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Analysis and optimization of micro-milling parameters for improving part quality in ultrafine graphite with varying workpiece inclination angles

Kramar, D.[a,*], Miljuskovic, G.[a], Cica, Dj.[b]

[a]University of Ljubljana, Faculty of Mechanical Engineering, Slovenia
[b]University of Banja Luka, Faculty of Mechanical Engineering, Bosnia and Herzegovina

A B S T R A C T

Micro-milling is recognized as one of the most important manufacturing technologies for producing micro-components/products. Amongst various materials, graphite has an important role in conventional micro-electrical discharge machining electrodes. This paper is focused on the investigation of the effect of micro-milling process parameters on the dimensional accuracy and surface quality of ultrafine grain graphite TTK-4. Depth of cut, spindle speed, stepover distance and feed rate have been considered as process variables of micro ball-end milling in experimental design. Moreover, the influence of the workpiece's inclination angle was also investigated. Taguchi's L_9 (3^4) orthogonal array was chosen to design the experiments, whereas grey relational analysis (GRA) was utilized for the multi-objective optimization of the micro ball end milling process with minimum dimensional deviation and minimum arithmetic mean roughness as objective functions. Furthermore, principal component analysis (PCA) was used to extract principal components and identify the corresponding weights for performance characteristics. In order to determine the significance of micro-milling parameters on overall machining performance, analysis of variance (ANOVA) was performed. The result of the study revealed that the proposed approach is adequate to address the multi-objective optimization of micro-milling parameters.

A R T I C L E I N F O

Keywords:
Micro-milling;
Graphite;
Workpiece inclination angle;
Optimization;
Dimensional accuracy;
Surface quality;
Taguchi method;
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**Corresponding author:*
davorin.kramar@fs.uni-lj.si
(Kramar, D.)

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1. Introduction

Micro-milling is extensively used for machining of inclined and free-form surfaces with very high precision, e.g., in mold manufacturing, automotive and aerospace industries, optics, biomedical industries, etc. Camara *et al.* [1] characterized the micro-milling process by the size of the cutting-edge diameter of the tool, which ranges from 1 µm and 1 000 µm. Among various applications of micro-milling, the mold making industry is one of the most important due to the rapid and accurate machining of high aspect ratio in the micro-domain [2]. The dimensional accuracy and surface roughness of the micro-parts manufactured with this micro-mechanical cutting process plays a major role in defining the quality of a die. In complex engineering environments, predicting product quality based on performance parameters represents a challenging task [3]. There are some problems associated with the micro-milling process primarily induced by excessive cutting forces and cutting tool vibrations that can deteriorate the part quality or limit the overall productivity.

These performance characteristics are highly affected by the process parameters such as depth of cut, stepover distance, cutting speed, feed rate, workpiece material type, cooling/lubrication conditions, etc. Hence, the selection of optimum control parameters is a very important step to obtain desired quality of the machined parts [4, 5].

Numerous studies have been carried out to improve different quality performance indices in micro-milling and carry out parameter's optimization. For instances, Ray *et al.* [6] conducted an experimental analysis on Zr-based bulk metallic glass to evaluate the influence of the micro-milling process parameters, such as feed per tooth, spindle speed and axial depth of cut on average line roughness, average area roughness and the dimensional accuracy of the machined micro-channels. Moreover, desirability function approach was used to determine the cutting parameters that optimizes the surface roughness and the average micro-channels width. Wojciechowski and Mrozek [7] carried out an analysis of dynamics of micro-ball end milling of hardened steel with various tool axis inclination angles. The optimization of the feed per tooth and tool inclination with cutting force components and accelerations of vibrations as objective functions were also conducted. An adaptive control optimization system to optimize feed rate and spindle speed for micro-milling (grooving) operations of AISI H13 tool steel in accordance with the estimation of tool wear state was proposed [8]. This study considers surface roughness and dimensional accuracy in terms of dimensional and form error as main aspects that define part quality. Vázquez *et al.* [9] utilized a particle swarm optimization (PSO) algorithm to identify optimal levels of micro-milling process parameters (depth per pass, axial depth of cut, spindle speed and feed) with surface roughness and geometrical and dimensional features of micro-channels fabricated on aluminium and titanium alloys as objective functions. Kuram and Ozcelik [10] utilized Taguchi based grey relational analysis (GRA) for multi-objective optimization in micro-milling of aluminium material Al 7075. The feed per tooth, spindle speed and depth of cut were studied as the process parameters, while the considered performance characteristics were surface roughness, cutting forces and tool wear. The effects of feed rate, spindle speed and depth of cut on the surface roughness, cutting forces and tool wear in micro-milling of two superalloys, namely, Ti6Al4V and Inconel 718, were investigated and optimized with Taguchi method [11]. Beruvides *et al.* [12] optimized the surface quality and machining time in micro-milling of tungsten-copper alloys using the non-dominated sorting genetic algorithm (NSGA-II). The desirability function approach has been used for optimization of the process parameters (feed, cutting speed and depth of cut) in micro milling of titanium alloy Ti-6Al-4V in order to simultaneously optimize surface roughness, tool wear and tool vibration [13]. Natarajan *et al.* [14] also used desirability function approach to obtain maximum surface quality and productivity in micro-end milling of aluminium, considering the spindle speed, feed and depth of cut as the machining parameters. The NSGA-II was employed to address multi-objective optimization problem for enhancing surface quality and dimension accuracy in micro-milling of thin-walled parts [15]. The surface quality in micro-milling of Al 2011 aluminium alloy was optimized by Cardoso and Davim [16]. Thepsonthi and Özel [17] has studied the use of PSO algorithm to optimize multiple characteristics, i.e. surface quality, tool life and burr formation, in micro-milling of Ti-6Al-4V alloy. The considered machining parameters were tool path strategy, spindle speed, feed per tooth and depth of cut. In another study [18], same authors also used PSO algorithm for optimizing the process parameters in micro-milling of titanium alloy Ti-6Al-4V for minimizing surface roughness and top burr width. Aslantas *et al.* [19] reported the use of Taguchi-based GRA in multiple parameters optimization in micro-milling for Ti-6Al-4V titanium alloy. Three cutting parameters, namely, cutting speed, feed rate and depth of cut were optimized for minimal surface roughness and burr formation. Optimization of multiple performance characteristics, such as surface quality, tool wear and tool vibration in micro-milling of AISI304 stainless steel has been conducted using a hybrid approach combining the Taguchi method-based graph theory and matrix approach and utility concept [20]. The spindle speed, depth of cut and feed rate were the cutting parameters studied in this paper. Suneesh and Sivapragash [21] identified optimal parameters for micro-milling of magnesium alloy and its alumina composites using GRA and techniques for order of preference by similarity to ideal solution. Three objectives including cutting forces, surface roughness and tool wear were considered in the optimization model, which are affected by three variables, namely spindle speed, cutting depth and feed per tooth. Miljušković and Cica [22] studied the impact of the micro-milling parameters such as depth of cut, stepover, feed and spindle speed to the mean roughness depth on a graphite electrode, followed by the differential evolution algorithm to identify the optimal machining conditions. A model based on Taguchi's signal-to-noise ratio has been used for optimization of process parameters in micro-milling of polycarbonate substrate to obtain minimum surface roughness [23]. Krimpenis *et al.* [24] employed genetic algorithm to find out optimal micro-milling process parameters with consideration of surface quality and machining time as objective function. The optimal condition of process parameters in micro milling process of hardened tool steel was found to minimize cutting forces, surface roughness, vibrations and burr formation and to maximize the material removal rate [25]. Sredanovic *et al.* [26] conducted optimization of machining parameters, including depth of cut and feed per tooth, in micro-milling of the superalloy Inconel 718 with surface roughness, cutting forces, burr formation and channel depth deviation as the optimization objectives. The slime mold sequence algorithm was suggested to solve the optimal combination of process parameters with MRR, machining cost and machining time in the CNC micro-milling process as the optimization objectives, while the machining forces, surface roughness, tool deformation and parameter uncertainty were considered as constraints [27]. Guo *et al.* [28] optimized process parameters (spindle speed, feed rate, depth of cut and tool cantilever length) for glow discharge polymer micro-milling to achieve lower cutting force and surface roughness.

Part quality is crucial to enhancing productivity, profitability and sustainability of manufacturing companies in Industry 4.0 [29]. Based on the previously mentioned literature review, the research on optimizing micro-milling parameters in terms of dimensional accuracy and surface quality has focused on the conventional metals and alloys and there is limited work available dedicated to micro-milling of graphite material in the available literature. As a result of its high thermal and chemical stability, good electrical conductivity and increasing strength with higher temperature, graphite is considered to be still the primary option for electrode materials at meso/micro scale [30]. Apart from the erosion process, the performance of the micro die-sinking electrical discharge machining process is also related to the micro-milling process of the 3D form electrodes because any potential errors are copied into a micro mold [31]. Hence, dimensional accuracy and machined surface roughness of the 3D micro die sink electrode are very important in order to attain extremely strict tolerances of a machined micro-mold. On the other hand, when milling the graphite, its inconsistent polycrystal structure undergoes localized fractures instead plastic deformation and chip formation. This process forms short fragments resulting in the formation of graphite powder, rather than chips. Thus, graphite machining has its unique characteristics dissimilar from those of metal cutting that can diminish the surface quality and the dimensional accuracy of the machined micro-features. To achieve desired level of quality characteristics, selection of optimum combination of input process parameters is crucial. However, due to complicated cutting process mechanisms linked to physical characteristics of graphite and the presence of many process factors, determination of optimal micro-milling parameters accuracy is a challenging task.

This study is based on dry micro-milling of ultrafine graphite electrodes through a set of experiments, varying four process parameters such as depth of cut, spindle speed, stepover distance and feed rate. The material used was an isostatically pressed ultrafine graphite. Results were obtained by evaluating the dimensional accuracy and arithmetic mean roughness of the part with different angles of surface inclination. Taguchi-based GRA has been employed to optimize micro-milling parameters by simultaneously minimizing dimensional deviation and minimum arithmetic mean roughness as most important indicators for high-quality manufacturing. Additionally, in the present investigation, principal component analysis was introduced to estimate actual weights of performance characteristics under optimization.

2. Research methodology and methods

The flowchart of the research approach used in the study is illustrated in Fig. 1. Firstly, the experimental plan was designed to select material, machine tool, cutting tool, micro-milling parameters and their levels and performance characteristics. The quality characteristics chosen to evaluate the processes were dimensional accuracy and arithmetic mean roughness, whereas the corresponding micro-milling parameters were depth of cut, spindle speed, stepover distance and feed rate. Experiments were performed using the Taguchi L_9 orthogonal array. The influence of micro-milling parameters on performance characteristics was determined using response surface methodology (RSM). Next, grey relational analysis (GRA) coupled with principal component analysis (PCA) has been utilized for multi-objective optimization of the machining parameters in micro ball end milling of inclined surfaces. GRA was employed to transform multiple performance characteristics into an equivalent single performance criterion, while PCA was applied to establish the corresponding weights for each performance characteristic. ANOVA was employed to analyse which of the process parameters notably affect the multiple performance characteristics.

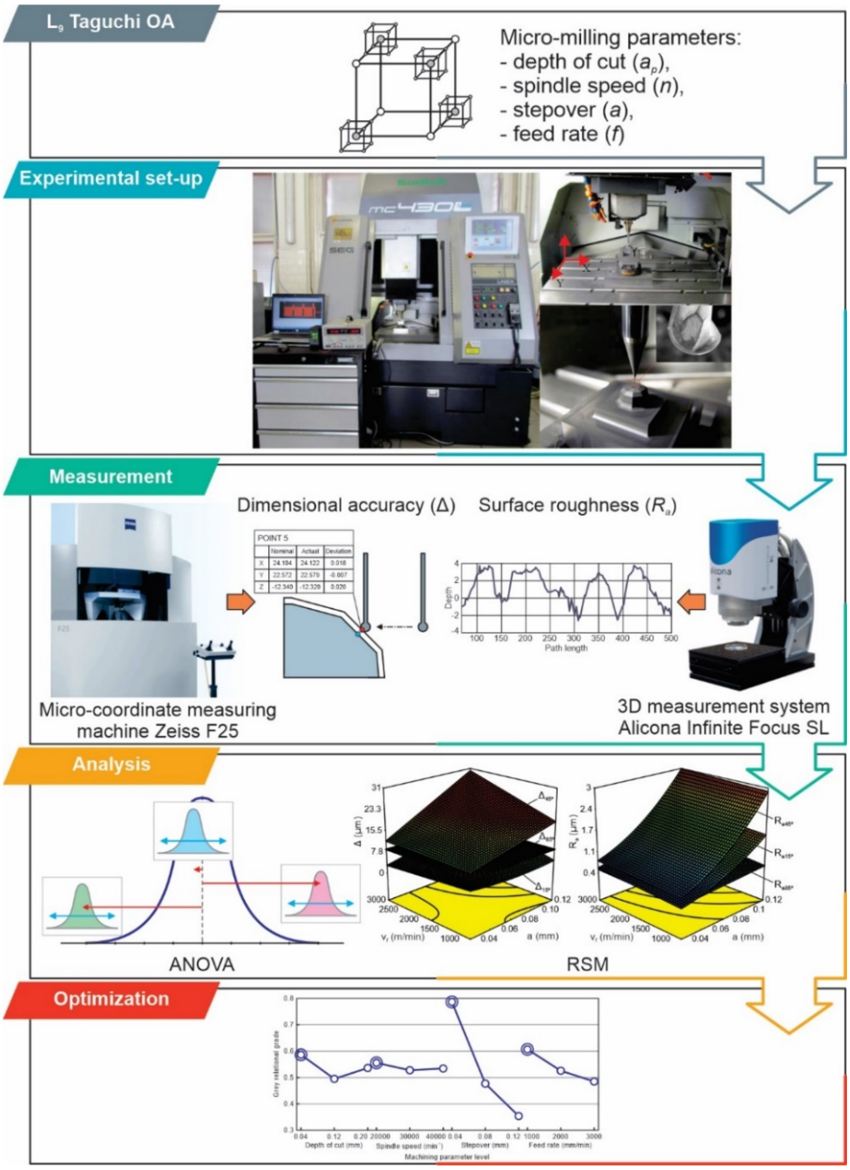

Fig. 1 Flowchart of the research methodology

3. Experimentation

The three-axis milling centre that was used to conduct the experimentation was Sodick MC430L. The maximum rotational speed is 40 000 rpm and axis travels are 420 mm, 350 mm and 200 mm for X, Y and Z axes, respectively. The feed system is fitted with linear drives and linear encoders with an absolute position accuracy of 1.5 μm. A standard heat-shrink fit HSK-E25 tool holder was employed in all experiments to minimize errors. The cutter used in the experiments was a carbide ball nose micro end-mill with a 10 μm-thick CVD diamond coating. The milling tool had a diameter d = 0.6 mm and neck length l = 6 mm.

The workpiece material tested in this study was ultrafine graphite TTK-4 (average particle size 4 μm) with the following mechanical properties: bulk density 1.78 g/cm^3, hardness 72 HSD, electrical resistivity 14 μΩ·m, tensile strength 49 MPa, flexural strength 73 MPa, compressive strength 135 MPa, Young's modulus 10.9 MPa, coefficient of thermal expansion $5 \cdot 10^{-6}$ K^{-1} and thermal conductivity 90 W(m·K)$^{-1}$. The sample had a rectangular prism shape with dimensions: 27 mm × 27 mm × 29 mm. To obtain three planes inclined at 15°, 45° and 85° as shown in Fig. 2, a workpiece was machined in two steps: roughing and semi-finishing to gain a determined constant depth of cut. While machining all inclined surfaces, contour operation from top to bottom in climb milling mode was carried out. All experiments were conducted without coolant to avoid contamination and air blow in a feed direction was performed throughout the experimental trials to keep the cutting zone clean.

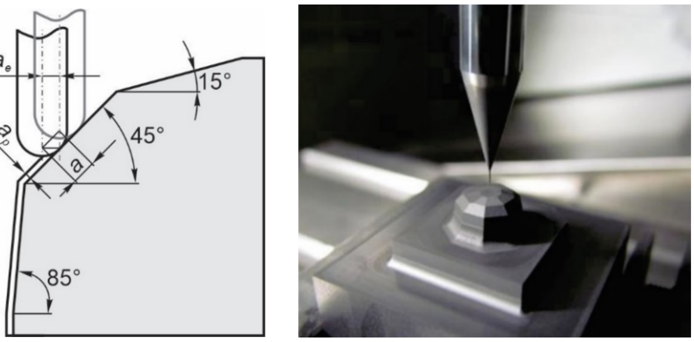

Fig. 2 The geometry of the test part

In precision engineering, coordinate measuring machines are typically used to determine the quality of dimensional and geometric part parameters [32]. Hence, dimensional accuracy was investigated by high accuracy 3D coordinate measuring machine Carl Zeiss F25, which is suitable for measuring micro-parts with linear measuring tolerance 0.5(μm) + L(mm)/666. The dimensional error of the inclined surface (Δ) was defined as the deviation between the machined and designed surface profile $\Delta = \sqrt{\Delta x^2 + \Delta y^2 + \Delta z^2}$. Hence, the dimensional error was specified as the difference between the CAD model and the inspected part using 3D coordinate measuring machine. The dimensional error response is the average value of five measurements taken as points per surface. Although the deflection of long micro end-mills has a major impact on the dimensional accuracy of the machined part, there are also additionally sources of errors, such as positional accuracy and repeatability of the machine tool, spindle thermal expansion, radius tolerance of ball nose end-mill, diameter and tool length measuring accuracy, etc.

The arithmetic mean roughness R_a was measured by using non-destructive device InfiniteFocus Alicona because typically used stylus type surface roughness tester might damage the surface of the brittle graphite. Measurements of the arithmetic mean roughness were undertaken in the pick feed direction and the average value of surface finish at three different areas under each set of micro-milling conditions was captured as the basis for further analysis. During the measurement process, the cut-off length was selected as 0.8 mm and the sampling length as 2.5 mm.

The investigation conducted in the present study used the Taguchi method to design the experiments to reduce the number of experimentations. Moreover, this method is also effective for investigating the interactions between the control factors and the responses, as well as to find out optimal levels of cutting parameters. Four control factors including depth of cut a_p, spindle speed n, stepover distance a and feed rate v_f were considered as micro-milling parameters, while the response factors include dimensional accuracy and arithmetic mean roughness. Each control factor was divided into three levels according to the recommendations of the tool manufacturer, literature findings and trial runs. The micro-milling parameters and their levels are shown in Table 1. Then, the experimental design for four cutting parameters with three levels was arranged by Taguchi's L_9 orthogonal array as shown in Table 2.

Table 1 Design of experiments

Parameter	Unit	Levels		
		Level 1	Level 2	Level 3
Depth of cut (a_p)	mm	0.04	0.12	0.20
Spindle speed (n)	rpm	20 000	30 000	40 000
Stepover (a)	mm	0.04	0.08	0.12
Feed rate (v_f)	mm/min	1 000	2 000	3 000

4. Results and discussions

Table 2 shows the experimental results for dimensional deviation and arithmetic mean roughness. The observed values of these results along surfaces with different inclination angles can be used as a favourable indicator for determining the shape characteristics of the machined profile during micro-milling of ultrafine graphite. With the aim to analyse the effect of micro-machining parameters on measured values of the output variables, response surface models were developed. Through the backward elimination process, the final models of dimensional accuracy and arithmetic mean roughness for 15°, 45° and 85° workpiece inclination angles in a form of reduced second-order polynomials with regression coefficients are presented in Table 3. Model terms that are not significant are not included in the reduced models. However, these models contain subset of all possible effects that retain hierarchy for statistical reasons.

Table 2 Experimental results of part dimensional accuracy and arithmetic mean roughness

No.	Micro-milling parameters				Experimental data					
	a_p (mm)	n (rpm)	a (mm)	v_f (mm/min)	$\Delta_{15°}$ (µm)	$\Delta_{45°}$ (µm)	$\Delta_{85°}$ (µm)	$R_{a15°}$ (µm)	$R_{a45°}$ (µm)	$R_{a85°}$ (µm)
1	0.04	20 000	0.04	1 000	0.9	2.3	1.9	0.47	0.49	0.55
2	0.04	30 000	0.08	2 000	2.4	8.0	5.8	0.89	1.25	0.61
3	0.04	40 000	0.12	3 000	11.9	19.8	12.6	1.77	2.74	0.90
4	0.12	20 000	0.08	3 000	5.6	20.4	17.7	1.03	1.58	0.81
5	0.12	30 000	0.12	1 000	5.0	19.3	15.7	1.62	2.89	0.68
6	0.12	40 000	0.04	2 000	6.4	12.7	13.8	0.47	0.53	0.47
7	0.20	20 000	0.12	2 000	4.6	18.7	16.6	1.66	3.02	0.77
8	0.20	30 000	0.04	3 000	0.3	5.2	8.2	0.55	0.64	0.52
9	0.20	40 000	0.08	1 000	3.7	7.4	3.9	0.79	1.34	0.55

Table 3 Summary of model's coefficients

Resp.	b_0	a_p	n	a	v_f	$a_p \times n$	$n \times v_f$	$a \times v_f$	a_p^2	a^2
$\Delta_{15°}$	1.094	123.75	$1.82 \cdot 10^{-4}$	-184.6	-0.0045			0.074	-496.09	593.75
$\Delta_{45°}$	-10.43	341.67		20.833	-0.0027			0.0679	-1342.45	
$\Delta_{85°}$	-26.77	520.63	$7.79 \cdot 10^{-4}$			-0.0073			-1182.29	
$R_{a15°}$	0.3067			-3.833	$7.8 \cdot 10^{-5}$					116.667
$R_{a45°}$	0.071		$2.7 \cdot 10^{-5}$	-21.04	$5.6 \cdot 10^{-4}$		$-1.73 \cdot 10^{-8}$			313.542
$R_{a85°}$	0.586		$-3.5 \cdot 10^{-6}$	0.25	$-5 \cdot 10^{-5}$			0.00156		

Table 4 Evaluation of the models

Response	F-value	P-value	Hierarchical terms	Influential terms	R^2	R^2_{adj}	R^2_{pred}	S/N ratio
$\Delta_{15°}$	95.46	0.0295	a_p	n, a, v_f, $a \times v_f$, a_p^2, a^2	0.9998	0.9983	0.9745	87
$\Delta_{45°}$	64.43	0.0030	a_p	a, v_f, $a \times v_f$, a_p^2	0.9908	0.9745	0.9457	21.06
$\Delta_{85°}$	38.38	0.0019	a_p, n	$a_p \times n$, a_p^2	0.9746	0.9492	0.8146	15.01
$R_{a15°}$	430.83	< 0.0001	-	a, v_f, a^2	0.9961	0.9938	0.9857	48.63
$R_{a45°}$	3517.08	< 0.0001	-	n, a, v_f, $n \times v_f$, a^2	0.9998	0.9995	0.9962	141.96
$R_{a85°}$	20.22	0.0065	n	a, v_f, $a \times v_f$	0.9529	0.9057	0.7487	12.06

The statistical significances of the developed quadratic models were evaluated based on the F and P-values calculated within analysis of variance (ANOVA), as shown in Table 4.

The obtained models were regarded statistically significant when the P-values are smaller than 0.05 (95 % confidence). Moreover, models were also analysed using determination coefficient R^2, adjusted determination coefficient R^2_{adj}, predicted determination coefficient R^2_{pred} and S/N ratio.

The results show that the developed response surface models provide adequate approximation of investigated process under the given experimental domain.

The 3D surface plots of dimensional accuracy are presented in Fig. 3. The highest values of dimensional error were observed at 45° workpiece inclination angle, whereas the best dimensional accuracy is evident at the 15° inclined plane for all considered parameters. Tool deflection caused by cutting forces is considered as the main factor that influences machining error [33]. As the diameter the of micro ball-end milling tool is extremely small, the stiffness is most sensitive to influence by cutting force than any other parameter and consequently bending deformation. The cutting forces generated while micro-milling of inclined surface cause tool deflection that leads to the form error of part surface. The cutting force components are affected by the workpiece's inclination angle. Axial force decreases and radial force increases in magnitude as the inclination angle increases. The change in the workpiece inclination angle has a significant effect on the tool deflection as a result of the lower stiffness in the radial as compared to the axial direction which is attributed to the lower stiffness. Consequently, better dimensional accuracy can be achieved with lower workpiece inclination angle values. The variation of the dimensional accuracy with depth of cut and spindle speed indicate that lower values of both parameters lead to smaller dimensional errors (Fig 3a). As depth of cut and spindle speed increases, that results increase in the MRR, that has a positive correlation with cutting forces. The experimental results prove that the dimensional error of the machined surface is considerably influenced by the stepover, as shown in Fig. 3b. The results indicate that smaller values of stepover distance will lead to a significant increase in the dimensional accuracy for all workpiece inclination angle values. An increase in stepover during micro-milling operation leads to an increase in the metal removal volume and therefore to an increase of cutting forces. Higher cutting forces cause a larger tool deflection which results in higher dimensional errors. Moreover, a similar trend for feed rate was observed as in stepover distance, where increasing the values of feed rate results in higher dimensional deviations. The reason being, increased feed rate value leads to large chip sizes and hence the growth of the cutting forces in micro-milling operation. Moreover, an increase in the feed rate also results in an increase of self-excited vibration (chatter). Subsequently, an increase in cutting forces and vibrations results in large values of cutting tool deflections which lead to geometric errors on the machined part.

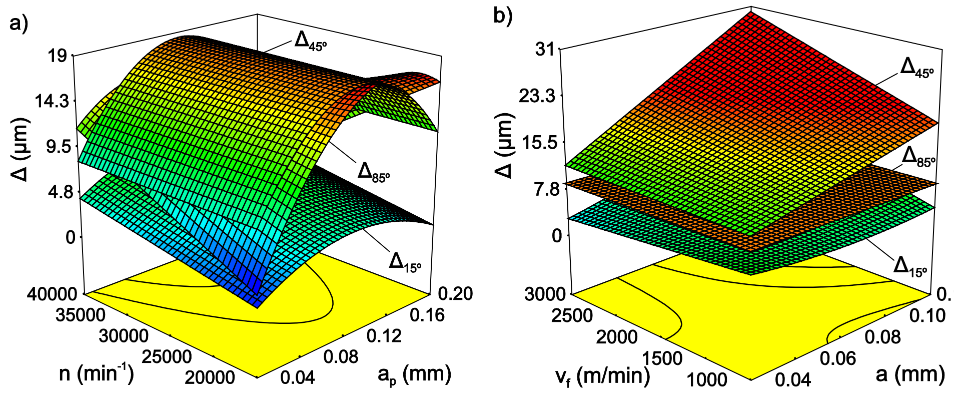

Fig. 3 Effect of micro-milling parameters on dimensional accuracy

Fig. 4 show the 3D surface plots of the arithmetic mean roughness. From this figure, it is seen that the highest arithmetic mean roughness was observed for 45° workpiece inclination angle, while the best machined surface finish is noted for 85° inclination angle. This was because during machining remarkably steep surfaces (almost vertical), the cylindrical segment of the ball end mill is mostly in contact with the machined surface causing generation of linear cusps with lower profile height as compared to spherical shaped cusps. As viewed in surface response in Fig. 4a, the highest surface quality is obtained with the combination of the highest spindle speed and the lowest feed rate. Increased spindle speed results in higher tooth passing frequencies and shorter plane area/reduction in chip thickness, lowering surface roughness. The increase in feed rate increases the heat generation and vibration due to increase in MRR, leading to higher surface roughness. Fig. 4b shows the interaction effect between the stepover and the feed rate on the surface quality. The stepover distance is the most significant factor associated with the arithmetic mean roughness. The surface finish significantly improved with decrease in stepover distance. This variation is identically changed for all workpiece inclination angle values. This can be attributed to the fact that in the ball end milling process the stepover defines the overall peripheral area of the cutting tool which is in contact with the workpieces surface. The increase in stepover value increases overlap between cutting paths and it produces higher cusps height of the machined surface resulted in a deterioration of surface quality. Hence, smaller values of stepover distance must be selected to achieve the better arithmetic mean roughness. It is seen that the arithmetic mean roughness decreases with the decrease in the feed rate. This phenomenon can be explained by the higher cutting forces and the heat generation due to the larger cutting area at high feed rate. Besides that, increase in feed rate also increases the chatter resulting in poor surface finish.

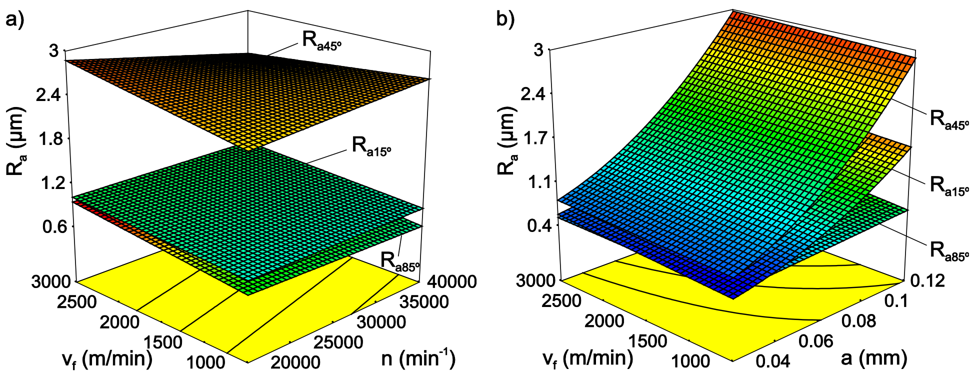

Fig. 4 Effect of micro-milling parameters on the arithmetic mean roughness

5. Multi-objective optimization of micro-milling process by Taguchi based grey relational analysis

As depicted in the previous section, dimensional accuracy of part produced by micro-milling operation as well as surface quality varies significantly with the changes in the machining parameters. Presented multi-objective optimization method aimed to obtain the optimum micro-milling parameters to minimize both dimensional errors and the arithmetic mean roughness. The performance characteristics, i.e. dimensional accuracy and arithmetic mean roughness for 15°, 45° and 85° workpiece inclination angles, obtained from the experimental results, are firstly converted into S/N ratio. The S/N ratios matching to each of the studied single quality characteristics are normalized, because larger values of the normalized results indicate better performance. Thereafter, the grey relational coefficients were calculated.

Frequently, in order to calculate the GRG, the equal weight factors of each performance characteristic were selected for simplicity. However, this approach may not be an appropriate, due to fact that the importance of various quality characteristics is different in real engineering problems. Hence, PCA was employed to determine the appropriate weight of each performance characteristic. The grey relational coefficients of each performance characteristics have been used to determine the correlation coefficient matrix and calculate the corresponding eigenvalues. The variance contribution for the first principal component characterizing the six performance characteristics is as high as 68.2 %. Accordingly, the squares of corresponding eigenvectors were chosen as the weighting factors of the associated performance characteristic and the coefficients w_1, w_2, w_3, w_4, w_5 and w_6 are consequently set as 0.0952, 0.1829, 0.1358, 0.2198, 0.2241 and 0.1423, respectively. Finally, the grey relational grades were calculated by multiplying grey relational coefficients with their corresponding weight of performance characteristics.

Table 5 The calculated grey relation coefficients and grey relational grades for six different machining responses

No.	Grey relational coefficient						Grey relational grade	Grey order
	$\Delta_{15°}$ (µm)	$\Delta_{45°}$ (µm)	$\Delta_{85°}$ (µm)	$Ra_{15°}$ (µm)	$Ra_{45°}$ (µm)	$Ra_{85°}$ (µm)		
1	0.6262	1.0000	1.0000	1.0000	1.0000	0.6739	0.9181	1
2	0.4695	0.4668	0.5000	0.5094	0.4926	0.5547	0.4993	5
3	0.3333	0.3364	0.3710	0.3333	0.3457	0.3333	0.3418	9
4	0.3860	0.3333	0.3333	0.4580	0.4371	0.3737	0.3948	6
5	0.3954	0.3391	0.3457	0.3489	0.3388	0.4679	0.3658	7
6	0.3755	0.3898	0.3601	1.0000	0.9206	1.0000	0.7244	2
7	0.4027	0.3424	0.3398	0.3444	0.3333	0.3969	0.3540	8
8	1.0000	0.5722	0.4328	0.8084	0.7730	0.7626	0.7181	3
9	0.4228	0.4829	0.6081	0.5608	0.4748	0.6739	0.5367	4

Table 5 shows the calculated grey relational coefficients and grey relational grades based for each experiment using the Taguchi L_9 orthogonal array. From Table 5, it has been noted that experiment No. 1 has the highest value of grey relational grade as 0.9180, whereas the lowest value was found for experiment No. 3 as 0.3418.

Furthermore, the means of the weighted grey relational grade of each micro-machining parameter have been computed and listed in Table 6 and depicted in Fig. 5. From the analysis of the response table and main effect plot for weighted grey relational grade, the optimal level setting of micro-machining parameters is as follows a_p = 0.04 mm, n = 20 000 min^{-1}, a = 0.04 mm and v_f = 1 000 mm/min. Thus, the optimal combination of micro-milling parameters for minimum dimensional deviation and minimum arithmetic mean roughness under the given experimental design was obtained when they are at their minimal level. This optimal process parameters setting that optimize the considered multiple objective function corresponds to experiment No. 1 shown in Table 2. Nevertheless, the relative significance among the micro-milling process parameters for optimized the quality indicators needs to be further analysed and understood to obtain the best parametric combination more clearly. Apart from analysis of the means accomplished for the obtained grey relational grade, in Table 6 is also listed the rank of the micro-milling parameter affecting the grey relational grade. The grey relational grade for each control factor is ranked according to the difference between its maximum and minimum values. This difference can be also defined as the effect contribution of machining parameters. The response table indicates that stepover distance has the maximum level difference value of grey relational grade. Hence, this is the most influential factor affecting the overall characteristic. The second most significant factor is feed rate, followed by the depth of cut and spindle speed that has the least prominent effect on the multi-performance characteristic. These values are depicted graphically in Fig. 5. The graph indicates that higher levels of depth of cut, spindle speed, stepover distance and feed rate have negative effect on the weighted grey relational grade, that is, dimensional inaccuracy and arithmetic mean roughness increase with increase in value of these micro-milling parameters.

An analysis of variance (ANOVA) was conducted to determine the influence of each machining parameter on the multi-performance characteristic. Since the degrees of freedom (DOF) for residual error was zero, the test for significance is not possible. Consequently, ANOVA pooling was performed. Pooling is the process of merging the influence of the insignificant factors with the error term to create a new error term that can be tested further. Normally, this occurs because selected orthogonal array L_9 with four parameters varied through three levels does not provide enough data. In general, pooling process start with the factor that has the least influence. In present paper, spindle speed was found insignificant (pooled). From the pooled ANOVA table (Table 7), it is obvious that the stepover distance is the most significant factor that contributes towards the overall performance characteristic, since it contributes to the highest percentage of variation of 89 %. This is followed by feed rate and depth of cut which contribute 6.9 % and 3.7 %, respectively. The percentage of error was considerably low at 0.4 %.

Table 6 The response table for weighted grey relational grade

Control parameter	Grey relational grade			Max-min	Rank
	Level 1	Level 2	Level 3		
Depth of cut (a_p)	0.5864	0.4950	0.5363	0.0914	3
Spindle speed (n)	0.5556	0.5277	0.5343	0.0279	4
Stepover (a)	0.7869	0.4769	0.3539	0.4330	1
Feed rate (v_f)	0.6069	0.5259	0.4849	0.1220	2
Total mean of the grey relational grade: 0.5393					

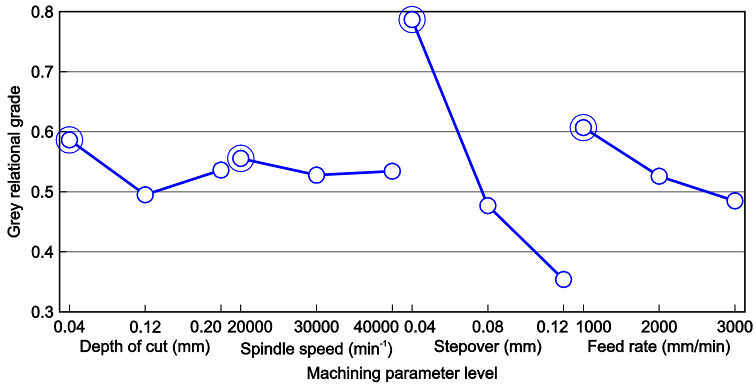

Fig. 5 Main effect plot for weighted grey relational grade

Table 7 Results of the pooled ANOVA for grey relational grade

Source	Sum of squares	DOF	Mean square	*F*-value	*P*-value	PC (%)
a_p	0.01257	2	0.00629	9.85	0.0922	3.7
a	0.29869	2	0.14935	233.97	0.0043	89.0
v_f	0.02311	2	0.01156	18.1	0.0523	6.9
Residual	0.00128	2	0.00064			0.4
Total	0.33565	8				100

5. Conclusion

In this study, experimental investigation and multi-objective optimization of the dry micro-milling process while machining of ultrafine graphite TTK 4 has been carried out. Response surface methodology was used to investigate effects of depth of cut, spindle speed, stepover distance and feed rate on dimensional deviation and arithmetic mean roughness along surfaces with three angles of inclination: 15°, 45° and 85°, whereas the grey relational analysis coupled with principal component analysis was employed to optimize the process parameters. Based on the experimental findings of this study, the following conclusions can be drawn:

- Workpiece inclination angle was discovered to have a large influence on dimensional deviation and arithmetic mean roughness in micro ball-end milling process. Best dimensional accuracy was observed at the smallest angle of inclination that is 15°, followed by 85° and 45° workpiece inclination angles. On the other hand, minimum arithmetic mean roughness was observed for the 85° inclination angle of workpiece, while maximum value of this parameter was achieved at the inclination angle of 45°.
- Taguchi based grey relational analysis greatly simplifies the optimization of the multi-response problems due to conversion of the multiple performance characteristics into single performance measure. Moreover, principal component analysis is a well-suited technique for obtaining the corresponding weighting values of each performance characteristics.
- Optimization procedure revealed that the optimum micro-milling conditions for minimum dimensional deviation and minimum arithmetic mean roughness were at a low level of depth of cut, spindle speed, stepover distance and feed rate, i.e. a_p = 0.04 mm, n = 20 000 min^{-1}, a = 0.04 mm and v_f = 1 000 mm/min.

- The results of ANOVA showed that the stepover distance is the most influential factor among the four micro-milling parameters used on the multi-performance characteristics contributing by 89 %, while feed rate and depth of cut contribute 6.9 % and 3.7 %, respectively.

The analysis and subsequent optimization of micro-milling of ultrafine graphite electrodes with high aspect ratio and different angles of surface inclination was performed in this research. These results are expected to be valuable for micro-milling of other brittle materials, for example, silicon, glass, etc. In future works, the experimental area can potentially be expanded and more response variables such as tool wear, work materials, etc. could be included. Finally, it will be interesting to examine machining of more complex surfaces.

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