Development of intelligent knowledge-based computing environment for controling the proces parameters and nonmetalic inclusions in steels

Razvoj inteligentnega, na znanje oprtega računalniškega okolja za kontrolo procesnih parametrov in nekovinskih vključkov v jeklih

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Abstract: An intelligent knowledge-based computing environment for controling the steel production is proposed. CAE non-parametric mathematical model was developed based on the measured industrial data. Analysis of the obtained results reveals that there is a strong correlation between chemical composition of melts, Al blocs for dezoxidation and different supplements added at various stages, and nonmetalic inclusions. Relatively small number of input parameters taken into account in the existing model resulted in large scatter of the obtained results. Use of a higher number of input parameters will reduce the scatter and improve the prediction. It is evident that the standard ISO 4967 systematically overestimates some types of nonmetalic inclusions, which may be the result of a subjective human assessment or deliberately conservative estimate. The nonmetalic inclusions can be most effectively influenced at the early stages of the EAF process. As there is still long way to sufficiently describe the whole phenomenon of nonmetalic inclusions in steels, the results presented in this study are very promissing and they will eventualy lead us to the better models in the future.

Original scientific paper

Izvleček: Predlagano je inteligentno, na znanje oprto računalniško okolje za kontrolo proizvodnje jekla. Na podlagi izmerjenih industrijskih podatkov je bil razvit neparametrični matematični model CAE. Analiza dobljenih rezultatov je pokazala, da obstaja močna korelacija med kemično sestavo šarže, Al bloki za dezoksidacijo in drugimi dodatki, dodanimi v različnih fazah procesa, in nekovinskimi vključki. Zaradi relativno majhnega števila upoštevanih vhodnih parametrov je raztros rezultatov dokaj velik. Upoštevanje večjega števila vhodnih parametrov bo zagotovo zmanjšalo raztros in izboljšalo napovedi. Očitno je, da standard ISO 4967 sistematično precenjuje nekatere tipe nekovinskih vključkov, kar je lahko posledica subjektivnega vrednotenja posameznikov ali pa namerno bolj konservativne ocene. Na nekovinske vključke lahko najbolj učinkovito vplivamo v zgodnjih fazah EAF-procesa. Čeprav je pred nami še dolga pot, preden bo mogoče v celoti opisati fenomen nekovinskih vključkov, so rezultati, predstavljeni v tem prispevku, zelo spodbudni in nas bodo v prihodnosti pripeljali do boljših modelov.

Key words: steel production, SQL database, non-parametric models, CAE neural network, nonmetalic inclusions

Ključne besede: proizvodnja jekla, SQL-baza podatkov, neparametrični modeli, nevronska mreža CAE, nekovinski vključki

Introduction

Production of steel, which includes many intermediate stages with high energy consumption, is a complex and costly procedure. Optimization of steel manufacturing process is therefore highly desirable. It can be achieved through better in-depth understanding of various influential parameters which determine the technological path of material in the production process. The problem is extremely complex due to the large number of influential parameters and consequently there is still lack of useful comprehensive solutions in the everyday steel production. Luckily, artificial intelligence and modern information and communication technologies now offer better opportunities for solution of this problem.

In recent years we have witnessed an intensive development of both physical and metallurgical models which can adequately describe various processes taking place in steels during their thermo-mechanical processing as well as solutions in the field of artificial intelligence and optimization methods, which are possible by means of the modern computer technology.

Numerous publications demonstrate that the methods of artificial intelligence provide a set of tools with great practical value for complex industrial processes.[1–5] Range of applications of artificial intelligence methods in materials research is wide.[6–10] Practical applications can be found both in research of metallic materials in virtually all phases of their production, such as casting, rolling, forging, heat treatment, etc.[10–16] Especially popular are applications of neural networks, which are becoming an indispensable component of such systems for manufacturing automation and IT solutions that are designed to process control of metallurgical processes.[17–19] Recently, Fazel-Zarandi and Ahmadpour[2] have used neural networks in developing expert system to control the parameters of electric arc furnaces in steel by means of a variety of independent modules, which coordinated the operation with regard to other modules. Zhou[3] used the dynamic neural networks and computer vision to predict the quality of the sintered products. Badheshia and colleagues used the methods of artificial intelligence in the development of materials and to find relations between the various parameters of their production.[6–8, 15, 16] Reviewed literature reveals that neural networks are often used to find the complex relations between the large number of influential parameters within individual processes. Research which address the entire manufacturing process or, where the method of artificial intelligence would be coupled with optimization methods that would allow the search of optimal values of influential parameters, are very rare.

In this paper we present briefly the results of research which was focused on the development of intelligent knowledge-based computing environment for controling and optimizing the real industrial steel production. Due to the complexity of the problem only the solutions of aquirying and managing information from real steel production, development of non-parametric model and analysis of underlying trends in the formation of nonmetalic inclusions, defined by different standards, are presented.

IT solution for information management and optimization in steel production

General

In practice, a lot of the optimization in steel-making process is still based on »trail and error« procedures and/or expert knowledge of process engineers, who based on their empirical experience of tuning the process parameters control the production. From a theoretical point of view it is the most appropriate to describe the manufacturing processes by means of abstract mathematical models in order to to represent mathematical relationships. However, due to the problems in the real steel production mentioned in the introduction section, these processes can be most effectively simulated by analogue models based on electronic devices (computers) using the measured data. Whitin this there are two main problems: (1) data aquisition and mathematical presentation of data as well as expert knowledge and (2) development of appropriate analog models with modern computer technology. It is clear that measurements and mathematical models represent mutually interdependent components in optimizing steel production.

Data acquisition in Metal Ravne has been implemented several years ago. DBSteel is an integrated software solution for process control in the steel production. It was implemented by Siemens VAI Metals Technologies. The solution enables comprehensive data management process, quality control, planning process, steel production control per charge, networking and communication with the ERP (Enterprise Resource Planning) systems and to generate various reports.

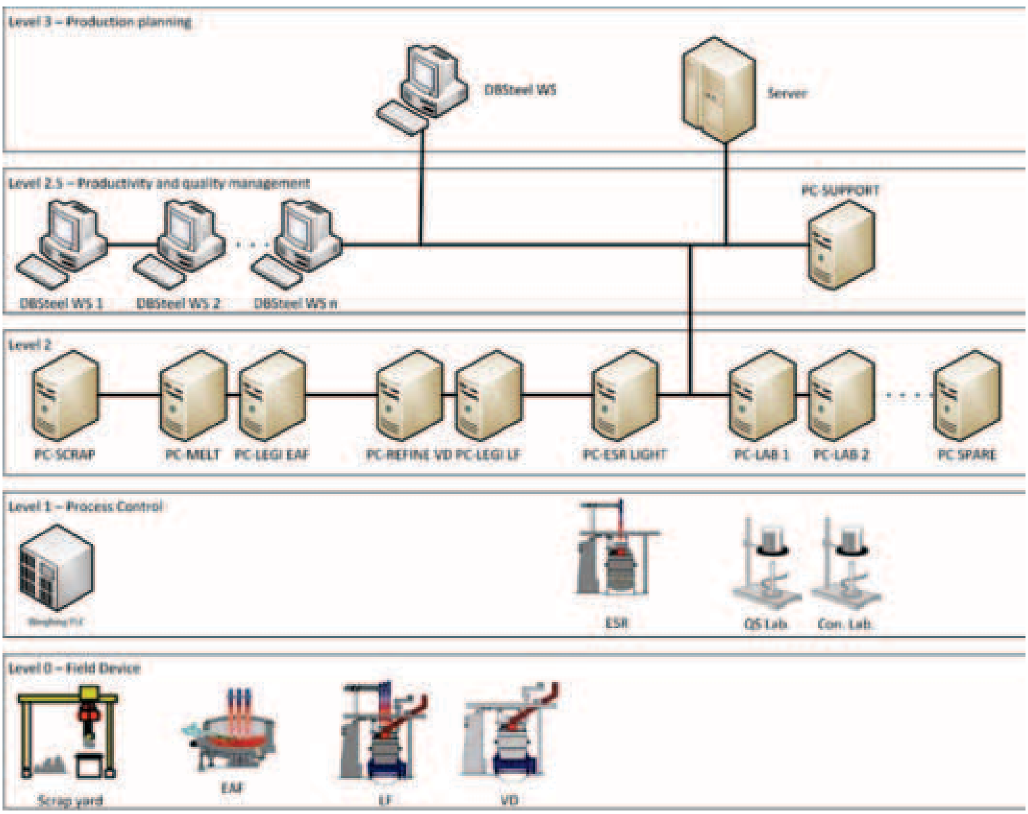


Figure 1. Schematic presentation of the main building blocks of DBSteel integrated software solution.

Client - server environment

The server part consists of a High-Availability (HA) cluster,[20] nine processing computers and fifteen workstations (Figure 1). HA cluster is based on IBM BladeCenter™ technology and is composed of three physical servers, where completely identical combination of 64-bit operating system Windows Server 2008 R2 and relational database Microsoft Windows SQL Server 2008 R2 is installed.

All three servers connected into a HA cluster use database mirroring technique. One of the servers plays the role of principal database server, another server is a mirror site, while the third server provides a smooth transition to the secondary (MIRROR) server in the event of principal server failure.

Processing computers

Figure 1 shows different levels and connection between those levels of the DBSteel integrated software solution. At the zero-level there is a production unit. First level consists of programmable logic controllers (PLC's), e.g. for weighing system. PLC is special computer, that is used for automation of electromechanical processes and designed to operate in heavy industrial conditions (vibration, electrical noise and dust resistant). Processing computers on the second level control/support the production process, while the workstations on the third level enable the planning of charges.

Processing computers control the following operations:

- PC-scrap supports the preparation of inlay material (scrap metal, overhead cranes, computerized scales). By using the specific software the module operator determines the composition of the charge, reads data from the scale, records inlay material consumption, etc.
- PC-MELT and PC-LEGI EAF support the melting and then alloying process on the electric arc furnace (EAF), respectively. The software is intended to record the various events (for example, charge start time), to record consumption of electricity, recording the results, obtained with CELOX device, etc.
- PC-REFINE VD in PC-LEGI LF support the process of secondary treatment of steel in a vacuum ladle furnace (LF/VD).
- PC-ESR LIGHT supports the electro slag remelting (ESR).
- PC-LAB 1 in PC-LAB 2 are special-purpose computers for supporting the implementation of chemical analysis in the plant and a chemical laboratory. PC-LAB 1 is connected with the spectrometer at the plant site while PC-LAB 2 is connetced with two spectrometers located in the chemical laboratory.
- PC-SPARE is a spare computer that

is ready to replace any of the above eight processing computers in case of their failure.

Data structure

Physical partition of steel-making process is followed by the similar structure of the DBSteel database. Description of the tables revelas that each process is characterized by a specific prefix. Thus, for example, table, which is linked to the processes in the electric arc furnace, gets the prefix »EAF«, table which is linked to vacuum furnaces and ladle gets the prefix »LF/VD«, etc. The key tables are:

- The main table of charges at the EAF
- The table of events at the EAF
- The main table in charges at the LF/VD
- The table of events at the LF/VD

Structure of the databases is well documented. After applying different scripts we got one database for further processing. It contains numerical empirical data which allow a mathematical description of the various phenomena in the steel production process (see Chapter 3).

Matemathical tools for modeling of manufacturing processes

Development of appropriate mathematical models is necessary to optimize the steel production at high-tech level. Today, in addition to the usual physical models, the models which exploit the principles of artificial intelligence, especially neural networks, are widely used. Among the neural networks is the most common use of BP neural networks, which describe the phenomenon on the basis of measured data and obtained results. Unfortunately, the rate of learning for very complex problem with large number of parameters and with large database is relatively slow and depends on settings of the parameters of learning. An additional weakness of these networks for »real-time« production is that the BP network must be constantly retrained with new data supply in order to improve the optimization. We have therefore in this study decided to use CAE neural network, [21–23] which enables faster analyses and is significantly more robust.

MATHEMATICAL MODELING OF INCLUSIONS BY USING CAE NEURAL NETWORK

Any type of nonmetalic inclusion (i.e. type A_d according to the ISO 4967 standard [24]) of a specimen (e.g. charge) is characterized by a sample of observations/experiments on N test specimens. The mathematical description of the observation/experiment on a single specimen is called a model vector. Consequently, the whole phenomenon can be described by a finite set of model vectors

$$\{\mathbf{X}_1, ..., \mathbf{X}_n, ..., \mathbf{X}_N\} \quad (1)$$

It is assumed that the observation/experiment on one particular specimen can be described by a number of variables, which are treated as components of a model vector

$$\mathbf{X}_n = \{b_{n1}, ..., b_{nl}, ..., b_{nD}, c_{n1}, ...c_{nk}, ..., c_{nM}\} \quad (2)$$

The vector $\mathbf{X}_n$ can be further composed of two truncated vectors **B** and **C**

$$\mathbf{B}_n = \{b_{n1}, ..., b_{nl}, ..., b_{nD}\}$$

$$\text{and } \mathbf{C}_n = \{c_{n1}, ..., c_{nk}, ..., c_{nM}\} \quad (3a)$$

Vector $\mathbf{B}_n$ is complementary to vector $\mathbf{C}_n$ and therefore their concatenation yields the complete data model vector $\mathbf{X}_n$. The prediction vector, too, is composed of two truncated vectors, i.e. the given truncated vector **B** and the unknown complementary vector $\hat{\mathbf{C}}$

$$\mathbf{B} = \{b_1, ..., b_l, ..., b_D\}$$

$$\text{and } \hat{\mathbf{C}} = \{\hat{c}_1, ..., \hat{c}_k, ..., \hat{c}_M\} \quad (3b)$$

The problem now is how an unknown complementary vector $\hat{\mathbf{C}}$ can be estimated from a given truncated vector **B** and the model vectors $\{\mathbf{X}_1, ..., \mathbf{X}_n, ..., \mathbf{X}_N\}$, i.e. how the inclusion $\hat{A}_d$ can be estimated from known input parameters and the available data in the database. By using the conditional probability density function, the optimal estimator for the given problem can be expressed as

$$\hat{c}_k = \sum_{n=1}^{N} A_n \cdot c_{nk} \, , \quad A_n = \frac{a_n}{\sum_{i=1}^{N} a_i}$$

and (4)

$$a_n = \frac{1}{(2\pi)^{D/2} w^D} \exp\left[-\sum_{l=1}^{D} \frac{(b_l - b_{nl})^2}{2w^2} \right]$$

where $\hat{c}_k$ is the estimate of the k-th output variable, c_{nk} is the same output variable corresponding to the n-th model vector in the database, N is the number of model vectors in the database, b_{nl} is the l-th input variable of the n-th model vector in the database (e.g. $b_{n1}, b_{n2}, b_{n3}, ..., b_{nL}$), and b_l is the l-th input variable corresponding to the prediction vector. D is the number of input variables, and defines the dimension of the sample space. Note that Equation (4) requires the input parameters to be normalized, generally in the range from 0 to 1 if we want to use the same width w of the Gaussian function for all of the input variables (dimensions).

The Gaussian function is used for smooth interpolation between the points of the model vectors. In this context the width w is called the "smoothing" parameter. It determines how fast the influence of data in the sample space decreases with increasing distance from the point whose coordinates are determined by the input variables of the prediction vector.

A general application of the method does not include any prior information about the phenomenon. Equation suggest that the estimate of an output variable is computed as a linear combination of truncated vectors $\boldsymbol{C}_n$, while the coefficients A_n are non-linear functions of all the input variables ($\boldsymbol{B}_n$) in the database. Thus, non-linear phenomena can be modeled by this approach. The weights A_n depend on the similarity between the input variables of the prediction vector, and on the corresponding input variables pertinent to the model vectors stored in the database. Consequently, the unknown output variable is determined in such a way that the computed vector, composed of given and estimated data, is most consistent with the model vectors in the database.

An intermediate result in the computational process is the estimated probability density function $\hat{\rho}$ of known input variables

$$\hat{\rho} = \frac{1}{N}\sum_{n=1}^{N} a_n \tag{5}$$

It helps to detect the possible less accurate predictions due to the data distribution in the database and due to local extrapolation outside the data range. The higher the $\hat{\rho}$ value is, the more steel ingots (relatively to the total number of test steel ingots in database) with input parameters similar to the input parameters of the prediction vector exist in the database.

In the case of using CAE for the estimation of the inclusions, which depends on, e.g. three input parameters, namely content of oxygen (O) and sulphur (S) in charge on one side and the amount of Al blocs (Al) relative to the total weight of charge on the other side, the equation for a_n can be written as:

$$a_n = \frac{1}{(2\pi)^{3/2} w^3} \exp \left[-\frac{(O-O_n)^2 + (S-S_n)^2 + (Al-Al_n)^2}{2w^2} \right] \tag{6}$$

RESULTS AND DISCUSSION

Due to the complexity of the entire process of steel-making, in this paper only the problem of nonmetalic inclusions is studied and discussed. Note, that all chemical analyses for different charges, along with information about the plant where the sample was taken from, the grade of the sample, sample number, etc. are stored in DBSteel database as separate entries. Consequently, sample numbers in the range between 1 and 4 indicate charge sample taken during steel processing at EAF, while sample numbers in the range between

5 and 9 indicates charge samples taken during steel processing at LFVD.

Standards used for the determining the inclusion content of steel

Purity of steel is defined by the amount of nonmetallic inclusions. Nonmetallic inclusions can be found practically in any steel. The quantity, chemical composition and distribution of inclusions depends on the manufacturing process of steel. In general, nonmetallic inclusions lower the quality, workability and mechanical properties of steel.

Different test methods for determination of content of nonmetalic inclusions exist (e.g. standards ISO 4967 [24], ASTM M45 [25] – **ISO**, DIN 50 602 [26] – **M** and **K** method). They cover a number of recognized procedures (macroscopic and microscopic methods) for determining the nonmetallic inclusion content of wrought steel. The methods

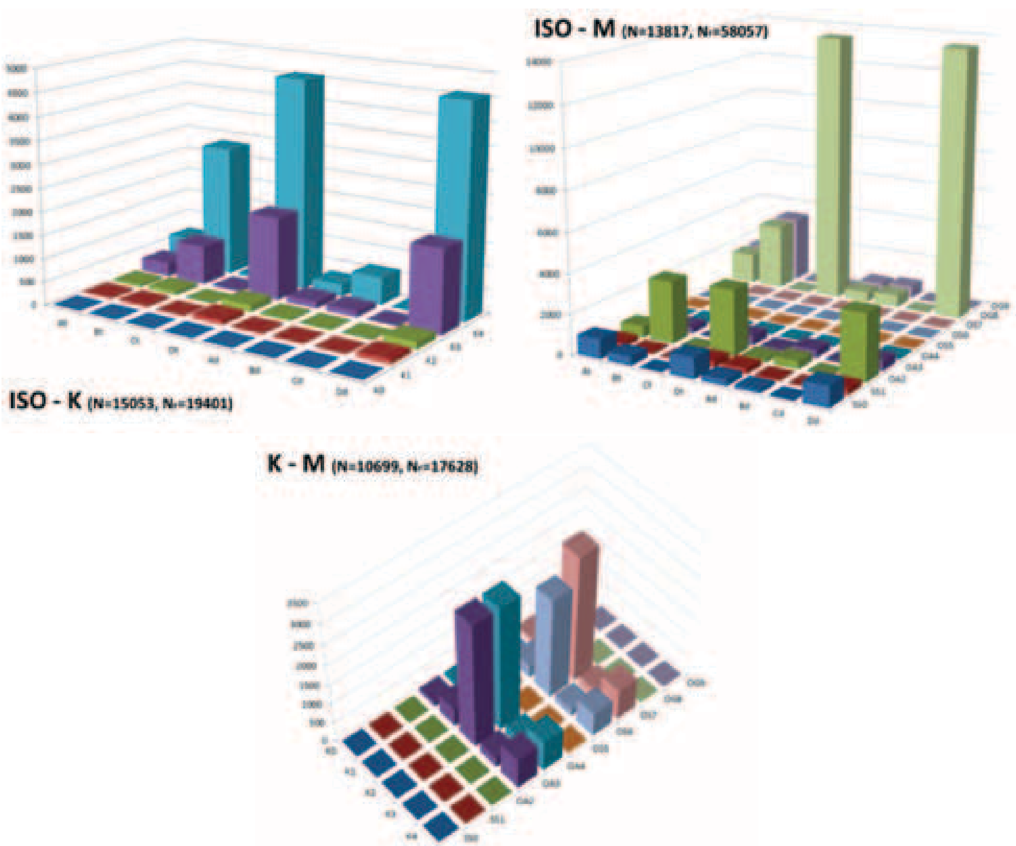


Figure 2. Correlations between different standards, taking into consideration only the incidence but not the absolute value of the inclusions. *N* and *Nr* indicate the number of charges and number of inclusions, respectively, used in the analysis.

are primarily intended for rating inclusions. Constituents such as carbides, nitrides, carbonitrides, borides, and intermetallic phases may be rated using some of the microscopic methods. However, in order to model the phenomena of inclusions mathematicaly (i.e. developing of the non-parametric model), a mathematical representation of such knowledge is neeeded. To this end, we first look for correlations between different standards in order to identify the most appropriate method for modeling inclusionss. The purpose of this study was not to understand precisely the methods and physical background of each type, size and amount of inclusions, but the mathematical formalization of knowledge, contained in different standards.

DBSteel database contains information of the same charges that were inspected using two or three standars simultaneously. Correlations between different standards, taking into consideration only the incidence but not the absolute value of the inclusions, were shown in Figure 2. Note that in one charge different type of inclusions may appear (therefore $Nr \geq N$). Graphs indicate that the standards differ from each other and describe inclusions in different ways. Consequently, customers according to their needs, require consideration of inclusions using the desired standard. Figure 2 indicates that mapping from one standard to another is more reliable than vice versa (e.g. mapping ISO to K or ISO to M).

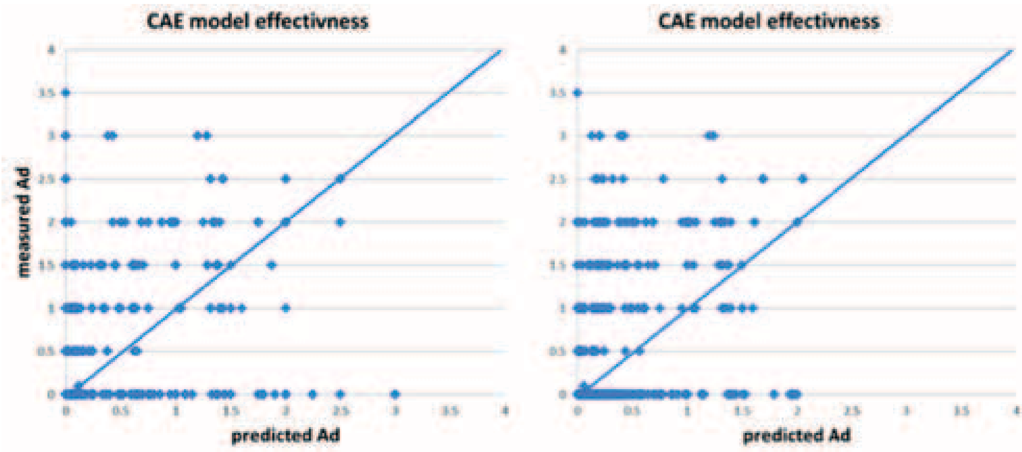
Effectivness of the non-parametric CAE model

The effectivness of the CAE model can be estimated by the average prediction error E_k. It is defined for k-th output variable and can be determined with the "leave one out cross validation method". The method computes the prediction of k-th inclusion for every charge sample, whereas the predicted k-th charge sample is excluded from the database. With averaging of the absolute errors of predictions for all N charge samples E_k is calculated as:

$$E_k = \frac{1}{\overline{c}_k} \sqrt{\frac{1}{N} \sum_{n=1}^{N} \left(\hat{c}_{nk} - c_{nk} \right)^2} \tag{7}$$

where $\overline{c}_k$ is the average of the known k–th outputs of all the model vectors c_{nk} (charge samples) and $\hat{c}_{nk}$ is the prediction of the measured value c_{nk} of the k–th output (inclusion of some type) of the n-th model vector (charge sample).

Figure 3 shows the results of »leave one out cross validation method« for two different smoothing parameters. Studied is the inclusion of type Ad according to the ISO 4967 standard. In the CAE non-parametric model some important chemical elements (C, S, Si, Mn, …), some most influential suplements (FeSi, FeCrC, …), Al blocs and oxygen were



$w = 0.01$, $E_1 = 3.598$ $w = 0.05$, $E_1 = 3.492$

Figure 3. Results of the »leave one out cross validation method« for inclusion type Ad, using two different smoothing parameters.

taken into account. The obtained results reveal large scatter. It can be concluded that (1) there is high uncertainty in the (subjective) determination of inclusions, and (2) in order to reduce the scatter in the predictions more influential input parameters must be taken into account. Nevertheless, existent model can give a sound qualitative relations between input parameters and different types of inclusions, as shown in the next section. The optimal smoothing parameter was found to amount around 0.05, however, in order to reveal clear qualitative relationships somewhat larger value was used (e.g. 0.1 or 0.2).

Influence of important parameters on inclusions according to the ISO 4867 standard

Due to the limited space only a few selected results are presented and discussed in this paper. In order to show different behaviour in nonmetalic inclusions, results for four different types, namely Ad, At, Dd and Dt are shown and discussed.

Figure 4 reveals that higher content of sulphur increases nonmetalic inclusions of type At and Ad. Its influence is unfavourable, but more for inclusions of type Ad. Influence of oxygen (Figure 5) is very important and amounts up to 5 % of total contribution. In general, more oxygen increases nonmetalic inclusions of type Dd, whereas the influence of Al blocs is relatively small. Note, that use of smaller value of smoothing parameter reveals localy larger influence of Al blocs which may be taken into account when optimization is applied.

Figure 6 reveals the influence of oxygen and Al blocs on nonmetalic inclusions of type Dt. Influence of both parameters is now reversed. Moreover, in absolute terms, both influences are small and relatively insignificant.

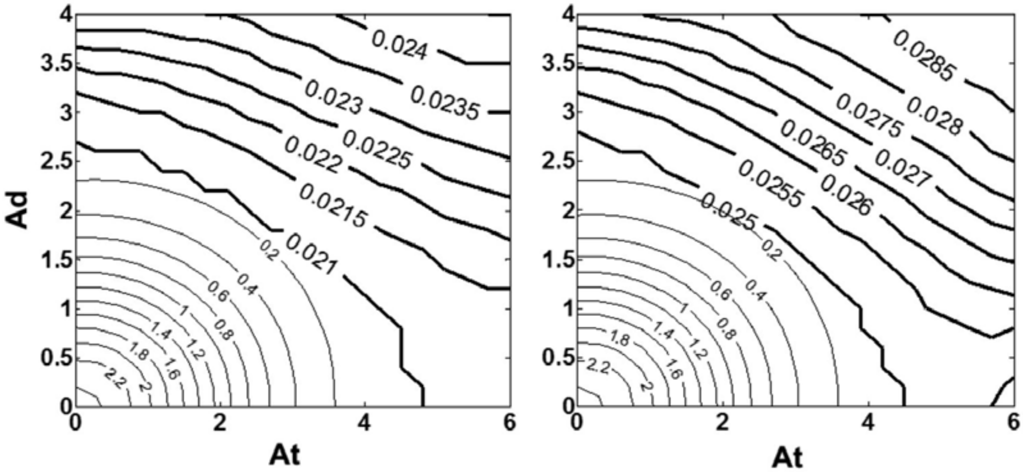
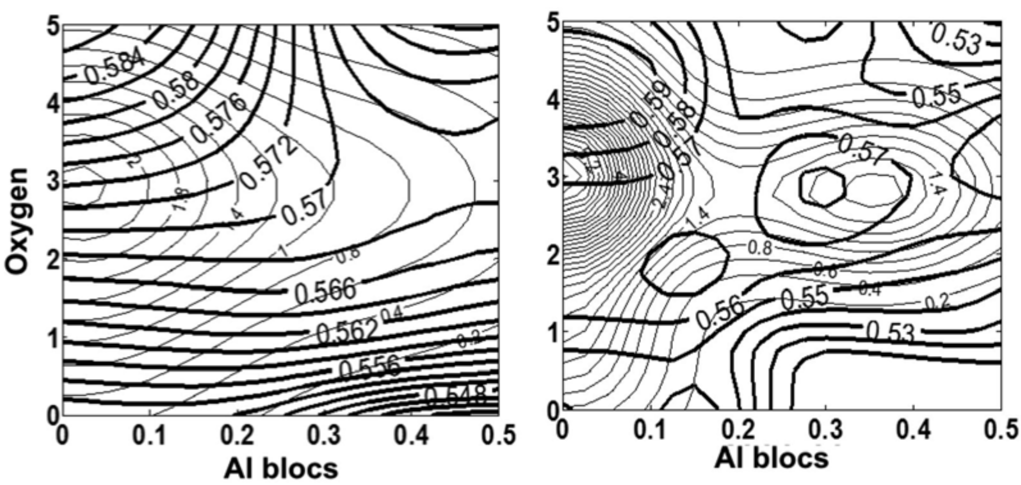
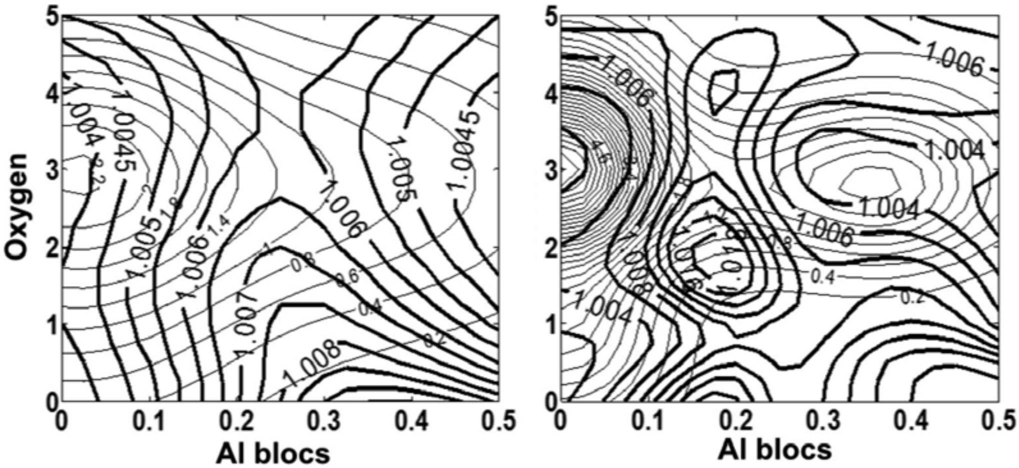


Figure 4. Influence of sulphur (S) after taking first (left) and second (right) charge sample on nonmetalic inclusions At and Ad.



$w = 0.2$ $w = 0.05$

Figure 5. Influence of Al blocs and oxygen (tapping weight in mass fractions w/%) on nonmetalic inclusion Dd after taking second charge sample.



w = 0.2 *w* = 0.1

Figure 6. Influence of Al aluminium blocs and oxygen (tapping weight in mass fractions *w*/%) on nonmetalic inclusion Dt after taking second charge sample.

In general, it can be observed the important impact of different input parameters at different stages, suggesting that a specific physical phenomena is associated with a specific type of the nonmetalic inclusion. The results also suggest that some types of inclusions can be influenced more efficiently at earlier stages and some types of inclusions at later stages of the production process.

Conclusions

In the paper the development of intelligent knowledge-based computing environment for controling the processes in the real industrial steel production was presented. The problem addressed is extremely complex due to the large number of influential parameters. Application of modern information and communication technologies and some artificial intelligence methods enables us to develop and propose one possible solution to this problem.

Within this study the CAE non-parametric mathematical model of nonmetalic inclusions was developed. Analysis of the obtained results lead us to the folowing conclusions:

- There is a strong correlation between chemical composition of melts, Al blocs for dezoxidation and different supplements added at various stages, and nonmetalic inclusions. Relatively small number of input parameters (a limited number of elements of chemical composition and a limited number of some most important suplements) taken into account in the existing model reveals large scatter of the obtained results. It is expected that use of a higher number of input parameters will reduce the scatter and improve the prediction.

- It is evident that the standards ISO 4967 and ASTM E45 systematically overestimates the value of smaller At (between 0.5 and 1.5). This probably result from a subjective human assessment or deliberately conservative estimate of nonmetalic inclusions by the producer. It should also be noted that the standard itself has shortcomings which may result in the above overestimations, when it tries to address a physical phenomenon, which is not linear.
- The majority of nonmetalic inclusions can be most effectively influenced at the early stages of the EAF process (e.g. during the time of taking the first or second charge samples). But closer to the end of the process we approach the harder it become to influence the nonmetalic inclusions.

There is still long way to sufficiently describe the whole phenomenon of nonmetalic inclusions in steels. However, the results presented in this study show that the entire process can be fully mathematicaly described and then optimized in order to minimize the nonmetalic inclusions.

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