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MULTI-RESPONSE OPTIMIZATIONS FOR HIGH SPEED DUCTILE MODE MACHINING OF SODA LIME GLASS

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ABSTRACT

Ductile regime end milling of soda lime glass needs consideration from commercial standpoints as well as in research and development. High speed machining is capable to obtain ductile mode at an increased material removal rate and at the same time tool wear rate can be optimized at higher value of cutting speed. This paper presents a simple and workable approach to process parameters optimization, to achieve ductile mode machining of soda lime glass applying high speed using the experiment design and parameter optimization capabilities of Response Surface Methodology (RSM). The particular ranges of cutting parameters were chosen based on initial tests conducted to ensure ductile mode machining during the experiments. The machining parameters such as cutting speed, depth of cut, and feed rate were varied from 30000 to 50000 rpm, 20 to 50 µm and from 45 to 75 mm/min (0.45 to 1.25 µm per tooth) respectively. Based on the experimental results empirical mathematical models relating the machining parameters to response parameters, namely, surface roughness, tool wear and tool life, were first developed. Multi-criteria optimization was conducted applying the desirability function of RSM based on the developed models, with the aim of determining the combination of machining parameters that would lead to optimal settings of responses. The quality criteria considered to establish optimal parameters were the minimization of surface roughness (R_a), tool wear (T_w) and maximization of tool life (T_l). Obtained results demonstrated that optimal combination of the response parameters, 0.78 µm Ra, 107 µm (Tw) and 0.56 min (T_l) were achieved with maximum desirability 77%, at the lowest depth of cut 20 µm at spindle speed of approximately 40000 rpm with feed rate of 69 mm/min.

Keywords: ductile mode machining, high speed machining, optimization, soda lime glass.

1. INTRODUCTION

Brittle materials like glass have become worthwhile topics of research due to fine chemical properties, thermal and corrosion resistance etc. Soda lime glasses are commonly used in camera lens, windowpanes, optics, chemical spouts, micro gas turbine etc. Conventional machining is not suitable for glass machining because of its low fracture toughness. Furthermore, fine polishing is always needed to remove the cracks and subsurface damages left by the non-predictive material removal mechanism of the abrasive based processes; as a result the production process becomes slow and costly [1]. On the other hand, for complex shape machining additional processing steps such as chemical etching, lithography and beam technology (laser beam or ion beam or electron beam) reduced the productivity and increased the overall manufacturing cost [2]. Ductile Regime Machining (DRM) is a relatively new, but promising technology, in which plastic deformation is the predominant nature of material removal mechanism and crack propagation due to fracture in the cutting zone is prevented from reaching the final machined surface [3].

Over the past two decades, researchers performed extensive work to evaluate the plastic deformation of brittle materials. They concluded that hydrostatic compressive shear stress suppresses any existing cracks propagation in the chip formation zone. Selection of appropriate cutting tool geometry and cutting parameters are necessary to perform DRM. In order to accomplish DRM, high precision, non-conventional machine tools has been used [4]. High pressure phase at the cutting edge which is necessery to perform ductile mode machining was achieved by using single point diamond turning [5]. Extensive literature review shows that most of the work was performed using low cutting speed and the ductile mode machining was achieved due to the cutting mechanism involved in the process. The feed rate and depth of cut was limited to micro-meter and nanometer ranges for the transition between ductile and brittle modes of material removal [6].

Although DRM turning is already an established field, DRM end milling is relatively less explored area of research. In case of peripheral up milling of tungsten carbide four distinct modes were identified by Arif *et al* [7]. In this case radial depth of cut was greater than the sub surface damage depth to achieve fracture free machined surface. The cutting tool edge radius and rake angle has significant influence in DRM machining. The un-deformed chip thickness is less than cutting tool edge radius for ductile mode machining of glass [8] and usually tool edge radius is less than 1 mm. Critical un-deformed chip thickness increases significantly with the decrease of rake angle from 0° to -40° [9].

Several researchers have tried to machine glass by milling operations. At a small depth of cut, a free form surface was machined on glass workpiece by Takeuchi *et al.* [10]. In a large radial depth of cut (more than 10µm) and at low feed per edge Matsumura *et al.* [11], performed up cut milling. Micro cutting of soda lime glass using side milling at low cutting speed (less than 10 m/min) showed

that feed per edge is the most dominant factor that governs the mode of machining and when feed per edge was less than 0.875 µm , fracture free surface was achieved at higher value of radial depth of cuts [12]. However, mode of machining was transited from ductile to brittle mode due to chipping of the cutting edge as a result of extreme wear.

High material removal rate in glass machining is yet to achieve. Sajjadi *et al.* [13] achieved higher critical chip thickness at higher cutting speeds. High speed cutting can be applied to increase material removal rate. Increased cutting speed increases materials strain rate, consequently temperature generated at chip formation zone allows more plastic deformation than at low speed cutting. Problem with high speed cutting is that, the resulting surface is usually contaminated with the ductile and almost molten chips due to the high temperature at which they are formed. Tool wear rate is also increased. Therefore, the selection of machining parameters to produce desired surface finish at increased MRR while reducing tool wear to reasonable value is a challenging task in high speed machining.

Surface quality is commonly characterized using average surface roughness (Ra). Flank wear occurs on the flank face of the tool as a result of mechanical abrasion between the machined surface of the work piece and the tool flank. Flank wear is characterized by the wear land height. If the amount of flank wear exceeds some critical value (hf > 0.5~0.6 mm), the excessive cutting force may cause tool failure [14]. The machining parameters that can produce good surface quality, low tool wear and high material removal rate is the most acceptable in this era of manufacturing. Hence Surface roughness (Ra), Tool flank wear (Tw) and tool life (Tl) were selected as response parameters for optimization. This paper establish the empirical models developed for surface roughness, tool wear and tool life in terms of spindle speed, feed rate and depth of cut within the ductile regime using Response Surface Methodology (RSM). Moreover, these multi-factors responses were optimized using the numerical optimization feature of RSM.

a) Research objectives

Ductile mode machining of brittle material is a complex task. The selection of appropriate range of machining parameters and cutting condition can facilitate DRM. The proper recipe of DRM to achieve good surface finish with reduced tool wear is not yet achieved. In addition to that the use of high speed to achieve DRM is not yet studied adequately. Hence, this research seeks to find the optimal condition for high speed machining of DRM that will provide desired surface roughness, minimized tool flank wear and reasonable amount of material removal rate. The study is, therefore, focused on-

- Identification of machining parameters of high speed machining that will provide ductile regime machining.
- Development of empirical model for surface roughness, tool flank wear and tool life in terms of cutting speed, feed rate and depth of cut.
- Validation of the developed models both statistically and experimentally.
- Detection of optimum machining conditions that would minimize both the surface roughness and tool flank wear and maximize the tool life at high material removal rate.

2. RESPONSE SURFACE METHODOLODY (RSM)

In order to evaluate the efficiency of a processing operation, the relationship among cutting speed, feed rate and depth of cut need to be established with the measure of process efficiency. The surface roughness, tool wear and tool life are the most important measures of process efficiency. RSM is commonly used for predicting and optimizing the process parameters due to its capability of reducing large number of experimental trail and mathematical model development facility. RSM is a collection of statistical and mathematical techniques that are useful for modelling and analyzing engineering problems where a response is influenced by several factors and the objective is either minimize or maximize or equal to a defined target value of the responses [15]. The relationship between the response y and a set of independent measureable and controllable variables {x_(1,) x_(2,) x_(3,)…,x_(n,) } can be expressed as Equation 1:

$$y = f(x_1, x_2, x_3, \ldots, x_n) + \epsilon \quad (1)$$

where, ϵ represents error observed in the response y.

Initially in RSM, the form of relationship between the response and the independent variables are unknown, hence to optimize y, the true functional relationships between y and independent factors are approximately taken as a second order, second degree model as Equation 2:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j} \sum_{j=2}^{k} \beta_{ij} x_i x_j + \epsilon \quad (2)$$

Where, $\beta_{i,j}$ = *0, 1, k* and ϵ are regression coefficients and error to be determined from least square method. Usually second order model is used when the response function is not known, non-linear or five levels are selected for independent variables. For multi-response optimization RSM can also be applied to navigate the design space and make an optimal decision [16]. In this research RSM is adopted for multi factor optimization.

a) Multi-response optimization

In this work, the influence of cutting speed, feed rate and depth of cut are investigated on multiple responses such as surface roughness, tool flank wear and tool life. Hence, the numerical optimization was used by setting the desired goal for each input factors and

responses. Numerical optimization is based on the overall desirability function (D). This approach first converts each response y_i into an individual desirability function d_i that varies from 0 to 1 ($0 \leq d_i \leq 1$). The variable are then combined to give overall desirability, D as Equation 3:

$$D = \sqrt[m]{d_1, d_2 \ldots . d_m} \quad (3)$$

where, m is number of responses.

The desired quality criteria for optimizations were the minimization of tool wear (T_w), surface roughness (R_a) and the maximization of tool life (T_l). The overall desirability can be expressed by Equation 4:

$$D = \sqrt[3]{d_{Ra} \times d_{Tw} \times d_{Tl}} \quad (4)$$

The desirability function to minimize R_a and T_w, is in given Equation 5.

$$d(y_i) = \begin{cases} 1 & y < T \\ \left(\frac{U - y_i}{U - T}\right)^r & T \leq y \leq U \\ 0 & y > U \end{cases} \quad (5)$$

The desirability function to maximize tool life (T_l), is given in Equation 6:

$$d(y_3) = \begin{cases} 0 & y < L \\ \left(\frac{y_3 - L}{T - L}\right)^r & L \leq y \leq T \\ 1 & y > T \end{cases} \quad (6)$$

where, upper limit, weightage and lower limit is denoted by U, r and L respectively. In this work, the value of r is equal to one for linear desirability function.

The optimization steps are shown in Figure-1.

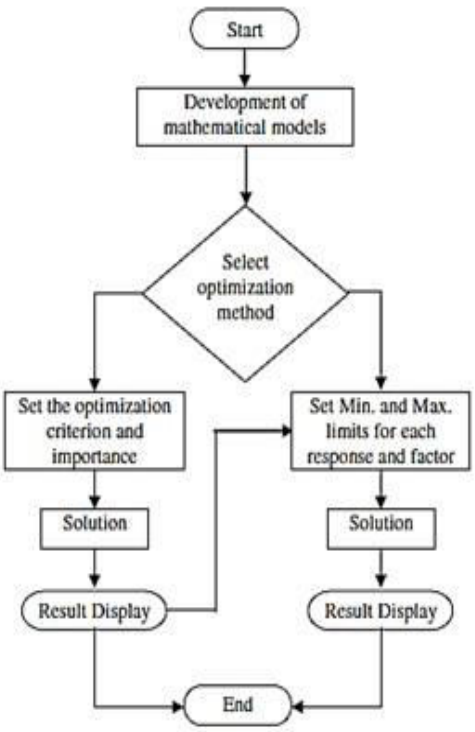

Figure-1. The optimization steps.

3. MATERIALS AND METHODS

a) Work material, tool and equipment

The soda lime glasses with dimension of 20 x 20 x 5 mm^3 were used in the experiment. The slot milling was carried out on a numerically controlled vertical milling centre (Model: ECM 1). This machine was upgraded to a high speed machine by installing a NSK Planet 550 high speed milling attachment directly into its main spindle. Nakanishi AL-0201 Air Line Kit attached with high speed supplement delivers the necessary compressed air to control the high speed. Air was blown to the tool and work interface to remove chips produced during machining. The total experimental setup is shown in Figure-2. 2-flute carbide coated flat end mill (MS2MS) with 2 mm diameter, helix angle and rake angle, 30º and -5º were used for cutting. In order to lessen the tool deflection, relatively higher diameter tool was selected. The cutting edge radius was 12μm which is greater than uncut chip thickness (0.45 to1.25μm) to obtain crack free machined surface.

The slot milling was performed along the whole length of the work piece. Each experimental run was performed using a new cutter of the same specification. KISTLER Ceramic Shear Accelerometers Type 8774A50 was attached on the stationary tool shank of the machine for sensing and acquiring the vibration data. Low and constant vibration amplitude level during machining ensured the ductile regime machining.

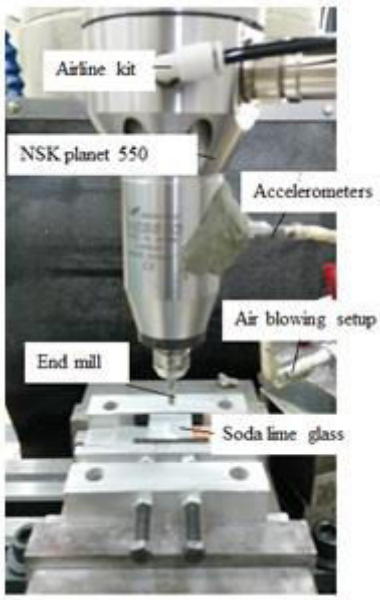

Figure-2. Experimental set up.

b) Experimental design

The central composite rotatable design with small replication was planned for the experiment. The design expert version 7 was used to make the design matrix and to analyse the data. This study considered spindle speed (A), feed rate (B) and depth of cut (C) as controllable

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input variables and five levels of these parameters were taken as in Table-1. The lower limits of spindle speed, 30000 rpm was selected based on previous research and the upper limit, 50000 rpm was on capacity of high speed milling attachment. Feed rate was varied from 45 to 75 mm/min. By changing one of the input parameter, at the same time keeping the rest at constant value, range of depth of cut was identified at some trial runs. The mathematical models of T_w, R_a and T_l in terms of spindle speed, feed rate and depth of cut were developed using same software. The developed models adequacy, significant model terms were measured by Analysis of Variance (ANOVA) and others adequacy measures. Finally optimal setting of cutting speed, feed rate and depth of cut to ensure minimum R_a , T_w and maximum T_l were determined using the developed mathematical model.

Table-1. Experimental conditions.

Input factors	Limits				
	-1.414	-1	0	+1	+1.414
Spindle speed(rpm)	25857	30000	40000	50000	54142.14
Feed rate (mm/min)	38.79	45	60	75	81.21
Depth of cut(µm)	13.79	20	35	50	56.21
Response factors	Surface roughness (µm), Flank wear(µm), Tool life(min)				

c) Experimental work and mechanical characterization

According to the design matrix fifteen runs were conducted in a random order to avoid systematic error. Samples were levelled using a diamond grinder and exact zero setting of z axis was ensured by a zero setting device. After machining the surface was cleaned using acetone to remove chips stick to the finished surface. The surface integrity was observed using Scanning Electron Microscope (SEM, JSMT330). The average surface roughness (R_a) was measured using Mitutoyo Surftest (SV 514) as shown in Figure-3. Measurements were made perpendicular to the feed marks direction.

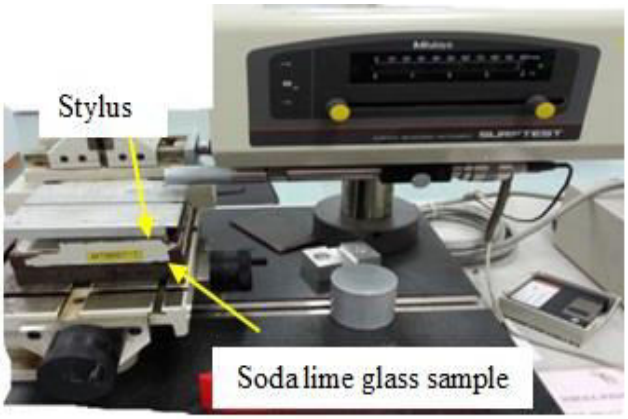

Figure-3. Setup to measure surface roughness.

Optical microscope (Nikon mm-400), was used to characterize the tool flank wear for every run. Then tool life was calculated based on machining time and tool wear rate. The process input factors and the measured mean responses are summarized in Table-2.

Table- 2. The process input factors and the measured mean responses.

Input factors						Responses factors		
Spindle speed (rpm)		Feed rate (mm/min)		Depth of cut (µm)		surface roughness (µm)	flank wear (µm)	tool life (min)
Actual	coded	Actual	coded	Actual	coded			
40000.00	0	60.00	0	13.79	−∝	0.59	135	0.58
40000.00	0	60.00	0	35.00	0	0.8	154	0.545
40000.00	0	60.00	0	35.00	0	0.68	156	0.565
54142.14	+∝	60.00	0	35.00	0	0.28	179	0.5
30000.00	-1	45.00	-1	20.00	-1	1.8	198	0.48
40000.00	0	60.00	0	56.21	+∝	0.97	158	0.48
40000.00	0	60.00	0	35.00	0	0.8	154	0.545
25857.86	- ∝	60.00	0	35.00	0	1.8	131	0.64
30000.00	-1	75.00	1	50.00	1	1.8	130	0.48
40000.00	0	60.00	0	35.00	0	0.97	150	0.6
50000.00	1	75.00	1	20.00	-1	0.38	128	0.345
40000.00	0	38.79	-α	35.00	0	1.38	211	0.6
40000.00	0	60.00	0	35.00	0	1.2	153	0.61
40000.00	0	81.21	+∝	35.00	0	0.45	107	0.405
50000.00	1	45.00	-1	50.00	1	0.43	160	0.66

4. RESULTS AND DISCUSSION

a) Development of mathematical models

The sequential model sum of square, in the fit summary selects the highest order polynomial where additional model terms are significant and the model is not aliased. Model summery statistics focuses on the model that maximizes predicted R^2 and low press values. Based on fit summery, the regression equations of R_a and both the T_w and T_l, to describe their relation with experimental data can be chosen as linear and quadratic model respectively. The value of R^2_{adj} are 80%, 99%, 88% for R_a, T_w and T_l respectively. It is suggested that for model adequacy and accuracy, R^2_{adj} should be greater or equal to 70% [17]. This indicates that experimental data are adequate to form other prediction model. Assessment of the significance of the model and the model terms were checked by the sequential F test and lack of fit test.

b) Analysis of variance (ANOVA)

The analysis of variance of R_a, T_w and T_l and their significant model terms are illustrated by the resulting ANOVA Tables-3, 4 and 5 respectively. The calculated "Model F" and " p- value" values are respectively, 19.33 and 0.0001 for R_a model, 294.60 and < 0.0001 for T_w model, and 19.66 and 0.0004 for T_l model. These Models F and p values implies that the selected models are highly significant and there is respectively, 0.01 % chance for R_a model, less than 0.01% chance for T_w model and only 0.04% chance for T_l model that the large model F value could occurs due to noise. The respective p values of the model are less than 0.05 indicate that the models are statistically significant [18]. The ANOVA Table 3, for R_a model shows that the effects of spindle speed (A) and feed rate (B) are significant and depth of cut (C) is added to support the model hierarchy. The ANOVA results for reduced quadratic model shown in Table - 4 and 5 illustrate that, the main effects of A, B, and C, the quadratic effects of feed rate (B^2), and depth of cut (C^2) along with the interaction effects of speed and feed rate, feed rate and depth of cut are the significant model terms for both flank wear and tool life model. Only the interaction term spindle speed and depth of cut are insignificant for tool life model. The insignificant terms were eliminated manually by backward regression method to improve model adequacy. All the other adequacy measures like R^2, adjusted R^2 and predicted R^2 are in logical agreement and indicate significant relationships. Furthermore the adequate precision ratios in all cases are larger than 4 indicating adequate models discrimination.

Table-6 shows the lack of fit value of the selected models is insignificant and it is desirable. It can be concluded that the developed models are accurate and can be used for prediction within the same design range. According to design expert software the finalize models in terms of coded factors are given in Equation. 7, 8 and 9.

Table-3. ANOVA table for R_a, Linear model.

Source	Sum of Squares	df	Mean Square	F value	p-value (Prob > F)	
Model	3.33	3	1.11	19.33	0.0001	Significant
A(speed)	3.05	1	3.05	53.18	< 0.0001	
B(feed rate)	0.23	1	0.23	4.06	0.0500	
C(depth of cut)	0.043	1	0.043	0.75	0.4044	
Residual	0.63	11	0.057			
Lack of fit	0.47	7	0.067	1.64	0.3304	Not significant
Pure error	0.16	4	0.041			
Cor total	3.96	14				
$R^2 = 0.8406$ Adj. $R^2 = 0.7971$ Pred. $R^2 = 0.6436$ Adeq. Precision=14.121						

Table-4. ANOVA table for T_w, Reduced Quadratic Model.

Source	Sum of Squares	df	Mean Square	F Value	p-value (Prob > F)	
Model	10205.62	8	1275.70	294.60	< 0.0001	Significant
A(speed)	1152.00	1	1152.00	266.03	< 0.0001	
B(feed rate)	5408.00	1	5408.00	1248.86	< 0.0001	
C(depth of cut)	264.50	1	264.50	61.08	0.0002	
AB	586.99	1	586.99	135.55	< 0.0001	
AC	277.04	1	277.04	63.98	0.0002	
BC	1454.82	1	1454.82	335.96	< 0.0001	
B^2	64.24	1	64.24	14.84	0.0084	
C^2	87.52	1	87.52	20.21	0.0041	
Residual	25.98	6	4.33			
Cor Total	10231.60	14				
R^2=0.9975 Ad.j R^2=0.9941 Pred. R^2=0.9758 Adeq. Precision= 64.520						

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Table-5. ANOVA table for T_l, reduced quadractic model.

Source	Sum of Squares	df	Mean Square	F Value	p-value (Prob > F)	
Model	0.10	7	0.015	19.66	0.0004	Significant
A(speed)	9.800E-003	1	9.800E-003	13.23	0.0083	
B(feed rate)	0.044	1	0.044	58.90	0.0001	
C(depth of cut)	5.000E-003	1	5.000E-003	6.75	0.0355	
AB	0.026	1	0.026	35.15	0.0006	
BC	7.381E-003	1	7.381E-003	9.96	0.0160	
B^2	0.013	1	0.013	17.59	0.0041	
C^2	5.766E-003	1	5.766E-003	7.78	0.0269	
Residual	5.185E-003	7	7.407E-004			
Cor Total	0.11	14				
R^2=0.9516 Ad.j R^2=0.9032 Pred. R^2=0.6304 Adeq. Precision 15.355						

In terms of actual factors are given in Equation 10, 11 and 12.

$$R_a = +0.96 - 0.62\,A - 0.17\,B + 0.073\,C \quad (7)$$

$$T_w = +153.86 + 16.9A - 36.77B + 8.13C + 17.13A \times B - 11.77A \times C + 26.97B \times C + 2.88B^2 - 3.37C^2 \quad (8)$$

$$T_l = 0.57 - 0.049\,A - 0.074B - 0.035\,C - 0.11A \times B - 0.061B \times C - 0.041B^2 - 0.027C^2 \quad (9)$$

$$R_a = +3.93642 - 6.17451E-005A - 0.011377B + 4.89501E-003C \quad (10)$$

$$T_w = +657.87928 - 2.40941E-003A - 12.75328\,B - 2.46427\,C + 1.14212E-004A \times B - 7.84637E-005A \times C + 0.11987B \times C + 0.012817B^2 - 0.014960C^2 \quad (11)$$

$$T_l = -2.05054 + 4.06924E-005\,A + 0.056859\,B + 0.022342\,C - 7.60702E-007\,A \times B - 2.69989E-004\,B \times C - 1.82540E-004B^2 - 1.21429E-04C^2 \quad (12)$$

c) Model validation

The Normal probability plots of data for surface roughness, flank wear and tool life are shown in Figure- 4(a)-(c) respectively, shows that the experimental points are reasonably aligned with the fitted points and this demonstrated the normality of the data and from internally studentized residuals versus predicted response it was shown that all the points are within $\pm 2\,\sigma$ limits.

The relationship between predicted and actual values of surface roughness, flank wears and tool life are depicted in Figure-5(a-c) respectively shows that the residual are close to the diagonal line.

Table-6. Lack of fit test.

Source	Sum of square	df	Mean square	F value	P value (prob>F)	
For surface roughness linear model						
Lack of fit	0.4	7	0.067	1.64	0.330	not significant
Pure error	0.16	4	0.041	58.90	0.0001	
For flank wear reduced quadratic model						
Lack of fit	6.78	2	3.39	0.71	0.5461	not significant
Pure error	19.20	4	4.80			
For tool life reduced quadratic model						
Lack of fit	1.455E-003	3	4.851E-004	0.52	0.6909	not significant
Pure error	3.730E-00	4	9.325E-004			

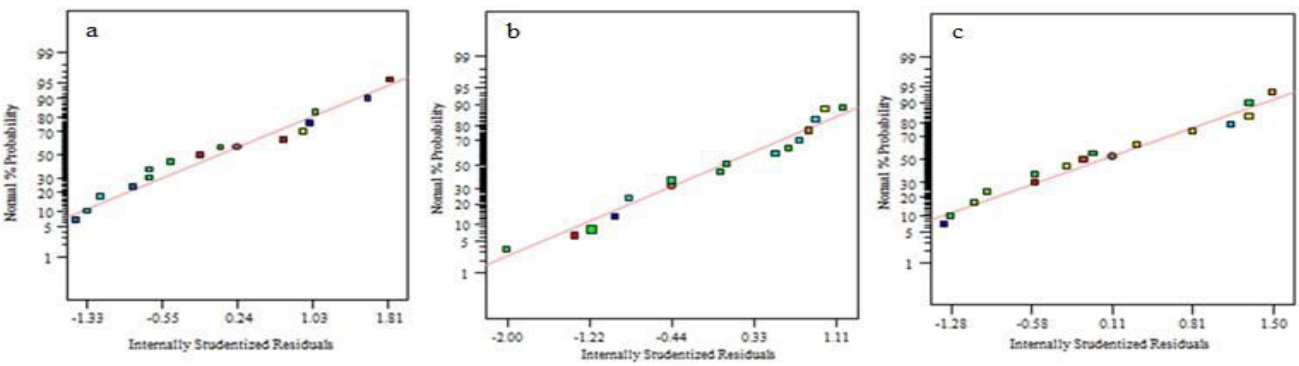

Figure-4. Normal probability plot for (a) Surface roughness, (b) Flank wear and (c) Tool life.

This indicates the model adequacy and predicted results are in decent promise with the measured data. In order to validate the developed response models derived from multiple regression analyses, three verification tests were carried out by randomly selecting machining parameters within the range from which the equations were developed. Table-7 summarizes the actual results (mean) of each response; the predicted results and the small error percentage of confirmation tests demonstrate that model can predict nearly accurate results.

d) Process parameter optimization

The ranges of parameters were restricted to ductile regime machining. The comparative influences of cutting parameter on surface roughness, tool flank wear and tool life is shown in the perturbation plots in Figure-6 (a-c), respectively.

Higher feed rate is beneficiary for tool wear, as cutting tool rapidly passed comparatively soft work piece. With the increase of the feed rates, the reduced tool path length (for a given length of the work piece) decrease the cutting time. Consequently tool wear and surface roughness decreased. High spindle speed produces good surface but not suitable for tool flank wear and also for tool life. At high cutting speed, thermal softening increased the ductility of material which leads to reduce fracture. Concurrently due to temperature tool wear rate increased. In this experiment each run was carried out by a new tool. The result of flank wear gives significant effect on tool life. As a result, at low speed and feed rate increased tool life is achieved. Due to size effects, as depth of cut decreases large angle induced in the cutting edge increases the specific cutting energy. As a result low depth of cut produces reduced surface roughness, lower tool wear and tool life become higher.

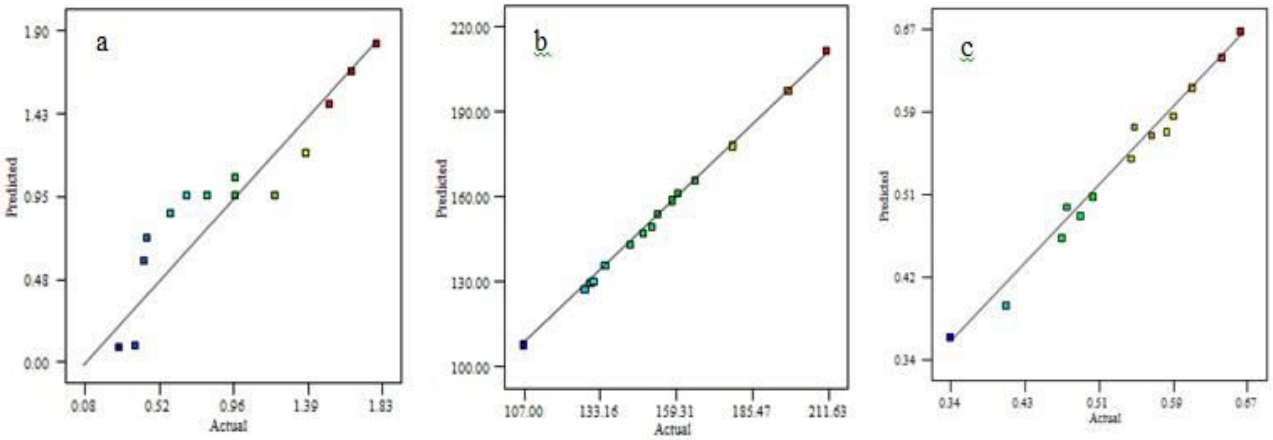

Figure-5. Scatter plots of (a) Surface roughness, (b) Flank wear and (c) Tool life.

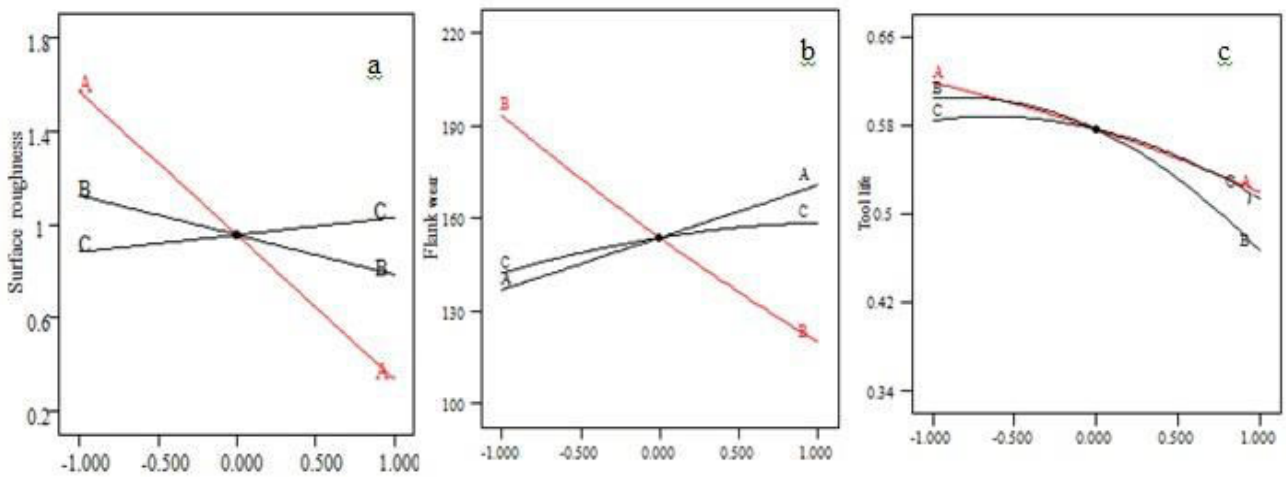

Figure-6. Perturbation plot: (a) surface roughness, (b) flank wear and (c) tool life.

Table-7. Confirmation experiments.

	Process parameters				Response factors		
	Spindle speed(rpm)	Feed rate (mm/min)	Depth of cut (µm)		Surface Roughness (µm)	Tool wear (µm)	Tool life (min)
Expt. 1	50000	45	56.21	Actual	0.6	139	0.62
				Predicted	0.612	143.342	0.651
				Error (%)	2.058	3.124	4.963
Expt. 2	40000	60	35	Actual	0.97	150	0.6
				Predicted	0.955	153.859	0.572
				Error (%)	-1.513	2.572	-4.648
Expt. 3	30000	75	20	Actual	1.301	108	0.7
				Predicted	1.329	110	0.690
				Error (%)	2.1299	1.852	-1.490

In order to optimize the input parameter to obtain optimal value of responses, the developed model of R_a, T_w and T_l were used for multiple response optimizations using the optimization criteria as in Table-8 and desirability function as in Equation. (5-6). Using the design expert software, the maximum desirability was 77% (Figure-7). This corresponds to the optimum condition of spindle speed, 40028 rpm; feed rate, 69 mm/min and depth of cut, 20 µm. This condition predicted the generation of surface finish 0.78 µm Ra, 107 µm tool wear (T_w) and 0.56 min tool life (T_l) on end milling of soda lime glass. The experiments conducted to confirm this optimal combination of cutting parameters ensured surface finish 0.75 µm (Ra), 112 µm tool wear (T_w) and 0.51 min tool life (T_l). Figure 8 shows the optical and SEM image of soda lime surface after performing the experiment at optimized parameters. This image clearly shows the obtained ductile surface. The optical images of tool wear, shown in Figure-9 also demonstrate the effects of cutting parameter on tool flank wear.

Table-8. The optimization criteria.

	Limit		Goal	Imp.
	Lower	Upper		
Speed (rpm)	30000	50000	is in range	3
feed rate (mm/min)	45	75	is in range	3
depth of cut(µm)	20	50	is in range	3
surface roughness(µm)	0.28	1.8	minimize	5
flank wear(µm)	107	211	minimize	5
tool life(min)	0.345	0.66	maximize	5

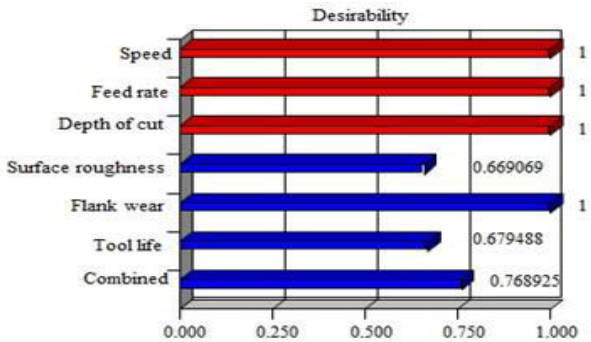

Figure-7. The Bar graph showing the maximum desirability of 0.77 for the combined objective.

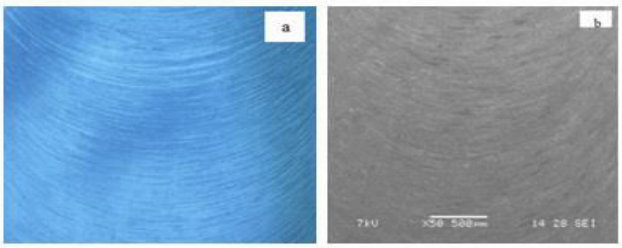

Figure-8. Image of surface after performing machining at optimum cutting conditon (a) optical image (b) SEM image.

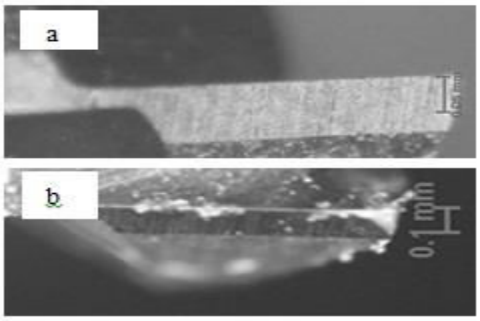

Figure-9. Tool flank wear (a) fresh tool (b) After cutting at optimal condition.

5. CONCLUSIONS

The ductile regime machining of soda lime glass was performed. RSM was used to relate the input parameters to the response factors. Based on the mathematical relationship developed using RSM, optimization using the desirability function was done to identify the most desirable combination of the response parameters and the corresponding values of the input variables, i.e., the cutting parameters. From the obtained results and the optimization exercise the following conclusions can be drawn:

- Linear model for surface roughness and quadratic model for both tool wear and tool life are developed within the experimental region i.e., spindle speed 20000-50000 rpm, depth of cut 20-50µm and feed rate 45 -75 mm/min. These models are capable to navigate the design space.
- In this study, R^2_{adj} are 80%, 99%, and 88% for R_a, T_w and T_l models respectively. This indicates that the data measured from the experiment are sufficient to build other prediction model.
- Cutting speed is the most significant factor for surface roughness followed by feed rate and depth of cut. Cutting speed needs to be increased and feed rate to be decreased to get lower surface roughness.
- With respect to flank wear feed rate is the most dominating factor followed by cutting speed and depth of cut. Feed rate and cutting speed need to be reduced to get higher tool life.
- The quadratic effects of feed rate and depth of cut along with the interaction effects of speed and feed rate, feed rate and depth of cut are the significant for both flank wear and tool life model. The speed and depth of cut interaction are insignificant for tool life.
- SEM and optical images of machined surface and tool wear clearly demonstrate that using optimal machining conditions obtained from numerical optimization, surface roughness of desired quality and desired tool life can be obtained in high speed end milling of soda lime glass.

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