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Multi-response Analysis of Chemical Assisted Ultrasonic Machining of UL-752 and BS-476 Glass by GRA approach

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Abstract This paper is developed an innovative process of chemical assisted ultrasonic machining of polycarbonate bullet proof UL-752 and acrylic heat resistant BG-476 glass and conducted an investigational to optimize the machining parameters associated with multiple performance characteristics using Grey relational analysis. Machining of polycarbonate bullet proof UL-752 and acrylic heat resistant BS-476 glass are difficult process via conventional machining, however, it can be easily machined by Ultrasonic machining. Carefully selected parameters gives the optimum results. In this experimental work input parameters abrasive slurry concentration, type of abrasive, power rate, grit size of abrasive particles, hydro-fluoride acid concentration and tool material are selected. The effect of input parameters viz material removal rate, tool wear rate and surface roughness are investigate. Grey relational analysis and analysis of variance are performed to optimize the input parameters and better output results. In PBPG UL-752, increment in material removal rate by 80%, tool wear rate by 50% and surface roughness by 40%. In other hand, in AHRG BS-476, increment in material removal rate by 70%, tool wear rate by 30% and surface roughness by 25%.

Keywords USM, Polycarbonate bullet proof glass, Acrylic Heat resistant glass, HF acid, Grey Relational Analysis

1. Introduction

Ultrasonic machining (USM) is known as the non-conventional machining process (Kuriakose et al. 2017; Wang et al. 2016). In which the material is removed by erosion mechanism. The selection of input process parameters play an important role in the USM process (Li et al. 2016; Lin et al. 2016). In this paper, the input parameters are abrasive slurry concentration, type of abrasive particles, power rate, grit size of abrasive particles, hydro-fluoride (HF acid) concentration, tool material are selected (Khairay 1990; Choi et al. 2007). The output parameters are material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR).

Machining of polycarbonate bullet proof (PBPG UL-572) and acrylic heat resistant BS-476 (AHRG BS-476) are too tough job, because it have alternative layers of glass, polycarbonate and acrylic material. Acrylic and polycarbonate material are easily machined by conventional processes and glass is machined by non-conventional processes like USM, water jet machining (WJM) and abrasive water jet machining (AWJM) (Choi et al. 2007; Guzza et al. 2004). Other non-conventional processes like Laser beam machining (LBM) is not utilized because it produced heat effected zone, electron beam machining (EBM) is applicable only on conductive materials and conventional machining will damage the PBPG UL-752 and AHRG BS-476. In last USM is best alternative for machining of this material. Some important properties of PBPG UL-752 and AHRG BS-476 are shown in the Table 1.

Table 1. Important properties of PBPG UL-752 and AHRG BS-476

Properties	PBPG UL-752	AHRG BS-476
Tensile strength (Depend on thickness)	120-180 MPa	105- 155 MPa
Compressive Strength	1000 MPa (at 73°F)	1200 MPa (at 73°F)
Linear expansion (20 to 300°C)	$9x10^{-6}$ m/(m-k)	8.23 $x10^{-6}$ m/(m-k)
Thermal Conductivity at 23°C	0.30 W/(m-K)	0.86 W/(m-K)
Reactivity with HF Acid	poor	poor
Hardness	58 HRC	61 HRC
Density 7 g/cm^3	7 gm/cm^3	8.3 g/cm^3

In the experiment, selected parameters having three different level shown in Table 2. Design of experiment is prepared by Minitab 6.7 software in which L_{27} orthogonal array is used. The levels are selected by pilot experiments. For calculating MRR and TWR the initial and final weight of

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tools and work sample respectively measured by weight machine and surface roughness of check by Taylor Hobson Surtronic 25 surface roughness tester.

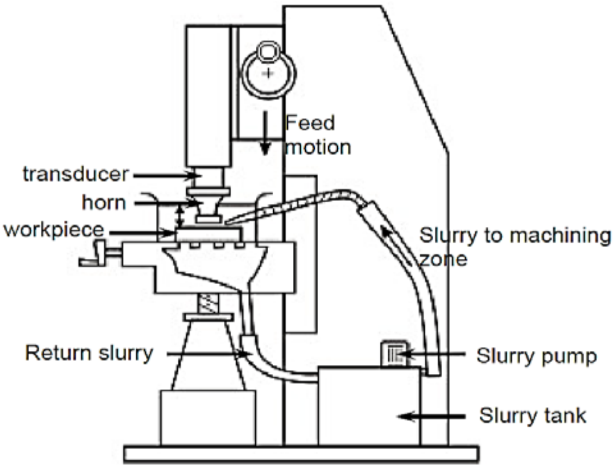

Figure 1. Schematic Diagram of Chemical Assisted Ultrasonic Machine

Experiment are performed on Sonic Mill 500W USM and schematic diagram of machine is shown in Fig.1. 500W Sonic-Mill ultrasonic machine have vibrating spindle kit, feeding system at constant pressure and abrasive slurry flow pump system. Fig. 1 show the schematic figure of USM apparatus. The ultrasonic vibration kit contains an ultrasonic spindle, 25.4 mm diameter cylindrical horn, and power supply (Hofy 2012; Jatinder & Khamba 2010). The power supply unit convert 50Hz electric supply input to sonic frequency 20 kHz output. 500W Sonic-Mill vibrating kit having piezoelectric transducer, it convert electric signal input into mechanical vibration output signal (Lee & Chan 1997; Kanwal Singh & Ahuja 2014; Kanwal Singh & Singla 2014; Singh and Khamba 2008). The amplitude of the vibration is 0.0237-0.0268 mm and frequency of vibration 20 kHz ± 250 Hz. Static load for feeding the USM tool is fixed at 1.757 kg and abrasive slurry flow rate is 30 L/min (Singh & Khamba 2007; Thoe et al. 1998; Vinod & Aniruddha 2008; Zhang et al. 1999).

Table 2. Different input or controllable machining parameters & their levels

Factor	Levels		
	Level 1	Level 2	Level 3
Concentration (A)	20	30	40
Abrasive (B)	Al_2O_3+B_2C	SiC+ B_2C	Al_2O_3+ SiC+ B_2C
Power Rate (C)	20	40	60
Grit Size (D)	280	400	600
HF Acid (E)	0.5%	1%	1.5%
Tool Material (F)	D2	High-Carbon Steel	High-Speed Tool Steel

Table 3. Design of experimentation (Orthogonal Array L27) and their levels

Trail	Concentration	Type of Abrasive	Power Rate	Grit Size	HF Acid	Tool Material
1.	20	Al_2O_3+B_2C	20	280	0.5%	D2
2.	20	Al_2O_3+B_2C	20	280	1%	HCS
3.	20	Al_2O_3+B_2C	20	280	1.5%	HSTS
4.	20	SiC+B_2C	40	400	0.5%	D2
5.	20	SiC+B_2C	40	400	1%	HCS
6.	20	SiC+B_2C	40	400	1.5%	HSTS
7.	20	Al_2O_3+SiC+B_2C	60	600	0.5%	D2
8.	20	Al_2O_3+SiC+B_2C	60	600	1%	HCS
9.	20	Al_2O_3+SiC+B_2C	60	600	1.5%	HSTS
10.	30	Al_2O_3+B_2C	40	600	0.5%	HCS
11.	30	Al_2O_3+B_2C	40	600	1%	HSTS
12.	30	Al_2O_3+B_2C	40	600	1.5%	D2
13.	30	SiC+B_2C	60	280	0.5%	HCS
14.	30	SiC+B_2C	60	280	1%	HSTS
15.	30	SiC+B_2C	60	280	1.5%	D2
16.	30	Al_2O_3+SiC+B_2C	20	400	0.5%	HCS
17.	30	Al_2O_3+SiC+B_2C	20	400	1%	HSTS
18.	30	Al_2O_3+SiC+B_2C	20	400	1.5%	D2
19.	40	Al_2O_3+B_2C	60	400	0.5%	HSTS
20.	40	Al_2O_3+B_2C	60	400	1%	D2
21.	40	Al_2O_3+B_2C	60	400	1.5%	HCS
22.	40	SiC+B_2C	20	600	0.5%	HSTS
23.	40	SiC+B_2C	20	600	1%	D2
24.	40	SiC+B_2C	20	600	1.5%	HCS
25.	40	Al_2O_3+SiC+B_2C	40	280	0.5%	HSTS
26.	40	Al_2O_3+SiC+B_2C	40	280	1%	D2
27.	40	Al_2O_3+SiC+B_2C	40	280	1.5%	HCS

Table 4. Design of experimentation (Orthogonal Array L27) and their levels

Trail	Polycarbonate Bullet proof (UL-752) glass			Acrylic Heat Resistant (BS-476) Glass		
	MRR (mm^3/min)	TWR (mm^3/min)	(SR) Ra (Micron)	MRR (mm^3/min)	TWR (mm^3/min)	(SR) Ra (Micron)
1.	6.47	0.089209	1.57	4.25	0.088853	1.29
2.	6.42	0.079284	1.86	3.86	0.071071	1.86
3.	6.83	0.038295	1.42	4.32	0.037189	1.42
4.	7.53	0.082232	1.51	4.78	0.084845	1.51
5.	7.77	0.074125	1.68	4.25	0.064513	1.68
6.	6.88	0.036479	1.59	4.35	0.037273	1.59
7.	8.19	0.082788	1.33	4.84	0.080889	1.33
8.	7.48	0.084926	1.43	5.77	0.106384	1.43
9.	7.07	0.029241	1.29	5.48	0.033212	1.29
10.	5.45	0.048754	1.24	4.38	0.057549	1.03
11.	6.29	0.033464	1.34	4.34	0.035739	1.34
12.	5.67	0.072275	1.18	4.60	0.089643	1.18
13.	6.33	0.079673	1.46	5.03	0.098258	1.46
14.	6.95	0.053041	1.77	5.17	0.059348	1.77
15.	6.12	0.106128	1.32	4.63	0.107305	1.32
16.	7.52	0.085062	1.44	5.43	0.099815	1.44
17.	7.64	0.054312	1.59	5.00	0.049939	1.59
18.	6.81	0.095251	1.48	4.74	0.103339	1.48
19.	6.26	0.046235	1.12	3.75	0.042181	0.93
20.	5.63	0.085143	1.27	4.27	0.102664	1.27
21.	6.38	0.084632	1.09	3.89	0.083415	1.09
22.	7.12	0.040692	1.14	4.29	0.036937	1.14
23.	6.26	0.086954	0.97	4.67	0.109564	0.97
24.	6.43	0.069166	1.02	4.16	0.071609	1.02
25.	7.23	0.060492	0.99	5.02	0.063506	0.99
26.	8.75	0.239698	1.06	5.09	0.211508	1.06
27.	8.27	0.111256	1.10	4.59	0.101542	1.1

2. Material and Methods

Selected parameters and levels are shown in Table 2. For the design of experiment orthogonal array L_{27} is used and design is prepared by Minitab 6.7 software. The design of experiment is shown in Table 3. All the experiments are performed according to the design experiment. MRR and TWR are calculated by the equation 1 and equation 2, in which density of work material ρ is 8.3 gm/cm^3, W_i is initial weight, W_f final weight after processing, t is time take in machining. T_i initial and T_f weight of tool and ρ = Density of D2 Steel 7.83 gm/cm^3, Density of HC steel 7.85 gm/cm^3, Density of HST steel 8.13 gm/cm^3 (Hasani et al. 2012; Hasiao et al. 2008)

$$MRR = \frac{W_i - W_f}{\rho\ X\ t}\ 1000\ (mm^3/min) \qquad (1)$$

$$TWR = \frac{T_i - T_f}{\rho\ X\ t}\ 1000\ (mm^3/min) \qquad (2)$$

Surface roughness is measured is R_a, it is the universally recognised and most used international parameter of roughness. It is the arithmetic mean of the absolute departure of the roughness profile from the mean line.

After machining the MRR and TWR are calculated and SR is checked, machining data is shown in Table 4. In which MMR and TWR is calculated in mm^3/min and surface roughness in R_a.

3. Results and Discussion

In grey relation analysis, data pre-processing is necessary to sequence scatter range. Data pre-processing is a process in which original sequence is transferred into comparable sequence. The experiment results are normalized in the range between zero (0) and one (1). Depending on output parameters, data pre-processing methodologies are adopted (Lin et al. 2002; Lin & Lee 2009; You et al. 2017). MRR is the governing output parameter in USM, which decided the machinability of work material under deliberation. "Larger-the-better" characteristics is used for

MRR to normalize the original sequence by equation 3.

$$X_i^*(k) = \frac{X_i(K) - MinX_i(K)}{MaxX_i(K) - MinX_i(K)} \quad (3)$$

Where, $X_i^*(K)$ is the sequence after the data processing, $X_i\ (K)$ is the comparability sequence, K=1 and k=4 for MRR; i= 1,2,3………27 for experiment number 1 to 27.

TWR and SR are the important measure of USM, these output parameters are represent the machining accuracy under selected input parameters (Patil & Patil 2016; Das et al. 2016). To get the optimum performance the “Smaller-the-better” characteristic has been preferred to normalize the original sequence date by equation 4.

$$X_i^*(K) = \frac{MaxX_i(K) - X_i(K)}{MaxX_i(K) - MinX_i(K)} \quad (4)$$

Where, $X_i^*(K)$ is the sequence after the data processing, $X_i(K)$ is the comparability sequence, K=2, K=5 for TWR and K=3, K=6 for SR; i= 1,2,3………27 for experiment number 1 to 27. $X_i^*(K)$ is the value after grey relational generation, Min $X_i(K)$ and Max $X_i(K)$ are the smallest and largest value of $X_i(K)$. After normalized MRR, TWR and SR of PBPG UL-752 and AHRG BS-476 comparable sequence is shown in the Table 5.

Now $\Delta_{0i}(K)$ is the deviation sequence between reference sequence $X_i^0(K)$ and the comparability sequence $X_i^*(K)$ (Ahmad et al. 2016). Deviation sequence is calculate by the equation 5 and maximum and minimum difference is found, K=1, 2 and 3 and i= 1, 2, 3…27.

$$\Delta_{0i}(K) = \left| X_0(K) - X_i(K) \right| \quad (5)$$

Table 5. The sequences of each performance characteristic after data processing

Trail Reference Sequence	Polycarbonate Bullet proof (UL-752) glass			Acrylic Heat Resistant (BS-476) Glass		
	MRR	TWR	SR	MRR	TWR	SR
	1	1	1	1	1	1
1.	0.309091	0.715058	0.325843	0.247525	0.687929	0.612903
2.	0.293939	0.762217	0	0.054455	0.787662	0
3.	0.418182	0.956979	0.494382	0.282178	0.977694	0.473118
4.	0.630303	0.74821	0.393258	0.509901	0.710409	0.376344
5.	0.70303	0.786731	0.202247	0.247525	0.824444	0.193548
6.	0.433333	0.965608	0.303371	0.29703	0.977223	0.290323
7.	0.830303	0.745568	0.595506	0.539604	0.732596	0.569892
8.	0.615152	0.735409	0.483146	1	0.589604	0.462366
9.	0.490909	1	0.640449	0.856436	1	0.612903
10.	0	0.907283	0.696629	0.311881	0.863502	0.892473
11.	0.254545	0.979934	0.58427	0.292079	0.985827	0.55914
12.	0.066667	0.795521	0.764045	0.420792	0.683498	0.731183
13.	0.266667	0.760369	0.449438	0.633663	0.63518	0.430108
14.	0.454545	0.886913	0.101124	0.70297	0.853412	0.096774
15.	0.20303	0.634666	0.606742	0.435644	0.584438	0.580645
16.	0.627273	0.734763	0.47191	0.831683	0.626447	0.451613
17.	0.663636	0.880874	0.303371	0.618812	0.906184	0.290323
18.	0.412121	0.686349	0.426966	0.490099	0.606682	0.408602
19.	0.245455	0.919252	0.831461	0	0.949696	1
20.	0.054545	0.734378	0.662921	0.257426	0.610468	0.634409
21.	0.281818	0.736806	0.865169	0.069307	0.718429	0.827957
22.	0.506061	0.94559	0.808989	0.267327	0.979108	0.774194
23.	0.245455	0.725773	1	0.455446	0.571768	0.956989
24.	0.29697	0.810294	0.94382	0.20297	0.784645	0.903226
25.	0.539394	0.851509	0.977528	0.628713	0.830092	0.935484
26.	1	0	0.898876	0.663366	0	0.860215
27.	0.854545	0.6103	0.853933	0.415842	0.616761	0.817204

The deviation sequence table is shown in the Table 6, Maximum (ΔMax) and Minimum (ΔMin) are obtained and shown below.

ΔMax = $\Delta_{10}(1)$ = $\Delta_{26}(2)$ = $\Delta_{02}(3)$ = $\Delta_{19}(4)$ = $\Delta_{26}(5)$ = $\Delta_{02}(6)$ =1

ΔMin = $\Delta_{26}(1)$ = $\Delta_{09}(2)$ = $\Delta_{23}(3)$ = $\Delta_{08}(4)$ = $\Delta_{09}(5)$ = $\Delta_{19}(6)$ =0

After per-processing data, the next step in calculate the Grey relational coefficient and Grey relation grade with the pre-processed data (Lin et al. 2009). It define the relationship between ideal and actual normalized results. Grey relational coefficient ξ can be expressed as equation 6 is shown below.

$$\xi_i(K) = \frac{\Delta Min + \rho\Delta Max}{\Delta_{0i}(K) + \rho\Delta Max} \tag{6}$$

Where, $\Delta_{0i}(K)$ is the deviation sequence of the reference sequence $X_i^0(K)$ and the comparability sequence, ρ is distinguishing or identification coefficient. In this calculation ρ =0.5 because all parameters are given equal preference (Lin 2012). The Grey relation coefficient for each experiment of the L27 orthogonal array is calculated by using equation 6 and shown in Table 7.

After obtaining the Grey relation coefficient, the Grey relation grade γ_i is obtained by averaging the Grey relation coefficient corresponding to each performance characteristic and represent by $\xi_i(1)$, $\xi_i(2)$, $\xi_i(3)$ $\xi_i(4)$, $\xi_i(5)$ and $\xi_i(6)$ Equation 7 (Manivanna et al. 2011) show the general formula of Grey relation grade and equation 8 is for three output parameters, shown in Table 7.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\{\xi_i(K)\} \tag{7}$$

$$\gamma_i = \frac{1}{3}\{\xi_i(1) + \xi_i(2) + \xi_i(3)\} \tag{8}$$

Table 6. The deviation sequences

Deviation Sequence	$\Delta_{0i}(1)$	$\Delta_{0i}(2)$	$\Delta_{0i}(3)$	$\Delta_{0i}(4)$	$\Delta_{0i}(5)$	$\Delta_{0i}(6)$
1.	0.690909	0.284942	0.674157	0.752475	0.312071	0.387097
2.	0.706061	0.237783	1	0.945545	0.212338	1
3.	0.581818	0.043021	0.505618	0.717822	0.022306	0.526882
4.	0.369697	0.25179	0.606742	0.490099	0.289591	0.623656
5.	0.29697	0.213269	0.797753	0.752475	0.175556	0.806452
6.	0.566667	0.034392	0.696629	0.70297	0.022777	0.709677
7.	0.169697	0.254432	0.404494	0.460396	0.267404	0.430108
8.	0.384848	0.264591	0.516854	0	0.410396	0.537634
9.	0.509091	0	0.359551	0.143564	0	0.387097
10.	1	0.092717	0.303371	0.688119	0.136498	0.107527
11.	0.745455	0.020066	0.41573	0.707921	0.014173	0.44086
12.	0.933333	0.204479	0.235955	0.579208	0.316502	0.268817
13.	0.733333	0.239631	0.550562	0.366337	0.36482	0.569892
14.	0.545455	0.113087	0.898876	0.29703	0.146588	0.903226
15.	0.79697	0.365334	0.393258	0.564356	0.415562	0.419355
16.	0.372727	0.265237	0.52809	0.168317	0.373553	0.548387
17.	0.336364	0.119126	0.696629	0.381188	0.093816	0.709677
18.	0.587879	0.313651	0.573034	0.509901	0.393318	0.591398
19.	0.754545	0.080748	0.168539	1	0.050304	0
20.	0.945455	0.265622	0.337079	0.742574	0.389532	0.365591
21.	0.718182	0.263194	0.134831	0.930693	0.281571	0.172043
22.	0.493939	0.05441	0.191011	0.732673	0.020892	0.225806
23.	0.754545	0.274227	0	0.544554	0.428232	0.043011
24.	0.70303	0.189706	0.05618	0.79703	0.215355	0.096774
25.	0.460606	0.148491	0.022472	0.371287	0.169908	0.064516
26.	0	1	0.101124	0.336634	1	0.139785
27.	0.145455	0.3897	0.146067	0.584158	0.383239	0.182796

Table 7. The calculated Grey Relational Grade and its order in the optimization process

Expt. No.	Grey Relational Coefficient						Grey Relation Grade	Rank
	$\{\xi_i(1)\}$	$\{\xi_i(2)\}$	$\{\xi_i(3)\}$	$\{\xi_i(4)\}$	$\{\xi_i(5)\}$	$\{\xi_i(6)\}$	$\gamma_m = \frac{1}{6}\{\xi_i(1)+\xi_i(2)+\xi_i(3)$ $+\xi_i(4)+\xi_i(5)+\xi_i(6)\}$	
1.	0.419847	0.63699	0.425837	0.39921	0.61571	0.563636	0.510205	24
2.	0.414573	0.677706	0.333333	0.34589	0.701914	0.333333	0.467792	26
3.	0.462185	0.920775	0.497207	0.410569	0.957293	0.486911	0.62249	12
4.	0.574913	0.665079	0.451776	0.505	0.633239	0.444976	0.545831	19
5.	0.627376	0.700998	0.385281	0.39921	0.740131	0.382716	0.539285	20
6.	0.46875	0.935643	0.41784	0.415638	0.956431	0.413333	0.601273	14
7.	0.746606	0.66275	0.552795	0.520619	0.651547	0.537572	0.611982	13
8.	0.565069	0.653944	0.491713	1	0.549212	0.481865	0.623634	11
9.	0.495495	1	0.581699	0.776924	1	0.563636	0.736292	2
10.	0.333333	0.843573	0.622377	0.420833	0.785548	0.823009	0.638112	9
11.	0.40146	0.961416	0.546012	0.413934	0.972435	0.531429	0.637781	10
12.	0.348837	0.709744	0.679389	0.463303	0.612368	0.65035	0.577332	17
13.	0.405406	0.676013	0.475936	0.577143	0.578155	0.467337	0.529998	21
14.	0.478261	0.815545	0.35743	0.627329	0.77329	0.356322	0.56803	18
15.	0.385514	0.577812	0.559749	0.469768	0.546113	0.54386	0.513803	23
16.	0.572917	0.653392	0.486339	0.748148	0.572375	0.476923	0.585016	16
17.	0.597826	0.80759	0.41784	0.567416	0.842012	0.413333	0.60767	14
18.	0.45961	0.614514	0.465968	0.495098	0.559711	0.458128	0.508838	25
19.	0.398551	0.860959	0.7479	0.333333	0.908589	1	0.708222	3
20.	0.345912	0.653064	0.597315	0.402391	0.562093	0.57764	0.523069	22
21.	0.410448	0.655141	0.787611	0.349481	0.639737	0.744	0.597736	15
22.	0.503049	0.90186	0.723577	0.405623	0.959892	0.688889	0.697148	4
23.	0.398551	0.645805	1	0.478673	0.538658	0.920792	0.663747	5
24.	0.415617	0.724947	0.89899	0.385496	0.698954	0.837838	0.660307	6
25.	0.520505	0.771021	0.956989	0.573864	0.746371	0.885714	0.742411	1
26.	1	0.333333	0.831775	0.597633	0.333333	0.781513	0.646265	7
27.	0.774647	0.561987	0.773914	0.461187	0.566098	0.732283	0.645019	8

The higher value of Grey relation grade is represent that the corresponding experiment result is much closer to the ideally normalized value. Experiment number 25 get the best multiple performance characteristics among the 27 experiment because it have the highest value of grey relation grade. Now the experimental design is orthogonal, it is possible to separate out the effect of each parameters on the basis of Grey relation grade. Mean of Grey relation grade is calculated for level 1, 2 and 3 by averaging the Grey relation grade of the experiment 1to 9, 10 to18 and 19 to 27 are shown in Table 8. The mean of Grey relation grade for abrasive, power rate, grit size, HF acid and tool material are calculated in same manner. The total mean of Grey relation grade for 27 experiment is also shown in the Table 8. *Level for optimum grey relational grade. Optimum level parameters are find out from response table and shown in the Fig.2. Larger value of Grey relation grade is closer to the ideal value. Therefore, the optimum parameters setting for higher MRR and lower TWR and SR are $A_3B_3C_2D_3E_1F_3$.

Furthermore, **analysis of variance (ANOVA)** is performed on Grey relation grade to achieve contribution of each input parameter affecting the output parameters. ANOVA for Grey relational grade is shown in Table 9. In addition, F-test is also used to find out the percentage contribution of each parameters. From Table 9 it is clear that material of tool have the significant role in the machining which have 30% contribution, 25% contribution of concentration, 21% contribution of grit size, 9% contribution of abrasive, 4% contribution of HF acid and 3% contribution of power rate in the machining of PBPG UL-752 and AHRG BS-476.

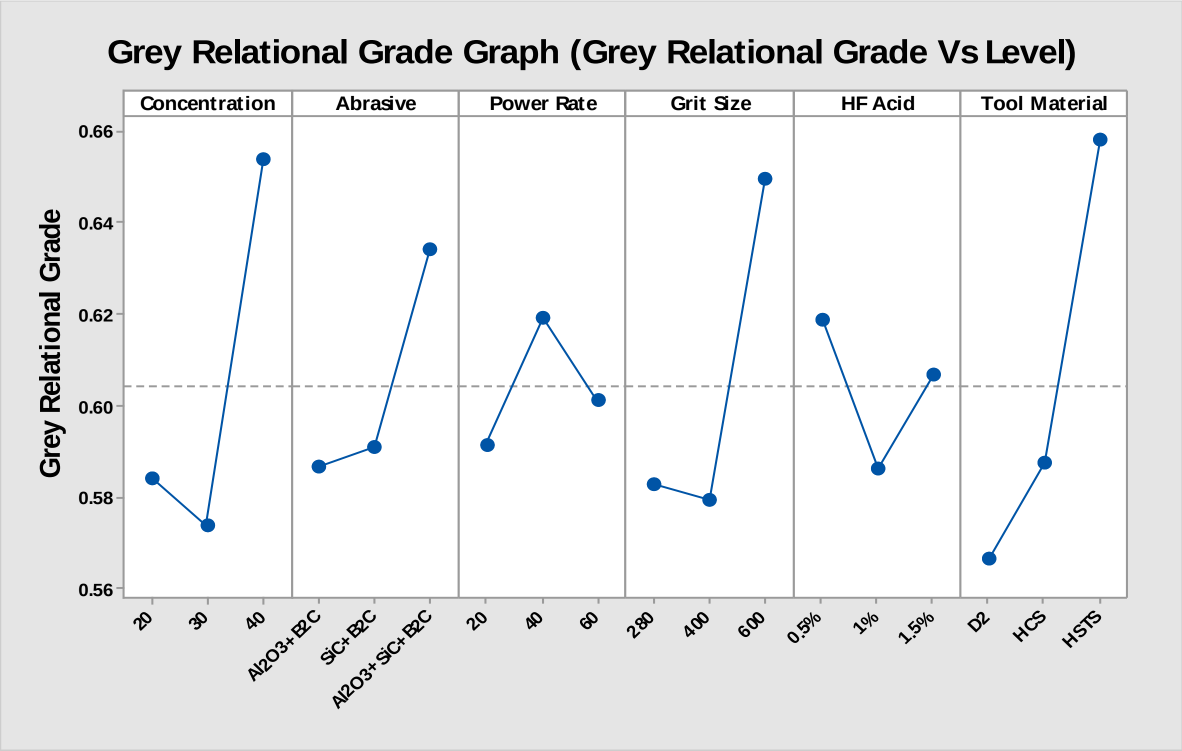

Figure 2. Effect of USM parameters on the multiple performance characteristics

Table 8. Response Table for the Grey Relational Grade

Symbol	Machining Parameters	Grey Relation Grade			Main Effect (Max- Min)	Rank
		Level 1	Level 2	Level 3		
A	Concentration	0.5843	0.5741	0.6538	0.0797	2
B	Abrasive	0.5870	0.5910	0.6341	0.0471	4
C	Power Rate	0.5915	0.6193	0.6014	0.0278	6
D	Grit Size	0.5829	0.5797	0.6496	0.0699	3
E	HF Acid	0.6188	0.5864	0.6070	0.0324	5
F	Tool Material	0.5668	0.5874	0.6579	0.0911	1
Total men value of the Grey relational Grade $\gamma_m = 0.6040$						

Table 9. ANOVA of Grey relation grade

Parameter	**Degree of Freedom**	**Sum of Squares**	**Mean Squares**	**F Ration**	**Percentage Contribution**
Concentration (A)	2	0.033848	0.016924	36.98	24.87%
Abrasive (B)	2	0.012288	0.006144	13.42	9.03%
Power Rate (C)	2	0.003568	0.001784	3.90	2.62%
Grit Size (D)	2	0.028051	0.014025	30.64	20.61%
HF Acid (E)	2	0.004844	0.002422	5.29	3.56%
Tool Material (F)	2	0.041104	0.020552	44.90	30.20%
Error	6	0.002746	0.000458	2.41	2.01%
Total	18	0.136067			

After getting the optimum parameters for machining the experiment is performed by those input setting ($A_3B_3C_2D_3E_1F_3$). Fig.3 show the Scanning electron microscope (SEM) images of PBPG UL-752 machining setting $A_1B_1C_1D_1E_1F_1$, In which machining by USM is performed and some crack are also found on the work surface. In other hand in Fig. 4 the USM machining of PBPG UL-752 is performed by optimum parameters which are found by Grey relational analysis $A_3B_3C_2D_3E_1F_3$, there is smoother and crack free surface. Similarly, in Fig.5 show the

Scanning electron microscope (SEM) images of AHRG BS-476 machining setting $A_1B_1C_1D_1E_1F_1$, in which machining by USM is performed and some crack are also found on the work surface. In other hand in Fig. 6 the USM machining AHRG BS-476 is performed by optimum parameters which are found by Grey relational analysis $A_3B_3C_2D_3E_1F_3$, there is smoother and crack free surface.

MRR and TWR are also compared between optimum Grey relational analysis $A_3B_3C_2D_3E_1F_3$ and $A_1B_1C_1D_1E_1F_1$ input parameters. It observed that optimum parameters ($A_3B_3C_3D_3E_1F_3$) gives 73.02% improved MRR with comparison of $A_1B_1C_1D_1E_1F_1$ USM experiment setting. TWR is decreased by 37.25%. It is evident from SEM image, optimum parameters setting also give the better surface roughness which is 43.33% improved. Fig 7 shown the percentage contribution of optimum Grey relational analysis parameters.

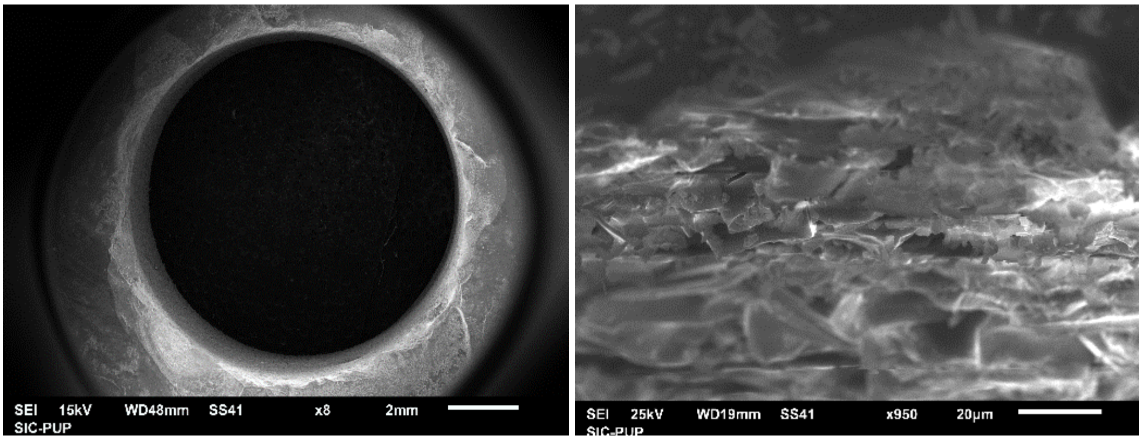

Figure 3. SEM image of PBPG UL-752 $A_1B_1C_1D_1E_1F_1$ experiment

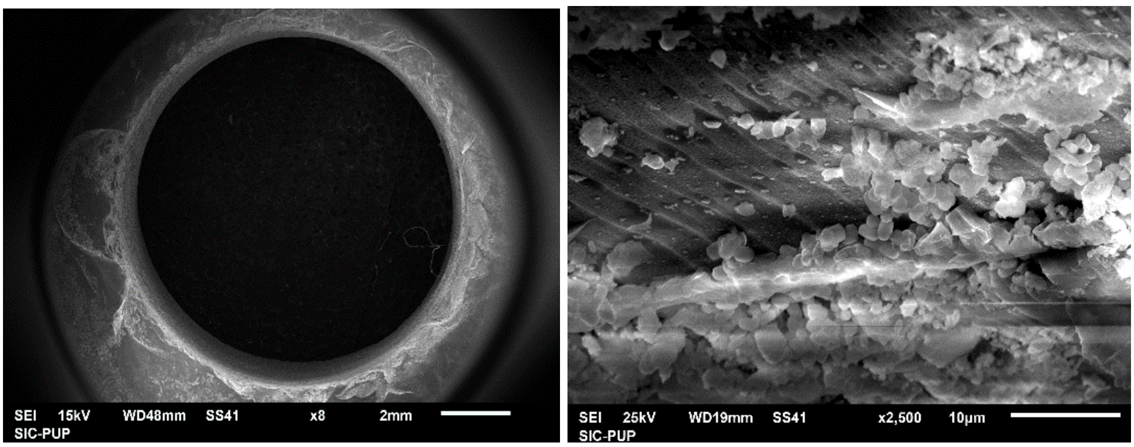

Figure 4. SEM image of PBPG UL-752 $A_3B_3C_2D_3E_1F_3$ optimum Grey relational analysis

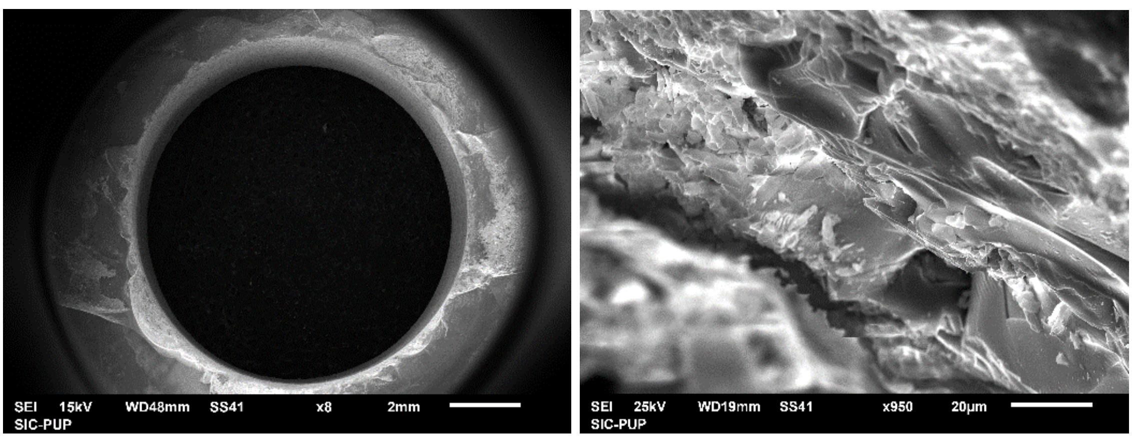

Figure 5. SEM image of AHRG BS-476$A_1B_1C_1D_1E_1F_1$ experiment

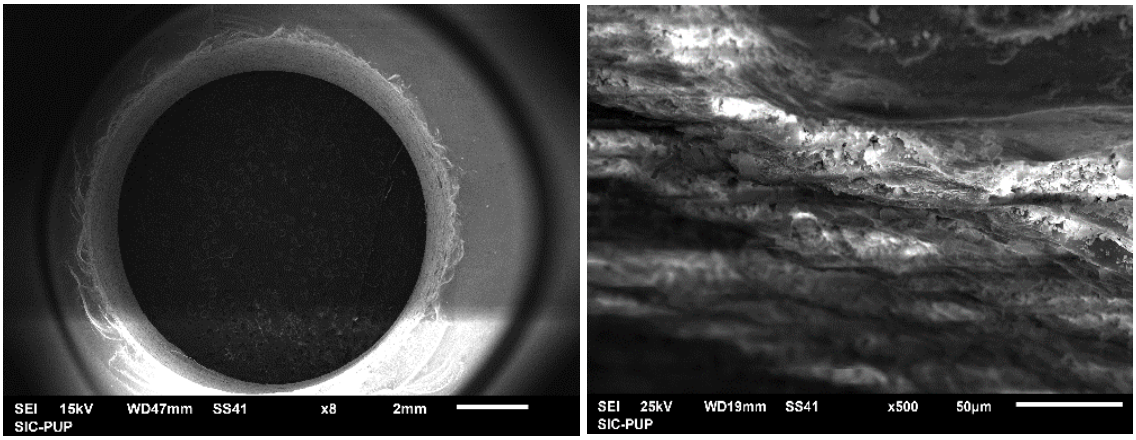

Figure 6. SEM image of AHRG BS-476$A_3B_3C_2D_3E_1F_3$ optimum Grey relational analysis

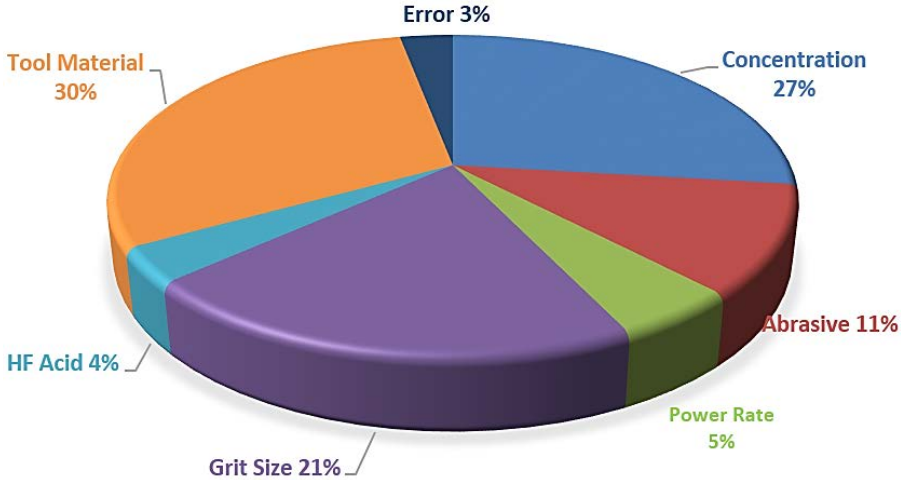

Figure 7. Percentage contribution of factor on Grey Relational Grade

Table 10. Improvement in Grey relational grade with optimized USM machining parameters

Condition Description	Optimal Machining Parameters		
	Machining Parameters in First trail of OA	**Grey Theory Prediction Design PBPG UL-752**	**Grey Theory Prediction Design AHRG BS-476**
Level	$A_1B_1C_1D_1E_1F_1$	$A_3B_3C_2D_3E_1F_3$	$A_3B_3C_2D_3E_1F_3$
MRR (mm^3/min)	5.36	9.41	8.64
TWR (mm^3/min)	0.089031	0.04866	0.06102
SR (micron)	1.43	0.94	1.08
Grey Relational Grade	0.5642	0.6751	
Improvement in Grey relational grade =0.1109			

Confirmation test is carried out to verify the improvement of performance characteristics in machining of PBPG UL-752 and AHRG BS-476 by USM. The optimum parameters are shown in the Table 10. The estimated Grey relational grade $\hat{\gamma}$ using the optimal level of machining parameters can be calculated by using equation 9 (Meena & Azad 2012; Singh et al. 2004; Sreenivasulu & srinivasarao 2012).

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{n} \{\overline{\gamma}_i - \gamma_m\} \tag{9}$$

Where, γ_m is the total mean of Grey relational grade, $\overline{\gamma}_i$ is mean of the Grey relational grade at optimum level and n is the number of parameters that significantly affect multiple-performance characteristics. It is clearly show that the multiple-performance characteristics in USM process is greatly improved through this study.

4. Conclusions

The optimum machining parameters are identify by Grey relational grade for multiple performance characteristics that is MRR, TWR and SR. This experimental research paper presented the multi-objective optimization of USM machining parameters of polycarbonate bullet proof UL-752 and acrylic heat resistant BS-476 glass for drilling application by Grey relational analysis method. Following conclusion are conclude from the experimentation analysis.

1. Concentration of abrasive slurry, concentration and grit size of abrasive play the significant role for optimum output performance parameters.

2. ANOVA of Grey relational grade for multiple performance characteristics reveals that the concentration have the significant role in the MRR.
3. Based on SEM images, it is evident that optimum parameter improve the surface roughness and give better smooth surface.
4. PBPG UL-752 have improvement in MRR, TWR and SR is 80%, 50% and 40% respectively, based on confirmation test.
5. AHRG BS-476 have improvement in MRR, TWR and SR is 70%, 30% and 25% respectively, based on confirmation test.
6. It proof that, the performance characteristic of USM process like MRR, TWR and SR are improved together by using the Grey relational study and the effectiveness of this method is effectively recognised by authentication experiment.

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