant terms for this model, in contrast to the remaining terms. ANOVA analysis for cutting force in Table VI shows that the individual effect of depth of cut (d) has the highest significance in the tool vibration model as it has the lowest p-value. Apart from this, feed rate (f), spindle speed (n), second order term of feed rate (f^2), second order effect of depth of cut

(d^2), and interaction effect of spindle speed depth of cut (*n-d*) are significant terms for this model. The remaining terms are not significant. Although the models are statistically significant in all cases, non-significant terms can be eliminated to improve the performance of the models.

TABLE VI. ANOVA FOR CUTTING FORCE

Source	Sum of squares	*df*	Mean square	*F*-value	*p*-value	% contribution
Model	97,002	9	10,778	2,014.3	6.25E-24	99.906
A-n Speed	4,258.1	1	4,258.1	795.79	1.02E-15	4.386
B-f Feed	19,090	1	19,090	3,567.7	3.37E-21	19.662
C-d DOC	66,003	1	66,003	12,335	9.11E-26	67.979
AB-n×f	13.189	1	13.189	2.4649	0.13484	0.014
AC-n×d	3,551.6	1	3,551.6	663.75	4.61E-15	3.658
BC-n×d	1.2352	1	1.2352	0.23085	0.63702	0.001
A^2-n^2	6.5245	1	6.5245	1.2194	0.28487	0.007
B^2-f^2	1,938	1	1,938	362.19	6.73E-13	1.996
C^2-d^2	550.72	1	550.72	102.92	1.25E-08	0.567
Residual	90.964	17	5.3508			0.094
Total	97,093	26				100.000

R^2 = 0.99906 R^2(Pred.) = 0.99742 R^2(Adj.) = 0.99857

The predicted R^2 of 0.97261 (Table IV), is in reasonable agreement with the adjusted R^2 of 0.98254, as the difference is less than 0.2. Adequate precision measures the signal-to-noise ratio, which is desirable to be greater than four. A ratio of 38.934 indicates an adequate signal. This model can be used to navigate the design space:

$$Ra = 2.8084 - 0.0095 \times n + 4.2830 \times f + 2.1344 \times d - 0.0001 \times n \times f + 0.0037 \times n \times d + 5.0333 \times f \times d + 7.4000 \times f^2 - 3.7000 \times d^2 \quad (3)$$

The analysis shows the percentage effect of different parameters on surface quality. Feed contributes 92.583%, RPM contributes 2.118%, and DOC contributes 0.928%. The analysis is performed to evaluate the quality of the sample, specifically the surface roughness. A parametric ANOVA analysis reveals the individual percentage contributions of each parameter. The predicted R^2 of 0.99608 (Table V), is in reasonable agreement with the adjusted R^2 of 0.99759, as the difference is less than 0.2. Adequate precision measures the signal-to-noise ratio. A ratio greater than four is desirable. A ratio of 116.941 indicates an adequate signal. This model can be utilized to navigate the design space:

$$V = 77.445 - 0.11276 \times n + 82.691 \times f + 9.4155 \times d - 0.059492 \times n \times f - 0.0060661 \times n \times d - 4.7542 \times f \times d + 0.00018759 \times n^2 - 10.272 \times f^2 + 1.7569 \times d^2 \quad (4)$$

The analysis indicates the individual parameters percentage contribution to vibration. Speed accounts for 64.807%, cutting feed for 23.917%, and DOC for 2.540%. The parametric analysis focuses on evaluating the quality, specifically vibration, of the sample. ANOVA analysis demonstrates the percentage contribution of each parameter displayed in the table above. The predicted R^2 of 0.99742 (Table VI), is in reasonable agreement with the adjusted R^2 of 0.99857, as the difference is less than 0.2. Adequate precision measures the signal-to-noise ratio. A ratio greater than four is desirable. A ratio of 155.339 indicates an adequate signal. This model can be employed to navigate the design space:

$$Fc = -336.88 + 0.29234 \times n + 999.23 \times f + 883 \times d + 0.074012 \times n \times f - 0.60726 \times n \times d + 16.042 \times f \times d - 5.30E-05 \times n^2 - 1797.2 \times f^2 - 239.51 \times d^2 \quad (5)$$

The preceding analysis demonstrates the extent to which each parameter contributes to the cutting force. The DOC accounts for 67.979% of the total contribution, while the feed and cutting speed account for 19.662% and 4.386%, respectively. A parametric analysis was conducted to assess the quality of the sample, with a particular focus on the force. The ANOVA method is employed to ascertain the individual percentage contributions of the parameters. The regression models developed can be utilized to predict tool surface roughness, vibration, and cutting force. Figure 5 depicts the predicted and actual values, illustrating the patterns, whereas Figure 6 displays the normal probability of the residuals.

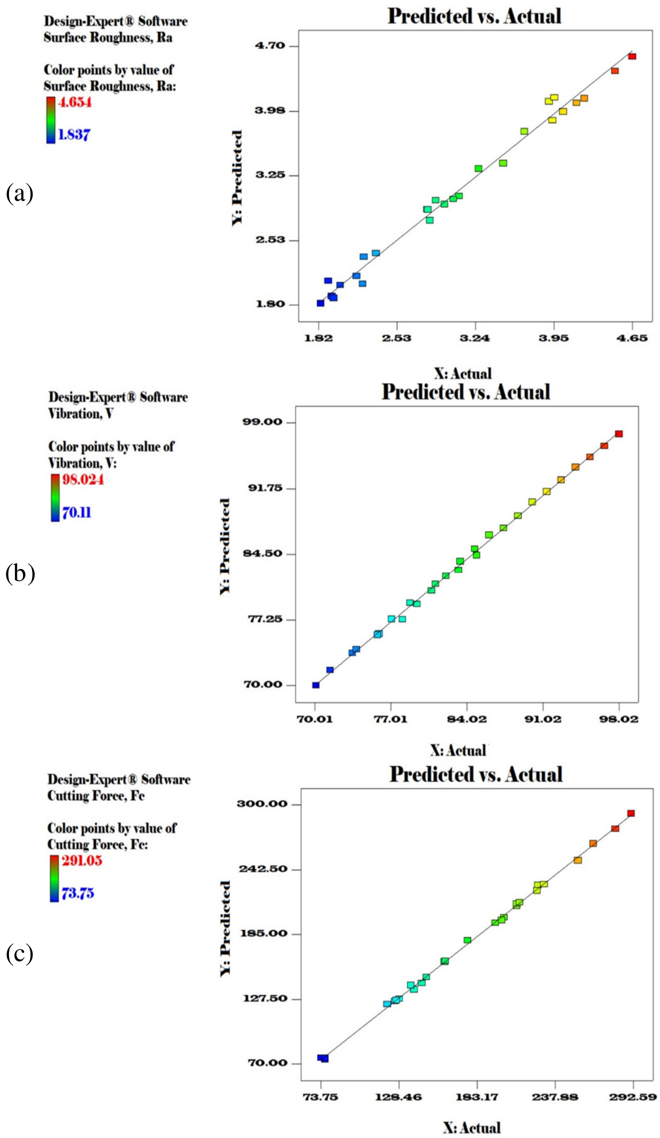

Fig. 5. (a) Predicted vs. actual response plot of surface roughness, (b) Predicted vs. actual response plot of tool vibration, (c) Predicted vs. actual response plot of cutting force.

(a)

(b)

(c)

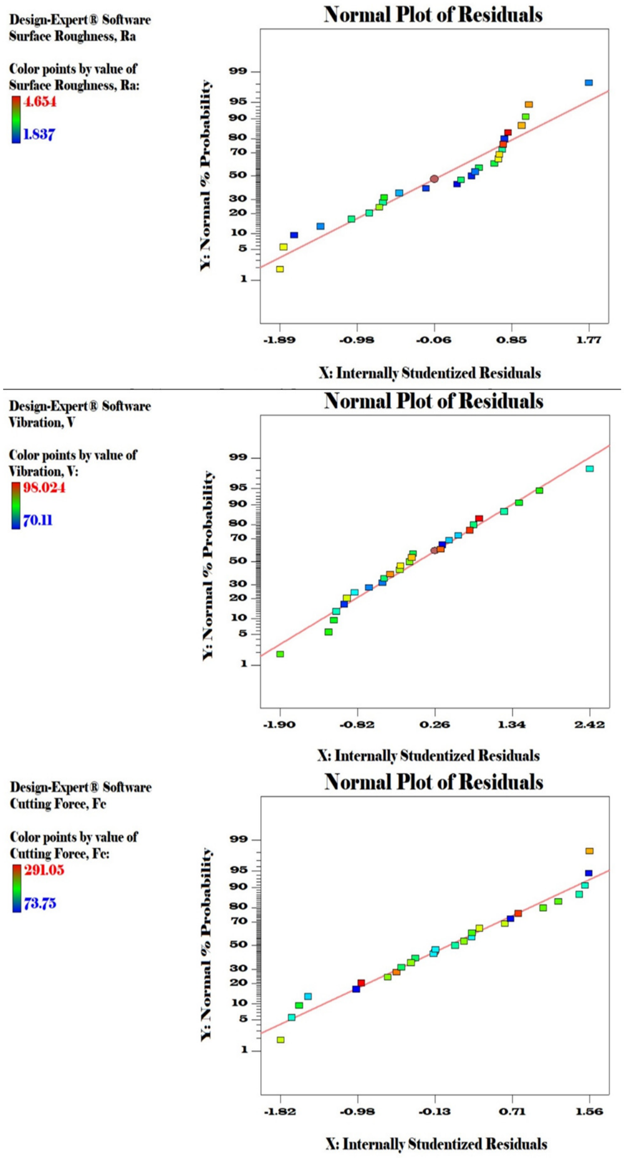

Fig. 6. (a) Normal probability plot of residuals for surface roughness, (b) Normal probability plot of residuals for tool vibration, (c) Normal probability plot of residuals for cutting force.

The residual points are distributed along a straight line, indicating that the errors are normally distributed. This shows that the regression model developed is an appropriate fit for the given experimental range. An examination of the residuals has verified the adequacy of the model. The residuals, defined as the difference between the observed response and the predicted response, are examined using two statistical plots: the normal probability plot of the residuals and the plot of the residuals versus the predicted response. If the model is deemed adequate, the points on the normal probability plots of the residuals should form a straight line. Conversely, the plots of the residuals versus the predicted response should exhibit no discernible pattern. The normal probability plots of the residuals and the plots of the residuals versus the predicted response for the surface roughness values are presented in Figures 5(a) and 6(a). The results demonstrated that the residuals exhibited a tendency to fall on a straight line, indicating that the errors were normally distributed. This suggests that the proposed model is adequate and that there is no evidence of any violation of the independence or constant variance assumptions.

(a)

(b)

(c)

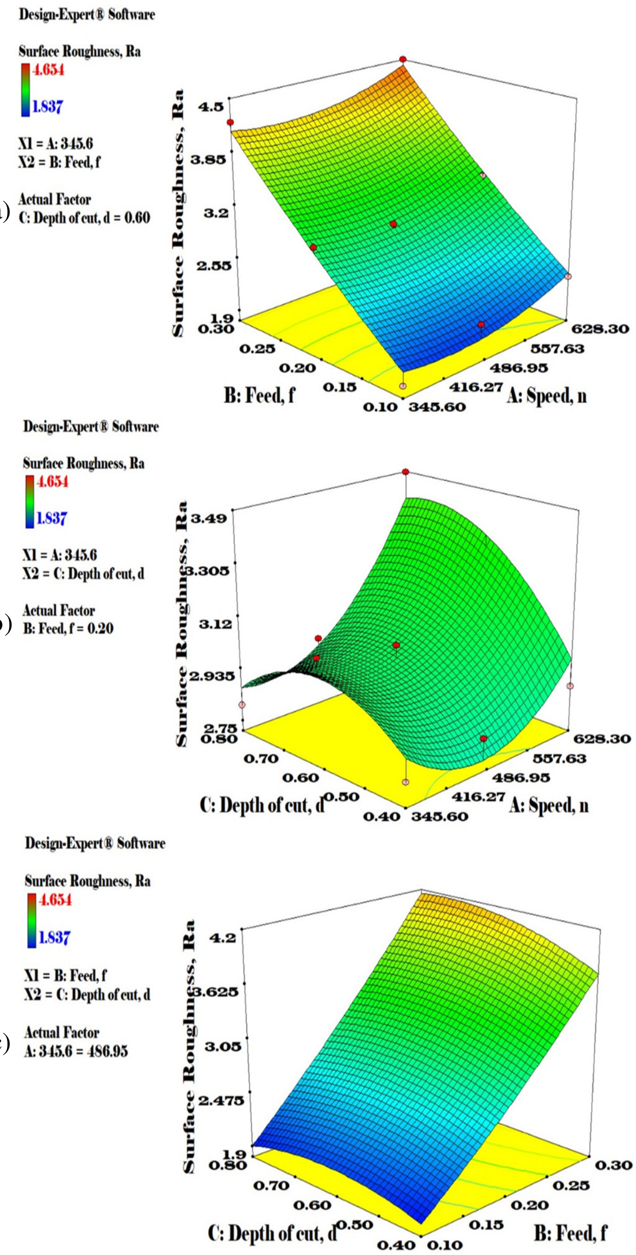

Fig. 7. (a) Surface Roughness, A: Speed, B: Feed, (b) Surface Roughness, A: Speed, C: DOC, (c) Surface Roughness, B:Feed, C:DOC.

Figure 5 illustrates that the predicted and actual values of surface finish exhibited minimal deviation, confirming the efficacy of the developed mathematical model in predicting optimized machining process parameters. Three-dimensional response surface plots are constructed based on (3), (4), and (5) to facilitate a more comprehensive understanding of the interaction effects of independent variables on responses. As each model comprises three independent variables, one variable has been maintained at its central level for each plot. Figure 7 depicts a three-dimensional surface plot for surface roughness, Figure 8 represents a three-dimensional surface plot for tool vibration, and Figure 9 shows a three-dimensional surface plot for cutting force.

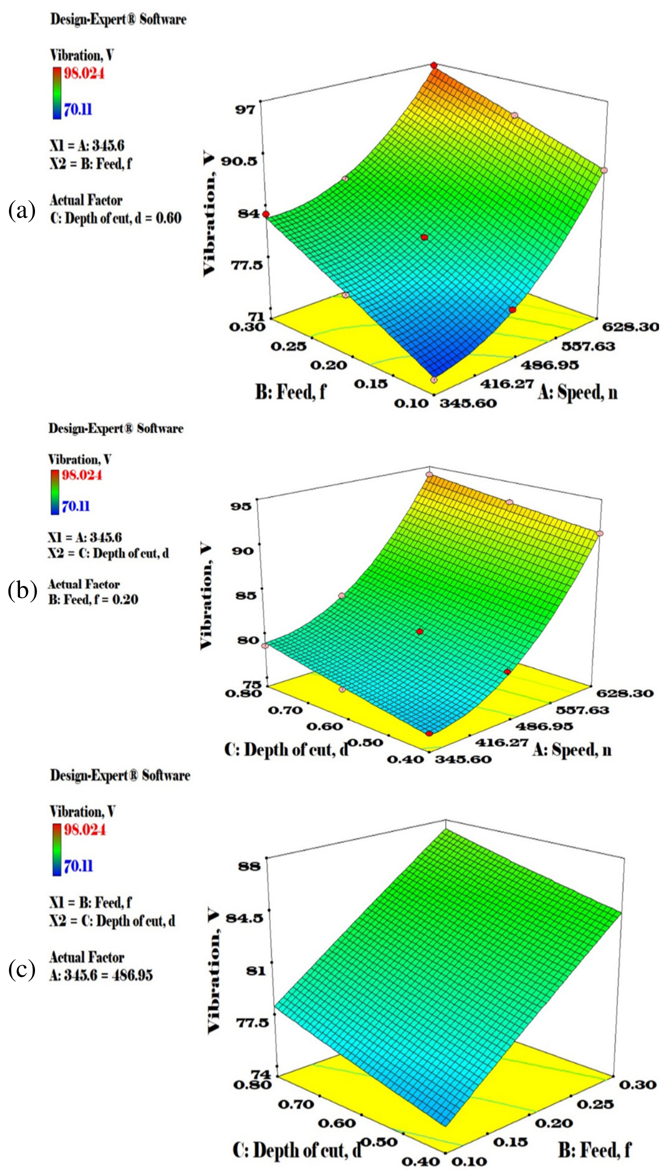

Fig. 8. (a) Vibration, A: Speed, B: Feed, (b) Vibration, A: Speed, C: DOC, (c) Vibration, B: Feed, C: DOC.

With the exception of the effect of DOC on surface roughness and tool vibration, all independent variables demonstrate a curvature trend in their responses, indicating a non-linear variation. The 3-D surface plots in Figure 7 are generated based on the regression (4). It can be observed that an increase in the rotational speed and feed rate results in an increase in surface roughness. Three-dimensional surface plots for tool vibration were constructed using (5). An examination of the plots concludes to a vibration increase for all three input parameters. Three-dimensional surface plots for cutting force were constructed using (6). From the data presented in the plots, it can be concluded that cutting force increases for all three input parameters.

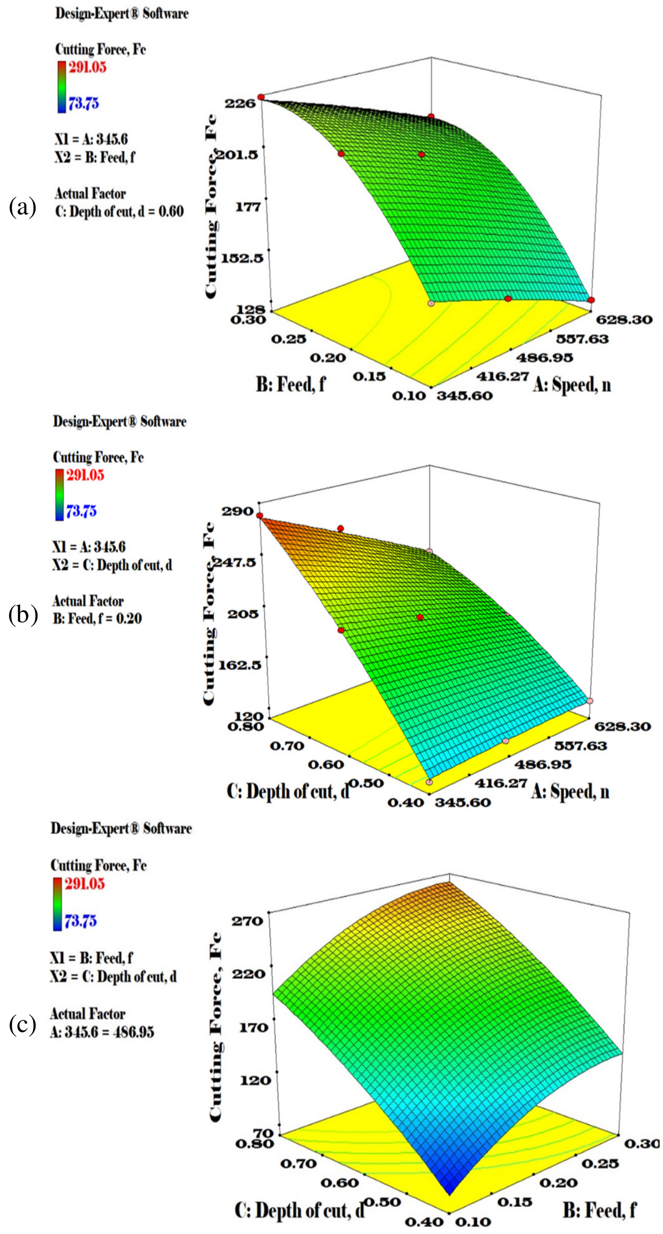

Fig. 9. (a) Cutting Force, A: Speed, B: Feed, (b) Cutting Force, A: Speed, C: DOC, (c) Cutting Force, B: Feed, C: DOC.

The impact of the primary factor and its interactions are presented in Figures 10 and 11, respectively. The major impact of surface roughness is found to be the feed rate, which exerts the most significant influence on the surface roughness. The influence of cutting speed is considerably less substantial, and the impact of DOC is also inconsequential (Figure 10(a)). An increase in cutting speed has proven to enhance surface quality. This result supports the argument that high cutting speeds reduce cutting forces, in conjunction with the effect of natural frequency and vibrations, thereby resulting in a superior surface finish. The optimal surface quality values can be attained at a low feed rate, a medium cutting speed, and a low DOC. The main effects of vibrations indicate that cutting speed has the greatest impact on vibration. The influence of feed is minimal, as is that of DOC, as shown in Figure 10(b). An increase in cutting speed results in an increase in vibration. The lowest vibration levels can be achieved at low speeds, feeds, and depths of cut. The most significant impact on cutting force is the depth of the cut. The effect of feed is less considerable, and the effect of speed is negligible, as presented in Figure 10c). An increase in the DOC results in an increase in the magnitude of the cutting force.

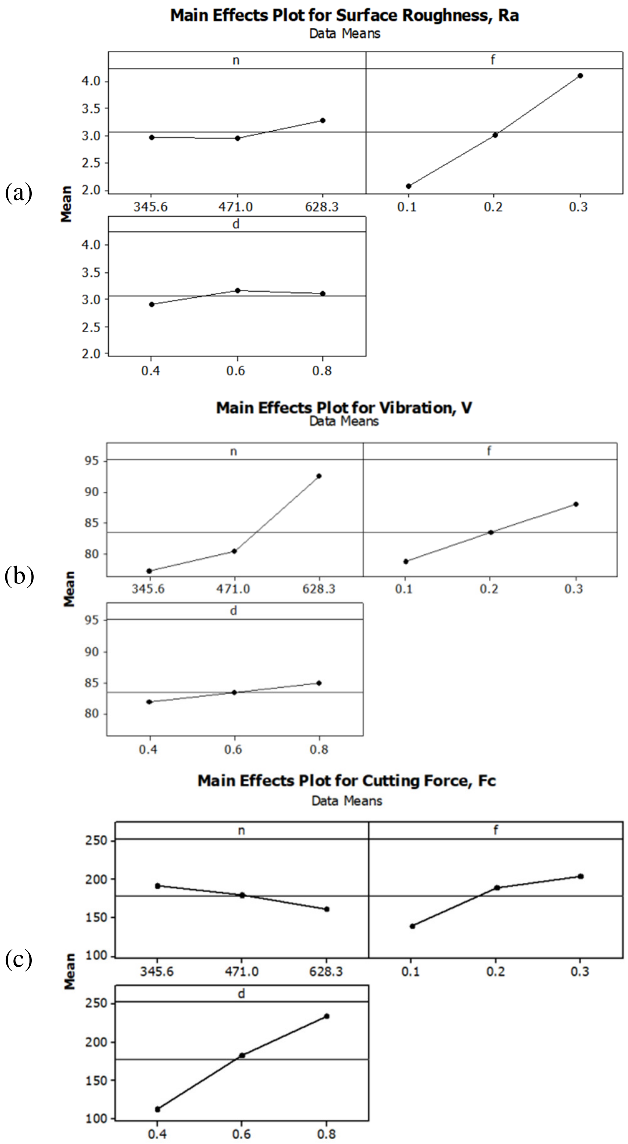

Fig. 10. (a) Main effect plots of Surface Roughness, (b) main effect plots of Vibration, (c) main effect plots of Cutting Force.

The lowest force can be achieved at a reduced DOC, feed, and speed. Figure 11 exhibits the interaction plot for surface roughness. Surface roughness is high when there is a variation in the feed rate at any DOC (row 3, column 2) and at any cutting speed (row 1, column 2).

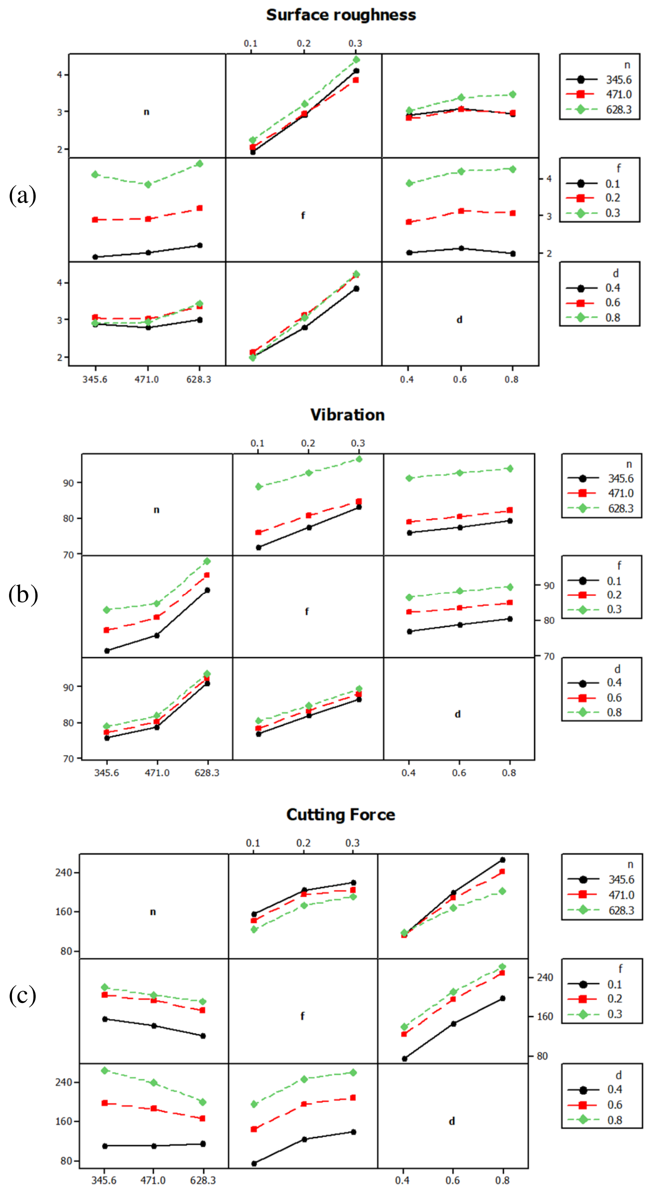

Fig. 11. (a) Interaction plot for multi-objective function of Surface Roughness, (b) interaction plot for multi-objective function of Vibration, (c) interaction plot for multi-objective function of Cutting Force.

This is evidenced by the minimum surface roughness, which is close to 2 μm for level 1 feed rate and all levels of DOC and cutting speed. Conversely, the maximum surface roughness is more than 4 μm for level 3 feed rate as well as all levels of DOC and cutting speed. The impact of DOC on surface roughness is inconsequential when cutting speed is taken into account (row 1, column 3), given the narrow spacing between the lines, as presented in Figure 11(b). The vibration is notably elevated in conjunction with speed fluctuations at any feed rate (row 2, column 1) and at any DOC. Data presented in Figure 11(c) demonstrate that cutting force is significantly elevated when there is a variation in DOC, irrespective of the cutting speed and feed rate.

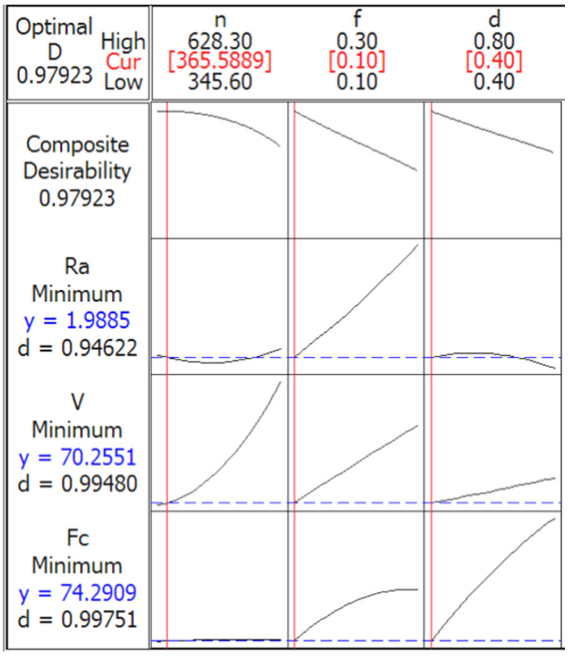

Fig. 12. Response surface optimization plot for optimum machining parameters and multi-objective function.

TABLE VII. CONFIRMATION RESULTS FOR SURFACE ROUGHNESS, VIBRATION AND CUTTING FORCE

Methodology	**Optimum machining parameters**			**Surface roughness**	**Vibration**	**Cutting Force**
	n (m/min)	f (mm/rev)	d (mm)	R_a (μm)	V (db)	F_c (N)
Best experimental run	345.60	0.10	0.40	2.0130	70.110	76.450
Proposed model	365.589	0.10	0.40	1.9885	70.2551	74.2909

The primary objective of this study is to identify the optimal values of machining parameters that simultaneously minimize surface roughness, vibration, and cutting force. A desirability function analysis associated with RSM was performed using MINITAB to obtain the results. The results of the desirability function analysis optimization are presented in Figure 12. The optimal machining parameters for simultaneously minimizing surface roughness, minimum vibration, and minimum cutting force are: cutting speed of 365.589 m/min, feed of 0.10 mm/rev, and a DOC of 0.40 mm. The desirability value is 0.979226, which is nearly equal to 1. The outcomes of the confirmation run for surface roughness are presented in Table VII. The optimal machining parameters predicted by the developed model are expected to result in reduced vibration, cutting force, and enhanced surface finish.

VII. CONCLUSION

MOO-MPP is a robust tool that can optimize the machining parameters for EN series materials, thereby enhancing product quality, reducing production costs, and increasing productivity. A variety of techniques for optimizing multi-objective parameters is available, each with its own set of advantages and disadvantages. The optimal technique is contingent upon the particular application and the desired outcomes. The aforementioned study presented an integrated application of Design of Experiments (DOE) and Analysis of Variance (ANOVA) techniques for the modeling and optimization of process parameters, with the objective of achieving a good surface finish, lower tool vibration, and the minimization of cutting force in the Computerized Numerical Control (CNC) turning process. The findings of the study can be summarized as follows:

- The analysis of surface roughness revealed that the feed rate exerts a greater influence (92.583%) than the cutting speed (2.118%), while the Depth of Cut (DOC) has a negligible impact on the surface roughness.
- In the analysis of vibration, it was determined that the cutting speed exhibited a greater contribution of 64.807%, followed by a feed rate of 19.662%. DOC demonstrated a comparatively minimal impact, with a value of 2.54%.
- In the analysis of cutting force, it was determined that the DOC exhibited the greatest contribution, at 67.979%. The feed rate and cutting speed also demonstrated notable influence, with respective contributions of 19.66% and 4.386%.
- 3D surface counterplots are a valuable tool for identifying the optimal conditions for achieving specific surface roughness values. The 3D surface plots of the responses versus the process parameters indicate the existence of interaction effects. The 3D surface and contour plots constructed during the study can be utilized to identify the optimal machining parameters for the attainment of specific surface roughness, vibration, and cutting force values. These findings can be utilized by machine tool manufacturers to provide a range of cutting speeds, feeds, and DOC for specific applications.
- The response surface methodology employed in the recent study has been proven to be an efficacious instrument for the analysis of the CNC turning process.
- The aforementioned approach may be recommended for the modeling and multi-output optimization of diverse machining processes.

Further research could investigate the integration of real-time adaptive control systems, enabling the optimization framework to modify machining parameters in response to real-time data. Furthermore, the inclusion of a more diverse range of EN series materials and machining conditions in the dataset would enhance the model's ability to generalize across a broader range of scenarios. An investigation into the environmental impact and sustainability of optimized machining processes may also prove beneficial. Ultimately, collaboration with industry partners to validate the optimization and predictive models in real-world settings would ensure practical applicability and facilitate further advancements in machining technology.

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