THE USAGE OF FUZZY CLUSTERING IN A PRODUCTION SCHEDULING SEQUENCE OF MELTINGS

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Abstract

The paper deals with the optimal layout of smelting's sequences in continuous steel casting device (CCM) using K-Means clustering methods as well as using fuzzy clustering. This optimization is trying to achieve a positive effect to the mold's durability. During the production of steel by continuous casting are subsequently casting different steel grades. That steel grades differ in their composition and production efficiency and to increase the life of the mold is necessary to determine the appropriate sequence of the casting. The parameters on whose basis the cluster analysis was made were chemical composition, liquids temperature, superheat and other technological parameters.

Keywords: Steel mill, production scheduling, control, fuzzy clustering

1. SEQUENCE CONCASTING

One of the basic prerequisites for increasing the productivity of the continuous casting machine (CCM) is increasing the number of melting sings cast in a single sequence. To achieve this goal must be sufficient attention paid to production scheduling and thus the development and implementation of new automated production planning systems.

Current planning methods are based on creating a "plan of marking the times", which are based on the technical state of aggregates, available time, stocks of batch materials, of the agreed oxygen uptake and energy, the amount of steel, etc. Subsequently, delivery times are calculated on the following technology aggregates and created a plan sequence casting. From a logistical point of view constitute this procedure so called "push principle", whose goal is to quickly "push" material whole production chain. [1]

However, the real situation of the steel plant in terms of material flow is controlled by the so called from a logistics viewpoint "pull principle", at which the material is "pulled" stream of inducing end element of the chain, rather than being pushed forward by Command Plan. In terms of the actual situation of the steel plant, this means that the material flow (melting) is controlled by the needs of the CCM. Underpinned this approach will thus create "plans sequences".

2. CLUSTERING ALGORITHMS

To solve issue of planning melting sequences method was used K-Means and Fuzzy K-means. These are some of unmanaged learning algorithms for problem solving data clustering. Its effectiveness lies particularly in the utilization of a simple classification of data groups into individual clusters. K-Means clustering is an iterative algorithm. The algorithm is based on the distance of points in many dimensional space. Each evaluation of object is represented by just a single point, every monitored attribute is represented a single axis. [2] K-means method is particularly suitable for large sets of data that are to be grouped into a small number of clusters.

In classical cluster analysis each entry assigned to a single cluster. Fuzzy cluster analysis reflects this requirement by assigning individual points so called "rate of membership" point to a single cluster. Most of fuzzy cluster algorithms are based on the objective function. Determine the optimal classification by minimizing the objective function. The objective function based on clustering usually each cluster is represented in the prototype cluster. The prototype consists of a cluster of midpoint and further information about the size and shape of the cluster. The size and shape of the cluster the parameters specify the extension cluster in different groups and are calculated distance data point from the midpoint of the cluster with regard to the size and shape of the cluster as further information. The closer the data point is on the midpoint of the cluster, the greater is the rate of membership of membership to this cluster. Therefore the concern to divide the data set into groups is given by the solution to the task of minimizing the distance of the data points from cluster midpoint. Most analytical fuzzy clustering algorithm is based on optimizing the basic k-means. [3]

2.1. Method of Fuzzy k-means

In the fuzzy k-means for each element calculates probability from 0-1 belong to the cluster. Using this method can well describe the distribution of points in clusters. The points on the edges of the cluster does have a lower degree of jurisdiction to a cluster of points than in the vicinity of its center. One element can belong to multiple clusters at the same time. Membership in a cluster is expressed by the coefficient of membership. The sum of all coefficients of membership to one element must be equal to one. Process method (see **Fig. 1**):

1) At the beginning of the set parameter m> 1, ε >0 set $U^{(0)}$ and l= 0.

2) For each cluster $V_i^{(l)}$, calculate a new midpoint according to the formula (1):

$$V_i^{(1)} = \frac{\sum_{k=1}^{N}\left[u_{i,k}{}^{(l)}\right]^m \cdot z_i}{\sum_{k=1}^{N}\left[u_{i,k}{}^{(l)}\right]^m} \quad i = 1, \cdots, c \tag{1}$$

3) Calculation of the distance of individual points from the midpoint using a Euclidean distance by the formula (2):

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n}\left(x_{ik} - x_{jk}\right)^2} \tag{2}$$

4) By adjusting matrix jurisdiction $u^{(l+1)}$ for every k = 1, ..., N so as to

4.1) for all i = l, ..., c, for which applies that $d(z_i, v_i) > 0$ is set formula (3):

$$u_{i,k}^{l+1} = \frac{1}{\sum_{j=k}^{c}\left[\frac{d\left(z_k, v_i^{(l)}\right)}{d\left(z_k, v_i^{(l)}\right)}\right]^{\frac{2}{m-1}}} \tag{3}$$

4.2) for all i = l, ..., c, for which applies that $d(z_k, v_k) = 0$ is made $u_{i,k}^{(l+1)}$ equal the negative an arbitrary numbers so that to meet the condition and others and is put is $u_{i,k}^{(l+1)} = 0$.

5) Result of present decomposition of l + 1 is compared with the previous result of step l (see formula (4)).

$$e = max_{k=1,N; i=l,\ldots,c}\left|u_{i,k}^{l+1} - u_{i,k}^{l}\right| \tag{4}$$

If e <ε algorithm terminates, if not, increase the step counter l about 1 and then continue with step 2.

The result of the algorithm fuzzy k-means is a matrix U (l) which contain rate of membership of clusters each vector Vi (l), with midpoint vi(l) [4].

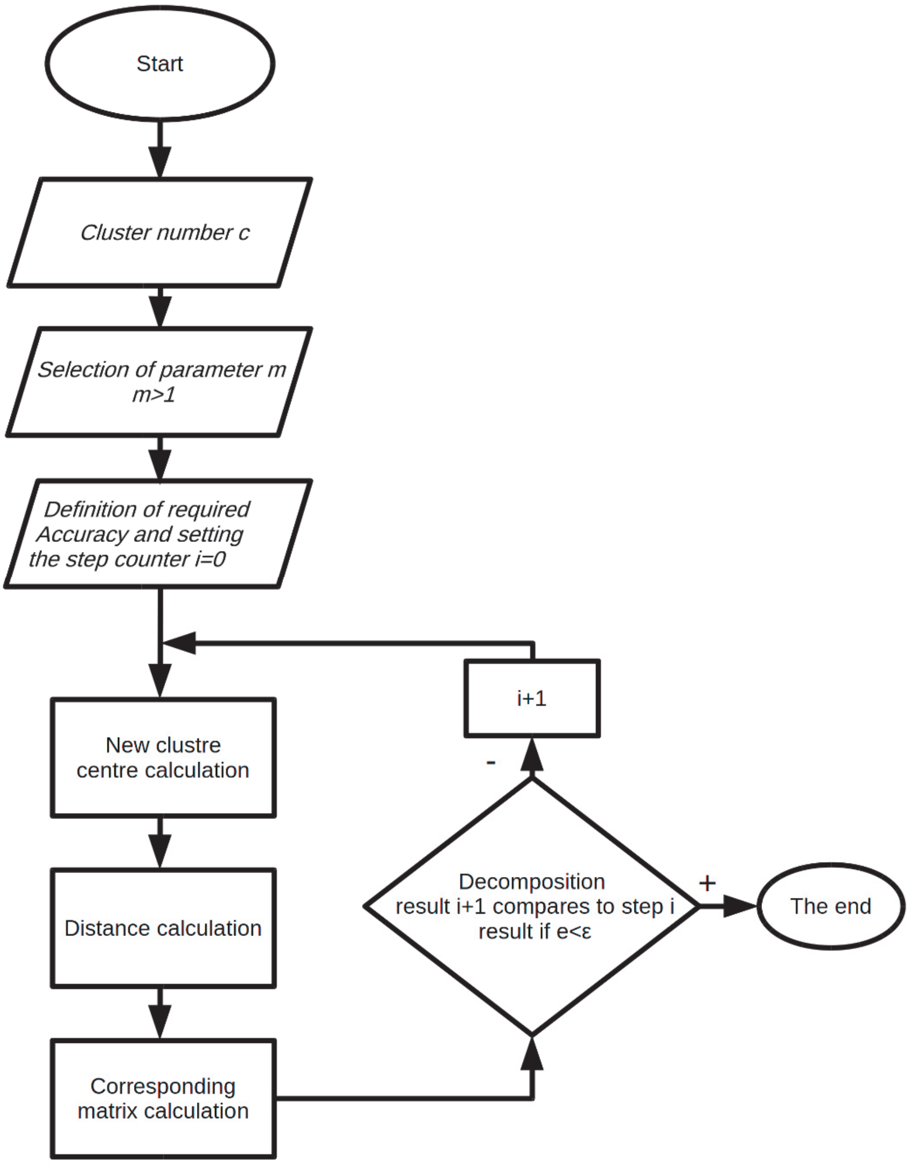

Fig. 1 Algorithm of method of fuzzy k-Means

In **Table 1**, a comparison method of k-means, fuzzy k-means based on several considerations. The + sign means that the method satisfies a given property - sign indicates the opposite.

Table 1 A comparison method

Property	k-means	Fuzzy k-means
The number of clusters must be determined in advance	+	+
Depends on the initial conditions	+	+
One element can belong to more clusters	-	+
Hierarchical methods	-	-

2.2. Gustafson-Kessel algorithm

Gustafson-Kessel algorithm expanded standard fuzzy k-means algorithm to will employ adaptive distance norm in order to determine clusters of different geometric shapes and orientations. Clusters in this method are compared with the fuzzy k-means ellipsoidal and moreover represented by a symmetric positive definite matrix P_i. This is sometimes called matrix of deformation since modifies the shape of clusters, which have a two dimensional space ellipse. To calculate P_i uses covariance matrix S_i [5].

$$S_i = \frac{\sum_{k=1}^{N}(u_{i,k})^m (z_k - v_i)^T (z_k - v_i)}{\sum_{k=1}^{N}(u_{i,k})^m}$$
$$P_i = [det(S_i)]^{\frac{1}{N}} S_i^{-1} \tag{5}$$

Moreover for P_i defined constraint det (P) = ρ, where ρ is a constant determined for each matrix. This is determined by the volume clusters. Rotation their half-axis is determined eigenvectors matrix P_i and the size of their of the half-axis corresponding powers of eigenvalues P_i [5].

3. CLUSTERING OF MARKS OF STEELS

Clustering algorithm of marks of steels is not limited amount of marks that can be arbitrarily added to the solution according to the manufactured products. The same situation is also in cast formats. In initialization is set the number of clusters to which on the output we require (hence the k-Means). It is designed k of points with random coordinates (future midpoint clusters - called centroid). The object is assigned to the nearest centroid initial (detected distance from this centroid is smaller than the distance from the other centroids) cluster is thus represented by all the points that are closest to the same centroid. [6]

In addressing the issue were created five random clusters and calculations were tested on 151 of marks of steels (ed. marks of steels are describe with numbers from one to one hundred and fifty.), Each mark has been characterized by 27 parameters (T_STEEL, T_LIKVIDU, C, Al, Mn, Si, P, S, Cu, Cr, Ni, Mo, Co, V, Ti, As, Sn, B, Ca, H, N, Nb, Zr, Sb, Pb, W, Zn).

From the initial raw data were calculated variances of the individual elements. Data, which had greater variance than 0.0001, was chosen for algorithm methods, k-means and fuzzy k-means.

Importance of using fuzzy clustering algorithm consists in the connection of individual, already scheduled sequence through "related" marks, i.e. marks with approximately the same degree of membership into two clusters.

The basis of this approach is to assign each meltings rate of membership in the range of ⟨0, 1⟩. Rate of membership of 0 implies that the meltings certainly isn't in the cluster, while 1 unequivocally determines the assignment of the given sequence. If meltings can be assigned into more clusters (an overlapping clusters), it is determined of membership of the meltings to each clusters. These overlapping clusters, then gives the possibility to combine individual clusters (sequences) into longer sequences through marks included in both clusters.

A result of solving is compiled schedule meltings so that in one sequence was cast as much as possible melting signs of one brand respectively. More kinds of marks of steels, which have very close chemical composition and temperature. The basis of the algorithm is a cluster of manufacturing of marks of steels into groups using both traditional and fuzzy cluster analysis methods, ie. that one cluster can simply be regarded as a sequence of meltings. [7]

Test calculations were done in MS Excel, where they were using clustering methods of marks of steels are divided into clusters. These final clusters were used to design of the algorithm for planning sequences melting signs of and further reviewed by fuzzy clustering methods for maximizing capacity utilization of one sequence. **Table 2** is a finite distribution of individual points using k-means.

Table 2. The distribution of points in clusters

Clusters	Individual points
S1	5-8; 10-14; 18-19; 22; 55; 56; 58; 59; 62; 63; 65; 66; 78; 88; 92; 96; 103; 105; 106; 111; 117; 126; 131; 135; 136; 139; 141; 149; 151
S2	27; 29-33; 35; 37; 39-41; 43-45; 47-49; 54; 86; 145; 148; 152
S3	89
S4	4; 9; 15-17; 20; 23; 24; 50; 51; 60; 70; 71; 76; 79; 83; 90; 94; 99; 100; 102; 104; 110; 112; 113; 115; 119-125; 127; 129; 133; 142; 143
S5	2; 3; 21; 25; 26; 28; 34; 36; 38; 42; 46; 52; 53; 57; 61; 64; 67-69; 72-75; 77; 80-82; 84; 85; 87; 91; 93; 95; 97; 98; 101; 107-109; 114; 116; 118; 128; 130; 132; 134; 137; 138; 140; 144; 146; 147; 150

Table 3 shows the resultant distribution of individual points using fuzzy k-means.

Table 3 Distribution of individual points in clusters using fuzzy k-means

Clusters	Individual points
S1	4; 9; 16; 17; 19; 20; 22-24; 50; 51; 55; 56; 70; 71; 76; 79; 96; 100; 104; 111-113; 120-123; 125; 127; 129; 142; 143
S2	27; 29-33; 35; 37; 39; 41; 43; 47; 48; 145; 148; 152
S3	5-8; 10-14; 18; 58; 59; 62; 63; 65; 66; 78; 88; 89; 92; 103; 105; 106; 117; 126; 131; 135; 136; 139; 141; 149; 151
S4	15; 21; 25; 53; 57; 60; 83; 87; 90; 91; 98; 99; 101; 102; 110; 115; 133
S5	2; 3; 26; 28; 34; 36; 38; 40; 42; 44-46; 49; 52; 54; 61; 64; 67-69; 72-75; 77; 80-82; 84-86; 93-95; 97; 107-109; 114; 116; 118; 119; 124; 128; 130; 132; 134; 137; 139; 140; 144; 146; 147; 150

4. CONCLUSION

The paper deals with the application of clustering methods for planning sequences meltings. Fuzzy clustering method is applied to solutions subsection task scheduling sequences meltings of steel in the continuous casting of steel. The task consisted in find similar of marks of steels that can be cast in one sequence. The application of fuzzy clustering allows finding related marks which have the chemical composition and temperature very close and thus tie a sequence of further the meltings of the other groups, but with relative properties which we determine membership rate expressed for each mark and for each cluster. The role of the clustering marks was solved by using the initially method of k-means and then using fuzzy k-means with the assumption that the specified of marks of steels will be grouped into five clusters.

The result of the whole solution is algorithm development this role and validation of the chosen approach to technological parameters of 151 of marks of steels. The results show that distribution of marks of steels of in applying the fuzzy k-means is more even than in the classical k-means, which are defined as "sharp boundaries" individual clusters.

The advantage of fuzzy k-means in resolving scheduling sequence of meltings at CCM is determining the rate of membership of individual clusters. The maximum rate of membership both of marks of steels be included in the respective cluster, but other rates allow you to find the membership to other clusters. This information about the membership between the individual clusters, then gives the possibility to combine individual clusters (sequences) into longer sequences via marks related to both clusters. Timing this approach, it gives us new possibilities when planning sequences meltings of at CCM and thus increase the efficiency and productivity of the process.

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REFERENCES

[1] DAVID, J., SVEC, P., FRISCHER, R. Support for maintenance and technology control on slab device of continuous casting. In METAL 2013: 22nd International Conference on Metallurgy and Materials. Ostrava: TANGER, 2013, pp. 1650-1655, WOS: 000333163100273.

[2] DAVID, J. SVEC, P., FRISCHER, R., STRANAVOVA, M. Usage of RFID Wireless Identification Technology to Support Decision Making in Steel Works. In METAL 2012: 21st International Conference on Metallurgy and Materials. Ostrava: TANGER, 2012, pp. 1734-1738.

[3] FRISCHER, R., POLLAK, M., TUHY, T. PRAZAKOVA, V., Usage of clustering analysis in diagnostics of metallurgical devices. In METAL 2013: 22nd International Conference on Metallurgy and Materials. Ostrava: TANGER, 2013, pp. 1881-1886, WOS: 000333163100312.

[4] NAWARECKI, E.; KLUSKA-NAWARECKA, S. REGULSKI, K. Multi-aspect Character of the Man-Computer Relationship in a Diagnostic-Advisory System. HUMAN-COMPUTER SYSTEMS INTERACTION: BACKGROUNDS AND APPLICATIONS 2, PT 1. Book Series: Advances in Intelligent and Soft Computing. 2012, Vol. 98, pp. 85-102.

[5] DAVID J., VROŽINA M., NOVAKOVÁ H. Control of dependability of metallurgical processes such as logistics chains. In METAL 2012: 21st International Conference on Metallurgy and Materials. Ostrava: TANGER, 2012, pp. 1702-1708, WOS: 000318506500263.

[6] DAVID J., ŠVEC P., FRISCHER R., GARZINOVÁ R. The Computer Support of Diagnostics of Circle Crystallizers. METALURGIJA, Vol. 53, No. 2, 2014, pp. 193-196.

[7] DAVID J., JANČÍKOVÁ Z., FRISCHER R., VROŽINA M. Crystallizer's Desks Surface Diagnostics with Usage of Robotic System. ARCHIVES OF METALLURGY AND MATERIALS, Vol. 58, No. 3, 2013, pp. 907-910.