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USE OF MACHINE LEARNING FOR SMART AND CLEAN STEEL

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Abstract

This study leverages machine learning in Electric Arc Furnaces steel waste recycling to enhance sustainable steel production, reduce the level of environmental pollution and resource consumption. It focuses on balancing material and energy efficiency, particularly managing degradation elements like Mn and Si. In addition, the approach mitigates recycling limitations by effectively reducing the accumulation of Cu and Sn in the end product, thus enhancing its overall quality. Analyzing and predicting the behavior of different parameters in different process conditions, it is possible to optimize the simultaneous use of materials and the removal of impurities. This approach also contributes to the reduction of the steel industry's carbon footprint, aligning with global decarbonization efforts and advancing sustainable manufacturing practices. As the steel industry continues to evolve under the influence of Industry 4.0 technologies, analytic methods of processing process data are becoming increasingly important in achieving environmental sustainability and economic efficiency.

Keywords: *EAF, carbon footprint, machine learning*

Introduction

The global steel industry, an integral part of economic development and infrastructure, is currently dealing with significant environmental challenges. This industry is a major contributor to global carbon dioxide emissions, accounting for approximately 7-9% of total world emissions. This is additionally related to the significant energy consumption in the industry, which represents 20% of the total industrial energy consumption. The traditional linear economic models which are most often used in steel production get worse these problems, characterized by a take-do-dispose approach that leads to overuse of resources and significant environmental degradation. Such models, although historically effective in

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meeting market demand, now face a number of sustainability issues, particularly in light of growing global environmental awareness and regulatory pressures [1].

In response to these challenges, the circular economy is emerging as a transformation model, moving away from traditional linear practices. It is based on the principles of resource efficiency, recycling and sustainability, with the aim of keeping resources in use as long as possible, extracting maximum value (while in use) and effectively recycling these products and materials at the end of their working life. Such a model has significant potential for the secondary steel industry, in which an average of 160 million tons of steel is produced annually in more than 500 locations in the European Union alone. This industry is facing increasing cost and quality problems due to the variety of materials and the decreasing quality of steel scrap [1].

In the concept of Industry 4.0, the Internet of Things (IoT) shall be used for the development of so-called smart products. Industry 4.0 technologies, including the Internet of Things (IoT), artificial intelligence (AI) and big data analytic, present revolutionary opportunities to apply circular economy principles to steel production. By using these advanced technologies, the industry can transition to more sustainable practices. These technologies enable more precise control and optimization of process parameters, solving the complexity of the steel making process that has traditionally relied heavily on operator experience. For example, in electric arc furnaces, machine learning techniques have shown good results in achieving material and energy efficiency. In this way, it optimizes the use of resources, which play a key role in reducing the carbon footprint of steel production, aligning with global decarbonization efforts, creating a path to a more sustainable, efficient and economically viable steel industry [1-3].

Methods

For the calculation, real data were taken for melting in a furnace with a capacity of 60 tons of liquid steel with a transformer with a capacity of 60 MVA. The diameter of the metal bath (D) is 4100 mm, and the depth (H) is 920 mm. A typical D/H ratio is relatively small compared to conventional ratios of 4.8 to 6.2 and is associated with radiant heat, energy losses through water cooling, and effects on the intensity reaction between slag and steel. The electrodes are of the ultra high power type and are controlled automatically with a separate control system.

The total energy input consists of electrical and chemical energy, with about half going to the melting of waste material, and 25-30% going to gases and dust (Figure 1). Chemical energy is obtained from natural gas, through the reaction of oxygen with carbon and other exothermic reactions. The gas inside the furnace chamber consists mainly of carbon monoxide and carbon dioxide. After leaving the chamber, the carbon monoxide changes to carbon dioxide, releasing a significant amount of heat. This heat can be used to preheat the input material or to treat waste dust that is rich in elements such as zinc and lead.

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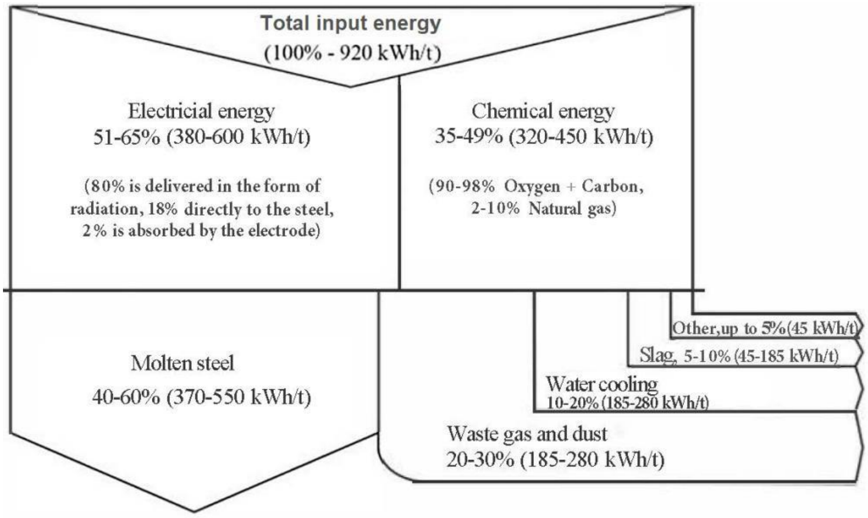

Figure 1. Energy and material flows in an electric arc furnace

The input material for the electric arc furnace is a mixture of steel scraps of different qualities, bulk densities and surface/volume ratios. The shape and composition of the waste affects the heat transfer inside the furnace and thus the total consumption of electricity. Waste is batched in baskets by placing waste of relatively high bulk density (eg. cast scrap) on the bottom to accelerate heat transfer from the hot bath to the waste. Waste of relatively low bulk density (eg. tin) is placed on top of the basket, so that this waste comes directly into contact with the electric arc, absorbs the radiant energy and melts quickly. After melting the waste, the liquid steel is discharged and leaves about 5-10% of the liquid metal from the total capacity of the furnace due to the easier melting of new waste, thus reducing the total energy consumption. The charging baskets are from 10 to 30 tons, the charging time per basket is about five minutes. Two to three baskets are batched. The time from pouring to pouring is about 50 minutes. A typical strategy for a single smelter is as follows: charging the scrap to the furnace, where the liquid metal from the previous smelting is left, melting, second charging, melting, third charging, melting, refining, temperature adjustment and reduction and pouring. The waste melting strategy also affects energy consumption, and the losses are most often related to work interruptions, which can occur due to various factors such as the preparation of the spout, refractory materials, problems with batching. Coke and lime are added as additional materials in the furnace, which affect the composition and foaming of the slag. Sparkling slag has multiple contributions to the melting process in an electric arc furnace, such as: control of oxidation and reduction of iron, carbon, impurities, protection of refractory material from electric arc radiation and improvement of energy transfer from electric arc to steel.

The data used for this example was collected over five years (from 2015 to 2020), with approximately 14,800 melts (inputs), with 42 process parameters monitored. Data quality is one of the basic criteria for improving the performance of machine learning models. The algorithm for quality improvement and data management is given in Figure 2.

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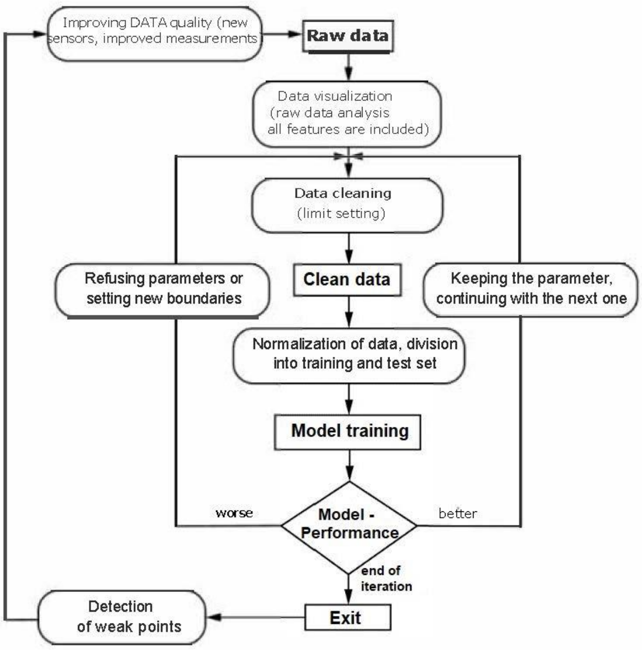

Figure 2. Algorithm for improving data quality and machine learning model performance

After the initially obtained performance of the model, according to the algorithm in Figure 2, the iteration procedure is repeated for further improvement: new limits are set or parameters that entered the model are discarded. If it turns out that better performance of the model is obtained, the examined parameter is saved with the set limits and moved to the next one. At the end of the iterations, 24 influential process parameters were selected for training the machine learning model, the training set contains 10521 and the test set 1169 inputs (melting).

The goal of the model is to predict the consumption of electricity per ton of steel produced, the consumption of manganese and silicon, the distribution of certain elements and impurities in steel (such as copper and tin) depending on the change of the selected process parameters. It is also possible to select other model prediction targets, such as arc furnace operating time or steel utilization (the percentage ratio of the mass of steel obtained to the metal batch). Since the objective depends on many interrelated parameters, PDP and SHAP have been used to visualize and find quantitative relationships between process parameters and model objectives [4].

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Results and discussion

Solving the optimization problem of the melting process in an electric arc furnace can generally be divided into simulation and optimization using physical-chemical models and using statistical models. Physical-chemical models rely on phenomena that are described by physical laws and chemical reactions that are well studied and clearly defined. However, the disadvantage of these models is the influence of various factors that occur in real conditions, so it is necessary to set numerous limitations, simplifications and assumptions. On the other hand, statistical models use data from real conditions, which makes it possible to avoid assumptions and simplifications in the extremely complex and dynamic conditions that occur when melting waste in electric arc furnaces. The main advantage of statistical models is the comprehensive analysis of all process parameters. The main drawback is the quality of the data used for these models. The quality of the data depends primarily on the accuracy and number of sensors used to measure the process parameter. In addition, in the literature statistical methods are said to be superficial and vague, because they do not take into account physical-chemical processes, so they are compared to a black box. However, for an engineer who knows the process well, by obtaining the correlation between individual parameters of the process using statistical methods, a deeper analysis can be obtained and the influence of individual parameters can be quantified.

The data management process begins with the analysis and visualization of raw data. In this way, they are identified, and by setting limits for each parameter, irregularities and deviations in the raw data are removed (Figure 1). Electricity consumption ranged from 320 to 550 kWh/t of produced steel. The RF and XGBoost methods were shown to have the best metrics on the training set when predicting electricity consumption. However, when the models are checked on the test set, SVM shows the best performance (Table 1).

Example of data display and parameter correlation after cleaning and setting limits on the raw data is given in Figure 3.

Table 1 Comparison of the results of different machine learning methods

Model	Metrics				
Trening	MAE	R^2	RMSE	MAX	MAPE
SVM – rbf	6,17	0,904	8,37	61,0	0,0150
RF	2,51	0,984	3,39	33,5	0,0061
XGBoost	1,89	0,991	2,55	13,8	0,0046
ANN	5,73	0,921	7,60	56,3	0,0152
Test	MAE	R^2	RMSE	MAX	MAPE
SVM – rbf	6,37	0,901	8,36	48,2	0,0155
RF	6,83	0,888	8,94	39,3	0,0165
XGBoost	6,63	0,894	8,64	42,0	0,0161
ANN	6,62	0,897	8,60	46,4	0,0160

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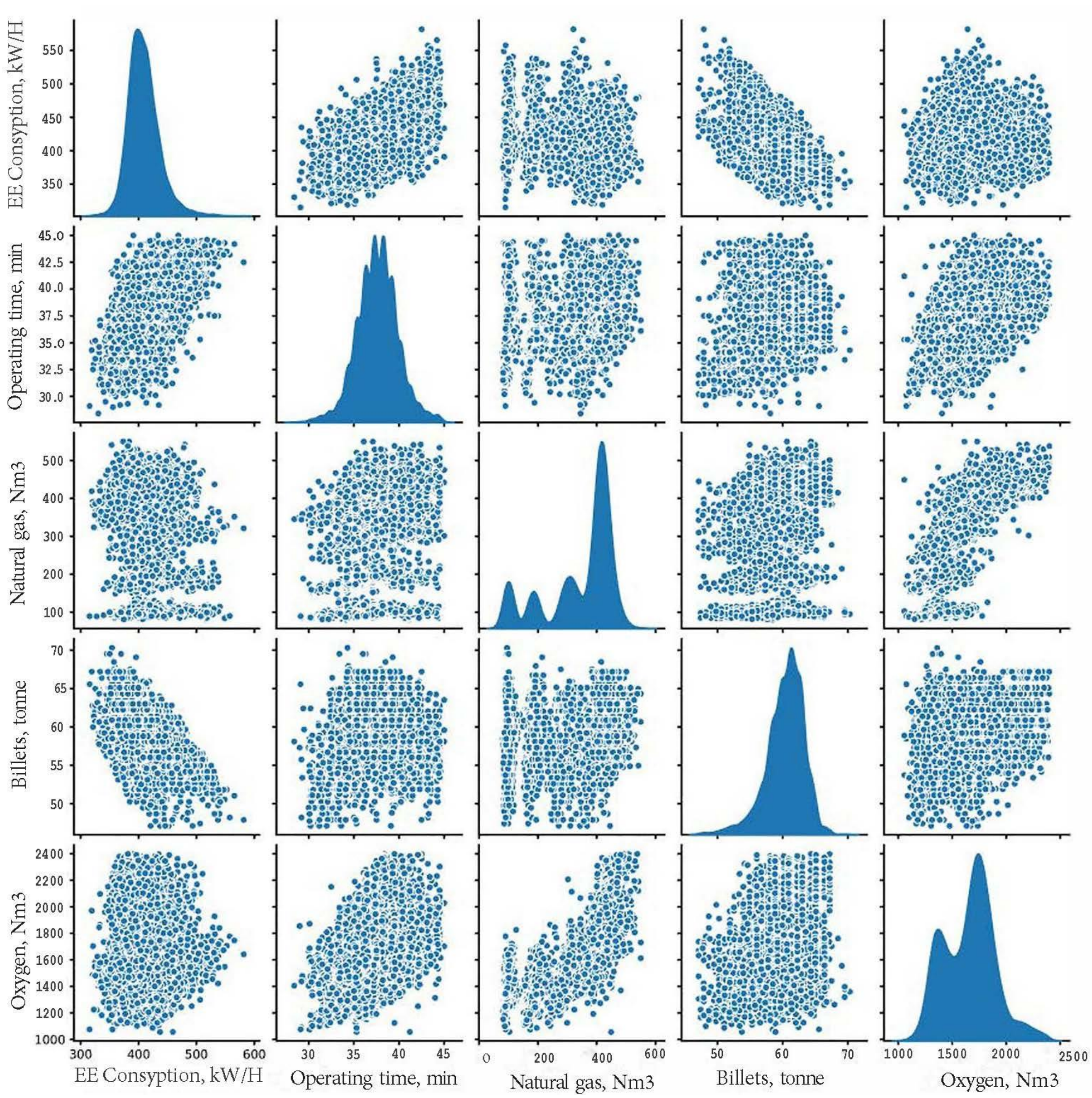

Figure 3. Example of data display and parameter correlation after cleaning and setting limits on the raw data

The integration of predictive machine learning methods in electric arc furnaces is an example of the transition from traditional steel making methods to intelligent, data-driven operations. By enabling real-time adjustment of process parameters based on predictive analytic, these models significantly increase energy efficiency. For example, the rational use of input materials and fine-tuning of operational parameters, based on predictive models, not only reduces energy consumption but also maintains the quality of produced steel. Such precision in the management of electricity consumption directly contributes to reducing the environmental footprint of the steel industry, aligning with the principles of the circular economy of minimizing waste and environmental impact.

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In the steel making process, especially in electric arc furnaces (EAF), managing material degradation is as important as saving electricity. The transfer of elements, such as manganese, to the slag during the steel production process is an example of the degradation of an important and valuable raw material (ferromanganese is used for alloying and deoxidation of steel). Insights from the machine learning analysis, in Figure 4, show that the use of coke, ferro-silicon-manganese (FeSiMn), as well as elements of iron (Fe) and silicon (Si) has a significant effect on the transition of Mn in the slag, as well as as expected. On the other hand, the influence of zirconium (Zr), whose contribution to the transition of manganese is less studied in the literature, is also significant. These results indicate the complex interaction of various parameters in the steel making process, improving our understanding of such complex processes.

The presence and behavior of valuable elements such as Mn and Si are crucial to maintaining the quality and integrity of the final steel product. In contrast, the increasing presence of impurities such as copper (Cu) and tin (Sn) in the recycling chain presents a significant challenge to the circular economy model in steel production. These elements, when present in higher concentrations, can degrade the mechanical properties of steel, thereby reducing its quality and utility value. This trend of accumulation of impurities during successive recycling cycles threatens the sustainability and efficiency achieved by the circular economy.

Solving these challenges requires a deeper approach that goes beyond the scope of this work, with the aim of balancing between retaining valuable elements in steel (Mn, Si) with the simultaneous removal of harmful impurities (Cu, Sn).

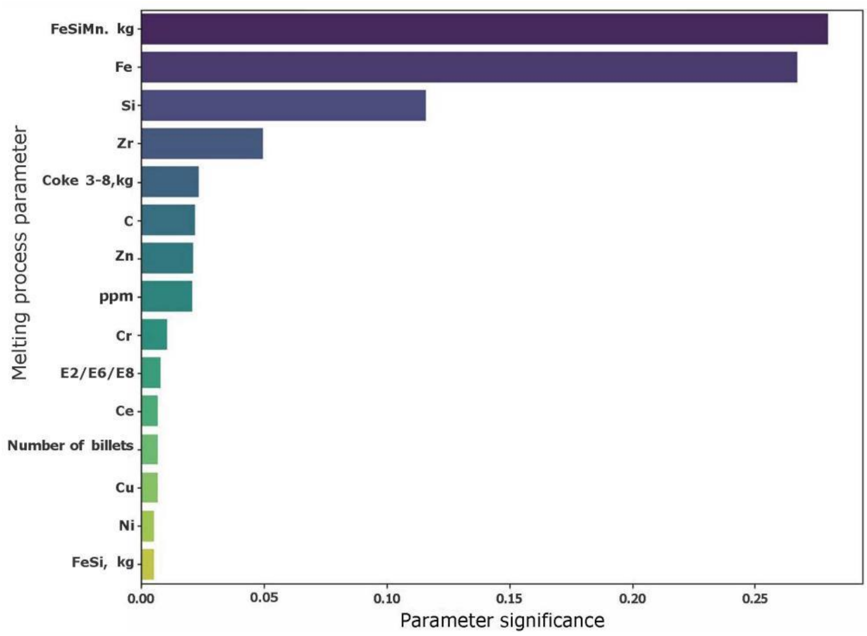

Figure 4. Process parameters in the electric arc furnace that affect the transition of manganese to slag

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Conclusion

The concept of a smart city must take into account the industries located in or near the cities, that is why the concept of smart metallurgy is very important.

The application of machine learning in the optimization of electric arc furnace processes, especially within the principles of Industry 4.0, represents a significant advance in sustainable steel production. From the results presented in this paper, the complex relationship between the parameters of the steel production process and their influence on the consumption of electricity and on the transition of elements such as manganese and silicon to slag has been demonstrated. By analyzing and predicting the behavior of different parameters in different process conditions, it is possible to optimize the simultaneous use of materials and the removal of impurities.

This approach is in line with the objectives of the circular economy, but also ensures the production of quality steel, thus maintaining the value of the material in the production cycle. As the steel industry continues to evolve under the influence of Industry 4.0 technologies, analytic methods of processing process data are becoming increasingly important in achieving environmental sustainability and economic efficiency. Technologies of the Industry 4.0 create fundamentally new infrastructure of the "smart city".

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