

Sparking-out optimization while surface grinding aluminum alloy 1933T2 parts using fuzzy logic

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Abstract. The article presents the results of a search for optimal sparking-out strokes when surface grinding aluminum parts by high-porous wheels Norton of black silicon carbide 37C80K12VP using fuzzy logic. The topography of grinded surface is evaluated according to the following parameters: roughness – R_a, R_{max}, S_m ; indicators of flatness deviation – EFE_{max}, EFE_a, EFE_q ; microhardness HV, each of these parameters is represented by two measures of position and dispersion. The simulation results of fuzzy logic in the Matlab medium establish that during the grinding of alloy 1933T2, the best integral performance evaluation of sparking-out was given to two double-strokes ($d=0.827$) and the worst – to three ones ($d=0.405$).

1. Introduction

Surface grinding is the most efficient and known method of ensuring the high levels of accuracy and quality of the processed surfaces of the parts. Taking into account a small depth of cutting and the great pliability of the technological system during the grinding, the roles of elastic deformations of the workpieces are increasing. In this regard, at the end of the processing cycle the surface sparking-out is often made; it is done without cutting-in into the depth. It is used to remove the layer of elastically deformed material, eliminate the poor shape precision due to elastic deformations of the workpiece and possible surface defects such as small burn marks, scratches, etc., as well as to reduce surface roughness. According to [1, 2], surface sparking-out can reduce roughness height parameters, macro-fluctuations and increase surface microhardness and compressive residual stresses by modulus.

High quality characteristics and new required properties of modern machines and assemblies in the aerospace, automobile, electronic and other branches of mechanical engineering require the use of precision components and parts. The problem under discussion is multi-purpose. It is provided for diagnostics, optimization of adaptive control and other methods at different stages of the product life cycle: manufacturing, research, exploitation in working conditions, repair and adjustment processes. For each of them there are special requirements to identify the quality (accuracy, localization of parameters, operational efficiency) of the objects involved. In this study, fuzzy logic (FL) was used to increase the efficiency of sparking-out.

FL is one of the few scientific research fields that were created in the United States, developed in Japan and newly accepted by the Americans after the hopeless loss of the strategic initiative [3]. FL is based on the fuzzy-set theory where the membership function of the element set is not binary (yes/no), and can take any value in the range of [0;1]. It gives the opportunity to define concepts that are fuzzy



by their very characteristic: "high", "fast", etc. FL helps to evaluate residual stresses and cutting abilities of grinding wheels [4]. The work [5] discusses the use of FL in databases queries and its advantages over classical logic.

The aim of this work is to determine the optimal sparking-out strokes on a surface topography while the surface grinding aluminum alloy 1933T2 using fuzzy logic. Surface topography is characterized by the roughness parameter – R_a, R_{max}, S_m (GOST 25142–82), indicators of flatness deviation – EFE_{max}, EFE_a, EFE_q (GOST 24642–81), which are named as the greatest arithmetical mean and quadratic mean, and by microhardness HV (GOST 9450–76).

Methods of their measurement and calculations are presented in works [6,7].

2. Methods of experimental study

The methodology comprises three successive steps: the conditions of a natural experiment, interpretation techniques of experimental data based on statistical methods and application of FL.

2.1. The methodology of a natural experiment. The research has the following conditions of experiments realization: surface grinding machine model - 3G71M; the subject of investigation – samples of high strength aluminum alloy 1933T2 ($\sigma_{UST}=480-490$ MPa; $\sigma_{0.2}=175$ MPa) with dimensions $V \times V \times N=40 \times 40 \times 45$ mm and grinded area - $V \times V$; the shape and size of the high-porous wheels (HPW) Norton of black silicon carbide – 01 250 \times 20 \times 76 37C80K12VP [8]; technological parameters: wheel speed - $v_w=35$ m/s, longitudinal feed - $s_l=7$ m/min, cutting depth - $t=0.015$ mm, the operating allowance - $z=0.15$ mm; flooded coolant - 5% emulsion Akwol–6 (TU 0258-024-00148845-98) with 7-10 l/min flow. The spindle with the wheel is lowered to depth t in the time point when the longitudinal table with the workpiece is shifted to the leftmost position relative to the operator. Taking into account the fact that the scheme of feed specifying s_c is selected in mm/double-stroke, and an abrasive tool has a clockwise rotation, from left to right; the table stroke is working and running while the upper wheel is cutting-in. Its reverse is considered as sparking-out, finally forming the topography of the grinding surface in the conditions of down cutting. The samples were fixed with clamps on the clamping plate of the universal modular fixture, which excluded the error of location when the form deviation takes place.

With the aim of the information content reduction, the variable grinding conditions were described by a code (e, i), which is particularly convenient when the response is presented in the form of y_{ei} . Index $e = (1;7)$ is distributed according to the quality parameters of the surface. Roughness is characterized by parameters: $R_{ai} = y_{1i}$, $R_{maxi} = y_{2i}$, $S_{mi} = y_{3i}$ which are located on the surface in the direction of vector s_l and exceeding their analogues in the orthogonal direction (along vector s_l).

Flatness deviations are measured by three indicators: the main one is $EFE_{maxi} = y_{4i}$ and two other auxiliary arithmetic means are $EFE_{ai} = y_{5i}$ and a square mean is $EFE_{qi} = y_{6i}$. Microhardness HV_i is marked as y_{7i} . Code $i = \overline{0;8}$ characterizes the amount of sparking-out strokes, which are represented by odd numbers: 0 – without sparking-out, 2, 4, 6, 8 – reflect 1-4 double passes.

2.2. Experimental statistics. The processes of modeling, prediction and optimization of grinded workpiece surface quality are based on the use of experimental data. Application of the statistical method in the study of grinding is due to the fact that the abrasive grains have an arbitrary shape, different height in the radial direction, a chaotic arrangement in the bundle, a different number of active grains and cutting edges per unit of the wheel contact area when cutting-in. The foregoing allows considering the observations as continuous random quantities (RQ) and evaluating their behavior on the basis of probability-theoretic approaches. To accelerate the computation, the authors selected program Statistica 6.1.478.0. The experimental data are presented in the form of independent sets [9–11]:

$$\{y_{eiv}\}, e = \overline{1;7}, i = \overline{1;4}, v = \overline{1;30}, \quad (1)$$

where v is the number of parallel experiments, which are advisable to carry out with the same v (in this case $v = 30$).

Statistical methods are divided into two groups: parametric and nonparametric, in particular the rank group. Each of them has "the home field" [9] for effective application. For the first method, two

constraints on the RQ (1) are required: homogeneity of deviation dispersions and normality of distributions. During grinding, these requirements are often violated in varying degrees, and that may be accompanied by a significant shift in assessments. In such situation, it is better to use the rank criteria. They do not use the properties of a particular family of distributions; because of this, they have an edge over the normal theory competitor "on the home field".

To estimate the RQ, the following one-dimensional distributions of frequencies were involved [9–11]:

- measures of position (reference values)

$$\text{average } \bar{y}_{ei} = y_{ei}, \quad (2)$$

$$\text{medians } \tilde{y}_{ei}; \quad (3)$$

- measures of dispersion (precision)

$$\text{standard deviations } SD_{ei}, \quad (4)$$

$$\text{ranges } R_{ei} = |y_{\max} - y_{\min}|_{ei}, \quad (5)$$

$$\text{quartile latitude } QL_{ei} = |y_{0.75} - y_{0.25}|_{ei}; \quad (6)$$

the parametric method is based on (2), (4), (5), and rank statistics - on (3), (6). Acceptance of null hypothesis H_0 regarding (about) the homogeneity of dispersions and normality of distributions (1) is considered in [6,7].

2.3. The simulation method (technique) of fuzzy logic. FL is equivalent to the theory of fuzzy sets A_{ei} , i.e. classes with defuse boundaries represented by sets of ordered pairs, composed of elements y_{eiv} of universal sets $\{y_{eiv}\}$ and the corresponding grades of membership $\mu_A(y_{eiv})$:

$$A_{ei} = \{(y_{eiv}, \mu_A(y_{eiv})) | y_{eiv} \in \{y_{eiv}\}\},$$

where $\mu_A(y_{eiv})$ is the characteristic functions which indicates the degree of membership y_{eiv} of fuzzy sets A_{ei} .

Execution of the FL simulation process for the experimental values was carried out in Matlab, using a special bump pack Fuzzy Logic Toolbox. The last has a simple and well-designed interface that makes it easy to design and diagnose fuzzy models [4,5]. Desirability function d_{ei} proposed by Harrington [12] is used to evaluate the surface quality of workpieces. In the basis of its construction, there is the idea of conversion of the natural values of particular responses into the dimensionless scale of desirability or preference. The scale of desirability refers to the psychophysical categories. FL is implemented as three sequentially executed procedures: differential selection sparing-out strokes $i = \overline{0; 8}$ for each parameter of surface quality; the separate assessments of the material machinability for all the attributes of roughness are $e = \overline{1; 3}$ and form accuracy $e = \overline{1; 7}$; integral evaluation of the material machinability takes place for all attributes of output parameters.

3. The results of the study and their discussion

Table 1 presents the test results of the observations for homogeneity of dispersions (acceptation of null hypothesis H_0) according to three criteria: 1 – Levene's, 2 – Hartley's, Cochran's and Bartlett's (presented in the program with one set); 3 – Brown–Forsythe's.

Table 1. Test of dispersions homogeneity at a confidence level of $p=0.05$

Parameter	Expected confidence level p for criteria			Acceptance of H_0
	Levene's	Hartley's, Cochran's and Bartlett's	Brown–Forsythe's.	
R_{a1}	0.0853	0.0430	0.2831	–
$R_{\max 1}$	0.5587	0.2018	0.8939	–
S_{m1}	0.2158	0.0221	0.2253	–
EFE_{\max}	0.0557	0.0867	0.2438	–
EFE_a	0.0001	0.0001	0.0261	+
EFE_q	0.0001	0.0012	0.0206	+
HV	0.0321	0.0001	0.0468	+

In table 1, the sign «+» means that indicators of H_0 for observations were taken at least for two criteria, and the sign «-» means that H_0 indicators were rejected.

Verification of distribution normality (H_0) of observations (1) using the Shapiro–Wilk’s test (W) is shown in table 2. According to theoretical statistics, H_0 is confirmed in satisfaction of inequalities: $p_i > 0.5$, $i=\overline{0;8}$. Thus, the total number of analyzed situations is $N=7 \times 5=35$. Test results (table 2) showed that H_0 indicators have been accepted in 1 of 35 cases, which is highlighted in the table. In connection with the foregoing information, the nonparametric statistics method is characterized by the measures: (2) and (6) were chosen as "the home field" for interpretation (1). The nonparametric method does not impose restrictions on the random values; it is less sensitive to "noise" and gross errors, which has got into a random sampling for one reason or another.

Table 2. Normality check of H_0 distributions for the Shapiro–Wilk’s criterion

Parameter	Sparking-out $i=\overline{0;8}$				
	0	2	4	6	8
	H_0 for normal distribution				
R_{a1}	0.0322	0.0539	0.0011	0.0013	0.3873
R_{max1}	0.1874	0.0555	0.0011	0.0098	0.4715
S_{m1}	0.0077	0.0637	0.0018	0.2118	0.0123
EFE_{max}	0.0113	0.0409	0.0154	0.0000	0.0002
EFE_a	0.0009	0.0000	0.1547	0.0033	0.0042
EFE_q	0.0011	0.0015	0.0067	0.0005	0.0011
HV	0.5676	0.0001	0.0001	0.0009	0.0039

Table 3. Input data of workpieces surface quality for FL modeling

Parameter ($e = \overline{1;7}$)	Measures μ	Number of sparking-out strokes $i = \overline{0;8}$				
		0	2	4	6	8
R_{ai} (1)	\tilde{y}_{1i}	0.167	0.172	0.147	0.161	0.191
	QL_{1i}	0.074	0.096	0.070	0.077	0.054
R_{maxi} (2)	\tilde{y}_{2i}	1.111	0.992	0.864	1.030	1.179
	QL_{2i}	0.405	0.384	0.466	0.497	0.368
S_{mi} (3)	\tilde{y}_{3i}	65.13	96.80	92.15	97.65	92.49
	QL_{3i}	26.93	46.86	28.10	29.85	26.33
EFE_{maxi} (4)	\tilde{y}_{4i}	8	6.5	7.5	8	6
	QL_{4i}	4	3	2	2	4
EFE_{ai} (5)	\tilde{y}_{5i}	4.58	3.25	3.75	3.79	3.67
	QL_{5i}	2.35	1.23	0.73	1.73	1.96
EFE_{qi} (6)	\tilde{y}_{6i}	5.02	3.88	4.38	4.81	4.14
	QL_{6i}	2.67	1.81	0.54	1.62	2.26
HV_i (7)	\tilde{y}_{7i}	1469.7	1724.8	1735.5	1698.1	1723.9
	QL_{7i}	128.1	169.8	163.8	211.5	164.6

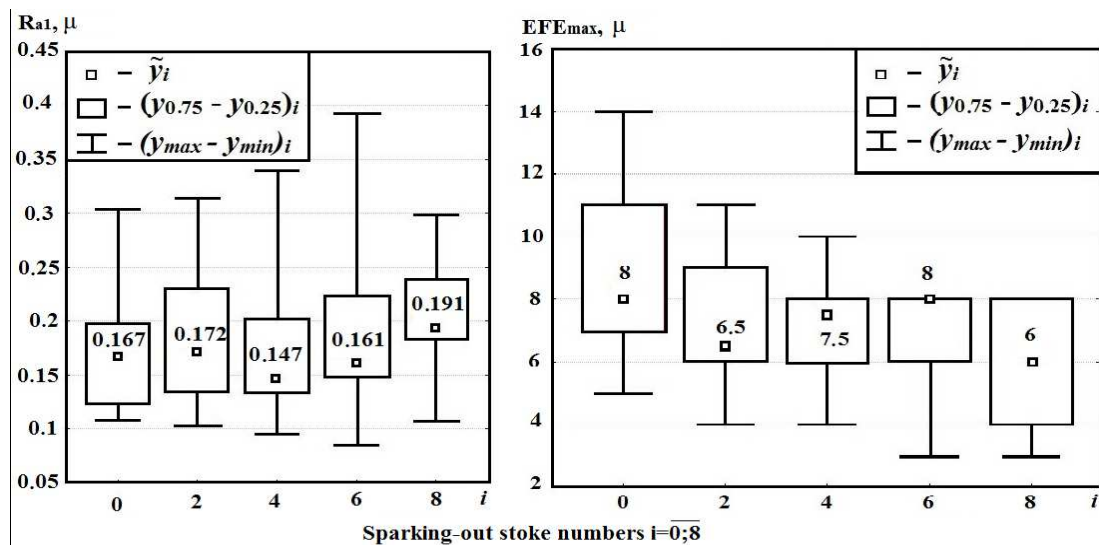


Figure 1. Descriptive non-parametric statistics for parameters R_a and EFE_{max}

Experienced reference values and measures of dispersion of the parameters, which were obtained during the grinding of high-strength aluminum alloy 1933T2, are presented in table 3 and figure 1.

As can be seen from table 3 and figure 1, the smallest measure of dispersion for value R_a occurs when $i=4$ and for EFE_{max} - when $i=2$. It was found that the greatest process stability for QL has been observed when: $i=8$ - for parameters R_a , R_{max} , and S_m ; $i=4,6$ - for EFE_{max} and $i=2$ for HV.

Hereby, the variance analysis of observations for several quality parameters are not allowed to receive a single recommendation for the choice of sparking-out stroke numbers. For this reason, NL was involved in the study. In MATLAB simulation, the experimental data after their statistical interpretation are usually considered to be input variables: \tilde{y}_{ei} , $K_{III_{ei}}$, $e = \overline{1;7}$, $i = \overline{0;8}$ (table 3).

The procedure of FL fulfilment was conducted in three sequentially executed stages:

1. Differential assessment of the impact of sparking-out stroke numbers on surface qualities $i = \overline{0;8}$ for each parameter ($e = \overline{1;7}$).
2. Differential assessment of the impact of the number of sparking-out strokes on the surface qualities for groups of roughness parameters $e = \overline{1;3}$ and flatness deviations ($e = \overline{4;6}$). In this case, the indicator of microhardness ($e=7$) is excluded because in the analysis of the surface topography it describes a single feature.
3. Integral choice of the optimal sparking-out strokes $i = \overline{0;8}$ for all quality indicators of the workpiece surface qualities, which made it possible to develop guidelines for sparking-out strokes choosing for flat grinding of workpieces of high strength aluminum alloy 1933T2.

The results of fuzzy modeling at stages 1 and 2 should be used when solving local problems. For example, the search of the number of sparking-out strokes should be carried out considering only the surface roughness or workpiece form accuracy and etc.

The FL procedures are described in the works [13]. Table 4 presents the results after the first stage; they were estimated by the attributes while simultaneous considering \tilde{y}_i , QL_i , $i = \overline{0;8}$ separately for each parameter. From table 4 it follows that by parameter R_a , the best result by attributes (2), (6) is ensured for $i = 4$, when $d_{41} = 0.857$, and the worst - $i = 2$, when $d_{21} = 0.158$.

Table 4. Results of the first stage of fuzzy modeling

Sparking-out $i=0; 8$	Desirability function d_{ie} for parameters						
	Parameter ($e = \overline{1; 7}$)						
	R_{ai} (1)	R_{maxi} (2)	S_{mi} (3)	EFE_{maxi} (4)	EFE_{ai} (5)	EFE_{qi} (6)	HV_i (7)
0	0.528	0.467	0.882	0.130	0.130	0.130	0.528
2	0.158	0.700	0.159	0.577	0.886	0.807	0.847
4	0.857	0.640	0.566	0.643	0.886	0.886	0.886
6	0.545	0.158	0.430	0.528	0.518	0.409	0.477
8	0.528	0.528	0.576	0.528	0.474	0.484	0.884

Based on the results shown in table 4, let us start the second stage of the simulation, the task of which was the separate evaluation of grinding quality by two sets of attributes: $e = \overline{1; 3}$ and $e = \overline{4; 6}$.

Table 5. Ranges of input variable

Type of estimation	Input parameters		
Linguistic	Bad	Normal	Good
Numerical	[0.1;0.5]	[0.1;0.5;0.5;0.9]	[0.5;0.9]

Table 6. Ranges of output variable

Type of estimation	Output parameters				
Linguistic	VB	B	Sat	G	VG
Numerical d	[0.0; 0.2)	[0.2; 0.37)	[0.37; 0.63)	[0.63; 0.80)	[0.8; 1.00]
Note: VB – very bad, B – bad, Sat – satisfactory, G – good, VG – very good.					

The value for each variable input lies in the interval of [0;1] (table 5), and the degree of desirability including 5 estimates: VB, B, Sat, G, VG (table 6), was involved in the output variable. Microhardness was excluded from the analysis of the input parameters due to the fact that it is represented by one attribute.

Table 7 shows the simulation results obtained after the second and third stages. It was found that using the fuzzy model made it easy to evaluate and search for the individual and cumulate parameters.

Table 7. Impact of complex estimation of the sparking-out stroke numbers on workpiece surface quality of alloy 1933T2

Sparking-out $i=0; 8$	Roughness		Form accuracy		Microhardness		Integral estimation	
	$d_{i..}$ $e = \overline{1; 3}$	Conclusion	$d_{i..}$ $e = \overline{4; 6}$	Conclusion	$d_{i..}$ $e = 7$	Conclusion	$d_{i..}$	Conclusion
0	0.705	G	0.114	VB	0.528	Sat	0.422	Sat
2	0.230	B	0.741	G	0.847	VG	0.602	Sat
4	0.723	G	0.781	G	0.886	VG	0.827	VG
6	0.287	B	0.479	Sat	0.477	Sat	0.405	Sat
8	0.524	Sat	0.500	Sat	0.884	VG	0.714	G

From table 7 it is seen that the number of strokes $i=4$ ($d=0.723$) has the best estimate for roughness parameters; and the worst – $i=2$ ($d=0.23$). In terms of form of accuracy, the highest estimate is predicted when the number of strokes is $i=4$ ($d=0.781$), and the smallest - when $i=0$ ($d=0.114$); for microhardness, respectively – when $i=4$ ($d=0.886$) and $i=6$ ($d=0.477$). As seen from table 7, the best integral assessment of sparking-out efficiency is given for $i=4$ ($d=0.827$) and the worst – for $i=6$ ($d=0.405$).

4. Conclusion

The involvement of non-parametric estimates of measures of position and dispersion, which includes median and quartile latitude, was justified in terms of violations of homoscedasticity and normality of the distributions of experimental data for implementation of the FL.

The statistical interpretation results of the data predicted that the smallest measure of dispersion for value R_a takes place when $i=4$, for EFE_{max} $i=2$. The highest process stability for QL has been observed when $i=8$ for parameters R_a , R_{max} and S_m ; $i=4, 6$ for EFE_{max} ; $i=2$ for HV, i.e. it does not reveal an unique estimate.

The simulation results determined that the best integral assessment of sparking-out efficiency was given $i=4$ ($d=0.827$) and the worst – $i=6$ ($d=0.405$).

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