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Selection of abrasive wheels by surface topography of parts from hardened steel 30ChGSA

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ABSTRACT

In this research the surface roughness parameters: R_a, R_{max}, S_m and – the flatness deviations EFE_{max} of plane parts made of hardened steel 30ChGSA, are used to estimate the cutting ability (CA) of grinding wheels made from traditional abrasives with different porosities. These parameters need to evaluate not only the position measures, but also the precision. Statistical methods allow predicting them individually, but do not have the ability to provide a comprehensive assessment. For these purposes, the fuzzy logic was attracted as an innovative direction of mechanical engineering. To realize the process of modeling a special bump pack of Fuzzy Logic Toolbox in MATLAB was used. As the results of fuzzy logic modeling in MATLAB, it was established that the wheel 5NQ46I6VS3 (i=5) (d_i=0.878) had the best comprehensive assessment by CA and the wheel 34AF60K6V5A (i=14) (d_i= 0.383) - the lowest rate. Therefore, the wheel 5NQ46I6VS3 can be selected as a basic wheel in the robust design of grinding operations. In manufacture, if there is not a grinding wheel 5NQ46I6VS3, the tools, which also had integral assessment of cutting ability "very high": 25AF46M10V-PO (i=7) or 5A46L10VAX (i=15) can replace it.

Keywords: Desirability scale; flatness deviation; fuzzy logic; grinding; roughness.

Nomenclature

GW	grinding wheel
d	desirability function
RV	random variables
CV	categorical variables
CA	cutting ability
AW	abrasive wheel with standard porosity
HPW	high porous wheel
R_a	arithmetical mean deviation of the roughness profile, µm
R_{max}	maximum height of the roughness profile, µm
S_m	average spacing roughness profile, µm
EFE_{max}	maximum flatness deviation, µm

$\bar{y}_e$; $y_{e\bullet}$	experimental averages, µm
$\tilde{y}_e$	experimental medians, µm
SD_e	deviation standards, µm
R_e	range, µm
QL_e	quartile latitudes, µm
v_c	cutting speed, m/s
s_l	length feed, m/min,
s_c	cross feed, mm/double pass,
t	cutting depth, mm,
z	operational allowance, mm
σ_{UST}	ultimate tensile strength, MPa
δ_{E}	elongation after fracture, %
H_0	null hypotheses
VL	very low
L	low
M	medium
H	high
VH	very high

INTRODUCTION

The weakest segment in the technological grinding system is an abrasive wheel. Its characteristics directly influence the effectiveness of grinding process by different parameters including the surface topography. Selection of GW is very important in the robust design of grinding operations. When the part process is necessary to carry out by the best (base) tool, which could allow optimizing the most efficiency of all the process target functions. Various factors may project as the target functions. The surface roughness and flatness deviations were chosen by us to study the surface topography. These parameters need to evaluate not only the position measures but also the precision. Statistical methods allow predicting them individually but do not have the ability to provide a comprehensive assessment. The problem becomes more complicated when the quantity of such target functions was increased (Soler Y.I. & Nguyen V.K., 2014; Soler Y.I. & Nguyen V.L., 2015). In these conditions, a fuzzy logic was used. It allows analyzing a large quantity of grinding variables and uses the words and phrases for values of linguistic variables and inaccurate reasoning. At that, content, information meaning, and processing logic are transmitted in the form of probability for solving problems, which could not be described precisely.

A fuzzy logic controller is successful application of fuzzy set theory. This method was introduced by Zadeh (1965) as an extension of the set theory by replacement of the characteristic function by a membership one. Many researchers have used fuzzy logic for modeling the manufacturing process parameters, in particular, grinding. An adaptive neuro-fuzzy system was built for online monitoring and predicting surface roughness during grinding (Maity & Chakraborty, 2013; Samhouri & Surgenor, 2005), face milling (Yang et al., 2006) and turning (Jiao et al., 2004) processes. A fuzzy logic model was created by Ahmed el al. (2012) to predict surface roughness of a machined surface in glass milling operation using CBN grinding tool. Jaya et al. (2010) have offered a fuzzy logic model for predicting the roughness performance of TiAlN coating. At that, the process input parameters were the substrate sputtering power, bias voltage and temperature. The result indicated good agreement between the fuzzy model and experimental results with the 96.39% accuracy. A three-layer fuzzy model included 16 input variables was developed by Ali & Zhang (1999) to predict ground surface roughness. Ali & Zhang (2004) have used a fuzzy model for predicting the surface burns of steel part during grinding process. Sardar et al. (2011) have offered an analysis and application of fuzzy logic for optimized evaluation of database queries. Faran Baig et al. (2013) have proposed a design and simulation of fuzzy logic based to control electrolytic in-process dressing grinding system. Alexander et al. (2010) used a fuzzy model for optimizing the constraints imposed on design of the US naval ships. A fuzzy logic was used to modeling and analyzing the surface roughness during drilling process of glass fiber–reinforced plastic composites (Latha & Senthilkumar, 2010; Palanikumar, 2006). Yilmaz et al. (2006) have used a user-friendly fuzzy-based system for the selection of electro-discharge machining process parameters. Lin et al. (2007) have used a fuzzy logic approach to determine the best combination of mobile phone form elements for matching a given product image.

The goal of this article is to select the abrasive wheels during flat grinding of hardened steel parts by micro- and macrogeometry parameters using fuzzy logic.

METHODS OF EXPERIMENTAL DATA INTERPRETATION

For realizing the conception of the fuzzy logic experimental data received while grinding was used. The specificity of grinding is that abrasive grains in the wheels have an arbitrary shape, a chaotic arrangement in the bonded, difference in height in radial axis and a different number of operating grain and cutting edges per unit area of its contact with the entry into the workpiece. This makes it possible to examine the observation of RV and to estimate their behaviour on the base of probability-theoretic approaches. In this case, the experimental data presentation is supposed to be given in the form of independent sets $e = \overline{1;k}$:

$$\{y_{ev}\},\ v = \overline{1;n}, \tag{1}$$

where v is a number of replicate tests, which preferably carried out with equal n.

The statistical methods are divided into two groups: parametric and non-parametric, specifically, rank ones. Each of them has “its own field” (Hollander & Wolfe, 1999) for the effective use. In the first case, it is necessary to ensure the fulfillment of the two constraints imposed on RV: homogeneity of variance of deviation and normalcy of distribution. The discussed grinding requirements are often violated to any extent that can be accompanied by a considerable bias of estimator, confidence bounds and factors (Hollander & Wolfe, 1999). In such a situation, it is reasonable to use a non-parametric method that is not connected with a certain family of distributions and does not use its properties. RV are estimated by the following univariate frequency allocation (Soler Y.I. & Nguyen V.K., 2014; Soler Y.I. & Nguyen V.L., 2015):

- position measures (reference values)

averages $\overline{y_e} = y_{e\bullet}$, (2)

medians $\widetilde{y_e}$; (3)

- scattering measures (precision)

deviation standards SD_e, (4)

range $R_e = (y_{max} - y_{min})_e$, (5)

- quartile latitudes $QL_e = (y_{0,75} - y_{0,25})_e$. (6)

From the theoretical statistics it is known that a parametric method is based on the univariate frequency allocation Equations (2), (4), (5) and the rank statistics is related to Equations (3), (6). The acceptance of the null-hypothesis (H_0) by the homogeneity of variance of deviation and the normalcy of distribution Equation (1) is discussed in Soler Y.I. & Nguyen V.K. (2014) and Soler Y.I. & Nguyen V.L. (2015). To decrease labor content of the statistical calculations the software Statistica 6.1.478.0. is used in the research work.

The received experimental data after processing by the statistical methods Equations (2)-(6) was analyzed by the fuzzy logic while realizing the process of modeling in MATLAB using a special bump pack of Fuzzy Logic Toolbox. At that, the fuzzy sets A_e are the ordered couple package made of the elements y_{ev} of the universal sets $\{y_{ev}\}$ and the corresponding grade of membership $\mu A(yev)$:

$$A_e = \{(y_{ev}, \mu_A(y_{ev})) \mid y_{ev} \in \{y_{ev}\}\}, \quad (7)$$

where $\mu A(yev)$ are characteristic functions which indicating the degree of membership to the fuzzy set A_e.

Structure of fuzzy system was shown in Figure 1 and includes the following components (Leonenkov, 2005):

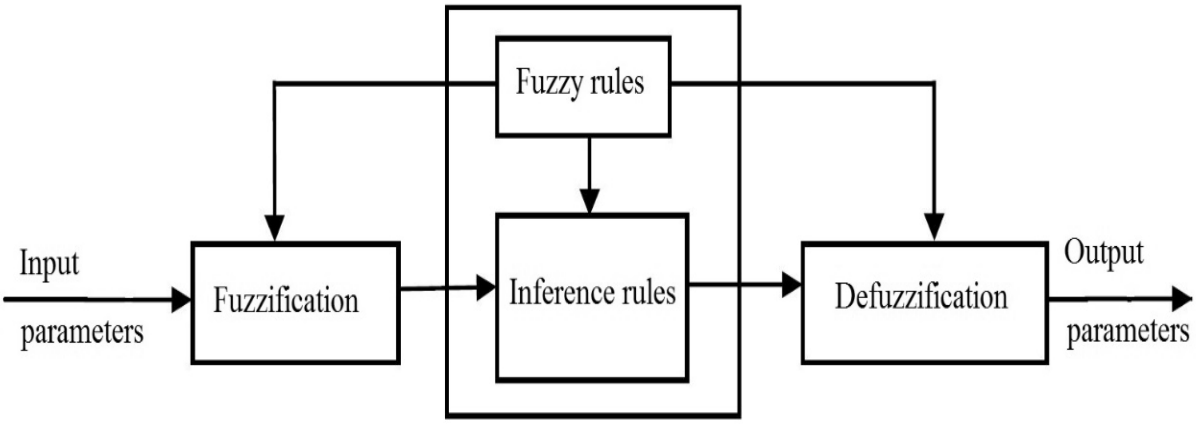


Fig. 1. The structure of a fuzzy system

1. Input parameters are the roughness parameters and flatness deviations in the present study.

2. Fuzzification (making something fuzzy) is a process or procedure for determining the values of the membership functions of fuzzy sets based on the initial data.

3. Fuzzy rules are a finite set of the fuzzy production rules, which agreed relatively used linguistic variables. In this study, a fuzzy rule was presented in the form of a structured text: If "condition 1" and "condition 2" and…"condition n", then "conclusion 1"…

4. Inference rules includes the following procedures:

- aggregation, which is a procedure for determining the degree of conditions truth by each from the fuzzy rules;

- activation, which is a process of finding the truth degree of each from the connections of fuzzy rules;

  - accumulation, which is a process of finding the membership functions for each of output linguistic variables of a fuzzy set. The purpose of this procedure is to combine or accumulate all truth degrees of the conclusions for membership functions of each output variable.

5. Defuzzification, which is a process of finding a normal (non-fuzzy) values for each output linguistic variable. There are 5 defuzzification methods: center of gravity; the center of gravity for the one-point set; centroid area; method of the left modal of values; method of the right modal of values. In the present study, a centroid area method is used due to its wide acceptance and capability in giving more accurate result to compared an other methods (Leonenkov, 2005). Figure 2 shows the graphical representation of centroid area defuzzification

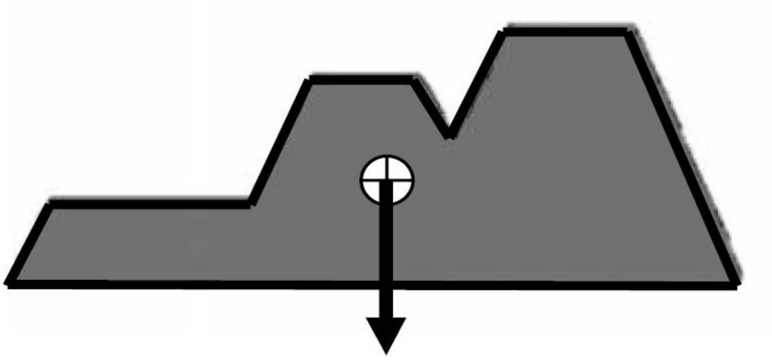


Fig 2. Graphical of centroid area method

method. The shape refers to the remaining area of active fuzzy sets that are controlled by the related fuzzy rules (Jaya et al., 2010; Yilmaz et al., 2006).

6. The output parameter is CA of GW, which is estimated by a desirability function d offered by Harrington (1965).

In the construction of desirability function, there is an idea of natural value conversion of individual response into a dimensionless desirability or preference scale being related to psycho physical ones. Its purpose is to set up compatibility between physical and psychological parameters. The physical parameters are thought to be some possible responses characterizing the functioning of the object under study. Experimentally assigning the desirability scale is the identifying of the compliance between the received surface quality values and their desirability assessment.

EXPERIMENTAL TECHNIQUE

The experiments were carried out under the following constant conditions. The 3G71 plane-grinding machine was used. The wheel forms 1 (01) with the sizes of 250×20×76 mm (GOST R 527812007-; Norton, 2009) were used. Cutting mode parameters were: cutting speed v_c=35 m/s, length feed s_l=7 m/min, cross feed s_c=1 mm/double pass, cutting depth t=0.015 mm, operational allowance z=0.15 mm. The cutting cooling fluid, which is supplied by watering to the workpiece at a rate of 710- l/min, was the 5% Akvol-6 emulsion containing by weight [%]: extract of phenolic purification – 18; industrial oil – 18; chloroparaffin – 27; oleic acid – 4; water – the rest. A diamond pen was used to dress wheel before grinding every part. The number of repetitions of the experiments was n=30. The object of research was the parts made from hardened steel 30ChGSA (σ_{UST}=1080 MPa, δ_E = 10%) with the sizes of $B\times L\times H$=40×50×40 mm ground by the area $B\times L$. The chemical composition of steel 30ChGSA is presented in Table 1.

Table 1. Chemical composition of steel 30ChGSA

Element	C	Si	Mn	Ni	S	P	Cr	Cu	Fe
Contents (%)	0.28-3.4	0.9-1.2	0.8-1.1	<0.3	<0.025	<0.025	0.8-1.1	<0.3	~96

In the experimental conditions, the variable "*e*" in Equation (1) was transformed into the form "*ij*". The characteristics of GW were presented by the code $i = \overline{1;16}$ in Table 2. The process inputs parameters: R_a, R_{max} etc. were concretized by the index "*j*", which are considered from the statistical position in the form Equation (1).

The parameters of surface roughness were measured by the profilograph-profilometer of 252

Table 2. Characteristics of grinding wheels and their producers

Wheel characteristics ($i = \overline{1;16}$)		**Note**
HPW	5SG 46 K 12 VXP (1)	5-ratio between the grains SG, NQ and conventional aluminum oxide is equal 1:1 (Norton company, USA)
HPW	5SG 46 I 12 VXP (2)	
HPW	5SG 60 K 12 VXP (3)	
HPW	TGX 80 I 12 VCF5 (4)	
AW	5NQ 46 I 6 VS3 (5)	
HPW	25A F60 M 10 V5-PO (6)	Luga abrasive factory (Russian Federation)
HPW	25A F46 M 10 V5-PO (7)	
HPW	25A F46 M 10 V5-PO3 (8)	
HPW	25A F46 K 10 V5-PO3 (9)	
HPW	25A F46 L 10 V5 KF35 (10)	St. Petersburg abrasive factory “Ilyich” (Russian Federation)
HPW	25A F46 M 12 V5-PO (11)	Luga abrasive factory (Russian Federation)
HPW	25A F46 M 12 V5-PO3 (12)	
AW	92A/25A F46 L 6 V20 (13)	St. Petersburg abrasive factory “Ilyich” (Russian Federation)
AW	34A F60 K 6 V5A (14)	Moscow abrasive factory (Russian Federation)
HPW	5A 46 L 10 VAX (15)	5A-monocrystalline alumina; the wheel was manufactured by pressing (Dorfner, Germany)
AW	EKE 46 K 3 V (16)	EKE- monocrystalline alumina; the wheel was manufactured by casting; K- medium structure, 3-soft hardness, (Dorfner, Germany)
Note: HPW – high porous wheel; AW- abrasive wheel with standard porosity; 5SG, TGX, 5NQ, 25A, 92A/25A, 34A, 5A, EKE – abrasive marks; 46, 60, 80, F46, F60 – grains; I, K, M, L – wheel hardness; 6, 10, 12–porosity; VXP, VCF5, VS3, V5, V20, V5A, VAX – bond types; PO, PO3, KF35 – pore-formers.		

type produced by “Caliber” in two mutually orthogonal directions $l = \overline{1;2}$: correspondingly according to the vectors s_c and s_l. The most significant parameters were included in the process modeling. They determine the part reliability in sections of their greatest values. These roughness parameters are arithmetical mean deviation of the primary profile ($R_{a1}(i)$ (y_{i1})), maximum height of the primary profile ($R_{max1}(i)$ (y_{i1})), mean spacing between peaks ($S_{m2}(i)$ (y_{i3})) (GOST 25142,82-1982). The methods of searching for the attributes of flatness deviation EFEmax(i) (yi4) (GOST 246311984 ,81-) were discussed in the articles Soler Y.I. & Nguyen V.K. (2014) and Soler Y.I. & Nguyen V.L. (2015).

The observation Equation (1) is considered with the dispersion homogeneity when the inequalities Equation (8) are strict confirmed.

$$\alpha_m < 0.05, \tag{8}$$

where α_m – the calculation level of significance by statistics $(m = \overline{1;3})$: 1 - Hartley, Cochran, Bartlett criteria; 2 - Leuven criteria and 3 - Brown-Forsythe criteria.

The testing results were shown in Table 3. The marks “+” in the last column of Table 3 are the

Table 3. Testing of dispersion homogeneity for research parameters in the accepted significance level

Parameter	Calculation significance level α_m for the sets (1) $i=\overline{1;16}$ by criterion $m=\overline{1;3}$			Acceptance H_0 Equation (8)
	1	2	3	
R_{a1}	0.000	0.000	0.000	+
R_{max1}	0.000	0.000	0.000	+
S_{m2}	0.000	0.007	0.082	+*
EFE_{max}	0.000	0.000	0.000	+

Note: $m=\overline{1;3}$: 1 - Hartley, Cochran, Bartlett criterion; 2 - Leuven criterion and 3 - Brown-Forsythe criterion.

evidence of that the null hypotheses (H_0) of the dispersion homogeneity are confirmed by three criterion and the marks "+*" for the mean spacing S_{m2} – only by statistics – m=1; 2. It allows us to predicate that the observation dispersion for the roughness parameters and flatness deviation are homogeneity.

The distribution normality (H_0) of the sets Equation (1) was tested using the Shapiro-Wilk criterion. The theoretical statistics showed that they are confirmed when the inequalities $\alpha_i > 0.5$, $i=\overline{1;16}$ are held. Table 4 shows that the observations Equation (1) are approximated by a normal distribution curve in only two of 64 cases.

Violation of the distribution normality almost for all wheel, therefore, tested parameters are done to pay attention to non-parametric method and its characteristics of one-dimensional frequency distribution Equation (1) are: medians $\tilde{y}_{ij}$ Equation (3), quartile latitudes QL_{ij} Equation (6). Their values were given in Table 5.

Table 4. Normalcy of distribution testing according to Shapiro-Wilk criterion

Calculated significance level α_i with variables $i=\overline{1;16}$				
Wheel	R_{a1i}	R_{max1i}	S_{m2i}	EFE_{maxi}
1	0.00	0.00	0.00	0.00
2	0.03	0.06	0.00	0.00
3	0.00	0.00	0.00	0.11
4	**0.59**	**0.93**	0.00	0.16
5	0.00	0.00	0.00	0.00
6	0.01	0.00	0.05	0.00
7	0.02	0.18	0.15	0.00
8	0.00	0.47	0.00	0.00
9	0.00	0.01	0.00	0.00
10	0.06	0.48	0.03	0.10
11	0.03	0.03	0.00	0.02
12	0.01	0.04	0.49	0.07
13	0.02	0.02	0.04	0.00
14	0.07	0.02	0.00	0.15
15	0.00	0.00	0.00	0.00
16	0.03	0.12	0.00	0.00

Table 5. Input data of roughness parameters and flatness deviations by position and scatting measures

Wheel $i=\overline{1;16}$	**Parameter**							
	R_{a1i}**. µm**		R_{max1i}**. µm**		S_{m2i}**. µm**		EFE_{maxi}**. µm**	
	$\tilde{y}_{i1}$	QL_{i1}	$\tilde{y}_{i2}$	QL_{i2}	$\tilde{y}_{i3}$	QL_{i3}	$\tilde{y}_{i4}$	QL_{i4}
1	0.110	0.040	0.722	0.230	58.845	22.887	9.000	4.000
2	0.112	0.087	0.837	0.527	71.522	30.987	10.000	2.000
3	0.088	0.053	0.633	0.333	68.847	39.343	12.000	3.000
4	0.134	0.051	0.836	0.330	58.495	24.645	11.000	4.000
5	0.087	0.023	0.553	0.157	64.687	22.443	9.000	2.000
6	0.101	0.032	0.682	0.180	59.353	28.362	10.500	3.000
7	0.098	0.027	0.680	0.198	59.259	36.195	8.000	2.000
8	0.152	0.050	1.053	0.403	74.065	33.290	9.000	2.000
9	0.121	0.055	0.862	0.475	70.407	43.442	10.000	4.000
10	0.162	0.037	1.127	0.190	62.292	21.953	12.000	5.000
11	0.124	0.059	0.851	0.436	56.959	34.204	10.000	2.000
12	0.117	0.128	0.772	0.743	67.637	29.700	11.000	3.000
13	0.154	0.140	0.981	0.749	59.572	15.950	10.000	4.000
14	0.155	0.093	0.998	0.573	62.725	41.373	9.500	4.000
15	0.098	0.053	0.623	0.283	60.825	16.863	9.000	2.000
16	0.108	0.052	0.719	0.387	59.695	32.555	14.000	2.000

Table 5 shows that the experimental medians of studied parameters of surface topography are in the range: R_{a1i} [0.087 (0.10); 0.162 (0.20)] µm; R_{max1i}[0.553 (0.63); 1.127 (1.60)] µm; S_{m2i} [56.959 (63); 74.065 (80)] µm; EFE_{maxi} [8 (TFE6); 14 (TFE7)] µm. In the parentheses, the CV (GOST 27891973 ,73-) are reduced for roughness parameters and for flatness deviations – their accuracy quality class TFE (GOST 246311981 ,81-). A wheel cutting abilities produced the median variation by CV: for R_{a1i} – four CV, R_{max1i} – five, *Sm2i* – two, *EFEmaxi* – one accuracy quality class. Statistics allows revealing the wheels with minimum or maximum $\tilde{y}_{ij}$ or Q_{Lij}, $i=\overline{1;16}$, $j=\overline{1;4}$. For example, the minimum experienced medians for parameters R_{a1}(5), R_{max1}(5) are shown while grinding with the wheel 5NQ (*i*=5), for S_{m2}(11) – HPW 25AF46M12V-PO; EFE_{max}(7) – HPW 25AF46M10V-PO. Even without reference to scattering measures, it is difficult to select the wheel with the best cutting ability based on position measures. In connection with stated the fuzzy logic methods were involved. They allow creating an expert system of the wheel classification with reference to parameter values received while grinding. Input parameters of the modeling fuzzy logic system are $\tilde{y}_{ij}$ Equation (3) and Q_{Lij} Equation (6) or their attributes. The output one is a CA of researched wheels. Realization of the fuzzy logic includes two following stages:

1. The differential assessment of wheel CA d_{ij}, $i = \overline{1;16}$, $j = \overline{1;4}$ in the conditions of simultaneous reduction of position and scatting measures for each wheel by roughness parameters and flatness deviations separately.
2. The integral assessment of wheel CA, which by the attributes of quality parameters gives a linguistic and numerical ($d_{i\bullet}$) comprehensive assessment of the surface micro- and macrogeometry.

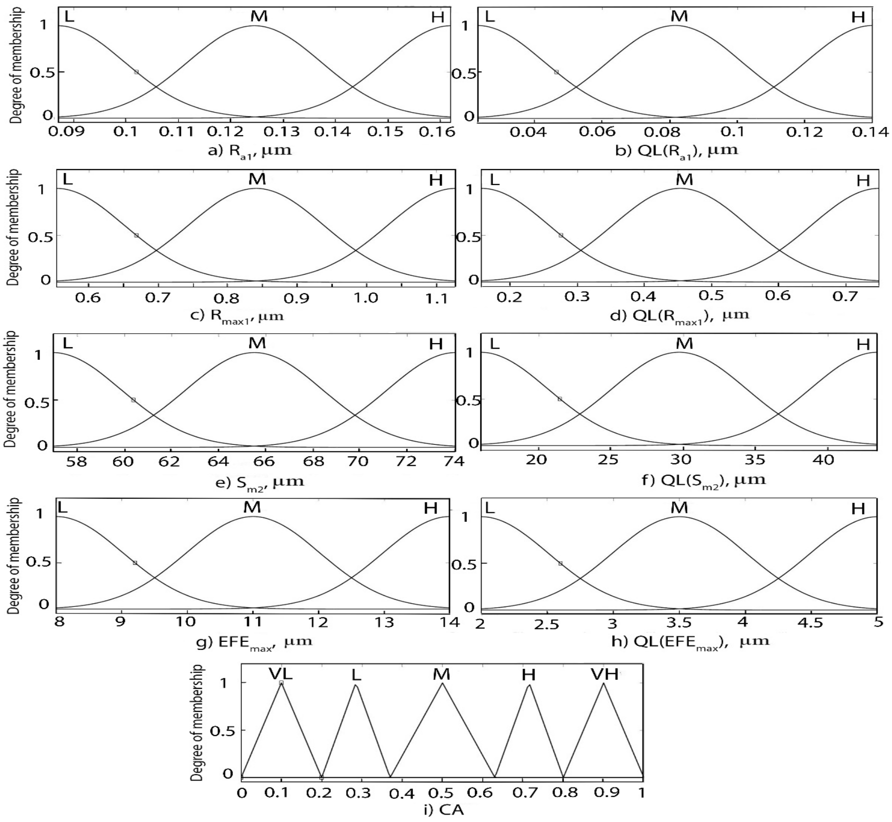
Table 6 presents the fuzzy linguistic variables for input and output parameters and their ranges for the first stage of modeling. At that three linguistic expressions: low, medium and high were

used for Equation (3) and Equation (6). For the output variable, a desirability scale was involved. It includes the variables: very low, low, medium, high and very high. For describing the fuzzy sets of output variables (Figure 3a-h) the membership functions of Gauss shape are used and for output parameter - the membership functions of triangular shape (Figure 3i).

Table 6. Fuzzy assessments for input and output variables and their ranges of each researched parameters

Input parameters					**Range, µm**
Parameter		**Linguistic variables**			
R_{a1i}	$\tilde{y}_{i1}$	Low (L), medium (M) and high (H)			[0.087; 0.162]
	QL_{i1}				[0.023; 0.140]
R_{max1i}	$\tilde{y}_{i2}$				[0.553; 1.127]
	QL_{i2}				[0.157; 0.749]
S_{m2i}	$\tilde{y}_{i3}$				[56.959; 74.065]
	QL_{i3}				[15.950; 43.442]
EFE_{maxi}	$\tilde{y}_{i4}$				[8.000; 14.000]
	QL_{i4}				[2.000; 5.000]
Output parameters					
d_{ij}		Very low (VL), low (L), medium (M), high (H) and very high (VH)			$d_{ij} \in [0; 1]$
Desirability scale, d_{ij}					
VL		L	M	H	VH
[0.0; 0.2]		[0.2; 0.37]	[0.37; 0.63]	[0.63; 0.80]	[0.8; 1.00]

A set of all possible combinations of input variables 32=9 of fuzzy rules has been constructed based on an empirical criterion for all researched parameters (Table 7).



a) R_{a1}, µm b) $QL(R_{a1})$, µm

c) R_{max1}, µm d) $QL(R_{max1})$, µm

e) S_{m2}, µm f) $QL(S_{m2})$, µm

g) EFE_{max}, µm h) $QL(EFE_{max})$, µm

i) CA

Fig. 3. Membership functions for input and output variables

In the batch of Fuzzy Logic Toolbox, there are two graphic interfaces simplifying the user's view of the rules of reasoning (Rule Viewer) (Figure 4a) and the reasoning surface (Surface Viewer) (Figure 4b). Using the graphic format all possible reductions are shown, that makes it possible to forecast an output variable - Output. Every change of the input variables is displayed in the view of the output rules changing it accordingly. Figure 4 shows the procedure realization

Table 7. Fuzzy rules for estimating CA of GW for each roughness parameters and flatness deviations

No	**Structure of Fuzzy Rules**
1	If($\tilde{y}_e$ - L) and (QL_e - L), then (CA - VH)
2	If ($\tilde{y}_e$ - L) and (QL_e - M), then (CA - H)
3	If ($\tilde{y}_e$ - L) and (QL_e - H), then (CA - M)
4	If ($\tilde{y}_e$ - M) and (QL_e - L), then (CA - H)
5	If ($\tilde{y}_e$ - M) and (QL_e - M), then (CA - M)
6	If ($\tilde{y}_e$ - M) and (QL_e - H), then (CA - L)
7	If ($\tilde{y}_e$ - H) and (QL_e - L), then (CA - M)
8	If ($\tilde{y}_e$ - H) and (QL_e - M), then (CA - L)
9	If ($\tilde{y}_e$ - H) and (QL_e - H), then (CA - VL)

Figure 4b illustrates that on the reasoning surface desirability function d51 while grinding by Norton Vitrium wheel (i=5) reached its maximum when $\tilde{y}_{51} = 0.087$ µm, QL_{51}=0.023 µm and minimum when $\tilde{y}_{51} = 0.162$ µm, QL_{51}=0.140 µm.

for parameter R_{a15} while grinding by GW 5NQ46IVS3 (i=5).

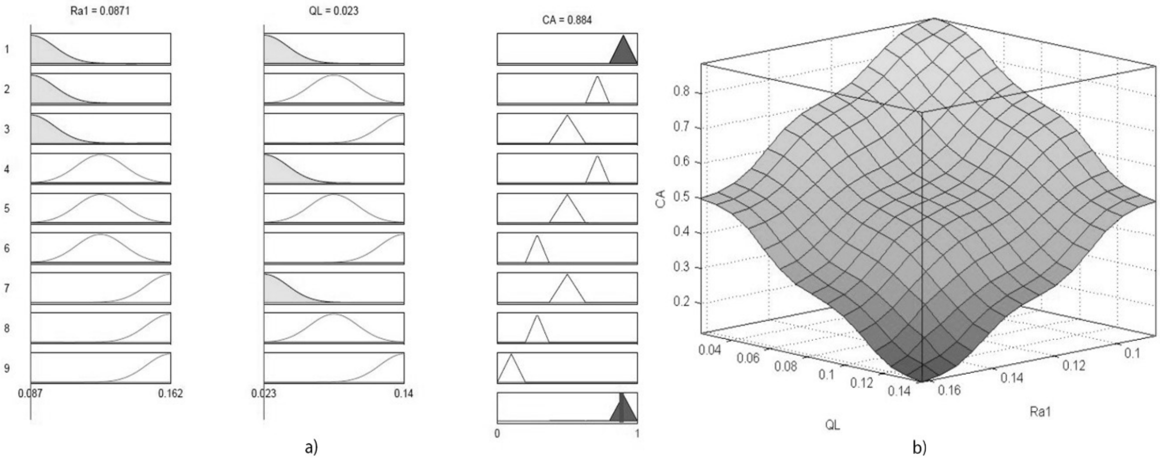


Fig. 4. Assessment results review of CA of GW i=5 for R_{a15}:
reasoning rule review (a); reasoning surface (b)

Table 8 shows the fuzzy logic results to assessment CA of GW by the attribute under conditions of simultaneous calculation of the position and scatting measures, which were reduced in Table 5 for each roughness parameters and flatness deviations separately. The CA of GW is quickly and easily evaluated and classified using the fuzzy logic. At the same time based in the fact, if

Table 8. Fuzzy logic results to assessment CA of GW for each researched parameters

Wheel *i*, $i=\overline{1;16}$	**Researched parameters**							
	R_{a1i}		R_{max1i}		S_{m2i}		**EFE$_{maxi}$**	
	d_{i1}	rate	d_{i2}	rate	d_{i3}	rate	d_{i4}	rate
1	0.720	H	0.737	H	0.767	H	0.582	M
2	0.531	M	0.476	M	0.335	L	0.756	H
3	0.799	H	0.727	H	0.281	L	0.500	M
4	0.560	M	0.561	M	0.741	H	0.461	M
5	0.884	VH	0.884	VH	0.606	M	0.850	VH
6	0.818	VH	0.812	VH	0.670	H	0.559	M
7	0.850	VH	0.804	VH	0.558	M	0.884	VH
8	0.460	M	0.359	L	0.260	L	0.850	VH
9	0.580	M	0.486	M	0.173	VL	0.500	M
10	0.483	M	0.495	M	0.674	H	0.244	L
11	0.552	M	0.502	M	0.640	H	0.756	H
12	0.356	L	0.336	L	0.476	M	0.539	M
13	0.130	VL	0.198	VL	0.856	VH	0.500	M
14	0.295	L	0.323	L	0.375	M	0.538	M
15	0.745	H	0.782	H	0.813	VH	0.850	VH
16	0.671	H	0.592	M	0.617	M	0.500	M

a wheel has CA rate (*dij*) is closer to unity, then it works better. For parameter Ra1i, the wheels $i=\overline{5;7}$ had VH rate by CA and the wheels *i*=1; 3; 15; 16 – H, the wheels $i=2;3;\overline{8;11}$ - M, wheel *i*=12 – L and wheel *i*=13 – VL. The similar results were obtained for the parameter R_{max1i} with the exception of the following wheels: *i*=8 – L *i*=16 – VL. It has been established that by the roughness parameter the best CA was received by the wheel 5NQ46I6VS3 (*i*=5) – d_{51}=0.884 and the lowest CA – the wheel 92A/25AF46L6V20 (*i*=13) – d_{131}=0.13. The wheel *i*=5 has a normal structure (6), but it is made from a mixture of Norton Quantum and customary aluminum oxide grains in equal proportions. The 5NQ grain is a new generation of abrasive materials. Norton Vitrium wheel is designed to increase the productivity and accuracy of the grinding process. By parameter S_{m2i} the wheels *i*=13; 15 received VH-rate; *i*=1; 4; 6; 10; 11 – H-rate; *i*= 5; 6; 12; 14; 16 – M-rate; *i*=2; 3; 8 – L-rate and *i*=9 – VL-rate. For parameter EFEmaxi the wheels *i*=5; 7; 8; 15 can be combined into one group with VH-rate of CA and the wheels *i*=2; 11 – H-rate group, *i*=1; 2; 4; 6; 9; 11; 12; 13; 16 – M-rate group, the HPW *i*=10 – L-rate. By the mean spacing S_{m2} AW 92A/25AF46L6V20 (*i*=13) received the highest assessment and by parameter EFE_{maxi} – HPW 25A46M10V-PO (*i*=7) with d74=0.884 (VH-rate). Two GW are located with the same assessment di4 = 0.85, i=5; 15. In comparison, with CA assessment of GW by medians (Table 5), two new solutions were marked. They are: for parameters R_{max1} and R_{a1} the wheel *i*=5 was replaced by the wheel i=15; for the parameter S_{m2}, the wheel *i*=13 was replaced by the HPW 25AF46M12V-PO (*i*=11). The stated allows considering that the selection of GW with the calculation of the surface topography parameters is a complicated problem because one wheel can win one topography parameter but lose other.

The second stage of the fuzzy model in the present study is to find the optimal wheel among GW, which would minimize the attributes by the position and scattering measures for the altogether complex of the studied quality parameters. For this purpose a model from five variables: four inputs and one output was developed.

Table 9. Fuzzy linguistic and numeric input variables on the results of the first stage of modelling

Parameter	Linguistic variables	Numeric assessments
d_{i1}	Low (L), Medium (M), High (H)	[0.130; 0.884]
d_{i2}		[0.198; 0.884]
d_{i3}		[0.173; 0.856]
d_{i4}		[0.244; 0.884]

To describe the fuzzy sets of input parameters the membership functions of Gauss shape were used. They use the attributes of researched parameters for each wheel (by the analogy of Figure 3a). Five quality classes and desirability scale present the membership function of the output variable. It coincides with the fuzzy reasoning for individual quality parameters (Table 6, Figure 3i). The fuzzy rules for the developed system based on empirical criterion include N=34=81 possible combinations of the input parameters and quality linguistic assessments of ground parts (Table 10).

The results of GW selection using comprehensive assessment of the surface micro- and

Table 10. Structure of fuzzy rules for overall assessment CA of GW

No	Structure of fuzzy rules: (If (d_1) and (d_2) and (d_3) and (d_4), then ($d_\bullet$))				
	CA$_1$	CA$_2$	CA$_3$	CA$_4$	CA$_\bullet$
1	L	L	L	L	VL
2	L	L	L	M	L
3	L	L	L	H	L
4	L	L	M	L	L
5	L	L	M	M	L
6	L	L	M	H	M
7	L	L	H	L	L
8	L	L	H	M	M
9	L	L	H	H	M
10	L	M	L	L	L
11	L	M	L	M	L
12	L	M	L	H	M
13	L	M	M	L	L
14	L	M	M	M	M
15	L	M	M	H	M
16	L	M	H	L	M
17	L	M	H	M	M
18	L	M	H	H	H
19	L	H	L	L	L
20	L	H	L	M	M
21	L	H	L	H	H
22	L	H	M	L	M
23	L	H	M	M	M
24	L	H	M	H	H
25	L	H	H	L	M
26	L	H	H	M	H
27	L	H	H	H	H
28	M	L	L	L	L
29	M	L	L	M	L
30	M	L	L	H	M
31	M	L	M	L	L
32	M	L	M	M	M
33	M	L	M	H	M
34	M	L	H	L	M
35	M	L	H	M	M
36	M	L	H	H	H
37	M	M	L	L	L
38	M	M	L	M	M
39	M	M	L	H	M
40	M	M	M	L	M
41	M	M	M	M	M
42	M	M	M	H	H
43	M	M	H	L	M
44	M	M	H	M	H
45	M	M	H	H	H
46	M	H	L	L	M
47	M	H	L	M	M
48	M	H	L	H	H
49	M	H	M	L	M
50	M	H	M	M	H
51	M	H	M	H	H
52	M	H	H	L	H
53	M	H	H	M	H
54	M	H	H	H	VH
55	H	L	L	L	L
56	H	L	L	M	M
57	H	L	L	H	M
58	H	L	M	L	M
59	H	L	M	M	M
60	H	L	M	H	H
61	H	L	H	L	M
62	H	L	H	M	M
63	H	L	H	H	H
64	H	M	L	L	M
65	H	M	L	M	M
66	H	M	L	H	H
67	H	M	M	L	M
68	H	M	M	M	M
69	H	M	M	H	H
70	H	M	H	L	M
71	H	M	H	M	H
72	H	M	H	H	VH
73	H	H	L	L	M
74	H	H	L	M	H
75	H	H	L	H	H
76	H	H	M	L	H
77	H	H	M	M	H
78	H	H	M	H	VH
79	H	H	H	L	H
80	H	H	H	M	VH
81	H	H	H	H	VH

macrogeometry of the part made from hardened steel 30ChGSA were presented in Table 11.

Table 11. Integral assessments of wheel cutting ability

Wheel, $i=\overline{1;16}$	$d_{i\bullet}$	**Linguistic assessment**	**Wheel,** $i=\overline{1;16}$	$d_{i\bullet}$	**Linguistic assessment**
1	0.775	H	**9**	0.488	M
2	0.556	M	**10**	0.493	M
3	0.576	M	**11**	0.635	H
4	0.649	H	**12**	0.437	M
5	0.878	VH	**13**	0.488	M
6	0.767	H	**14**	0.383	M
7	0.867	VH	**15**	0.838	VH
8	0.518	M	**16**	0.583	M

Table 11 shows that the wheels i=5; 7; 15 sequentially took the first three places (VH-rate) by $d_{i\bullet}$, which provide a comprehensive reduction of the position and scattering measures for all researched parameters of part surface topography. The next places were sequentially taken by the wheels *i*=1; 6; 4; 11 having H-rate and the wheels *i*= 16; 3; 2; 8; 10; 9; 13; 12; 14 having M-rate. It was established that the wheel 5NQ46I6VS3 (*i*=5) ($d_{i\bullet}$ =0.878) had the best comprehensive assessment by CA and the wheel 34AF60K6V5A (*i*=14) ($d_{i\bullet}$ = 0.383) – the lowest rate.

The integral assessments of CA of GW with the differential analogues (Table 8), which were obtained by the individual parameter of the surface topography, were matched. As shown in Table 8, linguistic assessment of cutting ability the wheel *i*=5; 7 were equaled three VH-rates while one M-rate. However by d_{ij}, $i=\overline{1;16}$, $j=\overline{1;4}$ the wheel Norton Vitrium (*i*=5) has two functions d_{5j}, $j=\overline{1;2}$ (VH-rate) greater than the HPW *i*=7, which exceeds the wheel *i*=5 only by d74. In connection with stated the AW *i*=5 is received the first position and HPW *i*=7 – the second position. The tool 5A46L10VAX made by company Dorfner (Germany) (*i*=15), which previously was not in the top three (with assessments: VH – 2 and H – 2), was occupied the third position by integrated $d_{15\bullet}$.

CONCLUSIONS

Based on the received results, the conclusions can be formulated as following:

1. The expediency of attracting fuzzy logic in the problem of selecting the optimal wheel for robust design of grinding operations, which are necessary to carry out by the best (base) tool, which would optimize all the target functions with the greatest efficiency, was confirmed.
2. As the results of fuzzy logic modelling in MATLAB, it was established that the wheel 5NQ46I6VS3 provides a comprehensive reduction of the position and scattering measures for all researched roughness parameters and form accuracy of part surfaces. Therefore, we can select it as a basic wheel in the robust design of grinding operations. It can be replaced by the wheels: 25AF46M10V-PO (*i*=7) and 5A46L10VAX (*i*=15), which also have integral assessment of CA “VH”.

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اختيار عجلات التجليخ بواسطة طبوجرافيا السطح لأجزاء من الفولاذ المقوى 30CHGSA

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الخلاصة

في هذا البحث، تم استخدام معلمات خشونة السطح: Ra، Rmax، Sm والتفاوت في الاستواء EFEmax لقطع طائرة مصنوعة من الفولاذ المقوى 30CHGSA، لتقييم قدرة القطع (CA) لعجلات التجليخ المصنوعة من مواد تجليخ تقليدية ذات مساميات مختلفة. وتتطلب هذه المعلمات ليس فقط تقييم القياسات، ولكن أيضا الدقة. وبالرغم من أن الطرق الإحصائية تسمح بالتنبؤ بها بشكل فردي، لكن ليس لديها القدرة على تقييمها بشكل شامل. ولذلك، تم اتخاذ المنطق الضبابي كاتجاه مبتكر في الهندسة الميكانيكية. ولفهم عملية النمذجة، تم استخدام حزمة خاصة من صندوق أدوات المنطق الضبابي (Fuzzy Logic Toolbox) في برنامج MATLAB. وثبت من النتائج أن العجلة 5NQ46I6VS3 (i=5) (d_i=0.878) كان لديها أفضل تقييم شامل من حيث CA وأن العجلة 34AF60K6V5A (i=14) (d_i= 0.383) كان لديها أقل معدل. ولذلك، يمكن اختيار 5NQ46I6VS3 كعجلة أساسية في عمليات التجليخ. وإذا لم تتوفر تلك العجلة في التصنيع، يمكن استخدام العجلات الحاصلة على تقييم "عالي جداً" من حيث قدرة القطع، مثل: 25AF46M10V-PO (i=7) أو 5A46L10VAX (i=15).