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USAGE OF CLUSTERING METHODS FOR SEQUENCE PLAN OPTIMIZATION IN STEEL PRODUCTION

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The paper deals with production scheduling of heat sequences while are steel types casted on continuous casting device. For production scheduling are used k-means clustering and fuzzy clustering methods. The parameters for cluster analysis are chemical composition liquids temperature and another values. From these values were selected parameters, which has been processed by clustering methods. Proposed clustering algorithm for sorting steel grades on continuous steel casting device is aimed to cast as many single graded smelts as possible, respectively more steel grades, which has similarities in chemical composition and liquid temperature. These resulting clusters are used when designing algorithm for smelting sequence scheduling. The goal of the production scheduling is to make schedule of production tasks, so how to achieve the agreement between order requirements and capabilities of production in given time scale.

Key words: production, steel, scheduling, optimization, steel grades, clustering

INTRODUCTION

One of the main basic presumption for increasing continuous steel casting devices productivity is increasing smelting count in one sequence. For achieving this goal it has to be pay attention to production schedule and to development and implementing new automated production planning systems.

Present scheduling ways are based on planning “smelting times”, which are derived from technical state of the smelting aggregates, available time, batch material reserves state, concerted take off of oxygen, electric energy, steel amount and so on [1].

PRODUCTION SEQUENCE PLAN

In the beginning is good to mention technological point of view on continuous steel casting problems in area of inter melting pot in relevance with occurrence, analysis and effort to minimize so called mixed area.

If there is a situations, during sequential continuous steel casting, when next smelting contain too different steel chemical composition, it starts in the inter smelting pot to mix older steel grade with the new one (when the furnace ladle is open).

This situation has direct effect to grade of casted steel, which does not comply with previous casted grade, neither current casted grad – this is so called mixed area.

From above mentioned results, that production scheduling on casting devices represent complicated, complex task, which involve many impacts, which are given by technological parameters and production – marketing parameters [2,3].

The basic idea when scheduling production is steel grade, final product shape and size, quantity and date of delivery. The goal of the production scheduling is to make schedule of production tasks, so how to achieve the agreement between order requirements and capabilities of production in given time scale. It must stand, that in one sequence are casted smelting with regards to the date of delivery of final product, same format and the same or similar steel grades in that way, to be minimized mixed area [4].

STEEL GRADES CLUSTERING

To solve issues about similarities of casted steel grades were used clustering methods, such as K-Means a Fuzzy K-Means methods. These are one of the uncontrolled learning algorithms intended to solve problems about data clustering. The effectivity lies especially in usage of simple classification of data groups to single clusters. K-Means method is clustering international algorithm. It is based on point distance in multi-dimensional space. Each evaluating object is represented exactly by one, single point, every tracked attribute then by single coordinate. Method K-Means is suitable especially for huge data groups, which should be unscrambled to small amount of clusters. In initialization part is setup number of clusters k, which should be on the output (the “k” letter, for the k-means). It is created k of points with random coordinates (future group centers - Centroids). The object is assigned to the closest initial centroid (find out distance from this centroid is smaller, than the distance to the rest of the centroids), the cluster

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is represented by all points, which are closest to this centroid [5,6].

For every cluster is then calculated new centroid, whereby is m-dimensional vector consisting of mean values of each variable. Then are repeatedly verified distances of each object from each centroid. In case, that he object is closer to another centroid, of another cluster, the object is moved to this cluster.

Whole procedure is repeated so long the movements are present. It is proved, that the algorithm is final. To determine initial centroids exists various approach, it can for example be k – first objects from group. Then are calculated distances of each object from each initial centroid so that for each pair calculate Euclid distance.

He ground of algorithm for Fuzzy Clustering is assigning membership degree to each smelt in range < 0,1 >. The membership degree with value 0 says, that smelt surely do not lies in given cluster, on the contrary value 1 says, that the smelt surely identify given cluster. If the smelt is assigned to the cluster uniquely, in current row is one time value 1 and the other values are assigned to 0. If it is able to assign given smelt to more clusters (clusters are overlapping), then is determined membership of given smelt to all clusters. These overlapping clusters then give opportunity to interconnect clusters (sequences) to another sequences through the grades which are present in both clusters.

The result of this part is distribution of casted grades, which are chemically and temperature closer, to groups with usage of K-Means method and Fuzzy K-Means. It means, that steel grades, which has similar parameters are in the same cluster after algorithm is done.

The same situation is when casting different formats. In the term of actual solution of current problems was created 5 random clusters and calculations were tested on 151 steel grades (remark: steel grades are tagged by numbers from 1 to 151) [7].

Each single steel grades were characterized by 27 parameters containing chemical composition and liquid temperature and temperature in inter smelting pot. The solution does not contain all 27 parameters, but only significant ones, which has been determined by scatter analysis. From the initial raw data were calculated scatters of parameters according to equation:

$$s^2 = \frac{1}{n-1} \cdot \sum_{\forall i} \left(x_i - \bar{x} \right)^2 \tag{1}$$

where s^2 is selective scatter, n - values number,
x_i - each single values, $\bar{x}$ - arithmetic average

The parameters Table 1, whose scatter was greater than 0,0001, were marked as a significant and was registered as proper to use in K-Means and Fuzzy K-Means.

THE ANALYSIS OF SELECTED PARAMETERS FROM THE ABBRASION POINT OF VIEW

In many literal sources is made an analysis of influence of continuous casting process parameters to the output product quality. It can be concluded, that the quality of continuously casted blanks is determined by the state of liquid steel ready to cast and conditions of given casting (it means technology and actual state of casting device).

Table 1 **Demonstration of significant parameters for grades clustering /wt. %**

T_STEEL	T_LIKVIDU	AL	C	MN	SI	P	S	CU	CR	NI	MO	V
1 523°C	1 486°C	0,02	0,37	1,39	0,55	0,02	0,05	0,05	0,16	0,03	0,01	0,10
1 530°C	1 487°C	0,03	0,43	0,81	0,28	0,01	0,03	0,03	1,14	0,03	0,18	0,01
1 539°C	1 508°C	0,03	0,16	1,35	0,38	0,02	0,03	0,09	0,12	0,03	0,01	0,00
1 551°C	1 508°C	0,02	0,18	1,21	0,25	0,02	0,01	0,03	0,14	0,21	0,01	0,02
1 550°C	1 506°C	0,03	0,17	1,30	0,45	0,02	0,01	0,03	0,22	0,02	0,00	0,04
1 549°C	1 513°C	0,03	0,16	1,07	0,15	0,01	0,01	0,03	0,05	0,02	0,01	0,00
1 546°C	1 507°C	0,02	0,19	1,34	0,23	0,02	0,02	0,03	0,08	0,02	0,00	0,01
1 538°C	1 509°C	0,03	0,18	0,94	0,32	0,02	0,02	0,02	0,20	0,01	0,00	0,01
1 558°C	1 513°C	0,03	0,16	0,73	0,26	0,01	0,01	0,06	0,04	0,04	0,01	0,01
1 553°C	1 515°C	0,03	0,16	0,47	0,25	0,01	0,01	0,05	0,07	0,05	0,02	0,00
1 550°C	1 512°C	0,03	0,17	0,62	0,30	0,01	0,01	0,05	0,04	0,02	0,00	0,00
1 557°C	1 512°C	0,03	0,18	0,63	0,25	0,01	0,00	0,04	0,04	0,02	0,01	0,00
1 551°C	1 507°C	0,03	0,18	1,38	0,28	0,02	0,02	0,07	0,08	0,03	0,00	0,00
1 524°C	1 508°C	0,03	0,17	1,29	0,30	0,02	0,01	0,07	0,05	0,03	0,01	0,00
1 536°C	1 508°C	0,02	0,18	1,16	0,30	0,01	0,03	0,05	0,22	0,02	0,01	0,04

The list of parameters, which are followed, or could be followed is phenomenal. There are casting devices, on which the count of followed parameters reach value 500 and more. All these parameters are stored. And so far this is not the end of the parameters description, because casting process is very complex.

In term of presented paper is attention target to influence of casting steel parameters, which were determined by the scatter analysis as a significant and is provided theirs analysis from the influence to mold abrasion point of view. The analysis is made by so called cumulative parameter model comes from the presumption, that significance of parameter to mold abrasion is given by size of regression curve linear direction Figure 1. This value is specified by experience of operational workers, with which the problems was consults [8].

This problems is greatly complex and exceed the term of this paper, however can be the gate to another development activities in this area.

CLUSTERING RESULTS

In Table 2 and Table 3 is presented final distribution of steel grades in given clusters, made by K-Means and Fuzzy K-Means methods.

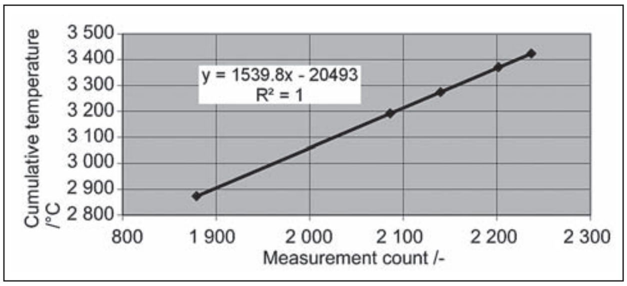

Figure 1 Example of cumulative model for carbon content in steel

Table 2 **Share of grades in given clusters – K-Means method**

K-Means	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Point count in clusters	36	22	1	38	54
Percent expression	23,2 %	15,1 %	0,7 %	25,2 %	35,8 %

Table 3 **Share of grades in given clusters – Fuzzy K-Means method**

Fuzzy K-Means	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Point count in clusters	32	16	32	17	54
Percent expression	21,2 %	10,6 %	21,2 %	11,2 %	35,8 %

It is obvious, from the results, that steel grades distribution when applying Fuzzy K-Means is more equal than using classic K-Means, where are define sharp edges of each clusters. Advantage of Fuzzy K-Means method when solving smelting's plan scheduling on continuous steel casting devices is determining membership degree for individual clusters. Maximum membership degree classify steel grade to appropriate cluster and also determine membership degree to the rest of the clusters. This information about membership between individual clusters then create possibility to interconnect individual clusters (sequences) into longer sequences over related grades for both clusters. This approach allows new features when planning smelting sequences on continuous steel casting device and thereby increase effectiveness and productivity of continuous steel casting process [9,10].

SEQUENCES SCHEDULING ALGORITMIZATION

The base of the scheduling process is sorting of individual contracts according to delivery time. Into the solution then enter contracts re-count on smelting outspread to planned day. In case of unachieved daily production capacity can be into the solution embodied future smelts. Whole solution then proceed in three levels.

In level 1 is evaluated delivery priority, so smelting planned to give work day is assigned attribute "High Priority", in other cases attribute "Low Priority". In second level is evaluated final product shape and dimensions, that means mold shape and format. In Figure 2 is that possibility simplified to two basic groups. By the term circle are marked circle cross section and term 4 square stand for rectangular formats. Algorithm work with individual particular casted formats.

The third level is for steel grades. On Figure 2 is displayed only 10 grades for simplifying, however the algorithm is not restricted to certain number of grades. The steel grades can be so ever added according production scale. The same situation is when concerning casted formats.

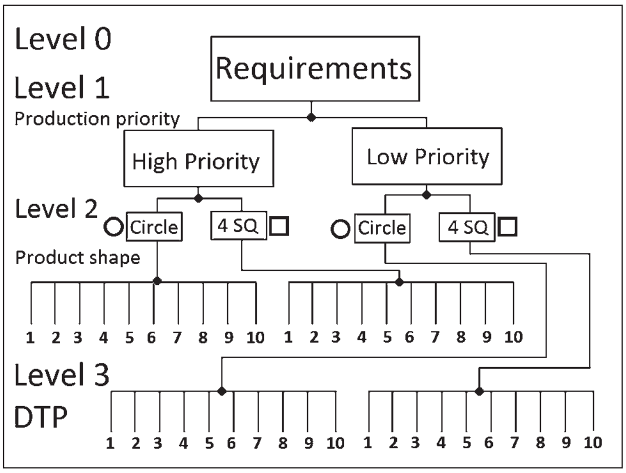

Figure 2 Hierarchical model parameter's structure

In terms of solving this problems was on department of automation and computing in metallurgy, VSB-TU Ostrava, made up an algorithm for production scheduling support of smelting sequences. This algorithm uses clustering method for casting steel grades.

CONCLUSION

Proposed clustering algorithm for sorting steel grades on continuous steel casting device is aimed to cast as many single graded smelts as possible, respectively more steel grades, which has similarities in chemical composition and liquid temperature. This is intended to support smelting sequence scheduling.

Algorithm basis is clustering production steel grades into groups with usage traditional (K-Means) or improved (Fuzzy K-Means) algorithms. Its means that steel grades, which has similar parameters are finally in one cluster.

These final clusters are used when proposal algorithm for planning of smelting sequences and further revaluated with usage fuzzy clustering methods, for provision the highest capacity usage of one sequence.

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Note: The responsible person for English language is E. Tenzin, Ostrava, Czech Republic