SUPPORT OF THE OPERATIVE PLANNING WITH UTILIZATION OF THE GENETIC ALGORITHMS IN THE ENVIRONMENT OF MICROSOFT EXCEL

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Abstract

The contribution deals with model of operative scheduling of production on the facility for continuous casting of steels. Starting point for the increase of efficiency of complicated decision-making processes is the transfer to the decision-making based on the exact, scientific knowledge. Increase the exactivity means utilization of modeling and modern methods for problems solving. Modeling is basic methodological resource for solving of complicated problems, application of modern methods for realization of particular phases of model is then basic condition of the successful realization. Production scheduling at continuous casting of steel belongs to group of above mentioned problems. High emphasis is put on the efficiency of the processes with the compliance of the quality of products. It is necessary to search new innovative approaches with utilization of methods of artificial intelligence and knowledge management in this area, too. Model is compatible with INDUSTRY 4.0 concept when it utilizes genetic algorithm for establishing of the smelting plan. Proposed model is based on the model of crystallizer utilization and fatigue which use diagnostics. Utilization of the proposed model consists in the support of smelting planning in the sequences respectively campaigns. Proposed solution allows to find suitable combination of cumulative counts of smelts in the particular clusters after assignment of purposeful function, limiting conditions and residual life of crystallizer in the form of residual conicity change. Proposed model which is realized in MS Excel proposes to the user possible and effective variants of the scheduling of production in the next period according to the specified limited conditions.

Keywords: Metallurgy, continuous casting, mold, control, operative planning, genetic algorithms

1. INTRODUCTION

One of the basic prerequisites for increasing the productivity of a continuous casting machine is to increase the number of castings cast in a single sequence. To achieve this goal, sufficient attention has to be paid to scheduling production and thus developing and implementing new automated production planning systems [1]. Current planning methods are mostly based on the "tapping times" that are determined on the basis of the technical state of the aggregates, the available time, the stock of batch materials, agreed oxygen, electricity, steel, etc. Subsequently, delivery times are calculated on the following technological aggregates and a casting sequence plan. From a logistical point of view [2], this is the so-called push principle (push = push, push) which aims to push the material as quickly as possible throughout the production chain. However, the real situation in the steelworks in terms of material flows is controlled by the so-called pull (drag) pulling principle, in which the material is "pulled" by the current causing the end-of-line chain to be pushed forward according to the plan commands. From the point of view of the real situation at the steelworks, this means that the flow of material is controlled by the needs of continuous casting technology, based on the state of wear of the crystallizer as one of the most important technological components and the arrangement of individual steel brands in the planned sequence. This is of importance in terms of maintaining the quality of continuously cast billets, but also in terms of minimizing so-called mixed areas. These areas result in the casting of the steel marks. Each brand varies with its composition, and for the efficiency of production, it is necessary to determine the appropriate sequence of brand casting as well as the number of castings cast in one sequence. Innovations in continuous casting are the methods of artificial intelligence [3]. The paper aims in presenting an example of a model for supporting operative planning using genetic algorithms and fuzzy clustering realized in MS Excel.

2. GUSTAFSON-KESSEL´S ALGORITHM

During the change of the steel mark, successive casting takes place during continuous casting, which leads to the formation of steel which does not correspond to the previous brand or the casting brand. In order to minimize these differences, it is a convenient solution in clusters of steel grades to clusters, according to similar properties and chemical composition. And then inclusion in the melt sequence.

In order to optimize the planning process, it is necessary to classify the steel marks using cluster analysis methods. There are several clustering methods for clustering [4,5]. In this work, fuzzy Gustafson-Kessel algorithm will be used for algorithmization of clustering.

The Gustafson-Kessel´s algorithm is based on the extension of the standard fuzzy c-means algorithm by using the adaptive distance of the standard to detect clusters of different geometric shapes and orientations. The clusters in this method are ellipsoidal compared to the fuzzy c-means and are represented by a symmetrically positive definite P_i matrix. Sometimes this matrix is called the deformation matrix because it modulates the shape of the clusters, which have an ellipse in the two-dimensional space. To calculate P_i, the S_i covariance matrix is used using the following equations (1-3) [6].

$$S_i = \frac{\sum_{k=1}^{N} \left(u_{i,k}\right)^m \cdot (z_k - v_i)^T \cdot (z_k - v_i)}{\sum_{k=1}^{N} \left(u_{i,k}\right)^m} \tag{1}$$

$$P_i = [det(S_i)]^{\frac{1}{N}} \cdot S_i^{-1} \tag{2}$$

Where

P_i - defined matrix

S_i - covariance matrix

$U^{(l)}$ - affiliation matrix

$V_i^{(l)}$ - the degree of relevance of the input data to the clusters found

$v_i^{(l)}$ - centers of clusters

N - number of data clusters.

The restriction is defined for P_i

$$det(P_i) = \rho \tag{3}$$

where

ρ -the constant is given for each matrix.

This determines the volume of clusters. The rotation of their driveshafts is determined by their own vectors of the P_i matrix and the magnitude of their half-axes corresponds to the powers of their own numbers of the P_i.

One of the most difficult tasks in cluster analysis is to find a suitable number of clusters. The magnitude of the "fuzzification" in the solution can be measured by the Dunn's partition coefficient, which has the largest participation. The Dunn distribution coefficient is expressed by the equation (4).

$$F(U) = \frac{1}{N} \sum_{k=1}^{K} \sum_{i=1}^{N} m_{ik}^2 \tag{4}$$

The value of the coefficient lies in the range from *1/K* to 1. For *F(U)* = 1/K, all participations are equal to 1/K. The value *F(U)* = 1 is valid for each object and the unit equals zero. The Dunne partition coefficient can also be normalized so that its value is changed from 0 (full fuzzy) to 1 (solid cluster) the standard version has the shape

$$Fc(U) = \frac{F(U) - 1/K}{1 - 1/K} \tag{5}$$

Another coefficient is Kaufman's partition coefficient

$$D(U) = \frac{1}{N}\sum_{k=1}^{K}\sum_{i=1}^{N}(h_{ik} - m_{ik})^2 \tag{6}$$

and the coefficient occurs in the range from *D(U)* = 0 (solid clusters) to *D(U)* = 1- (1/K) (complete fuzzy). The standard version of this coefficient is shaped

$$Dc(U) = \frac{D(U)}{1 - (1/K)} \tag{7}$$

Both normalized coefficients *Fc(U)* and *Dc(U)* together provide a good indication of the optimal number of clusters. Integer *K* should be chosen so that *Fc(U)* will get small and *Dc(U)* large values [6].

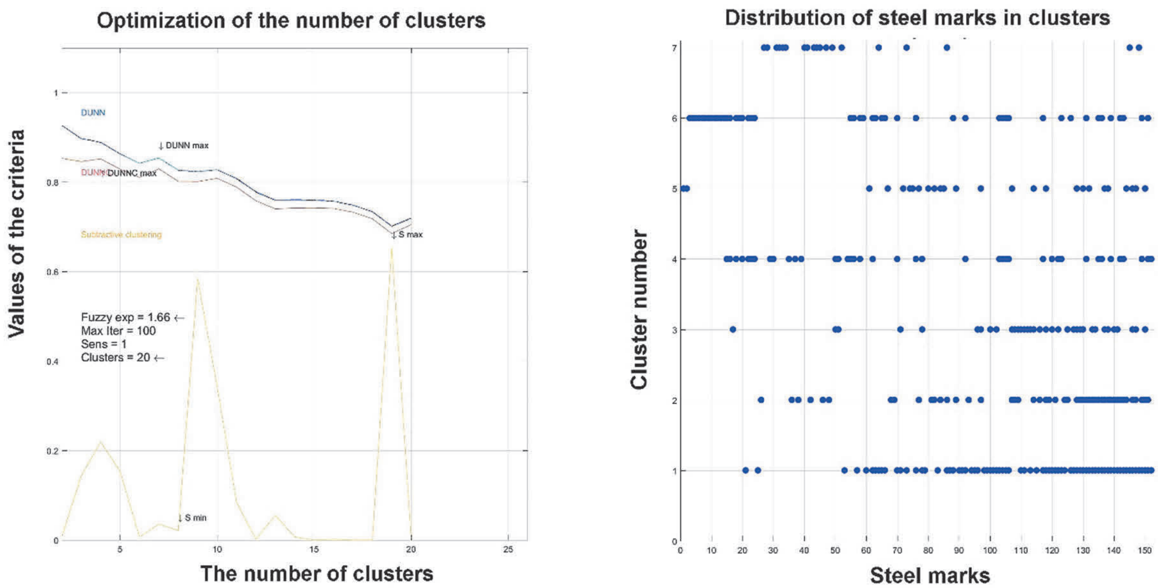

Figure 1 The results of clustering [own]

The results obtained are used for the simplified design of the plotting sequence algorithm (**Figure 1**).

3. OPTIMIZATION OF PLANNING OF MELTING PROCESS SEQUENCES

The efficiency of the entire optimization solution is decisively influenced by the quality of the purposeful function. The purposeful function in this case represents a deterministic model based on the analytical diagnosis [7] of the state of the crystallizer - on its wear (**Figure 2**).

For this purpose, the wear measurements were made during the technical life on the copper inserts of the circular mold, which have RFID tags for unambiguous identification, of system MKL 100/420 by DASFOS v. o. s. This system measures the circularity of the internal cross section of the crystalliser insert along its entire circumference and the height at 18 levels.

The measured values were then related to the operating records relating to the parameters of the cast steels on the selected crystals. The present solution, in the form of a crystalliser insert wear model, using both conventional and nonconventional process modelling techniques, develops this issue with a new, comprehensive approach that includes support for predictive crystallization maintenance, which can also be used to optimize production scheduling of melt sequences on continuous casting [8-10].

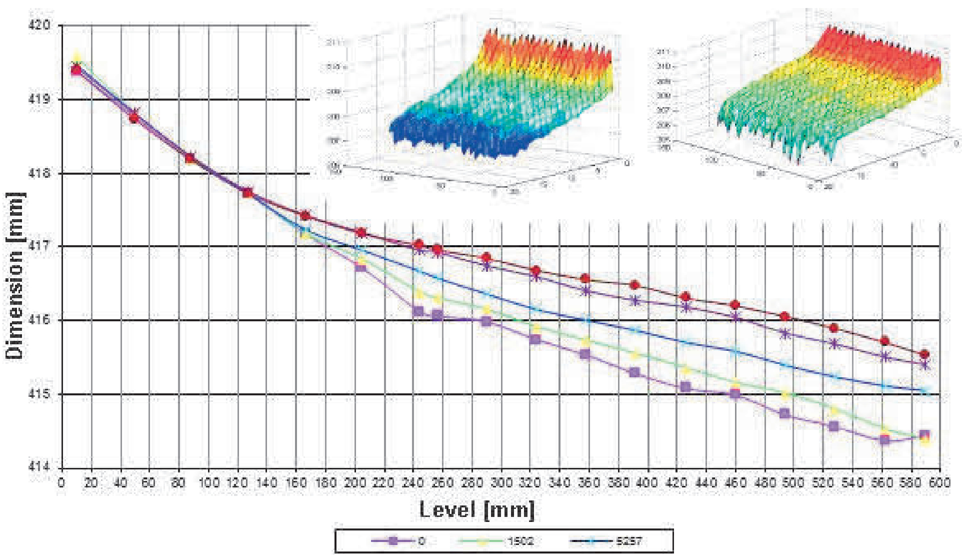

Figure 2 Visualization of mold's wear through entire service life [own]

In this phase of the solution, a multidimensional linear regression model is tested

$$\beta_0 + \beta_1 \cdot f_1 + \beta_2 \cdot f_2 + \beta_3 \cdot f_3 + \beta_4 \cdot f_4 + \beta_5 \cdot f_5 = \Delta k_d \qquad (8)$$

Where

f_1 to f_7 - the cumulative frequencies of cast marks in S_1 to S_7

β_1 to β_7 - coefficients of significance of S_1 to S_7 aggregates for crystallization wear

β_0 - linear regression coefficient

Δk_d - change of average lower conicity of circular crystallizer of individual periods.

By solving the obtained system of equations, the coefficients of significance of the aggregates S_1 to S_7 were obtained for the wear of the crystallizer. The resulting model has the following form:

$$\begin{aligned} &-0{,}019734 \cdot f_1 + 0{,}010912 \cdot f_2 - 0{,}000998 \cdot f_3 + \\ &-0{,}064704 \cdot f_4 - 0{,}008246 \cdot f_5 + 0{,}018815 \cdot f_6 + 0{,}005276 \cdot f_7 = \Delta k_d \end{aligned} \qquad (9)$$

Where

Δk_d - change of lower relative conicity

f_1 to f_7 - cumulative numbers of castings in clusters 1 to 7 in the specified period.

The lower average relative conicity for a given time point is then determined by the relationship

$$k_d(t) = k_d(t-1) - \Delta k_d \tag{10}$$

Where

$k_d(t)$ - lower average relative conicity at time t

$k_d(t-1)$ - lower average relative conicity at time $t-1$

Δk_d - change of the lower relative conicity in the time interval (t; $t-1$).

The proposed Sequence Planning optimization algorithm was implemented in Microsoft Excel, using the Solver tool, which implements an evolution algorithm. The solution took place in the environment of MS Excel. The tool called "Solver" was utilized which has implemented evolutional algorithm. The screenshot of the Solver window is depicted on the **Figure 3**.

The model was implemented in the Microsoft Excel 2010 environment. The reason for choosing this environment was the breadth of this table process, its possibilities, and the fact that the software is currently installed on a number of operating computers and working with it.

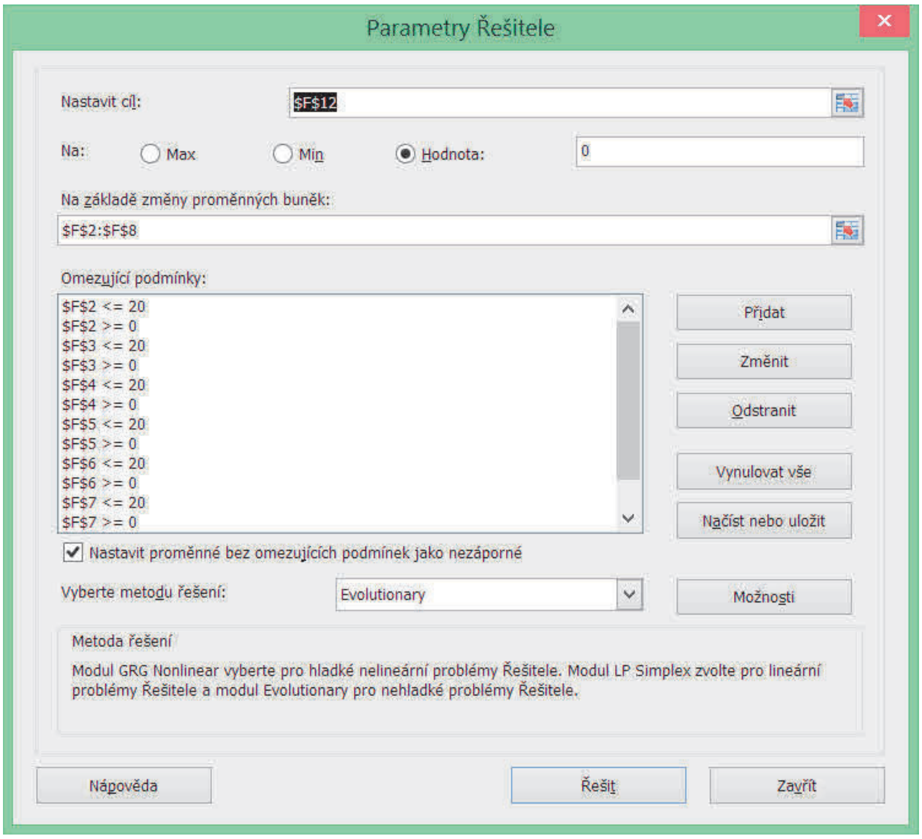

Figure 3 Window of the Solver add-in [own]

The target of the solution is to find suitable combination of cumulative frequency of casted marks in the clusters S_1 to S_7 which corresponds with required change of the bottom conicity and with entered limiting conditions.

Process of the solving using the Solver add-in consist in addition of the cells' addresses for target, of variable and of assignment of limiting conditions which define searching area and they can characterize some technological limitations in the production.

Example of the solution is depicted on the **Figure 4**. Only the searching area was defined and no technological restrictions were used. It is evident from the results shown in the columns J to T that the task has infinite number of solutions at the same input parameters.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Coefficients of cluster significance					Cumulative rate cast brand				Smelting								
2		β_1 =	-0,019734			8,254695	8			8	5	4	11	13	12	3	5	8
3		β_2 =	0,010912			12,68653	12			13	16	18	11	9	8	9	10	12
4		β_3 =	-0,000998			11,61004	11			0	0	8	9	0	6	5	4	11
5		β_4 =	-0,064704			0,611717	0			2	1	3	0	0	0	4	1	0
6		β_5 =	-0,008246			14,3204	14			6	9	9	9	1	3	5	7	14
7		β_6 =	0,018815			12,05574	12			17	10	12	14	11	12	18	10	12
8		β_7 =	0,005276			10,98883	10			0	0	11	8	16	15	10	10	10
9										0,124955	0,125154	0,124986	0,12538	0,124801	0,124682	0,1254	0,124942	0,12519
10																		
11						Formula	Worth											
12						0,00019	0,125											

Figure 4 Sample data of operational production scheduling model [own]

Example of the solution with the limiting conditions including the technological requirements respectively production requirements is shown on the **Figure 5**. User can exactly define quality composition which wants to produce as well as quantity.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	Coefficients of cluster significance					Cumulative rate cast brand				Smelting					
2		β_1 =	-0,019734			0	0			0	0	0	0	0	0
3		β_2 =	0,010912			17,3466	17			17	0	0	0	0	0
4		β_3 =	-0,000998			9,47082	9			9	8	0	0	0	0
5		β_4 =	-0,064704			4,003774	4			4	3	1	0	0	0
6		β_5 =	-0,008246			8,468983	8			8	11	10	16	0	0
7		β_6 =	0,018815			12,17057	12			12	18	10	10	3	0
8		β_7 =	0,005276			9,879555	9			9	15	16	13	13	24
9										0,125002	0,125008	0,125402	0,124802	0,125033	0,126624
10															
11						Formula	Worth								
12						2E-06	0,125								

Figure 5 Sample data of operational production scheduling model [own]

It is evident from the presented results that tool Solver with the evolutional method of solving allows to get results which can be utilized as support for production scheduling based on the reliability model of lifetime.

Simplicity (programming and/or creation of rules' base are not needed) and variability of solution which is given by the choice of limiting conditions are the advantages of the proposed method.

Disadvantage of the proposed approach is that Solver does not have generator of solutions and therefore it provide only one solution in the single launch. It is necessary that user strictly and exactly must define requirements of the production in the form of limiting conditions.

CONCLUSION

Model of the operative scheduling of production with the utilization of the diagnostics in the period of the end of lifetime of crystallizer allows to fulfill the function of support for smelts planning in the sequences respectively in the campaigns when the proposed solution allows to get cumulative numbers of smelts in particular smelts which is possible to cast to the limiting state of crystallizer given by user without the influence at the production quality and at given limitations. Residual lifetime of the crystallizer in the form of residual change of the conicity must be given to the calculation. The fuzzy cluster analysis solution also gives the possibility of "joining" steel grades in different clusters, thereby minimizing the formation of mixed areas when casting different brands.

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