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Knowledge-Based Intellectual DSS of Steel Deoxidation in BOF Production Process

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Abstract This article describes one of possible approaches to deoxidant cost optimization in steel production, based on the expert system. Education of the system is based on successfully completed heats. Bayesian networks and decision trees are suggested as the mechanisms for knowledge extraction.

Keywords: *Bayesian networks, decision trees, decision-making, deoxidizing, knowledge, management, rules*

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1. Introduction

Liquid or solid iron, scrap, deoxidants, alloying and slag-forming materials are used as basic material in the manufacture of steel-making. Several major problems are being resolved at redistribution of iron and scrap into steel: melting and heating blend to the temperature that provides the following operations (typically 1600-1650°C), refining steel from impurities (typically, these include sulfur, phosphorus, hydrogen and nitrogen), alloying, and finally obtaining steel ingot or continuous casting billet from liquid steel [1].

Heating up to the desired temperature, partial refining and alloying are performed in steelmaking units, particularly in the basic oxygen furnace, final refining and alloying - in steel teeming ladle after the release of the unit using specialized facilities and spill - through molds or continuous casting machines (CCM).

2. Problem Description

Released from the converter, non-deoxidized liquid steel contains a significant amount of dissolved oxygen. Lowering of the metal temperature during filling and crystallization is accompanied by oxygen solubility decrease, leading to carbon monoxide formation and separation, bubble castings and leaky bars [2]. The first task of deoxidation is to reduce dissolved oxygen in the steel and linking it into the stable compounds that do not give gaseous emissions during the solidification of the metal. Another problem is the maximum removal of liquid steel deoxidation products (non-metallic inclusions). Non-metallic inclusions are characterized by physical properties different from the base metal, causing the formation of local stress concentration, contact fatigue of metals, intercrystalline fractures, depleting and crashes of moving parts. To acquire high quality steel, the content of nonmetallic inclusions shouldn't be more than 0.005-0.006% [1].

The most common steel deoxidants are silicon, manganese and aluminum. Calcium, chromium, vanadium, cerium, titanium are used in some cases. Meanwhile, ferrosilicon, silicomanganese and ferromanganese are often used in the domestic metallurgy. All of them have different deoxidization ability, extirpation quality (silicon is the best for oxygen binding, although it is the worst for oxides deriving from the melt) and price. The problem of optimization of alloys used in the deoxidation seems to be actual because the price of alloys makes quite a substantial share of the cost of finished steel.

This problem is one of the integrated system control functions of the multistage steel production. The main approaches to solving the problem, principles structure and functioning are set out in [3] and [4]. In particular, the system should implement the optimality principle of each production stage to obtain optimal process plan by generalized economic criterion [5].

Generalized process control at the stage of deoxidation is presented in scheme in Figure 1.

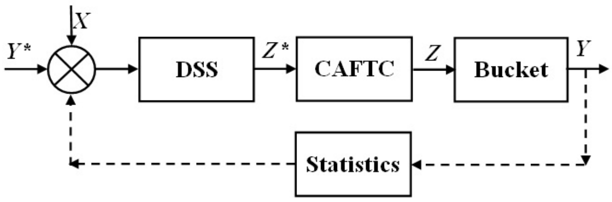

Figure 1. Scheme of deoxidation process control

As inputs for decision support system (DSS) of deoxidation process control a number of parameters, which are caused by produced steel brand (vector Y^*) and parameters of steel in the converter (vector X which in general is a disturbance) was selected. Depending on the component values of these vectors, DSS generates control action (vector Z^*) as the task of different kind deoxidants that served in buckets. The task is mined by closed automatic ferroalloy tract control (CAFTC) which consists of the regulator, dispenser, valves system and sensors [5]. At the initial phase of converter steel production selected ferroalloys (vector Z) are added to the bucket, that helps to maximize deoxidants absorption by steel melt and reduces their consumption in the slag zone [1]. As a result we have control vector Y that describes the chemical composition of the obtained steel.

Figure 1 shows the main feature of the deoxidation control system: it is open-loop and uses the principle of management by objectives. The usage of any present feedback system in the process is impossible: because when the numerical characteristics that describe the output are obtained, the meaning of the control action will be lost as steel becomes cold ingot, in which deoxidation processes are completed.

Existing techniques used in manufacturing [1,2] provide the usage of empirical formulas for deoxidants calculating depending on their chemical composition, considering grade of steel, carbon, silicon and manganese content before turndown and casting kind, either steel cast is boiling or calm. Target carbon and alloying elements value content in finished steel (vector Y^*) defined as the average value of the range allowed for this brand by standard. These formulas are made with some reserve and do not provide ferroalloys savings.

Research objective: To propose a mechanism of previous positive steel deoxidation experience using knowledge extracted from fusions databases and their inclusion in decision support systems, introducing feedback into a deoxidizing control system.

3. Materials and Methods

Decision support systems that use intelligent (including fuzzy) conclusion are used in industry, particularly in the ferroalloys production. A mathematical model of fuzzy optimization of multicomponent mixture and methods and algorithms that improve the predictions consequences control action quality in the face of uncertainty regarding the structure and parameters of the processes and actions of uncontrolled disturbances are proposed in [6]. Thus, neuro-fuzzy model using is optimal regarding the economic criterion of the charge composition.

Similar ideas developed in [7], allow simulating steel alloying process and predicting the mechanical properties of rolled results by chemical analysis of steel in the ladle, using fuzzy production rules, in particular, Mamdani model. Even a small number of rules in such intelligent systems have high resolution in result space.

There is also another approach [8] to modeling the optimal behavior of the BOF production operator based on the use of standards. Under this approach, during the smelting of steel and brand known initial conditions of melting, the example that most accurately describes the current conditions is sought in a database containing information about all previous melting. It applies multidimensional mathematical optimization of a model interpolated to the conditions that are different. The authors propose taking the main charge materials and ferroalloys similar to previously known successful examples from the database.

In this paper, key features of both approaches are proposed to be used in an expert DSS. As a production model, the so-called naive Bayes network [9] is proposed to be used.

This method of processing knowledge has several important features. Firstly, because the model determined the relationship among all the variables, the situation when the values of some changes are unknown is easily handled. Secondly, the approach allows combining patterns derived from the data and background knowledge obtained in an explicit form (e.g., experts) in a natural way. Finally, using the described method avoids the problem of overfitting, i.e. excessive models complexity which many methods are affected (such as decision trees) because of too close distribution of noisy data imitation.

Despite its simplicity, speed and ease of interpretation of results, naive Bayes algorithm has several disadvantages, the key one of which is the basic assumption of mutual uncorrelatedness of all input variables (reason of the "naive" in the title). However, the method does not permit the direct processing of continuous variables - they must be divided into a number of intervals to discretize values.

Considering all the method above, the data from the database of fusion performed in the converter shop of PJSC "Evraz - DMP named after Petrovsky" in 2008 and 2009 (12039 fusions in total) were discretized, and then factor analysis was conducted for them to determine the linearly independent factors. The results are reported in Table 1, where the separation of variables (control action, disturbance, and state variables) is presented in accordance with the scheme of Figure 1.

Table 1. Research problem variables

Variable	Dimension	The value in the database	Range of variation	Number of intervals
X1	°C	The temperature of the metal in the converter	1559-1698	3
X2	%	Mn content before deoxidation	0,03-0,8	4
X3	%	S content before deoxidation	0,012-0,05	4
X4	%	P content before deoxidation	0,002-0,031	3
X5	%	C content before deoxidation	0,04-0,86	6
X6	%	Mn content in FeMn	68,5-79,2	3
X7	%	Mn content in SiMn	66,2-74,9	3
X8	%	Si content in FeMn	0,41-2,8	3
X9	%	Si content in SiMn	16,67-18,2	3
Y1	%	Set Mn content in the finished steel	0,5-0,8	3
Y2	%	Set S content in the finished steel	0,013-0,05	3
Y3	%	Set P content in the finished steel	0,002-0,038	3
Y4	%	Set C content in the finished steel	0,28-0,37	3
Y5	%	Set Si content in the finished steel	0,05-0,12	3
Z1	kg.	FeMn deoxidizer weight	0-1070	5
Z2	kg.	SiMn deoxidizer weight	0-675	4
Z3	kg.	FeSi deoxidizer weight	0-360	3

Separation of continuous variables values was carried out according to the ranges of these recommendations [10]:

- If the value distribution law is uniform or normal - 3 bands ("small", "medium" and "high") at values intervals of the basic scale;
- If the distribution law is negative or it is difficult to establish - the minimum number for quantile with equal (or as close as possible) probability density intervals.

Since the variables z_k, $k=\overline{1,3}$ depend not only on the semi-independent x_i, $i=\overline{1,9}$ and y_j, $j=\overline{1,5}$, but are also interdependent (ferroalloys are complementary and interchangeable), each combination of their linguistic values needs to match a specific class. According to reports such classes made up 34. These included all possible combinations of terms of output variables, which met in the database at least once.

According to the method [9] all variables were quantized and for each interval central values and priori probabilities were calculated. In particular, for the output variables were defined probabilities $P(z=c_r)$, where c_r makes vector combinations of central importances, r interval of output variables, such as $z_1=$ «Little» | $z_2=$ "Many» | $z_3=$ "Nothing".

Putting independent variables into line to output variables, posteriori probability formula can be defined.

$$P(x_i=c_{i,j}, y_k=c_{k,j} \mid z=c_r)=$$
$$=\frac{P(z=c_r)\cdot\prod_i\left(P(x_i=c_{i,j})\right)\cdot\prod_k P(y_{1k}=c_{1k1j})}{\sum_r\left(P(z=c_r)\cdot\prod_i\left(P(x_i=c_{i,j})\right)\cdot\prod_k P(y_k=c_{k,j})\right)}, \quad (1)$$

where $r=\overline{1,34}$ is the current number of output class; $c_{i,j}$, $i=\overline{1,9}$ and $c_{k,j}$, $k=\overline{10,14}$ are central values of input terms, with individual number (3 to 6) for each variable (see Table. 1).

Thus, we calculate probability for complex rules, such as "If $x_1=c_{1,j}$ and $x_9=c_{9,j}$ and ... $y_1=c_{10,j}$ and ... $y_5=c_{14,j}$ then $z=c_r$ ". The total number of such rules with certainty $P_\Sigma=1$ describing the specified subject area makes up 1589.

Defuzzification of fuzzy solutions to precise is performed using the formula

$$z_m=\sum_{r=1}^{34}\mu(c_r)\cdot c_{m,r}\ ,\quad m=\overline{1,3} \quad (2)$$

where $c_{m,r}$ is the central meaning of each term that refers to the necessary mass of m ferroalloys.

As an alternative to the technique of obtaining precise production rules, membership of which is estimated at probability occurrence conditions and result in the database chosen for study, a method for constructing decision trees was proposed. This method, detailed in [10], is widely used in the construction of expert systems as an algorithm for knowledge discovery.

To build a knowledge base based on decision trees partitioning results presented in Table 1 were used. Let us consider in detail the variable selection criterion for which a partition is produced in the next node. If the variable x_k takes h values $c_{k1}, c_{k2}, ..., c_{kh}$ then partitioning T by variable x_k will subset $T_1, T_2, ..., T_h$. Variable chosen is based on information about how classes $c_{m,r}$ of output variables distributed on the set T and its subsets.

Let $freq(c_r, I)$ is the number of objects from subset I belonging to the same class c_r .Then the probability that randomly chosen object from subset I belongs to the class c_r is equals

$$P=\frac{freq(c_r, I)}{|I|}, \quad (3)$$

According to information theory, estimation of the average amount of information needed to classify an object from a set T, calculated from

$$Info(T)=-\sum_{j=1}^{l}\left(\frac{freq(c_r,T)}{|T|}\right)\log_2\left(\frac{freq(c_r,T)}{|T|}\right), \quad (4)$$

Because we are using the logarithm to the base 2, this expression provides a quantitative assessment in bits. The same assessment, but after splitting sets T by x_k, gives the following expression:

$$Info_{x_k}(T)=\sum_{i=1}^{h}T_i / |T| \, Info(T_i), \quad (5)$$

The criterion for selecting a variable, which hold partitioning at the next node is

$$\max_k\left(Gain(x_k)\right)=Info(T)-Info_{x_k}(T), \quad (6)$$

Variable with the highest $Gain$ becomes the key in the current node. Further, tree building continues regarding its value. The principle of choice (3) - (6) is applied to the resulting subsets $T_1, T_2, ..., T_h$ thus, recursive tree construction continues until the node contains only the objects of one class.

In order to limit the depth of the tree to its basic algorithm next rule was added: stop dividing in the next node, if subset that is associated with this node contains objects which belong to no more than 10% of the classes of the total number of the study samples. The restriction above does not materially affect the classifying ability of the tree, but can significantly reduce the total number of rules. After constructing, the tree was truncated, thus reducing the number of rules from 2152 (clear rules identifying at least one object) to 422. Truncation was carried out with a minimal level of support in 0.1% (for training data of 8023 fusion it included 9 fusions).

Levels of 10% of the minimum variation and 0.1% of the minimum support were chosen empirically while retaining ranging capability during the structure maximum simplify.

4. Results

Testing of knowledge discovery methods within DSS was performed using fusions data for 2008-2009. The evaluation of the accuracy of approximating productive models of root mean square error is given in Table 2.

Table 2. The mean square error of approximation

Sample	Deoxidants	Bayesian network		Decision Tree	
		Absolute, kg	Relative	Absolute, kg	Relative
Training	FeMn	37.40	0.0926	45.089	0.1116
	SiMn	40.59	0.0551	47.138	0.0640
	FeSi	2.83	0.0195	2.849	0.0196
Test	FeMn	36.86	0.0844	71.026	0.1625
	SiMn	44.16	0.0601	58.139	0.0791
	FeSi	4.54	0.0325	4.1411	0.0296

You can see that the knowledge base developed on naive Bayesian networks, gives accurate results approximations both in the training sample and the test. The prediction error does not exceed 10%, which is close to the instrumental error of ferroalloys supply RSA and can be considered as acceptable for the rest of this production.

The number of rules in the knowledge base for the following methods differs significantly - for Bayesian network they are 1598, for decision trees – 422, but studies have shown that the speed of knowledge processing bases and calculation of the final result in both systems embedded in real-time limits of this process.

Application of the existing knowledge bases in practice showed that the predicted mass required for melting alloys exceed the value calculated theoretically. That is, in practice, the operator of converter production, consciously or not, often uses excess ferroalloys, which affect the cost of steel.

The study was conducted to determine the boundaries of ferroalloys economy in which the central values of output terms gradually decreased. In this case, the projected steel parameters, consumption of ferroalloys and prediction error was controlled.

With a shift in terms center of the naive Bayes network by 20%, compromise optimum is achieved: total savings of ferroalloys 0.398 kg / t DSS approximation error increases by only 1%. In monetary terms, 4013 meltings made in 8 months corresponds to saving $206 thousands, which in turn provides monthly savings at $26 070 and yearly saving about $312 000. Further shift of the central values of the terms leads to a redistribution of training examples and a sharp increase in errors of approximation.

Unfortunately, while using decision trees, even slight shifting of terms causes significant changes in the structure of the tree, altering hundreds of rules. However, the displacement of some terms down by up to 10% can provide saving ferroalloys in average 0.118 kg / t, which financially give $147 000 per year.

5. Conclusions

To form the task at deoxidizing, controls DSS were proposed production model of expert system. As methods of obtaining knowledge probabilistic approach was used regarding buildings Bayesian networks and ID3 algorithm of constructing decision trees. The first knowledge base contains 1589 probabilistic rules with generalizing fuzzificator, the second one – 422 clear rules concluded in a tree of 14 variables.

DSS on Bayesian network shows higher accuracy of approximation at the training and the test sample. Prediction error does not exceed 10%, which is acceptable for this process.

With a shift in terms of the naive Bayes network by 20% is compromise achieved: with total savings of ferroalloys at 0.398 kg / t DSS approximation error increased by 1%. In monetary terms, this corresponds to savings of about $312 thousands per year.

Prospects for the development of this subject are seen at applying the proposed method to other metallurgical industries, including electric one, which also uses ferroalloys. Another possible direction of development involves the use of a neural network with radial basis functions, which is equivalent to the simultaneous classification and approximation of nonlinear dependencies.

To improve the accuracy of forecast models, it necessary pay attention to the factors of production processes, which are usually not included in the passport of melting, for example, the degree of wear of the lining, casting method, and etc.

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