USE OF CLUSTER ANALYSIS FOR THE CLASSIFICATION OF ABRASIVE WHEELS IN TERMS OF GROUND FACE QUALITY OF 1933T2 ALUMINIUM ALLOY PARTS

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Abstract

Abrasive wheels are normally classified by the various signs that have to be assured at the manufacture stage. Until now, there has been a lack of the information on the assessment of the impact of abrasive wheels on output parameters of the part surface quality. This study uses the cluster analysis method to group subjects or phenomena under consideration subject to the measures of position (means, medians) and dispersion. Abrasive wheels of 14 types are classified into three groups that have similar cutting power in terms of the quality of 1933T2 high-strength aluminium alloy ground parts. The first cluster comprises the following wheels: 37C46I12VP, 37C(46,60,80)K12VP, 39C(46,80)(I,K)12VP, 08C(46,70)12V01(P01,P02), 63C40L7V; second – 5SG46K12VXP, TGX80I12VCF; third – 39C(46,60)K8VK. It has been established that, other than Russian abrasive tool 63C40L7V, the first cluster comprises high-porous wheels (HPW) by Norton and Mole mad of 12th structure that yield the most precise forms and micro-hardness of parts. Cluster 3 comprises two Norton wheels with normal pores (grade 8) that yield the cleanest surface: one-two categorial values (GOST 2789–79) lower than HPW. Cluster 2 wheels were tested and showed the lowest performance.

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Keywords: Flat grinding, abrasive wheels, nonparametric statistics, median, measure of dispersion, cluster analysis.

I. Introduction

Machine engineering cannot advance without improving finish machining operations that ensure high-quality and operational output characteristics of parts and machines. Grinding is the most common high-performance way to obtain finished critical parts with stable quality parameters. In the nearest future, grinding technology development trends will be determined by high finish standards and enhanced performance requirements. To develop this trend, abrasive tools must meet part process requirements and ensure equipment capabilities and properties of the work material.

All abrasive wheels are classified by various signs: shape, geometry, type and grade of abrasive material, etc. that must be ensured at the manufacture stage. When choosing wheels, their individual signs such as hardness or grain may prove to matter more than the type of abrasive. Until now, there has been a lack of assessment of the impact of wheels on output parameters of the part surface quality presented as full (integrated) estimates. The most important output parameter when grinding is the part roughness that comprises nine normalized parameters. Another important quality measure of parts and articles is the accuracy of their manufacturing, the role of which increases with increase in loads and relative motion rates and reliability requirements. Surface micro-hardness reflects abrasive tool thermodynamic impact on a ground part and its increase results in higher reliability of machines.

The cluster analysis (CA) method enables multidimensional clustering of subjects or phenomena under study into the groups that characterize their homogeneity in a sense. It is assumed that the source data may be of a considerable volume, i.e. both the number of objects under observation and signs describing these objects may be a lot bigger. The main benefit of CA is that it enables object clustering by a set of signs instead of a single sign. Unlike most statistical methods, CA does not impose any restrictions on the type of objects under study, which allows to study a host of source data of virtually any nature. It enables consideration of the major data multidimensionality effect; it broadens possibilities for laconic and simpler formation of multivariate structures; it helps reveal real not directly observed regularities using the factors or main components obtained.

The objective of this study is to cluster abrasive wheels by cutting power (CP) into the classes, each of which matches a certain group. Observations included in the same group feature the same probability of wheel CP estimate, which further on ensures the equal surface quality of ground parts. Statistica 6.1.478.0 was chosen for CA.

II. Study Method

It organically comprises three consecutive stages: real experiment conditions; method of experimental data interpretation based on statistical methods and CA.
Real Experiment Conditions: Experiments were conducted with the abrasive wheel face in line with the pendulum grinding pattern in the following constant conditions: 3G71М flat surface grinder; straight section abrasive wheels of 01 (1) shape with dimensions 250×20×76 mm; operational parameters: cutting speed \( v = 35 \) m/s, longitudinal feed \( s_l = 7 \) m/min, cross feed \( s_c = 1 \) mm/double pass, cutting depth \( t = 0.015 \) mm, interpass allowance \( z = 0.15 \) mm, lubricant-coolant– 5% Akvol-6 emulsion (TC 0258–024–001482–98) sprinkled onto a blank in the amount of 7–10 l/min; test object – samples of 1933Т2 high-strength aluminium alloy (\( \sigma_{USt} = 480–490 \) MPa; \( \sigma_f = 175 \) MPa) with dimensions \( L \times B \times H = 40 \times 40 \times 45 \) mm ground in the area of \( L \times B \). The wheel spindle was lowered to \( t \) depth when the bed table with the blank was moved to left most position in reference to the operator. Since the \( s_c \) stepping pattern is selected in mm/double pass and the abrasive tool rotates clockwise, the table operational stroke is from left to right and it occurs when the wheel counter-penetrates the blank. Its reverse stroke is deemed to be sparking-out; it finally forms the grinding surface topography in the context of climb cutting. The samples were secured on the clamp plate of the modular work holder with clamp straps, which ruled out the error of locating when forming form deviations.

As will be shown below, the statistical approaches, the feasibility of which is conditioned by the statistically distributed nature of grinding were used to interpret observations. In this case, it is feasible to represent the general grinding output parameter as \( y \equiv q v \) variable, where \( qv \) indices comprise the following handy and concise transient data of the process: \( e \) – abrasive wheel characteristics; \( q \) – univariate frequency distributions; \( v \) – number of replicate tests equal to \( v = 1; 30 \). Uneven indices \( q = 1, 3, 5, \ldots \) reflect the measures of location for each surface topography parameter and even indices \( q = 2, 4, 6, \ldots \) reflect matching measures of dispersion.

The characteristics of the wheels under study \( e = 1; 14 \): 1 – 37C46I12VP, 2 – 37C46K12VP, 3 – 37C60K12VP, 4 – 37C80K12VP, 5 – 39C46I12VP, 6 – 39C46K12VP, 7 – 39C80K12VP, 8 – 39C46K8VK, 9 – 39C60K8VK, 10 – 5SG46K12VXP, 11 – TGX80I12VCF (Altos), 12 – 63C40L7V, 13 – 08C070I12V01P01, 14 – 08C046I12V01P02. Tools \( e = 1; 9; 12; 14 \) made of silicon carbide: green –39С, 63С, 08С, black – 37С. Wheels with 5G sinterkorund grains and TGX fibrous grain are experimentally included in the study to check if they can be used to grind aluminium alloy parts. All the tools other than \( e = 8, 9, 12 \) are high-porous wheels (HPW) with 12th structure.

Silicon carbide is the hardest of all conventional abrasives, although quite brittle. It is used to make wheels for iron castings, hard metals, glass and stone. It also features high performance when grinding aluminium and its alloys.

The part ground face quality was assessed by: roughness factors – \( R_a, R_{max}, S_m \), measured parallel to vector \( s_c \); flatness fault factors – \( EFE_{max}, EFE_a, EFE_q \), referred to as highest, arithmetic mean and mean square; micro-hardness \( HV \). Their measuring and calculation methods are provided in.
Method of Experimental Data Interpretation based on Statistical Methods: Considering instability of the grinding process and random nature of tool surface topography formation, it is feasible to present observations as sets:

\[
\{y_{eq}\}, e = 1; 14, q=1,3,5,...,27, v = 1; 30, \quad (1)
\]

the elements of which are independent random variables (RV).

Statistical methods are divided into two groups: parametric and nonparametric, in particular, rank group. Each has its “own field” for the efficient application. The first method requires compliance with the two restrictions imposed on RV (1): homogeneity of dispersion deviations and normality of distributions. The grinding requirements provided are most often violated to one degree or another, which may bring about major displacement of parametric estimators. In this case, it makes more sense to use rank tests. They do not use properties of a particular family of distributions, which makes them superior to their competitor from the normal theory “in their own field”. Statistical methods yield the following information on univariate frequency distribution (1):

– by the measures of position (reference values),

mean \( \bar{y}_{eq} = y_{eq} \), \( e = 1; 14, q=1,3,5,...,27 \)

median \( \tilde{y}_{eq} \); \( e = 1; 14, q=1,3,5,...,27 \)

– by the measures of dispersion (precision), \( e = 1; 14, q=2,4,6,...,28 \)

standards of deviation \( S_{Deq} \), \( e = 1; 14, q=2,4,6,...,28 \)

ranges \( R_{eq} = |y_{max} - y_{min}|_{eq} \), \( e = 1; 14, q=2,4,6,...,28 \)

quartile latitudes \( Q_{Leq} = |y_{0.75} - y_{0.25}|_{eq} \), \( e = 1; 14, q=2,4,6,...,28 \)

The parametric method is based on (2), (4), (5) and rank statistics is based on (3), (6). (2) – (6) testing criteria and results are discussed in [24]. The grinding practice has shown that RV requirements imposed by the parametric method are not fully met, so this study uses its competitor from nonparametric statistics with (3) and (6) parameters.

**Cluster Analysis Method:** Suppose \( G = \{G_1, G_2 ,... G_e \} \) set means \( e \) of objects (individuals) belonging to a certain population. In our study, \( e = 1; 14\). Wheel characteristics are used as such. Let us also assume that there is a set of quantitative measurements \( C = \{C_1, C_2 ,... C_q \}^T \) (\( \tau \) is a vector transformation sign) that each individual from \( G \) has. These are surface quality parameters. When nonparametric statistics is used, they are described by roughness – \( R_a(\tilde{y}_{e1}, QL_{e2}), R_{max}(\tilde{y}_{e3}, QL_{e4}), S_m(\tilde{y}_{e5}, QL_{e6}) \); flatness faults – \( EFE_{max}(\tilde{y}_{e7}, QL_{e8}), EFE_{a}(\tilde{y}_{e9}, QL_{e10}), EFE_{d}(\tilde{y}_{e11}, QL_{e12}) \); micro-hardness – \( HV(\tilde{y}_{e13}, QL_{e14}) \).

When implementing CA, \( G = \{G_{eq}\} \) sets should be divided into \( K \geq 1 \) clusters (subsets) so that each \( G_{eq} \) object belongs to one and only one subset that has similar ob-
jects. As the same time, objects belonging to different clusters should be heterogeneous. CA task solution is the division that conforms to a certain criterion of optimality. It may be a certain composed function that reflects levels of desirability of different methods of division and clustering. It is commonly referred to as an objective function.

CA method comprises the following consecutive stages: data standardization; finding distances between objects and clusters.

Standardization of variables. Signs are most often reflected in various parameters and units, which is why they have to be converted to dimensionless values:

\[
\begin{align*}
    z_q &= \frac{y_q - \bar{y}}{\sigma_y}, \quad q = 1,3,5, \ldots ,27 \quad (7) \\
    z_{q+1} &= \frac{QL_q - QL_{q+1}}{\sigma_{QL_{q+1}}}, \quad q = 2,4,6, \ldots ,28 \quad (8)
\end{align*}
\]

where \(\bar{y}_q\) and \(QL_{q+1}\) are mean medians and quartile widths for wheels \(e = 1;14\) by one of surface topography parameters; \(\sigma_y\) and \(\sigma_{QL_{q+1}}\) are mean-square deviations of \(y_q\) and \(QL_{q+1}\).

Finding the distance (metrics) between objects. CA introduces the notion of distance (metrics) for the quantitative estimation of similarities. Similarity of objects classified is established depending on the metric distance between them. Thus, distances between \(d(z_i, z_j), (i,j) \in \text{vector pairs}\) may be presented as a distance matrix:

\[
\Delta = \begin{bmatrix}
    0 & d_{i2} & \cdots & d_{ij} & \cdots & d_{ie} \\
    d_{i2} & 0 & \cdots & d_{ij} & \cdots & d_{ie} \\
    \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
    d_{ij} & d_{i2} & \cdots & 0 & \cdots & \cdots \\
    \vdots & \vdots & \cdots & 0 & \cdots & \cdots \\
    d_{ie} & d_{i2} & \cdots & d_{ij} & \cdots & 0
\end{bmatrix} \quad (9)
\]

It is a non-negative real function that meets the following expressions:

\[d_{ij} \geq 0, d_{ij} = d_{ji}, d_{ij} + d_{ic} \geq d_{ic} \text{ and } d_{ii} = 0.\]

To find the distance between objects, the Manhattan distance (taxicab geometry) has been used since it is the most powerful one. For two objects \(i\) and \(j\), it is deduced from (10).

Manhattan distance (taxicab geometry) is defined as a sum of absolute differences by coordinates:

\[
d_M(z_i, z_j) = \sum_{k=1}^{14} |z_{ik} - z_{jk}|, (i,j) \in \text{vector pairs} [e = 1;14] \quad (10)
\]

CA hierarchic algorithms may be of two types – agglomeratic and divisional. In agglomeratic procedures, the division comprising \(K\) one-element classes is starting and the division comprising one class is ending, whereas it is vice versa in divisional procedures. The principle of operation of hierarchic agglomeratic (divisional) algorithms
implies consecutive agglomeration (division) of clusters, i.e. creation of a hierarchic class structure. Normally, classification result is represented as a dendrogram, a chart that reflects consecutive agglomeration of two clusters into one specifying distances between them.

**Distance between Clusters:** At the first stage, when each object represents an individual cluster, distances between these objects are determined by a chosen measure. However, when multiple objects are grouped together, there is a question as to how to find the distance between clusters. In other words, a rule of aggregation or connection for two clusters is needed.

There is a good deal of clustering methods. This study is based on the Ward’s method that uses the sum of squared deviations within cells as an objective function. The latter is nothing but only a sum of squared distances between each point (object) and mean of the cluster comprising this object. The two clusters that result in the minimum increase in the objective function, i.e. the sum of squared (SS) deviations within cells are combined at each stage. This method is targeted at the aggregation of close clusters.

## III. Results and their Discussion

Testing (1) for the homogeneity of dispersions (acceptance of null hypotheses $H_0$) for $e = 1; 14$ sets is based on criteria ($m = 1; 3$): 1 – Levene, 2 – Hartley, Cochren and Bartlett (represented as an aggregate in the program), 3 – Brown-Forsythe. Its results are provided in table 1. It has been found that all $H_0$ surface topography parameters under (11) were accepted on the 5% confidence level, i.e. the difference between deviation dispersions is of random nature.

**Table 1: Testing (2) for the homogeneity of dispersions (11) for sets $e = 1; 14$**

| Parameter | $H_0$ homogeneity of dispersions: $\alpha_{em} < 0.05$ (11) | Acceptance $H_0$ |
|-----------|-------------------------------------------------|------------------|
|           | $m=1$ | $m=2$ | $m=3$ |
| $R_{e1}$  | 0.001 | 0.001 | 0.001 | + |
| $R_{max1}$ | 0.001 | 0.001 | 0.001 | + |
| $S_{m1}$  | 0.001 | 0.001 | 0.003 | + |
| $EFE_{max}$ | 0.001 | 0.001 | 0.001 | + |
| $EFE_{e}$  | 0.001 | 0.001 | 0.001 | + |
| $EFE_{q}$  | 0.001 | 0.001 | 0.001 | + |
| $HV$       | 0.003 | 0.001 | 0.004 | + |

Note. Criterion m: 1 – Levene, 2 – Hartley, Cochren and Bartlett, 3 – Brown-Forsythe

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Table 2: Checking the normality of distributions (12) by the Shapiro-Wilk criterion

| Parameter (q) | $H_0$ normality of distributions: $\alpha_{eq} > 0.5$ (12) |
|---------------|----------------------------------------------------------|
|               | Wheels e 1 2 3 4 5 6 7 8 9 10 11 12 13 14 |
| $R_a$ (1)     | 0.18 0.20 0.23 0.03 0.03 0.72 0.00 0.00 0.02 0.82 0.02 0.13 0.54 0.12 |
| $R_{max}$ (3) | 0.16 0.08 0.15 0.19 0.01 0.24 0.00 0.00 0.01 0.38 0.27 0.72 0.09 0.79 |
| $S_m$ (5)     | 0.42 0.02 0.13 0.00 0.02 0.09 0.00 0.33 0.01 0.13 0.03 0.17 0.14 0.68 |
| $EFE_{max}$ (7)| 0.00 0.00 0.06 0.01 0.00 0.19 0.13 0.11 0.07 0.53 0.01 0.11 0.66 0.13 |
| $EFE_q$ (9)   | 0.03 0.03 0.39 0.00 0.00 0.72 0.81 0.30 0.16 0.13 0.04 0.03 0.23 0.25 |
| $EFE_q$ (11)  | 0.01 0.00 0.48 0.00 0.00 0.38 0.38 0.63 0.26 0.02 0.94 0.05 0.20 0.11 |
| $HV$ (13)     | 0.12 0.00 0.11 0.57 0.12 0.23 0.29 0.04 0.08 0.25 0.02 0.00 0.64 0.18 |

Note. Wheels e: 1 – 37C46I12VP, 2 – 37C46K12VP, 3 – 37C60K12VP, 4 – 37C80K12VP, 5 – 39C46I12VP, 6 – 39C46K12VP, 7 – 39C60K12VP, 8 – 39C80K12VP, 9 – 39C60K8VK, 10 – 5SG46K12VXP, 11 – TGX80I12VCF, 12 – 63C40L7V, 13 – 08С070I12V01P01, 14 – 08С046I12V01P02

Normal distribution laws were analysed using Shapiro-Wilk statistics for all indicators individually and for each abrasive wheel. Thus, the total number of analysed situations was $N=7\times14=98$. Testing results (table 2) have shown that (12) were violated in 14 out of 98 cases shown in the table. In view of what has been said above as to normality of distributions with “its own field”, nonparametric statistical method characterized by measures (3) and (6) was chosen for interpretation (1).

Part quality parameters have been normalized using “Standardize” tool in Statistica software package. In order to reduce the publication volume, table 4 provides results of 4 (7), (8) in full only for wheels $e = 1; 4$.

distances for all the matrix lines and columns (9) have been obtained for (10), which are shown in table 4. Their methods are presented in.

Table 3: Normalized signs for wheels $e = 1; 4$

| Sign $q = 1; 14$ | Observed object |
|------------------|-----------------|
|                  | 1   | 2   | 3   | 4   |
|                  | $Z_{1q(y)}$ | $Z_{1q(QL)}$ | $Z_{2q(y)}$ | $Z_{2q(QL)}$ | $Z_{3q(y)}$ | $Z_{3q(QL)}$ | $Z_{4q(y)}$ | $Z_{4q(QL)}$ |
| $R_a$ (1,2)      | 1.01 | 0.62 | 0.30 | 1.46 | 0.18 | 0.17 | -1.14 | -0.40 |
| $R_{max}$ (3,4)  | 0.97 | -0.86 | 0.01 | 1.49 | -0.03 | 0.46 | -0.97 | -0.55 |
| $S_m$ (5,6)      | 0.86 | 1.89 | -0.75 | -0.90 | -0.70 | 0.52 | -1.59 | -0.48 |
| $EFE_{max}$ (7,8) | -0.34 | 1.86 | -0.98 | -0.51 | -0.77 | -1.30 | -0.77 | -0.31 |
### Table 4: Matrix of the Manhattan distance

|      | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   | 13   | 14   |
|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 1    | 0.0  | 22.  | 19.  | 18.  | 18.  | 18.  | 11.  | 10.  | 24.  | 26.  | 16.  | 17.  | 11.  | 15.  |
| 2    | 22.  | 0.0  | 12.  | 12.  | 15.  | 14.  | 17.  | 18.  | 18.  | 18.  | 18.  | 19.  | 17.  | 15.  |
| 3    | 19.  | 12.  | 0.0  | 13.  | 13.  | 13.  | 13.  | 12.  | 12.  | 16.  | 15.  | 15.  | 13.  | 13.  |
| 4    | 18.  | 12.  | 13.  | 0.0  | 20.  | 14.  | 11.  | 13.  | 12.  | 17.  | 16.  | 14.  | 13.  | 7.8  |
| 5    | 18.  | 15.  | 13.  | 20.  | 12.  | 22.  | 24.  | 32.  | 27.  | 23.  | 18.  | 19.  | 19.  | 19.  |
| 6    | 11.  | 14.  | 13.  | 12.  | 0.0  | 13.  | 21.  | 23.  | 17.  | 15.  | 10.  | 11.  | 13.  | 3.   |
| 7    | 10.  | 17.  | 16.  | 11.  | 22.  | 13.  | 0.0  | 18.  | 19.  | 17.  | 20.  | 13.  | 8.   | 11.  |
| 8    | 24.  | 18.  | 16.  | 12.  | 12.  | 21.  | 18.  | 8.   | 13.  | 11.  | 23.  | 10.  | 11.  | 10.  |
| 9    | 26.  | 18.  | 22.  | 32.  | 23.  | 19.  | 8.   | 0.0  | 12.  | 12.  | 22.  | 13.  | 15.  | 11.  |
| 10   | 16.  | 21.  | 19.  | 27.  | 17.  | 17.  | 13.  | 12.  | 6.7  | 13.  | 15.  | 17.  | 15.  | 15.  |
| 11   | 17.  | 18.  | 17.  | 23.  | 15.  | 20.  | 11.  | 12.  | 6.7  | 13.  | 14.  | 15.  | 14.  | 14.  |
| 12   | 11.  | 16.  | 15.  | 18.  | 10.  | 13.  | 23.  | 22.  | 13.  | 0.0  | 13.  | 13.  | 15.  | 15.  |
| 13   | 15.  | 16.  | 13.  | 19.  | 11.  | 10.  | 13.  | 15.  | 13.  | 13.  | 8.   | 0.0  | 5.1  | 115  |

Note. Wheels e: 1 – 37C46L12VP, 2 – 37C46K12VP, 3 – 37C60K12VP, 4 – 37C80K12VP
Fig. 1: Vertical dendrogram of the observed objects obtained using the Ward method and the Manhattan distance (10)

The first stage of CA in the software uses a vertical dendrogram (Fig. 1) and diagram of associations (Table 5). Fig. 1 shows observed objects – codes of $e = 1; 14$, wheels under study on X axis and aggregation distances on Y axis. In Table 5, the first column contains distances of object aggregations in a corresponding cluster. Each line of the table describes the cluster composition by signs of $e = 1; 14$ wheels in the step being performed.

Table 5: Diagram of associations: Manhattan distance, Ward’s method

| $d_{as}$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|----------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|
| 5.13     | 13| 14|
| 6.65     | 10| 11|
| 8.13     | 8 | 9 |
| 9.32     | 4 | 13| 14|
| 10.13    | 6 | 12|
| 10.74    | 1 | 7 |
| 12.65    | 2 | 3 |
| 14.29    | 1 | 7 | 6 | 12|
| 15.15    | 2 | 3 | 5 |
| 17.58    | 8 | 9 | 10| 11|
| 25.29    | 1 | 7 | 6 | 12| 4 | 13| 14|

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It follows from fig. 1 that all the $e = 1; 14$ wheels under study may be preliminarily divided into three groups (table 6).

The dendrogram should be studied from top for each wheel in its own cluster. Once you start to go down, the abrasive wheels that “come into a closer contact with each other” come together and make up a cluster. Each unit of the above diagram represents an aggregate of two or more clusters. Position of the units on Y axis determines the distance, at which they were combined into relevant clusters. One may assume from the visual presentation of results that the wheels make up three natural clusters. Let us check this assumption by segregating source data using the K-mean method into 3 clusters.

**Table 6: Preliminary classification of abrasive wheels on a vertical dendrogram**

| Cluster $K = 1; 3$ | Wheel          |
|-------------------|----------------|
| 1                 | $e = 1, 7, 6, 12, 4, 13, 14, 2, 3, 5$ |
| 2                 | $e = 8, 9$     |
| 3                 | $e = 10, 11$   |

Note. Wheels e – shown in table 2

Select the *K-Mean Method Clustering* window in the home panel of the *Cluster Analysis* module.

**Fig.2:** Diagonal window while clustering using the K-mean method

Press *Variables*, select *All*, in the *Objects – Observations (lines)* field, set 3 division clusters.
The *K-mean method* is as follows: calculations start with K random observation (in the case under study, K=3) that become group centers, following which the cluster object composition changes in order to minimize variability within clusters and maximize variability between clusters. Each subsequent observation (K+1) belongs to the group with the minimum measure of similarity to the center of gravity. After the cluster composition has changed, the new center of gravity is found (in the case under study – as a vector of means). The algorithm goes on until the cluster composition no longer changes. After classification results have been obtained, the mean indicator of each cluster may be calculated in order to assess differences between them.

Press *Cluster Elements and Distances* in the *K-Mean Method Results* window to view the observations comprised in each cluster. This option also displays Euclidean distances of objects from the centers (mean) of their corresponding clusters. The results obtained are given in Table 7. It has been found that the K-mean method results obtained comply with the preliminary classification provided in table 6 based on vertical dendrogram building results. According to the CP integral estimation of wheels, the first cluster comprised ten wheels: all HPWs by *Norton* $e = \frac{17}{10}, 7$, Russian wheel $63C40L7V (e=12)$ of standard porosity and two HPWs by *Molemad* – $08C046I12V01P02 (e=13)$ and $08C070I12V01P01 (e=14)$. Formally, K=1 wheels have equal CP. For this reason, there is a need to test wheels by differential exponents: $R_\alpha, EFE_{\max}, EFE_{\max}$, (table 8) that gives categorical values (CV) for $R_\alpha$ parameter and $TFE$ surface finish for $EFE_{\max}$ flatness fault in brackets.

### Table 7: Elements of the cluster and distance to the cluster center

| Cluster | 1 | 2 | 3 |
|---------|---|---|---|
| Wheel $e = \frac{17}{10}$ | 1 | 2 | 3 |
| Distance to the cluster center | 1.0 | 1.0 | 0.8 |

*Note. Wheels e – shown in table 2*
Table 8: Group mean parameters $R_a$, $EFE_{max}$ and HV

| Cluster $K = 1; 3$ | $R_a$, $\mu m$ | $EFE_{max}$, $\mu m$ | HV, MPa |
|-------------------|----------------|-----------------|-------|
| 1                 | 0.269 (0.32)   | 9.25 (TFE 6)    | 1,719.89 |
| 2                 | 0.330 (0.40)   | 18.98 (TFE 8)   | 1,567.36 |
| 3                 | 0.173 (0.20)   | 17.55 (TFE 8)   | 1,419.32 |

Note: Cluster: 1 – 37C46I12VP, 37C46K12VP, 37C60K12VP, 37C80K12VP, 39C46I12VP, 39C46K12VP, 39C80K12VP, 63C40L7V, 08C070I12V01P01, 08C046I12V01P02; 2 – 5SG46K12VXP; TGX80I12VCF; 3 – 39C46K8VK; 39C60K8VK.

According to study results, HPW grinding increases surface micro-roughness heights by one-two CVs, as the distance between cutting grains increases in their work surface, but, at the same time, thanks to their lower fouling, heat build up in the grinding area is reduced by 1.5–2 times. These papers lack the information on flatness faults. Everything mentioned in occurs when aluminium blanks are ground. Decrease in grinding temperatures when using HPW indirectly confirms an increase in micro-hardness of 1933T2 finished parts. In view of the above, it is feasible to use HPW of the first cluster in the two instances: during finish grinding of aluminium blanks when high requirements are imposed to their form precision; this results in reduced overheating of 1933T2 alloy, which overheating is inadmissible; during preparatory grinding under more productive conditions of stock removal. $K=3$ comprises Norton wheels made of green silicon carbide with normal pores (grade 8). Compared to the 1st cluster, they ensure decrease in $R_a$ from 0.269 to 0.173 $\mu m$, i.e. by two CVs. Their most feasible application is finish grinding of 1933T2 parts with reduced metal removal. The third place in terms of $R_a$ and $EFE_{max}$ parameters is occupied by sint-korund (e=10) and Altos (e=11) HPWs that turned out to be inefficient.

IV. Conclusions

1. The method of abrasive wheel CP classification based on cluster analysis has been developed. It features low labor intensity, environmental safety and broad usability in any applications with high efficiency, especially when large databases are handled.

2. This paper deems it feasible to divide wheels into 3 clusters: $K=1– e=1; 7, 12; 14; K=2 – e = 10.11; K=3 – e = 8.9$. 

3. It has been established that the wheels of the first cluster are the indisputable leader in terms of CP of all surface topography parameters. They should be used in the first place: for finish grinding of 1933T2 alloy aluminium blanks when high requirements are imposed to their form precision and for preparatory grinding under more productive conditions of stock removal.

4. The following wheels should be used when high requirements are imposed to the grinding surface roughness of 1933T2 alloy blanks: 39C(46;60)K12VP with normal pores.

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