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CLASSIFICATION OF FLAT INSTRUMENTAL PLATES BY TOPOGRAPHY OF GROUND SURFACE USING CLUSTER ANALYSIS

Yakov Iosifovich Soler, Van Canh Nguyen and Denis Yurievich Kazimirov
Irkutsk National Research Technical University, Lermontov Street, Irkutsk, Russia Federation
E-Mail: solera@istu.irk.ru

ABSTRACT

In the contemporary mechanical engineering, we often face the problem of classification of processed parts according to the different criteria. In this research, we used hierarchical cluster analysis (CA) to form the groups of six grades of tool steels according to flat grinding machinability by wheel 5NQ46I6VS3 (Norton Vitrium). The topography of parts was estimated according to ten parameters of roughness, measured in two orthogonal directions coinciding with the vectors of transverse and longitudinal traverses. It was revealed that for the classification three clusters should be assigned, they include: 1 - W18, W6Mo5, W9Co5, W9Mo4Co8; 2 - W12V3Co10Mo3; 3 - Cr12. Clusters are put into a sequence of the deterioration of the topography of ground surface and, first, for flatness deviation and a decrease of its micro-hardness.

Keywords: cluster analysis, classification of steels, metrics (distance), dendrogram, scheme of union, machinability, grinding

1. INTRODUCTION

At the present moment, in many branches of mechanical engineering a wide range of various materials is used. They differ from each other by their chemical content, metallography, physical and mechanical properties. They are often grouped according to the most important characteristics for particular operating conditions: electrical conductivity, magnetic properties, thermal conductivity, radiation resistance, cuttability, etc. [1-2]. The question arises: how to classify the materials according to many properties. The only way to solve this problem is to cut off the most criteria and the return to the small-sized classical tasks or to unite the criteria, replace the “bunches” of them by one, artificially built on its base. That is how the direction of “multidimensional analysis” appeared, which is efficient for the classification of objects of CA [3]. In English cluster means “bunch”, “bunch of grape”, “cluster of stars”, etc. This method of research was developed in the recent years due to the possibility of computer processing of large databases. It provides the distinguishing of compact groups of objects remote from each other, “natural” division of total into areas of the cluster. It is used when the initial data is presented in the form of proximity matrix or distances between the objects or in the form of points in the multidimensional space. Sets of the second type are the widest spread; for them CA is oriented to distinguish some geometrically remote groups, inside which the objects are close. This method allows taking into account the effect of significant data multidimensionality; it gives the possibility of laconic and simpler formation of multidimensional structures; it reveals objectively the existing, directly non-observable regularities by means of obtained factors or main components [3-5].

This research is devoted to the clustering of tool steels according to the quality of grinding surfaces using the hierarchical CA, the essence of which is in the sequential union of smaller clusters or in the division of them into smaller ones [3; 5]. Such approach to the estimation of grindability of steels is innovative. It is not practically used by mechanical engineers but it can decrease the labour-intensiveness of the development of standards of cutting modes and technological recommendations, in particular, grinding of dies and high-speed steel tools. The calculations were made using the program *Statistica* 6.1.478.0.

2. METHOD OF RESEARCH

The method of research includes three sequentially performed stages: conditions of the performance of natural experiment; interpretation of experimental data using the statistical methods and its clusterization.

2.1 Conditions of the performance of the natural experiment

Experiments were carried out by the peripheral of an abrasive wheel according to the scheme of pendulum grinding at the following unchangeable conditions: flat grinding machine model 3G71; wheel *Norton Vitrium*form 01, dimensions $250\times20\times76$ mm and characteristics 5NQ46I6VS3, cutting properties were accepted as the best among 16 tested wheels; technological parameters: cutting speed v_c = 35 m/s, longitudinal traverse s_l = 7 m/min, transversal traverse s_t = 1 mm/double pass, cutting depth t = 0.015 mm, operating allowance z = 0.15 mm, coolant cutting fluid 5% emulsion Akvol 6 (Technical Specifications 0258-024-0014842-98), supplied by watering on the workpiece in the amount of 7-10 l/min; the subject of the research is patterns of cylindrical form, dimensions: diameter D = 40 mm, height H = 40 mm, end served as a grinding surface; number of duplicating tests n=30 ($v=\overline{1;30}$).

Experimentally the observed objects $i=\overline{1;6}$ carry the following information of tool steels: 1 – W9Co5 (64-66 *HRC*), 2 – W9Mo4Co8 (66-68 *HRC*), 3 – W18 (64-66 *HRC*), 4 – W6Mo5 (62-64 *HRC*), 5 – W12V3Co10Mo3 (66-68 *HRC*), which are used to manufacture high-speed steel plates (HSSP) of assembled edge tools; $i=6$ – Cr12

(61-63 *HRC*) - for shape-generating parts of matrix and punches of cold stamping.

Main features for the estimation of topography of the tool surface were chosen: roughness parameters [9-10; 12] -R_{a1}, R_{z1}, R_{q1}, R_{max1}, S_{m1}, $t_{20(1)}$, $t_{50(1)}$, $t_{80(1)}$ (in parallel with s_{tr}), R_{a2}, R_{z2}, R_{q2}, R_{max2}, S_{m2}, $t_{20(2)}$, $t_{50(2)}$, $t_{80(2)}$ (in parallel withs_{l}); deviations from the planeness [13] – EFE_{max}, EFE_a, EFE_q and micro-hardness *HV* [11]. Methods of its measurement and calculation are specified in the works [14-15].

2.2 The interpretation of experimental data using statistical methods

Taking into consideration the instability of grinding process and accidental nature of the formation of topography of tool surface, the observations should be reasonably shown in the form of sets:

$$\{y_{iv}\},\ v=\overline{1;30}. \qquad (1)$$

Sets (1) should be analyzed using statistic methods divided into parametric and non-parametric, in particular, into rank sets. The studies [6-8] serve as the characteristics of the unidimensional distribution of frequencies for (1): for the first direction -medium $\bar{y}_i = y_{i\bullet}$, deviation standards $(SD)_i$, ranges $R_i = \left|y_{\max} - y_{\min}\right|_i$; for the second direction – medians $\tilde{y}_i$, quartile widths $QW_i = \left|y_{0.75} - y_{0.25}\right|_i$, covering 50% of observations (1). The first frequency for both statistics characterizes the measure of position (reference value), and the following one characterize the measure of dispersion (precision). Each of these directions of statistics has its own "field" for the efficient use in engineering [6-7].

2.3 The method of the performance of cluster analysis

CA allows using all these measures of position and dispersion without additional analysis of observations in order to find out the uniformity of dispersions and normality of distributions. To enlarge the databases each object is estimated by five homogeneous frequency distributions ($q=\overline{1;5}$): by two measures of position - $\bar{y}_i = y_{i\bullet}$ and $\tilde{y}_i$; by three measures of dispersion – (SD, R, QW)$_i$ – for each steel $i=\overline{1;6}$ and parameter of surface topography $j=\overline{1;20}$. Thus, every object in the research is presented by the features in total $N = q \times j = 5 \times 20 = 100$.

When realizing CA sets $G=\left\{G_{iN}\right\}$, $i=\overline{1;6}$, $N=\overline{1;20}$ should be divided into $C \geq 1$ clusters (subsets) for the reasons that every object G_{iN} belongs to the one and the only subset, and objects included in different clusters were in their general populations. Division into clusters shall satisfy some condition of optimality reflecting the level of desirability. They are called objective functions that approach to a minimum at some set of restrictions.

The method of clusterization includes the following stages performed sequentially: data standardization, determination of the distances between objects, determination of the distances between clusters.

2.4 Standardization (normalization) of variables (features).

Features can be reflected in different parameters and units. In such case, it is not possible to express the distance between them. They should be transformed into the non-dimensional values [3-4]. The program uses the transformation of the following type:

$$z = \left(y - \bar{y}\right)/\sigma \qquad (2)$$

where $\bar{y}, \sigma$ – average and root-mean-square deviation of y correspondingly.

2.5 A search of distance (metrics) between objects

In CA, for the qualitative estimation of similarity, the notion of metrics (distance) is introduced. The similarity of the classified objects is determined depending upon the metric distance between them. Thus, the distances between the pairs of vectors $d(y_i, y_j)$ can be presented in the form of the matrix of distances:

$$\Delta = \begin{bmatrix} 0 & d_{12} & \dots & d_{1j} & \dots & d_{1n} \\ d_{21} & 0 & \dots & d_{2j} & \dots & d_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ d_{i1} & d_{i2} & \dots & d_{ij} & \dots & d_{in} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ d_{n1} & d_{n2} & \dots & d_{nj} & \dots & 0 \end{bmatrix},\ d_{ii} = 0. \qquad (3)$$

The distance between objects is called an absolute value that corresponds to the axioms: $d_{ij} \geq 0$, $d_{ij} = d_{ji}$ and $d_{ij} + d_{jc} \geq d_{ic}$.

The main methods of determination of the distance between the objects are the following: linear, Euclidean, Euclidean square, Minkowskian generalized degree distance, Chebyshev distance and Manhattan distance (distances of city blocks). In this research, we used Euclidean distance and Manhattan distance because they showed itself the most powerful [3-5].

Euclidean distance is the most popular metrics in CA and represents a geometric distance in multidimensional space. Geometrically it unifies better the

objects in globular clusters and it is defined by the equation:

$$d_{Eij} = \left[\sum_{k=1}^{j} \left(y_{ki} - y_{kj} \right)^2 \right]^{1/2}. \quad (4)$$

Manhattan distance (distances of city blocks) is calculated as an average of differences according to coordinates:

$$d_M \left(y_i, y_j \right) = \sum_{k=1}^{j} \left| y_{ki} - y_{kj} \right|. \quad (5)$$

In most cases (5), it leads to the results according to (4). However, for it, the impact of some runs is decreasing in comparison with (4) because the coordinates are not squared.

Hierarchical algorithms of CA can be of two types - agglomerative and divisional. In agglomerative procedures, the initial stage is division, consisting of *n*simplex classes, and final stage - consisting of the same class; in division algorithm, it is vice versa. The principle of work of hierarchical agglomerative (divisional) algorithms consists in the sequential unification (division) of groups of elements, i.e. in the creation of the hierarchical structure of classes. Usually, such classification is presented in the form of a dendrogram, i.e. a graph reflecting the sequential unification of two clusters into one specifying the distance between them.

2.6 The distance between clusters

At the first stage, when every object is a single cluster, distances between these objects are determined by the selected measure. However, when several objects are connected together, the question arises of how to determine the distance between the clusters. In other words, there is a rule of union or the connection of two clusters.

There are many methods of the union of clusters: distance of the "nearest neighbor" (single connection), a distance of "remote neighbor" (complete connection), unweighted pairwise average distance, weighted pairwise average distance, unweighted centroid method, weighted centroid method (median) and Ward's method [3-5].

In this research, two methods to determine the distance between the clusters are used: unweighted pairwise average distance and Ward's method.

In the method of unweighted pairwise average, the distance between two clusters is calculated as an average distance between all pairs of objects in them. The method is efficient when the objects actually form various groves. However, it works equally well in extensive (chain type) clusters. In Ward's method intragroup sum of squares of deviations was used as an objective function, that is, the sum of squares of distances between each point (objects) and an average of the cluster containing this object. At each stage, such two clusters are united, and they lead to the minimal increase of objective function, that is, the intragroup sum of squares (*SS*). This method was directed to the union of close located clusters.

The research uses two methods of determination of the distance of clusters at the classification of machinability groups of tool materials. Then it is necessary to reveal which one suits for classification of ground tools.

3. RESULTS AND DISCUSSIONS

Quality parameters of parts are measured in different units: in μm for roughness and macro deviations; in percent for relative bearing length and in MPa for micro-hardness. Normalization of its dimensionality was carried out using the tool "Standardization" in program package *Statistica*: *Open data file* $\Rightarrow$ *Data* $\Rightarrow$ *Standardize*. After activation of line "Standardize", the box appears on the screen of PC for setting the parameters of data normalization: *variables* – all 10 features are selected; *observations*- all 6 materials are selected. Obtained normalized features according to (2) for HSSP $i = \overline{1;2}$ are shown in full in Table-1.

Table-1. Normalized features for HSSP $i = \overline{1;2}$.

Feature $j = \overline{1;20}$	Observable object									
	W9Co5					W9Mo4Co8				
	$y_{\bullet}$	$\tilde{y}$	*SD*	*R*	QW	$y_{\bullet}$	$\tilde{y}$	*SD*	*R*	QW
R_{a1}	0.89	0.97	-0.24	-0.56	0.82	-0.19	0.07	0.00	0.56	-0.41
R_{z1}	0.04	0.22	-0.39	-0.63	-0.95	-0.52	-0.39	-0.74	-1.12	-0.38
R_{q1}	0.74	0.93	-0.53	-0.50	0.00	-0.15	-0.27	-0.04	0.00	0.00
$R_{\max 1}$	0.56	0.92	-0.42	-0.24	1.33	-0.27	-0.09	-0.41	-0.90	0.44
S_{m1}	1.21	1.30	-0.07	-0.43	1.43	0.90	0.68	1.90	1.90	0.10
$t_{20(1)}$	1.30	1.25	0.63	1.03	-0.84	0.53	0.71	1.01	1.00	0.93
$t_{50(1)}$	1.12	1.25	-0.04	-0.58	0.38	0.18	0.32	1.17	1.50	0.35
$t_{80(1)}$	0.15	0.58	0.73	0.10	1.08	-0.23	-0.58	-0.51	-0.87	0.52
R_{a2}	-0.22	-0.41	-0.01	0.44	-0.41	-0.37	-0.41	1.16	1.11	-0.41
R_{z2}	-0.28	0.63	-0.33	-0.19	-0.32	-0.38	-1.63	1.22	0.73	0.65
R_{q2}	-0.30	0.65	-0.48	-0.46	0.41	-0.22	-1.29	1.08	0.46	0.41
$R_{\max 2}$	-0.21	0.29	-0.55	-0.72	-0.10	-0.04	-1.17	1.08	0.95	1.64
S_{m2}	0.35	0.05	1.65	1.77	0.42	-0.76	-0.53	-1.00	-0.54	-2.00
$t_{20(2)}$	-0.91	-0.85	-1.29	-0.90	-0.38	-0.36	-0.50	-0.30	-0.80	-0.17
$t_{50(2)}$	-0.54	-0.60	1.00	-0.17	0.57	-0.53	-0.47	-0.19	-0.40	0.20
$t_{80(2)}$	-0.58	-0.21	1.29	1.06	1.46	-0.26	-0.15	0.95	1.05	0.44
$EFE_{\max}$	0.47	0.36	0.01	0.42	-0.65	0.08	0.36	0.34	0.78	-0.65
EFE_a	-0.49	-0.39	0.07	0.57	-0.27	0.33	0.47	0.46	1.17	-1.15
EFE_q	-0.30	-0.24	0.00	0.66	-0.35	0.25	0.32	0.59	1.19	-1.15
HV	0.10	0.07	0.99	1.36	0.44	1.74	1.74	0.03	0.16	1.26

For plates W18, W6Mo5 ($i = \overline{3;4}$) and W12V3Co10Mo3, Cr12 ($i = \overline{5;6}$) normalized features aiming to decrease the data volume are given in the Tables 2, 3 in a short variant for the most significant parameters of surface topography.

Table-2. Selected normalized features at grinding $i = \overline{3;4}$.

Feature	Observable object									
	W18 (*i*=3)					W6Mo5(*i*=4)				
	$y_{\bullet}$	$\tilde{y}$	*SD*	*R*	QW	$y_{\bullet}$	$\tilde{y}$	*SD*	*R*	QW
R_{a1}	0.24	0.07	-0.52	-0.56	-1.63	-0.26	-0.37	0.32	0.00	0.82
$R_{\max 1}$	0.44	0.61	0.07	0.26	0.15	-0.23	-0.09	-0.14	0.10	0.44
S_{m1}	-1.10	-1.32	-0.35	-0.13	-0.94	0.35	0.35	0.06	0.17	0.87
S_{m2}	-0.48	-0.51	-0.46	-0.77	0.48	-0.23	-0.56	0.26	0.24	0.70
$EFE_{\max}$	-1.46	-1.49	-0.94	-1.02	-0.65	-0.85	-0.87	-1.34	-1.38	-0.65
HV	0.45	0.47	-0.13	-0.51	0.69	-0.72	-0.71	-0.92	-0.90	-0.10

Table-3. Selected normalized features at grinding $i = \overline{5;6}$.

Feature	Observable object									
	W12V3Co10Mo3 (*i*=5)					Cr12 (*i*=6)				
	$y_\bullet$	$\tilde{y}$	***SD***	***R***	**QW**	$y_\bullet$	$\tilde{y}$	***SD***	***R***	**QW**
R_{a1}	-1.73	-1.72	-1.27	-1.12	-0.41	1.03	0.97	1.72	1.68	0.82
$R_{\max 1}$	-1.71	-1.87	-1.00	-0.98	-1.03	1.21	0.53	1.90	1.76	-1.33
S_{m1}	-0.20	-0.01	-0.63	-0.72	-0.38	-1.16	-1.00	-0.92	-0.80	-1.07
S_{m2}	-0.75	-0.44	-0.90	-0.94	0.05	1.86	1.99	0.44	0.23	0.35
$EFE_{\max}$	0.45	0.36	1.39	1.14	1.29	1.32	1.28	0.53	0.06	1.29
HV	-0.78	-0.87	-1.23	-1.07	-1.37	-0.80	-0.71	1.27	0.95	-0.92

According to (4), (5) the distances are obtained $(d_E, d_M)_{ij}$ of all lines and columns of Table-3, that are shown in the Tables 4, 5 correspondingly.

Table-4. Matrix of Euclidean distance according to (4).

Observer	W9Co5	W9Mo4Co8	W18	W6Mo5	W12V3Co10Mo3	Cr12
W9Co5	0.0	10.3	12.9	9.1	14.2	16.0
W9Mo4Co8	10.3	0.0	13.2	11.6	14.6	16.3
W18	12.9	13.2	0.0	9.5	15.1	16.4
W6Mo5	9.1	11.6	9.5	0.0	13.0	15.7
W12W3Co10Mo3	14.2	14.6	15.1	15.1	0.0	20.0
Cr12	16.0	16.3	16.4	16.4	20.0	0.0

Table-5. Matrix of Manhattan distance according to (5).

Observer	W9Co5	W9Mo4Co8	W18	W6Mo5	W12V3Co10Mo3	Cr12
W9Co5	0	81	102	70	109	136
W9Mo4Co8	81	0	112	88	117	143
W18	102	112	0	68	127	137
W6Mo5	70	88	68	0	101	136
W12W3Co10Mo3	109	117	127	101	0	180
Cr12	136	143	137	136	180	0

Distances (4) and (5) obtained in the Tables 4, 5 are subjected to clusterization, and for this,we call up the module "cluster analysis" in the program via menu: *Analysis* $\Rightarrow$ Multidimensional explorative analysis $\Rightarrow$ Cluster analysis. Then we choose the method of clusterization- hierarchical classification. Then clusterization dialogue box by means of hierarchical method with characteristics appears: variable - all features for analysis; Data file – initial data; objects – observations (lines); rule of union -unweighted pairwise average or Ward's method; proximity measure - Euclidean distance or Manhattan distance; deletion of missed data - replacement of average or line-by-line deletion.

After setting of all necessary parameters for clusterization, click OK and the box appears with the results of classification. In the program at the first stage, we used the vertical dendrogram (Figures 1, 2) and schemes of the union (Tables 6, 7). In the Figures 1, 2 along the abscissa axis there are observed objects - code of steels $i = \overline{1;6}$, and along the ordinate axis, there are distances of unions. In the Tables 6, 7 the first column contains the distances for the corresponding clusters, the latter is the coefficients of unions (K_u) for two sequential clusters. Each line in the table characterizes the content of cluster of the performed stage.

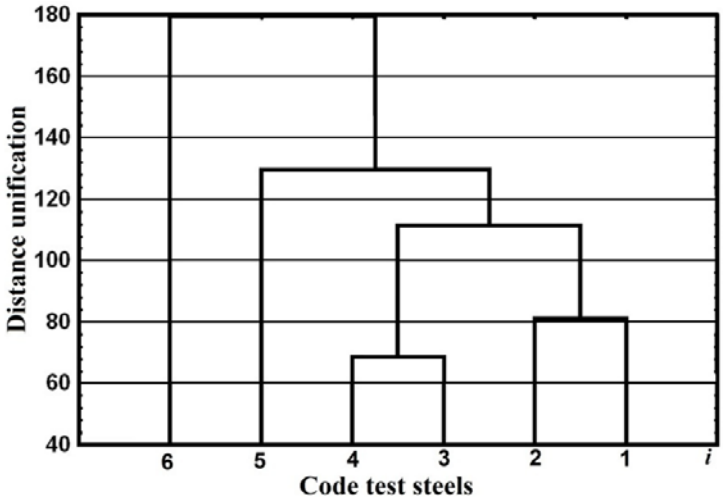

Figure-1. Vertical dendrogram of observed objects, obtained by Ward's method and (4).

Table-6. Scheme of the union. Manhattan distance.

Distance of clusters	Ward's method						
	Object 1	Object 2	Object 3	Object 4	Object 5	Object 6	K_u
68.42	W18	W6Mo5					1.00
80.94	W9Co5	W9Mo4Co8					1.18
111.39	W18	W6Mo5	W9Co5	W9Mo4Co8			1.38
129.69	W9Co5	W9Mo4Co8	W18	W6Mo5	W12V3Co10Mo3		1.16
179.37	W9Co5	W9Mo4Co8	W18	W6Mo5	W12V3Co10Mo3	Cr12	1.38
Method of unweighted pairwise average							
68.42	W18	W6Mo5					1.00
80.94	W9Co5	W9Mo4Co8					1.18
93.04	W18	W6Mo5	W9Co5	W9Mo4Co8			1.15
113.65	W9Co5	W9Mo4Co8	W18	W6Mo5	W12V3Co10Mo3		1.22
146.67	W9Co5	W9Mo4Co8	W18	W6Mo5	W12V3Co10Mo3	Cr12	1.29

Figure-1 shows a dendrogram of observed objects when using Ward's method and Manhattan distance. It illustrates that at the first stage W18 was united with W6Mo5, and W9Co5 was united with W9Mo4Co8. The distances between them characterize the deviation of clusters. In Figure-1 and in Table-6, it is expressed by the values: 68.42 – for W18, W6Mo5 and 80.94 – for W9Co5, W9Mo4Co8. At the final stage, all steels $i = \overline{1;6}$ with the distance 179.37 come into the cluster. When there are two clusters (k = 2) the first cluster will include steels $i = \overline{1;5}$, and the second one will include Cr12 ($i = 6$). At k = 3, the first cluster will be formed by steels W18, W6Mo5, W9Co5, W9Mo4Co8 with the union distance 111.39; the second cluster will be formed by steel W12V3Co10Mo3 (distance 129.69), the third one – Cr12 (distance 179.37).

When using the method of unweighted pairwise average and measure of Manhattan distance the division of steels into clusters was the same (Table-6) but the distances between them and coefficients K_u were changed.

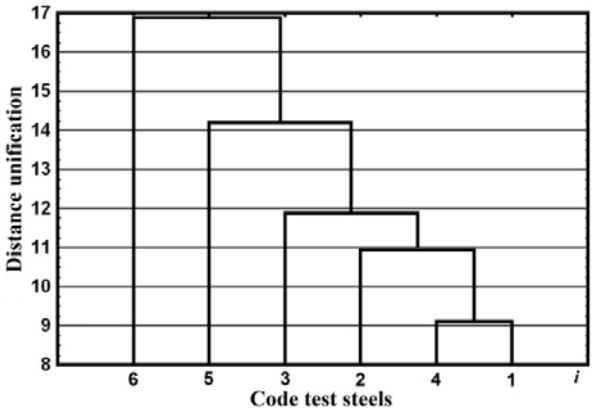

Figure-2. Vertical dendrogram of observed objects, obtained by the method of unweighted pairwise average and (5).

As seen from the Figure-2 and the Table-7, for Euclidean distance and method of unweighted pairwise average the smallest distance d_E(W9Co5, W6Mo5) = 9.1 is between the steels W9Co5 and W6Mo5, and the biggest distance is 16.88 between the steels W12V3Co10Mo3 and Cr12. Certainly on the dendrogram and the scheme of the union at the first stage steels W9Co5 and W6Mo5 were in the same cluster with the distance of cluster 9.11. The obtained cluster differs from the similar cluster at the scheme of union "Manhattan distance" in which the high-speed cutting plates W18 and W6Mo5 were included earlier. At the next stage, W9Mo4Co8 with W9Co5, W6Mo5 (Table 7) were united into one group because the distances between them differ insignificantly (Table-4): d_E(W9Co5,W9Mo4Co8) = 10.3 andd_E(W6Mo5,W9Mo4Co8) =11.6, etc.

Table-7. Scheme of unions. Euclidean distance.

Ward's method							
Distance of clusters	**Object 1**	**Object 2**	**Object 3**	**Object 4**	**Object 5**	**Object 6**	**K_u**
9.11	W9Co5	W6Mo5					1.00
11.56	W9Co5	W6Mo5	W9Mo4Co8				1.27
12.65	W9Co5	W6Mo5	W9Mo4Co8	W18			1.09
16.05	W9Co5	W6Mo5	W9Mo4Co8	W18	W12V3Co10Mo3		1.27
19.91	W9Co5	W6Mo5	W9Mo4Co8	W18	W12V3Co10Mo3	Cr12	1.24
Method of unweighted pairwise average							
9.11	W9Co5	W6Mo5					1.00
10.95	W9Co5	W6Mo5	W9Mo4Co8				1.20
11.88	W9Co5	W6Mo5	W9Mo4Co8	W18			1.08
14.19	W9Co5	W6Mo5	W9Mo4Co8	W18	W12V3Co10Mo3		1.19
16.88	W9Co5	W6Mo5	W9Mo4Co8	W18	W12V3Co10Mo3	Cr12	1.19

As seen from the Table-7, Ward's method showed the identical results in comparison with the method of unweighted pairwise average when dividing the steels into clusters with the close values of union coefficient. It is preferable to have two –three clusters because if there are more clusters the visualization of clusterization will be lost.

At the second stage, we used the descriptive statistics. The Table-8 shows that the observed objects W6Mo5, W9Co5, W18 and W9Mo4Co8 have close varied ranges of normalized features, and therefore they were grouped at the first or at the second stage (in the first or in the second cluster).

Table-8. Normalizeddescriptivestatistics.

Steels ($i = \overline{1;6}$)	**Average**	**Standard deviation**
W9Co5 (1)	0.179643	0.701927
W9Mo4Co8 (2)	0.132872	0.801630
W18 (3)	-0.374898	0.761789
W6Mo5 (4)	-0.274551	0.547314
W12V3Co10Mo3 (5)	-0.479523	0.978490
Cr12 (6)	0.816457	0.950650

To estimate the results of CA, we will decrease the total number of features (N=100) up to three, they are the most significant in the increase of the reliability of parts: R_{a1}, EFE_{max} and HV (Table 9). In brackets for the parameter R_{a1} there are categorical values (CV) [16].

Similarly to the value of deviation from planeness, there is accuracy quality class *TFE* [17]. Thus, the clusters were obtained: the first cluster – W18, W6Mo5, W9Co5 and W9Mo4Co8; the second cluster - W12V3Co10Mo3 and the third one - Cr12.

Table-9. Group average values of parameters R_{a1}, EFE_{max} and *HV*.

Cluster $k = \overline{1;3}$	R_{a1}, µm	EFE_{max}, µm	*HV*, MPa
1	0.0567 (0.063)	13.91 (*TFE*7)	7,572.325
2	0.0390 (0.040)	15.37(*TFE*7)	6,417.04
3	0.0647 (0.080)	16.80(*TFE*8)	6,395.96
Note: Cluster: 1 – W18, W6Mo5, W9Co5, W9Mo4Co8; 2 – W12V3Co10Mo3; 3 – Cr12.			

Integral estimation of grindability of steels $i = \overline{1;6}$ according to clusters is difficult to make, and we will make it differentially for every topography parameter. HSSP W12V3Co10Mo3 showed the smallest values of roughness altitudes (CV) = 0.04 µm, the second position takes cluster 1 (HSSP W18, W6Mo5, W9Co5, W9Mo4Co8) -R_{a1} 0.0567 (0.063). The third cluster for die steel Cr12 is characterized by R_{a1} = 0.0647(0.08). Clusters 1 and 2 are in the range of the same set *TFE*7 according to the deviations from planeness, but the observed values EFE_{max}= 13.91 µm for steels of the cluster 1 (W18, W6Mo5, W9Co5, W9Mo4Co8) are 1.1 times lower than for HSSP W12V3Co10Mo3. According to micro-hardness *HRC,* they are in the following decreasing sequence: 2; 1; 3. According to *HV* measured in the samples after grinding, the sequence is the following: 1; 2; 3. Grinding of steel W12V3Co10Mo3 is accompanied by the intensive heat generation, burns and decrease of micro-hardness. Thus, according to two parameters of surface topography (EFE_{max}, *HV*) undisputed leader is the cluster 1 (HSSP-W18, W6Mo5, W9Co5, W9Mo4Co8).

Steel W12V3Co10Mo3 differs by its lower machinability by grinding. Die steel for cold forming Cr12 completes the sequence of the researched materials.

4. CONCLUSIONS

a) The method of grouping or classifying of materials is presented using the hierarchical cluster analysis. Its positive features are: low labor input, environmental safety, possibility to use in any working conditions and efficiency when processing of large databases.

b) It was revealed that when classifying the groups of the machinability of tool materials by cluster analysis the proximity measure of Manhattan distance provided more accurate result in comparison with the proximity measure of Euclidean distance and other more reliable estimations.

c) In this research, it was accepted reasonable to select 3 clusters: the first cluster for HSSP W18, W6Mo5, W9Co5 and W9Mo4Co8; the second cluster for HSSP W12V3Co10Mo3; the third cluster for parts of dies Cr12. Grindability estimation between the clusters requires additional research, for instance, using the statistic methods.

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