INNOVATION IN METALLURGICAL INDUSTRIAL AND LABORATORY EQUIPMENT, TECHNOLOGIES AND MATERIALS

ИННОВАЦИИ В МЕТАЛЛУРГИЧЕСКОМ ПРОМЫШЛЕННОМ И ЛАБОРАТОРНОМ ОБОРУДОВАНИИ, ТЕХНОЛОГИЯХ И МАТЕРИАЛАХ

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Experience in implementing machine learning to calculate the quality and production of agglomerate

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Abstract. In 2020, EVRAZ United West Siberian Metallurgical Combine JSC (EVRAZ ZSMK JSC) completed work on the creation of a mathematical modeling system for all processing units of the metallurgical plant. During testing of the system, a high error was found in the existing factor model for predicting agglomerate production, which was developed taking into account the specific sintering rate of individual concentrates. The paper proposes the use of linear regression to predict the productivity of sintering machines, which, unlike nonlinear methods, is optimal for integration into high-performance optimization systems. A feature of the work is forecasting, taking into account the proportion of the agglomeration charge. The model was tested at EVRAZ ZSMK JSC and showed sufficient accuracy ($R^2 > 90$). A large economic effect is expected from the model. A separate study of existing agglomerate quality forecasting systems was conducted. Machine learning (ML) methods have recently made a great contribution to the development of forecasting models used to assess the quality of the agglomerate. This is due to the fact that the sintering process is a very complex dynamic with non–linearity and a large delay. The physico-chemical phenomena involved in this process are complex and numerous. The neural network can constantly adjust the parameters of the model to reflect changes in systemic causes. A linear method was also studied to predict the agglomerate quality. Due to the poor quality of the resulting linear model, the "random forest" machine learning method was applied. Currently, the model is being operated as part of the integrated optimization program SMM Prognoz for the entire plant. For the convenience of the user, when implementing the module, visualization of the model quality using historical data was added, as well as the statistical metrics obtained.

Keywords: agglomerate production, mathematical model, planning, machine learning, forecasting

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Опыт внедрения машинного обучения для расчета качества и производства агломерата

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Аннотация. В 2020 г. на АО «ЕВРАЗ Объединенный Западно-Сибирский металлургический комбинат» (АО «ЕВРАЗ ЗСМК») была завершена работа по созданию системы математического моделирования для всех переделов металлургического комбината. В процессе тестирования системы была обнаружена высокая погрешность существующей факторной модели прогнозирования производства агломерата, которая разрабатывалась с учетом удельной скорости спекания отдельных концентратов. В работе предлагается использование линейной регрессии для прогнозирования производительности агломашин, которая в отличие от нелинейных методов оптимальна для встраивания в высокопроизводительные системы оптимизации. Особенностью работы является прогнозирование с учетом долей шихты агломерации. Модель была опробована на АО «ЕВРАЗ ЗСМК» и показала достаточную точность ($R^2 > 90$). От модели ожидается большой экономический эффект. Отдельно проведено исследование существующих систем прогнозирования качества агломерата. Методы машинного обучения (ML) в последнее время внесли большой вклад в развитие моделей прогнозирования, используемых для оценки качества агломерата. Это связано с тем, что процесс спекания – очень сложная динамика с нелинейностью и большим запаздыванием. Физико-химические явления, вовлеченные в этот процесс, сложны и многочисленны. Нейронная сеть может постоянно корректировать параметры модели, чтобы отразить изменение системных причин. Для прогнозирования качества агломерата используется линейный метод. Из-за низкого качества полученной линейной модели применяется метод машинного обучения «случайный лес». В настоящее время модель эксплуатируется в составе программы комплексной оптимизации всего комбината СММ «Прогноз». Для удобства пользователя при внедрении модуля была добавлена визуализация качества модели с использованием исторических данных, а также полученные статистические метрики.

Ключевые слова: производство агломерата, математическая модель, планирование, машинное обучение, прогнозирование

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Introduction

Presently, the primary manufacturers of steel are integrated full-cycle enterprises that function utilizing the sintering and blast furnace methodology [1]. The reduction process of iron, which facilitates the production of cast iron, is executed within blast furnaces. This is followed by the oxidation of impurities, which occurs in converters and electric furnaces, with further refinement conducted outside of the furnace [2].

It is established that for the production of cast iron in blast furnaces, agglomerates, pellets, and briquettes are utilized. Concurrently, the necessity to process fine ore and concentrate into larger aggregates is underscored, as their application in blast furnace smelting is pivotal for ensuring high gas permeability of the layer – a critical condition for the efficient operation of the blast furnace [3]. Among the trio of sintering methods – briquetting, agglomeration, and pelletizing – agglomeration emerges as the prevalent choice, presenting several notable benefits over the alternatives. Notably, agglomeration facilitates the integration of by-products and in-house waste (such as sludge, blast furnace dust, etc.) into the production cycle [4]. This incorporation aids in moisture retention and contributes to the diminution of harmful emissions into the atmosphere, thereby enhancing environmental sustainability.

Market analysis over the past five years has highlighted the significance of augmenting agglomerate production, primarily due to the cost-effectiveness of producing agglomerate from purchased concentrate in comparison to the acquisition costs of pellets. Generating an additional ton of agglomerate yields financial benefits for the enterprise through the substitution of the more expensive pellets, which are subject to limitations regarding their maximum proportion within the agglomeration charge. This limitation is attributed to the "swelling" phenomenon observed in pellets during the reduction process [5]. For instance, at EVRAZ United West Siberian Metallurgical Combine JSC (EVRAZ ZSMK JSC), the pellet proportion should not surpass 30 %. Therefore, to optimize cast iron production, merely procuring pellets is insufficient; there is a clear necessity to escalate the production of agglomerate.

The enhancement of agglomerate production is facilitated through several strategies [6]:

– expansion of agglomerate production capacity (extensive way);

– amplification of the sintering process efficiency (intensive way);

– improvement of the yield quality, achieved through enhancements in agglomerate quality, including the reduction of fines production;

– employment of sub-standard agglomerate in blast furnace smelting (compromise).

The optimization of the charge composition during sintering crucial for enhancing the quality of agglomerate and the efficiency of sintering machines, potentially increasing the enterprise's profit margins at no extra cost [7 – 11].

This article presents the outcomes of mathematical modeling and optimization of the aglocharge forming process under the specific conditions at EVRAZ ZSMK JSC.

Data collection

For the purposes of this research, two distinct datasets were obtained from the operations of the sinter plant at EVRAZ ZSMK JSC. The initial dataset spans from 2018 to 2021, providing a detailed, shift-by-shift analysis of all relevant technical parameters for each of the three sintering machines. This includes data on operating time, pressure differential, temperature in the hearth, total material consumption measured by the main scales, layer height, as well as the volume and quality of the agglomerate produced, return volumes, among other technical metrics. The process of data collection for this dataset is fully automated and the information is stored within MSSQL databases.

The second dataset required the assembly of data concerning the consumption volumes of concentrates, fluxes, and fuels for each sintering machine, broken down on a daily basis. Initially, this data was manually collected and recorded in Excel files. However, during the preparation of this article, the data collection process was automated, with information systematically transferred to a database by recording the item numbers of materials and their respective consumption volumes.

The culmination of this effort resulted in a comprehensive dataset comprising raw, unprocessed data.

Data processing

The data was subjected to a day-by-day analysis under specific criteria:

– the volume of consumed fuel must not equal zero;

– the volume of produced agglomerate must not equal zero;

– the volume of returns must not exceed the volume of agglomerate produced.

Observations failing to meet any of these criteria were excluded. Except for consumed coke volume and agglomerate production, all indicators were set to zero in cases of missing data, treating such absences as zeroes.

Furthermore, to analyze model behavior with aggregated data, monthly dynamics indicators were derived from the dataset.

Given that the charge is not individually supplied to each sintering machine and is considered uniformly distributed, a proportional allocation of charge consumption and agglomerate production volumes was employed for individual machine analysis, based on data from the main scales at EVRAZ ZSMK JSC.

Rationale for developing a mathematical model of the agglomerate production process

The enhancement of agglomerate production can be achieved through the construction of new facilities or the implementation of technical advancements, such as [4]:

– the application of lime and lime milk (hydrate $Ca(OH)_2$, produced by CaO reacting with water) which exhibit strong binding qualities, significantly boosting the granulation speed of the charge and the robustness of the resulting granules. This enhancement in turn improves the gas permeability of the sintered charge layer, leading to increased efficiency of the sintering machines;

– preheating the charge, typically with hot return and steam, is crucial especially when sintering finely ground concentrates to prepare the charge for sintering by preheating, thus preventing granule disintegration due to over-moistening;

– elevating the depression in the gas manifold, which augments the rate of fuel combustion and the vertical speed of sintering;

– diminishing the basicity of the agglomerate through a reduction in the consumption of fluxes such as lime, dolomite, and limestone.

Factors of agglomerate production intensification

Факторы интенсификации производства агломерата

Factor	Variation limits	Variation value	
		Δa	$\Delta \Pi$
Lime in charge, %	0 – 1.5 1.5 – 2.0 2.0 – 3.0	1.0 1.0 1.0	+3.5 +2.0 +1.0
Oxygen for ignition, mm^3/tonn	4 – 10	1	+0.2
Charge heating up, °C	0 – 55	55	+15.0
Increase of the returns content in charge, %	30 – 45	1.0	–1.0
Increase of +5 mm fraction content in the returns, %	0 – 10	1.0	–0.4
Increase of the proportion of fine-grained concentrates, %	50	1.0	–0.3
Increase of depression in gas manifold, mmHg	750	100	+3.0
Increase of the height of the charge layer, mm	250 – 300	10	–0.6
Increase of FeO content in agglomerate, %	14 – 18	1.0	–0.5
Increase of agglomerate basicity, unit fraction	0.90 – 1.20	0.05	–1.0
Increase of iron content in agglomerate, %	55 – 58	1.0	–1.5

The sintering process at EVRAZ ZSMK JSC is influenced by a variety of factors, some of which may conflict with one another. For instance, an increase in lime content can enhance production by 1.0 – 3.5 %, yet concurrently, it elevates the basicity of the agglomerate, adversely impacting productivity.

Furthermore, the specific productivity of sintering machines is affected differently by various concentrates. To refine the accuracy of the charge planning process, experimental sintering involving diverse concentrates was conducted, with the specific productivity assessed. The anonymized results, in compliance with commercial confidentiality requirements, are illustrated in Fig. 1. It was observed that productivity rates for sintering machines fluctuate markedly across different concentrates. From the test outcomes, a model for estimating charge productivity was formulated, delivering satisfactory performance. However, due to the substantial expense associated with the process (the cost of pilot sintering can approach 1 million rubles), these experiments have not been replicated nor the coefficients reevaluated for over a decade. A universal correction factor was incorporated into the model to facilitate its validation.

The variability in component composition of concentrates, as well as in the composition of fuel, fluxes, and the basicity and chemical composition of the produced agglomerate, during operations at sintering plants indicates that the specific productivity of concentrates alone is not adequate for accurately calculating the productivity of sintering machines. Simply revising the coefficients does not suffice to achieve the necessary precision in the model.

Consequently, the comprehensive assessment of the impact of all these factors on the productivity of sinter machines and the quality of agglomerate can only be accurately conducted through the application of machine learning techniques, utilizing archival data.

The review of literature [12 – 17] confirms the extensive application of machine learning not only in evaluating the quality of agglomerate but also in forecasting its production.

In 2021, EVRAZ ZSMK JSC initiated a project aimed at developing a mathematical model to evaluate the productivity of its sintering machines.

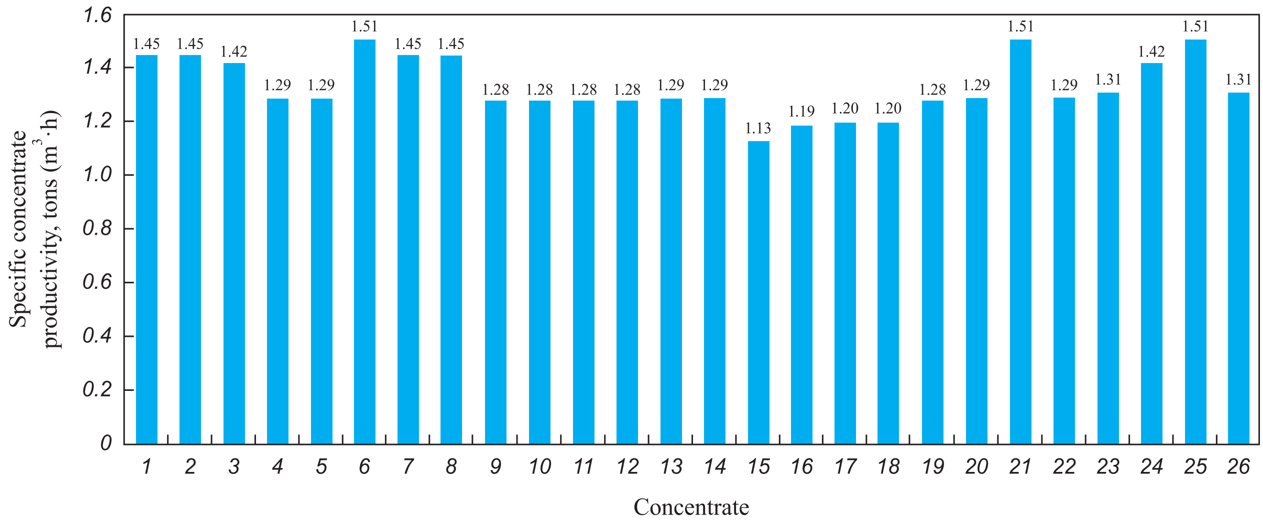

Fig. 1. Specific productivity of various concentrates at EVRAZ ZSMK JSC

Рис. 1. Удельная производительность различных концентратов на АО «ЕВРАЗ ЗСМК»

Defining objectives for applying machine learning

The regression mathematical model for calculating the productivity of the sinter plant is as follows:

$$y = b_0 + b_1 x_1 + b_2 x_2 + ... + b_n x_n, \quad (1)$$

where y the predicted volume of bin agglomerate, tonn; b_0 is the intercept; b_1, b_2, b_n are the regression coefficients corresponding to the factors; and x_1, x_2, x_n are the factors influencing the volume of bin agglomerate.

The objective of this project is to refine a mathematical model through the training on historical data concerning concentrate consumption and sinter machine productivity, aiming to:

– enhance the precision of mathematical modeling;

– increase confidence in the system by allowing users to verify results against archived data;

– identify new charging modes for the charge to optimize agglomerate production.

The system prototype operates in a "Train the model" mode, performing the following functions:

– loading the specified period of sintering data;

– training a performance model utilizing the archived data;

– training a quality model based on the data;

– presenting a table/graph of actual versus predicted data;

– displaying model quality indicators, such as (R^2).

Upon completion, the program notifies the user that the task is finished, detailing the outcomes of the most recent model training.

Users should also have the capability to toggle between different graphs to evaluate the model's accuracy on various metrics (actual/forecast), including agglomerate quality, sieve quantity, bin agglomerate, and skip agglomerate.

The input data for the model encompassed the following indicators:

– consumed concentrates clarification;

– volume of consumed concentrates, tonn;

– consumption of fluxes (limestone, dolomite, lime, brucite), tonn;

– fuel consumption;

– agglomerate strength;

– chemical composition of agglomerate (content of Fe, CaO, SiO_2, basicity);

– sintering machine process parameters (layer height, depression in the header);

– volume of agglomerate production.

Forecasting agglomerate quality

The Random forest method was employed for predicting agglomerate quality, given its superior forecasting accuracy compared to regression analysis. *The Random Forest* algorithm, developed by Leo Breiman and Adele Cutler, is a machine learning approach that employs an ensemble of decision trees. It integrates the Breiman Bagging method with the random subspace method introduced by Tin Kam Ho, making it versatile for classification, regression, and clustering tasks. The strength of this algorithm lies in its utilization of a large number of decision trees, each individually contributing to low classification accuracy. However, when aggregated, these trees produce significantly improved results [18]. Fig. 2 illustrates the correlation between actual agglomerate quality and the outcomes estimated by the model. With a coefficient of determination at 60 %, the model's adequacy is affirmed, as the benchmark for the coefficient of determination is set at a minimum of 50 % [19].

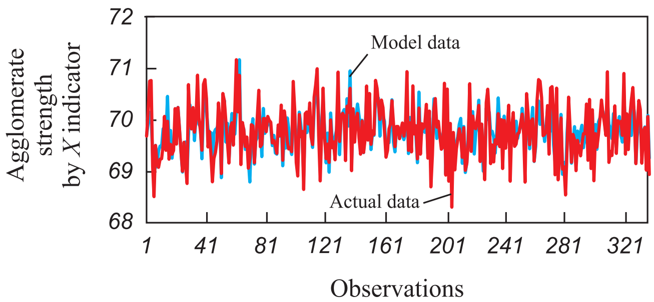

Fig. 2. Comparative analysis of model and actual data

Рис. 2. Сравнительный анализ модельных и фактических данных

This approach forms part of a comprehensive model that encapsulates both technical and economic aspects, delineating the interplay between chemical, thermodynamic, mechanical processes, and productivity, alongside considerations for product availability and logistics costs.

A notable characteristic of the Prognoz system is its capability to seamlessly incorporate third-party software modules into its computations. A screenshot presented in Fig. 3 displays the user interface of the Prognoz system in operation.

To enhance user experience, functionalities for visualizing the quality of the model were introduced alongside the

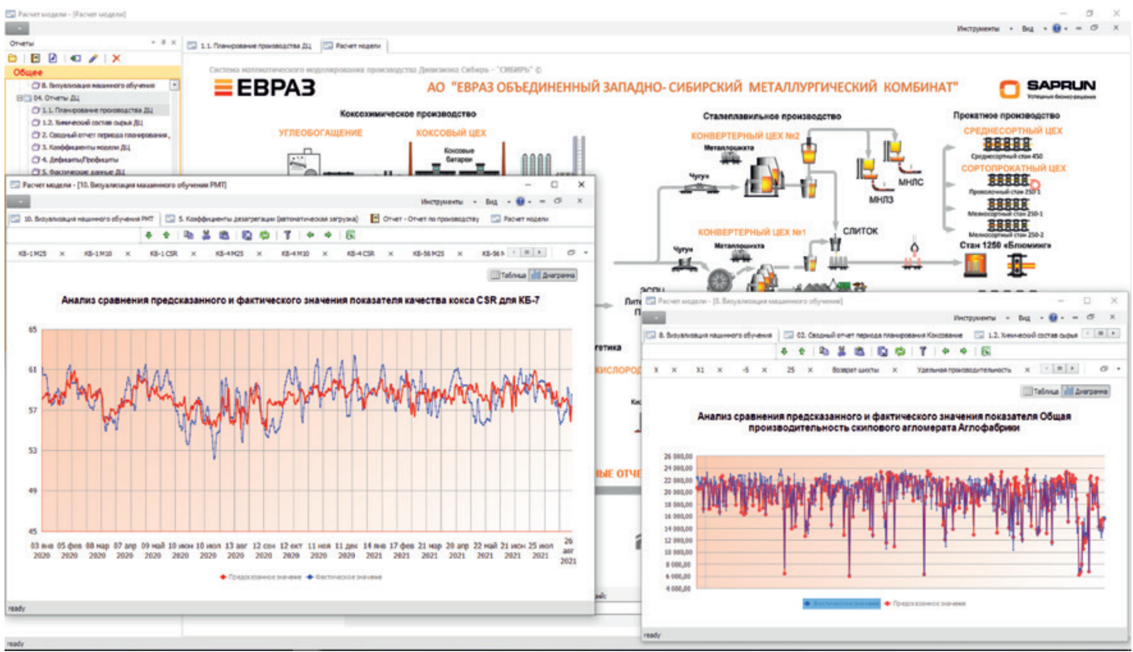

Fig. 3. Working window of the SMM system Prognoz

Рис. 3. Рабочее окно системы СММ «Прогноз»

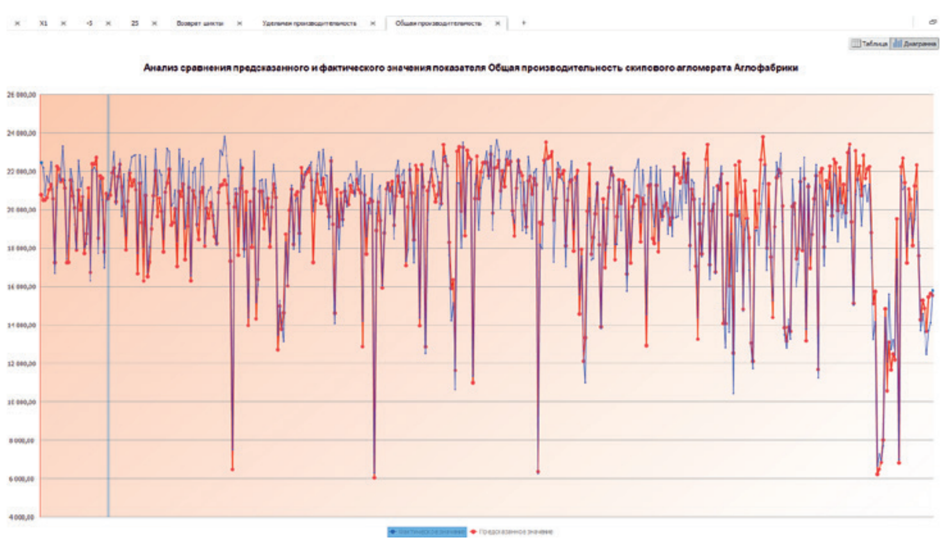

Fig. 4. Visualization of the learning quality of the model

Рис. 4. Визуализация качества обучения модели

Метрики КЦ | Метрики АФ

Метрики обучения по Аглофабрике

Модель	R2	Ошибка	Процент_ошибки	Пользователь	Начало_периода	Конец_периода	Дата_расчета	Передел
af_total_capacity	0,90777	870,98469	0,045	leontev_as	01.01.2020 0:00:00	31.05.2021 0:00:00	30.09.2021 8:49:00	Аглофабрика
X	0,70046	0,21368	0,0031	leontev_as	01.01.2020 0:00:00	31.05.2021 0:00:00	30.09.2021 8:49:00	Аглофабрика
X1	0,61444	0,05339	0,0125	leontev_as	01.01.2020 0:00:00	31.05.2021 0:00:00	30.09.2021 8:49:00	Аглофабрика
-5	0,80446	0,2876	0,0188	leontev_as	01.01.2020 0:00:00	31.05.2021 0:00:00	30.09.2021 8:49:00	Аглофабрика
+25	0,67968	0,75338	0,0497	leontev_as	01.01.2020 0:00:00	31.05.2021 0:00:00	30.09.2021 8:49:00	Аглофабрика
af_return_rm	0,63601	860,26026	0,0785	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:46:17	Аглофабрика
af_unit_capacity	0,0792	0,03967	0,0372	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:46:17	Аглофабрика
af_total_capacity	0,88771	761,41506	0,038	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:46:17	Аглофабрика
X	0,68194	0,21904	0,0031	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:46:17	Аглофабрика
X1	0,59338	0,06785	0,0136	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:46:17	Аглофабрика
-5	0,72132	0,21867	0,0146	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:46:17	Аглофабрика
+25	0,59075	0,70216	0,0449	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:46:17	Аглофабрика
af_return_rm	0,75358	930,30077	0,0924	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	30.09.2021 8:30:49	Аглофабрика
af_unit_capacity	0,1545	0,0437	0,0417	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	30.09.2021 8:30:49	Аглофабрика
af_total_capacity	0,90768	843,69297	0,0432	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	30.09.2021 8:30:49	Аглофабрика
X	0,72196	0,20758	0,003	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	30.09.2021 8:30:49	Аглофабрика
X1	0,62853	0,05358	0,0125	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	30.09.2021 8:30:49	Аглофабрика
-5	0,81637	0,26671	0,0168	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	30.09.2021 8:30:49	Аглофабрика
+25	0,68181	0,7131	0,047	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	30.09.2021 8:30:49	Аглофабрика
af_return_rm	0,63601	860,26025	0,0785	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:23:03	Аглофабрика
af_unit_capacity	0,0792	0,03967	0,0372	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:23:03	Аглофабрика
af_total_capacity	0,88771	761,41506	0,038	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:23:03	Аглофабрика
X	0,66361	0,22463	0,0032	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:23:03	Аглофабрика
X1	0,59948	0,05714	0,0134	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:23:03	Аглофабрика
-5	0,71554	0,21756	0,0146	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:23:03	Аглофабрика
+25	0,59197	0,70214	0,0449	leontev_as	01.01.2020 0:00:00	31.12.2020 0:00:00	30.09.2021 8:23:03	Аглофабрика
af_return_rm	0,75358	930,30077	0,0924	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:07:11	Аглофабрика
af_unit_capacity	0,1545	0,0437	0,0417	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:07:11	Аглофабрика
af_total_capacity	0,90768	843,69297	0,0432	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:07:11	Аглофабрика
X	0,72339	0,20882	0,003	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:07:11	Аглофабрика
X1	0,61528	0,06436	0,0127	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:07:11	Аглофабрика
-5	0,8229	0,24719	0,0162	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:07:11	Аглофабрика
+25	0,67753	0,70987	0,0467	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:07:11	Аглофабрика
af_return_rm	0,75358	930,30077	0,0924	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:03:15	Аглофабрика
af_unit_capacity	0,1545	0,0437	0,0417	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:03:16	Аглофабрика
af_total_capacity	0,90768	843,69297	0,0432	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:03:15	Аглофабрика
X	0,71388	0,21223	0,003	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:03:15	Аглофабрика
X1	0,60916	0,05517	0,0129	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:03:15	Аглофабрика
-5	0,81693	0,26611	0,0168	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:03:16	Аглофабрика
+25	0,67349	0,71413	0,047	leontev_as	01.01.2020 0:00:00	30.04.2021 0:00:00	23.09.2021 11:03:16	Аглофабрика

Fig. 5. History of calculations and metrics

Рис. 5. История расчетов и метрик

module implementation (Fig. 4). Post-training, users have the facility to visually assess the training outcomes. Additionally, there's provision to review the history of model training, enabling users to select the optimal period for further training based on specific metrics (Fig. 5).

Conclusions

Throughout this project, archival data from the sinter plant of EVRAZ ZSMK JSC was meticulously gathered and analyzed. Utilizing statistical methodologies, the study identified and quantified the relationships between various input factors – such as the consumption rates of charge components, operational technical parameters of the sinter machines, and the chemical composition of the agglomerate – and the resulting productivity and quality of the agglomerate. Both linear and nonlinear correlations were discovered, with the proportions of charge component consumption being highlighted as having a significant impact on forecasting accuracy. These insights were subsequently incorporated into the forecasting module of the SMM mathematical modeling system, Prognoz, developed for EVRAZ ZSMK JSC.

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