Scholar Publishing Group
Machine Learning Theory and Practice
https://doi.org/10.38007/ML.2020.010104
ISSN 2790-0983 Vol. 1, Issue 1: 33-40

Prediction and Optimization of Blast Furnace Parameters Based on Machine Learning and Genetic Algorithm

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Keywords: Machine Learning, Genetic Algorithm, Blast Furnace Parameters, Distribution Matrix

Abstract: Iron and steel smelting is an industry with high energy consumption and high pollution. In the process of industrial transformation, it is of great theoretical significance and practical application value to carry out the concept of "green manufacturing" in the main links such as sintering, coking, iron making and steel making, and use advanced control technology to improve production efficiency and reduce pollution emission. This paper mainly studies the prediction and optimization of blast furnace parameters based on machine learning and genetic algorithm. In this paper, the optimization method based on genetic algorithm is established by deeply learning genetic algorithm in inverse calculation of distribution matrix. In this paper, the error of charge distribution is taken as the optimization objective, and the genetic algorithm is used to solve the model, and the purpose of charging the bellless blast furnace according to the expected ore/coke ratio distribution is realized.

1. Introduction

Metallurgical industry is the most important fundamental industry in a country. The development of steel industry directly affects the development of military industry, steel structure, equipment and other industries. At the same time, the steel industry is also a high consumption, high pollution industry, therefore, the implementation of optimized control of the steel industry, energy conservation and emission reduction has become particularly important. The smelting process of high furnace is the most basic process of comprehensive metallurgical industry, which provides raw materials for subsequent steel rolling and finished products, and the quality and output of finished products are determined by the state of high furnace [1-2]. In the process of blast furnace ironmaking, the temperature in the furnace cannot be directly detected, but it can be reflected by relevant parameters. The temperature of molten iron is not only a key parameter in the process of blast furnace smelting, but also one of the important reference indexes of blast furnace temperature, which indirectly reflects the operation state of blast furnace [3-4]. Therefore, the accurate prediction of molten iron temperature is helpful to improve the quality of molten iron, and to evaluate the current trend of high furnace, so as to provide a basis for the stable operation of blast furnace conditions [5]. The construction and equipment replacement cost of high furnace is quite high. Whether the furnace condition is in normal working condition directly determines the production cost and profit of enterprises [6]. And furnace smelting is a complicated physical-chemical synthesis, and there are many daily production parameters, it is difficult to accurately describe the relationship between them. If the regulation is not timely or appropriate, the abnormal situation will be aggravated, or even cause safety accidents, thus causing major damage [7].

The study on multi-objective optimization control of blast furnace ironmaking has always been a key issue of blast furnace ironmaking. Both the study on blast furnace batchings optimization, blast furnace smelting process optimization, and single objective optimization and multi-objective optimization reflect the attention to the optimization control of blast furnace [8]. At present, there are two kinds of methods in the research of blast furnace coke ratio model, one is traditional modeling method the other is artificial intelligence method. Research on traditional BP neural network mostly starts from the algorithm itself, without in-depth analysis of the characteristics of coke ratio consumption in blast furnace, so as to ignore the characteristics of relevant data [9]. In the research of prediction model of hot metal temperature and yield of blast furnace, the characteristics of hot metal temperature and yield of blast furnace are not comprehensively analyzed, and the selected input variables often have some coupling relations, which have great influence on the prediction results. In addition, the data of some input variables cannot be obtained or predicted in advance, which brings great difficulties to the prediction and seriously affects the accuracy of the prediction model. Sometimes, there is a contradiction between the accuracy and complexity of the prediction model: In order to obtain high-precision prediction effect, the model must be refined, or even the combined model should be used for hierarchical prediction, but this will inevitably lead to a geometric increase in model complexity and increase prediction time, thus affecting the practicability of the prediction model [10-11]. In the study of multi-objective optimization control of blast furnace ironmaking, the problem of the optimal charging of blast furnace is mainly solved by multi-objective synthesis (such as cost and energy consumption, etc.), which greatly reduces energy consumption and cost. However, there is still a certain shortcoming that direct variables affecting blast furnace cannot be manipulated [12].

The prediction and optimization control model of blast furnace iron-making parameters can not only provide strong support for the overall energy planning scheme of iron and steel enterprises, but also play an important role in increasing the output of molten iron, reducing the ratio of coke into the furnace and improving the quality of molten iron.

2. Distribution Optimization of Blast Furnace Based on Genetic Algorithm

2.1. Blast Furnace Ironmaking

High furnace iron making is the most basic link in modern metallurgical production. From the perspective of smelting production process of high furnace, the component of high furnace is composed of a furnace body and six auxiliary facilities [13].

Smelting and training is the combination of complicated material and chemical processes, which do not occur independently, but synergistic effect of several processes. The process of ironmaking is roughly as follows: the feeding system in front of the furnace mixes iron ore and coke according to the ratio, is sent to the furnace by the feeding trolley, and then is loaded from the upper side, and the hot air is blown into the furnace by the air supply device. The coke in the raw material will be burned when it meets high temperature oxygen in the furnace, generating a large amount of heat energy and gas. The hot rising gas will react with the falling charge, and finally obtain liquid molten iron [14]. The debris in the raw material is mixed with the added white ash to form a residue, which is discharged out of the furnace, while the gas is taken out of the export pipe, purified by the dust removal equipment, and stored in the gas tank or used elsewhere [15].

The complexity of high furnace smelting process is firstly reflected in that it is the largest single production equipment in the existing complex production system, with more than 10,000 tons of daily items in and out, and it is also necessary to control and ensure the coordination and balance between input and output [16]. Secondly, the coupling relationship between hundreds of parameters in each sub-link of production strengthens the complexity of smelting. At the same time, the characteristics of energy consumption during production also aggravate the chaos of the process. Energy consumption includes energy consumption between equilibrium systems in the furnace, as well as energy loss caused by state transition and relative motion of objects in the furnace [17].

Long operating mainly in the high furnace, led by the harmonious working system on the implementation of each workstation, this undoubtedly also increased the difficulty of system control, although there have been some key system to complete part of the intelligent control, but to the entire refining intelligence is still in the process of producing intelligent trend of a challenge, the challenge of the key lies in the complexity of the blast furnace metallurgy process. The most important part of smelting and training automation is furnace temperature control, and temperature control lies in furnace state. There is no unified standard for the determination of furnace state, which increases the difficulty of furnace state prediction. What is more difficult to solve is that normal conditions may contain abnormal factors [18].

Production practice shows that abnormal furnace conditions have a serious impact on iron making and its follow-up process, resulting in the decrease of pig iron quality, output, and increase of energy consumption, and even lead to equipment damage and shorten the service life of blast furnace. The blast furnace is a large time delay system, and it takes too much time for various adjustment measures to be put in place. Therefore, it is necessary to predict the current state of the high furnace and take appropriate measures in time to avoid the bad change of the furnace condition. Abnormal furnace condition generally includes furnace temperature fault, charge forward fault and furnace type fault, among which furnace type fault is mainly furnace cylinder stacking.

The most obvious manifestation in the process of smelting is the fluctuation of furnace temperature. Furnace temperature fault including to cool and to hot two conditions, to cool or hot development is not conducive to production, furnace temperature is too high, will make the furnace reaction speed intensifies, gas flow increases and active, easy to make the material column suspension, thus affecting the quality of molten iron; If the furnace temperature is too low, the reaction speed will become slow and insufficient, and the yield and quality of molten iron will be affected. Only suitable and stable furnace temperature environment is the primary guarantee for normal production of blast furnace.

2.2. Implementation of Genetic Algorithm

In blast furnace operation, the rotation range of rotary chute is generally 15 °to 45 °, and its value belongs to the real number domain. If the binary encoding is adopted for the parameters of the rotating chute, the binary codes of the adjacent integers will have a large Hamming distance, which leads to the crossover and mutation are difficult to cross during the genetic operation, and the whole value range cannot be traversed when searching for the optimal value, and it is easy to fall into the situation of local optimum.

$$\begin{cases} g_l = b_l \\ g_i = b_{i+1} \oplus, i = l-1, l-2, \ldots, 1 \end{cases} \tag{1}$$

In decoding, the Gray code of chromosome is first converted from the inverse operation of (Equation 1) to binary code, and then the decoding formula of (Equation 1) is used to decode, and the rotation chute Angle under constraint regulation is obtained.

Setting of initial population: the initial population pop can randomly generate an m×n matrix from the following formula, where m is the number of cloth circles, n is the number of chromosomes in the population, and the length of Gray code is l.

$$pop = rands[X]_{m \times n}\ X \in (0000....00000, 1111....11111) \tag{2}$$

Design of fitness function: According to the optimization model, it can be seen that the appropriate chute inclination array α to be selected will minimize the performance index function J(α). Therefore, the above objective optimization function is an optimization problem to obtain the minimum value, so the fitness function can be selected as follows:

$$F(\alpha) = c_{\max} - J(\alpha) \tag{3}$$

Where F(α) is the fitness function, and cmax is a fixed constant with a large value to ensure that the fitness function F(α) is always greater than 0 in the solution space satisfying the chute Angle array α.

Selection operation: In order to avoid falling into local optimum, random ergodic sampling method is adopted, that is, the probability of individual i being selected in the selection population with the assumed value of M is:

$$P(\alpha_i) = \frac{F'(\alpha_i)}{\sum_{i=1}^{M} F'(\alpha_i)} \tag{4}$$

Crossover operation: Firstly, a string w is randomly generated within the value range of the decision variable, and the length of the string is consistent with the individual encoding string. Secondly, the following rules of crossover operation are formulated so that the new offspring chromosomes A and B can be generated from the two parental chromosomes A and B through the crossover rules.

3. Cloth Simulation Experiment

In this paper, the furnace opening data of a plant is adopted, in which the blast furnace throat radius is R=4.5 meters, and the coke and ore batch weights are set as 30 tons and 60 tons, respectively. The shape of the bottom material surface (r) is determined by the test of the opening data. It can be known that on the premise of knowing the shape of the bottom material surface, given the desired material surface output shape optimization target, the optimization calculation of the cloth matrix can be realized by genetic algorithm, so as to get the value of the cloth matrix.

With the development of blast furnace, large blast furnace occupies a dominant position in the process of blast furnace ironmaking. Single ring cloth gradually can not meet the requirements of distribution control of large blast furnace, instead multi - ring cloth. Therefore, when the chute Angle is set as 35°, the shape of the charge is compared with the shape of the multi-ring cloth. Among them, the furnace throat radius is 4.5m. See Table 1 for other parameters in the simulation process.

Table 1. Production data of blast furnace cloth

	1	2	3	4	5
y	0	0.84	1.75	0.85	2.54
γ(y)	0	0.51	1.07	0.57	1.48
f(y)	0.7	1.32	1.83	1.36	2.01

4. Analysis of Experimental Results

In the process of stepwise concentric circle distribution operation optimization using genetic algorithm algorithm, the variation curves of optimal individual fitness and population average fitness are shown in FIG. 1.

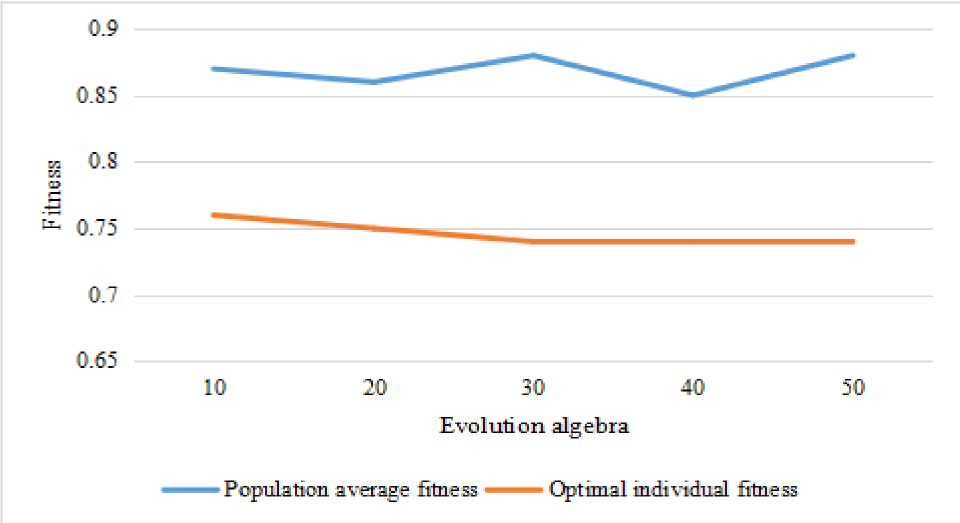

Figure 1. Fitness change curve

As can be seen from FIG. 1, the average fitness value of the population gradually decreases, indicating that the whole process is moving in the direction of optimization. The optimal individual has reached the optimum in 50 generations of evolution, and the corresponding optimization result, namely the optimal cloth operation, is shown in Table 2.

Table 2. Stepping concentric circle cloth chute tilt Angle

	Mining dip Angle / °	Angle of coke / °
1	51.43	51.78
2	51.37	50.66
3	51.42	49.23
4	50.75	46.89
5	49.87	46.81

The mathematical model of blast furnace charging is adopted to simulate the falling process of charge, and the distribution state of charge is obtained. The ore/coke ratio of charge distribution after charging is calculated, and the data as shown in Table 3 is obtained.

Table 3. Radial ore coke ratio distribution

	1	2	3	4
Set expectations	1.20	3.50	4.8	6.12
Actual ore coke ratio	0	3.91	3.64	6.12

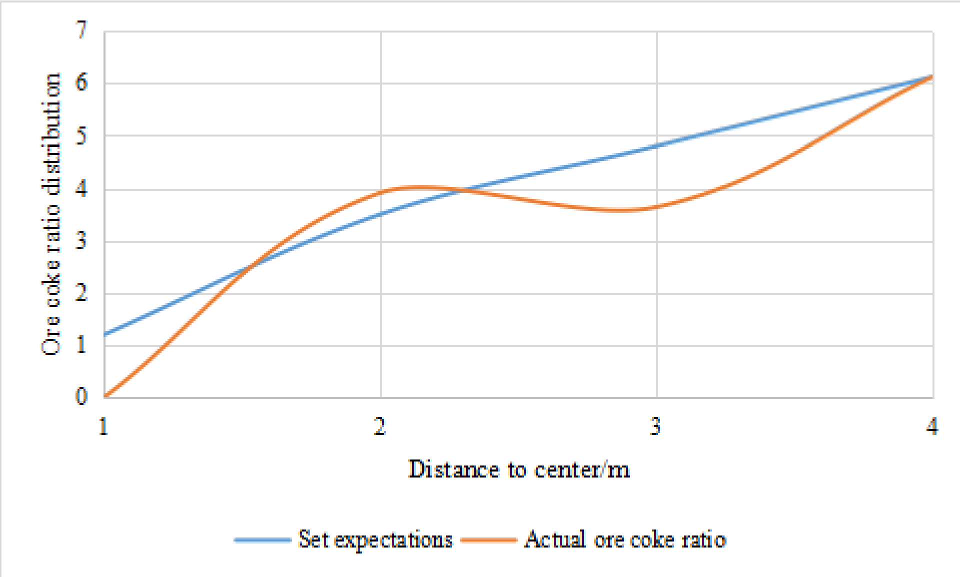

Figure 2. Radial ore focal ratio distribution curve

In FIG. 2, the optimized blast furnace distribution can better achieve the desired ore/coke ratio distribution, indicating that the operation optimization model without blast furnace distribution based on genetic algorithm is suitable for industrial production. Because the set ore/coke ratio distribution function is a smooth curve, the actual furnace throat material surface is multi-ring accumulation, the shape of the material surface is uneven, so the actual ore/coke ratio distribution is difficult to completely coincide with the expected value, which also shows that the optimization of ore/coke ratio is very important for the blast furnace charging operation.

5. Conclusion

Furnace metallurgy is a complex physical and chemical process. The traditional methods for predicting the key parameters of blast furnace and classifying the operation status of blast furnace are increasingly difficult to meet the big data characteristics of blast furnace, which tend to be large and informationized. In this paper, a method of inverse calculation of the distribution matrix based on genetic algorithm is presented to solve the problems of relatively lack of flexibility and poor adjustment effect in the process of BF charging at present. This study not only provides a theoretical basis for the formulation of distribution matrix in the future, but also provides a model basis for improving the inner running state of blast furnace.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Andonovski G, Tomažič S. Comparison of Data-Based Models for Prediction and Optimization of Energy Consumption in Electric Arc Furnace (EAF). IFAC-PapersOnLine, 2020, 55(20): 373-378.

[2] Sadowski Ł, Nikoo M, Shariq M, et al. The Nature-Inspired Metaheuristic Method for Predicting the Creep Strain of Green Concrete Containing Ground Granulated Blast Furnace Slag. Materials, 2019, 12(2): 293. https://doi.org/10.3390/ma12020293

[3] Kavousi-Fard A, Su W, Jin T, et al. A Predictive KH-Based Model to Enhance the Performance of Industrial Electric Arc Furnaces. IEEE Transactions on Industrial Electronics, 2018, 66(10): 7976-7985. https://doi.org/10.1109/TIE.2018.2880710

[4] Sau D C, Murmu R, Senapati P, et al. Optimization of Raceway Parameters in Iron Making Blast Furnace for Maximizing the Pulverized Coal Injection (PCI) Rate. Advances in Chemical Engineering and Science, 2020, 11(02): 141.

[5] Wang X, Hu T, Tang L. A Multiobjective Evolutionary Nonlinear Ensemble Learning with Evolutionary Feature Selection for Silicon Prediction In Blast Furnace. IEEE Transactions on Neural Networks and Learning Systems, 2020, 33(5): 2080-2093.

[6] Jawahery S, Visuri V V, Wasbø S O, et al. Thermophysical Model for Online Optimization and Control of the Electric Arc Furnace. Metals, 2020, 11(10): 1587. https://doi.org/10.3390/met11101587

[7] Herasina O V, Husiev O Y, Korniienko V I. Neuro-Fuzzy Forecasting of Non-Linear Processes of Blast Furnace Production. Радіоелектроніка, інформатика, управління, 2019 (1 (48)): 89-97. https://doi.org/10.15588/1607-3274-2019-1-9

[8] Agrawal A, Kothari A K, Kumar A, et al. Advances in Thermal Level Measurement Techniques Using Mathematical Models, Statistical Models and Decision Support Systems in Blast Furnace. Metallurgical Research & Technology, 2019, 116(4): 421. https://doi.org/10.1051/metal/2019019

[9] Shyamal S, Swartz C L E. Real-Time Dynamic Optimization-Based Advisory System for Electric Arc Furnace Operation. Industrial & Engineering Chemistry Research, 2018, 57(39): 13177-13190. https://doi.org/10.1021/acs.iecr.8b02542

[10] Ruiz E, Ferreño D, Cuartas M, et al. Machine Learning Methods for the Prediction of the Inclusion Content of Clean Steel Fabricated by Electric Arc Furnace and Rolling. Metals, 2020, 11(6): 914. https://doi.org/10.3390/met11060914

[11] Murav'eva I G, Togobitskaya D N, Bel'kova A I, et al. Predictive-Analytical Evaluation of

High-Temperature Properties of Iron-Ore Materials with Respect to their Distribution in the Blast Furnace Zones. Steel in Translation, 2020, 51(3): 195-200. https://doi.org/10.3103/S0967091221030074

[12] Spirin N A, Rybolovlev V Y, Lavrov V V, et al. Scientific Problems in Creating Intelligent Control Systems for Technological Processes in Pyrometallurgy Based on Industry 4.0 Concept. Metallurgist, 2020, 64(5): 574-580. https://doi.org/10.1007/s11015-020-01029-1

[13] Hay T, Reimann A, Echterhof T. Improving the Modeling of Slag and Steel Bath Chemistry in an Electric Arc Furnace Process Model. Metallurgical and Materials Transactions B, 2019, 50(5): 2377-2388. https://doi.org/10.1007/s11663-019-01632-x

[14] Ruiz E, Ferreño D, Cuartas M, et al. Machine Learning Algorithms for the Prediction of the Strength of Steel Rods: an Example of Data-Driven Manufacturing in Steelmaking. International Journal of Computer Integrated Manufacturing, 2020, 33(9): 880-894. https://doi.org/10.1080/0951192X.2020.1803505

[15] Barbasova T A. A Multilevel Resource-Saving Blast Furnace Process Control. Вестник Южно-Уральского государственного университета. Серия: Компьютерные технологии, управление, радиоэлектроника, 2020, 21(1): 136-146.

[16] Canan A, Calhan R, Ozkaymak M. Investigation of the Effects of Blast Furnace Slag Ratio, Total Solid, and Ph on Anaerobic Digestion: Modeling and Optimization by Using Response Surface Methodology. Biomass Conversion and Biorefinery, 2020, 11(5): 2219-2232.

[17] Oyebisi S O, Ede A N, Olutoge F A. Optimization of Design Parameters of Slag-Corncob Ash-Based Geopolymer Concrete by the Central Composite Design of the Response Surface Methodology. Iranian Journal of Science and Technology, Transactions of Civil Engineering, 2020, 45(1): 27-42. https://doi.org/10.1007/s40996-020-00470-1

[18] Murav'eva I G, Togobitskaya D N, Ivancha N G, et al. Concept Development of an Expert System for Selecting the Optimal Composition of a Multicomponent Blast-Furnace Charge and Functional and Algorithmic Structure. Steel in Translation, 2020, 51(1): 33-38.