



RESEARCH ARTICLE

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ROLE OF SHIM-INDUCED PASSIVE DAMPING ON SURFACE ROUGHNESS OPTIMIZATION IN FACE MILLING

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ABSTRACT

The presence of machining induced vibrations in face milling has a severe impact on surface roughness and, therefore, effective passive damping is a critical part of process stability and surface integrity. This research work examines how passive damping effect of shim material is a prevailing factor in control of surface roughness (SR), in addition to depth of cut, feed rate and cutting speed. A Response Surface Methodology using a Central Composite Design was utilized to predict surface roughness with three shim conditions which are no shim, stainless steel shim, and carbide shim. The findings reveal that carbide shims are more effective in damping vibrations and always produce lower surface roughness as compared to the other designs. The optimum cutting speed of 200 m/min, depth of cut of 0.8 mm, and feed rate of 0.1 mm/tooth produced surface roughness of 0.189 μm , and this is close to the predicted value. The model was highly predictive with a coefficient of determination (R^2) of 98.59%. These findings prove that the choice of shim material, especially use of carbide shims is a vital factor in improving surface finish during face milling processes.



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I. INTRODUCTION

Surface quality is a very important measure of machining performance, as it directly affects wear resistance, fatigue life, dimensional accuracy, functional reliability and aesthetic appearance of manufactured parts. Surface roughness in face milling is to be controlled by a complicated interplay of cutting parameters mainly spindle speed, feed rate and depth of cut jointly with tool workpiece engagement conditions and machining dynamics including vibration and chatter [1-7]. A high-quality surface finish can therefore be attained through both a systematic optimization of the parameters as well as a sound control of machining stability. Surface roughness optimization has been well researched on face milling by employing statistical and experimental design method. Classical Design of Experiments (DOE) methods that use Taguchi method, Response Surface Methodology (RSM), regression, grey relational analysis and Analysis of Variance (ANOVA) have been extensively used to establish optimal cutting conditions of a wide variety of materials, including aluminum alloys, carbon steel, alloy steel, and titanium alloys [1], [8-15].

Roughness maps are advanced as a new optimization of face milling using PCD inserts to divide kinematic and stochastic roughness to establish the insert micro-geometry, axial placement, and feed rate, which are experimentally confirmed [16]. The studies also consistently determine feed rate and cutting speed as the most important parameters that can influence surface roughness, but their relative importance can depend on the workpiece material, tool geometry, and cutting environment [6],[7],[17-19]. Even more recent studies have expanded this method by including vibration responses together with surface roughness as part of multi-objective and Box-Behnken-based optimization models and have shown that vibration amplitude and surface integrity are tightly coupled [20]. Advanced modeling and artificial intelligence-based techniques have become more popular because of the need to have a higher level of prediction and represent the nonlinear interactions between the machining variables.

The artificial neural networks, fuzzy logic, genetic algorithm and hybrid data-driven models have also been shown to have better predictive performance than the traditional regression methods [8], [21-25]. Similar studies also prove that AI-assisted approaches could be especially effective in terms of the multi-objective optimization of surface roughness, material removal rate, tool wear, and energy use [26], [27]. Machining dynamics and chatter suppression have also been under continued interest since they are known to have a strong impact on surface integrity, tool life, and productivity, in addition to parametric optimization. Chatter vibrations cause surface waviness, surface roughness, dimensional error, and tool wear. The classical and modern methods of chatter prediction and prevention that include stability lobe diagrams, frequency and time-domain, as well as dynamic system modeling, have been thoroughly explored [19], [28-31]. More recent state of the art reviews also categories chatter mechanisms, recognize sources of uncertainty in stability prediction, and leave unsolved problems in chatter modelling of more complex machining systems, such as thin-walled structures and flexible tooling [32],[33]. Systematic review has also been conducted on chatter suppression techniques including passive, active and hybrid control techniques. Passive methods of damping have been improving in popularity, owing to their simplicity, strength, and the simplicity of attaching them to the current tooling.

Research works on vibration control point out that properly designed passive damping system, coupled with the optimization of cutting parameters, can be very helpful in improving machining stability and quality of the final surface and eliminating the disadvantages of active systems [23], [34-36]. Although active control methods may be very effective, they are expensive, complex to install, and lack scalability and thus they are not very popular in industries [37]. In addition to prediction of chatter, major advancements have been made in detecting and suppressing strategies of chatter. Extensive surveys have suggested that chatter detection has changed to include not just analytical methods but experimental signal-based methods that use vibration, cutting force and acoustic emission signal in conjunction with the time-frequency signal processing techniques of the FFT, Wavelet Transform, HHT, and STFT. The use of Artificial Intelligence-based classifiers such as Artificial Neural Networks, Support Vector Machines, Fuzzy Logic, Hidden Markov Models and k-nearest neighbor algorithms have increasingly been used in real-time chatter detection and decision support, and the significance of data driven strategies in contemporary machining settings should not be undervalued [38]. Although there has been a significant development in regards to optimization of surface roughness, analysis of chatter stability, detection, and suppression, it is evident that there is still a research gap on the systematic application of shim material as passive damping component to machining parameter optimization models especially in face milling processes.

Most of the literature available is interested in either optimization of cutting parameters including speed of spindle, feed rate and depth of cut [1-6],[8-13],[17],[21],[26-29], or in predicting and suppressing chatter using stability analysis and signal-based detection methods [19],[28],[30-33],[37],[38]. Nonetheless, the choice of shim material despite its direct relationship with tool-holder dynamic stiffness, damping ability, amplitude of vibrations, and surface finish has not been considered as one discrete design variable alongside surface roughness modeling. Majority of previous studies have only taken passive damping concepts conceptually or comparatively without quantitatively integrating shim material properties into the structured statistical analysis programs like Response Surface Methodology or multi objective optimization paradigms [34],[35],[37],[39],[40]. This means that the interaction of shim induced damping and customary machining parameters as well as its synergistic influence on the surface roughness and process stability is not well comprehended. In order to fill this gap, shim material is introduced into the current work as a separate input parameter in addition to cutting speed, feed rate, and depth of cut in a Response Surface Methodology approach of CNC face milling. This work seeks to quantify the importance of passive damping in enhancing machining stability and surface integrity by methodically assessing individual effects and interaction of shim material and machining parameter on surface roughness to generate useful guidelines on successful, chatter free and high-quality face milling processes.

II. MATERIALS AND METHODS

II.1 EXPERIMENTAL FACILITY

All experiments were performed on a Vertical Machining Centre (VMC) shown in Figure 1, to examine the effect of cutting parameters on the surface roughness of a milled workpiece.



Figure 1: CVM 640 Milling Machine.

Source: Authors, (2026).

The interaction between cutting speed, the feed rate, the depth of cut and the shim type was studied systematically to determine the machining parameters that produce better surface quality.

Surface roughness, recorded after each milling process and taken as the main indicator of process performance. The experimental results were comparatively studied to evaluate the consequence of the single cutting parameter on surface quality, which made it possible to identify the desirable machining conditions in order to increase the process stability and the accuracy at which machining is performed. All the experiments were performed on a CVM 640 VMC in the LDRP-ITR workshop. The reason why the machine was chosen is that it is able to work at high spindle speeds and high material removal rates whilst still maintaining precision in machining. It has the maximum spindle speed of 8000 rpm, spindle motor 5.5 Hp and positioning accuracy of 0.01 mm. These properties guaranteed the stability of the cutting process, the ability to control the machining parameters as well as the repeatability of the results of the experiments, which made it possible to reliably evaluate the consequence of cutting constraints on the surface quality.

II.1.1 Measurement Of Surface Quality

The surface roughness was determined out by a SJ-201 Mitutoyo surface roughness tester as shown in Figure 2. The instrument works based on the principle of the differential inductance to capture the surface profile variations accurately using a diamond-tipped stylus with a tip radius of 5 μm . The tester has a measurement range of -200 μm to +150 μm and a low measuring force of 4 mN (0.4 gf), which guarantees that the surface suffers minimum damage during measurement. The specifications offer good measurement accuracy and repeatability, which allows good quantification of surface height variation in various machining environment.



Figure 2: Surface roughness tester SJ 210.
Source: Authors, (2026).

II.2 MATERIAL

II.2.1 Material of Work Piece

The material of workpiece of this study was IS 2062 mild steel with a hardness of 130 HB as shown in Figure 3. The dimensions of the workpiece were 75 x 25 x 300 mm. These material and dimensional specifications were chosen so that they gave a uniform and standardized platform to assess the face milling process. Reproducible and reliable experimental results are possible with the help of the selected workpiece characteristics, which allowing to determine the outcome of process parameters on the surface quality with accuracy.

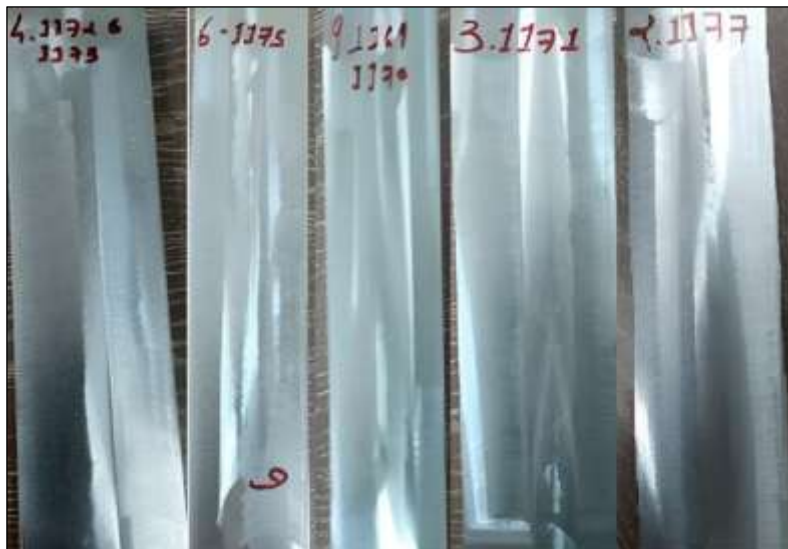


Figure 3: Workpiece material.
Source: Authors, (2026).

Table 1: IS 2062 Grade B plate's chemical composition

Grade	Si %	C %	Mn %	S %	P %
IS 2062	0.4	0.22	1.5	0.045	0.045

Source: Authors, (2026).

II.2.2 Cutting Inserts



Figure 4: Cutting insert.
Source: Authors, (2026).

Figure 4 illustrates the TPNK 1603 PPR cutting insert used in this study. A total of five inserts were employed during the face milling operation. The milling process was carried out using TPNK-type indexable carbide inserts, selected for their positive rake geometry and suitability for machining mild steel. Table 2 presents the size and detailed specifications of the insert.

Table 2: Specifications of the TPNK 1603 PPR insert

Symbol	Description
T	Insert shape: <i>Triangular</i> (three cutting edges)
P	Clearance angle: <i>11° positive</i>
N	Tolerance class: <i>Normal</i>
K	Insert type / clamping style
16	Inscribed circle (≈ 16 mm)
03	Insert thickness (≈ 3.18 mm)
PPR	Chip breaker geometry

Source: Authors, (2026).

II.2.3 Cutting Tools

Two types of face milling tools were employed in this study, as shown in figure 5:

- **Conventional Face Milling Tool:** The conventional face milling tool has a diameter of 63 mm and is equipped with five cutting inserts. This tool does not incorporate any shim during the milling process.
- **Shim installed Face Milling Tool:** This face milling tool also has a diameter of 63 mm and is fitted with five cutting inserts. Unlike the conventional tool, it incorporates a shim positioned beneath the insert to modify the cutting characteristics. The shim material was selected based on the desired alteration of tool–insert dynamic behavior.



Figure 5: 63mm Diameter Face milling tool with 5 inserts.
Source: Authors, (2026).

II.2.4 Materials Of Shim

Figure 6 present carbide shims which is used, aimed at raising the rigidity of the tool-insert-holder assembly. Carbide shims have a high elastic modulus and compressive strength, which makes them play a huge role in ensuring that the elastic deformation at the tool–insert interface during cutting is minimized.



Figure 6: Carbide shim (SW0603 series).
Source: Authors, (2026).

Figure 7 presents the stainless steel (SS) shim used in this study, manufactured from AISI 4340 steel. This material exhibits high strength, toughness, and fatigue resistance. Compared with carbide, stainless steel exhibits lower stiffness, allowing greater energy dissipation through material damping.



Figure 7: SS shim (AISI 4340 series).
Source: Authors, (2026).

II.3 RSM DESIGN OF EXPERIMENT

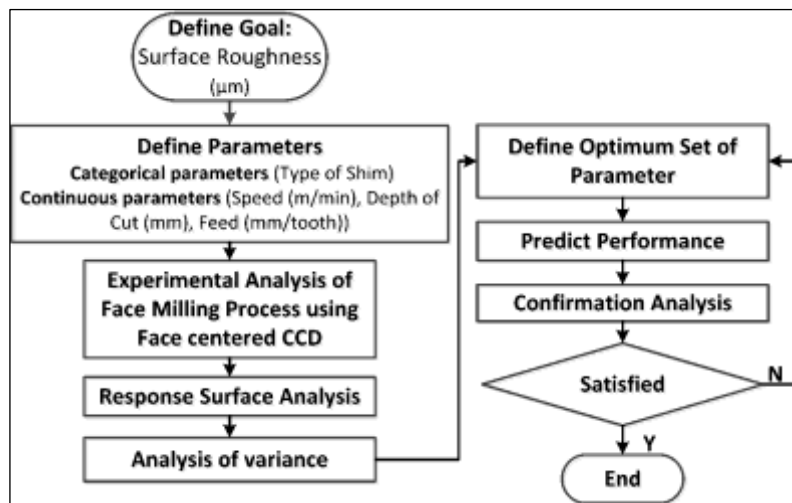


Figure 8: Stepwise experimental methodology.
Source: Authors, (2026).

Figure 8 shows the sequential experimental approach which is used to minimize the surface roughness (R_a , μm) in face milling. The critical machining factors were determined and grouped into one category variable shim type and three continuous variables: feed (mm/tooth), speed (m/min), and depth of cut (mm). The Central Composite Design (CCD) was adopted to model experiments for estimation of second order effects as well as the interaction of parameters over the experimental domain effectively. The CCD was chosen instead of Box Behnken design due to the inclusion of the axial points at extreme factors levels, which is beneficial in nonlinear machining behavior capturing.

The analytical model of the surface roughness was developed using RSM. The results were statistically analyzed with Minitab 18 software and to test the adequacy of the model, ANOVA was used at the confidence level more than 95%. Any factor and interaction with a p-value of less than 0.05 was considered statistically significant and the overall significance of the model was tested using F-test. The developed RSM model was used to determine the optimum machining conditions and the model was confirmed by conducting confirmation experiments. Correlation of the predicted and experimental results were used to check the reliability of proposed optimization methodology.

II.3.1 Setting Of Input Variable

The machining parameters systematically varied in the course of milling process were the input variables that were used in the experimental design to determine their effect on surface roughness and machining performance. The control variables were shim material, cutting speed, feed rate, and depth of cut. Cutting speed (m/min) was tested at three variations of 150, 200, and 250 m/min to determine its impact on the quality of the surface. Feed rate (mm/tooth), which is a linear movement of tool per engagement of the tool with the tooth, was adjusted as 0.05, 0.10 and 0.15 mm/tooth since this directly controls surface quality. The depth of cut (mm), which is a factor that defines how much material is cut in each pass and has a significant effect on cutting forces and vibration behavior, was tested at 0.8, 1.0 and 1.2 mm.

Shim material was treated as a categorical factor with three levels: no-shim, stainless steel (SS) shim, and carbide shim. Shim act as passive damping or stiffness-increasing elements within the tool assembly and modify vibration transmission during cutting. By comparing carbide and stainless-steel shims with the no-shim condition, the influence of material-dependent damping on surface roughness and machining performance was systematically evaluated. An experiment was performed to generate the data required to develop the RSM model for predicting surface roughness. The input factors S, F, D, and M were selected according to the Central Composite Design framework to ensure adequate coverage of the experimental domain. The continuous variables were investigated at three coded levels (-1, 0, 1), while the categorical factor was assigned three discrete levels, as summarized in Table 3.

Table 3: Variables and levels of variable.

Variable	Symbol	Levels		
		-1	0	1
Speed (m/min)	S	150	200	250
Feed (mm/tooth)	F	0.05	0.10	0.15
Depth of cut (mm)	D	0.8	1.0	1.2
Type of shim material	M	No-shim	Carbide	SS

Source: Authors, (2026).

The CCD framework allowed a systematic assessment of the main effects and the interface effects of the selected input parameters. The total number of experimental runs was determined using the standard CCD formulation given by Equation (1), based on the four factors considered in this study.

$$N = (2^m + 2 \times m + n)k = (2^3 + 2 \times 3 + 6) \times 3 = 60 \quad (1)$$

Where N represents the total number of experiments, m denotes the number of quantitative factors, k signifies the number of qualitative factor levels, and n indicates the number of center-point replicates. The experimental trials were performed in accordance with the CCD matrix. The effect of the selected parameters on surface irregularity was evaluated based on the experimental design shown in Table 4. Total 60 experiments were conducted to develop the RSM model, and the corresponding surface roughness values obtained for each run are listed in Table 4.

Table 4: Experiment runs and corresponding SR.

Run	S	D	F	M	SR (μm)
1	-1	-1	-1	-1	3.314
2	-1	-1	-1	0	1.501
3	-1	-1	-1	1	3.464
4	-1	-1	1	-1	3.607
5	-1	-1	1	0	0.424
6	-1	-1	1	1	2.745
7	-1	0	0	-1	2.099
8	-1	0	0	0	0.749
9	-1	0	0	1	2.613
10	-1	1	-1	-1	3.132
11	-1	1	-1	0	2.223
12	-1	1	-1	1	4.922
13	-1	1	1	-1	2.408
14	-1	1	1	0	1.375
15	-1	1	1	1	4.350
16	0	-1	0	-1	2.768
17	0	-1	0	0	0.189
18	0	-1	0	1	2.664
19	0	0	-1	-1	2.698
20	0	0	-1	0	0.532
21	0	0	-1	1	3.535
22	0	0	0	-1	2.189
23	0	0	0	-1	2.192

24	0	0	0	-1	2.188
25	0	0	0	-1	2.190
26	0	0	0	-1	2.191
27	0	0	0	-1	2.190
28	0	0	0	0	0.294
29	0	0	0	0	0.296
30	0	0	0	0	0.295
31	0	0	0	0	0.293
32	0	0	0	0	0.298
33	0	0	0	0	0.295
34	0	0	0	1	2.993
35	0	0	0	1	2.995
36	0	0	0	1	2.995
37	0	0	0	1	2.991
38	0	0	0	1	2.989
39	0	0	0	1	2.998
40	0	0	1	-1	3.030
41	0	0	1	0	0.805
42	0	0	1	1	4.170
43	0	1	0	-1	2.347
44	0	1	0	0	1.221
45	0	1	0	1	4.274
46	1	-1	-1	-1	2.352
47	1	-1	-1	0	0.470
48	1	-1	-1	1	3.031
49	1	-1	1	-1	3.904
50	1	-1	1	0	1.023
51	1	-1	1	1	3.726
52	1	0	0	-1	2.175
53	1	0	0	0	0.396
54	1	0	0	1	3.272
55	1	1	-1	-1	2.987
56	1	1	-1	0	2.446
57	1	1	-1	1	5.360
58	1	1	1	-1	3.423
59	1	1	1	0	2.087
60	1	1	1	1	5.487

Source: Authors, (2026).

Table 5 summarizes results of ANOVA of the developed RSM model. The regression model is statistically significant, with an F-value of 172.66 and a p-value value of 0.001, which shows that the model is accurate in predicting the experimental data at more than 95% confidence level. The coefficient of determination ($R^2 = 98.59\%$) and the adjusted coefficient of determination ($R^2 \text{ adj} = 98.02\%$) attest to the high predictive power of the developed model. The linear effects show that S, D, and M are statistically significant contributors to the roughness of the surface. Among them, depth of cut demonstrates the strong influence ($F = 150.57$, $p < 0.001$) and shim material has the most significant contribution ($F = 1061.74$, $p < 0.001$), which indicates that passive damping dominates in surface quality control. The consequence of speed on surface quality is statistically significant but moderately less ($F = 9.59$, $p = 0.003$). However, feed rate (F) is not statistically significant as a linear term ($F = 0.33$, $p = 0.568$). The quadratic terms show the effects of curvature in the response surface are significant. The squared terms depth of cut (D^2) ($F = 40.41$, $p < 0.001$) and feed rate (F^2) ($F = 87.40$, $p < 0.001$) are significant but the squared term of cutting speed (S^2) is not significant ($F = 0.36$, $p = 0.554$).

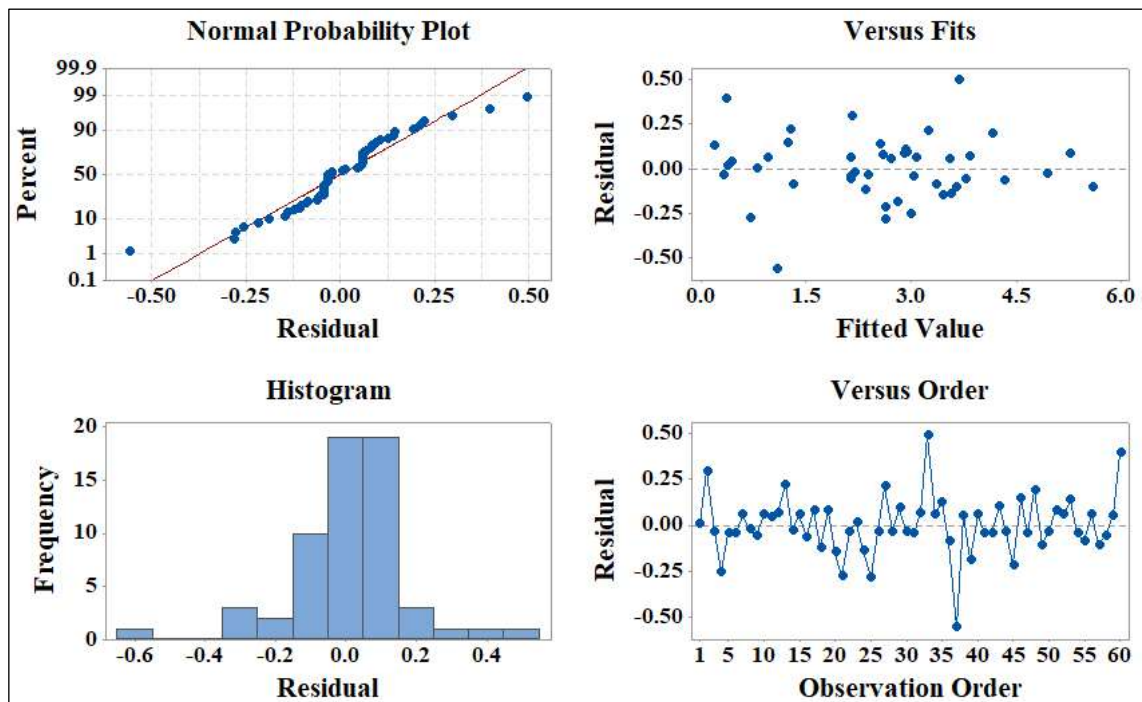
These findings support the fact that a second order model is a good choice of predicting surface roughness. There is also statistical significance in interaction effects between machining parameters, which implies a high degree of coupling between process variables. Significant interaction terms include $S \times D$ ($F = 17.92$, $p < 0.001$), $S \times F$ ($F = 51.33$, $p < 0.001$), $S \times M$ ($F = 6.12$, $p = 0.005$), $D \times F$ ($F = 12.16$, $p = 0.001$), $D \times M$ ($F = 79.43$, $p < 0.001$), and $F \times M$ ($F = 7.81$, $p = 0.001$). These interactions confirm that surface roughness is governed by the combined influence of cutting conditions and shim-induced damping behavior rather than by individual parameters alone. The error term has a low adjusted mean square value (Adj MS = 0.0359) meaning the experimental repeatability is good. In addition, the lack of fit is not substantial as compared to the pure error, which proves that the established model is suitable to fit the experimental data and model the underlying process behavior. In general, the findings of the ANOVA table outline that the M is the most significant factor that would influence the surface roughness, next is the D, F, and S. The high performance of the carbide shim can be explained by its higher level of stiffness and damping properties that properly suppress tool vibrations and increase surface finish in comparison to stainless steel and no-shim situations.

Table 5: Analysis of variance for Surface Roughness (μm).

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	17	105.372	6.1984	172.66	0.000
S	1	0.344	0.3442	9.59	0.003
D	1	5.405	5.4054	150.57	0.000
F	1	0.012	0.0119	0.33	0.568
M	2	76.230	38.115	1061.74	0.000
S ²	1	0.013	0.0128	0.36	0.554
D ²	1	1.451	1.4508	40.41	0.000
F ²	1	3.138	3.1375	87.40	0.000
S×D	1	0.643	0.6432	17.92	0.000
S×F	1	1.843	1.8427	51.33	0.000
S×M	2	0.440	0.2198	6.12	0.005
D×F	1	0.437	0.4367	12.16	0.001
D×M	2	5.703	2.8516	79.43	0.000
F×M	2	0.561	0.2803	7.81	0.001
Error	42	1.508	0.0359		
Lack of Fit	27	1.508	0.0558	*	*
Pure Error	15	0.000	0.0000		
Total	59	106.880			
Determination Coefficient (R^2): 98.59 %					
Adjusted Determination Coefficient (R^2): 98.02 %					

Source: Authors, (2026).

Regression analysis requires the assumption of normality, constant variance, randomness, and the absence of outliers, which were evaluated by the residual plots presented in Figure 9. The normal probability plot indicates that the data distribution of the residual values is near-normal, because most of the points do not deviate far much, and then there are minor anomalies. The histogram supports this trend because it has a symmetric and bell-shaped distribution, with an average near to zero thus this proves the normality assumption.

Figure 9: Residual plots for surface roughness (μm).

Source: Authors, (2026).

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The residual versus fitted values plot has a random distribution around zero, which means a constant variance and that there is no systematic trend. Equally, the residuals versus the order of observation give no discernible trend, which proves that the residuals remain independent and have no autocorrelation. Collectively, these diagnostic results demonstrate that the developed RSM model satisfies the key regression assumptions and can reliably predict surface roughness within the investigated parameter range.

Regression equations were developed on the data of the experiment to predict the surface roughness under each shim condition using the main effects and interaction terms. Separate second-order polynomial expressions were formulated for the face milling tool without a shim, with a carbide shim, and with a stainless-steel shim.

The regression equation for surface roughness (μm) corresponding to the face milling tool without a shim is given by Equation (2).

$$\text{SR}(\mu\text{m}) = 2.1315 + 0.0282 S - 0.1649 D + 0.1889 F + 0.0393 (S \times S) + 0.4193 (D \times D) + 0.6167 (F \times F) + 0.1637 (S \times D) + 0.2771 (S \times F) - 0.1349 (D \times F) \quad (2)$$

Equation (3) presents the regression model for surface roughness (μm) when a carbide shim is employed.

$$\text{SR}(\mu\text{m}) = 0.3290 + 0.0150 S + 0.5622 D - 0.1459 F + 0.0393 (S \times S) + 0.4193 (D \times D) + 0.6167 (F \times F) + 0.1637 (S \times D) + 0.2771 (S \times F) - 0.1349 (D \times F) \quad (3)$$

Equation (4) represents the regression model for surface roughness (μm) for the face milling tool fitted with a stainless-steel shim.

$$\text{SR}(\mu\text{m}) = 3.0415 + 0.2781 S + 0.8761 D + 0.0166 F + 0.0393 (S \times S) + 0.4193 (D \times D) + 0.6167 (F \times F) + 0.1637 (S \times D) + 0.2771 (S \times F) - 0.1349 (D \times F) \quad (4)$$

III. RESULTS AND DISCUSSIONS

III.1 MODEL ADEQUACY AND PREDICTION ACCURACY

The adequacy of the developed response surface model was evaluated by comparing experimentally measured surface roughness values with those predicted by the regression model. Figure 10 illustrates the scatter plot comparing the actual and predicted surface roughness. The close clustering of data points around the 45° reference line indicates robust agreement between the experimental observations and model estimates. An R^2 value of 0.9859 indicates a very high degree of correlation, meaning that 98.59% of the variance in surface roughness is explained by the predictive model.

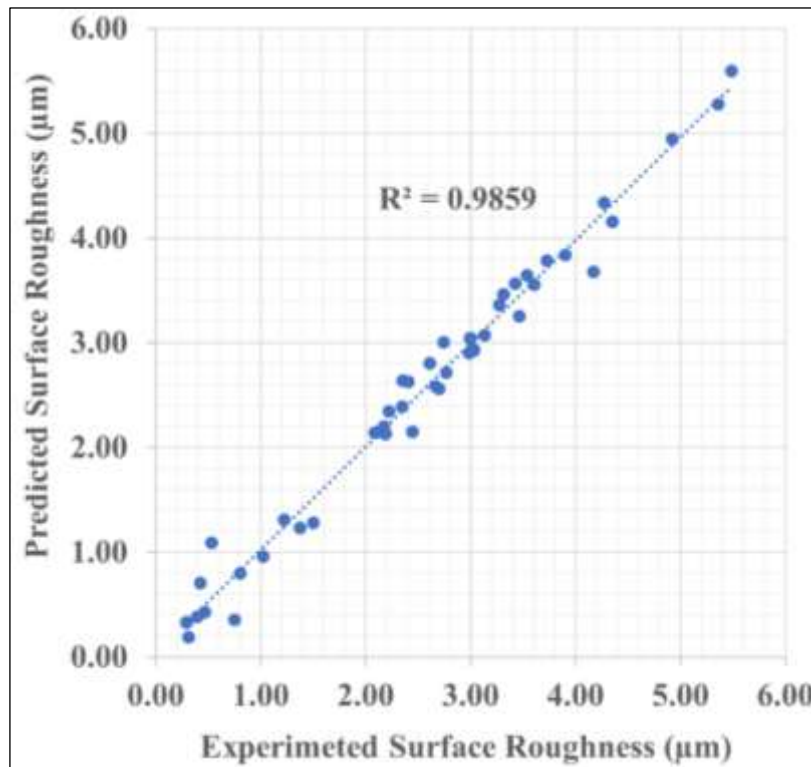


Figure 10: Actual SR v/s Predicted SR.

Source: Authors, (2026).

The limited scatter and absence of systematic deviation suggest that the model effectively captures the combined effects of machining parameters and shim material. The small residual errors observed fall within acceptable experimental uncertainty, supporting the suitability of the developed RSM model for reliable surface roughness prediction and optimization in face milling operations.

III.2 EFFECTS OF ONE PARAMETER AT A TIME ON RESPONSE

As it can be seen in Figure 11, the one-parameter-at-a-time plots depict the impact of the feed rate, depth of cut (DOC) and cutting speed on the surface roughness in three different scenarios: in the absence of a shim, with a stainless steel (SS) shim, and with a carbide shim.

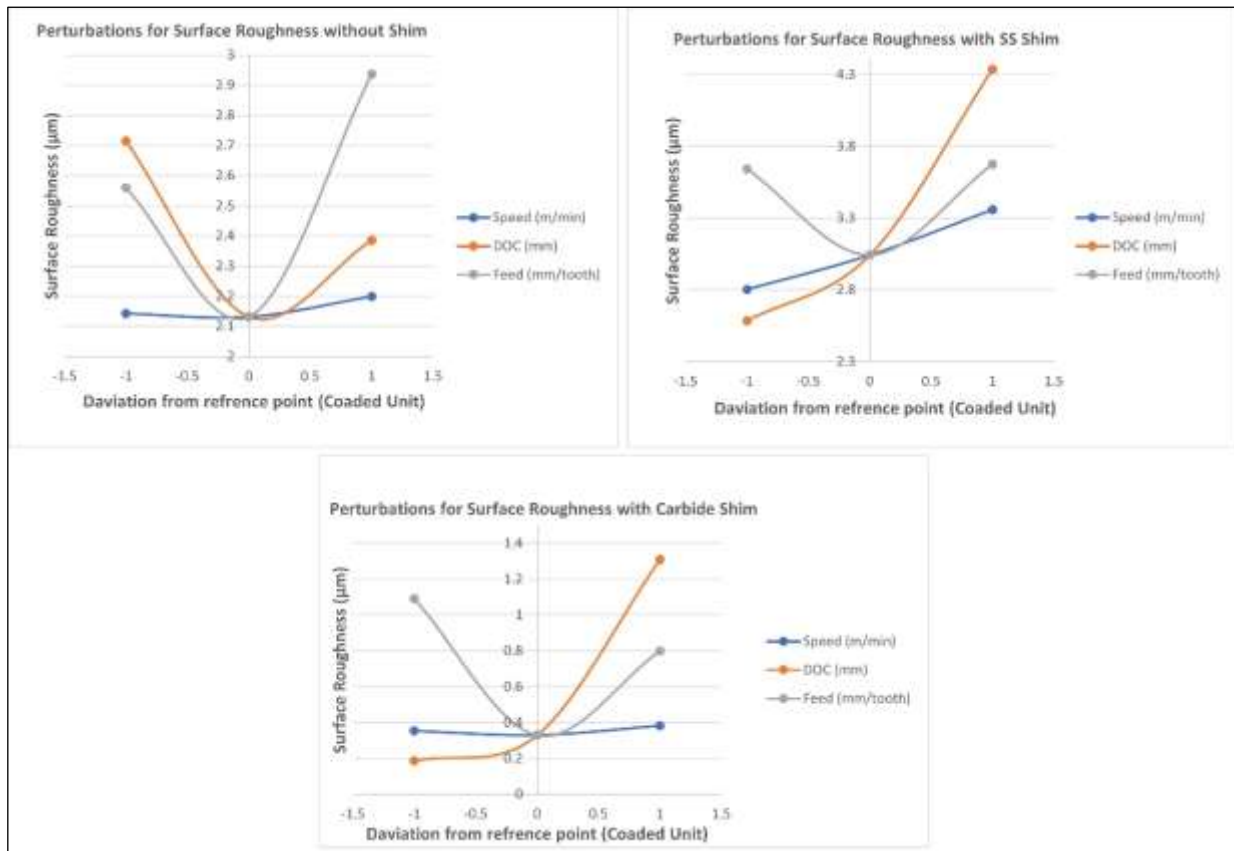


Figure 11: One parameter at a time plot for no shim, with SS shim and with Carbide shim.

Source: Authors, (2026).

Surface roughness with no shim shows a sharp parabolic behavior with respect to rate of feed and depth of cut, feed rate having the greatest effect. Changes in the reference feed rate and DOC values result in a higher surface roughness, but cutting speed has a relatively weak effect. This behavior indicates that, without additional damping, variations in chip load and cutting force fluctuations are directly transferred to the machined surface, resulting in increased surface irregularities. When a carbide shim is introduced, the surface roughness significantly decreases at all levels of machining parameters.

Even with the influence of feed rate and DOC, their effect on surface roughness is much less than in the no-shim condition. The cause of this reduction is the improved dynamic stiffness of the tool-insert-holder assembly that is offered by the carbide shim. In contrast, the SS shim results in consistently higher surface roughness values. Under this condition, depth of cut becomes the dominant factor, followed by feed rate, while cutting speed again exhibits the least influence. The pronounced increase in surface roughness, with the increasing DOC indicating that the SS shim is less effective in mitigating cutting force-induced vibrations, leading to unstable cutting behavior and degraded surface quality.

III.3 INTERFACE EFFECTS OF CUTTING SPEED AND DEPTH OF CUT

The interface effect of cutting speed and depth of cut on surface quality is represented on contour plots (Figure 12) and corresponding three-dimensional surface plots (Figure 13) at constant feed rate of 0.10 mm/tooth. These plots help show how machining parameters influence each other when different shims are used.

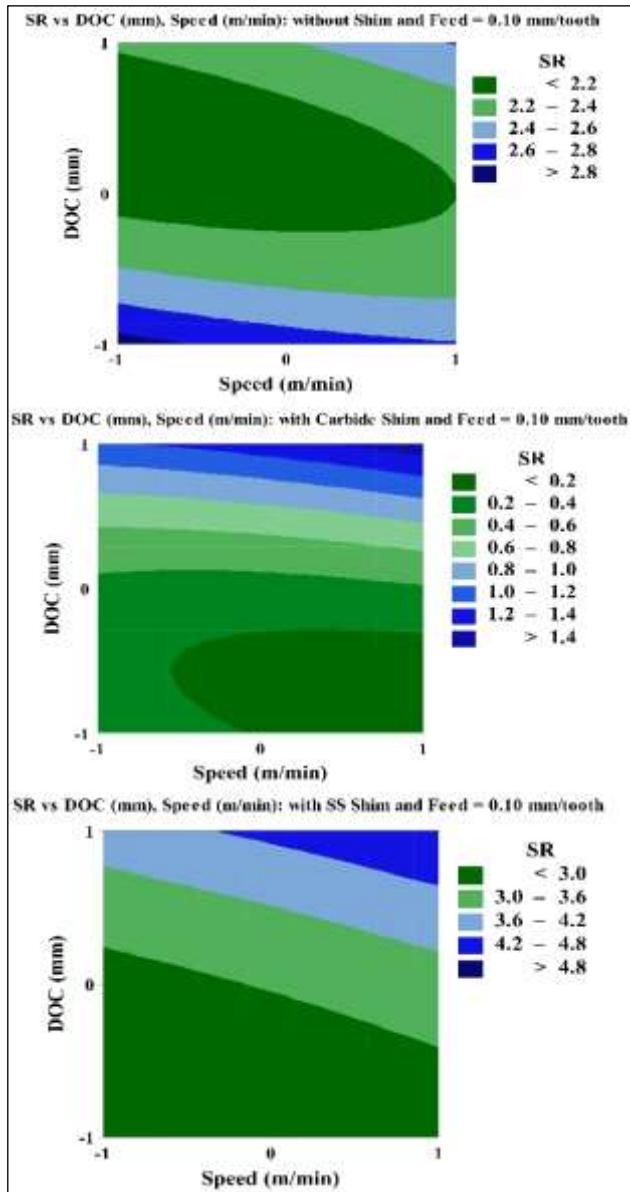


Figure 12: Contour plot for speed and depth of cut.
Source: Authors, (2026).

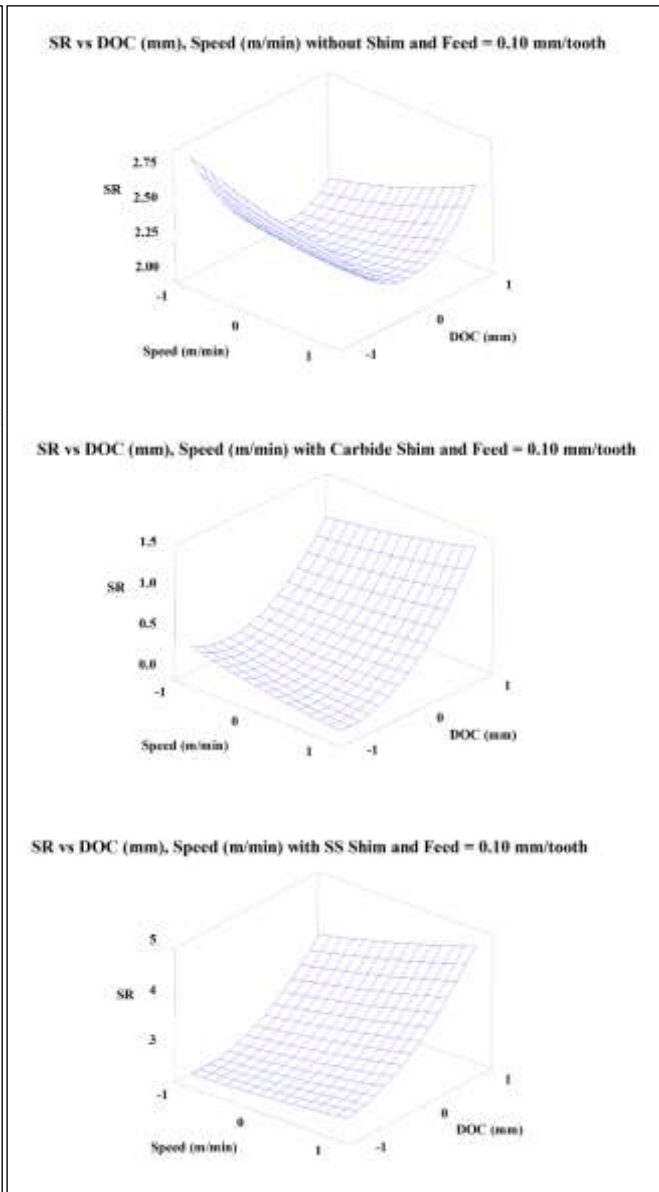


Figure 13: 3d surface plot for speed and depth of cut.
Source: Authors, (2026).

In the no-shim condition, the contour plots indicate moderate surface roughness levels, with minimum values occurring at intermediate cutting speed and DOC. However, variations toward higher or lower DOC values result in a rapid increase in surface roughness, indicating the sensitivity of the process to depth of cut variations in the absence of a damping element. The SS shim condition shows the highest surface roughness values across the entire parameter space. Surface roughness does not fall below 3.0 μm and increases sharply with increasing DOC, reaching maximum values at extreme combinations of cutting speed and depth of cut. This result indicates reduced stability margins and ineffective vibration suppression, reviling stainless steel shims unsuitable for precision face milling applications.

In contrast, the carbide shim consistently yields the lowest surface roughness values over the entire range of cutting speed and DOC. Even at higher depths of cut, the surface roughness remains limited, and surface roughness values are maintained below 1.4 μm . The relatively flat response surface with respect to cutting speed further indicates that DOC is the dominant parameter, while the carbide shim effectively stabilizes the cutting process. Regarding machining stability, one can explain these trends by the increased stiffness and decreased contact compliance of the carbide shim that increases the dynamic stiffness of the tool-holder-insert system. The benefit of this enhancement is that regenerative chatter is suppressed and the vibration levels are lowered, which leads to a better surface quality. On the other hand, greater compliance of the SS shim eases the transfer of energy into the structural vibrations which enhances the chatter and surface roughness.

III.4 SURFACE ROUGHNESS PARAMETERS OPTIMIZATION

The optimization of surface roughness was carried out with the aid of the created RSM model taking into account three levels of shim material, cutting speed, feed rate, and depth of cut, thus, the number of potential combinations of parameters became 81. Regression models (Equations 2-4) were used to derive the analytical expressions that indicate the machining conditions that optimize the surface roughness.

In the optimization results, the minimum predicted surface roughness of 0.1861 μm is obtained with the use of a carbide shim for process parameters, speed 200 m/min, a feed rate 0.10 mm/tooth, and a depth of cut 1.0 mm. Confirmation experiments were conducted in order to confirm this result under these optimum machining conditions. The measured surface roughness experimentally under these conditions was 0.189 μm which is very close to the predicted value leading to an error of prediction of only 1.53%, as summarized in Table 6. This close correspondence validates the robustness of the designed RSM model and its potential to embody the physical essence of the influence of damping of shim on the surface generation. The dominance of shim material observed in the ANOVA analysis further reinforces the conclusion that passive damping plays a key role in improving surface finish. The superior performance of the carbide shim highlights its effectiveness in enhancing machining stability, suppressing chatter, and enabling consistent, high-quality surface finishes in face milling operations.

Table 6: Validation experiment results for optimum set of parameters.

Optimum Set of Parameter							
Response	Shim Type	Speed (m/min)	Feed (mm/tooth)	Depth of cut (mm)	Experimented Value (μm)	Predicted Value (μm)	Error %
SR (μm)	Carbide	200	0.1	0.8	0.189	0.1861	1.53

Source: Authors, (2026).

IV. CONCLUSIONS

- A Central Composite Design-based RSM was effectively used to determine and optimize face milling surface roughness taking into account both machining and shim material as a damping element.
- Shim material was found to be the most important variable that affects surface roughness, which proved the usefulness of passive damping in enhancing machining stability and surface finish.
- Among the investigated configurations, carbide shims consistently produced lower surface roughness compared with stainless steel shims and the no-shim condition, owing to their superior vibration suppression capability.
- Depth of cut and cutting speed exhibited significant main and interaction effects with shim material, highlighting the strong coupling between machining parameters and damping induced process stability.
- The tested RSM model showed high predictive accuracy, where adjusted coefficient of determination (R^2_{adj}) is 98.02 %, which confirms the reliability of the model in predicting surface roughness in face milling operation.
- Under the optimal machining conditions with carbide shim, the predicted surface roughness closely matched the experimental results, with a prediction error below 2% conforms the reliability of the proposed optimization approach.

The results show that the carbide shims are a useful and inexpensive passive damping method in improving surface finish and machining stability during face milling processes. Carbide shims are also potentially useful in decreasing trial-and-error experimentation as well as provides an effective means of enhancing process reliability in industrial machining settings.

IV.1 FUTURE SCOPE

The incorporation of force and vibration analysis with the surface roughness modelling into future studies will help create a more complete picture of machining dynamics. In addition, future work will extend the investigation to stability lobe diagram development and comparison for different shim materials to further elucidate their role in chatter suppression and dynamic stability in face milling operations.

V. AUTHOR'S CONTRIBUTION

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Investigation: Vijaykumar V Patel, Divyang H Pandya and Kaushal Bhavsar.

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Resources: Vijaykumar V Patel, Divyang H Pandya and Kaushal Bhavsar.

Supervision: Vijaykumar V Patel.

Approval of the final text: Vijaykumar V Patel, Divyang H Pandya and Kaushal Bhavsar.

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