La Metallurgia Italiana
International Journal of the Italian Association for Metallurgy

AI-based monitoring of steel scrap properties for improved utilization in scrap based steelmaking

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Scrap-based steelmaking in the Electric Arc Furnace (EAF) allows to produce high quality steel grades on the basis of secondary raw materials. However, due to the fluctuation and quality impairment a tight control of the properties of steel scrap is required.

In the framework of the EU-funded project "Artificial Intelligence Technologies for European Process Industry digital transformation (s-X-AIPI)", an intelligent, AI-based system for continuous monitoring of scrap properties, directly coupled with a scrap mix optimisation for steel qualities to be produced was developed and implemented at the Sidenor Electric steelmaking plant in Basauri, Spain. The system is designed to enhance the selection process of the charge materials for EAF steelmaking through the integration of a self-managing AI framework. Predictive machine learning models are used to improve the reliability and precision for characterisation of scrap properties like metallic yield, composition and specific energy requirements from historical and most recent production data, to provide up-to-date information to a scrap mix optimization calculation. When significant deviations between predicted and actual liquid steel composition occur, an autonomous event handler initiates a retraining of both the prediction models and the scrap characterisation tools, to adjust the scrap property parameters, the predictive AI models, and/or the scrap mix optimizer constraints. Supported by a knowledge base, this AI framework ensures consistent and reliable scrap management under varying and changing process conditions.

KEYWORDS: ELECTRIC ARC FURNACE, SCRAP CHARACTERISATION, SCRAP MIX OPTIMISATION, PREDICTIVE AI MODELS, SUPERVISION;

INTRODUCTION

The Electric Arc Furnace (EAF) is the most important aggregate for steelmaking by recycling of secondary raw materials. The scrap used as charge material in the EAF is characterised by a high variability in metallic yield, chemical composition and melting behaviour. Although the European scrap types are standardized, it is difficult to ensure the quality aspects of some of the scrap types due to the heterogeneity of the materials origin. This is essential to be considered in context with online monitoring and control of the EAF process. Within the framework of the Horizon Europe project "Artificial Intelligence Technologies for European Process Industry digital transformation" (s-X-AIPI), for the steel use case at Sidenor Aceros Especiales in Spain a supervision and decision support tool was developed, which allows on the one hand side to characterize the properties of the different scrap types in use and monitor their evolution over time, and on the other hand to use this information

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for scrap mix optimization of the EAF process. The overall target of this supervision and decision support tool is to reliably achieve the quality specific target composition of liquid steel produced in the EAF process, and to facilitate as much as possible the use of low-quality scrap types for the production of high-quality steel grades. These aspects contribute to the aims of the Green Deal of the EU, reducing the CO2 emissions of steel production and strengthening at the same time the circular economy. Even more, the scrap use is expected to increase due to the decarbonization strategy of EU steelmaking, and thus more pressure is expected on the scrap markets. The development of this supervision and decision support tool was based on previous work of the authors in different areas:

A statistical modelling approach for characterising the properties of the steel scrap in use by means of a multi-linear regression was first developed within the project FLEXCHARGE [1], which was funded in the European RFCS steel research fund. Within this project, also the first version of a scrap mix optimization software based on a simplex optimization was developed. It is evident that a scrap mix optimization allows to reduce the EAF production costs and to improve steel quality and environmental impact at the same time [2, 3]. The developed solutions were based on Matlab stand-alone applications, whereas within the Horizon 2020 project REVaMP [4, 5] a user-friendly web-based solution with direct data base access was developed. Also, this multi-linear regression calculation approach was extended towards an on-line supervision of scrap properties, to detect significant deviations in expected scrap quality on a short-term basis [6, 7].

The multi-linear regression calculation provides accurate results for those elements which do not react with oxygen, as e.g., copper, nickel, tin and molybdenum. However, for prediction of those elements which react with oxygen, e.g., Phosphorus, Manganese or Chromium, a non-linear approach is required. A fully dynamic process model using all relevant cyclic and even-driven input data, is of course able to predict the analysis of liquid steel regarding all chemical elements. This has been proven in the above-mentioned project REVaMP, where for example the phosphorus content could be predicted with excellent accuracy [5]. However, the effort to implement such a dynamic model is rather high. In contrast to that, AI-based non-linear models offer a solution for prediction of the element concentrations which can be implemented with a significantly lower effort.

Within this paper, the results of the s-X-AIPI project work for the steel use case are presented with respect to an AI-based supervision and decision support tool, which combines classical solutions for scrap characterisation with AI-based prediction models to detect deviations in the scrap properties and to react on them by providing up-to-date information to the scrap mix optimization for the EAF.

MATERIAL AND METHODS

Characterisation of steel scrap

The main charge material at the electric steelmaking plant of Sidenor is steel scrap from three different origins:

- Post-consumer scrap: Old scrap from the demolition of the metal structure of industrial buildings, machinery, railway and naval scrap, used cars etc.;
- Pre-consumer scrap: Industrial or new scrap that is generated in processing industries that use steel as raw material in their manufacturing processes
- Internal recoveries: Scrap generated along the steelmaking process itself, in melt shops, rolling mills and other processes inside the Sidenor plant.

Pre-consumer scrap is usually very clean in its chemical composition and its variability is lower compared to post-consumer scrap. However, its use is limited due to the high price. Well managed, internal recoveries can also provide a stable chemical composition that can lead to huge savings on ferroalloys additions, however the available amounts are not very high. The critical scrap types are the post-consumer scraps with only roughly known composition and high variability in their properties. As a first step, multi-linear regressions were performed based on historical process data regarding used scrap types, achieved meltdown analysis and tap weight, with the objective of visualizing statistically the variability of the 11 scrap grades currently in use at Sidenor. In Figure 1 is shown as example the copper content of each of the 11 scrap types, visualized as a so-called violin diagram with average contents and their statistical distributions.

Especially the post-consumer scrap types D and E show high Cu contents with a large variability. Similar figures were created for all other important elements included in the scrap, as Mn, Cr, P, etc., as well as for the overall metallic yield.

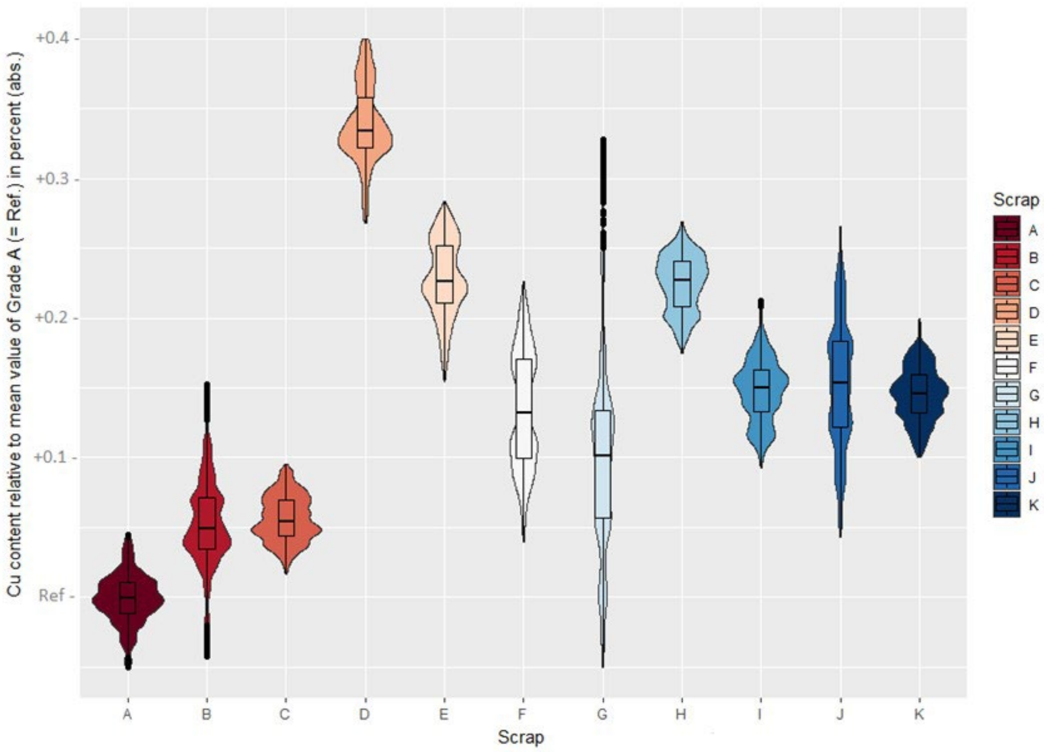


Fig.1 - Copper content variability by scrap type at Sidenor

These investigations of Sidenor were the basis for VDEh-Betriebsforschungsinstitut (BFI) to develop a web-based tool for easy and comfortable assessment of scrap properties (metallic yield, element composition, specific meltdown energy requirement) on the basis of a data base access for the above-mentioned process data. The calculation of the scrap properties is based on finding the optimal solution for the two overdetermined systems of linear by the least square method:

$$\text{Solve for } y_{sc}(i): \quad m_{st}(k) = \sum_i y_{sc}(i) \cdot m_{sc}(i,k) \tag{Eq.1}$$

$$\text{Solve for } w'_{sc}(j,i): \quad w_{st}(j,k) = \frac{1}{m_{st}(k)} \sum_i w'_{sc}(j,i) \cdot m_{sc}(i,k) \tag{Eq.2}$$

with:

$m_{st}(k)$	Mass of tapped steel of k-th heat
$y_{sc}(i)$	Metallic yield for the i-th scrap type
$m_{sc}(i,k)$	Charged mass of i-th scrap type in the k-th heat
$w_{st}(j,k)$	Measured concentration of element j in steel for the k-th heat
$w'_{sc}(j,i)$	Effective concentration of element j in the i-th scrap type

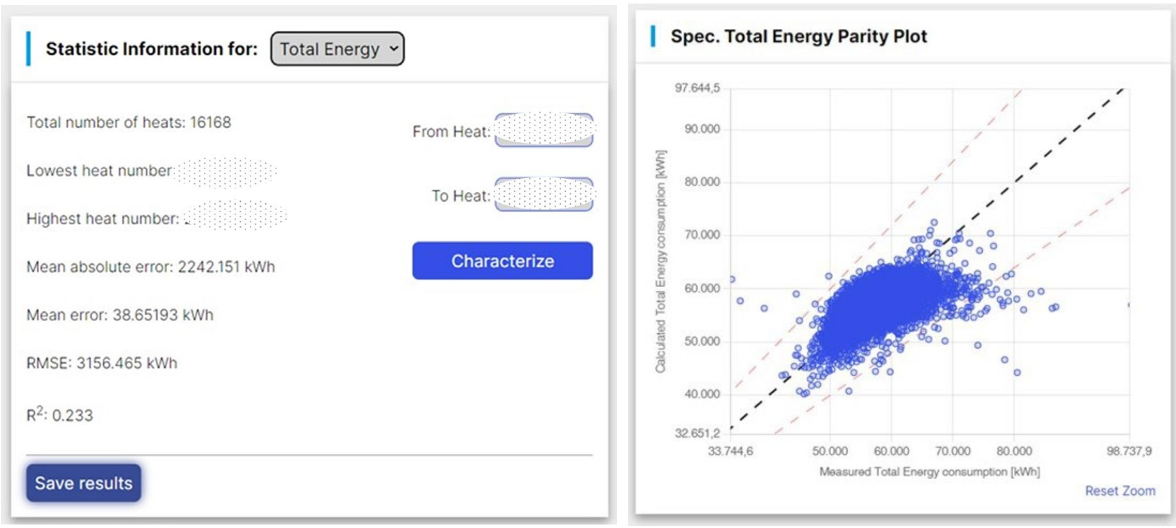
To rule out unreasonable solutions, appropriate constraints for metallic yield and element concentration are defined.
In order to predict the energy required in the EAF process for processing the individual heats, it is necessary to determine the specific meltdown energy demands for the individual scrap types. Assuming a linear dependence, the amount of energy required for any heat with given scrap masses is described by the following approach:

$$E_{\text{pred}}(k) = \sum_i q_{sc}(i) \cdot m_{sc}(i,k) \qquad \text{(Eq.3)}$$

with:

$E_{\text{pred}}(k)$	Energy input for k-th heat to to reach a fixed reference temperature of the melt
$q_{\text{sc}}(i)$	Meltdown energy demand for the i-th scrap type

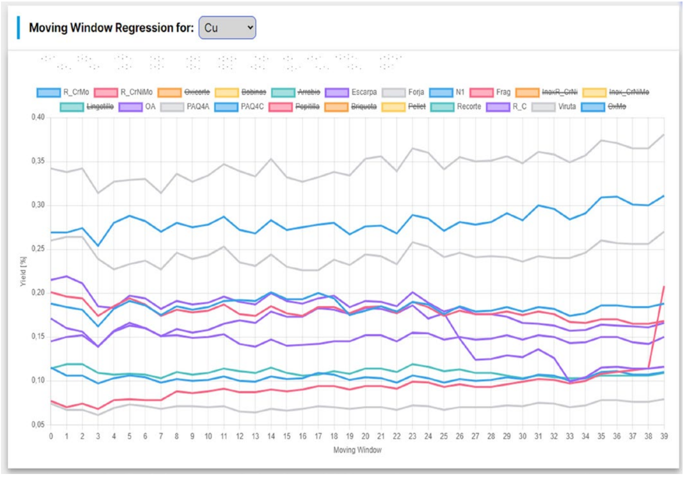
Figure 2 shows exemplarily the Graphical User Interface (GUI) for selection of the evaluation period via heat numbers. A multi-linear regression calculation determines the properties of the different scrap types with mean value and standard deviation. The accuracy of the characterisation is visualised by a graph plotting the predicted versus the measured respectively analysed values of tap weight, steel analysis and electrical energy consumption. The latter one is shown in the graph of Figure 2. Also, mean values and standard deviation of the prediction error and the R^2 correlation value are provided.



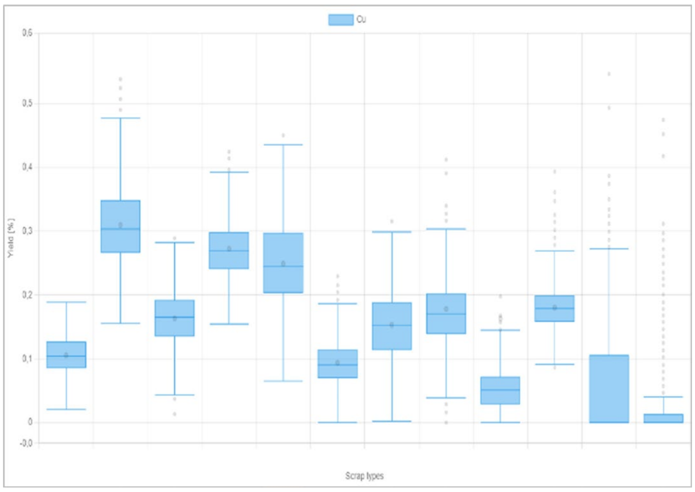
(a) (b)

Fig.2 - GUI for selection of heats to be evaluated and accuracy of prediction (a) and evaluation results for electrical energy consumption (b) of the web-based tool for scrap type characterisation

Furthermore, the timely evolution and the statistical distribution of the different scrap properties are determined and displayed by applying the multi-linear regression in moving window calculations with selectable window and step size. Exemplary results for the copper content of the scrap types are shown in Figure 3.



(a)

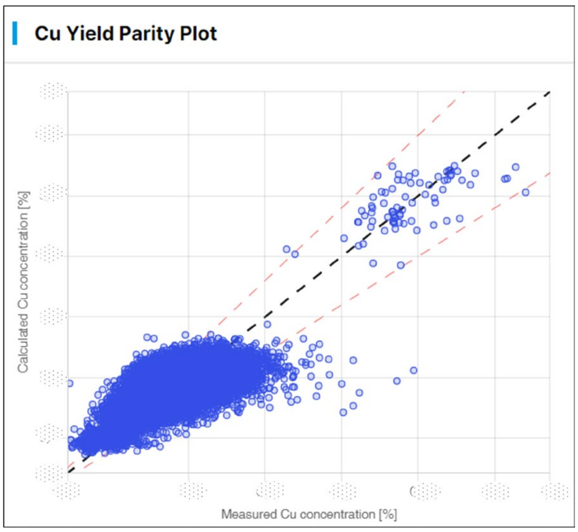


(b)

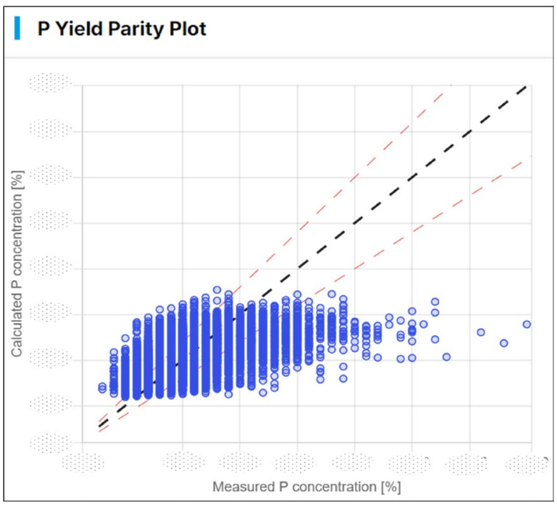
Fig.3 - GUI for displaying the timely evolution (a) and the statistical distribution (b) of the scrap types in use.

Prediction of element concentration in liquid steel

The multi-linear regression calculation provides accurate values for the scrap composition for those elements, which are more noble (Cu, Sn, Ni and Mo). For these elements, the correlation between predicted and analysed concentration in liquid steel is good, as can be seen in Figure 4a. However, for those elements which are partly oxidized during the EAF process (P, Mn, Cr), the correlation is rather weak (see Figure 4b). Thus, the values for scrap composition determined by the multi-linear regression are not reliable enough. Further process data besides the charged amounts of scrap like the amount of injected oxygen and carbon and the addition of lime have to be considered to achieve a better correlation.



(a)



(b)

Fig.4 - Prediction accuracy of the multi-linear regression for copper (a) and for phosphorus (b).

As for Sidenor especially the phosphorus content plays a critical role to produce high-quality steels, its prediction based on the scrap properties needs to be improved. To consider the effect of the metallurgical reactions of dephosphorisation, relevant operational process data had to be involved:

- amount of injected oxygen in relation to the injected carbon
- amount of lime addition via the 5th hole
- amount of injected lime

The surplus of injected oxygen creates FeO in the slag, which promotes in combination with lime additions the dephosphorisation reaction. To avoid the effort to implement a fully dynamic model for dephosphorisation within the EAF process, as it has been demonstrated in [5], a non-linear regression approach based on AI methods was selected. The best performance was achieved by a Random Forest Regression method. A Random Forest Regressor is an ensemble method that builds multiple decision trees and combines their predictions for higher accuracy and stability. It handles non-linear relationships, is robust to outliers, and provides feature importance scores to identify key variables [8]. This AI-based non-linear regression method has already been applied to evaluate the energy efficiency parameters of an Electric Arc Furnace [9].

As shown in Figure 5, by consideration of the above-mentioned additional process data the correlation coefficient R^2 can be improved significantly.

Only Scrap Data

	P
LinearRegression_r2	0.408563
LinearRegression_MAE	0.001736
LinearRegression_RMSE	0.002268
XGBRegressor_r2	0.422343
XGBRegressor_MAE	0.001712
XGBRegressor_RMSE	0.002241
RandomForestRegressor_r2	0.405781
RandomForestRegressor_MAE	0.001732
RandomForestRegressor_RMSE	0.002273

Scrap + Operational Data

	P
LinearRegression_r2	0.460546
LinearRegression_MAE	0.001636
LinearRegression_RMSE	0.002166
XGBRegressor_r2	0.526400
XGBRegressor_MAE	0.001517
XGBRegressor_RMSE	0.002029
RandomForestRegressor_r2	0.545186
RandomForestRegressor_MAE	0.001484
RandomForestRegressor_RMSE	0.001989

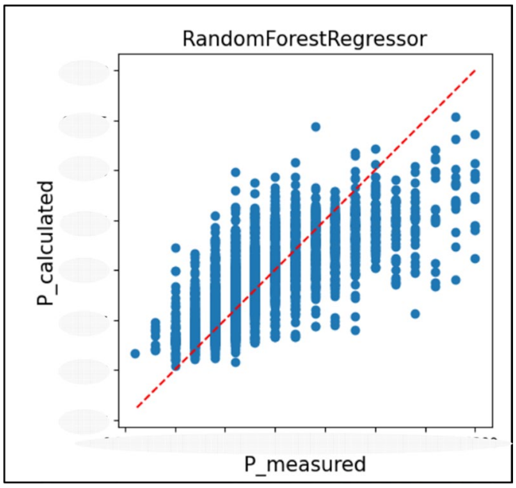


Fig.5 - Application of a non-linear Random Forest Regressor to improve the prediction accuracy for the phosphorus content.

RESULTS AND DISCUSSION

The above-described AI-based model is applied to predict for every produced heat the final content of quality critical elements with focus on the copper and the phosphorus content. The prediction result is compared to the analysis of a steel sample which is taken for every EAF heat before tapping. Figure 6 shows this comparison exemplarily for the phosphorus content. In general, it can be observed that the prediction result of the Random Forest Regressor is in line with the analysed results, with a scatter in the range which has been shown in Figure 5. Higher deviations between measured and predicted contents indicate that the properties of the charged scrap types may have changed.

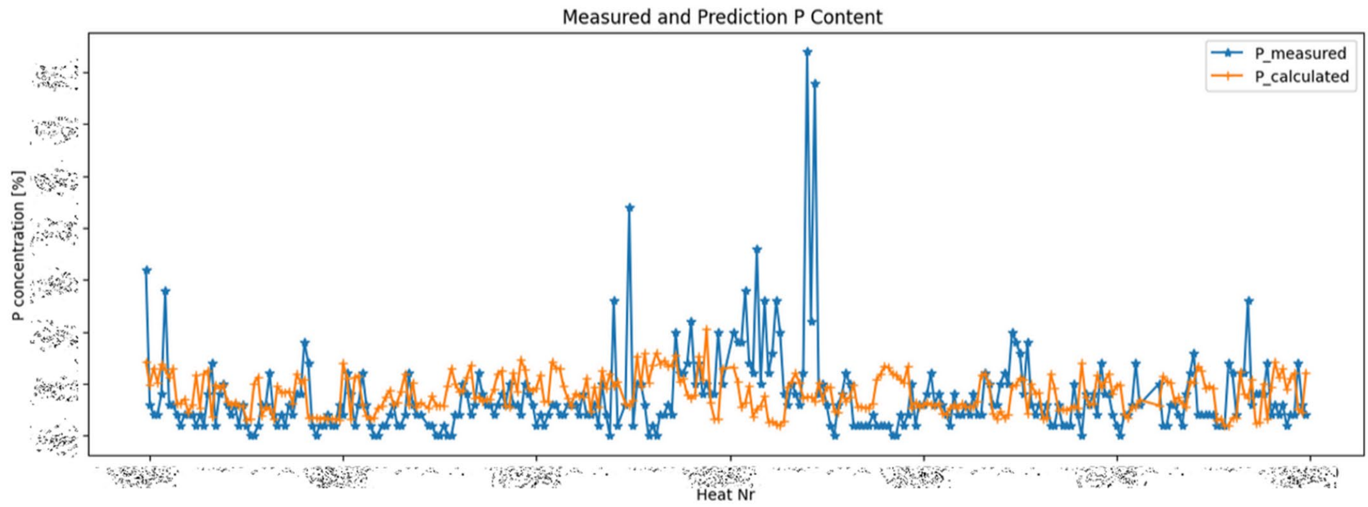


Fig.6 - Application of a non-linear Random Forest Regressor to improve the prediction accuracy for the phosphorus content.

When the deviation between measured and predicted element content is higher than a predefined threshold for several heats in a row (see in Figure 7 for the phosphorus content), a dedicated software tool, the so-called Autonomic Manager (AM) creates an alarm that possible anomalies in the scrap type properties have been detected. The Autonomic Manager functions as an autonomous coordinator of the AI data pipeline and acts as the primary decision-maker [10]. Within the s-X-AIPI project, it also has been applied to the Aluminium sector [11].

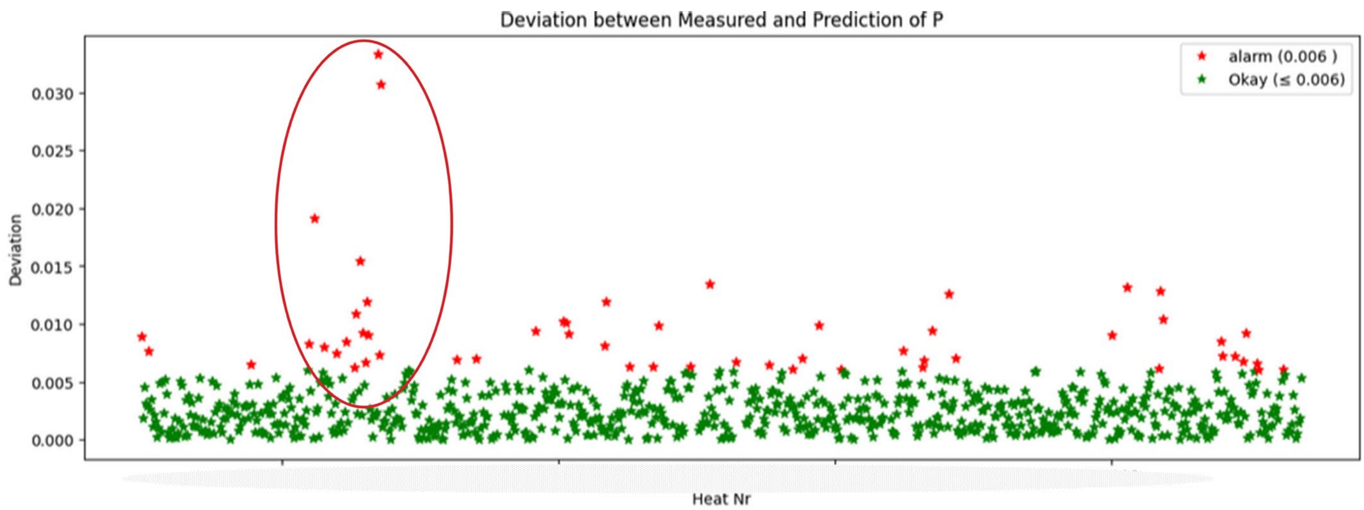


Fig.7 - Deviation between measured and predicted Phosphorus content with application of a threshold

Consecutively, a supervision procedure automatically activates an update of the scrap characterisation calculation to determine new and more accurate property values for the scrap types which are currently in use. A plant expert with metallurgical background knowledge checks if the new property values are reasonable and decides if they can be accepted to be used in the scrap mix optimisation calculation for the following heats, so that further violations of quality restrictions can be avoided. At the same time, a re-training of the AI-based prediction model is initiated, so that it will also be adapted to the new properties of the scrap types. This supervision of the model results is also an elaborated checking procedure of the scrap properties, useful to monitor the evolution of different scrap types in a changing market. The whole interaction between the different software modules is illustrated in Figure 8.

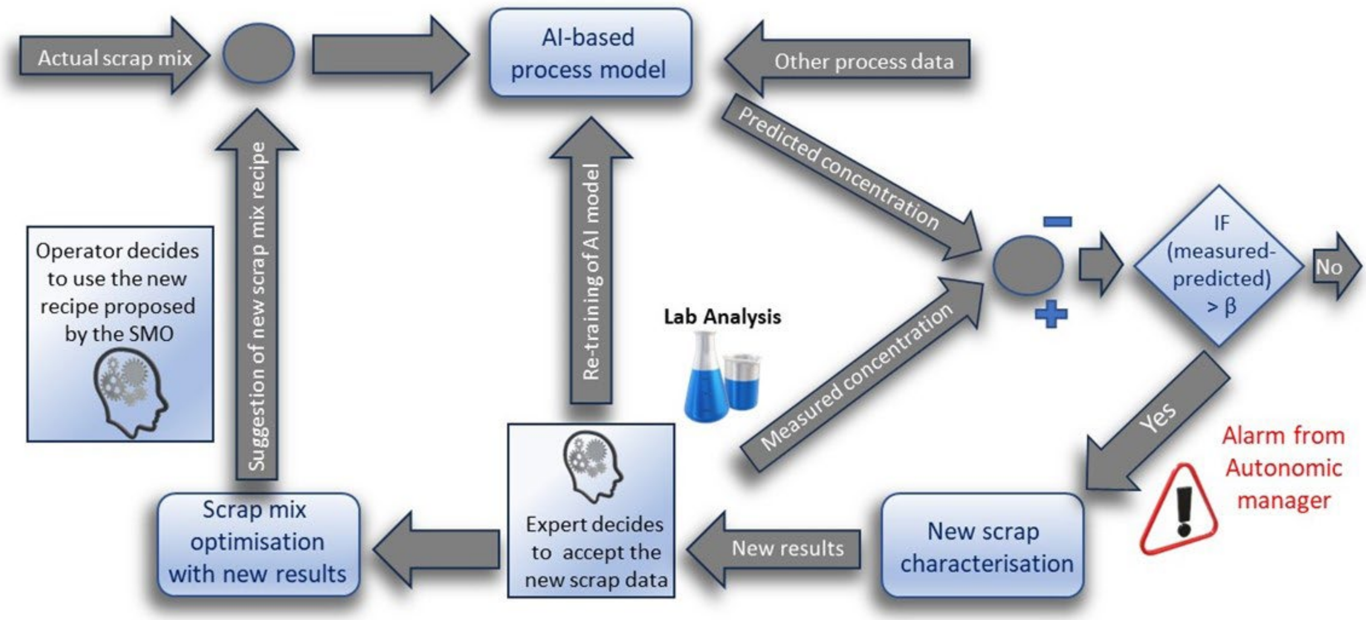


Fig.8 - Overall concept for AI-Driven supervision of scrap utilisation.

By this procedure, which includes automatic functions but also Humans in the Loop (HITL), it is ensured that the scrap mix optimization always uses up-to-date values regarding the scrap properties, which significantly affect the optimization results and thus the suggestions which scrap types with which amounts shall be charged. Consequently, it shall be ensured that a minimum of violations regarding the quality restrictions occur, and that on the other hand low-quality scrap types are used with the maximum allowable amount.

The task of the scrap mix optimiser is to calculate the cost and quality optimal scrap mix for each steel grade to be produced. The optimization calculation not only considers the scrap purchase costs, but also the costs for meltdown energy, which have been determined by the scrap characterisation. If accessible, also the direct CO2 emissions caused by the use of the different scrap types can be considered. This accounts to the fact that a scrap type which may be cheap on the scrap market can turn out to be an expensive scrap type when considering the costs for the required meltdown energy.

Figure 9 shows the user interface of the scrap mix optimization. The selected scrap types of the optimal scrap mix with their amounts are displayed numerically and as a pie chart on the left-hand side. The maximal allowable element concentrations for the produced steel grades are read from a data base and compared in a table with the concentrations which are predicted form the suggested scrap mix in the right-hand part of the user interface. Charging restrictions for the different scrap types like minimum or maximum amounts are defined in a separate screen.

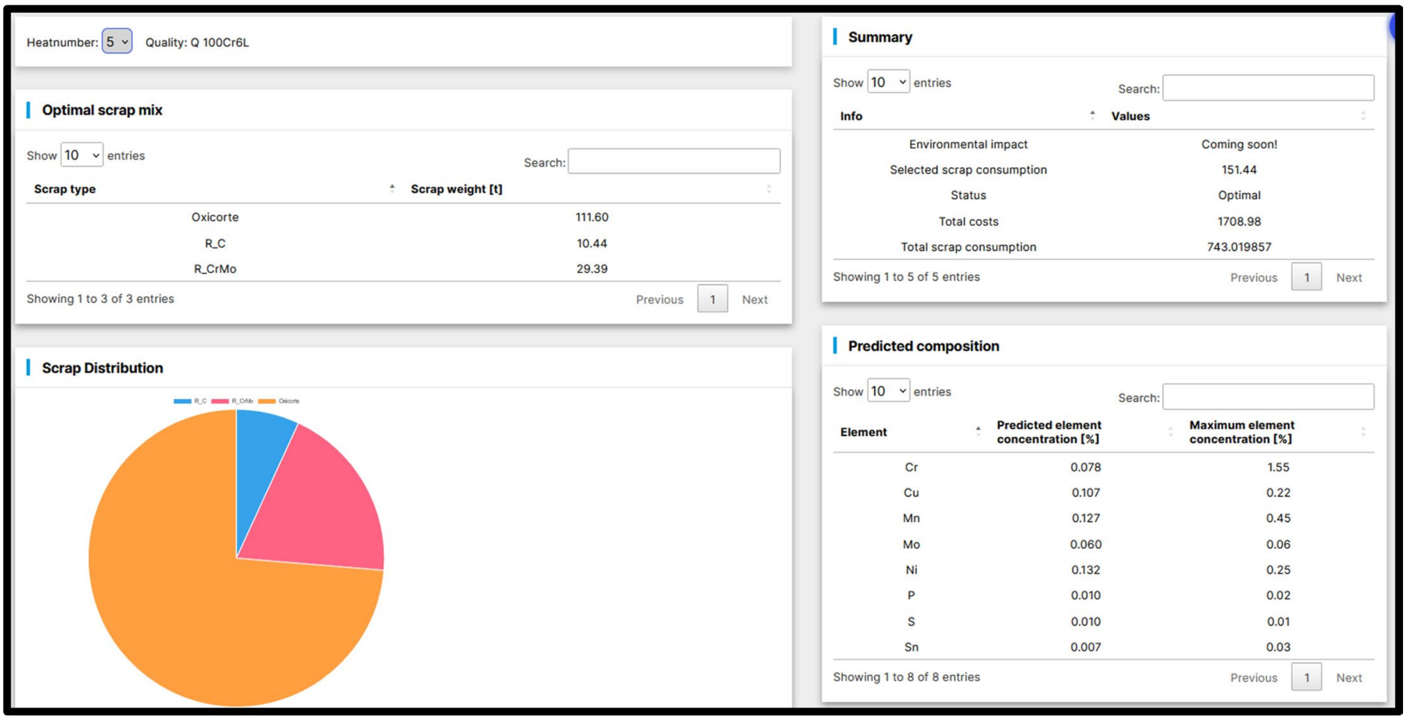


Fig.9 - User interface of the scrap mix optimization

CONCLUSIONS

Statistical models for scrap characterisation provide reliable and up-to-date information on the properties of the scrap types in use. The data are directly and dynamically fed into a scrap mix optimization for decision support and control of the scrap mix to be charged. As properties of scrap types in use vary with EAF operating conditions and scrap suppliers, a close monitoring of deviations and appropriate short-term reactions are required.

A comprehensive AI-based supervision and decision support system has been developed to react on detected anomalies in process and model performance caused by variations in scrap properties. Detection, diagnosis and self-repair modules support the operators and engineers to ensure an optimal performance of the EAF charge mix control tools. The whole decision support system has been implemented at the EAF plant of Sidenor Aceros Especiales in Spain and is currently tested in this industrial environment. Within a first test application of the scrap mix optimization Sidenor already identified cost savings of up to 12 €/t by increasing the percentage of low-cost scrap types in the charge mix [4].

ACKNOWLEDGEMENTS

This work has been supported by the project "self-X Artificial Intelligence for European Process Industry digital transformation" (s-X-AIPI), which has received funding from the European Union's Horizon Europe research and innovation program under grant agreement No. 101058715. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union. Neither the European Union nor the granting authority can be held responsible for them.

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