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OPTIMIZATION OF COAL BLENDING IN COKE-INTEGRATED STEEL MILLS: A REVIEW

OTIMIZAÇÃO DA MISTURA DE CARVÕES NA EM USINAS SIDERÚRGICAS INTEGRADAS A COQUE: UMA REVISÃO

OPTIMIZACIÓN DE LA MEZCLA DE CARBÓN EN PLANTAS DE ACERO INTEGRADAS ALIMENTADAS CON COQUE: UNA REVISIÓN

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ABSTRACT

The increase in the added value of the product from the steel making process, in the production of steel and different rolled products for the various industrial sectors, together with actions to reduce CO_2 emissions. The demand forecast for 2050 is considered and must be ensured by a 100% renewable system. The transition to a 1.5-2°C world will fundamentally change the existing resource flows of both metals and fossil fuels. It has been shown to be an option for the viability of environmental protection projects, such as a way to improve the profitability of the activity. Within this scenario, the circular economy and low carbon or by the optimization process itself with CO_2 sequestration in the process. It can only ever be one of a range of sustainability-oriented initiatives that manifests in the here and now. In countries such as Brazil, China, and India, coke-integrated steelmaking still has a relevant market. Coke directly affects the cost of steel produced for this production line model. Therefore, based on a bibliographic survey, this study listed the main optimization technologies, the countries with the highest number of scientific contributions, and a time series showing the evolution in the number of publications, considering that social, economic, and environmental areas are pillars for the conscious development of contemporary society.

Keywords: Coke. Quality. Mineral Coal. Prediction Models. Coking Plant. Optimization.

RESUMO

O aumento do valor agregado do produto do processo de fabricação do aço, na produção de aço e diferentes produtos laminados para os vários setores industriais, juntamente com ações para

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reduzir as emissões de CO_2. A previsão de demanda para 2050 é considerada e deve ser garantida por um sistema 100% renovável. A transição para um mundo de 1,5-2°C mudará fundamentalmente os fluxos de recursos de metais e combustíveis fósseis. Tem se mostrado uma opção para a viabilidade de projetos de proteção ambiental, como forma de melhorar a lucratividade da atividade. Dentro deste cenário, a economia circular e de baixo carbono ou pelo próprio processo de otimização com sequestro de CO_2 no processo. Só pode ser uma de uma série de iniciativas orientadas à sustentabilidade que se manifestam no aqui e agora. Em países como Brasil, China e Índia, a siderurgia integrada ao coque, ainda tem um mercado relevante. O coque afeta diretamente o custo do aço produzido para este modelo de linha de produção, portanto este estudo a partir de um levantamento bibliográfico relacionado às principais tecnologias de otimização, os países com maior número de contribuições científicas e uma série temporal com a evolução no número de publicações, sendo que áreas como social, econômica e ambiental são pilares para o desenvolvimento consciente da sociedade contemporânea.

Palavras-chave: Coque. Qualidade. Carvão Mineral. Modelos de Previsão. Coqueria. Otimização.

RESUMEN

El aumento del valor añadido del producto del proceso siderúrgico, en la producción de acero y diferentes productos laminados para los diversos sectores industriales, junto con las acciones para reducir las emisiones de CO_2. La previsión de la demanda para 2050 se considera y debe garantizarse mediante un sistema 100% renovable. La transición a un mundo de 1,5-2 °C cambiará fundamentalmente la salida de los flujos de recursos tanto de metales como de combustibles fósiles. Se ha demostrado que es una opción para la viabilidad de los proyectos de protección ambiental, como una forma de mejorar la rentabilidad de la actividad. Dentro de este escenario, la economía circular y baja en carbono o por el propio proceso de optimización con secuestro de CO_2 en el proceso. Solo puede ser una de una serie de iniciativas orientadas a la sostenibilidad que se manifiestan en el aquí y ahora. En países como Brasil, China e India, la siderurgia integrada en el carbono, todavía tiene un mercado relevante. O coque afeta diretamente o custo do aço produzido para este modelo de línea de producción, portanto este estudo a partir de un levantamento bibliográfico relacionou como principais tecnologias de otimização, os países com mayor número de contribuciones científicas e uma serie temporal com a evolução no número de publicaciones, sendo que áreas como social, La economía y el medio ambiente son pilares para el desarrollo de la conciencia de la sociedad contemporánea.

Palabras clave: Coque. Calidad. Carbón. Modelos de Predicción. Planta de Coque. Optimización.

INTRODUCTION

This study addresses a bibliographical survey of technological advancements and the countries that are at the cutting edge of applying optimization methods to the coking process of integrated steel mills in Brazil.

The study conducted a bibliographical survey of over 70 articles, seeking to relate the countries, optimization techniques, research over the years, and trends for the coming years.

Iron is a material widely used in society because it is abundant and adaptable to a wide range of conditions. According to Machado et al. (2003), there are two major groups in metallurgy: non-ferrous metallurgy and steelmaking.

WORLD STELL (2021) uses average steel consumption in kilograms (kg) per capita as an indicator of a country's domestic economic market development. Countries such as China with 590.1 kg/habitant, Germany with 495.5 kg/habitant, Canada with 469.0 kg/habitant, Poland with 390 kg/inhabitant, and the United States (USA) with 306.5 kg/habitant are ahead of Brazil with an average consumption of 100 kg/habitant.

The contribution of this study reinforces the importance of advancing optimization techniques, reducing CO_2 emissions, and implementing artificial intelligence to reduce costs in the Brazilian steel sector. This sector is under pressure in the domestic market due to narrow profit margins, high production costs, energy-intensiveness, and a significant contributor to CO_2 emissions. Therefore, this study seeks to contribute to the sector's sustainability.

Coke Production

Coking is the stage of transforming the mixture of mineral coal into coke, which is used in blast furnaces as fuel, a reducing agent, a carbon supplier, and a charge permeabilizer (Machado et al., 2003).

Metallurgical coke is a product of the coking process and plays a crucial role in the blast furnace reduction process, providing heat (thermal), reducing gas in the direct and indirect iron ore process (chemical), and structuring the solid charge (physical). The stage of structuring the charge inside the furnace is essential for the operational efficiency of the blast furnace (Carneiro, 2003).

Metallurgical coke must perform the functions of fuel, reducing agent, carburizer, and permeabilizer in the blast furnace process. Thus, its main characteristics are: High carbon content and low ash, sulfur, and moisture, suitable CO_2 and H_2O reactivity values, good particle size for the blast furnace charging stage, good resistance to mechanical, thermal, and chemical degradation.

According to data from the Brazilian Steel Institute (IABR), in 2024 Brazil produced approximately 33.9 million tons of crude steel. Of this total, it is estimated that around 75% came from integrated steel mills operating with coke blast furnaces (UFRGS, [n.d.]).

The acquisition of raw materials is a fundamental step in a steel mill's strategy, so coking coal is imported from various countries around the world. In Brazil, since 1990, the national steel industry has imported all of its coal demand (Coelho, 2004).

Good quality coal has higher prices and lower supply on the world market, so lower-priced coals are used in part of the mixture. When properly processed, lower-cost coals contribute to maintaining coke quality and battery productivity (Coelho, 2004).

Coke is very important in the steelmaking process and has a direct impact on the cost of steel production. Therefore, a strategic alternative is to blend coals in a way that does not compromise the quality of the coke to be used in the blast furnace (Coelho, 2004).

Coke Quality

According to Coelho (2004), the metallurgical quality of coke can be understood as its ability to meet the fundamental requirements of a blast furnace, which are determined based on an assessment of the roles played by the material in the steelmaking process and the factors that act on it as it passes through the reactor.

In addition to these aspects, assessing coke quality involves monitoring technological properties such as the CO_2 Reactivity Index (CRI) and the Reaction Resistance Index (CSR), which allow its performance in the blast furnace to be predicted. High-quality coke is characterized by low CRI values and high CSR values, ensuring greater process stability, better gas permeability, and greater efficiency in iron ore reduction (Kumar et al., 2022). In this sense, other parameters are also used to assess the quality of the material, such as ash content, sulfur, volatile matter, basicity index, mechanical strength (DI), reactive/inert composition balance index (CBI), and strength index (SI), which complement the analysis of coke performance in the steelmaking process (Silva et al., 2011).

Ash consists of silica alumina, iron oxides, calcium, sodium, and potassium. Ash is directly related to operational problems in blast furnaces and to the quality of pig iron, i.e., for every 1% of ash, there is a 10 kg increase in the coke rate (Monteiro, 1980).

Therefore, the sulfur content needs to be controlled. Ideally, it should be below 1%, since higher values compromise both the quality of the pig iron and the operation of the blast furnace.

In excess, moisture reduces the effective calorific value of coke and increases transportation costs, as additional mass with no energy value is moved For this reason, the moisture content of coke is usually kept at controlled levels, generally between 4% and 6%, so as not to compromise its use in the blast furnace (Díez; Álvarez; Barriocanal, 2002).

Optimization

More broadly, optimization is as the process of selecting the best possible solution to a given problem, while respecting previously established constraints or conditions. It is a central area of Operational Research, used in different productive sectors to support rational and efficient decision-making (Arenales et al., 2015).

Linear Programming (LP) is one of the best-known optimization techniques and its main feature is the use of linear functions both in the formulation of the objective function and in the constraints. This type of model is generally solved using the Simplex method, proposed by George Dantzig in the 1940s, which enabled the practical application of Operational Research to real-world problems (Dantzig, 1963).

The genetic algorithm (GA) was based on the observation of natural phenomena, and is therefore based on a simplified model of Charles Darwin's biological evolutionary theory. Darwinian theory suggests that individuals who are better adapted to their environment are more resilient and have a greater probability of reproduction than those who are less adapted. Thus, over generations, a population tends to be increasingly represented by individuals who have inherited characteristics from organisms with a greater capacity for survival (Pacheco, 1997).

Machine learning has emerged as a powerful tool in several areas (Ghorbani et al., 2022, 2023a; Hajihosseinlou et al., 2024; Madani et al., 2017; Zhang et al., 2024). The tool has already been used to predict the thermodynamic properties of hydrogen (Soltanian, et al., 2024) and the carbon dioxide adsorption capacity of porous organic metals (Abdi et al., 2021). The metallurgical industry has welcomed and rapidly adopted machine learning, as complex analyses to predict the response variable have shown that the models respond with good accuracy compared to traditional regression models (Chen and Bai, 2013). Subsequently, multiple machine learning models were developed, such as decision trees, K-nearest neighbors (KNN), random forests, and multilayer perceptrons (MLP) (Adhab, 2025).

In the era of Industry 4.0 and Technology 4.0, artificial intelligence (AI) has become crucial for the various challenges in many sectors. These machine learning model algorithms are used to analyze data in real time and predict processes (Polyanska et al., 2023).

Random forest is a machine learning method widely used when the goal is to make reliable predictions without relying on just one model. Proposed by Breiman (2001), it works like a "forest" made up of several decision trees. Each tree generates a result, and in the end, the model combines all these results to arrive at a more stable and accurate answer.

XGBoost (Extreme Gradient Boosting) is a machine learning algorithm based on decision trees, widely used in classification and regression problems. Its architecture is based on the boosting technique, which consists of combining multiple weak trees to form a robust, high-performance model. According to Chen and Guestrin (2016), XGBoost was designed with a focus on computational efficiency and scalability, being able to handle large volumes of data without significant loss of accuracy.

Fundamental Models: Analytical, Kinetic, and Statistical Approaches

Before the widespread adoption of machine learning techniques, coke quality prediction was explored using models based on physical-chemical and statistical principles. In the study by Álvarez, Díez, Barriocanal, and Díaz-Faes (2007), the authors propose a prediction model with an emphasis on the CSR index, using an analytical approach based on the chemical properties of coal mixtures. The model is based on the hypothesis that the CSR of the resulting coke depends directly on the composition of the ash and petrographic factors of the coals used, enabling a preliminary prediction of quality based on their intrinsic characteristics.

The authors Kurniawan et al. (2020) developed a mass balance-based kinetic model to predict the CRI index of coke, using Fe_2O_3 content, volatile matter, and ranking degree as variables. The model had a coefficient of determination $R^2$of 0.84 and an error of less than 5%, and was also able to predict the CSR via linear regression. When applied to industrial mixtures, the error remained below 3.7%, demonstrating high accuracy and practical applicability.

In a more elaborate statistical approach, Klika, Serenčíšová, Kolomazník, and Bartoňová (2020) developed a two-stage model to predict CRI and CSR indices for coke produced from blends (type II coke). The first stage performs an initial prediction based on regressions constructed from data on individual coal cokes (type I cokes). The second stage then applies a correction to the predicted values, taking into account the specific properties of the blends. With this approach, the authors were able to significantly increase the accuracy of the estimates.

Although analytical, kinetic, and statistical approaches provide a basis for cause-and-effect relationships, they may have limitations when dealing with multiple dimensions and the inherently nonlinear nature of the industrial coking process. The interactions between the multiple components of a coal mixture, coupled with operational variations, create a complex system that is difficult to capture using traditional regression models or predefined equations. Faced with this challenge, the scientific community and industry have progressively turned to machine learning techniques, which, through a data-driven approach, are capable of learning and modeling these complex patterns, seeking to achieve new levels of predictive accuracy and decision support.

Machine Learning in Quality Prediction

Artificial Neural Networks (ANN) represent a milestone in the ability to model the complex and nonlinear relationships of coking. Nascimento and Reis (2009) presented one of the first predictive models of industrial coke quality developed with ANNs, applied to the context of Brazilian integrated plants. The model sought to estimate CRI and CSR quality indices based on coal characteristics, reinforcing the viability of using AI techniques to support decision-making in coking plants.

To improve the implementation of ANN models, Yan et al. (2020) proposed an approach to mitigate the problem of overfitting. A regularization technique based on the sigmoid function was used, which eliminates the weights with the least impact and reduces computational complexity. Comparing different architectures, the cascaded neural network with validation performed best, with a prediction error of around 5%.

In an industrial application for real-time prediction, Dyczko (2023) presented an innovative approach using neural networks based on the GMDH (*Group Method of Data Handling*) methodology. The research, applied at the company Jastrzębska Spółka Węglowa SA, used variables such as degree of metamorphism, ash content, moisture, and volatile materials. The neural network model presented the best results, with R^2 of 0.81 for CRI and 0.66 for CSR.

The ability of ANNs to capture nonlinear relationships was also demonstrated by Chelgani, Mesroghli, and Hower (2010), who investigated the prediction of coal classification parameters, such as maximum vitrinite reflectance (R_{max}) and gross calorific value (GCV). While linear regression obtained R^2 values of 0.77 and 0.69, respectively, the ANN model achieved R^2 values of 0.90 for R_{max} and 0.84 for GCV, proving its superiority. Accurate prediction of intrinsic coal parameters, such as those addressed in the study, is a strategic step in the coking optimization process. Vitrinite reflectance (R_{max} or Ro), in particular, is considered the most representative metric for indicating the rank (degree of maturation) of coal. The rank determines the thermochemical behavior of coal during carbonization and, consequently, the quality of the resulting coke.

Despite the proven effectiveness of ANNs, research has sought to compare their performance with other *machine learning* techniques, especially *ensemble* models such as *Random Forest* and *boosting* algorithms.

In a study focused on predicting CRI and CSR, Oliveira et al. (2023) conducted a direct comparison between linear regression models and *Random Forest*. The results indicated superior performance of decision tree-based models, which demonstrated a greater ability to capture the nonlinear relationships between coal mix variables and quality indices.

Expanding on this analysis, Oliveira (2023) applied different supervised algorithms (*Random Forest*, XGBoost, and LightGBM) to a four-year database from a Brazilian steel mill. The results indicated that the LightGBM model performed best for predicting CRI (R^2=61%), while the *Random Forest* and XGBoost algorithms had greater adherence to CSR data (R^2=63%). A crucial methodological difference was the use of the SHAP (*SHapley Additive exPlanations)* technique, which allowed the interpretation of the importance of variables such as fluidity, ash content, and chemical composition in the predictive behavior of the models.

This approach of comparing multiple algorithms and seeking interpretability is corroborated by Sato et al. (2021), who, when analyzing a large dataset of individual coals, also identified LightGBM as the best-performing model for CSR prediction. The application of the SHAP technique in their study reinforced the importance of fundamental variables such as average vitrinite reflectance, maximum fluidity, and total inert content, demonstrating a consensus in the literature on the main factors that govern coke quality.

Application of interpretability techniques performed by Qiu et al. (2025) used SHAP not only to interpret but also to diagnose and correct the predictive model. In their work, SHAP was initially employed to identify that the Artificial Neural Network (ANN) had learned "spurious correlations" that contradicted fundamental knowledge of the process. Based on this diagnosis, the authors developed their own algorithm (CDRE) to force the model to align with domain knowledge, improving both the accuracy and reliability and transparency of the prediction.

The authors Adhab et al. (2025) applied multiple *machine learning* techniques (including *Extra Trees*, SVM, MLP, CNN, and *AdaBoost*) to estimate the CRI. The results confirmed the superiority of *ensemble* models, with *Random Forest* performing best, with an R^2 of 0.958. Variable importance analysis revealed that maximum fluidity and mean maximum reflectance (MMR) are directly correlated with CRI.

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Hybrid Approaches in Artificial Intelligence

The frontier of AI research for coking lies in the development of hybrid models and innovative approaches to address real-world challenges, such as missing data and the need for real- time optimization.

Agarwal et al. (2021) proposed a hybrid approach for real-time CSR prediction, integrating statistical time series models with neural networks. Using three years of operational data from an Indian power plant, the Unobserved Component Model (UCM) achieved 76% accuracy. The modeling enabled real-time monitoring, proactive process adjustment, and identification of optimal ranges for input variables, achieving a notable economic impact with an estimated cost reduction of $1.75 million due to the minimization of out-of-specification batches.

To optimize the process, Zhao et al. (2024) integrated machine learning with computational fluid dynamics (CFD) modeling to predict heat transfer in real time. The system combines detailed CFD simulations with supervised learning models, enabling not only prediction but also dynamic adjustment of process conditions, maximizing energy efficiency and thermal control in coke chambers.

Dealing with data representation, Qiu et al. (2024) presented an innovative approach based on "image expression." The method transforms numerical variables int r visual representations, which are processed by a convolutional neural network (CNN) combined with a Random Forest. The strategy used outperformed traditional models, achieving R^2 of 0.86 for CRI and 0.91 for CSR. For the challenge of incomplete data, Qiu et al. (2025) developed a model based on adaptive graphical neural networks (AGNN). The study's unique feature is the AGNN's ability to automatically impute missing coal properties while predicting CRI and CSR with high accuracy, offering reliable results even with 30% to 50% of data missing.

Finally, to improve the accuracy of the models, Adhab et al. (2025) proposed RF-GPO (Random Forest with Gradient Optimized Parameters). This model combines the robustness of Random Forest with hyperparameter optimization via gradient methods, resulting in an accurate and adaptable predictive system capable of supporting real-time decisions and automated operational adjustments.

The ultimate goal of modeling is not only to predict, but to optimize the process, balancing quality, cost, and resource utilization.

Mathematical optimization models, such as linear programming, offer a prescriptive approach. Bueno, Silva, Destro, and Assis (2009) and Seet and Sethi (2020) used linear programming to formulate the coal mix. The focus was on minimizing the total cost of the mixture while maintaining quality levels and meeting process constraints. The studies demonstrated a significant reduction in operating costs by finding optimal combinations among the available coals. Moving forward to intelligent optimization systems, Li (2025) proposed an integration between backpropagation (BP) neural networks and genetic algorithms (GA). The BP neural network learns the complex patterns between coal properties and coke quality, while the genetic algorithm acts to optimize the network weights and search for the best mixture composition. The application of the system resulted in significant reductions in ash and sulfur content, increased process stability, and reduced operating costs.

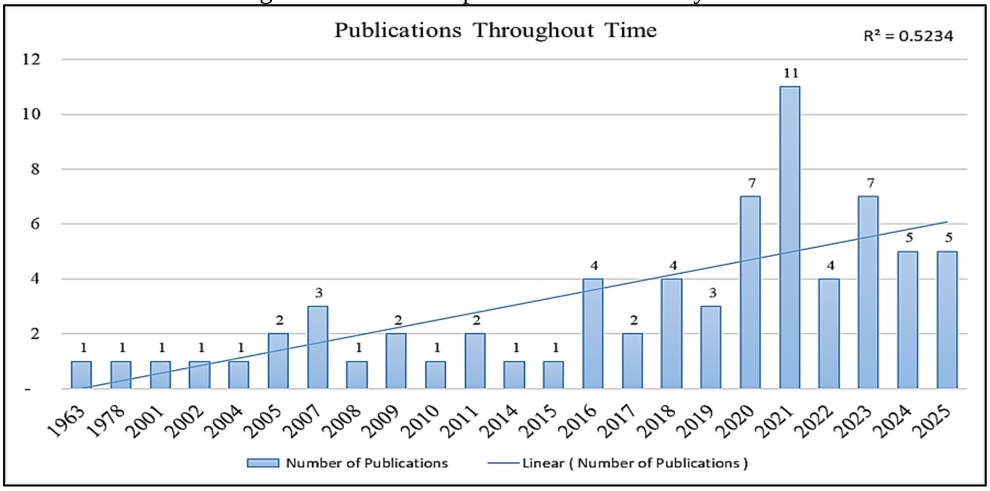
In addition to predicting quality, AI has also been applied to predict other process outcomes. Vasileva et al. (2019) developed a neural network model for predicting the yield of coking products (coke, tar, gas), proving to be a promising tool for planning coal mixes and coking plant operations.

Finally, the knowledge generated by these models has direct strategic application. Authors Kumar and Tiwari (2020) addressed the efficient use of lower-quality Indian metallurgical coals.

They demonstrated that it is possible to include up to 50% of Indian coal with high ash content in mixtures with imported coals, maintaining a CSR above 65. The study highlights the role of beneficiation technologies and intelligent blend formulation as strategic tools for the sustainable use of domestic reserves and reducing dependence on imports.

Figure 1 shows the number of publications over the years that were used in this study.

Figure 1. Number of publications over the years.

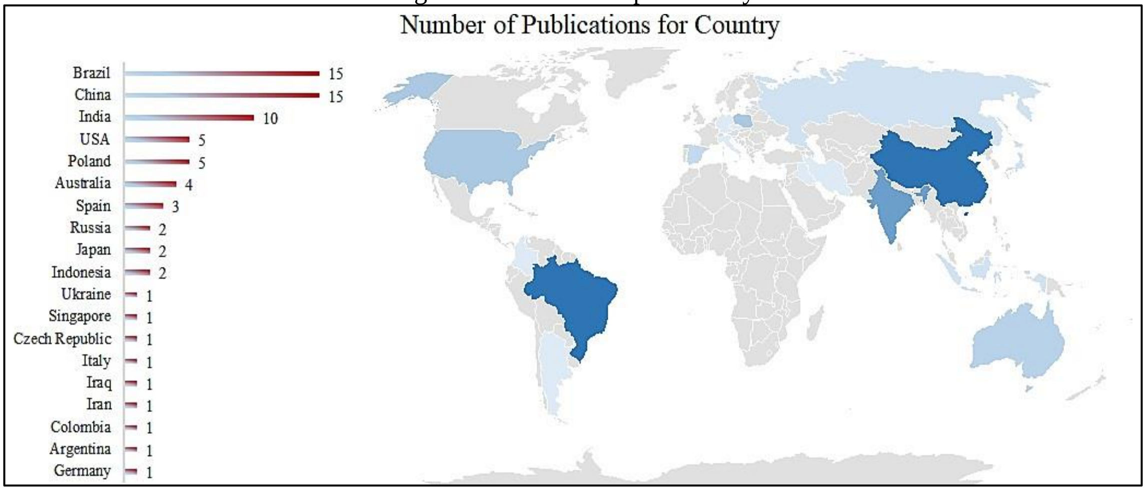


Source: By the author

Figure 1 shows that since 1963 there has been an increase in the number of publications over the years, and since 2020, and especially during the pandemic, the number of studies has risen. Considering this trend, where the correlation was $R^2 = 0.5234$, it is possible to analyze the increase in the number of publications, which in 2020 will reach 8 publications in relation to the research universe.

Figure 2 shows the number of publications per country, with Brazil, China, and India leading research in this area, and one hypothesis is due to the developed steel chain.

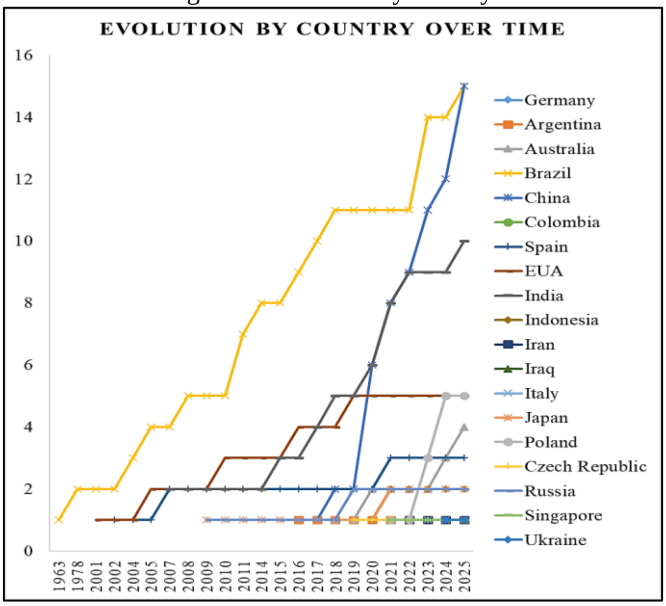
Figure 2. Publications per country



Source: By the author

Figure 3 shows the cumulative evolution of research by country. It can be seen that Brazil has grown gradually over the years, China has grown more sharply since 2019, and India has increased the number of publications since 2014.

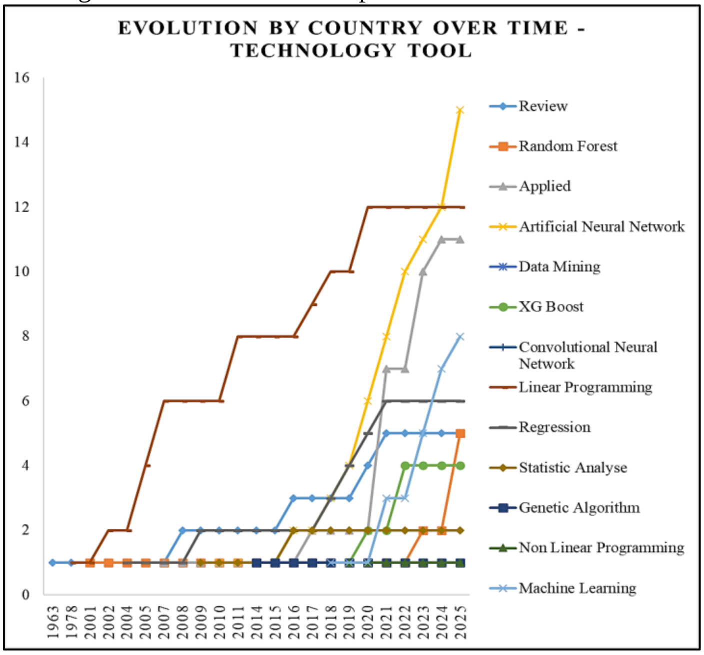
Figure 3. Evolution by country.



Source: By the author

Figure 4 presents cumulative research on the evolution of research by technology adopted in each study. According to Figure 4, linear programming grew gradually, but Artificial Neural Network surpassed all optimization technologies. The term Applied refers to articles where the data was experimental data.

Figure 4. Place where the experiments were conducted.



Source: By the author.

Research based on bibliographic surveys indicates that countries with significant steel markets, such as Brazil, China, and India, are conducting more and more research into process optimization, mainly through artificial neural networks, linear programming, and experimental testing. Investment in research and development directly affects the reduction of production costs and CO_2 emissions in the steel industry.

CONCLUSION

The conclusion of an articl This study conducted a bibliographic survey on mineral coal, its relevance in the steel chain, the main quality indices of coke, which is the final product of the coking process and plays a key role in reducing the iron load inside the blast furnace. The study also addressed the main quality indices of coke and the main technologies used for process optimization. The technologies are Random Forest, Artificial Neural Network, Data Mining, XG Boost, Convolutional Neural Network, Linear Programming, Genetic Algorithm, Non-Linear Programming, and Machine Learning. Each technology has modeling characteristics and mathematical techniques for representing production processes. In addition, the article segregated the studies by the number of publications per topic addressed and by the country of origin of each study. A time series was also presented with the studies over the years. The state-of-the-art study shows that countries where the coal market is relevant to integrated steel mills, such as Brazil, China, and India, had a greater number of studies on mineral coal, optimization, and its technologies. The study presented important results for the national and global steel industry, as it demonstrated that countries with traditional steel markets (blast furnaces) are the ones that have maintained research over the years and are increasingly focused on process improvements, particularly in reducing the cost of coke, which is an expensive and essential input for steel production in integrated mills. The study also demonstrated the main optimization and artificial intelligence techniques in the coke oven process, thus demonstrating that process improvements have proven essential for reducing costs and CO_2 emissions in the steel industry. There are opportunities to delve deeper into the study's main drivers, such as: techniques already implemented in the sector, per capita steel consumption in leading countries, the size of each country's steel market, and comparisons of results after implementing optimization technology to reduce CO_2 emissions and production costs.

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REFERENCES

ABDI J, HADAVIMOGHADDAM F, HADIPOOR M, *et al*. **Modeling of CO_2 adsorption capacity by porous metal organic frameworks using advanced decision tree-based models.** Scientific Reports 11(1): 24468, 2021. Disponível em: <https://www.nature.com/articles/s41598-021-04168-w>. Acesso em: 10 jun. 2025.

ADHAB, A. H. *et al.* **Machine learning frameworks to accurately predict coke reactivity index**. Energy exploration & exploitation, v. 43, n. 3, p. 1224–1248, 2025. Disponível em: <https://journals.sagepub.com/doi/full/10.1177/01445987251318353>. Acesso em: 10 jun. 2025.

AGARWAL, S. *et al.* **Prediction of coke CSR using time series model in Coke Plant.** Opsearch. Quarterly Journal of the Operational Research Society of India, v. 58, n. 4, p. 1238–1259, 2021. Disponível em: <https://link.springer.com/article/10.1007/s12597-020-00506-0>. Acesso em: 10 jun. 2025.

AHMAD, M.; KARIMI, I. A. **Revised learning based evolutionary assistive paradigm for surrogate selection (LEAPS2v2).** Computers & chemical engineering, v. 152, n. 107385, p. 107385, 2021. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0098135421001630>. Acesso em: 11

jun. 2025.

ÁLVAREZ, R. *et al.* **An approach to blast furnace coke quality prediction.** Fuel (London, England), v. 86, n. 14, p. 2159–2166, 2007. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0016236106004728>. Acesso em: 12 jun. 2025.

AMINI, S. H. *et al.* **Optimization of coal blending operations under uncertainty – robust optimization approach.** International journal of coal preparation and utilization, v. 42, n. 1, p. 30–50, 2022. Disponível em: <https://www.tandfonline.com/doi/abs/10.1080/19392699.2019.1574262>. Acesso em: 15 jul. 2025.

AN, B. et al. **Influence of uncoordinated N content on Ni N C electrocatalyst for CO_2 reduction: Combining first principle with machine learning.** Fuel (London, England), v. 333, n. 126563, p. 126563, 2023. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0016236122033877>. Acesso em: 18 jul. 2025.

ARENALES, M. N.; ARMENTANO, V. A.; MORABITO, R.; YANASSE, H. H. **Operational research: for engineering courses**. 2nd ed. Rio de Janeiro: Elsevier, 2015. Disponível em: <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4683856>. Acesso em: 18 jul. 2025.

BRAZIL STEEL IN STITUTE. **Industry data**. Disponível em: <https://www.acobrasil.org.br/site/dados-do-setor/>. Acesso em: 18 jul. 2025.

BREIMAN, L. **Random forests.** Machine Learning, v. 45, p. 5-32, 2001. DOI: https://doi.org/10.1023/A:1010933404324. Disponível em: <https://link.springer.com/article/10.1023/a:1010933404324>. Acesso em: 18 jul. 2025.

CARDOSO, W.; DI FELICE, R.; BAPTISTA, R. C**. Artificial neural network for predicting silicon content in the hot metal produced in a blast furnace fueled by metallurgical coke.** Materials research, v. 25, 2022. Disponível em: <https://www.scielo.br/j/mr/a/Vb3NRVfdDZpqsCP53YFkmsk/?lang=en>. Acesso em: 20 ago. 2025.

CARNEIRO, R. T. S. **The role of coke in blast furnaces. In: Continuing education program.** São Paulo: ABM, June 2003. pp. 1–9. Disponível em: <https://www.researchgate.net/publication/280713664_Exergy_Balance_of_Pulverized_Coal_Injection_Into_Blast_Furnaces>. Acesso em: 20 ago. 2025.

CHELGANI, S. C.; MESROGHLI, S.; HOWER, J. C. **Simultaneous prediction of coal rank parameters based on ultimate analysis using regression and artificial neural network.** International journal of coal geology, v. 83, n. 1, p. 31–34, 2010. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0166516210000558>. Acesso em: 20 ago. 2025.

Chen H.J., Bai JF. **A coke quality prediction model based on support vector machine.** Advanced Materials Research 690: 3097–3101, 2013. Disponível em:

<https://www.scientific.net/amr.690-693.3097>. Acesso em: 23 ago. 2025.

CHEN, T.; GUESTRIN, Cs. XGBoost: **A Scalable Tree Boosting System.** *In*: New York, NY, USA: ACM, 2016. Disponível em: <https://dl.acm.org/doi/abs/10.1145/2939672.2939785>. Acesso em: 25 ago. 2025.

COELHO, R. J. et al. **Models for predicting the metallurgical quality of coke based on the quality of individual coals and the coke obtained in the pilot coking oven**. Rem Revista Escola de Minas, v. 57, n. 1, p. 27–32, 2004. Disponível em: <https://www.scielo.br/j/remi/a/5d7QBYwKnZh55nYQbs4KLWB/?lang=en>. Acesso em: 28 ago. 2025.

COLORADO-ARANGO, L.; MENÉNDEZ-AGUADO, J. M.; OSORIO-CORREA, A**. Particle size distribution models for metallurgical coke grinding products**. Metals, v. 11, n. 8, p. 1288, 2021. Disponível em: <https://www.mdpi.com/2075-4701/11/8/1288>. Acesso em: 28 ago. 2025.

CÓRDOVA, M.; MADIAS, J.; BARREIRO, J. **Revisão De Modelagem de Misturas de Carvão Para Predição de Qualidade do Coque.** *In*: São Paulo: Editora Blucher, 2016. Disponível em: <https://www.academia.edu/download/110021171/revisao-de-modelagem-de-misturas-de-carvao-para-predicao-de-qualidade-do-coque.pdf>. Acesso em: 28 ago. 2025.

CRUZ, L. V. **Análise da adição de piche sólido em uma mistura de carvões para produção de coque metalúrgico**. Disponível em: <http://www.monografias.ufop.br/handle/35400000/5913>. Acesso em: 15 out. 2025.

DANTZIG, G. B. **Linear Programming and Extensions**. Princeton: Princeton University Press, 1963. Disponível em: <https://www.torrossa.com/en/resources/an/5793009>. Acesso em: 15 out. 2025.

DÍEZ, M. A.; ÁLVAREZ, R.; BARRIOCANAL, C. **Coal for metallurgical coke production: predictions of coke quality and future requirements for coke making**. *International Journal of Coal Geology*, v. 50, n. 1–4, p. 389-412, 2002. DOI: https://doi.org/10.1016/S0166-5162(02)00123-4. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0166516202001234>. Acesso em: 16 out. 2025.

DYCZKO, A. **Production management system in a modern coal and coke company based on the demand and quality of the exploited raw material in the aspect of building a service-oriented architecture.** Journal of Sustainable Mining, v. 22, n. 1, p. 2–19, 2023a. Disponível em: <https://bibliotekanauki.pl/articles/2201432.pdf>. Acesso em: 01 out. 2025.

DYCZKO, A. **Real-time forecasting of key coking coal quality parameters using neurais networks and artificial intelligence.** Mining-Geological-Petroleum Engineering Bulletin, v. 38, n. 3, p. 105–117, 2023b. Disponível em: <https://hrcak.srce.hr/ojs/index.php/rgn/article/view/26545>. Acesso em: 02 out. 2025.

DYCZKO, A. **The perspective of using neurais networks and machine learning algorithms for modelling and forecasting the quality parameters of coking coal—A case**

study. Geosciences, v. 14, n. 8, p. 199, 2024. Disponível em: <https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4791635>. Acesso em: 02 out. 2025.

GADHAVI, G.; SOLANKI, H. **A review: Sulfur in coal and petroleum coke.** International Association of Biologicals and Computational Digest, v. 1, n. 2, p. 282–286, 2022. Disponível em: <https://iabcd.org.in/index.php/iabcd/article/view/81>. Acesso em: 03 out. 2025.

GHORBANI, H.; GHORBANI, P.; GHORBANI S.; et al. **A Robust Approach for Estimation of the Bone Age**. IEEE, 2022. Disponível em: <https://ieeexplore.ieee.org/abstract/document/10036283>. Acesso em: 03 set. 2025.

GUPTA, A.; DAS, A. K.; CHAUHAN, G. I. S. **A coal-blending model: A tool for better coal blend preparation.** Coal preparation, v. 27, n. 1–3, p. 28–38, 2007. Disponível em: <https://www.tandfonline.com/doi/abs/10.1080/07349340701249760>. Acesso em: 03 set. 2025.

HAJIHOSSEINLOU M.; MAGHSOUDI A.; GHEZELBASH R. **Regularization in machine learning models for MVT Pb-Zn prospectivity mapping: Applying lasso and elastic-net algorithms**. Earth Science Informatics 17(5): 4859–4873, 2024. Disponível em: <https://link.springer.com/article/10.1007/s12145-024-01404-5>. Acesso em: 03 set. 2025.

HOMAFAR, A.; NASIRI, H.; CHELGANI, S. C. **Modeling coking coal indexes by SHAP-XGBoost: Explainable artificial intelligence method.** Fuel Communications, v. 13, n. 100078, p. 100078, 2022. Disponível em: <https://www.sciencedirect.com/science/article/pii/S2666052022000280>. Acesso em: 04 set. 2025.

ISBAEX, C., **Influência da densidade do carvão vegetal na produção de sílicio metálico.** Viçosa, MG, 2014. Disponível em: <https://poscienciaflorestal.ufv.br/wp-content/uploads/2023/05/Crismeire-Isbaex.pdf>. Acesso em: 06 set. 2025.

JEUKEN, R.; FORBES, M.; KEARNEY, M. **Optimal blending strategies for coking coal using chance constraints.** The Journal of the Operational Research Society, v. 72, n. 12, p. 2690–2703, 2021. Disponível em: <https://www.tandfonline.com/doi/abs/10.1080/01605682.2020.1811167>. Acesso em: 07 set. 2025.

KLIKA, Z. *et al.* **Prediction of CRI and CSR of cokes by two-step correction models for stamp-charged coals – Statistical analysis.** Fuel (London, England), v. 262, n. 116623, p. 116623, 2020. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0016236119319775>. Acesso em: 07 set. 2025.

KUMAR, M.; TIWARI, H. P. **Efficient utilization of Indian Coking Coal: Opportunities and challenges.** Metallurgical research & technology, v. 117, n. 2, p. 209, 2020. Disponível em: <https://www.metallurgical-research.org/articles/metal/abs/2020/02/metal200004/metal200004.html>. Acesso em: 07 set. 2025.

KUMAR, S. et al. **Variability in metallurgical coke reactivity index (CRI) and coke strength after reaction (CSR): an experimental study**. *ACS Omega*, v. 7, n. 4, p. 3879-3890, 2022. Disponível em: <https://pubs.acs.org/doi/full/10.1021/acsomega.1c04270>. Acesso em: 08 set. 2025.

KURNIAWAN, T. *et al.* **A kinetic model approach for predicting coke reactivity index from coal and coal blend properties.** International journal of coal preparation and utilization, v. 42, n. 5, p. 1318–1335, 2022. Disponível em: <https://www.tandfonline.com/doi/abs/10.1080/19392699.2019.1710498>. Acesso em: 08 jul. 2025.

LEDERER, J. **Activation Functions in Artificial Neural Networks: A Systematic Overview.** 10.48550/arXiv.2101.09957, 2022. Disponível em: <https://arxiv.org/abs/2101.09957>. Acesso em: 09 jul. 2025.

LI, H. *et al.* **Construction of intelligent coal blending system based on BP neural network and genetic algorithm.** Ironmaking and Steelmaking, n. 03019233241312762, 2025. Disponível em: <https://journals.sagepub.com/doi/abs/10.1177/03019233241312762>. Acesso em: 09 jul. 2025.

LI, W. *et al.* **Effects of additives on coke reactivity and sulfur transformation during co-pyrolysis of long flame coal and high-sulfur coking coal.** ACS omega, v. 6, n. 50, p. 34967–34976, 2021. Disponível em: <https://pubs.acs.org/doi/full/10.1021/acsomega.1c05642>. Acesso em: 10 jul. 2025.

MADANI, M. ABBASI, P. BAGHBAN, A. et al. **Modeling of CO2-brine interfacial tension: Application to enhanced oil recovery.** Petroleum Science and Technology 35(23): 2179–2186, 2017. Disponível em: <https://www.tandfonline.com/doi/abs/10.1080/10916466.2017.1391844>. Acesso em: 10 jul. 2025.

MACHADO, M. L. P.; SOBRINHO, V. P. F. M.; ARRIVABENE, L. F. **Steel industry for non-steelmakers.** Vitória: Brazilian Metal Association - ABM, 2003. Disponível em: <https://abmproceedings.com.br/en/page/historical-publications-1>. Acesso em: 10 jul. 2025.

MAGALHÃES, A. O.; AVELLAR, A. S.; BORGES, M. A. B. **Modelo de previsão para a resistência mecânica do coque metalúrgico**. Disponível em: <http://www.monografias.ufop.br/handle/35400000/5820>. Acesso em: 15 out. 2025.

MAZZINI, F. F. **Otimização do Plano de Compra, Estoque e Consumo de Carvões**. Disponível em: <https://repositorio.ufmg.br/items/e8d44b0e-bb40-4d0e-9542-b91130a144fb>. Acesso em: 15 out. 2025.

MIROSHNICHENKO, D. *et al.* **Effect of coal quality and preparation on the stamping performance and quality of coke.** Scientific reports, v. 14, n. 1, p. 27542, 2024. Disponível em: <https://www.nature.com/articles/s41598-024-78352-z>. Acesso em: 18 out. 2025.

MONTEIRO, M. R.. **Manufacture of metallurgical coke. Continuing education program**. São Paulo: ABM, June, 1980. P. 147-207. Disponível em:

<https://www.proquest.com/openview/0f603adc6e741fd41b468085ccee421b/1?pq-origsite=gscholar&cbl=18750&diss=y>. Acesso em: 18 out. 2025.

NASCIMENTO, L. M. *et al.* **Simulação a frio da elevação da densidade de carga da mistura de carvões metalúrgicos por vibração da mistura.** Tecnologia em metalurgia, materiais e mineracao, v. 13, p. 310–315, 2016. Disponível em: <http://www.tmm.periodikos.com.br/article/doi/10.4322/2176-1523.1070>. Acesso em: 19 out. 2025.

NORTH, L. *et al.* **Methods of coke quality prediction: A review**. Fuel **(London, England)**, v. 219, p. 426–445, 2018. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0016236118300711>. Acesso em: 29 set. 2025.

NORTH, L. A. *et al.* **Understanding the impact of coal blending decisions on the prediction of coke quality: a data mining approach.** International Journal of Coal Science & Technology. China. v. 6, p. 207–217, 2019. Disponível em: <https://link.springer.com/article/10.1007/s40789-018-0217-2 >. Acesso em: 29 set. 2025.

OLIVEIRA, D. S. **Avaliação de modelos de previsão da qualidade de coque baseado em abordagem de mineração de dados e aprendizado de máquina**. Disponível em: <https://lume.ufrgs.br/handle/10183/267714>. Acesso em: 15 out. 2025.

OOTSUKA, S. *et al.* **Effect of environmental factors on hydrogen absorption into steel sheet under a wet-dry cyclic corrosion condition.** ISIJ international, v. 61, n. 4, p. 1229–1235, 2021. Disponível em: <https://www.jstage.jst.go.jp/article/isijinternational/61/4/61_ISIJINT-2020-561/_article/-char/ja/>. Acesso em: 27 set. 2025.

PACHECO, M. A. C. **Genetic Algorithms: Principles and Applications.** 1999. Rio de Janeiro. v. 56, n. 9, p. 1043–1062, 2013. Disponível em: <https://ieeexplore.ieee.org/abstract/document/8140364>. Acesso em: 28 set. 2025.

PATEL, J. P. *et al.* **Optimization studies on a coal preparation plant**. International journal of coal preparation and utilization, p. 1–12, 2018. Disponível em: <https://www.tandfonline.com/doi/10.1080/19392699.2018.1494163>. Acesso em: 26 set. 2025.

PEREIRA, L. C. **Utilização de algoritmo genético para a solução do problema de proporção de carvões para produção de coque metalúrgico**. Disponível em: <https://repositorio.ufmg.br/items/fa83d92d-5025-4ac7-b95a-bb2bc29e7c81>. Acesso em: 15 out. 2025.

QIU, Y. *et al.* **A novel image expression-driven modeling strategy for coke quality prediction in the smart cokemaking process.** Energy (Oxford, England), v. 294, n. 130866, p. 130866, 2024. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0360544224006388>. Acesso em: 21 set. 2025.

QIU, Y. *et al.* **The interpretable deep learning-based coke quality prediction strategy aligned with domain knowledge for sustainable smart cokemaking applications.** Fuel (London, England), v. 398, n. 135533, p. 135533, 2025a. Disponível em: <https://www.sciencedirect.com/science/article/pii/S001623612501258X>. Acesso em: 20 ago. 2025.

QIU, Y. *et al.* **The novel adaptive graph neural network-based coke quality prediction for coal samples with missing properties in sustainable smart cokemaking applications.** Fuel (London, England), v. 397, n. 135377, p. 135377, 2025b. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0016236125011020>. Acesso em: 20 ago. 2025.

REJDAK, M. *et al.* **A study on bio-coke production—the influence of biochar addition to the coking blend on bio-coke quality parameters.** Energies, v. 17, n. 24, p. 6425, 2024. Disponível em: <https://www.mdpi.com/1996-1073/17/24/6425>. Acesso em: 22 ago. 2025.

REJDAK, M. STRUGAŁA, A., SOBOLEWSKI, A. **Stamp-charged coke-making technology—the effect of charge density and the addition of semi-soft coals on the structural, textural and quality parameters of coke**. Energies, v. 14, n. 12, p. 3401, 2021. Disponível em: <https://www.mdpi.com/1996-1073/14/12/3401>. Acesso em: 22 ago. 2025.

SEET, S., SETHI, P. **Blending Consideration In Coke Making Towards Optimum Coke Quality**. Coke and Chemistry, 2020. Disponível em: <https://link.springer.com/article/10.1007/s12665-020-09132-x>. Acesso em: 22 ago. 2025.

SHARMA, M. K. *et al.* **Development of new coal blend preparation methodologies for improvement in coke quality.** Coal preparation**,** v. 27, n. 1–3, p. 57–77, 2007. Disponível em: <https://link.springer.com/article/10.1007/s12665-020-09132-x>. Acesso em: 13 ago. 2025.

SILVA, G. L. R.; DESTRO, E.; MARINHO, G. M.; ASSIS, P. S. **Optimization of coal blends in coking plants**. In: Seminar On Iron Ore and Raw Material Reduction; Brazilian Iron Ore Seminar, 41st, 12th, 2011, Vila Velha. Proceedings [...]. São Paulo: ABM, 2011. Disponível em: <https://abmproceedings.com.br/pt-br/event/41-ironmaking-and-raw-materials-seminar-and-12-brazilian-symposium-on-iron-ore-6>. Acesso em: 13 ago. 2025.

SOLTANIAN M.R., BEMANI A., MOEINI F., et al. (2024) **Data driven simulations for accurately predicting thermodynamic properties of H2 during geological storage**. Fuel 362: 130768. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0016236123033823>. Acesso em: 14 ago. 2025.

TIWARI, H. P. *et al.* **Potential use of high ash Indian medium coking coal in stamp charged coke making**. International journal of coal preparation and utilization, v. 39, n. 2, p. 101–111, 2019. Disponível em: <https://www.tandfonline.com/doi/abs/10.1080/19392699.2017.1305959>. Acesso em: 15 ago. 2025.

TIWARI, H. P. *et al.* **Data mining – new perspectives on predicting coke quality in recovery stamp charged coke making process.** Metallurgical research & technology, v. 112,

n. 6, p. 603, 2015. Disponível em: <https://www.metallurgical-research.org/articles/metal/abs/2015/06/metal150038/metal150038.html>. Acesso em: 16 ago. 2025.

UFRGS – **Coal Network. Mineral Coal and Coke**. Porto Alegre: Federal University of Rio Grande do Sul, [n.d.]. Available at: https://www.ufrgs.br/rededecarvao/. Disponível em: <https://lume.ufrgs.br/handle/10183/129497>. Acesso em: 16 ago. 2025.

ULANOVSKII, M.L. **Parameters for optimization of coke quality (CRI and CSR).** Coke Chem. 52, 11–15, 2009. https://doi.org/10.3103/S1068364X09010049. Disponível em: <https://link.springer.com/article/10.3103/S1068364X09010049>. Acesso em: 17 ago. 2025.

ULHÔA, M. B., CARNEIRO R.T.S., SILVA E. G. S., PINHEIRO J. A. - **Carvão Aplicado à Fabricação de Coque de Alto-Forno**. Curso Interno da USIMINAS, Ipatinga-MG, Março 1999. Disponível em: <https://www.repositorio.ufop.br/server/api/core/bitstreams/4031c695-659d-49d3-81da-ad60ddd8a2e3/content>. Acesso em: 17 ago. 2025.

VASILEVA, E.V., DOROGANOV, V.S., PILETSKAYA, A.B. et al**. Neural-Network Model for Predicting the Yield of Coking Products.** Coke Chem. 62, 40–46 (2019). https://doi.org/10.3103/S1068364X19020091. Disponível em: <https://link.springer.com/article/10.3103/s1068364x19020091>. Acesso em: 18 ago. 2025.

VASKO, F. J.; NEWHART, D. D.; STRAUSS, A. D. **Coal blending models for optimum cokemaking and blast furnace operation.** The Journal of the Operational Research Society, v. 56, n. 3, p. 235–243, 2005. Disponível em: <https://www.tandfonline.com/doi/abs/10.1057/palgrave.jors.2601846>. Acesso em: 18 ago. 2025.

VEGA, M, F., DÍAZ, E., BARRIOCANAL, C. **Influence of the heating rate on the quality of metallurgical coke.** ACS omega, v. 6, n. 50, p. 34615–34623, 2021. Disponível em: <https://pubs.acs.org/doi/full/10.1021/acsomega.1c05007>. Acesso em: 19 ago. 2025.

WANG, B. X. *et al.* **Design and optimisation of charging ingredients and structure in an ironmaking system (Part II).** Ironmaking and Steelmaking, v. 44, n. 1, p. 59–65, 2017. Disponível em: <https://journals.sagepub.com/doi/abs/10.1080/03019233.2016.1156222>. Acesso em: 19 ago. 2025.

WOOD, R.; BANCO NACIONAL DO DESENVOLVIMENTO ECONÔMICO. DEPARTAMEN PROJETOS. **Mistura de carvões para coque metalúrgico.** 1964. Disponível em: <https://web.bndes.gov.br/bib/jspui/handle/1408/12374>. Acesso em: 19 ago. 2025.

WORLD STEEL ASSOCIATION. **January 2021 crude steel production**. Disponível em:

<https://www.worldsteel.org/media-centre/press-releases/2021/January-2021-crude-steel-production.html>. Acesso em: 17 abr, 2025.

XIANG, C. *et al.* **Prediction of Gray-King coke type from radical concentration and basic properties of coal blends.** Fuel processing technology, v. 211, n. 106584, p. 106584, 2021. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0378382020308754>. Acesso em: 11 set. 2025.

YAN, S. *et al.* **Application study of sigmoid regularization method in coke quality prediction.** Complexity, v. 2023, p. 1–1, 2023. Disponível em: <https://onlinelibrary.wiley.com/doi/full/10.1155/2020/8785047>. Acesso em: 10 ago. 2025

YUAN, Y. *et al.* **Modeling and optimization of coal blending and coking costs using coal petrography.** Information sciences, v. 522, p. 49–68, 2020. Disponível em: <https://www.sciencedirect.com/science/article/abs/pii/S0020025520301626>. Acesso em: 11 set. 2025.

YUSTANTI, E. *et al.* **Types and composition of biomass in biocoke synthesis with the coal blending method**. Energies, v. 14, n. 20, p. 6570, 2021. Disponível em: <https://www.mdpi.com/1996-1073/14/20/6570>. Acesso em: 11 set. 2025.

Zhang X, H. D, X. Z, *et al*.: **Energy-aware low-latency routing data driven model in mobile edge computing**. IEEE Transactions on Consumer Electronics, 2024. Disponível em: <https://ieeexplore.ieee.org/abstract/document/10769528>. Acesso em: 11 set. 2025.

ZHAO, P. *et al.* **A machine learning and CFD modeling hybrid approach for predicting real-time heat transfer during cokemaking processes.** Fuel. London, England, v. 373, n. 132273, p. 132273, 2024. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0016236124014212>. Acesso em: 11 set. 2025.

ZHENG, H. *et al.* **A comprehensive review of characterization methods for metallurgical coke structures.** Materials, v. 15, n. 1, p. 174, 2021. Disponível em: <https://www.mdpi.com/1996-1944/15/1/174>. Acesso em: 19 jun. 2024.

ZI, J. *et al.* **A multi-objective simulated annealing algorithm-based coal blending optimization approach in coking process**. *In*: IEEE, 2020. Disponível em: <https://ieeexplore.ieee.org/abstract/document/9251154>. Acesso em: 14 mai. 2025.