Improved analysis of post-consumer scrap

The EU-funded PURESCRAP project, a consortium comprised of 12 industry partners, has taken an ambitious step forward in the area of scrap analysis. By **Johannes Rieger[1]*, Melanie Leitner[1], Valentina Colla[2], Alice Petrucciani[2], Lars Sandberg[3], and Jonas Petersson[3]**

FORECASTS reveal that crude steel demand will be 30% higher in 2050 than it is today. Furthermore, increasing scrap availability means that the contribution of scrap in the total steel charge will likely grow to 40% in 2050 from the present level of 30% (see **Fig 1**).

Limits to the quantity and quality of available scrap also mean that decarbonizing primary (ore-based metallics, OBM) production remains critical to a net-zero future, which includes efforts to enhance the recycling of all available scrap qualities including low-quality post-consumer scrap. An increasing share of post-consumer scrap has also been predicted (see **Fig 2** [2]), which will not allow for the complete recycling of all high-quality steel grades.

For some steel grades, tramp elements, such as copper, tin, chromium, nickel or molybdenum, prevent the reuse of large shares of post-consumer scrap. This surplus in low-quality scrap within the EU generates enormous scrap exports. In 2022, these amounted to ~18Mt [3]. On the contrary, higher quality scrap is imported to the EU to fulfill the scrap demand for steel production.

Sensor-based scrap analysis

Spectroscopic sensor-based scrap material identification can be done by applying X-rays, spectroscopy with and without the formation of plasma, or neutron activation [4]. X-ray-based sensors mainly include X-ray transmission (XRT) and X-ray fluorescence (XRF). Plasma-based systems cover Optical Emission Spectroscopy (OES [5]) including Laser-Induced Breakdown Spectroscopy (LIBS [4, 5]). Further spectroscopic systems encompass Infrared (IR) and Near-Infrared (NIR) spectroscopy. Finally, neutron-based systems include Prompt Gamma Neutron Activation Analysis (PGNAA) or Pulsed Fast Thermal Neutron Activation (PFTNA). XRT sensors are used on an industrial scale by metal recyclers in belt-type particle sorters to separate light metal particles (Al, Mg) from dense non-ferrous metals (zinc, copper, brass). XRT is also applied

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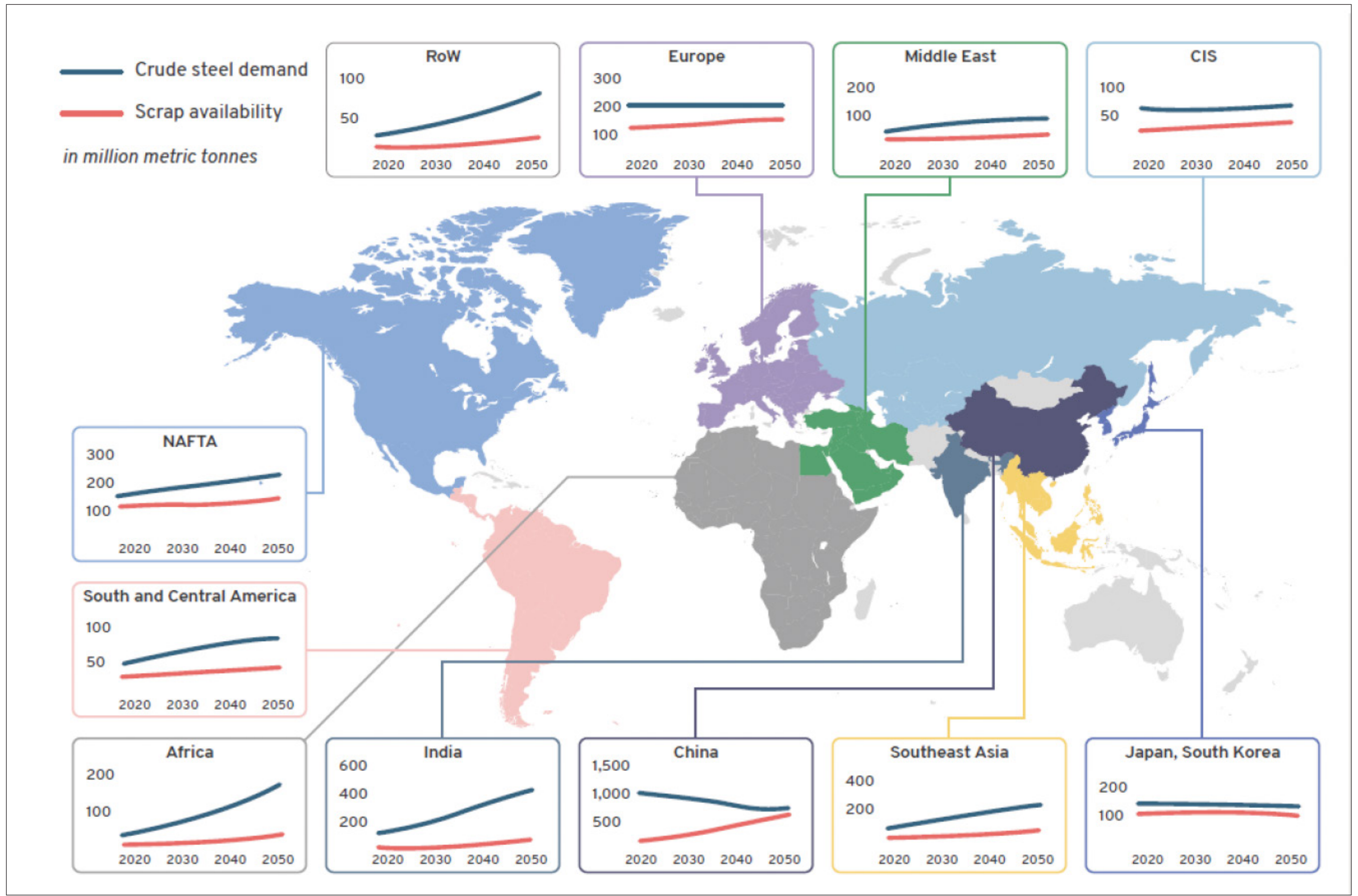


Fig 1. Expected global demand for crude steel and availability by region.

to sort out the non-metallics, e.g., from automotive shredder residue [4]. Handheld XRF systems gain importance in manually identifying alloys in the scrap yard by random analysis. XRF penetrates a few μm of the scrap surface, though it faces limitations in detecting light elements. LIBS is a point measurement technology which, in each laser-pulse, analyses surface composition. Although many LIBS systems are being installed at industrial sites, no full-scale LIBS analyzer system with complete area coverage (e.g., installed over a conveyor belt) for steel scrap is available yet [4-8]. IR and NIR are also not yet used for steel scrap (industrial systems exist for the sorting of e.g., glass or plastics [4]). PGNAA and PFTNA are well established in the mining industry to handle large volume flows. Research work was done to apply PGNAA for steel scrap (with no commercial solution available yet). One main challenge for PGNAA/PTFNA is to ensure safe operations due to radioactive materials used (e.g., Californium as a neutron source).

In recent years, digital technologies, including Artificial Intelligence (AI), have been applied in the steel industry to improve plant efficiency, support maintenance, and optimize resource and energy utilization. Machine Learning (ML) and computer vision were used for scrap recognition and classification [9] by utilizing images from cameras. The model architectures are generally based on Convolutional Neural Networks (CNN), such as the material segmentation and classification model of scrap (3D-2D CNN hybrid architecture) [10]. In addition, several studies were conducted to combine LIBS via ML, including by combining LIBS, ML, and deep learning (DL) and testing different ML algorithms to classify aluminium scrap [11]. Although several ML-based models for image-based automatic scrap detection systems have recently been developed, improvements are still needed to apply them at an industrial level.

Regarding scrap characterization at industrial level, optical scrap inspection is state-of-the-art (SoA). Especially at the scrap yard entrance (for both, the scrap supplier and the steelmaker) cameras record the incoming scrap on a truck or a wagon. Furthermore, 3D radars (mounted on crane grabbers) are used together with integrated weighing systems to create a 3D profile of the scrap yard and ensure a certain sorting of the different scrap qualities. However, scrap characterization and quality monitoring are often done manually. This subjective assessment, depending on the experience of the operators, provides a suboptimal way for a proper scrap classification.

Approach of the EU-funded PURESCRAP project

Compared to the above example, the PURESCRAP project, with a three-and-a-half-year duration (running since January 2023) and funded within the Clean Steel Partnership of the Horizon Europe Framework Program of the European Union (EU), takes an ambitious, major step forward. In concrete terms, the focus lies on the precise characterization of post-consumer scrap prior to melting the scrap

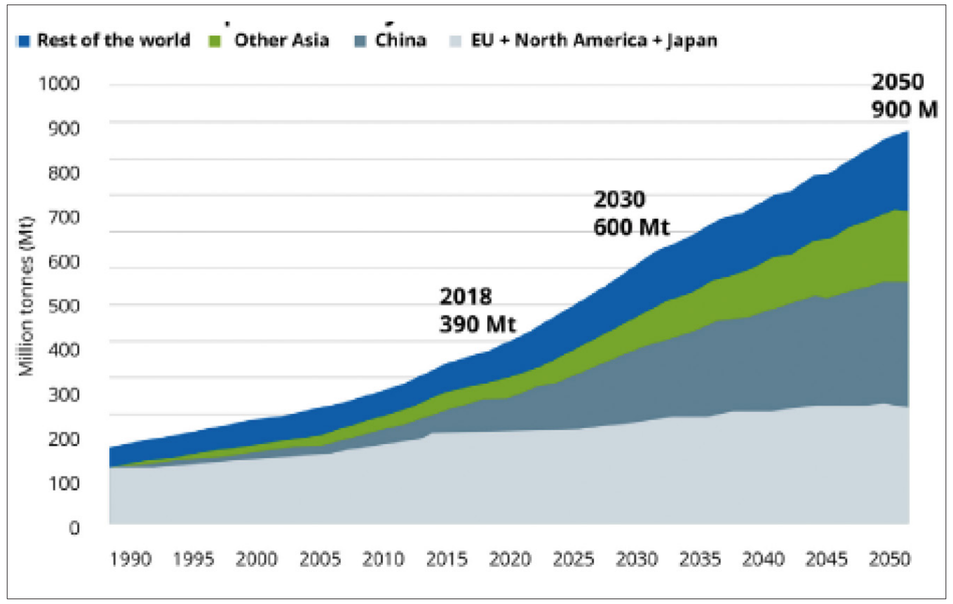


Fig 2. Expected global availability of post-consumer (end-of-life) scrap.

by applying highly efficient sensor stations (see **Fig 3**). The PURESCRAP approach goes beyond optimal scrap inspection by combining multiple sensors for a more complete analysis. Each sensor has its own unique advantages and limitations. This exceeds other previous studies, which used individual sensors using optical sensors to guide a LIBS sensor [12, 13]. For implementation in an industrial scrap-processing plant, sensor fusion is a completely novel concept.

The overall project goals are as follows:

- Concepts of a combined spectroscopic and vision system to characterize and analyze heavy and shredded scrap installed at a scrap supplier site
- Improving scrap characterization through image detection and processing models using Deep Learning solutions
- Use of sorted scrap to demonstrate its ability to produce standard steel grades at least in semi-industrial scale

The consortium comprises of 12 partners with a well-balanced mix of industry players (plant builder, scrap processor, steelmaker), academic institutions, research technology organizations (RTOs) as well as the European Steel Technology Platform (ESTEP) as an important link between all stakeholders along the steel value chain. The consortium includes (in alphabetical order) Danieli Automation SpA (ITA), ESTEP ASBL (BEL), K1-MET GmbH (AUT), Luleå University of Technology (SWE), REDWAVE Competence Centre of BT-Systems GmbH (AUT), Sant'Anna School of Advanced Studies – Pisa (ITA), Spectral Industries BV (NED), SSAB AB (SWE), Stena Recycling AB (SWE), Swerim AB (SWE, Project Co-ordinator), TU Dortmund (GER), and voestalpine Stahl Donawitz GmbH (AUT).

To reach the objectives set, smart combinations of optic and spectroscopic sensors were defined. This was done both to enhance scrap processing (i.e., sorting) efficiency, and improve analysis of scrap batches. The approach of batchwise scrap analysis enables a more reliable planning of scrap charging for crude steel production. **Fig 4** shows a test line to train the sensor concept for shredded scrap. The sensor chain comprises of a camera, LiDAR (Laser imaging, detection, and ranging) and depth camera to generate a high-resolution 3D map of the analyzed scrap, LIBS, and XRF. The sensors are coupled with a comprehensive information and communication technology (ICT) network and a hybrid ML approach to jointly exploit images and spectroscopic data. The sensor station will be installed on a real shredder line of a scrap processor.

Fig 5 shows the sensor station arrangement of the heavy scrap sensor station. The sensor module (grey part) will be installed at the output of the shear at the site of a scrap processor. Heavy scrap is less complex, but instead provides more demanding surface conditions compared to shredded scrap. The sensor station for

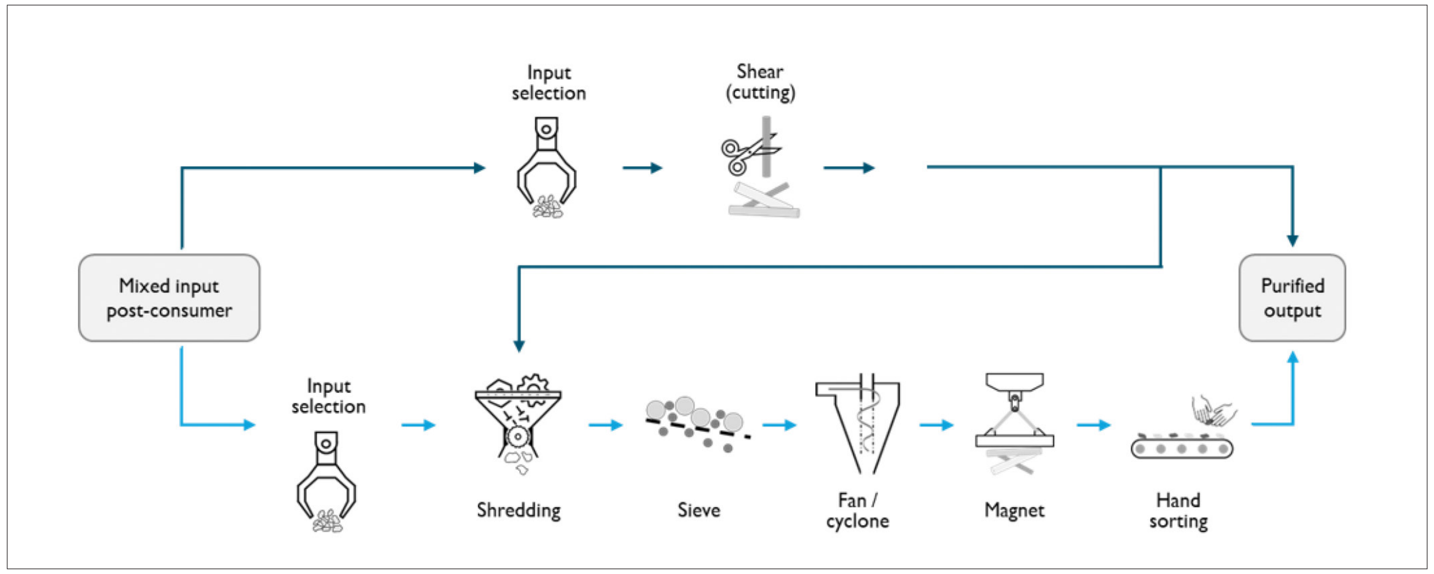
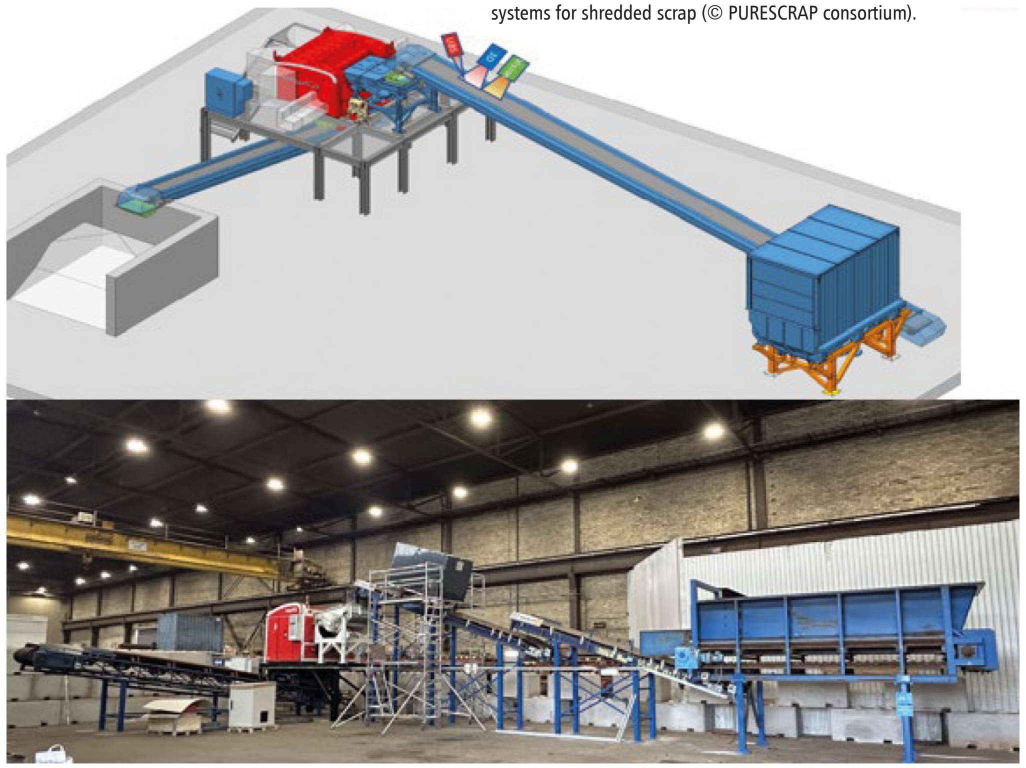


Fig 3. Concept of the PURESCRAP project including the characterization of post-consumer heavy and shredded scrap (© PURESCRAP project consortium, planned sensor stations not illustrated).

heavy scrap has no XRF and the LIBS sensor is mounted on a robot unit. Sensors are again coupled with an ICT network.

As one of the main Key Performance Indicators (KPIs), purity levels (limits for non-ferrous tramp elements) were specified for the sorted scrap product (outputs). Among others, limits for copper (ranges 0.05/0.10/0.15/0.20/0.25, all values in wt.%), nickel (ranges 0.05/0.15/0.25) or molybdenum (ranges 0.05/0.25/0.45) were defined (other metals, such as tin were also considered). These KPI values are important to validate the efficiency of the PURESCRAP sensor stations. It is crucial that the qualities of the sorted scrap products are fully in-line with the expectations of the steel producing consortium partners. The long-term goal focuses on the enhanced use of sorted post-consumer scrap to produce standard steel grades without a loss on quality or material properties relevant for final applications. To finally prove that sorted scrap is of sufficient quality to produce standard pre-defined steel grades, sorted scrap batches will be used for steelmaking sequences, at least on a semi-industrial scale. During this, the whole steelmaking and refining chain will be covered starting with scrap melting in a batchwise operated 5-ton induction furnace to simulate the operation of an electric arc furnace (EAF) for crude steelmaking. This will be followed by secondary metallurgical treatment in a vacuum degassing furnace and vertical continuous casting into round casted material (Ø 230 mm) or ingots (270x360 mm). Comprehensive material analyses will follow to ensure that typical

Fig 4. Test line for training and evaluation of sensor systems for shredded scrap (© PURESCRAP consortium).



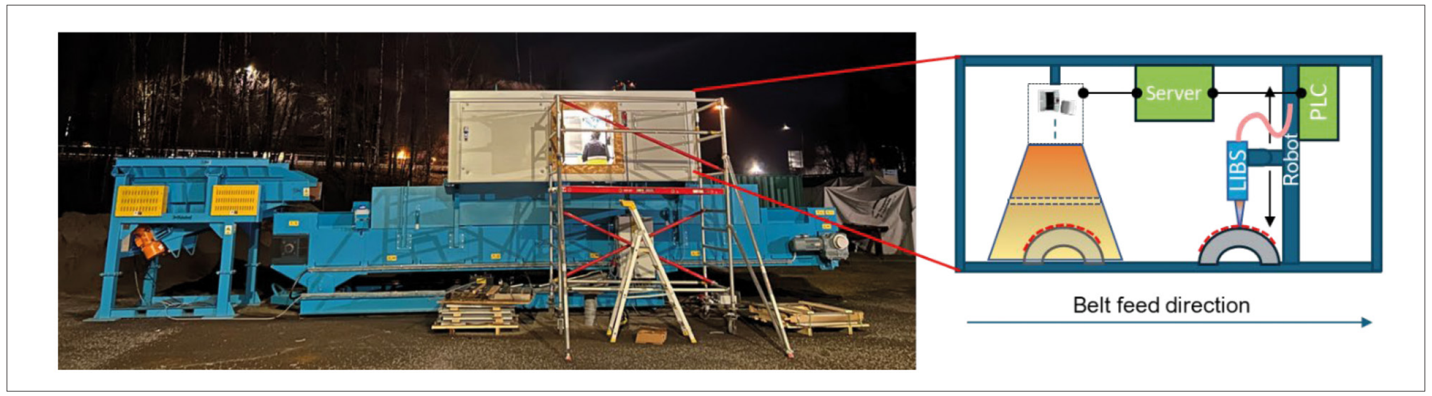


Fig 5. Sensor station arrangement for heavy scrap (© PURESCRAP consortium).

properties, such as material strength, are in-line with standard steel grade specifications. Furthermore, it is also envisaged to use sorted scrap batches in an industrial-scale Basic Oxygen Furnace (BOF) process.

Environmental impact assessment

As accompanying parts of the PURESCRAP project, Material Flow Analysis (MFA), Life Cycle Assessment (LCA) and Life Cycle Costing (LCC) have been executed in an aim to derive a comprehensive environmental and economic impact assessment for the reuse of post-consumer scrap. This also provides the basis for a business model development planned within the last period of the project. A cradle-to-gate approach is used for the LCA (life phase of a product, until it leaves the steelmaking production site). Since scrap processors plan to implement comprehensive sensor stations at their sites (possibly also steelmakers), workers at industrial sites need to be prepared since working practices will obviously change (other handling strategies of scrap, additional effort of maintenance work etc.). This topic will also be covered as part of the project via a social impact assessment. ■

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