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Highly efficient technologies for increased yields in steelmaking processes and reduced environmental impact - HIYIELD project

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HIYIELD project applies advanced technologies to enhance circular economy practices by increasing scrap usage in steel production and reducing reliance on pig iron from coal-fired blast furnaces. The project's objectives are structured across three industrial demo cases, each addressing a critical aspect of scrap utilization.

In demo case 1, industrial-scale trials were conducted to optimize scrap sorting through mechanical, physical, and sensor-based separation techniques. A hammer mill-based process achieved a ferrous yield of 99.5% purity, with a magnetic separation efficiency of 91%. In addition, a laser scanner system was implemented for real-time scrap volume estimation, improving charge optimization for steelmaking. A Deep Learning (DL) based classification model was developed to enhance automated scrap recognition, integrating Electric Arc Furnace (EAF) process data and real-time imaging for improved material characterization.

In demo case 2, industrial trials were conducted to optimize the identification, classification, and processing of pre-consumer scrap using X-Ray Fluorescence (XRF) based separation and DL-based models. The implementation of the Digital Scrap Information Card (DiSC) enabled efficient data exchange between suppliers and consumers, ensuring accurate scrap tracking. Furthermore, a DL-based scrap identification system utilizing Self-Supervised Learning (SSL) models for automated scrap classification was developed, improving scrap assessment.

In demo case 3, High-Speed Sampling (HSS) and an analysis system were developed for direct on-site characterization of liquid steel. The chemical compositions obtained from the combined HSS, and conventional lollipop sampling system were analysed, showing strong agreement between the two sampling methods. This high level of consistency confirms the accuracy and reliability of HSS sampling for immediate steel analysis. The project's findings support increased scrap usage in steelmaking, enhanced process efficiency, and reduced environmental impact, aligning with the EU's long-term decarbonisation and circular economy goals.

KEYWORDS: CIRCULAR ECONOMY; DECARBONISATION; DIGITALIZATION; SCRAP UTILIZATION; DEEP LEARNING; HIGH-SPEED SAMPLING; SCRAP CLASSIFICATION; STEEL PROCESS OPTIMIZATION;

INTRODUCTION

The global crude steel production reached 1,884 million tons (Mt) in 2024 [1]. On average, 1.8 t of CO_2 are emitted for every ton of steel produced [2]. The iron and steel industry accounts for approximately 7% of global CO_2 emissions, corresponding to around 2.6 Gt CO_2 annually. It ranks as the largest industrial contributor to CO_2 emissions and the second-largest industrial energy consumer worldwide. Therefore, efficient decarbonisation of the steel sector will play a key role in achieving the EU climate goals by 2050. Scrap-based steel production can contribute to decarbonisation by reducing the demand for pig iron and limiting iron ore reduction in coal-fired blast furnaces. This approach lowers CO_2 emissions and supports more sustainable steel production. The HIYIELD project [2] represents the effort of selected key representatives of the steelmaking value chain to contribute to the reduction of these emissions and thereby to compliance with EU climate targets. The project consortium was well-balanced, comprising steel manufacturers, scrap suppliers and technology providers. The main objectives that the HIYIELD project addressed, among others, were to maximize:

1. scrap quality through optimal technologies for impurity removal and optimal use of alloying elements;
2. scrap usage through improved scrap identification and classification, along with scrap tracking within a circular economy;
3. product quality with increased scrap uptake by optimizing the charge and ensuring accurate liquid steel analysis, thereby improving the final steel product quality.

HIYIELD targeted the implementation of innovative technologies such as Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL) and Big Data, aiming to increase scrap uptake in various scenarios that represented the prevailing European steelmaking routes [4-8]. The HIYIELD project was demonstrated through three industrial-scale demo cases, each designed to promote a more efficient and sustainable use of scrap within a circular economy framework. These three demo cases showcased how innovative technologies such as Deep Learning, High-Speed Sampling, and Digital Scrap Tracking could be applied to different stages of the steelmaking value chain to maximize scrap utilization and reduce environmental impact. Demo case 1 focuses on enhancing the quality of low-grade post-consumer scrap through mechanical, magnetic, and sensor-based separation methods.

Real-time scrap classification and laser-based volume estimation were implemented to optimize bucket charging strategies, directly contributing to better control of the raw material mix. Demo case 2 addressed the identification, separation, and traceability of pre-consumer scrap using X-Ray Fluorescence (XRF) based sorting and digital tools.

Digital Scrap Information Card (DiSC) ensured transparent communication between scrap suppliers and steelmakers, while Deep Learning models enabled highly accurate real-time scrap classification supporting closed-loop material cycles within circular economy. Demo case 3 implemented a high-speed Optical Emission Spectroscopy (OES) system enabling direct, on-site chemical analysis of liquid steel. This approach can minimize production delays and energy losses while improving the reliability of alloy control, thereby supporting increased scrap utilization without compromising product quality. The developed innovations were collectively validated, at an industrial scale, in terms of technical excellence, environmental impact reduction, and industrial/business case relevance.

HIYIELD framework integrated digitalization, advanced analytics, and high-speed analysis technologies to increase scrap utilization, improve process efficiency, and reduce CO_2 emissions in steel production. The project connected strategic objectives with demonstration cases, targeting increased scrap uptake while maintaining or improving product quality. The enabling methods are introduced in figure 1 and described in detail in the Methodology section.

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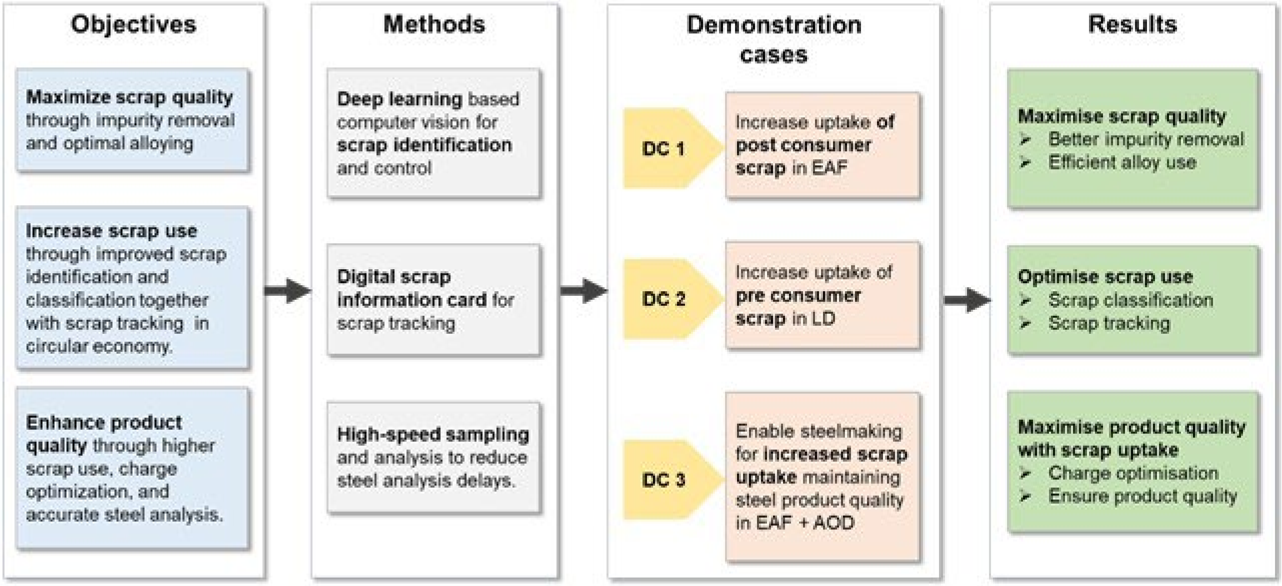

Fig.1 - Illustration of the HIYIELD concept including main objectives, methods, demonstration cases and expected results.

METHODOLOGY

The methodological framework of the HIYIELD project integrated industrial-scale experimental validation, digital data acquisition, and data-driven model development. The methodological framework of HIYIELD (see figure 1) consists of three main pillars:

- Deep Learning-based computer vision for scrap identification and control: DL and machine vision was applied to classify preconsumer and postconsumer scrap and correlate properties with process data for optimized charging prior to steelmaking. Data driven tool was also developed to support the optimal use of scrap.
- Digital Scrap Information Card (DiSC) for scrap tracking: a standardized digital interface enabled data exchange was developed between scrap provider and steel manufacturer. This includes digitization of scrap quality, analysis, quantity, and delivery timing.
- High-Speed Sampling (HSS) and analysis: a novel OES-based sampler was developed for direct on-site analysis of liquid steel, significantly reducing sampling time and energy consumption during steel melting and chemical control in the furnace.

Demonstration trials were conducted at multiple partner facilities to evaluate the performance of scrap sorting technologies, sensor-based separation systems, and analytical tools under real production conditions. Dedicated data acquisition systems were implemented to collect process-relevant information from scrap handling operations, XRF and laser-based systems, furnace monitoring systems, and High-Speed Sampling (HSS) analysis. The acquired datasets were used to develop and validate Deep Learning-based classification models and data-driven approaches for enhanced scrap characterization and process optimization. The datasets collected cover the following aspects:

- high-resolution scrap images taken at defined intervals;
- chemical composition data from XRF and OES;
- process parameters from real steelmaking operations;
- material flow and logistics data for Life Cycle Analysis (LCA).

Data-driven Deep Learning models were developed using validated datasets, applying cross-validation and industrial deployment trials. Performance indicators included classification accuracy, scrap purity, sampling time, and the level of agreement between analytical methods. The first demonstration case focused on improving the quality of post-consumer scrap through mechanical processing and sensor-based technologies. Scrap materials from end-of-life products often contain impurities and mixed materials that must be removed before use in steelmaking.

Industrial trials were conducted using a hammer mill-based processing route designed to fragment scrap and liberate metallic components. This process improved the effectiveness of subsequent magnetic separation, resulting in a ferrous yield purity of approximately 99.5% and magnetic separation efficiency of approximately 91%. These results demonstrate that mechanical processing can significantly improve scrap quality. In addition to mechanical processing, a laser-based scanning system was implemented to estimate scrap volume in real time. Accurate volume estimation is essential for optimizing bucket charging and reducing variability in furnace operation. The developed system enabled more consistent charging practices and improved control of the raw material mix. Deep Learning-based computer vision models were also developed to classify scrap types automatically. These models processed real-time images captured during scrap handling and were trained using industrial datasets. The classification results were used to support decision-making in scrap preparation and charging, reducing reliance on manual inspection in figure 2.

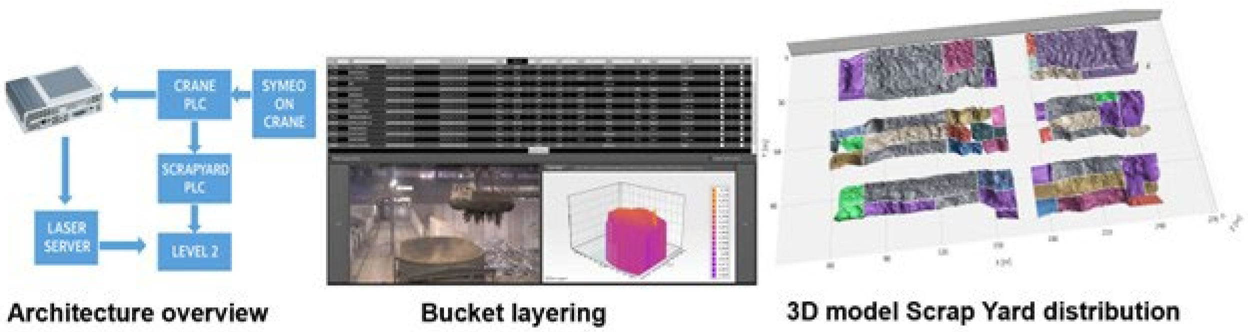

Fig.2 - Volume data obtained from the laser scanners are integrated into the scrap management software, including bucket loading and production recipes.

The second demonstration case addressed challenges related to the identification, classification, and traceability of pre-consumer scrap. Pre-consumer scrap often contains valuable alloying elements, but improper identification may lead to inefficient use or contamination of steel grades. X-Ray Fluorescence (XRF) systems were implemented to determine the chemical composition of scrap materials and enable separation based on alloy content. This approach improved control of tramp elements and supported more accurate scrap mix design. A key development in this demonstration case was the Digital Scrap Information Card (DiSC), a standardized digital system designed to facilitate the exchange of scrap information between suppliers and steel producers. The DiSC included data on scrap composition, origin, quantity, and delivery timing (figure 3). The digital infrastructure improves transparency and supports circular economy practices by enabling better tracking of material flows. Deep Learning models based on self-supervised learning techniques were developed to improve scrap classification without requiring large labeled datasets. These models learned meaningful features from unlabeled scrap images and demonstrated improved classification performance compared with traditional approaches. The use of self-supervised learning is particularly advantageous in industrial environments where labeled datasets are limited. The third demonstration case focused on improving real-time characterization of liquid steel. Conventional sampling methods often require significant time for sample preparation and laboratory analysis, which may delay process adjustments and increase energy consumption.

Fig.3 - Digital Scrap Card developed and integrated in real-time.

A High-Speed Sampling (HSS) system integrated with optical emission spectroscopy was developed in the third demonstration case to enable direct on-site chemical analysis of liquid steel. The system significantly reduced sampling time while maintaining high analytical accuracy. Comparative trials were conducted to evaluate the agreement between HSS and conventional lollipop sampling methods (refer figure 4). The results showed strong agreement in measured chemical compositions, confirming the reliability of the developed system. Faster analysis enabled quicker process adjustments, improved alloy control, and reduced energy losses during melting. For industrial verification of the high-speed analysis an in-line combination sample has been developed. The sampler was suitable for automated application. More than 500 in-line combination samplers comprising one lollipop sample and one HS sample were applied under standard industrial conditions. These combination samples were collected from several heats with different compositions for statistical evaluation. All samples were analysed by laboratory reference methods and by the HS analyser. Outliers were excluded based on predefined criteria. Overall, 98% of the HS samples met the specified limits and were compared with the independent laboratory reference analysis of the lollipop standard sample.

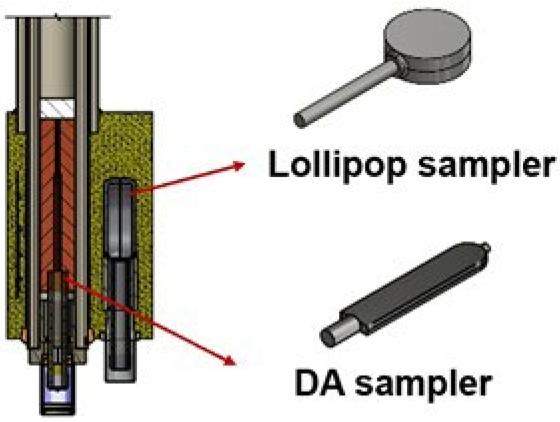

Fig.4 - Combination sampler setup used for pilot demonstration of High-Speed Sampling and analysis.

RESULTS AND DISCUSSIONS

Mechanical Processing and Separation

Post-consumer scrap often contains mixed materials, coatings, and non-metallic inclusions. Mechanical processing is therefore required to liberate metallic components and improve separation efficiency. In the HIYIELD project, hammer mill-based processing was evaluated under industrial conditions. The fragmentation process improved the effectiveness of downstream magnetic separation, resulting in a ferrous yield purity of approximately 99.5%. Magnetic separation efficiency reached approximately 91%, demonstrating the effectiveness of the processing route. Improved scrap purity reduces contamination risks in the furnace and enables higher scrap charging ratios without compromising product quality.

Laser-based volume estimation

Accurate estimation of scrap volume is essential for optimizing bucket charging and ensuring consistent furnace operation. Variations in scrap density and geometry often make manual estimation unreliable. A laser scanning system was developed to estimate scrap volume in real time. The system generated three-dimensional surface profiles of scrap piles and calculated volume using geometric reconstruction algorithms. Industrial trials showed that the system improved charging consistency and reduced variability in furnace operation. More accurate charging also contributes to improved thermal balance and reduced energy consumption.

Machine Learning-based scrap classification and optimization

Computer vision techniques and Deep Learning techniques were applied to automate scrap classification. High-resolution cameras captured images of scrap during handling and processing. Convolutional neural networks were trained using large datasets of labeled scrap images. The models learned to distinguish between scrap types based on geometric features, surface texture, and color patterns. In addition to supervised learning approaches, self-supervised learning based on contrastive learning were investigated to improve model robustness and reduce dependence on labeled data. This approach enables feature learning from large volumes of unlabeled industrial data, which is particularly valuable in scrap processing environments. Experimental evaluation demonstrated that self-supervised models achieved improved classification accuracy (98%) and robustness under variable lighting and environmental conditions. Industrial deployment demonstrated that automated classification can support optimized charging strategies and reduce reliance on manual inspection.

XRF-based sorting

Pre-consumer scrap often contains valuable alloying elements that must be properly identified to ensure efficient reuse. X-Ray Fluorescence (XRF) systems were implemented to measure chemical composition and enable sorting based on alloy content. The use of XRF-based sorting improved control of tramp elements and enabled more accurate scrap mix design. This contributes to improved metallurgical control and reduced risk of off-specification steel grades.

Digital Scrap Information Card (DiSC)

A key innovation of the project was the Digital Scrap Information Card (DiSC), a standardized digital system designed to improve scrap traceability. The DiSC stores information including:

- scrap origin;
- chemical composition;
- processing history;
- quantity and logistics data.

This digital infrastructure enables transparent communication between scrap suppliers and steelmakers, supporting closed-loop recycling and circular economy practices.

High-Speed Sampling system

Comparative trials demonstrated strong agreement for key alloying elements between the high-speed (HS) analyzer and conventional OES laboratory analysis for all investigated elements. Correlation analyses showed excellent consistency between measurements taken on both sides of the HS samples using the HS analyzer, as well as high agreement between HS and conventional laboratory OES results. For carbon and silicon, very high coefficients of determination confirm reliable analytical performance. Similarly, copper and aluminium measurements showed strong correlations and low standard deviations, indicating stable and precise analysis.

Overall, the results confirmed that the High-Speed Sampling system provided accurate and reproducible chemical measurements under industrial conditions, supporting its suitability for implementation in routine steelmaking operations.

Environmental and economic impact

Increasing scrap utilization reduces energy consumption and CO2 emissions by reducing the need for primary raw materials. The technologies developed in the HIYIELD project support the implementation of higher scrap ratios while maintaining productivity and quality. Digitalization helps improve operational efficiency by reducing delays, improving decision-making, and enabling predictive optimization. These improvements contribute to environmental sustainability and enhanced operational efficiency. LCA was conducted to evaluate the environmental impacts of HIYIELD innovations within EAF and BF-BOF route [8].

The analysis combined:

- primary data from scrap sorting processes;
- steelmaker data for traditional scrap compositions and emissions;
- secondary datasets including Ecoinvent 3.11 and WorldSteel databases.

The LCA showed that improved scrap sorting and classification technologies can reduce environmental impacts by enabling higher-quality scrap input and minimizing variability during melting. The gap between the design performance and the actual output highlighted the influence of feedstock variability, labour availability, and equipment efficiency under real industrial conditions. Despite these practical limitations, the trials confirmed that the upgraded infrastructure significantly improved scrap quality and process yield.

OUTLOOK

The results of the HIYIELD project provide a solid foundation for the further industrial deployment of digital scrap management and process optimization technologies in steel production. Future efforts should focus on large-scale implementation across different plant configurations and production routes to validate scalability and long-term operational stability. Further development of data-driven models, including adaptive and self-learning systems, will be essential to improve robustness under varying scrap qualities and fluctuating market conditions. Integration of real-time monitoring tools, advanced analytics, and predictive control strategies into plant-wide automation systems offers significant potential to further increase scrap utilization while maintain-ing stable process performance and product quality. In addition, continued assessment of environmental per-formance through comprehensive life cycle approaches will support transparent evaluation of sustainability benefits. Expanding digital traceability concepts, such as standardized scrap information systems, could fur-ther strengthen value chain integration and resource efficiency. Overall, the transition toward digitally ena-bled, resource-efficient steel production requires sustained collaboration between technology providers, steel producers, and research institutions to ensure continuous innovation and industrial impact.

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