# Автоматизированные системы управления технологическими процессами
# Automated process control systems

Original article
DOI: 10.14529/ctcr240409

## AUTOMATED INFORMATION CONTROL SYSTEM FOR OPTIMAL PLANNING OF BLAST-FURNACE IRONMAKING

***L.S. Kazarinov,*** *kazarinovls@susu.ru, https://orcid.org/0000-0001-6308-4596*
***T.A. Barbasova****, barbasovata@susu.ru, https://orcid.org/0000-0002-2248-2894*
***E.V. Bauman****, bauman.e.v@yandex.ru*
***P.A. Samoletova****, samoletovapa@susu.ru*
***S.A. Cherepanova****, cherepanovasa@susu.ru*
*South Ural State University, Chelyabinsk, Russia*

***Abstract.*** Increasing competition in the markets for metallurgical products issues a challenge for enterprises to increase production efficiency in economic term. One of the most important segments of the metallurgical industry is considered to be blast furnace ironmaking, which accounts for more than 50% of the energy costs of a metallurgical enterprise; in addition, there is a large consumption of resources for manufacturing. **Aim.** The article is aimed at increasing the efficiency of blast furnace smelting both from an economic point of view and from the technological process itself through the introduction of an automated information-control system for optimal planning of the work of a blast furnace shop. The system is capable of recommending optimal production of a blast furnace shop in terms of the minimum cost of cast iron, as well as making recommendations to personnel to correct operating parameters of blast furnaces in order to increase productivity and reduce coke rate. **Materials and methods.** It is proposed to use artificial intelligence methods in work to achieve these goals. In particular, clustering and dimensionality reduction methods are used to determine the optimal operating modes of technological equipment, and the problem of increasing the efficiency of the blast furnace shop is solved using nonlinear programming methods to plan blast furnace ironmaking, taking into account technological and economic limitations. The initial data for setting up and operating of optimal planning system is the production statistics of a metallurgical enterprise, the sources of which are monitoring and control systems for technological processes, the laboratory analyses of charge materials and smelting products, as well as expert assessments of the technological equipment state. **Results.** The results of the optimal value of blast furnace ironmaking seeking in terms of the minimum cost of cast iron and maximum efficiency of blast furnace smelting as well as the coefficients of the influence of production factors on the main indicators of blast furnace ironmaking: the productivity of blast furnaces and coke rate are shown. **Conclusion.** The developed automated information-control system for optimal planning of blast furnace ironmaking can be used as a decision support tool for both foremen, the head of the blast furnace shop, and the economic services of an industrial enterprise. Specialists can apply the obtained results for master production schedule of the sinter-coke-blast furnace ironmaking.

***Keywords:*** artificial intelligence, blast furnace ironmaking, clustering, optimization, information-control system

***For citation:*** Kazarinov L.S., Barbasova T.A., Bauman E.V., Samoletova P.A., Cherepanova S.A. Automated information control system for optimal planning of blast-furnace ironmaking. *Bulletin of the South Ural State University. Ser. Computer Technologies, Automatic Control, Radio Electronics*. 2024;24(4):103–112. DOI: 10.14529/ctcr240409

Научная статья
УДК 004.896, 004.942
DOI: 10.14529/ctcr240409

# АВТОМАТИЗИРОВАННАЯ ИНФОРМАЦИОННО-УПРАВЛЯЮЩАЯ СИСТЕМА ОПТИМАЛЬНОГО ПЛАНИРОВАНИЯ ДОМЕННОГО ПРОИЗВОДСТВА

***Л.С. Казаринов***, *kazarinovls@susu.ru, https://orcid.org/0000-0001-6308-4596*
***Т.А. Барбасова***, *barbasovata@susu.ru, https://orcid.org/0000-0002-2248-2894*
***Е.В. Бауман***, *bauman.e.v@yandex.ru*
***П.А. Самолетова***, *samoletovapa@susu.ru*
***С.А. Черепанова***, *cherepanovasa@susu.ru*
*Южно-Уральский государственный университет, Челябинск, Россия*

***Аннотация.*** Усиление конкуренции на рынках металлургической продукции ставит перед предприятиями задачу повышения эффективности производства с экономической точки зрения. Одним из наиболее важных звеньев металлургической отрасли считается доменное производство, на долю которого приходится более 50 % энергетических затрат металлургического предприятия, помимо этого при получении продукции идет большой расход ресурсов. **Цель исследования.** Статья направлена на повышение эффективности доменной плавки как с экономической точки зрения, так и со стороны самого технологического процесса за счет внедрения автоматизированной информационно-управляющей системы оптимального планирования работы доменного цеха, способной рекомендовать оптимальное производство доменного цеха с точки зрения минимума себестоимости чугуна, а также выдавать рекомендации персоналу по коррекции режимных параметров работы доменных печей с целью увеличения производительности и снижения удельного расхода кокса. **Материалы и методы.** Для достижения этих целей в работе предлагается использовать методы искусственного интеллекта. В частности, для определения оптимальных режимов работы технологического оборудования применяются методы кластеризации и снижения размерности, а для планирования доменного производства с учетом технологических и экономических ограничений решается задача повышения эффективности доменного цеха с применением методов нелинейного программирования. В качестве исходных данных для настройки и работы системы оптимального планирования выступает производственная статистика металлургического предприятия, источниками которой являются системы мониторинга и управления технологическими процессами, результаты анализов лабораторий исходных материалов и готовой продукции, а также экспертные оценки по состоянию технологического оборудования. **Результаты.** Приведены результаты решения задачи поиска оптимального значения производства доменного цеха с точки зрения минимума себестоимости чугуна и максимума эффективности ведения доменной плавки, а также коэффициенты влияния производственных факторов на основные показатели доменного производства: производительность доменных печей и удельный расход кокса. **Заключение.** Разработанная автоматизированная информационно-управляющая система оптимального планирования доменного производства может быть использована в качестве инструмента поддержки принятия решений как для мастеров, начальника доменного цеха, так и для экономических служб промышленного предприятия. Полученные результаты могут применяться специалистами для объемного планирования работы агло-коксо-доменного производства в целом.

***Ключевые слова:*** искусственный интеллект, доменное производство, кластеризация, оптимизация, информационно-управляющая система

***Для цитирования:*** Automated information control system for optimal planning of blast-furnace ironmaking / L.S. Kazarinov, T.A. Barbasova, E.V. Bauman et al. // Вестник ЮУрГУ. Серия «Компьютерные технологии, управление, радиоэлектроника». 2024. Т. 24, № 4. С. 103–112. DOI: 10.14529/ctcr240409

## Introduction

The iron and steel industry plays an important role in the global economy, influencing key industries. The largest countries all over the world support and develop the metallurgical products production as one of the promising areas of economic development. Due to increasing competition on the metallurgical products markets, enterprises need to solve problems to increase economic efficiency.

One of the key elements of the metallurgical industry is blast furnace ironmaking. It accounts for 50–75% of the energy costs of full-cycle enterprises. In this regard, it is necessary to reduce the energy and resource intensity of the resulting products.

The literature presents several strategies for increasing the economic efficiency of blast furnace ironmaking. The main strategy is to optimize the blast furnace smelting process itself. At different times, well-known Russian and foreign researchers N.N. Babarykin studied this issue [1], S.A. Zagajnov and L.Ju. Gileva [2, 3], Ju.N. Ovchinnikov [4], O.P. Onorin [5], N.A. Spirin [6], I.G. Tovarovskij [7], V.N. Andronov [8], B.P. Dovgaljuk [9] and many others. Another strategy for increasing the economic efficiency of blast furnace ironmaking is the optimal distribution of raw materials and fuel and energy resources between blast furnaces. The solutions to the resource allocation problem are presented in [10–11]. This strategy is also successfully used in other sectors of the economy [12].

This article solves the problem of optimal planning of blast furnace ironmaking using artificial intelligence methods. These methods allow to analyze large volumes of data, determine hidden patterns and dependencies, and solve complex optimization problems. In order to increase the efficiency and economical operation of blast furnace smelting, an automated information and control system (AICS) was developed. The functionality of the system determines the relevance of the research work. AICS allows to plan optimal volumes of pig iron production, taking into account production, technological and contractual restrictions, as well as the actual influence of quality indicators of coke, iron ore raw materials and operating parameters of blast furnaces on the efficiency of the blast furnace process.

## System description

The automated information and control system for optimal planning of blast furnace ironmaking is a hardware/software package. It provides information resources and functionality for searching optimal production parameters taking into account production, technological and contractual restrictions. The system is flexible and adaptable to the operating conditions of the blast-furnace shop and the enterprise demands.

Fig. 1 shows a generalized functional flow diagram of the automated information and control system for optimal planning of blast-furnace ironmaking.

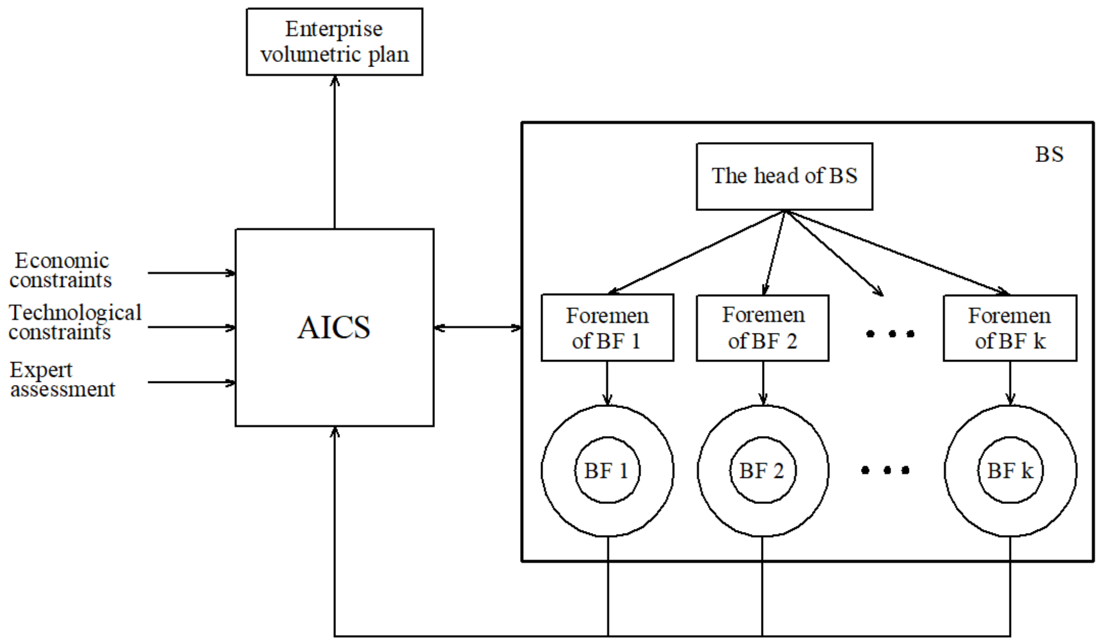


**Fig. 1. The functional flow diagram of AICS of optimal planning of blast-furnace ironmaking**

The system receives input data from various sources, such as blast furnace process monitoring and control systems, laboratory analyses of charge materials and smelting products, process reports, and log books. The system's functionality also provides the ability to manual entry of economic and technological constraints and expert assessments in the user interface. Based on this data, the system solves the optimization problem and provides the user with recommendations on changing the parameter values, which will increase the efficiency of blast furnace smelting and minimize the iron production costs. The obtained results are available to blast furnace shop (BS) specialists for effective control of the technological process and to economic services for volumetric planning of the metallurgical enterprise work as a whole.

**Blast furnace efficiency index**

To assess the efficiency of blast furnace smelting, it is proposed to use an indicator determined by the formula:

$$E_i = \alpha \cdot \frac{IP_i}{IP_{\max i}} + (1-\alpha) \cdot \left(\frac{SCR_i}{SCR_{base}^{BS}}\right)^{-1},$$

where $i = 1, 2, \ldots, k$ – blast furnace number;

$E$ – efficiency index;

$IP$ – predicted iron productivity, t/day;

$IP_{\max i}$ – maximum iron productivity, t/day;

$SCR$ – predicted specific coke rate, kg/t;

$SCR_{base}^{BS}$ – average specific coke rate of blast furnace shop for current period, kg/t;

α – weighting coefficient reflecting the importance of taking into account productivity and coke rate as part of the efficiency index.

Nowadays, factor models are widely used to predict productivity and SCR. These models are based on statistical data and do not require a detailed description of all processes occurring in the furnace. Factor models have the form of linear functions with coefficients determined on statistical data and expert assessments:

$$SCR_i = SCR_{base\,i} + \frac{SCR_{base\,i}}{100} \cdot \sum_{j=1}^{n}\left(k_{ij}^{SCR} \cdot \Delta P_{ij}\right) + k_{i\,NG}^{SCR} \cdot \Delta NG_{sp\,i} + k_{n\,i}^{SCR} + SCR_{rep};$$

$$IP_i = IP_{base\,i} + \frac{IP_{base\,i}}{100} \cdot \sum_{j=1}^{n}\left(k_{ij}^{IP} \cdot \Delta P_{ij}\right) + k_{n\,i}^{IP},$$

where $j = 1, 2, \ldots, n$ – parameter number influencing the SCR and productivity;

$SCR_{base\,i}$ – specific coke rate of $i$-th blast furnace in base period, kg/t;

$IP_{base\,i}$ – iron productivity of $i$-th blast furnace in base period, t/day;

$\Delta P_{ij}$ – change of $j$-th technological parameter of $i$-th blast furnace relative to the base period;

$k_{ij}^{SCR}, k_{ij}^{IP}$ – coefficient of influence of the $j$-th parameter of the $i$-th blast furnace on the SCR and productivity, respectively;

$k_{i\,NG}^{SCR}$ – coefficient of influence of specific rate of natural gas of the $i$-th blast furnace on the SCR;

$\Delta NG_{sp\,i}$ – change of specific rate of natural gas relative to the base period, m$^3$/t;

$SCR_{rep}$ – specific coke rate for repairs, kg/t;

$k_{n\,i}^{SCR}$ – coefficient of technology nonuniformity for SCR of the $i$-th blast furnace, kg/t;

$k_{n\,i}^{IP}$ – coefficient of technology nonuniformity for iron productivity of the $i$-th blast furnace, t/day.

The technology nonuniformity coefficients provided in the formulas are determined by a BS specialist based on his experience and knowledge of the operating characteristics of blast furnaces. The addition of these coefficients into the model allows to take into account the influence of parameters that are not included in factor models or cannot be measured and assessed quantitatively. Also, to improve the accuracy of the forecast of productivity and SCR using factor models, data mining methods are used in this research work to determine the coefficients of influence of parameters in the current operating conditions of the blast furnace shop.

**Cluster analysis of blast furnace operating modes**

The cluster analysis methods allow to automatically divide the statistical data of blast furnaces into groups (clusters) that correspond to different operating modes of the furnace. So, it becomes possible to compare and select the most suitable modes, taking into account the current operating conditions of the blast furnace shop.

Data pre-processing step is a necessary for the successful application of clustering methods, since the interpretability and utility of the results directly depends on the data quality. To reduce data volume and highlight the most significant features the data preprocessing step includes removing noise and omissions, converting data into a single format, aggregation and selecting. The random forest method was used to fill in the data gaps. This method allows taking into account nonlinear dependencies between variables and is highly accurate and resistant to noise [13]. Data corresponding to non-steady-state mode of blast furnace were also removed from the original data samples, as they could reduce the accuracy of the analysis and cause erroneous results. Data were aggregated daily to average variations in parameters throughout the day.

For cluster analysis, we used self-organizing Kohonen maps – neural networks with unsupervised learning. This method allows to display a multidimensional array of information on a two-dimensional grid, preserving the data topological properties. At the beginning of training, each grid node is a prototype of a cluster with a certain vector of weights that characterizes its position in the original space. When an input vector is received, the network finds the winning neuron that is closest to it, and adjusts its weights and the weights of its neighbors so that they become more similar to the input vector. This process is repeated for all input vectors until the specified accuracy or number of iterations is achieved [14]. As a results of the neural network training, we obtain data divided into clusters. The final number of clusters was selected using the silhouette coefficient.

After identifying the operating modes of blast furnaces, linear regression models were built and the corresponding factor coefficients for the influence of parameters on the efficiency of blast furnace smelting were determined in each cluster. Figs. 2–5 show the dependences of blast furnace productivity and specific coke rate (SCR) on abrasion coke strength (M10) and iron content in the charge.

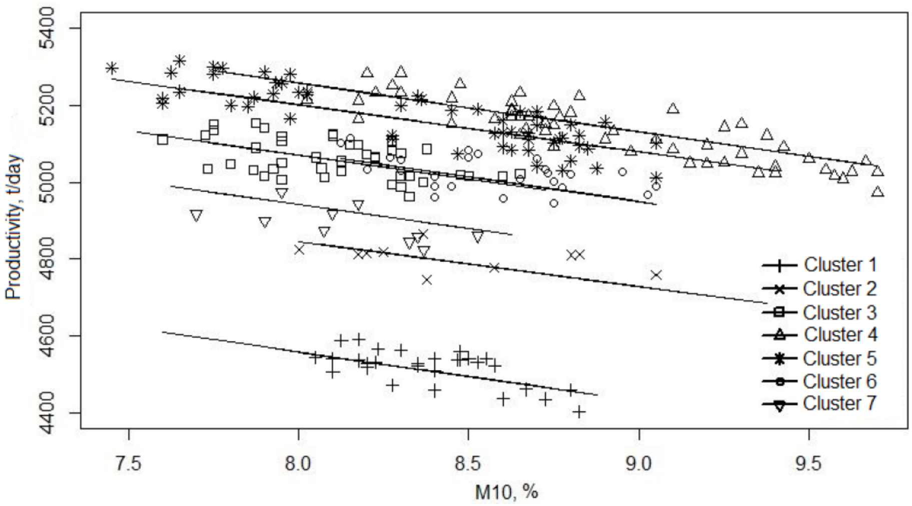


**Fig. 2. Graph of blast furnace productivity versus abrasion coke strength (M10)**

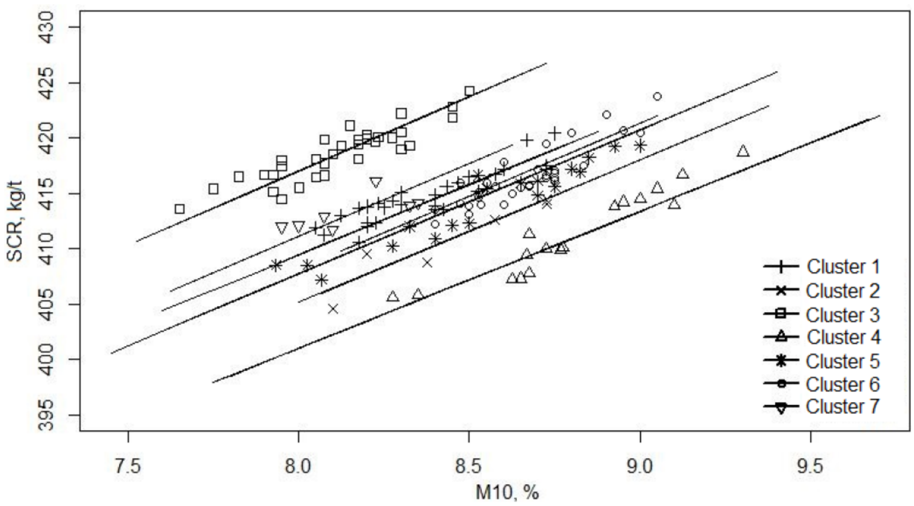


**Fig. 3. Graph of coke rate versus abrasion coke strength (M10)**

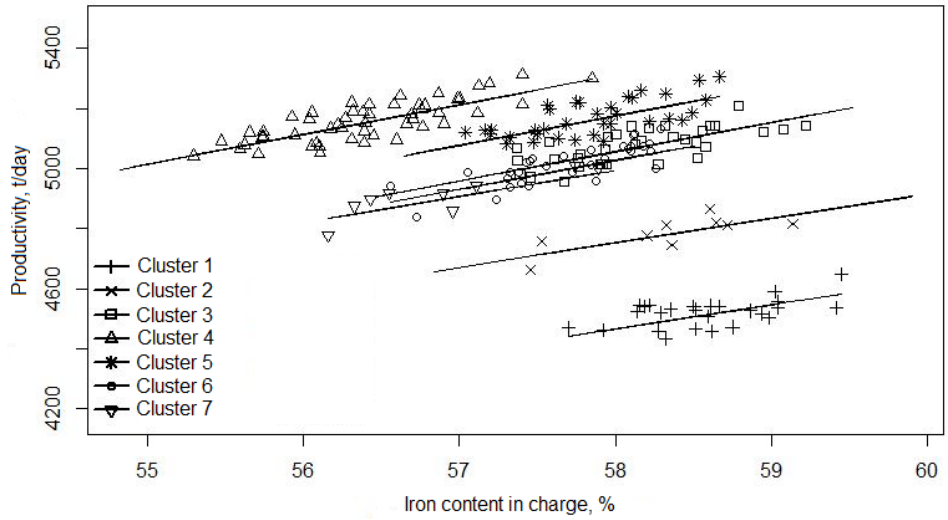


**Fig. 4. Graph of blast furnace productivity versus the iron content in the charge**

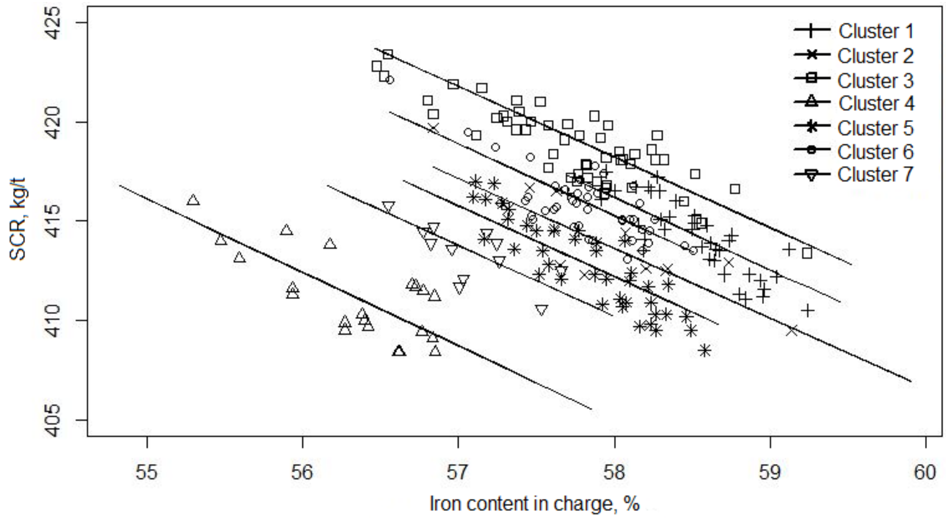


**Fig. 5. Graph of coke rate versus the iron content in the charge**

The Table 1 contains coefficients calculated in each cluster for the influence of abrasion coke strength and iron content in the charge on productivity and SCR.

**Table 1**

**Coefficients of influence of abrasion coke strength (M10) and iron content in the charge**

| Operating mode | Change in productivity (%) with an increase in M10 by 1 % | Change in specific coke rate (%) with an increase in M10 by 1 % | Change in productivity (%) with an increase in iron content in the charge by 1 % | Change in specific coke rate (%) with an increase in iron content in the charge by 1 % |
|---|---|---|---|---|
| 1 | –2.8 | 3.06 | 1.77 | –0.88 |
| 2 | –2.46 | 3.12 | 1.70 | –0.85 |
| 3 | –2.45 | 3.20 | 1.92 | –0.85 |
| 4 | –2.46 | 3.01 | 1.91 | –0.90 |
| 5 | –2.38 | 3.14 | 1.90 | –0.86 |
| 6 | –2.57 | 3.18 | 1.94 | –0.87 |
| 7 | –2.56 | 3.18 | 1.77 | –0.86 |
| **Average** | –2.53 | 3.13 | 1.84 | –0.87 |

The cluster database is constantly updated and adapts to changes in blast furnace smelting technology. The AICS for optimal planning of blast furnace ironmaking analyzes information about the operation of blast furnaces in the current period, determines the nearest cluster for each furnace and calculates the coefficients of the influence of selected parameters on productivity and SCR which are used in factor models.

**The solution of the optimization problem**

During planning of blast furnace ironmaking, the problem of multicriteria optimization is solved using a generalized optimality criterion.

The objective function is obtained by combining the weighted values of partial criterions and has the following form:

$$\beta_1 \cdot PC - \beta_2 \cdot \sum_{i=1}^{k} E_i \ \rightarrow \ \min,$$

where $\beta_1$, $\beta_2$ – weighting coefficient;

$PC$ – production cost of cast iron;

$E$ – efficiency index of $i$-th blast furnace.

The goal of optimization is to find such values of technological parameters that provide maximum efficiency and minimum costs for the production of cast iron under given constraints.

To calculate the production cost of cast iron, we use models obtained from the subsystem for optimizing the supply and consumption of coal and iron ore raw materials [15]. In this subsystem, the selection of the share participation of suppliers is carried out according to the criterion of minimum costs for the purchase and transportation of raw materials, taking into account technological and economic constraints. At the output of the subsystem, several charge variations are formed, for each of which their qualitative and quantitative characteristics are given, as well as the cost of coke and iron ore raw materials. One of the tasks of the AICS is to select the optimal charge option from those presented at the output of the subsystem to ensure a minimum of the objective function.

The production cost of cast iron also depends on the blast operating mode of blast furnaces. Therefore, the model takes into account not only the characteristics of the charge, but also the following parameters: oxygen content in the blast, specific rate of natural gas, rate of enriched blast, its temperature, pressure and humidity.

In this optimization problem, the following constraints were set:

1. The values of the optimized technological parameters should not exceed the minimum and maximum limits determined by the technical capabilities of the equipment, as well as the requirements for the quality of the products:

$$P_{\min ij} \leq P_{ij} \leq P_{\max ij},$$

where $P_{ij}$ – predicted value of $j$-th parameter of $i$-th blast furnace;

$P_{\min ij}, P_{\max ij}$ – minimum and maximum values of $j$-th parameter of $i$-th blast furnace.

2. The volumes of natural gas, blast and oxygen, as well as the volume of top gas should not exceed the permitted maximum value for the blast furnace shop:

$$V_{NG}^{BS} \leq V_{NG\max}^{BS},\ V_{O2}^{BS} \leq V_{O2\max}^{BS},\ V_{Blast}^{BS} \leq V_{Blast\max}^{BS},\ \ V_{TG}^{BS} \leq V_{TG\max}^{BS},$$

where $V_{NG}^{BS}$, $V_{O2}^{BS}$, $V_{Blast}^{BS}$, $V_{TG}^{BS}$ – predicted volume of natural gas, blast, oxygen and top gas for blast furnace shop respectively, m$^3$;

$V_{NG\max}^{BS}$, $V_{O2\max}^{BS}$, $V_{Blast\max}^{BS}$, $V_{TG\max}^{ДЦ}$ – maximum values of volume of natural gas, blast, oxygen and top gas for blast furnace shop respectively, m$^3$.

3. The theoretical combustion temperature for each blast furnace should not exceed the prescribed limits:

$$TCT_{\min i} \leq TCT_i \leq TCT_{\max i},$$

where $TCT_i$ – calculated theoretical combustion temperature for the $i$-th blast furnace in the forecast period, °;

$TCT_{\min i}$, $TCT_{\max i}$ – specified minimum and maximum values of the theoretical combustion temperature for the $i$-th blast furnace, °.

4. Constraints on SCR and blast furnace productivity should not exceed the prescribed limits:

$$SCR_{\min i} \leq SCR_i \leq SCR_{\max i};$$

$$IP_{\min i} \leq IP_i \leq IP_{\max i}.$$

5. The value of the ratio of natural gas and oxygen content in the blast for each furnace should be close to the optimal value from the forecast cluster:

$$Opt_i - \Delta_{opt} \leq \frac{Q_{NG\,i}}{Q_{O2\,i}} \leq Opt_i + \Delta_{opt},$$

where $Q_{NG\,i}$ – natural gas content in the blast for the i-th blast furnace, %;

$Q_{O2\,i}$ – oxygen content in the blast for the $i$-th blast furnace, %;

$Opt_i$ – optimal value of the ratio of natural gas and oxygen content from the forecast cluster;

$\Delta_{opt}$ – permissible deviation of the ratio of natural gas and oxygen content from the optimum.

To solve the problem under discussion, we used the differential evolution algorithm for global optimization with nonlinear constraints and self-adaptive parameters [16]. Fig. 6 shows an example of how the objective function depends on pig iron production of the blast furnace shop per month. In this case, the optimal production of cast iron was 843 thous. tons.

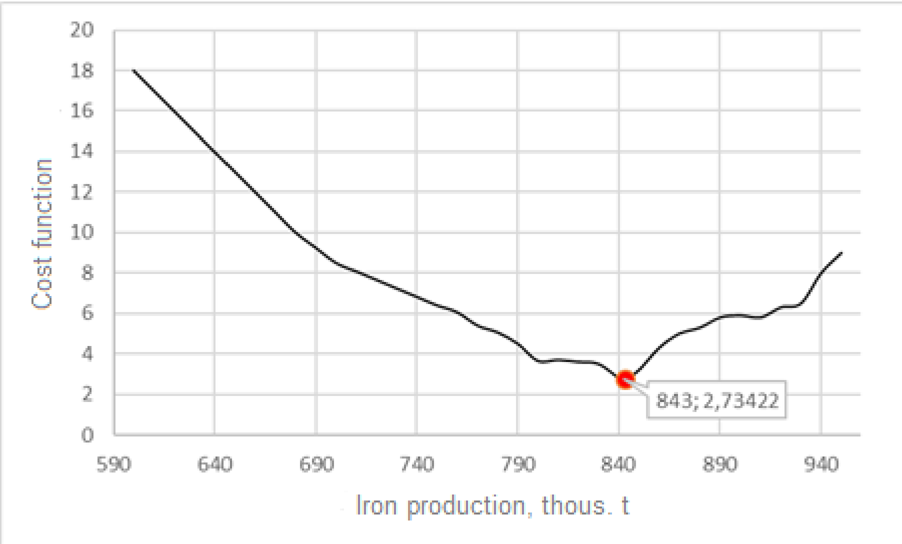


**Fig. 6. The results of optimal productivity value search**

As a result of solving the optimization problem, the optimal values of the technological parameters of the blast furnaces operation were obtained according to the criterion of minimum costs and maximum efficiency of blast furnace smelting.

## Conclusion

During the study, an automated information and control system for optimal planning of blast furnace production was developed. AICS is based on modern technologies for data processing and analysis, as well as artificial intelligence methods, such as clustering, dimensionality reduction and nonlinear optimization.

This system makes allow to evaluate the influence of technological factors on the efficiency indicators of blast furnace smelting under various operating modes of blast furnaces and to predict the optimal values of the blast furnace shop operating parameters, taking into account the given constraints. The results obtained in proposed system can be useful for making decisions at the technical and economic level of managing metallurgical production.

## References

1. Babarykin N.N. *Teoriya i tekhnologiya domennoy plavki* [Theory and technology of blast-furnace smelting]. Magnitogorsk, MSTU; 2009. 257 p. (In Russ.)

2. Zagaynov S.A., Onorin O.P., Gileva L.Yu., Volkov D.N., Tleugobulov B.S. [Development and implementation of mathematical support and software for flexible technological operating modes of blast furnaces]. *Steel*. 2000;(9):12–15. (In Russ.)

3. Zagainov S.A., Onorin O.P., Spirin N.A., Yaroshenko Y.G. Mathematical model of the blast-furnace process. *Steel in Translation*. 2003;33(12):1–5.

4. Ovchinnikov Yu.N., Moykin V.I., Spirin N.A., Bokovikov B.A. *Nestatsionarnye protsessy i povyshenie effektivnosti domennoy plavki* [Unsteady processes and increasing the efficiency of blast furnace smelting]. Chelyabinsk: Metallurgiya; 1989. 120 p. (In Russ.)

5. Onorin O.P., Spirin N.A., Terent'ev V.L. Gileva L.Yu., Rybolovlev V.Yu., Kosachenko I.E., Lavrov V.V., Terent'ev A.V. *Komp'yuternye metody modelirovaniya domennogo protsessa* [Computer methods for modeling the blast furnace process]. Ekaterinburg: USTU-UPI; 2005. 301 p. (In Russ.)

6. Spirin N.A., Lavrov V.V., Parshakov S.I., Denisenko S.G. *Optimizatsiya i identifikatsiya tekhnologicheskikh protsessov v metallurgii* [Optimization and identification of technological processes in metallurgy]. Ekaterinburg, USTU-UPI; 2006. 307 p. (In Russ.)

7. Tovarovskiy I.G. *Domennaya plavka* [Blast furnace smelting]. Dnepropetrovsk: Porogi; 2009. 765 p. (In Russ.)

8. Andronov V.N. *Ekstraktsiya chernykh metallov iz prirodnogo i tekhnogennogo syr'ya. Domennyy protsess* [Extraction of ferrous metals from natural and technogenic raw materials. Blast Furnace process]. Donetsk: Nord-Press; 2009. 377 p. (In Russ.)

9. Dovgalyuk B.P. [Methods for monitoring the efficiency of using fuel additives and process oxygen and their optimal distribution between blast furnaces]. *Steel*. 1987;(8):9–14. (In Russ.)

10. Gurin I.A., Spirin N.A., Lavrov V.V., Noskov V.Yu. Algorithmic provision and the software for optimal allocation of fuel-energy resources in blast furnaces production. *Automation. Modern technologies*. 2017;71(5):202–207. (In Russ.)

11. Spirin N.A., Gilyova L.Y., Lavrov V.V., Istomin A.S., Gurin I.A., Buriykin A.A., Shchipanov K.A. The optimization of natural gas distribution in a blast furnace when changing the parameters of melting. *Izvestiya vuzov. Chernaya metallurgiya = Izvestiya. Ferrous metallurgy*. 2014;57(6):45–49. (In Russ.) DOI: 10.17073/0368-0797-2014-6

12. Barkalov S.A., Moiseev S.I., Serebryakova E.A. Mathematical model of the optimal resources distribution in the construction sphere under conditions of their deficiency. *Bulletin of the South Ural State University. Ser. Computer Technologies, Automatic Control, Radio Electronics*. 2023;23(1):89–99. (In Russ.) DOI: 10.14529/ctcr230108

13. Hastie T., Tibshirani R., Friedman J. *The Elements of Statistical Learning Data Mining, Inference, and Prediction*. Springer; 2008. 784 p.

14. Kohonen T. The self-organizing map. *Proceedings of the IEEE*. 1990;78(9):1464–1480.

15. Lipatnikov A.V., Shmelyova A.E., Stepanov E.N., Shnayder D.A. Mathematical modeling and optimization of raw coal consumption in PJSC “MMK”. *Vestnik of Nosov Magnitogorsk state technical university*. 2018;16(4):30–38. (In Russ.) DOI: 10.18503/1995-2732-2018-16-3-30-38

16. DEoptimR: Differential Evolution Optimization in Pure R. Available at: https://cran.r-project.org/web/packages/DEoptimR/DEoptimR.pdf (accessed 24 June 2023).

**Список литературы**

1. Бабарыкин Н.Н. Теория и технология доменной плавки. Магнитогорск: МГТУ, 2009. 257 с.

2. Разработка и внедрение математического и программного обеспечения для гибких технологических режимов работы доменных печей / С.А. Загайнов, О.П. Онорин, Л.Ю. Гилева и др. // Сталь. 2000. № 9. С. 12–15.

3. Современные принципы построения математической модели доменного процесса для решения технологических задач / С.А. Загайнов, О.П. Онорин, Н.А. Спирин, Ю.Г. Ярошенко // Известия вузов. Черная металлургия. 2003. № 12. С. 3–7.

4. Нестационарные процессы и повышение эффективности доменной плавки / Ю.Н. Овчинников, В.И. Мойкин, Н.А. Спирин, Б.А. Боковиков. Челябинск: Металлургия, 1989. 120 с.

5. Компьютерные методы моделирования доменного процесса / О.П. Онорин, Н.А. Спирин, В.Л. Терентьев и др. Екатеринбург: УГТУ–УПИ, 2005. 301 с.

6. Оптимизация и идентификация технологических процессов в металлургии / Н.А. Спирин, В.В. Лавров, С.И. Паршаков, С.Г. Денисенко. Екатеринбург: УГТУ–УПИ, 2006. 307 с.

7. Товаровский И.Г. Доменная плавка. Днепропетровск: Пороги, 2009. 765 с.

8. Андронов В.Н. Экстракция черных металлов из природного и техногенного сырья. Доменный процесс. Донецк: Норд-Пресс, 2009. 377 с.

9. Довгалюк Б.П. Методы контроля эффективности использования топливных добавок и

технологического кислорода и их оптимального распределения между доменными печами // Сталь. 1987. № 8. С. 9–14.

10. Алгоритмическое и программное обеспечение оптимального распределения топливно-энергетических ресурсов в доменном производстве / И.А. Гурин, Н.А. Спирин, В.В. Лавров, В.Ю. Носков // Автоматизация. Современные технологии. 2017. Т. 71, № 5. С. 202–207.

11. Оптимизация распределения природного газа в доменном цехе при изменении параметров плавки / Н.А. Спирин, Л.Ю. Гилёва, В.В. Лавров и др. // Известия высших учебных заведений. Черная металлургия. 2014. Т. 57, № 6. С. 45–49. DOI: 10.17073/0368-0797-2014-6

12. Баркалов С.А., Моисеев С.И., Серебрякова Е.А. Математическая модель оптимального распределения ресурсов в строительной сфере в условиях их дефицита // Вестник ЮУрГУ. Серия «Компьютерные технологии, управление, радиоэлектроника». 2023. Т. 23, № 1. С. 89–99. DOI: 10.14529/ctcr230108

13. Hastie T., Tibshirani R., Friedman J. The Elements of Statistical Learning Data Mining, Inference, and Prediction. Springer, 2008. 784 p.

14. Kohonen T. The self-organizing map // Proceedings of the IEEE. 1990. Vol. 78, no. 9. P. 1464–1480.

15. Оптимизация потребления угольного сырья в ПАО ММК на основе математического моделирования / А.В. Липатников, А.Е. Шмелёва, Е.Н. Степанов, Д.А. Шнайдер // Вестник Магнитогорского государственного технического университета им. Г.И. Носова. 2018. № 4 (1). С. 30–38. DOI: 10.18503/1995-2732-2018-16-3-30-38

16. DEoptimR: Differential Evolution Optimization in Pure R. URL: https://cran.r-project.org/web/packages/DEoptimR/DEoptimR.pdf (дата обращения: 24.06.2023).

***Information about the authors***

**Lev S. Kazarinov**, Dr. Sci. (Eng.), Prof., Prof. of the Department of Automatics and Control, South Ural State University, Chelyabinsk, Russia; kazarinovls@susu.ru.

**Tatiyana A. Barbasova**, Dr. Sci. (Eng.), Prof., Head of the Department of Automatics and Control, South Ural State University, Chelyabinsk, Russia; barbasovata@susu.ru.

**Ekaterina V. Bauman**, Postgraduate student, South Ural State University, Chelyabinsk, Russia; bauman.e.v@yandex.ru.

**Polina A. Samoletova**, Lecturer, South Ural State University, Chelyabinsk, Russia; samoletovapa@susu.ru.

**Svetlana A. Cherepanova**, Lecturer, South Ural State University, Chelyabinsk, Russia; cherepanovasa@susu.ru.

***Информация об авторах***

**Казаринов Лев Сергеевич**, д-р техн. наук, проф., проф. кафедры автоматики и управления, Южно-Уральский государственный университет, Челябинск, Россия; kazarinovls@susu.ru.

**Барбасова Татьяна Александровна**, д-р техн. наук, проф., заведующий кафедрой автоматики и управления, Южно-Уральский государственный университет, Челябинск, Россия; barbasovata@susu.ru.

**Бауман Екатерина Вячеславовна**, аспирант, Южно-Уральский государственный университет, Челябинск, Россия; bauman.e.v@yandex.ru.

**Самолетова Полина Алексеевна**, преподаватель, Южно-Уральский государственный университет, Челябинск, Россия; samoletovapa@susu.ru.

**Черепанова Светлана Андреевна**, преподаватель, Южно-Уральский государственный университет, Челябинск, Россия; cherepanovasa@susu.ru.

***Contribution of the authors:*** the authors contributed equally to this article.
The authors declare no conflicts of interests.
***Вклад авторов:*** все авторы сделали эквивалентный вклад в подготовку публикации.
Авторы заявляют об отсутствии конфликта интересов.

***The article was submitted 31.05.2024***
***Статья поступила в редакцию 31.05.2024***