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ANALYSIS AND EVALUATION OF GROUPING METHODS FOR EFFECTIVE CUTTING TOOL OPERATION

Key words: similarity coefficient, clustering, tool flow control.

Abstract: This article presents the possibilities for using cluster analysis in the assignment of machine tools in automated manufacturing systems. Based on the similarity of manufacturing processes in the system, cutting tools have been grouped. The objective was to obtain groups of similar objects, which could potentially ensure the reduction of the frequency and time of setups, optimizing the maintenance of tool resources and improving the efficiency and quality of production. With the application of similarity coefficients and hierarchical clustering algorithms, tool sets were formed with their composition specified. The assumed key factor was the limited tool magazine capacity for the machine tool. Therefore, it was necessary to separate the group with the largest multiplicity, not exceeding the assumed tool magazine capacity, from each group. The final part of the study includes an evaluation of the obtained solutions with selected measures used.

Analiza i ocena metod grupowania dla efektywnego użytkowania narzędzi skrawających

Słowa kluczowe: współczynniki podobieństwa, grupowanie, sterowanie przepływem narzędzi.

Streszczenie: W niniejszym artykule przedstawiono możliwości zastosowania analizy skupień w przydziale narzędzi do obrabiarek w zautomatyzowanych systemach wytwarzania. Bazując na podobieństwie używanych w systemie procesów wytwórczych grupowaniu, poddano narzędzia obróbkowe. Celem było uzyskanie grup obiektów podobnych, które potencjalnie zapewnić mogły zmniejszenie liczby i czasu przezbrojeń, lepsze wykorzystanie zasobu narzędziowego oraz poprawę efektywności i jakości produkcji. Z wykorzystaniem współczynników podobieństwa i hierarchicznych algorytmów grupowania stworzono zestawy narzędziowe i określono ich skład. Jako czynnik kluczowy przyjęto ograniczoną pojemność magazynu narzędziowego obrabiarki. Koniecznym stało się zatem wyodrębnienie z każdej możliwej liczby grup grupy o największej liczności, która nie przekraczała założonej pojemności magazynu narzędziowego. W ostatniej części opracowania przeprowadzono ocenę uzyskanych rozwiązań z wykorzystaniem wybranych miar.

Introduction

The aim of clustering is transforming the input matrix of tool assignments into a form with diagonally arranged groups. This will allow determining the composition of a tool set loaded into the machine tool magazine to produce a specified part batch. Stages of the procedure can be referred to the realization of individual steps in an iterative way with the validation of obtained solutions [7]. The key question is whether the aim is to form tool sets that are as separable as possible, or, to allow sharing of tools between subsequent part groups. It is necessary to determine the number of tools within a set, what the minimum or maximum number of tools within a group should be, or, whether the aim is to keep the minimum or maximum number of tools in a set. The lower limit is the number of tools in a technological process and the upper limit is the tool magazine capacity.

In most cases, it is not possible to form tool sets where the tools would not have to be used by any of the parts from other groups. Hence, it is necessary to share the tools between different sets of parts/production tasks (see, e.g., Amoako-Gyampah, Meredith and Raturi [2]). The main reason for this phenomenon is the limited tool magazine capacity, which makes it impossible to assign all of the tools required to process all parts in the assumed time range. Possibilities of tool sharing by keeping the exceptional tools in the magazine longer than only for processing the parts of their group must include this strong limitation [6]. In the analysis, the duplication of the exceptional tools or using tool sharing procedures can be predicted.

The clustering methods can be divided into hierarchical methods and partitioning methods [8]. In the partitioning methods, objects are assigned to the created groups so that the assumed criteria are met. The most frequent methods are k-means and k-medoids. The objects are switched between the groups to minimize the variances within each group. The basic disadvantage of the partitioning methods is the requirement to assume the number of created groups earlier. However, this results in much shorter calculation time, as compared to the hierarchical methods. Due to the addressed objectives of the research, the following part of the study is focused on the hierarchical methods. These methods link the objects iteratively into larger or smaller groups. This is combined with agglomerative or divisive procedures [8].

The literature on the analysis of clusters presents many types of measures applied for the validation of the clustering results. Some of them are used mostly in the evaluation of manufacturing workcell forming based on grouping (see, e.g., Akturk and Turkcan [1], Kusiak and Cho [9]). The necessary evaluation with the use of various coefficients for that type of solution is related mainly to problems with their implementation in the industrial environment. On the stage of designing workcell systems, almost 25% of companies did not carry out any verification and evaluation of the obtained solutions. Designs were not verified until the implementation stage and almost 69% of companies changed the manufacturing routes with respect to the design [12, 13]. For effective maintenance of cutting tools, the utilisation of hierarchical methods in grouping analysis is of crucial importance.

1. Grouping of cutting tools with the application of agglomerative clustering methods

The case covered by this analysis related to a manufacturer of machinery parts. Necessary data related to the manufacturing processes were taken from the production control system. In this way, a set of production tasks to be performed on a machine tool station was defined. The data was compiled in a tool-production task (part) incidence matrix, which is then subject to clustering according to the assumed objectives. The assumption was that the tool maintenance time (lifetime) would not be exceeded for the entire set of parts; therefore, including tool duplicates is not required.

In practice, the resultant number of groups is defined based on different criteria. The most important ones include defining the number of groups based on heterogeneity between the groups. These values are specified on dendrograms, where individual distances are standardized. Another method is the analysis of variations of the similarity coefficient/distance measure. The number of groups is then specified in a point, where the function directional coefficient is changed and the resultant break takes a 'concave' form. Since the aim is usually to obtain a lower number of groups on charts, a dotted Line (I) is used to identify points that define the lowest possible number of groups according to this criterion. In case of the tool flow, a limiting factor is the maximum number of tools (qmax) that can be assigned to the machine, Sm, which is the tool magazine capacity. Hence, it is necessary to separate the largest group, qmax $\leq$ Sm, from the possible number of groups. In the discussed case, the maximum number that can be stored within a group corresponds to the tool magazine capacity, i.e. Sm = 12.

A full overview of the solutions is possible due to the analysis of results, which are presented as dendrograms, bar charts, as well as a curve of similarity coefficient values. Additionally, the numbers of groups resulting from the maximum heterogeneity between the groups (dotted Line III), changes of the similarity coefficient (dotted Line I), tool magazine capacity (dotted Line II), have been presented.

Similarity between the groups in the case of the Single Linkage (SL) method are defined as the minimum distance from all possible distances between the objects (tools) within specific groups, while, in the Complete Linkage (CL) method, it is the maximum distance. Due to this reason, these methods are also referred to as the "Nearest neighbour" and "Furthest neighbour" methods.

A comparison of the dendrograms and bar graphs, as well as the curves of the similarity coefficients, allow to state that, generally for the examined set of data in the case of CL and SL algorithms, a larger number of groups, regardless of the assumed criterion for counting the groups, is obtained (Fig. 1). The number of groups is also clearly different for each criterion. The SL and CL algorithms are created by 1–2 groups with a number of tools and a series of small groups. It can be observed in grouping based on the tool magazine capacity criterion and the Single Linkage method for which one large group and multiple small groups were generated.

Unlike the Single Linkage method (SL), the Average Linkage method (AL) includes calculation of an average out of all possible distances between the objects (tools) within groups. Due to this fact, this method is also referred to as the Between-Groups Linkage method. One of its variations is the Within-Groups Linkage method

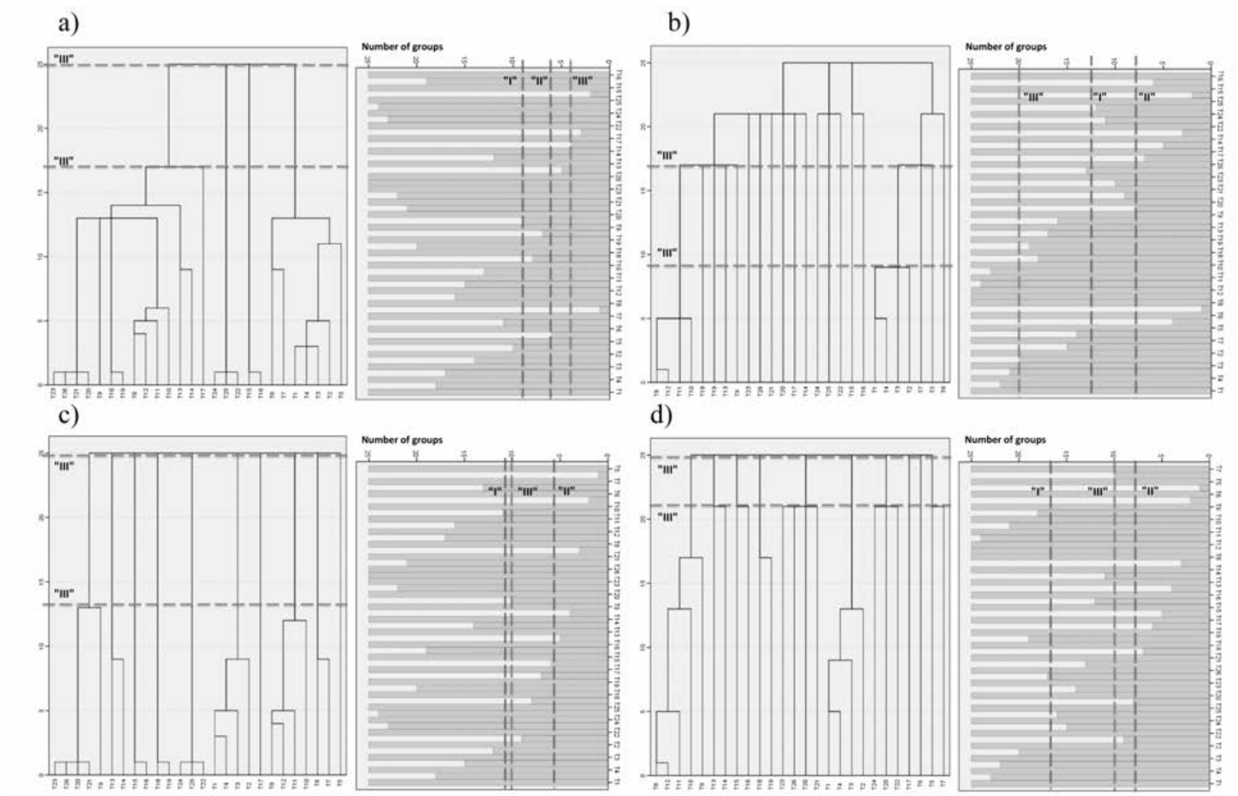

Fig. 1. **Dendrogram and bar chart for: the SL method and similarity coefficients: a) Sorenson – Dice – Czekanowski, b) Russell – Rao; the CL method and similarity coefficients: c) Sorenson – Dice – Czekanowski, d) Russell – Rao**

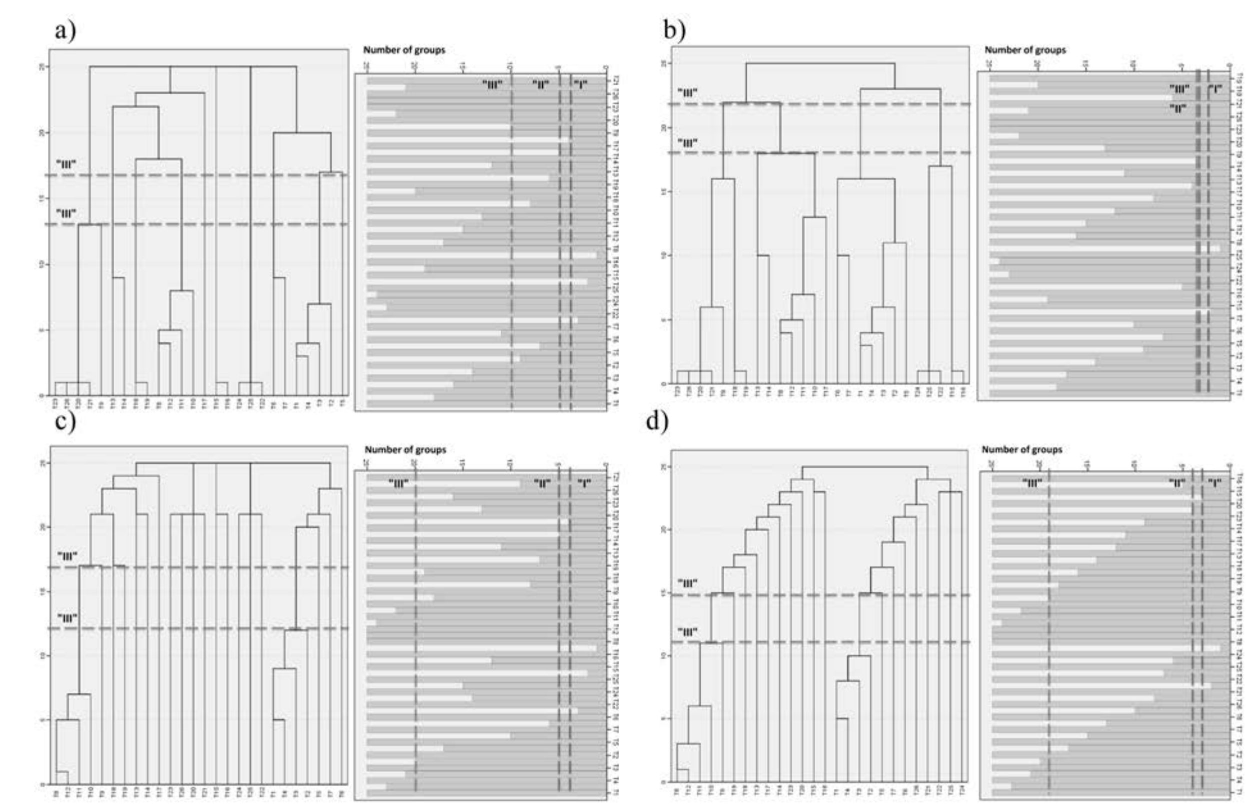

Fig. 2. **Dendrogram and bar chart for the Average Linkage method: a) (Between Groups), b) (Within Groups) and Sorenson – Dice – Czekanowski similarity coefficient; c) (Between Groups), d) (Within Groups) and Russell – Rao coefficient**

in which an average of all possible distances between objects (tools) within a single group formed by linking both examined groups is calculated. The application of both AL algorithms generated similar group numbers for the assumed variation of the directional coefficient value and tool magazine capacity criterion (Fig. 2).

The group heterogeneity condition is less significant than in previous algorithms, particularly the Single Linkage algorithm. A specific case covers groups selected for the Russell-Rao coefficient and SL and AL algorithms, where a very high number of groups were generated. The number of tools in groups generated in the two AL methods is much better balanced, as compared to the results for Single Linkage (SL) and Complete Linkage (CL).

The obtained results clearly show that a detailed evaluation of the assumed group counting criteria is necessary.

2. Analysis of the methods for creating tool groups

The assumed key factor was the limited tool magazine capacity for the machine tool. It was then necessary to separate the groups with the highest multiplicity, not exceeding the assumed tool magazine capacity of 12 slots, from all groups. Figure 3 presents a detailed distribution of the number of tools in individual groups formed.

The application of the Complete Linkage method resulted in creating one, very large group, and a large number of small groups. A similar situation was found in the case of the Single Linkage method; however, one more group with high multiplicity was clustered here. Both Average Linkage methods resulted in the generation of a lower total number of tool groups. As it can be observed, the application of these algorithms, in most cases, provides better balance of the number of tools in each of the groups (Fig. 3).

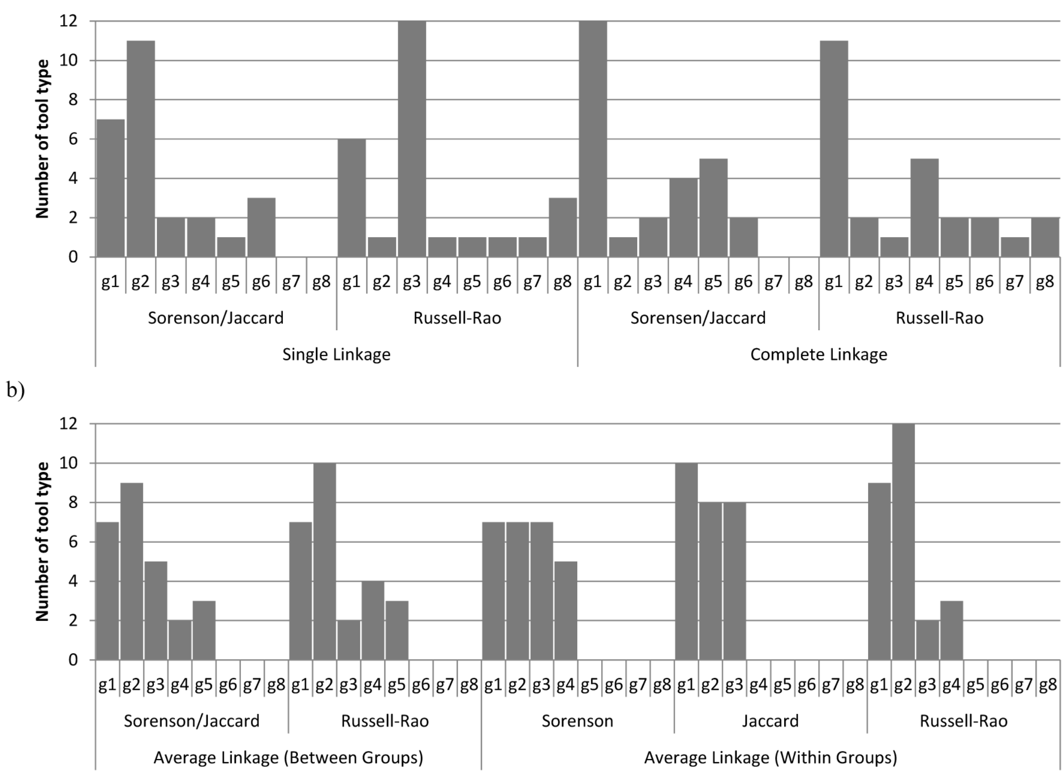

Fig. 3. The number of tools within each group specified with the criterion of tool magazine capacity taken into account for: a) SL and CL method, b) Average Linkage methods

The analysis of tool assignment to a matrix of groups, based on the SL algorithm, shows that the tools from the first group basically do not have to be kept in the tool magazine to perform the tasks related to other groups (for the Russell-Rao coefficient, the second group containing one tool performs one production task). Tools from another large group are shared with other groups resulting in the limitation of the tool exchange process (Fig. 4). Some tools are left in the tool magazine. Compared to the results obtained for SL, in CL, tools in the first group (with a large number of assigned tools) and the next (fourth) (Fig. 3a) large group will be also used by the subsequent production tasks, which require tool sets of subsequent groups. Unlike the SL algorithm, tools already from the first group are shared with the production tasks of the following groups (Fig. 5). The number of exchanges when using both algorithms is similar, while the number of tools left in the tool magazine for further processing is clearly higher and the number of unloaded and loaded tools decreases.

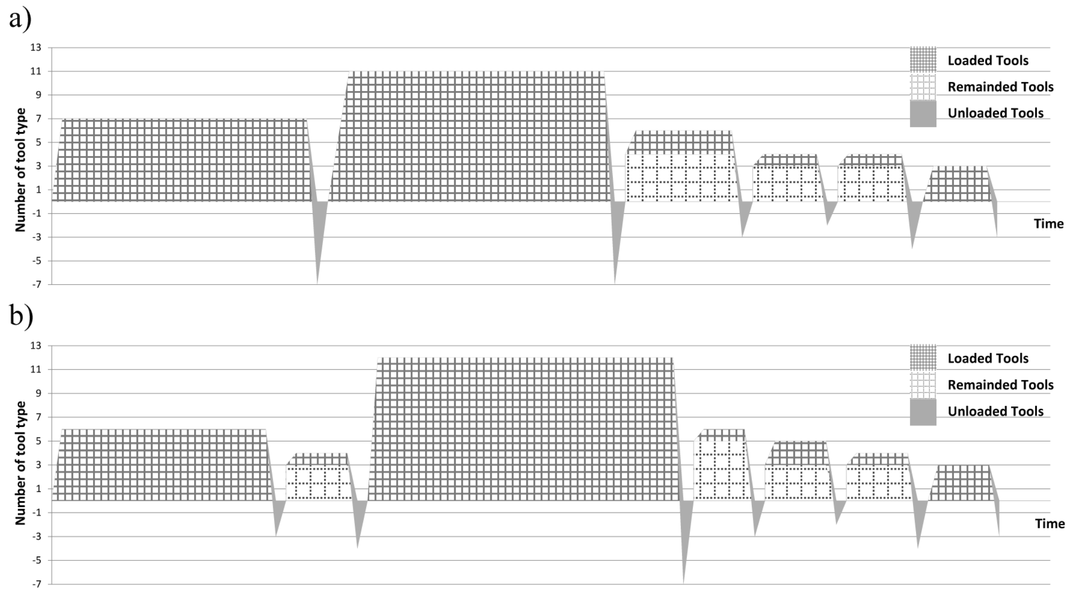

Fig. 4. The number of tools in the machine tool magazine and tool exchange process for groups formed according to SL for the following similarity coefficients: a) Sorenson, b) Russell – Rao

The application of the two Average Linkage algorithms formed tool sets characterized by the lowest level of sharing between the tasks of individual groups (Fig. 6). The tool exchange process is also less frequent; however, it is characterized by a large number of tools that have to be loaded to and unloaded from the machine tool magazines at the end of processing. This is related to an extended time for a single tool setup.

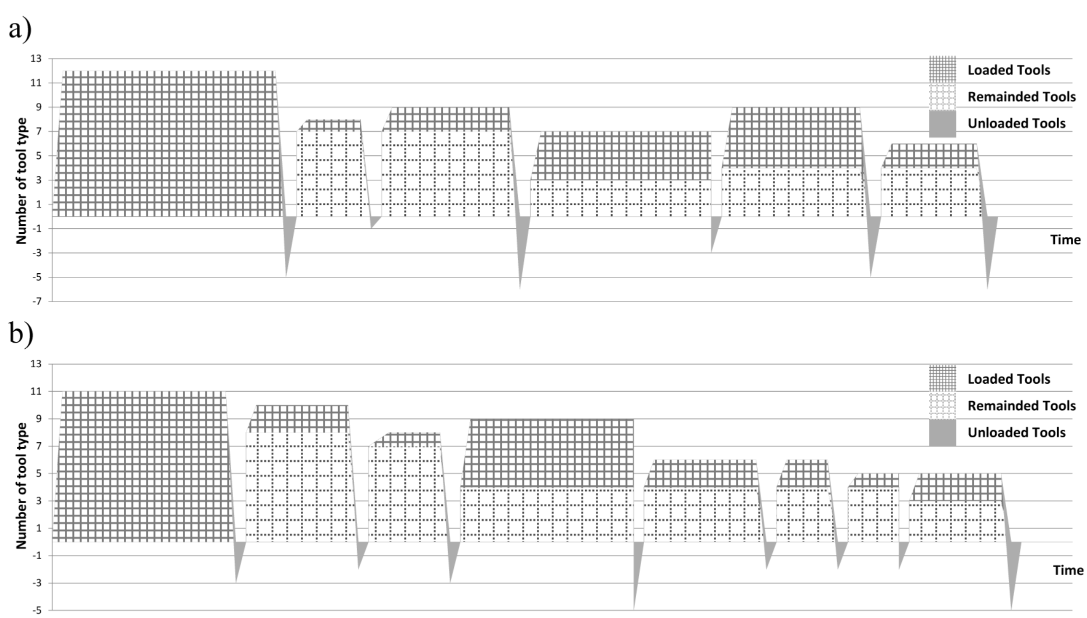

Fig. 5. The number of tools in the machine tool magazine and tool exchange process for groups formed according to CL for the following similarity coefficients: a) Sorenson, b) Russel – Rao

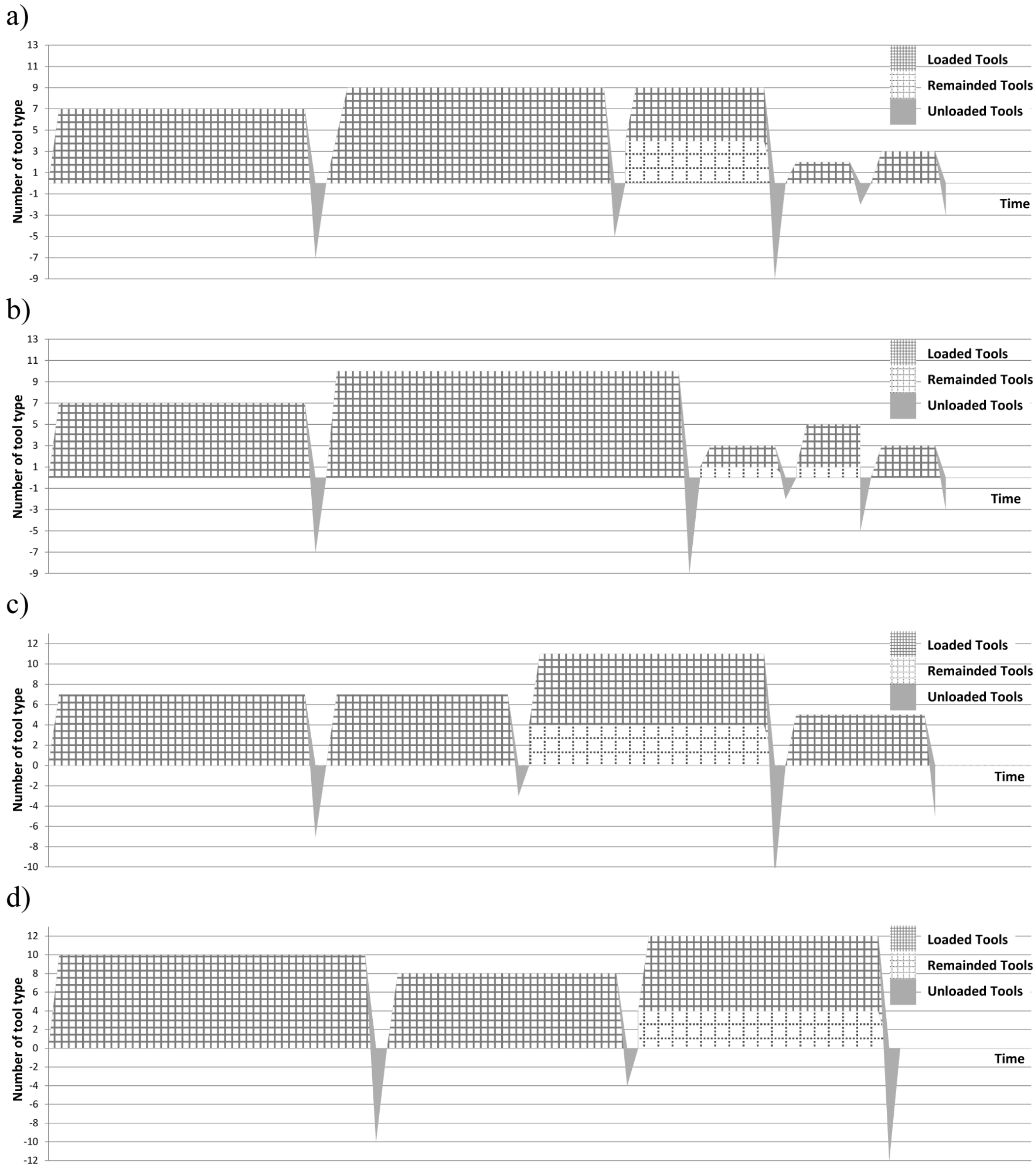

Fig. 6. The number of tools in the machine tool magazine and tool exchange process for groups formed according to the Between Groups method and coefficients: a) Sorenson, b) Russell – Rao; and Within Groups method for the coefficients of c) Sorenson, d) Jaccard

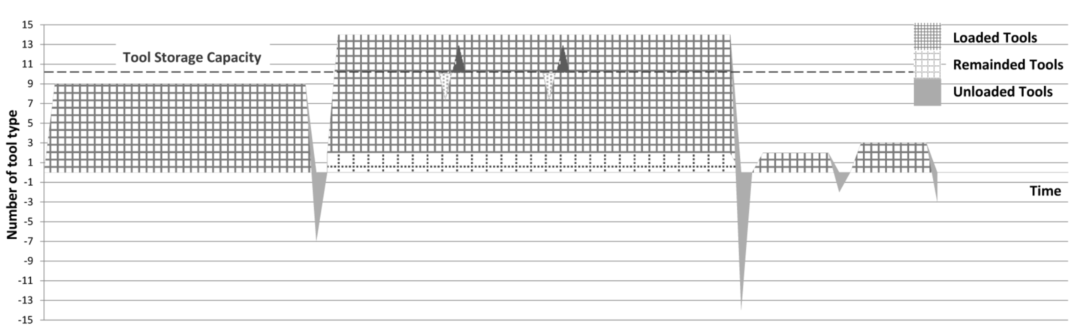

Fig. 7. The number of tools in the machine tool magazine and tool exchange process for groups formed according to the Within Linkage method and Russell – Rao coefficient

Groups formed for the Russell-Rao coefficient with the Within Groups method constitute a special case. Even limited sharing of tools between subsequent groups exceeded the capacity of the machine tool magazine (Fig. 7).

It can be expected that, when creating groups with a large number of tools (close or equal to the tool magazine capacity), the occurrence of even small tool sharing between subsequent sets of production tasks may result in exceeded the tool magazine capacity. There are two possibilities in such cases:

- Using the KTNS exchange rule: Keep the tools in the magazine that are needed soonest [11].
- The selection of a larger number of groups according to the proposed algorithm.

3. Validation of the obtained tool sets

In order to form tool sets with the use of cluster analysis, the following selected effectiveness measures were specified:

- Percentage of exceptional elements (PE),
- Coefficient of tool utilization (TU), and
- Grouping efficiency (GE).

The percentage of exceptional elements is defined as the share of elements {1} outside the groups (Table 1) related to an integer {1} in the assignment matrix (Chan and Milner [4]). Lower values of this coefficient (PE) confirm tool sets that do not share the tools when processing subsequent part groups (Table 2). For the purpose of evaluating the obtained solutions, the coefficient defined by Chandrasekharan and Rajagopalan [5] was also applied. This coefficient is represented in this study as the coefficient of tool utilization (TU). It will allow the evaluation of the percentage of tools located in the formed tool sets (groups) in the realized production. Higher values of this coefficient will indicate a lower number of tools that have to be left in the tool magazine for processing another part group. Due to this, the necessity to share the tools between subsequent part groups will be limited.

$$TU = \frac{N_{o1}}{\sum_{k=1}^{K} m_k n_k} 100 \quad [\%] \tag{1}$$

where
N_{o1} – number of elements {1} in all diagonal groups,
K – number of groups,
m – number of tools in k^{th} group,
n – number of parts in k^{th} group.

As it can be observed, there are cases when, despite the low value of the PE coefficient, tool utilization (TU) coefficients can be still low. It is seen in the Average Linkage (Between Group) method, where clearly different PE values are used and the TU values are comparable.

Table 1. Number of elements {1} outside diagonal tool groups for SL, CL and AL methods

Method	Similarity coefficient	Number of {1} outside the groups	Number of groups
Single Linkage	Sorensen/Jaccard	8	6
	Russel-Rao	6	8
Complete Linkage	Sorenson/Jaccard	26	6
	Russel	25	8
Average Linkage (Between Groups)	Sorensen/Jaccard	8	5
	Russel-Rao	1	5
Average Linkage (Within Groups)	Sorenson	13	4
	Jaccard	11	3
	Russel	2	4

Generally, PE values in the discussed case are characterized with variability, while the TU values are close to each other.

The coefficient that links the properties of the two above-mentioned measures was defined by Chandrasekharan and Rajagopalan [5] and named as the Grouping efficiency (GE) η. The coefficient is a weighted average with weigh q, which includes the significance of a factor related to tool utilization η_1 and a measure of flow between groups η_2. If we assume that it is preferable to form groups showing small sharing of tools, solutions with higher tool load values within groups and lower flow between tool groups are adequate. The Grouping Efficiency (GE) coefficient is defined as follows:

$$\eta = q\eta_1 + (1-q)\eta_2 \tag{2}$$

where:

$$\eta_1 = \frac{N_{o1}}{\sum_{k=1}^{K} m_k n_k}$$

$$\eta_2 = 1 - \frac{N_e}{MN - \sum_{k=1}^{K} m_k n_k}$$

N_e – number of elements {1} outside all diagonal groups,
MN – tool-part matrix size,
q – weight of the coefficient $0 \le q \le 1$.

The weight q is assumed on an arbitrary basis, depending on the objectives. The theorists propose assuming 0.5 for all discussions. However, Seifoddini [10] and Boe and Cheng [3] proved that, when comparing cases resulting in solutions with the same number of groups, it is recommended to assume lower weight values (q = 0.2), since they showed that such values allows correct evaluation of the obtained solutions, assuming the weight of 0.2 makes the reduction of flow between groups more significant.

Table 2. Percentage values of selected effectiveness measures of tool grouping

Method	Similarity coefficient	**PE [%]**	**TU [%]**	**GE 0.5 [%]**	**GE 0.2 [%]**
Single Linkage	Sorensen/Jaccard	11.59	51.69	74.61	88.36
	Russel-Rao	13.04	49.18	73.18	87.59
Complete Linkage	Sorenson/Jaccard	37.68	43.00	67.70	82.52
	Russel	36.23	55.00	74.05	85.48
Average Linkage (Between Groups)	Sorensen/Jaccard	11.59	52.59	75.07	88.55
	Russel-Rao	1.45	51.91	75.79	90.12
Average Linkage (Within Groups)	Sorenson-Dice	18.84	48.70	72.36	86.56
	Jaccard	15.94	38.67	67.45	84.72
	Russel-Rao	2.90	40.12	69.70	87.44

The application of the Within-Groups method for Sorenson-Dice and Russell-Rao coefficients brought four groups as a result. Evaluation of the obtained results for the weight of q = 0.5 indicates a more convenient solution is obtained for the Sorenson-Dice coefficient. However, assuming that the reduction in tool sharing is preferable, a better solution was obtained for the Russell-Rao coefficient, where the number of flows between the groups is lower (Table 1). It is also confirmed by the GE value for the weight of q = 0.2 (Table 2).

Conclusions

The aim of grouping is to determine the composition of a tool set loaded to the machine tool magazine to produce a specified part batch. The main objective of this article was to present the possibilities of forming cutting tool sets with the use of agglomerative clustering methods. The presented methods can be applied for analysing and developing the functionality of automated manufacturing systems. The results have referred to the accepted methods and assumed similarity coefficients and methods of counting the clusters. The presented dendrograms and bar graphs clearly show that the addressed issue is complex and possible solutions are diverse. The article also covers an analysis of creating tool sets with respect to their separability, multiplicity, as well as tool exchange operations. These operations were referred to the tool flow control and basic limitation found in the actual manufacturing systems, i.e. the limited capacity of tool magazines.

Generally, for the examined data set in the case of the Complete Linkage and Single Linkage algorithms, a higher number of groups are obtained when compared to both Average Linkage methods. The SL and CL algorithms are created by 1–2 groups with a high tool multiplicity and a series of small groups. It can be observed in grouping based on the tool magazine capacity criterion and Single Linkage method, where one large group and multiple small groups were generated. The criterion of heterogeneity between groups was significant in the case of clusters defined for the Russell-Rao coefficient and SL/AL algorithms. Very high numbers of clusters were then generated. The number of tools in clusters grouped in the two Average Linkage methods is much better balanced, as compared to the results for SL and CL. Based on the obtained results, it is clearly seen that it is required to evaluate the criteria set for defining the number and composition of tool groups in the following examination phase.

In order to form tool sets with the use of cluster analysis, the following selected effectiveness measures were specified: The percentage of exceptional elements (PE), Tool Utilization (TU), and Grouping Efficiency (GE). Lower values of PE confirmed creating tool sets that did not share the tools when processing subsequent part groups. Tool utilization (TU) allowed the evaluation of the percentage of tools stored in the formed tool sets (groups). Higher values of this coefficient will indicate a lower number of tools that have to be left in the tool magazine for processing another part group. Due to this, the necessity to share the tools between subsequent part groups was reduced. Generally, PE values in the discussed case were showing variability, while the TU values were close to each other. The calculated values of the Grouping Efficiency (GE) included the significance of the factor related to tool utilization and measures of tool flow between groups. If we assume that it is preferable to form groups showing limited sharing of tools, solutions with higher tool utilization values within groups and reduced flow between tool groups are adequate.

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