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FUZZY MODELING FOR STEEL MAKING PROCESSES

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ABSTRACT

Nowadays to expand assortment and execution of contracts iron and steel manufacturers facing fierce competition need to produce quality steel, satisfying the hardenability requirements, provided by certain alloying modes. One of the solutions of this problem is to develop models for predicting hardness of steel and optimal control algorithms for steel-making process with specified hardness, which will enable to increase process control effectiveness and quality of the obtained products. The article presents the model of relation between depth-distributed steel hardness and its chemical composition in the form of a system of fuzzy production rules (Takagi-Sugeno-Kang model - TSK) that allowed determining predicted values of the distributed steel hardness as weighted average outputs of a set of linear regression models and eliminating the problem of selection of the most adequate regression model.

Keywords: fuzzy modeling, Takagi-Sugeno-Kang model, optimal chemical composition of steel.

INTRODUCTION

Currently metals and alloys retain their prevailing position as the basic structural materials; primarily this refers to iron-based metal materials.

Metallurgical technology of steel production, and first of all steel-making practice, is the main factor of obtaining the required mechanical properties of steel and specified chemical composition.

The need to expand the assortment and production of steel, satisfying the hardenability requirements (final hardness of steel), made steel manufacturers revise their views on the steel-making practice.

Solution of problems relating to the search for optimal control of steel-making processes implies availability of the appropriate mathematical description, which is frequently complicated by the fact that use of industrial experiment results is only possible way to solve the problem.

Such results are a sample of the input and output variables measured in the same process or estimated on the basis of laboratory measurements, and in this case there is a time shift between the moment of action of the input variables and obtaining the estimation magnitude of response.

Unavailability of control over a number of parameters included in the mathematical description of the controlled metallurgical process makes the procedure of constructing mathematical models extremely difficult. If there is an analytic description of relation between the variables, included into the controlled process model, and the measured parameters of this process, the input variables can be estimated on the basis of such a description. However it may include empirical coefficients, which makes the obtained result fuzzy.

This determines the relevance of the task to analyze and improve models and optimal control algorithms for steel-making process in conditions of fuzzy and stochastic uncertainty.

LITERATURE REVIEW

Analyzing investigations in the area of the melting process control, one can assume that metallurgical units and the melting processes implemented therein refer to the facilities that can be effectively controlled based on the theory of fuzzy sets.

For example, electroslag remelting process control under uncertainty is studied in [1], demonstrating the possibility of building control system and solving identification problems for electro-slag remelting plants using neural networks and fuzzy logic. On the basis of the developed mathematical model of electroslag remelting control system using the theory of neuro-fuzzy identification, the author created a phenomenological model of thermal processes for electroslag remelting and offered the method for determining the slag bath (metal) level by ‘thermal portrait.’

The problems of mathematical modeling of steel-making process n electric arc furnaces (EAF) are investigated in [2]. Control over technological mode of the process is mainly selected under uncertainty, not only because of the controllable object properties, but also due to the lack of advanced information technologies enabling to improve the EAF control efficiency by better integration of information available.

Given that the composition of the scrap metal, charging materials, fluxes and ferroalloys as well as the state of the furnace hearth, the walls and roof changes from heat to heat, it is necessary to use not only the set of process operations altering the equilibrium state of the system ‘metal - slag, but also qualitative parameters of substances used in the individual melting stages as process control actions. In this case it is important to have the available database enabling to extract the necessary information for the melting process control.

In [3] Zmak and Filetin suggested a steel-making process control method based on predicting various mechanical and thermal properties of steel with definite chemical composition using artificial neural network. The goal of the learning algorithm is to adjust the neural network parameters based on a given set of input and output data and also to determine the optimal network parameter set that minimizes a performance index. The calculation of this index is based on the difference between the desired response and the actual neuron response. The error, which is calculated at the output layer, is propagated back to the input layer through the static neurons in the hidden layers. To determine the optimal network parameters minimizing the performance index, a gradient method is applied. Iteratively, the optimal parameters are approximated, by moving in the direction of steepest descent. Thus, as a result of modeling index of accuracy remains insensitive to the dynamic range of the learning data, and allows an easy comparison with other learning algorithms.

The use of artificial neural networks in steel-making process control based on prediction of its chemical composition to achieve the desired hardness is also considered in [4]. The modeling result shows that the network model can efficiently predict the mechanical properties of the material. To predict the properties of the materials it was proposed to use radial basis function and the feedback procedure. Application of the proposed method allows analyzing the influence of alloying elements, without additional experimental studies.

With the help of neural networks [5] presented modeling of the relationship between mechanical properties and chemical composition of steel, which also affects the efficiency of the steel-making process.

In [6] it is proposed to predict the micro hardness of a steel plate using an artificial neural network with two hidden feedforward layers. The authors carried out optimization of the neural network architecture to find the best equation for predicting the of micro hardness value with specific inputs.

Summarizing the results of the above papers devoted to the issues of fuzzy control over complex production facilities and systems, including melting processes, it can be assumed that modeling of the control processes for smelting steel and alloys of different grades involves the need to develop uncertainty models, which is determined by the inability to control many parameters in real-time environment, inability to accurately estimate system state, multifactorial nature of the process and the lack of sufficient information for the control implementation.

Taking into account this peculiarity, it can be concluded that the nonlinear regression methods and neural network methods might apparently describe the steelmaking process with a reasonable degree of accuracy. However, in terms of making further managerial decisions these methods cause some difficulties in choosing the required chemical composition. In this sense, it seems more appropriate to model predicted values based on fuzzy modeling.

EXPERIMENTAL SETUP

The main task of this study is to improve effectiveness of steel-making process control, which is, in fact, fuzzy control, and as a consequence, to increase the product quality by developing models for steel hardness prediction and optimal control algorithms for steel-making process with specified hardness.

It is known that steel production is carried out according to an individual custom specification, which indicates the form of the smelted product, permissible variation range for the chemical composition and hardenability, which is understood as the penetration depth of the hardened area or the steel hardness at different depths from the surface. Hardenability (hereinafter referred to as the final hardness of steel) is determined by many factors, among them chemical composition is the most relevant controlling factor that can be varied in the course of steel-making by adding the appropriate ferroalloys [7], [8].

To select the required chemical regressional relationship between hardness and the percentage of chemical elements is often used. In this case composition limits are selected in the set of admissible values of the concentrations of elements, with a definite, as a rule, linear regressional relationship model corresponding to the specified (but not any) set of values.

Then the experts are posed with the problem of selecting a model that is the most adequate to the specified initial conditions of the chemical composition of steel. According to the selected regression model the steel hardness distribution is predicted, and based on this prediction the required chemical composition is determined by exhaustion method. Inevitable errors, relating to the expert selection of the adequate model and chemical composition result in deterioration of the melted steel quality.

One of the solutions is to develop steel hardness prediction models. Control efficiency and quality of the melted steel may be increased obtaining a model-based prediction for 'composition-hardness' ratio by the system of fuzzy production rules of Takagi-Sugeno-Kang model (TSK). Thus, the relevance of analysis and improvement of models and melted steel hardness control algorithms under uncertainty is demonstrated [9], [10].

MATERIALS AND METHODS

It is known that a variety of methods can be used to build a mathematical prediction model; however, it is most suitable to apply fuzzy modeling for predicted values in the problem under study.

Let us denote chemical elements by sequential numbers, then x_i, i= 1.2,…, p – content of the i-th element. The number of intervals into which the variation range of the mass fraction of each i-th element is divided n_i = Z for all i = 1,…, p. Let us denote k-th variation interval of i-th chemical element by X_i^k. All possible combinations of interval classes for various elements are formed by the operation of the direct product of the sets of intervals,

X_i: $X_1 \times X_2 \times \ldots \times X_p = \{(X_1^1, X_2^1, \ldots, X_p^1); (X_1^1, X_2^1, \ldots, X_p^2); \ldots, (X_1^Z, X_2^Z, \ldots, X_p^Z)\}$.

Each vector inside the round parenthesis will be defined as a certain class of possible values of the chemical composition and denoted as K^j. The total number of such classes in our case is Z^P. Each class K^j s assigned a linear regression model in the form of a system of linear equations [11], [12]:

$$\bar{y}^j = \bar{a}_0^j + A^j \bar{x}, \; j=1.2,\ldots, D. \quad (1)$$

or in the expanded form

$$\begin{cases} y_1^j = a_{10}^j + a_{11}^j x_1 + a_{12}^j x_2 + \ldots + a_{1n}^j x_n \\ y_2^j = a_{20}^j + a_{21}^j x_1 + a_{22}^j x_2 + \ldots + a_{2n}^j x_n \\ \cdot \quad \cdot \quad \cdot \\ y_k^j = a_{k0}^j + a_{k1}^j x_1 + a_{k2}^j x_2 + \ldots + a_{kn}^j x_n \end{cases}, \quad (2)$$

The predicted value y is a random variable. Since the predicted values of steel hardness are restricted by the customer specification in terms of accuracy, it is advisable to consider the confidence interval of the prediction in accordance with its specified accuracy tolerances. The size of the confidence interval of the steel hardness prediction will vary with the changes in the chemical composition.

Prediction of steel hardness values by the regression equation (1) is justified, if the values of the chemical element content are within the range of values in the sample determined by the boundaries of the fragmentation intervals. In this case the best accuracy is achieved with the prediction at the point close to the expectation of mass fractions in the sample, which in turn is expected in the middle of the range. Prediction outside the range is possible, but it can lead to significant errors [11]; [12].

The performed analysis suggests the fuzzy nature of compliance of the linear models (1) with the selected classes of mass fraction variation of chemical elements K^J. Therefore, the current system of distributed steel hardness prediction models can be represented as follows:

If $\bar{x} \in K^j$ c $\mu_{Kj}(\bar{x})$, then $\bar{y}(h) = \bar{a}_0^j + A^j \bar{x}$ c $\mu_{Kj}(\bar{x})$ for all j, where – K_i^j – j-th variation interval of the i-th chemical element; $\mu_{Kji}(x_i)$ - value of the membership function x_i for the appropriate interval; $\mu_{Kj}(\bar{x})$ - value of the membership function $\bar{x}$ for the K^j class.

Value of function $\mu_{Kj}(\bar{x})$ is defined by values of $\mu_{Kji}(x_i)$ in accordance with the following expression:

$$\mu_{Kj}(\bar{x}) = \prod_{i=1}^{n} \mu_{Kji}(x_i),$$

where $\prod$ - symbol synonym of triangular t-norm

Application of Takagi-Sugeno-Kang model (TSK) for prediction requires defining membership functions $\mu_{K_i^j}(x_i)$.

A possible approach to solving the fuzzification problem is to use a triangular fuzzy numbers. It is assumed that the maximum value of the membership function ($\mu_{X_i^j}(x_i) = 1$) is located in the center of the class at a value of $x_i = \frac{b-a}{2}$, where $a < b$ – triangular number boundaries (class boundaries determined by an expert way), $\mu_{X_i^j}(a) = \mu_{X_i^j}(b) = 0$. In this case, fuzzification of tolerance class X_i^j is determined by the membership function:

$$\mu_{X_i^j}(x) = \begin{cases} \frac{2(x-a)}{b-a}, если\ a \le x \le \frac{b-a}{2} \\ \frac{2(b-x)}{a+b}, если\ \frac{b-a}{2} < x \le b \end{cases}.$$

In compliance with the TSK model discrete values of steel hardness are calculated by formula:

$$y_i = \frac{\sum_{j=1}^{D} \mu_{Kj}(\bar{x}) y_i^j}{\sum_{j=1}^{D} \mu_{Kj}(\bar{x})}, \text{ for all } i, \quad (3)$$

i.e. predicted value of steel hardness for each i-th line of A matrix is calculated for all available models taking into account the extent of compliance $\mu_{Kj}(\bar{x})$ of the input vector $\bar{x}$ for K^j class [13].

For the implementation of possible approaches to the control it is necessary to reduce the TSK model, represented by the system of fuzzy production rules, to a matrix form. For this purpose, we substitute the appropriate equations of the system (2) to (3):

$$y_i = \frac{\sum_{j=1}^{D} \mu_{Kj}(\bar{x}) y_i^j}{\sum_{j=1}^{D} \mu_{Kj}(\bar{x})} = \frac{\sum_{j=1}^{D} \mu_{Kj}(\bar{x})(a_{i0}^j + a_{i1}^j x_1 + \ldots + a_{in}^j x_n)}{\sum_{j=1}^{D} \mu_{Kj}(\bar{x})}$$

After transformation we get expression for calculation of y_i - steel hardness values in the *i-th* point of depth:

$$y_i = \frac{\sum_{j=1}^{D} \mu_{Kj}(\bar{x}) a_{i0}^j}{\sum_{j=1}^{D} \mu_{Kj}(\bar{x})} + \frac{\sum_{j=1}^{D} \mu_{Kj}(\bar{x}) a_{i1}^j}{\sum_{j=1}^{D} \mu_{Kj}(\bar{x})} x_1 + \ldots + \frac{\sum_{j=1}^{D} \mu_{Kj}(\bar{x}) a_{in}^j}{\sum_{j=1}^{D} \mu_{Kj}(\bar{x})} x_n$$

By taking the following notation:

$$a_{i0}(\bar{x}) = \frac{\sum_{j=1}^{D} \mu_{Kj}(\bar{x}) a_{i0}^j}{\sum_{j=1}^{D} \mu_{Kj}(\bar{x})}; \ldots \quad a_{in}(\bar{x}) = \frac{\sum_{j=1}^{D} \mu_{Kj}(\bar{x}) a_{in}^j}{\sum_{j=1}^{D} \mu_{Kj}(\bar{x})}.$$

We get the TSK model, which looks as follows in the matrix form:

$$\bar{y} = A^{TSK}(\bar{x})\bar{x} + \bar{a}_0^{TSK}(\bar{x}),$$

where $A^{TSK}(\bar{x}) = \begin{pmatrix} a_{11}(\bar{x}) & a_{12}(\bar{x}) & \ldots & a_{1n}(\bar{x}) \\ a_{21}(\bar{x}) & a_{22}(\bar{x}) & \ldots & a_{2n}(\bar{x}) \\ . & . & . & . \\ a_{k1}(\bar{x}) & a_{k2}(\bar{x}) & \ldots & a_{kn}(\bar{x}) \end{pmatrix}$

is a TSK model matrix, elements of which depend on the vector $\bar{x}$; $\bar{a}_0^{TSK}(\bar{x})$ – the transpose of the column vector of intercept terms depending on the vector $\bar{x}$.

Despite the fact that formally the TSK model is written in the matrix form, this model is nonlinear with respect to the vector $\bar{x}$. And also it satisfactorily describes the relationship and can be used to control the processes.

RESULTS

The analysis of the peculiarities of steel-making process control modeling demonstrated that statistical modeling techniques in combination with the methods of fuzzy inference are the most adequate approach to building models of relationship between the steel hardness and its chemical composition.

As a result of the research there was developed the model of the relation between depth-distributed steel hardness and its chemical composition in the form of a system of fuzzy production rules (the TSK model), enabling to determine predicted values of the distributed steel hardness as weighted average outputs of a set of linear regression models.

Each model includes acceptable ranges of steel hardness for each class from 1 to 8. These acceptable ranges can be used to verify the adequacy of the TSK model.

Figure-1 shows acceptable range of steel hardness values for a definite heat.

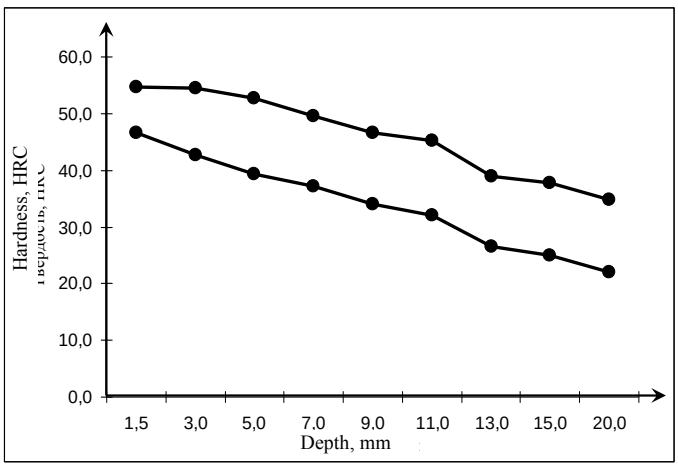

Figure-1. Acceptable range of steel hardness versus its depth using the TSK model.

The computations were carried out in the paper with steel hardness computation results presented for all eight existing models. Also each calculated steel hardness value of the models was tested for the range check [14]. After analyzing the data it is possible to conclude that the calculated values of steel hardenability fall in the acceptable range. Final values of steel hardness for the chemical composition No.1 are given in Table-1.

Table-1. Steel hardness for the chemical composition No.1.

Depth, mm	**1.5**	**3.0**	**5.0**	**7.0**	**9.0**	**11**	**13**	**15**	**20**
Hardness, HRC	51.4	50.5	46.1	41.7	39.6	36.7	35.6	34.1	31.8

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Acceptable range of steel hardness values for the chemical composition No.1 is shown in Figure-2.

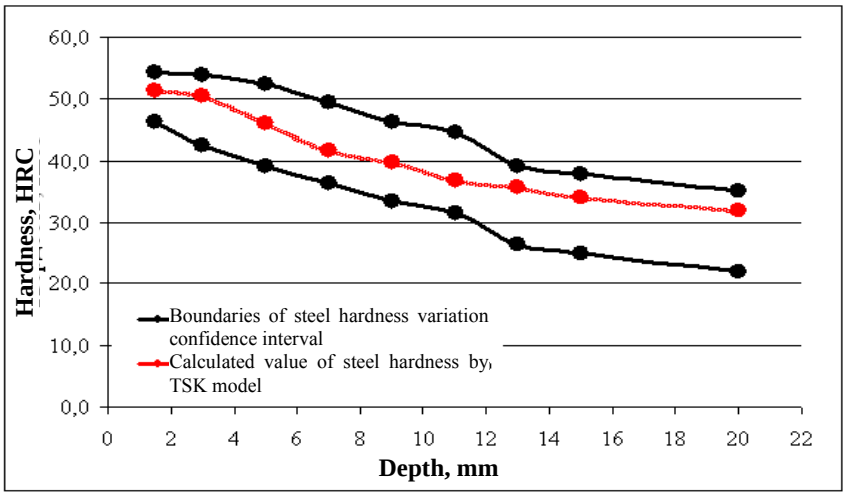

Figure-2. Confidence interval and steel hardness values calculated using the TSK model.

To estimate the prediction quality a numerical experiment was carried out - using TSK model predicted values were determined for output variable y_i and the predicted and actual distributions of hardness in the 308 points $\overline{x}$ of industrial statistics were compared.

The resulting average and maximum deviation of the predicted value from the actual hardness of steel is connected not only with the TSK model error. Also these deviations refer to the error associated with the determination of the actual hardness of the steel as well as the accuracy of determination of the chemical composition of the steel, which in turn serves as the initial data for hardness computation using the TSK model.

In all customer steel-making specifications the acceptable range of steel hardness for one point makes at least 6 units. Despite the fact that the maximum deviation of the TSK model and the minimum acceptable range of steel hardness were used, the calculated hardness of steel (including possible errors) almost always falls into the acceptable range of steel hardenability specified in the customer specifications (Figure-3).

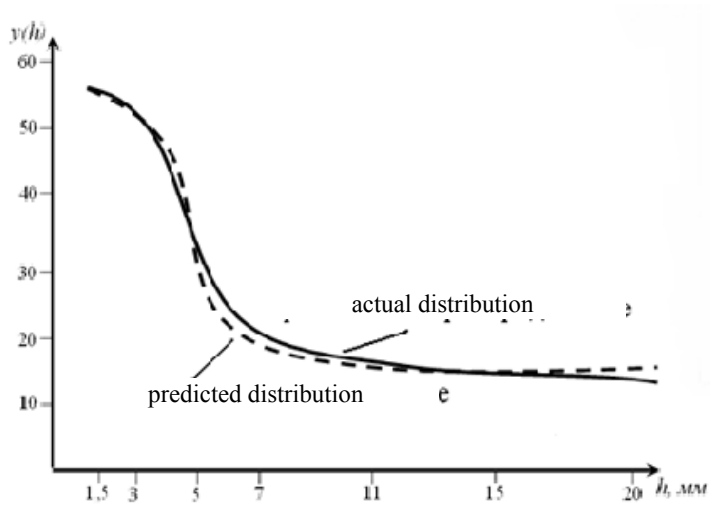

Figure-3. Predicted distribution of steel hardness using TSK model.

Thus, the obtained model eliminates the problem of selecting the most appropriate regression model, and therefore, inevitable errors of experts, which result in loss of quality of steel produced.

CONCLUSIONS

This study focuses on the issues of chemical composition impact on properties such as a stage, which is obligatory for the search for the optimal melting control. In practice, when selecting the desired chemical composition mathematical models are used in the form of regressional relationship between the hardness and the percentage of chemical elements. Given the complexity of building such a relationship, composition limits are selected in the set of admissible values of the concentrations of elements, with a definite, as a rule, linear regressional relationship model corresponding to the specified (but not any) set of values.

Such approach corresponds to a piecewise-linear approximation of a nonlinear multi-factor dependence. This raises the problem of selecting the model, which is the most appropriate to the given initial conditions of the chemical composition of steel. This problem is solved by exhaustion method based on empirical considerations of professional experts controlling steelmaking process.

According to the selected regression model, steel hardness distribution is predicted, and the required chemical composition is chosen by the exhaustion method based on this prediction. The inevitable errors associated with the expert selection of an adequate model and the chemical composition deteriorates the quality of steel produced. Effectiveness of steel-making process control and melted steel quality can be improved when obtaining a model-based prediction for 'composition-hardness' ratio by the system of fuzzy production rules of Takagi-Sugeno-Kang model (TSK) and optimization of selection of chemical composition of steel under parameter stochasticity of the regression models.

It should be noted that statistical modeling techniques in combination with the methods of fuzzy inference are the most appropriate approach to building models of relationship between the steel hardness and its chemical composition.

The steel-making process control (chemical composition selection) may be presented either as a solution of nonlinear equation systems, or in the form of optimal selection models. The suggested model of relationship between the depth-distributed steel hardness and its chemical composition in the form of fuzzy production rule system (the TSK model) provides determination of the predicted values for the distributed steel hardness as weighted average outputs of a set of linear regression models and elimination of the problem of selecting the most adequate regression model.

The result obtained allows using the proposed steelmaking control models for different groups of steel grades and adjusting the software system of SEP 1664 modeling and controlling by means of including the programs for implementation of the TSK model and algorithms of quasi-quadratic programming problems.

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