A New On-Line Scrap Quality Prediction System for Improved Raw Material Optimization During EAF Steelmaking





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Introduction

The Importance of Scrap Quality Prediction and Raw Material Optimization in EAF Steelmaking

Steel scrap is the most important input material for the electric arc furnace (EAF) route, and the availability of well-sorted and clean scrap is becoming increasingly limited. Today, 55% of the world's available steel scrap (approximately 880 million tons) is end-of-life scrap, the composition of which is highly uncertain. This is expected to increase to 65% by 2050.[1] In Europe, more than 60% of the available scrap already contains more than 0.3% of unwanted elements that cannot be removed by oxidation in the EAF process.[2] Such unwanted elements can only be diluted by primary iron sources such as direct reduced iron (DRI)/hot briquetted iron (HBI) or high-quality and expensive scrap.

Therefore, it is critical to either physically separate unwanted scrap fractions as much as possible, or to have accurate on-site knowledge of the exact properties of each type of scrap. These properties are the actual chemical composition, the metallic yield and the specific energy consumption of each individual scrap type in the scrap mix to be charged into the furnace. Only with precise knowledge of these scrap properties can a well-founded and valid optimization of the raw material input be carried out to ensure a sustainably and efficiently operated EAF process.

In addition to predicting the properties of the next melt before the scrap is melted, an accurate understanding of how scrap composition, yield and specific energy change over time, combined with an advanced material optimization software, could provide answers to all relevant questions along the raw material value chain:

- Supplier Evaluation: Are my suppliers delivering scrap according to my purchasing specification?
- Scrap Characterization: What are the current properties of my raw materials?
- Load Instruction: How should I charge my furnace considering the metallurgical processes?
- Heat Preview: What are the expected heat properties considering the actual charge?
- Overall Cost Reduction: How can I reduce the overall costs and CO_2 emissions?

Current Challenges and Limitations of Existing Systems

As of today, no technology has sufficiently addressed the requirement of properly determining the different properties of scrap such as the chemical composition, specific energy and metallic yield. Current technologies can be categorized and distinguished based on how they tackle the problem from several perspectives:

- Technology that physically separates scrap (e.g., metallic/nonmetallic fractions).
- Technology that performs on-line chemical analysis of the scrap.
- Technology based on computer vision models to identify different materials on a scrap pile or the conveyor belt of a shredder.
- Technology based on regression or data-driven models.

The major challenges and limitations in characterizing different scrap properties using physical analysis methods are mainly due to the heterogeneity of the scrap, which varies greatly both within a single scrap delivery and also between different deliveries. In addition, these methods are very time-consuming and expensive and are therefore only performed on a random basis. Technologies based on camera systems and computer vision are popular, but the challenges and limitations are in the quality and quantity of the training data and the quality of the live images (dust, sunlight, reflections, etc.). Finally, regression models[3–5] as well as data-driven artificial intelligence (AI) models are used to predict some characteristics of the scrap. These methods have great potential and are constantly being improved. However, it should be noted that very sophisticated AI architectures and techniques are often required and that there is a lack of standardization, which is essential to improve data compatibility and model interoperability.

Introduction of the Proposed On-Line Scrap Quality Prediction System

For any optimization process, including the charge optimization of the EAF process, a sound data basis builds the foundation for good optimization results. A common practice for most steelmakers is to work with predefined scrap compositions and yield figures, which are used for creating standard charging recipes for each steel grade. To account for unforeseen changes in scrap composition, these recipes often include a certain safety buffer to remain within the specification limits of the respective steel grade. For example, if the grade specification allows a maximum copper content of 0.3 wt. % Cu, the charge recipe might be designed for 0.2 wt. % Cu to account for the compositional uncertainty of the scrap. This, however, requires the use of cleaner scrap, which is typically more expensive than scrap with a higher copper content. In a reality of constantly changing prices for raw materials and electric energy, together with increasing uncertainty of scrap composition and its availability, it is necessary to rethink the practice of working with standard charging practices and raw material blends and be aware of the impact these parameters have on cost structure and quality assurance.

This article introduces a new tool for determining the raw material characteristics (chemical composition, metallic yield and specific energy consumption) in real time to enable steelmakers to enter a new era of optimizing the raw material usage during steelmaking. By combining powerful AI techniques with fundamental metallurgical modeling in a hybrid closed-loop approach, a new system has been developed that allows not only the scrap specific determination of tramp elements such as Cu or Sn, but also elements that are oxidized during the oxygen blowing process to enable a full-scale optimization potential. The results of this characterization step can be used to guide operators in their raw material selection by showing the real-time properties of each scrap in the scrap yard or can be integrated with any optimization software to calculate the ideal raw material utilization along the complete production route from melting to casting.

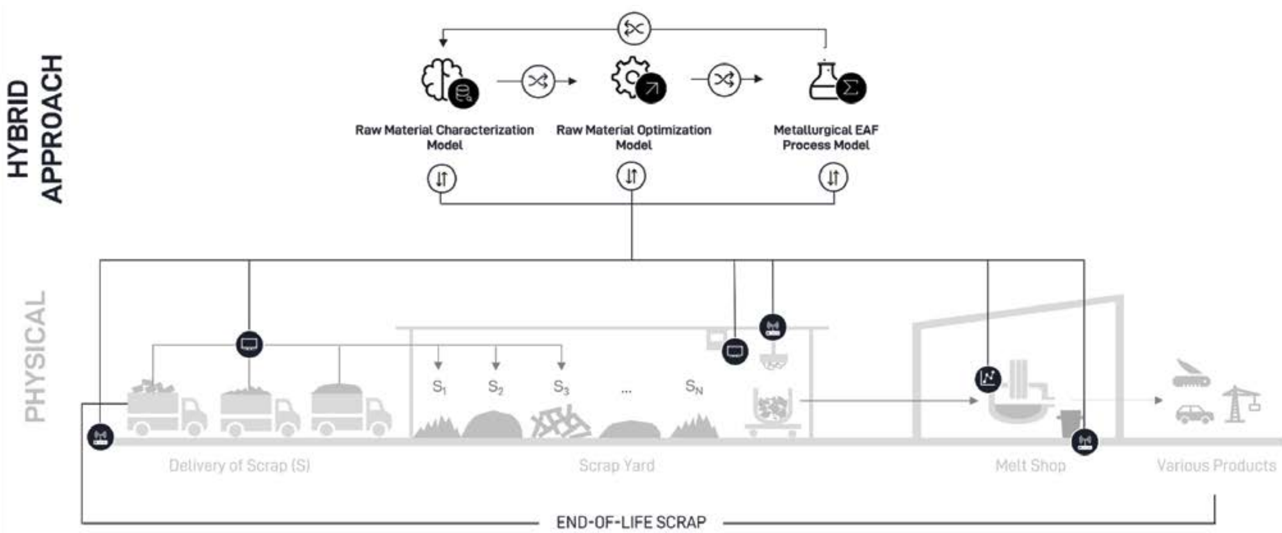
Methodology and Model Development

Description of the Model and Development Approach

The lower part of Fig. 1 shows in a simplified way the real processes that need to be considered in the context of a comprehensive model. This includes the entire ordering and purchasing process, the delivery of different scrap types from different suppliers, the optimized charging of the furnace, and finally the melting process in the EAF including the relevant metallurgical work. The upper part of the figure schematically shows the three different models that have been combined in the present work in the form of a hybrid approach. Before describing the individual models and their development in detail, the principles of hybrid modeling are described briefly. According to Kurz et al.,[6] hybrid models combine first principles-based models with data-based models into a joint architecture, supporting enhanced model qualities such as robustness and explainability. Data-based modeling analyzes and models trends in data using statistical and machine learning methods. Neural networks, decision trees, regression models and other data-driven algorithms are a few examples. Without explicit knowledge of the underlying physical processes, data-based models create predictions or judgments by learning from the patterns and relationships found in the available data. First-principles models are based on fundamental principles and laws that describe the underlying physics or dynamics of a system. They are based on theoretical knowledge and frequently include mathematical equations that show how various variables relate to one another. Laws of physics, chemistry or engineering are examples of scientific concepts that constitute the foundation of first-principles models. The hybrid model combines the strengths of both

Figure 1

Schematic illustration of the big picture of raw material optimization based on a hybrid approach that combines an artificial intelligence (AI)-based predictive model, a mathematical optimization model and a metallurgical model of the electric arc furnace (EAF).



approaches. The hybrid model seeks to improve accuracy and resilience by combining data-driven models, which can capture complex patterns and nuances seen in real-world data, with first-principles models, which give a solid theoretical framework and help in the incorporation of domain knowledge. This integration is especially beneficial when dealing with complex systems, where a purely data-driven or first-principles approach may have constraints.

For a comprehensive optimization of the scrap input to the EAF process, three models are needed:

- Raw Material Characterization Model.
- Raw Material Optimization Model.
- EAF Process Model.

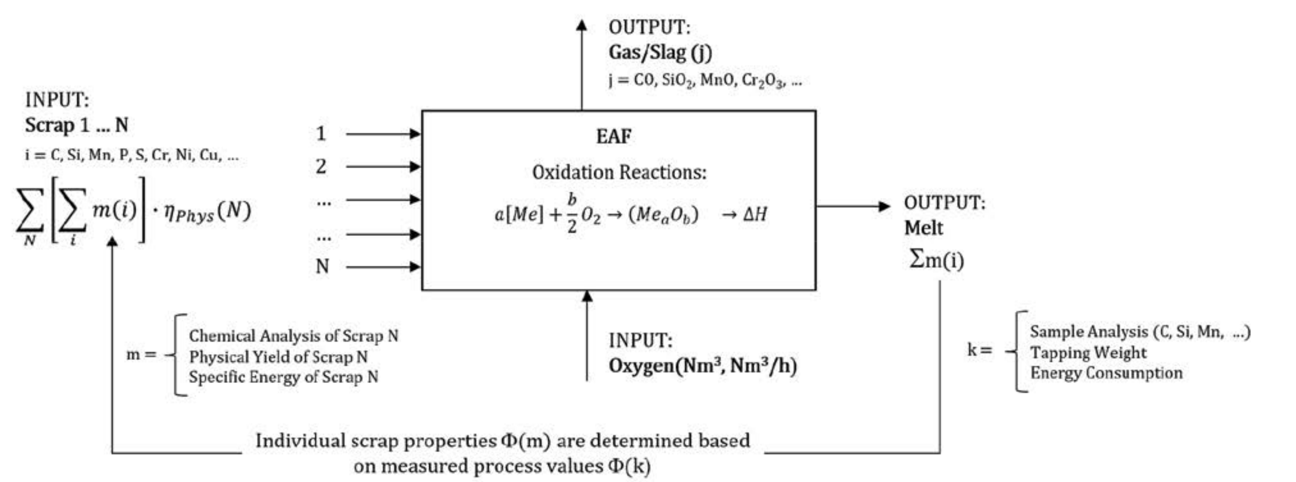
The optimization is performed by the Raw Material Optimization model (2) using a holistic optimization algorithm that considers all metallurgical processing units (EAF, ladle furnace (LF), vacuum degasser (VD)/vacuum oxygen decarburization (VOD), argon oxygen decarburization (AOD), etc.), all relevant process variables (melt and slag chemistry, chemical and electrical energy, CO_2 emissions, metallurgical reactions, etc.), boundary conditions and constraints, the input data, and the desired output. By combining this approach with the cost for materials, energy and CO_2, the Raw Material Optimization Model determines the most efficient raw material mix. Since a detailed description of this model with practical examples has already been published[7] and the focus of this article is on the determination of scrap properties, this part of the hybrid model will not be discussed in detail.

In order to better understand the need for hybrid modeling to determine the most important scrap properties, the basic problem is schematically illustrated in Fig. 2 and can be explained as follows: In simple terms, there is only one equation, but there are many unknown variables as there are different types of scrap (S1, S2, etc.) charged into the EAF. Even if only one type of scrap is used, it is only possible to determine the chemical analysis of the scrap based on the measured chemical composition of the melt if the oxidized quantity is known. Since several different types of scrap are used, a unique mathematical solution to the problem is impossible. For this reason, and because metallurgical reactions almost always occur and have a significant impact on the mass balance, a hybrid approach combining data-based and fundamental models is the best choice.

Therefore, a data-based scrap property determination model (the Raw Material Characterization Model) has been developed that calculates the scrap-specific composition, metallic yield, and specific energy based on the measured melt pool composition and the information on the charged scrap type and its mass. The data-based model is extended with a metallurgical model to account for losses due to oxidation reactions (chemical yield). This metallurgical model calculates the number of oxidized elements and their energy input (chemical energy) based on the amount of oxygen injected. This model approach can be used to determine not only the chemical analysis of the scrap, but also the specific electrical energy required to melt the scrap. In addition, by considering the

Figure 2

Simplified mathematical representation of the situation to be modeled.



chemical oxidation reactions, a distinction can be made between chemical and physical yields.

The approach presented here differs significantly from conventional data-based models, which usually work only on the basis of historical data and therefore cannot achieve the previously mentioned advantages.

Data Collection Process and Process-Relevant Information

To enable real-time capability, the model was developed with all interfaces necessary to interact with the production environment. It is important to note that no additional cameras, hardware or sensors are required. Input data for the model are the data typically available from process management systems, such as the furnace charge mix (i.e., scrap blend), melt chemistry samples and other measured production data. After the completion of each heat, these data are received by the model, checked for plausibility and completeness, and the according scrap properties F(n) are calculated. In the present article, production data from a 60-ton EAF are used to demonstrate the model capabilities, including:

- Furnace charge mix [kg].
- Melt chemistry samples [wt. %].
- Electric energy consumption [kWh].
- Injected oxygen [Nm^3].
- Oxygen consumers (natural gas [Nm^3], carbon [kg], etc.).
- Tapping weight [kg].

The furnace operates with average injection rates of 4 kg/ton carbon, 2.3 Nm^3/ton natural gas, 97 Nm^3/ton oxygen and consumes approximately 400 kWh/ton electrical energy. The furnace operations also involve a hot heel practice, which is also included in the model. After calculation of the current scrap characteristics after each heat, a forecast is made to predict the properties of the next heat based on the last known scrap characteristics of the previous calculation. This enables the model to be constantly self-learning and adjusting the respective scrap characteristics in real time, allowing the evaluation of the change of the individual scrap characteristics as a function of time.

Results and Discussion

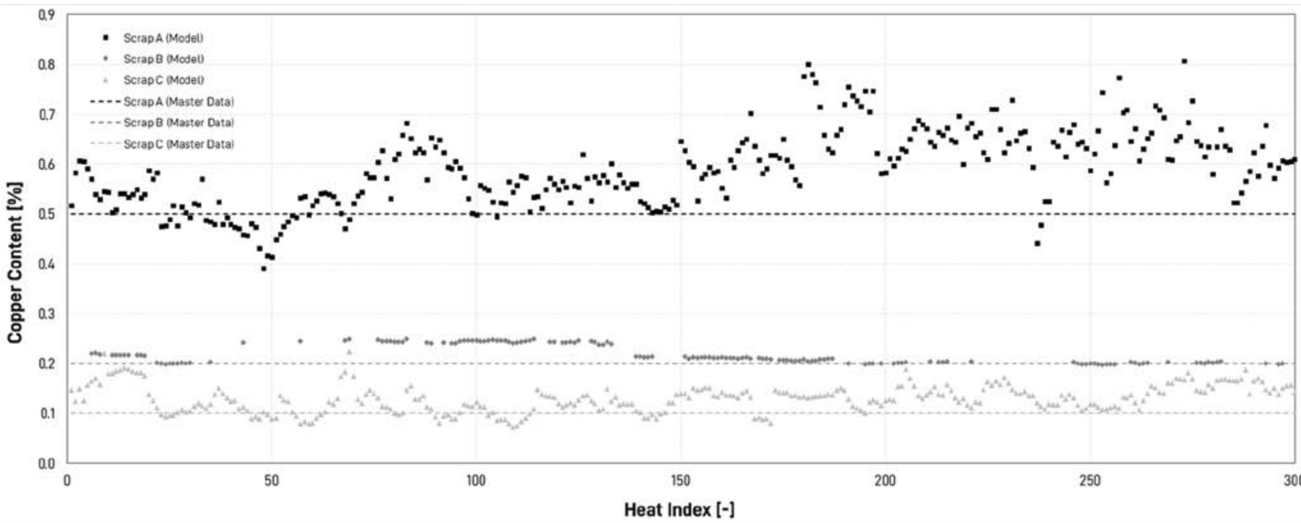
The calculation results obtained with the hybrid model described in the previous section are presented and discussed in this section. As mentioned earlier, the three main properties of scrap can be calculated using the developed model. These are the chemical composition, the metallic yield and the specific electrical energy. All of these parameters are important for a successful and proper optimization of the raw material utilization during steelmaking. The latter is particularly important for steelmakers, where material and electricity costs per kilogram of steel are in the same range, and even more so if electricity costs are very high.

Determination of the Scrap Composition

First, using Cu as an example, the findings of calculations of the chemical composition of three commonly utilized scrap types (A, B and C) are addressed. Copper does not oxidize during oxygen blowing, making it easier to determine the Cu content of the individual scrap types and less

Figure 3

Copper content of different scrap types over a duration of 300 heats.



dependent on whether a metallurgical model is included. However, because the benefits of the developed scrap analysis can be presented very clearly, it will be utilized as an example in the following. Furthermore, the inability to accurately determine the Cu content of scrap can result in significant quality issues and financial losses. This can clearly be seen in Fig. 3. The figure shows the results of 300 heats. The solid lines represent the Cu value of the individual scrap types that are stored in the master data management and was previously used by the operators for the charge mix calculations. This value is 0.5 wt. % for Scrap A, 0.2 wt. % for Scrap B, and 0.1 wt. % for Scrap C.

The dots represent the calculated Cu values for each scrap for each heat. It is immediately evident that the scrap with the highest Cu content (Scrap A) has the largest deviations/fluctuations from the master data value of 0.5 wt. %. At a heat index of >200, the prediction value is almost 0.2 wt. % higher than the master data value. For Scrap B, the master data value and the predicted value are almost at the same level of 0.2 wt. % Cu. For Scrap C, the model shows a small variation over all 300 heats in the range of about ±0.1 wt. %, with the predicted values tending to be higher than the master data value. Before discussing the implications of these results, the reliability of the calculations should be demonstrated.

Diagram A of Fig. 4 shows the measured versus the calculated Cu content of the melt for all heats. The calculation is based on constant master data values of the Cu content of each scrap type that is charged. It is easy to see that the calculated values have their mathematical limit at 0.5 wt. % Cu. However, Cu contents of up to 0.7 wt. % are measured in the melt, which already indicates that the constant master data values only reflect reality to a limited extent. This is certainly nothing new and steelmakers have learned to deal with it, mainly through the introduction of much smaller Cu limits (allowable grade-specific maximums) as a safety buffer. It is also evident that for measured Cu contents <0.3 wt. %, the calculated values are in good agreement. This can be explained by the small variations of the Cu content in clean and well-sorted scrap.

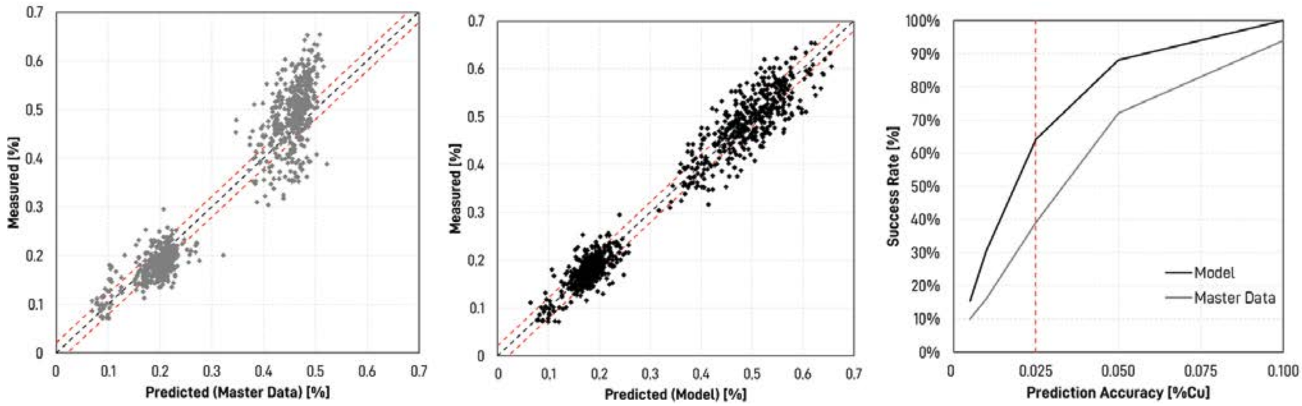
Diagram B of Fig. 4 shows the same situation, but the calculation is based on the values predicted by the hybrid model (see Fig. 3). Especially for higher measured Cu values, the hybrid model leads to significantly better predictions compared to the master data. Diagram C summarizes what can be seen at first glance from Charts A and B. In this graph, the prediction accuracy (absolute ± deviation from the measured value) is plotted on the x-axis, while the y-axis shows how many of the predicted values are within the corresponding ± deviation. In the example shown, the calculations based on the master data can only predict 40% of the heats with an accuracy of 0.025 wt. % Cu (the ±0.025 wt. % deviation is also shown in diagrams A and B as red dashed lines). The developed model leads to a success rate of 65% (i.e., 65% of all calculated heats are within ±0.025 wt. % Cu). Furthermore, the model can accurately predict approximately 90% of all heats with an accuracy of ±0.05 wt. % Cu. This is a significant improvement and demonstrates the potential of the model.

Determination of the Metallic Yield

As already shown in Fig. 2, a distinction is made between physical and chemical yield. The physical yield is a scrap-specific parameter and indicates the ratio of metallic to

Figure 4

Predicted vs. measured copper content of the melt using master data (a) and model results (b) as well as comparison of the prediction accuracy using the predicted model values and the master data values (c).



nonmetallic components. This value is of great importance for the overall economic evaluation of the scrap in the context of purchasing, as the usually unavoidable amount of dust, dirt, oxides, etc., can be quantified.

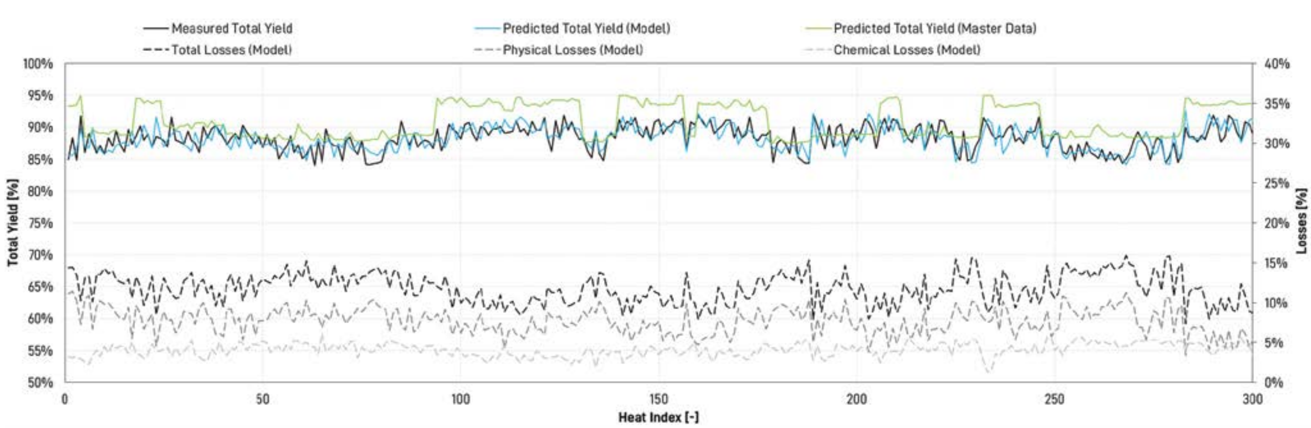
The chemical yield refers to the losses due to the EAF process and is quantified by the oxidation reactions. The integrated and fundamental metallurgical model is used for this purpose. An oxygen blowing model is used that calculates the oxygen distribution based on Gibbs energies. The model assumes that the oxygen injected into the metal bath reacts simultaneously with the elements. To distribute the amount of injected oxygen over the elements, the Gibbs free energy is calculated and proportionalized. This ratio is then used to distribute the oxygen to the individual oxidation reactions. To account for the reaction rates controlled by the transfer mechanisms, the simplified Fick's first law is introduced into the model.

In summary, it is important to distinguish between a scrap-specific physical yield and a process-specific chemical yield. These two contributions together then give an overall yield. However, this differentiation is typically not being made for master data values. Fig. 5 shows the results of the model calculations, which are described in the following.

The lower curves should be considered first. These are the determined chemical, physical and total losses with the corresponding values on the right y-axis. It can be seen that the chemical losses, i.e., the proportion that has been oxidized, represents about 5%. The variation of the physical losses is much greater than the chemical losses, ranging from 6 to 10%, resulting in total losses

Figure 5

Comparison of the measured total yield with the predicted yield using master data and model results.



between 10 and 15%. This corresponds to a typical yield of 85–90%, as shown in the upper part of the graph with the corresponding values on the left y-axis. These values agree reasonably well with the actual measured total yield. It is important to note that the exact hot heel amount cannot be determined accurately for each heat, which introduces a certain error in the determination of the physical yield. For the total yield calculation using the master data values for each scrap type, there are areas where the master data predicts higher yields that measured, e.g., heat index 120–160 or 170–220. In these areas, scrap types with high master data yields were used in the charge mix, indicating that the stored master data value cannot be correct.

Determination of the Specific Melting Energy

The EAF process uses several sources of energy to melt the scrap. Most of the energy comes in the form of electrical energy, with additional chemical energy contributions from the burners, carbon carriers and oxidation reactions. Typical values are 380–400 kWh/ton for the so-called useful energy (i.e., the energy contained in the molten steel), which represents approximately 45–60% of the total energy input.[8]

The energy required for melting is a thermodynamic quantity and can be determined from the phase-specific free energies (Gibbs energy) as a function of temperature. Iron-based thermodynamic data for these calculations are taken from literature.[9,10] Considering the chemical composition of the scrap, calculated values are between 350 and 360 kWh/ton. These values are roughly 10% smaller than the above-mentioned useful energy. This difference can be explained by the fact that with scrap (as already mentioned in the context of yield) not only the pure metallic part has to be heated and melted, but also oxides, dust, etc. Therefore, a scrap-specific energy factor was introduced into the model to account for this situation. As described previously for chemical composition and yield, this factor (and thus the scrap specific energy required for melting) can be determined using the hybrid model.

The calculated electrical energy requirement is compared with the actual energy consumed in Fig. 6. Diagram A shows the measured versus the calculated electric energy consumption for all heats. Diagram B reveals that 70% of the calculated heats using the model are within ± 20 kWh/ton.

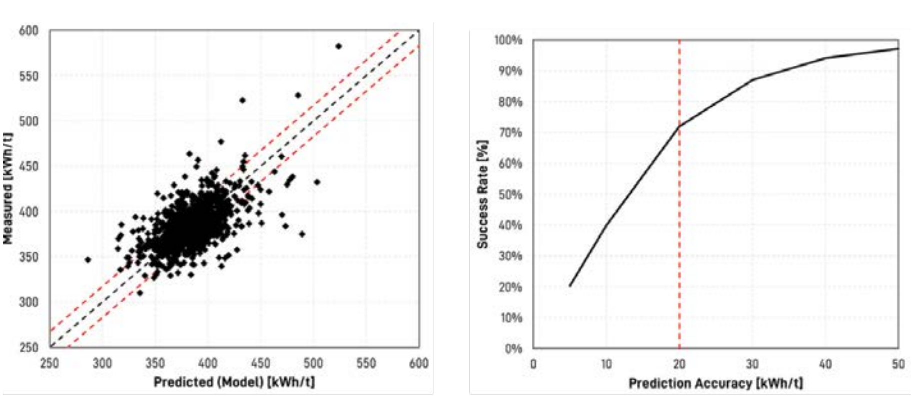
Benefits and Implications

Having information about how the properties of each individual scrap in the scrap yard change over time has substantial impact on various areas of steelmaking. For example, the information contained in Fig. 3 allows conclusions to be drawn about the risk of producing out-of-specification heats when using certain scrap types. In this figure, scrap A would be categorized as a raw material with high compositional uncertainty, while scrap B can be considered as a material with high compositional stability. Combining this time-resolved data with the timing of scrap supply provides valuable information that can be used in a supplier evaluation process to check whether the delivered scrap quality is in conformity with the purchase specification. In case of nonconformities, this information can provide negotiation power for the raw material purchasing department.

Fig. 7 shows a comparison of various charge mix recipes for a melt with max. 0.3 wt. % copper for different scenarios of steelmaking. Scenario a represents the standard charge mix for a defined steel grade based on predefined master data for each scrap type. This is the standard operating practice of most steelmakers. To account for the lack of exact knowledge of scrap properties, such standard charge mixes include a certain safety buffer to stay within the desired specification limits of the respective steel grade. This, however, means that, for example, in the case of copper content, more clean scrap with low copper content is charged than is required, acting as a buffer if the dirty scrap contains more copper than expected. This, in turn, leads to higher material cost, as clean scrap is usually more expensive than scrap types with higher content of trace elements.

Figure 6

Predicted vs. measured specific energy consumption using model results.



The right chart of Fig. 7 shows the resulting costs for the different scenarios (material and energy costs). The costs resulting from the standard recipe using master data amount to EUR382/ton. The charge mixes of all other scenarios b–f were calculated using the Raw Material Optimization Model. This ensures that no matter how the scrap changes in properties from delivery to delivery, the most cost-effective charge mix is used.

Scenario b is based on the same master data of the individual scrap types and includes a safety buffer to remain below the specification limits but is the result of a cost-optimized charge calculation, considering not only the chemistry of the scrap but also raw material and energy costs. The resulting cost savings are significant and amount to EUR13/ton. These results have been achieved by using a higher proportion of the cheaper scrap A. However, as mentioned earlier, this scrap is a material with high compositional uncertainty. In other words, this charge mix (although calculated with a safety buffer) can only be used if the Cu content is known precisely and with certainty.

In scenarios b–f, the real-time scrap properties from the raw material characterization model are used (instead of the master data). Scenario b serves as the reference scenario for all further comparisons. Scenarios c–f are based on varying copper content and metallic yield of scrap A according to the determined min and max values (see Figs. 3 and 5).

From scenario c, it is evident that when scrap A only contains 0.4 wt. % copper instead of 0.5 wt. % as defined in the master data, a modification of the charge mix yields a cost reduction of –EUR5/ton compared to scenario b. This is clear because even more of the cheapest scrap A can be used. The proportion of this scrap has now increased to 68%.

On the contrary, scenario d shows that when the copper content of scrap A increases to 0.8 wt. %, the charge recipe must be adjusted to avoid copper becoming out of specification. In this case, more clean scrap (i.e., scrap D) must be included in the charge mix to dilute the high amount of copper coming from scrap A.

Scenarios e and f show the same results for changing metallic yield of scrap A.

This underlines that in order to improve raw material utilization in steelmaking, a combined effort of raw material characterization and charge mix optimization is required to achieve a significant quality and cost advantage.

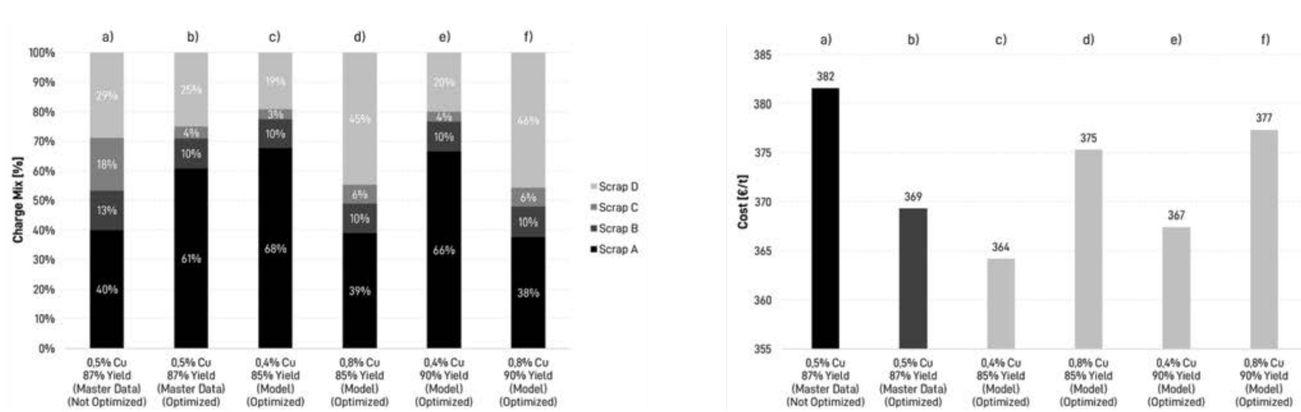
Conclusion

Scrap quality determination and raw material optimization are critical to the EAF-based steelmaking process. With 55% of the world's available scrap being end-of-life scrap, the scrap properties and the reliability of these properties will play an increasingly important role in maintaining a well-controlled production process. To optimize the use of raw materials, it is essential to have accurate knowledge of the chemical composition, metallic yield and specific energy consumption of each scrap type. Advanced material optimization software can provide answers to questions along the raw material value chain, such as supplier evaluation, scrap characterization, charging instructions, heat prediction and overall cost reduction. Current technologies face challenges in determining scrap properties due to heterogeneity, time and cost. Thus, a new on-line scrap quality prediction system was developed and introduced in the present work.

It was pointed out that a comprehensive model must take into account the reality of raw material procurement, scrap supply, charge mix preparation and the smelting

Figure 7

Impact of different scrap properties on the charge mix (left) and the resulting change in costs (right).



process. To reflect real-world conditions and operations, three models were combined in a hybrid modeling approach. The hybrid model combines the strengths of each approach and helps to handle complex systems. It calculates scrap-specific composition, metallic yield, and specific energy based on the measured melt composition and charged scrap type and mass. It is augmented with a metallurgical model to account for losses due to oxidation reactions, thus providing a distinction between chemical and physical yield. This approach differs significantly from traditional data-based models that rely solely on historical data.

The results presented for the chemical composition show that the scrap with the highest Cu content (end-of-life scrap) has the largest deviations from the master data value. The predicted value is almost 0.2 wt. % higher than the master data value. The reliability of the calculations was demonstrated by comparing the measured and predicted values. Regarding metallic yield, the model distinguishes between chemical and physical losses. The physical yield is a scrap-specific parameter that indicates the ratio of metallic to nonmetallic components and is vital for the overall economic evaluation of the scrap. The chemical yield refers to the losses due to the oxygen blowing process, quantified by oxidation reactions. The results show that the chemical losses are about 5%, while the physical losses are between 6 and 10%, resulting in a typical total yield of 85–90%. In order to account for scrap-specific enthalpies, the model uses thermodynamically determined values (thus taking into account the influence of chemical composition) and incorporates a scrap-specific energy factor. Using the measured and predicted electrical energy, it has been shown that 70% of the calculated heats are within ±20 kWh/ton, which is significantly better than calculations based on scrap-specific energy values predicted by linear regression models.

In the Benefits and Implications section, it was clearly shown how advanced models in the software can be used to create optimized charge mixes, taking into account current conditions. This process ensures that the most cost-effective charge mix is used, regardless of how scrap properties change from delivery to delivery.

Summarizing, a new raw material characterization model has been demonstrated that can be combined with a charge mix optimization model to enable steelmakers a significantly improved cost- and quality-optimized production process, being able to quickly react to changing scrap properties and production conditions.

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