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A MULTILEVEL RESOURCE-SAVING BLAST FURNACE PROCESS CONTROL

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A multilevel resource-saving blast furnace process control is considered. The resource-saving control is provided for operating, adaptation, technical and economic control in the automated systems of blast-furnace processes.

It is proposed to form optimal operation modes of blast furnace heating, metal charge structures, natural gas and oxygen consumption. Decisions are made using Kohonen neural networks taking into account current and planned parameters of coke quality, iron ore, raw materials and blast.

At the level of operating control, the work suggests a model predictive control to improve the resource conservation indicators. The method is based on decomposition of the general problem of the process dynamics identification on particular problems: dynamic synchronization and identification of process transfer functions.

At the level of adaptive control, optimal operating modes of blast furnaces are expedient to be developed with respect to blast furnace heating, structure of metal charge, natural gas and oxygen rate considering the current and planned parameters of coke, blasting. The blast furnace operating modes are suggested to be determined based on Kohonen neural networks.

In evaluating the efficiency of introducing the model predictive control, the existing actual statistics of scatter of BF mode parameters should be based upon. The fact is that the introduction of model predictive control assumes no radical change of the BF melt technology. Like in all the control systems, the BF process is considered as the set control object with all its characteristics. Changing process settings, raw material content does not introduce any cardinal variation in the scatter of process characteristics. However, in this case a transient process occurs which is necessary for the control system to identify the changing conditions. The transient process is inherent to all the control systems and the blast furnace process is not an exclusion. As a result of transient process, the control system is set to the optimal mode.

Keywords: blast furnace process, blast-furnace process optimization, self-organizing maps, Kohonen neural networks, cluster analysis, U-matrix, model predictive control.

Introduction

The blast furnace is a complex object for control, since such processes as fuel burning, metal smelting, iron reduction and carbonization etc. take place in it.

The modern methods for analysis of blast-furnace smelting processes are based on the achievements of multiple fields of science and technology. The blast furnace process models have been studied for over the course of many years [1–16]. Among the researchers, a considerable contribution into the development of blast furnace process studying were made by I.G. Tovarovskiy [1–3], N.A. Spirin, V.V. Lavrov, V.G. Lisienko [4], V.G. Lisienko [5], X. Wen, H. Cao, B. Hon, E. Chen, H. Li [6], J. Kule [7], M. Sasaki, K. Ono, A. Suzuki [8] et al.

One of the existing approaches to the blast furnace production maintenance is the use of the table of factors influencing the coke rate and blast furnace performance [1]. The method was developed based on generalization of the blast-furnace smelting dependencies and basic blast furnace process principles. It includes the charge mixture characteristics (the contents of iron, ore), coke quality (hardness M25, abrasion strength M10, size + 80 mm, ash), chemical composition of cast iron (Si, Mn, F, S), blasting parameters (blast temperature, oxygen concentration, humidity) and etc. In employing this approach to analyze the impact of the factors onto the coke rate and performance, their linearity and independence are assumed, however, in practice, the influence of the factors onto the coke rate and performance is non-linear and their interdependencies should be considered as well. Also, any blast-furnace smelting parameter should not be considered separately, since the process is influenced by the interrelated parameters. It should be noted that each particular blast furnace is unique in its operation and the values of factors shown in the table should be specified for a specific blast furnace. This is due to the fact that the raw material and process conditions of the blast furnace shops at metallurgical plants vary significantly.

In general, the blast furnace process monitoring and control requires considering multiple parameters, and the artificial intellect methods are very promising here [17]. These methods are already being actively employed in such fields as medicine, sociology, marketing etc. In the blast furnace practice, this area has not been sufficiently developed yet, but the activity is already in progress [17–25].

1. The structure of a multilevel expert system

The work considers an automated system of the multilevel resource saving control of the blast furnace process (Fig. 1). This automated system consists of three control levels. The upper one, technical and economic control level of the blast furnace process solves the problems of determining the process parameters of blast furnaces in the blast furnace shop according to the criterion of cast iron or steel minimum prime cost. At the medium level of adaptive control, optimal operating modes of blast furnaces are developed with respect to blast furnace heating, structure of metal charge, natural gas and oxygen rate considering the current and planned parameters of coke, blasting, technical condition of the equipment which are intended for operation in an advisor mode for a foreman.

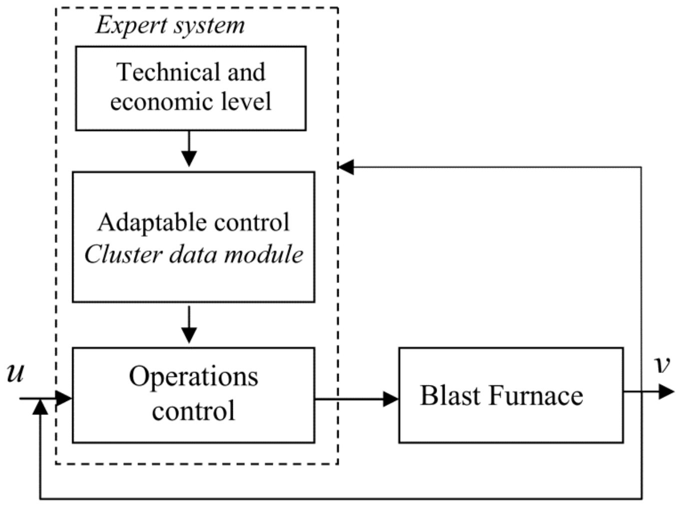

Fig. 1. Expert System Flow Chart

The criteria of the optimal adaptive control are the maximum cast iron production and the minimum coke rate.

Implementation of adaptive control is based on finding real effective characteristics of the blast furnace process for each blast furnace.

The adaptive control of the blast furnace mode ensures developing multidimensional solution regions on basic parameters characterising the blast furnace melting including quality characteristics of coke, metal charge, hot blasting for the subsequent use in solving the optimization tasks at the technical and economic level of control of sintering, coke and blast furnace production.

At the operational level of blast furnace process control, the problem of stabilizing the thermal condition of blast furnace production is solved.

A peculiar feature in developing the mathematical relations represented in the work is the use of the software tools for the in-depth analysis of the operational statistic data (the so-called Data Mining), cluster analysis based on the Kohonen neural network training [24] to detect the dependencies of effect caused by the control parameters onto the economic parameters of the blast furnace process, performance and coke consumption to improve the energy efficiency.

2. The method of adaptive control level

The existing control level of mode parameters of blast furnace is aimed at maintaining the parameter values within the admissible limits defined by process instructions and set process conditions. Such kind of control may be called admissible. In this kind of control makes mode parameters sporadically fluctuating within the admissible values. According to the studies, the fluctuation swing is frequently beyond the boundaries of the effective region of values of mode parameters. This results in the reduced furnace performance and increased coke rate. Therefore, stabilization of fluctuations of mode parameters within the effective region of their values with the use of current methods of model predictive control and intellectual technologies is a topical problem.

This problem is rather complex because the swing of mode parameter values is determined by multiple reasons, such as incompleteness of measured factors causing effect on the blast furnace process, low measurement precision, impossibility to measure the internal parameters of the blast furnace process, accidental fluctuations of the input parameters of charge, blast and etc. Accurately considering all this factors is extremely difficult at a modern level of the blast furnace process measurement and control technology. Therefore, the most expedient solution is determining current operating modes of blast furnace based on the cluster analysis in teaching the Kohonen neural network.

Let's consider building the mode diagrams in detail. Let's consider a set of unordered pairs of values of input parameters and output value obtained as a result of a set of observations over the BF $\{(x_s, y_s)\}$ as the source diagram. The diagram is given in Fig. 2.

The diagram x_s, y_s shows the values of some input and output parameters used for illustrating building of the mode diagram; $\{(x_s, y_s)\}$ – an ordered pair of the values of an input and output parameters.

These pair dependencies, while being built for the entire set of statistic observations of the dependence of the output parameter y over the input parameter x allows building a kinetic diagram of modes represented in Fig. 3.

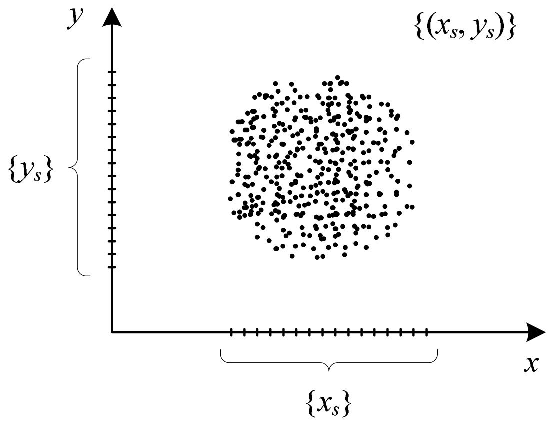

Fig. 2. The source diagram of blast furnace operating modes

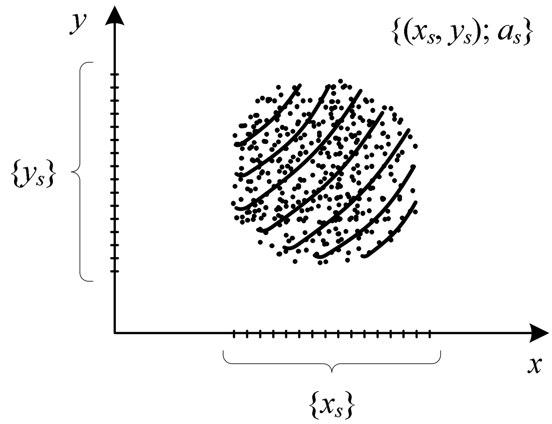

Fig. 3. Kinetic mode diagram

As a result, in a chaotic set of values of mode parameters (see Fig. 2) an order is introduced in a form of mode parameter variation lines. In fact, such a dependence will be stochastic, since it is impossible to consider all the BF input parameters. Therefore, in building such diagrams, the method of principal components shall be employed. In accordance with this method, the input parameter is determined first, which produces the maximum effect on the output parameter with building a diagram based on this method. Further, the next parameter in terms of the effect significance, shall be selected and the diagram building process proceeds iteratively until the significant input variables are no more left.

Based on the BF control practice, the principal input components are the volume of coke supply, ore burden, blast humidity, and, if justified, a number of other factors, A non-linear mode diagram is built for principal components. For other components, building non-linearized diagrams used to adjust the solution obtained with principal components, is sufficient.

Based on the diagrams built, a problem of selecting the input parameter values can be solved based on the condition of minimum deviation of the current value of the output parameter (y_k) from the set value (y_t):

$$(y_k - y_t)^2 \to \min. \quad (1)$$

The solution (1) may be found, for example, by the gradient method:

$$x_{j,k+1} = x_{j,k} - \gamma\left(y_k - y_t\right)a_{j,k}. \tag{2}$$

Here it is recommended to employ the coordinate-wise optimization method, since the simultaneous change of multiple input parameters is not allowed by the technical instructions.

The considered statistical calculation diagram is simplified since it does not consider a number of factors which stipulate the use of a considerably larger quantity of outgoing parameters for more accurately evaluating the BF condition.

Therefore, the diagrams of type shown in Fig. 4 shall be built for all the blast furnace process condition indicators. The blast furnace mode parameters are accidental processes depending on a large number of factors. Such factors are up to 70 parameters in number. Under such conditions, usual deterministic control methods of furnace modes do not allow reaching optimal values of mode parameters as a result of a large statistical dispersion of their values.

Therefore, the work suggests identifying the effective regions of the blast furnace melt in a multidimensional space of influencing factors by the cluster analysis methods.

The clustering tasks are of high dimensionality – they comprise more than 70 parameters including the parameters of quality of coke, sinter, charge composition, chemical composition of slag, iron, hot blast characteristics etc.

The example of the mode parameter chart of the blast furnace process obtained with artificial neural networks is given in Fig. 4. Data clustering was performed using the distance U-matrix analysis of the neural network trained at the statistical data over a long period of time.

The examples of the obtained BF flow charts are given in Figs. 5–7.

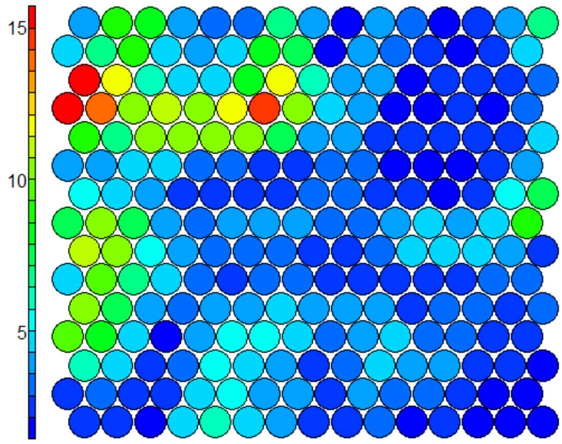

Fig. 4. U-matrix distance matrices

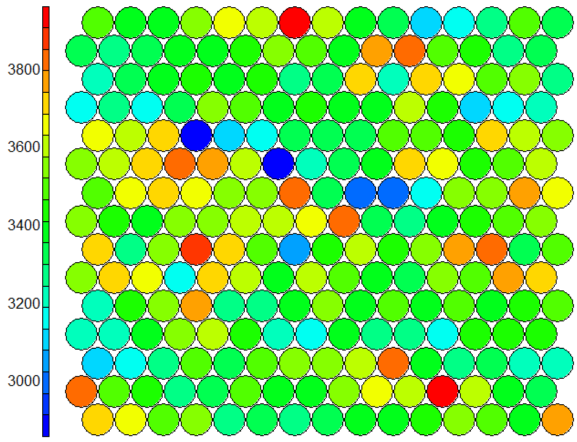

Fig. 5. The process flow chart by the BF performance mode

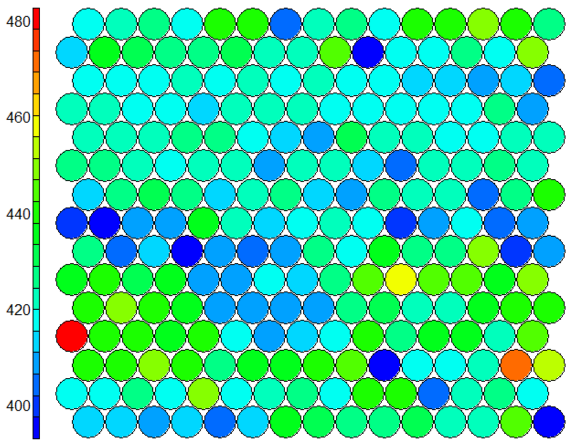

Fig. 6. The process flow chart for BF coke rate

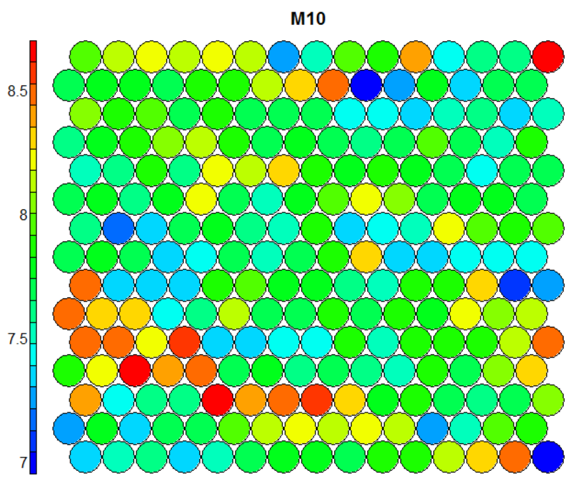

Fig. 7. The process flow chart for the BF coke quality (M10)

In the clusters found, the influence factors of process factors on the blast furnace performance and specific coke rate were determined. An example of the obtained influence factors of process parameter such as Si is given in Table 1. Each cluster corresponds to its individual blast furnace operating mode and an independent influence factor is determined in this mode.

Table 1

The impact factors of process parameters for the BF operating modes

Operating mode	Performance variation % with silicon increase in iron by 0.1%	Specific coke rate variation % with silicon increase in iron by 0.1%
1	–0.68	0.71
2	–0.58	0.60
3	–1.05	0.68
4	–1.09	0.56
5	–0.74	0.65
6	–0.71	0.50
7	–1.04	0.73
Mean	–0.84	0.63

Figs. 8 and 9 give an example of graphic representation of BF operating modes of depending on the silicon content in iron. Furthermore, the non-stationary BF operating mode is indicated by black dots.

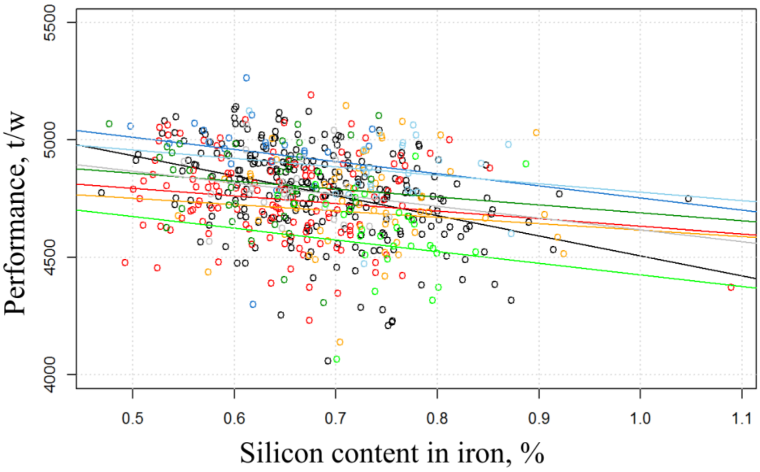

Fig. 8. The graphic representation of the BF operating mode influence on the performance depending on the silicon content in iron

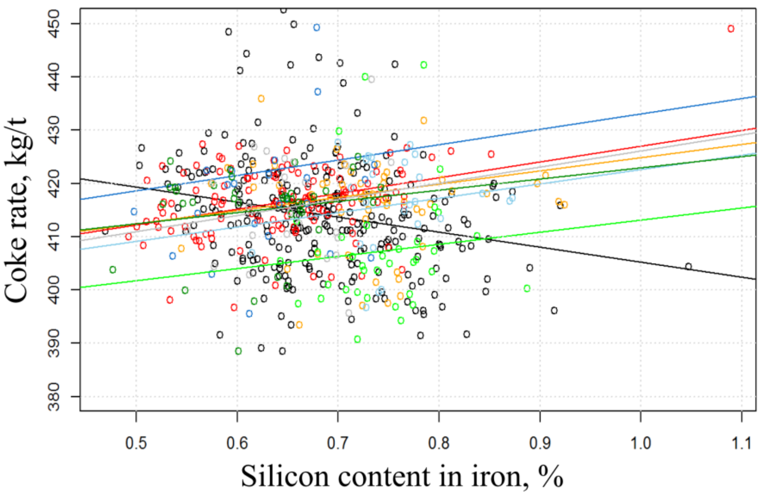

Fig. 9. The graphic representation of the BF operating mode influence on the specific coke rate depending on the silicon content in iron

3. The method for operating BF control

The basic characteristics of the operating control of thermal state of the BF process.

The basic connections of control parameters are given in Fig. 10. Here x_c – coke charge; $\{x_i\}$ – supply of adjusting materials; $u^C{}_{FR}$, $u^F{}_{FR}$, $y^F{}_{FR}$ – design value of specific fuel rate (FR), actual FR value and estimated FR value following the melting results, respectively; $\{u^C{}_i\}$ – calculated values of specific charge of the i-th adjusting materials; $u^{st}{}_\upsilon$ – indicator value of the process thermal state in the stack of blast furnace; $u^h{}_\upsilon$ – indicator value of the process thermal state in the blast-furnace hearth; $y^F{}_\upsilon$ – indicator value of the process thermal state at the furnace outlet.

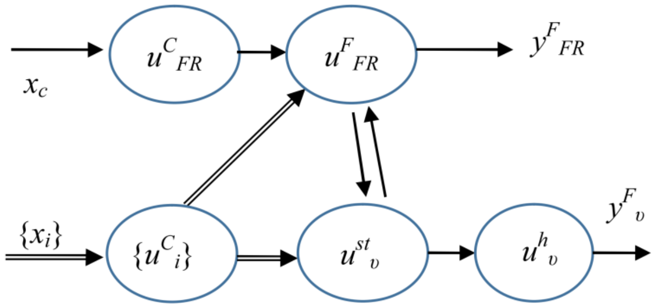

Fig. 10. The basic connections of control parameters

First of all, it should be noted that all the basic parameters given in (Fig. 10) are characterized by time and value of the action. The connections between parameters are characterized by transportation and inertial lag values. In addition, the main items in the operating control chart (Fig. 10): commands for supply, charge, iron tap, receipt of laboratory data occur at discrete time moments. These time moments are not well coordinated with each other, they have variable sequencing intervals. Such an asynchronous manner of actions considering non-stationary nature of lags results in a fact that the control system in general (furnace foreman – blast furnace process) are ill-defined coefficients of transfer between the setting actions and output parameters of the process. In extreme cases, coefficients of transfer may vary to the greatest extent up to the system stability loss and change of the response sign from negative to positive. For example, when a blast furnace foreman makes a decision following the results of current laboratory data which reflect the results of past effects as a result of lagging actions in the furnace. These effects are already implemented by the current moment of time and cannot be changed. All these may contradict to the current BF state, however the information on the current state has not been received yet or will be received with a delay.

Therefore it is no coincidence that one of the basic provisions of process instructions on maintaining the blast furnace modes is the requirement that blast furnace foreman should make sure after the adjusting action that the action is directed to the necessary direction. It is only after that when blast furnace foreman may perform the next adjusting action. This condition is the check of appropriateness of the action sign. But in the system in general the action is characterized not only by its sign of the coefficient of transfer but by its magnitude as well. The indefiniteness of the transfer coefficient value may result in low stability margin in the system and the occurrence of self-oscillations, which is observed in practice.

The solution in this situation is the model predictive control. The strategy of the model predictive control is implemented based on identification of the control object model based on current data and development of predictive control on its basis.

This strategy is based on consideration of the transportation and inertial lag of actions as well as nonlinear effects in the control system. In this case, the connection of the inlet design FR $\Delta u_{FR}(t_s)$ with the resulting value of output parameter $\Delta y_{\text{Si}}(t_s)$ is described in by a dynamic operator in the continuous case:

$$\Delta h_{\text{Si}}(t_s) = \int_0^\infty \Delta u_{FR}(t_s - \tau_{tl}^{\min} - \lambda) w(\lambda) d\lambda; \tag{3a}$$

$$\int_0^\infty w(\lambda) d\lambda = 1; \tag{3b}$$

$$\Delta y_{\text{Si}}(t_s) = F\,(\Delta h_{\text{Si}}(t_s)). \tag{3c}$$

Here a non-linear static part (3c) and a dynamic part (3a) with a unit transfer coefficient (3b) are distinguished in the explicit form, where $w(t)$ – is the weight function, $\tau_{tl}^{\min}$ – the minimum value of transportation lag.

In the discrete option, the formulas take the form

$$\Delta h_{\mathrm{Si}}(t_s) = \sum_k \Delta u_{FR}(t_s - \tau_{tl}^{\min} - \lambda_k) w_k \Delta\lambda_k; \tag{4a}$$

$$\sum_k w_k \Delta\lambda_k = 1; \tag{4b}$$

$$\Delta y_{\mathrm{Si}}(t_s) = F(\Delta h_{\mathrm{Si}}(t_s)). \tag{4c}$$

In this case, the dynamic connection formula, for example, for the first order inertial process takes the form

$$\Delta h_{FR}(T_L, t_s) = \int_0^{T_{in}} \Delta u_{FR}(t_s - \lambda) \frac{1}{T_L} \exp\left(\frac{\lambda}{T_L}\right) d\lambda. \tag{5}$$

Where T_L – time constant of lag; T_{in} – observation interval.

The formula of the forecast with the transportation lag value advance takes the form

$$\Delta y_{\mathrm{Si}}(t_s + \tau_{tl}^{\min}) = a_{FR} \Delta h_{FR}(T_L; t_s). \tag{6}$$

The transfer coefficient for coke is determined based on the ratio

$$a_{FR} = \max_{\{\tau_{tl,i}^{\min}, w_i\}} a_{FR}(\tau_{tl}^{\min}, T_L) = \frac{(\Delta y_{\mathrm{Si}}(t_s + \tau_{tl}^{\min}),\ \Delta h_{FR}(T_L; t_s))_s}{(\Delta h_{FR}(T_L; t_s),\ \Delta h_{FR}(T_L; t_s))_s}. \tag{7}$$

Where Δh_{FR}, Δy_{Si} – vectors of statistic data $(\cdot, \cdot)$ – scalar vector product.

In a more general case, a considered strategy is being implemented at all the inlet adjusting actions on the blast furnace process. The difference is that for many control actions having the gas nature, the action lag is low in its value as considered to the coke supply therefore lag can be neglected here which results in simplification of the identification problem solution.

4. Evaluating the parameters of forecast precision and stabilization of blast furnace parameters on its effectiveness

Stabilization of BF process parameter values (a smooth furnace operation according to the BF process terminology) directly improves the process efficiency with implementing the model predictive control. It is demonstrable on Fig. 11. Here σ_n – rated root mean square deviation of actual data; σ_{opt} – optimal nominal root mean square deviation of actual data, σ_T – target value.

Upon introducing the model predictive control, the root mean square deviation was reduced to σ_{opt}, which allowed bringing the process to the optimal mode.

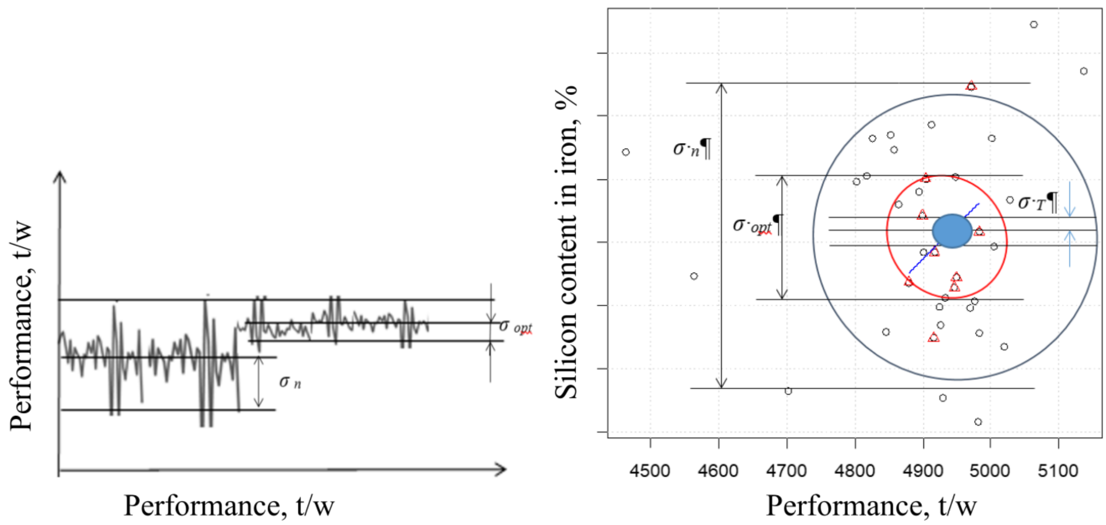

Fig. 11. The influence of stabilization of BF process mode parameters on its efficiency with the model predictive control

To illustrate this provision, Fig. 11 shows the ellipses of *Si* content scatter in iron based on the actual statistics of BF melts at a blast furnace. Here the effective mode is highlighted in red, which is distinguished subject to the blast furnace performance increase by 10% and corresponds to the conditions of implementation of the expert system of model predictive control of blast furnace modes.

In the central part the mode with the allowable deviation of Si content in iron of ±2% according to the terms of reference. It is obvious that root mean square deviation of the Si content in iron σ_T set by the assumed terms of reference stipulates stringent and unrealisable frameworks of blast furnace process with maintaining its basic technology.

Conclusions

The work suggests the method of multilevel resource-saving control of blast furnace process based on implementation of the automated system for operating, adaptation and technical and economic control of the blast-furnace process.

Statistical data show that based on introduction of model predictive control 10% stabilization of mode parameters can be reached. In this case the growth of profit of the blast furnace process exceeds the costs of introduction of the model predicative control by many times.

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МНОГОУРОВНЕВОЕ РЕСУРСОСБЕРЕГАЮЩЕЕ УПРАВЛЕНИЕ ДОМЕННЫМ ПРОЦЕССОМ

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Рассмотрены вопросы построения многоуровневого ресурсосберегающего управления доменным процессом. Ресурсосберегающее управление целесообразно выполнять на основе внедрения автоматизированной системы для оперативного, адаптивного и технико-экономического управления доменным процессом.

На уровне адаптивного управления целесообразно осуществлять формирование оптимальных режимов работы доменных печей по нагреву печей, структуре металлошихты, расходу природного газа, кислорода с учетом текущих и планируемых параметров качества кокса, железорудного сырья, дутья. Определение режимов работы доменной печи предлагается осуществлять на основе нейронных сетей Кохонена.

На уровне оперативного управления в работе предложен метод модельно-упреждающего управления, повышающий показатели эффективности использования ресурсов. Метод основан на декомпозиции общей задачи определения динамических характеристик сложных технологических процессов на частные задачи динамической синхронизации и идентификации передаточных свойств. Для решения сложных задач идентификации предложено использовать искусственные нейронные сети.

При оценке эффективности введения модельно-упреждающего управления необходимо исходить из существующей реальной статистики разброса режимных параметров доменного процесса. Дело в том, что введение модельно-упреждающего управления не предполагает коренной смены технологии доменной плавки. Как и во всех системах управления, здесь доменный процесс рассматривается как заданный объект управления со всеми своими характеристиками. Изменение уставок процесса, состава сырья не вносит кардинального изменения в разброс характеристик процесса. Однако при этом возникает переходный процесс, необходимый системе управления для идентификации изменившихся условий. Переходный процесс присущ всем системам управления, и доменный процесс не является исключением. В результате переходного процесса система управления настраивается на оптимальный режим.

Ключевые слова: доменный процесс, оптимизация доменного процесса, самоорганизующиеся карты, нейронные сети Кохонена, кластерный анализ, U-матрица, модельно упреждающее управление.

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