Development of an Application for Scrap Metallic Management in Electric Steelmaking

Authors

Amanda Cristina Lima da Fonseca, Vallourec Soluções Tubulares do Brasil S.A., Jeceaba, MG, Brazil
amanda.lima@vallourec.com

Laurent Chesseret, formerly with Vallourec

Bruna Borba de Carvalho, Vallourec Soluções Tubulares do Brasil S.A., Jeceaba, MG, Brazil

Beatriz Medanha Reis, Vallourec Soluções Tubulares do Brasil S.A., Jeceaba, MG, Brazil

Andrew Gonzaga de Souza, Vallourec Soluções Tubulares do Brasil S.A., Jeceaba, MG, Brazil

Paulo Henrique Santos, Vallourec Soluções Tubulares do Brasil S.A., Jeceaba, MG, Brazil

Carla de Barros Hermeto, Vallourec Soluções Tubulares do Brasil S.A., Jeceaba, MG, Brazil

Vallourec Soluções Tubulares do Brasil S.A.'s (VSB's) steel mill is equipped with a highly flexible Consteel® electric arc furnace (EAF) which can operate with solid and liquid charge in a wide range of mixes. Given the diversity in scrap origins and suppliers, VSB developed the Scrap Tool Online Resource Management (STORM) to ensure a more uniform metallic charge feed in density and chemical composition. The app integrates an artificial intelligence model for scrap classification, mixing rules for homogenization, supplier reputation and stockpile management. STORM 1.0 has been used since 2020; version 2, released in 2023, aims to reduce costs by decreasing misclassifications and enhancing scrap uniformity for the EAF.

Introduction

Vallourec Soluções Tubulares do Brasil (VSB) produces seamless steel tubes in an integrated process that starts with charcoal production and iron ore extraction and ends with the finishing of the product, such as rolling, drawing or forging, and heat treatment. The production of liquid steel for steel tubes is carried out through an electric arc furnace (EAF) process at VSB's Jeceaba plant. The process flow consists of continuously charging solid metals through the preheating conveyor — the Consteel® technology — and hot metal through a sidewall launder; steel production by electric arc furnace; refining of steel for temperature and chemical composition adjustment by ladle furnace (LF) or vacuum degasser (VD); and solidification of steel through continuous casting.

The metallic charge ranges from 20% to 50% carburized metallics (liquid and solid pig iron), the remainder being metallic scrap. Currently, the VSB catalog offers over 270 types of steel ranging from low to high carbon, 0.4% carbon and up to 5% alloys (Mo, Cr, Ni, etc.). For the oil industry, VSB produces steel with phosphorus below 0.10%.

Regarding the metallic scrap acquired in the market, which is the majority of the scrap consumed, there is a high variability in scrap size/density and chemical composition; their differences are related to their origin (by obsolescence or industrial); their processing (bundles press, scissor press, oxycut, shredder or in nature); the level of metallic alloys undesirable to the process (as copper, chromium, molybdenum and others); and related to the size of the scrap. The different scrap characteristics lead to different prices and the availability and demand on the market for each one of these metallics influence the price variability throughout the year.

An electric steel shop has flexibility in the simultaneous usage of several types of metallic scrap and pig iron. The metallic mix definition to be consumed to produce liquid steel is mostly related to the chemical composition of different steel grade, the raw material prices and the required productivity.

The metallic raw material represents a significant part of total crude steel cost. Furthermore, at VSB, the metallic charge loading corresponds to around 70% of the production time (power-on time) of a run in the EAF. Thus, the variability in the density of the metallic charge has a strong influence on the total cycle time. Thereby, the metallic mix must be defined in order to guarantee the steel grade chemical composition and to minimize the liquid steel production cost.

Discussion

The Importance of Scrap Classification

Currently, the external metallic scrap supply at VSB is provided by at least 100 different suppliers distributed across various states in Brazil. The quality and cost of the produced liquid steel depend on the quality and cost of the metallic charge fed into the EAF. Better control of the raw materials implies improved control over the cost and quality of the produced liquid steel.

The productivity of an electric furnace is also related to the quality of the raw material, especially its density, to ensure continuous supply and reduce loading time, consequently minimizing the cycle time.

To ensure continuous charging, scrap with good homogeneity in density and chemical composition to meet customer specifications is crucial. Density or chemical composition issues can lead to power-off in steel production due to deviations in chemical composition or lack of scrap on the conveyor.

Due to the vast variety of metallic scrap originating from industry and companies, standardization becomes relevant to ensure a homogeneous and continuous supply. Considering the heterogeneity in scrap concerning dimension, density, chemical composition and other characteristics, one way to control the variability of incoming scrap to a steel mill and minimize the chance of encountering scrap with high concentrations of undesirable chemical elements is through an activity known as scrap classification.

At VSB, scrap classification involves visually inspecting the type of scrap received from the supplier, validating or modifying the scrap type stated on the invoice for payment purposes, and determining the destination for stockpiling and homogenization into piles. Another function of scrap classification is to assess nonconformities, such as the presence of gas cylinders, pieces exceeding acceptable sizes for entry into the Consteel, bundles with dimensions out of specification, high concentrations of materials with undesirable chemical elements, presence of dirt, and others. This activity is mainly carried out during the unloading of scrap into the pile, and if any nonconformity is identified, the supplier is notified and incurs a penalty in payment. The presence of nonconforming items in the scrap load can result in losses related to the safety, costs and productivity of the EAF.

VSB avoids direct charging when scrap arrives from the supplier to be consumed by the EAF, to prevent the consumption of a material with concentrations of possible undesirable chemical elements for certain steel grades or to avoid density fluctuations during loading via the continuous conveyor. To achieve this, VSB has a scrap yard subdivided into three yards for stockpiling and homogenization of scrap. For this scrap homogenization, VSB employs a procedure called "Lasagna." It involves building scrap piles in layers, keeping the same type of scrap in each layer, and in the subsequent layer, changing the type, and so on until reaching the expected volume or maximum height for each pile, resembling lasagna. It is very similar to the Chevron method of building and consuming piles. The consumption of this pile is done perpendicular to the direction of the layers, ensuring that each removal of scrap with a grab removes a bit from each layer. This way, different densities are homogenized and the consumption of any concentration of unwanted residual chemical elements is avoided.

The scrap yard is divided into piles, and the piles are further divided and alternated based on these groups:

1. Prime scrap: Metal scrap originated from the industry → At VSB it is reserved for steels with high restrictions on chemical residuals.
2. Mix or low-cost scrap: Obsolete metal scrap from society → Intended for steels with fewer restrictions on residual elements.

The goal is to ensure that more expensive and premium scraps are homogenized among themselves and allocated to special steels, while mix-type scraps are homogenized as much as possible to ensure a blend of different densities and chemical compositions.

Considering the context above, a scrap yard is crucial for:

- Mixing scrap to homogenize density and chemical composition.
- Segregating nonmetals (dirt, plastics, wood, etc.).
- Avoiding the entry of nonstandard pieces.
- Separating prime scrap from low-cost scrap.
- Ensuring minimum stock and continuous delivery of scrap to the consumption bay.

The yard aims to deliver raw materials to EAF with homogeneous density; good metal yield; standard size (VSB Consteel restriction); appropriate chemical composition; continuous availability of scrap; and nonradioactive load.

In this way, scrap classification becomes more relevant to:

- Ensure quality material for EAF.
- Determine the best destination (which yard and discharge pile) for density and chemical composition homogenization.
- Apply a penalty to the load based on nonconformities.
- Make partial or total returns if necessary.
- Verify and, if necessary, alter the type of scrap stated in the invoice for payment processing.
- Record evidence for the classification report.

Taking into account the significance of the loading time for the charge in the steel production cycle of a Consteel electric arc furnace, one might consider solving the issue of scrap charging rating in Consteel by utilizing higher density for the scrap to consistently achieve a higher density in the liquid bath. However, this assumption is not accurate, as the Consteel process requires three essential elements:

1. Optimize the scrap layer on the Consteel to improve the heat exchange and so decrease energy consumption. By using only high-density scrap, the Consteel conveyor would be only with a small thickness of scrap at the bottom that would take no heat from the fumes.
2. Optimize the conveyor loading: by using only high-density scrap, the conveyor would suffer too much and would need higher maintenance.
3. Increase the scrap melting rate when the scrap comes in the bath. As the main part of the melting rate is due to the immersion of scrap in the molten steel and not to electrodes melting, if only high-density scrap is used, the melting rate would decrease in the bath (the effect is a floating "ice cube" that is last to melt).

Light scrap/low-density scrap is needed to counterbalance the three previous effects mentioned.

Some effects of using only high-density scrap are the availability and price of high density scrap. The availability of high-density scrap on the market does not allow 100% of the input of these prepared scrap: oxycut/bundles/shredded. If the demand on the market for these high-density scraps increase, the price will go up and then their usage will not be in demand anymore.

In summary, a balance between scrap density, price and electric furnace performance is necessary. These factors lead to the need for good metallic scrap optimization/management.

Given this context, and considering that, even with operational procedures for activities in a scrap yard, part of the decisions regarding scrap truck movement relies heavily on the tacit knowledge of the operators, VSB developed the STORM system: Scrap Tool Online Resource Management. The STORM application is an integrated metallic scrap management tool for consumption in the steel mill. It encompasses functionalities from the purchase of metallics, receiving, logistics, automatic scrap classification by machine learning model, destination, inventory, consumption, and supplier reliability. The primary objective of implementing this system was to enhance quality management and reduce costs associated with raw materials used in the EAF.

The STORM system was developed entirely in-house at VSB by the automation team, incorporating ideas and contributions from the process technology, methods, raw materials and logistics teams.

Use of Machine Learning Techniques for Scrap Classification

Recently, there has been a notable increase in the application of machine learning techniques for automatic scrap classification, significantly contributing to the efficiency and accuracy of sorting processes in the steel industry.

Kim et al. (2021) stand out by introducing an innovative signal processing method using laser-induced breakdown spectroscopy (LIBS). By integrating machine learning techniques, the study emphasizes the promising utility of LIBS for classifying spectra of metal scraps, specifically designed for high-speed sorting systems. However, the critical need for preprocessing LIBS spectra to ensure robust operation in dynamic industrial environments is highlighted.

Williams et al. (2023) address the classification of nonferrous metals based on their metal or alloy composition, employing magnetic induction spectroscopy (MIS) combined with machine learning. The study demonstrates that MIS alone achieves purity and recovery rates exceeding 80%, reaching over 93% for stainless steel. Challenges are observed in the Zorba waste stream due to the mixture of aluminum alloys, overcome by the introduction of color information, resulting in significant improvements in purity and recovery rates.

Diaz-Romero et al. (2022) propose an innovative approach for mass estimation and scrap classification using deep learning. Utilizing a DenseNet neural network for classification and a backpropagation neural network (BPNN) for mass prediction, the method achieves robust performance with high accuracy in mass prediction regression and a 95% classification accuracy for the C&W test data set.

Xu et al. (2023) present CSBFNet, a deep learning–based model for classifying and evaluating steel scraps automatically. Trained on simulated data of steel scrap quality inspection captured by a high-resolution vision sensor, CSBFNet is tested and refined at a Chinese steel mill, achieving an overall accuracy of 92.4% for all types of steel scraps.

Santos (2023) addresses the automation of ferrous scrap classification, proposing a deep learning approach with object detection. The trained model accurately detected 127 classes in a test set of 96 images, with opportunities for improvement highlighted by the authors for testing with different pretrained networks and database enhancement.

Reis (2023) conducted comprehensive literature review on scrap classification, citing works by Baumert et al. (2008) and Armellini et al. (2022). Both studies share the common goal of providing better traceability of scraps in facilities to feed accurate information into the electric arc furnace control system, thereby increasing production process efficiency. Reis (2023) emphasizes the benefits of automated scrap classification, such as ensuring the homogeneity of the charge sent to the electric furnace through density calculation and blending of scrap types, leading to a more stable operation of the electric furnace.

Another highlighted benefit is the reduction of human-operated subjectivity in the classification process, as determining characteristics are visual, such as size, shape, color and weight.

This literature context forms the basis for specific studies, showcasing the diversity of approaches used to enhance automated scrap classification in different contexts within the steel industry. Each study contributes to the understanding and implementation of advanced waste management systems, emphasizing the importance of these technologies for more sustainable and efficient practices.

Scrap Classification in VSB Before STORM

Despite continuous improvement in technical and operational standards and team training, the number of suppliers and consequently the receiving conditions imposed on VSB a complexity that required more sophisticated means to go further on improving the rework rate due to consumption of loads outside specification.

The following items include the main concerns related to the management of receiving and consuming metallic scrap and pig iron before the implementation of STORM:

- Nonintegrated information systems (logistics and raw materials).
- Decision-making relying solely on the operator's prior knowledge: destination of metallic load, classification, need for load dilution, etc.
- Nonstandardized reports in Excel spreadsheets.
- Records with photos only of metallic loads with "issues."
- Photos taken with the operator's mobile phone.
- Lack of a standardized storage pattern for photo records.
- Absence of a standard dilution pattern for out of specification loads.

STORM Benefits

The main idea of STORM is, based on the result of the automatic initial classification of the scrap truck, to suggest the best destination for each load, in order to reduce machine movements for scrap loading and unloading and to aim for homogenization of chemical composition and density. Additionally, the system records nonconformities and calculates supplier reputation.

Other advantages of STORM:

- Scrap classification (second classification) performed entirely within the application through photos of all loads obtained via tablets, with cloud storage for report generation as needed.
- Supplier "reputation" obtained through the supply and classification history. A supplier with a good cumulative rating will have a positive reputation, influencing decision-making regarding suppliers.
- Classification reports generated automatically, sent to suppliers, and emailed to internal recipients, including raw materials coordination, purchasing, and others.
- Storage of generated data throughout the system in the cloud.

The STORM system presents numerous advantages in the management of metallic within the steel mill. It facilitates meticulous control over raw materials, offering a detailed insight into suppliers and scrap types. Notably, the system enhances the uniformity of metallic load quality used in the EAF, mitigating substantial fluctuations between high- and low-quality loads. This approach results in reduced costs for raw materials in the medium term, as the scrap homogenization procedure eliminates the necessity of employing more expensive scrap for loads with low residual restrictions. The system assists in negotiations between buyers and suppliers through comprehensive records of metallic charge information, while the inclusion of supplier "reputation" data increases the classification focus during new scrap classification, ensuring more reliable results.

By implementing predefined logic, the system removes decision-making from operators, minimizing the likelihood of errors and biases in the decision-making process. It also reduces the probability of misclassifying anomalies and loads by utilizing photos and predefined lists. Additionally, the system provides traceability for loads destined for consumption or storage, contributes to improved raw material inventory management, and allows for the querying of information related to raw material flow, including bay levels, supplier history, and classifications by classifier and shift.

Process Flow of Receiving Scrap From the Market With STORM

The process of receiving metallic scrap for consumption in the electric furnace of the steel mill is divided into the following stages: sorting, radioactivity check, automatic classification, weighing, visual inspection, unloading, internal movement for consumption and consumption in the EAF (Fig. 1).

The sorting phase involves the generation of a scrap receipt control ticket, directing the vehicle to the classification area. Truck and scrap cargo details are recorded, and a tracking tag is given to the driver. The truck is requested to uncover the scrap load and pass through two radioactivity portals. Traffic lights indicate whether the load is cleared to proceed (green signal) or not (red signal) based on portal results. A fixed camera captures photos of the scrap surface as the truck passes through, sending this information to the automatic classification system. The first classification of the load is conducted using the photos and predefined rules. It is important to reinforce that the camera only captures images of the top of the truck. Even though several photos of the scrap surface are taken, they may not be representative of the entire load. Therefore, in light of this situation, a second visual inspection is conducted when the truck is unloaded in the scrap yard. This secondary inspection can either confirm or alter the initial classification.

The semaphore after the camera indicates if the truck is cleared to continue, and this information is displayed on the LED panel. The first classification data is sent to STORM. The STORM operator, located in the scrap yard, may manually request the scrap truck to leave the sorting area for unloading in the yard. However, the system prioritizes which trucks in the sorting area should be unloaded first to adhere to the mixing rule for creating the lasagna. The unloading information is relayed to STORM, appearing on a screen for the sorting team to determine which truck should go to the yard for unloading.

Upon arrival at the yard, the loaded truck passes through the road scale for weighing and undergoes visual confirmation of the automatic classification by an operator. Based on the automatic classification, the system automatically indicates the pile where the scrap should be unloaded. During unloading, another operator inspects the charge and performs the second classification, confirming the scrap type, checking for nonconformities, and taking photos with a tablet after unloading. The empty truck then passes through the road scale again, registering the net weight in STORM. The quantity of scrap is recorded as inventory in the unloaded pile, finalizing the classification. STORM registers the amount and types of scrap in each pile, calculating the weighted average of their characteristics. This average information aids in the mixing rule and automatic destination determination. Additional factors such as truck container type, supplier reputation, mixing constraints and waiting time in screening are considered.

Automatic Scrap Classification

The automatic scrap classification was built with a training of a deep learning model. The first step was collecting images through a fixed camera. The camera gets scrap images that are carried by trucks at the moment that the trucks arrive at the plant. After collecting a good number of images, each image was labeled and a data set was built. The labeling phase is one of the most important parts of the development of a deep learning model. In some situations, the scrap classes are very similar to each other, and small details differentiate them. Therefore, a huge effort to label each image correctly was applied, which was crucial for the model's success.

The model was trained using as a base the deep neural network EfficientNetV2 (Tan et. al, 2021). This network was adapted to classify 13 classes of scrap. The data set built has around 10,000 images and it was split into three partitions, 80% for training, 14% for validation and 6% for testing. The validation partition is used during the training to evaluate the model performance and guide the training to convergence. The testing partition is used only after the training to evaluate the model performance with images that the model has never seen before. After the training, this model had 96% accuracy on the testing partition. Fig. 2 shows a flow of the model classification; the picture is taken from the truck and the model identifies the scrap.

Many images can be taken for each truck. The classification inference is done for each image separately; in this way if 10 images are taken for a truck, 10 inferences are done. One truck is supposed to have all the same scrap on it; however,

Figure 1

Process flow of receiving scrap from the market.

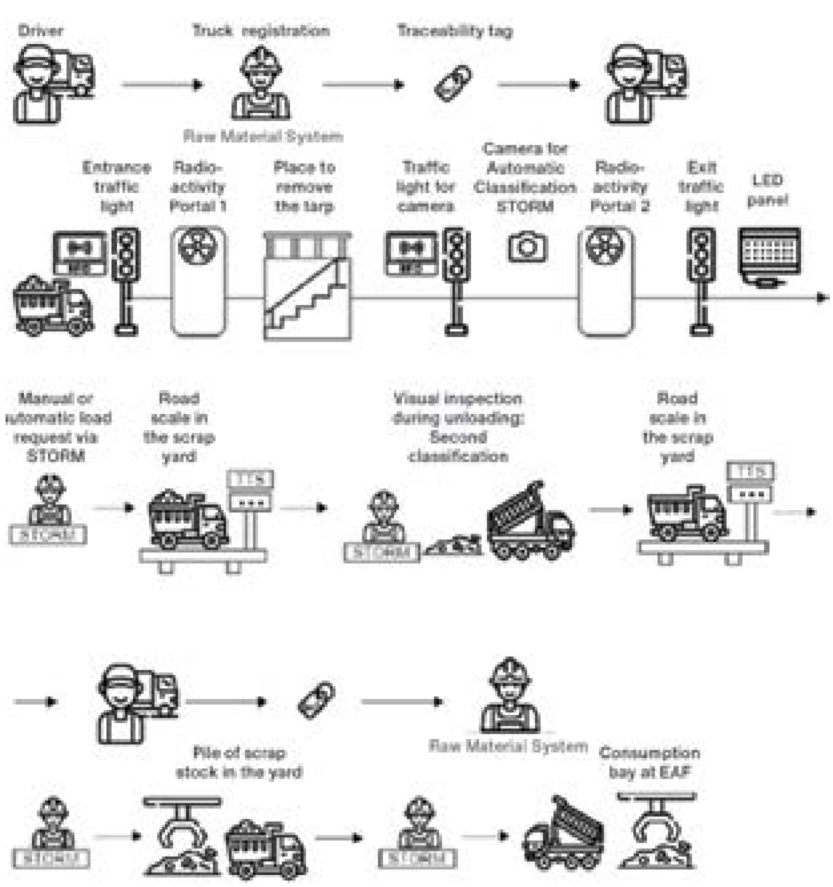
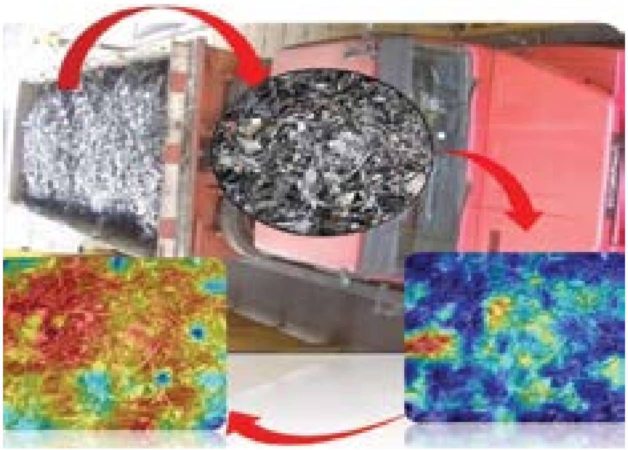


Figure 2

The flow of the model scraps classification.



sometimes a truck can be loaded with more than one class. As the model indicates one class per image, a set of images for the same truck can have different classes.

To solve this problem, a set of rules was developed to indicate what the final class of the truck is. For this, it checks the number of images of a respective class, and the quality of each class. For example, if in 10 images eight images are from Scrap A and two are from B, the rule will say in some cases that the final class is A, but if A is a high-quality scrap and B is a low-quality, Scrap A is contaminated by Scrap B and the rule will give a final class result different from A, even when the majority number of images are classified as A.

Therefore, the automatic scrap classification is done by the model and the rules. Improving the model with more training and adjusting the rules is what will guide the solution for better results.

Blending Rule

The concept of the Blending Rule, implemented in STORM 2.0, is outlined in the schematic diagram presented in Fig. 3. The decision-making model incorporates various pieces of information during the automated blending procedure for different scrap types. This model considers the following information:

1. Information about the scrap type during its initial automatic classification in the sorting process. Once the scrap type is determined through automatic classification, the blending model seeks the following registered information:
   a. Scrap type: whether it is low-cost or prime scrap. A predefined rule, derived from the automatic classification, determines whether the scrap is categorized as prime or low-cost.
   b. Average density registered for that scrap type.
   c. Specification of whether the scrap undergoes processing for packaging. This detail is crucial, as the destination model has preregistered the maximum percentage of packaged scrap allowed in each pile. It is assumed that a percentage exceeding 30% in the same pile could lead to scrap entanglement in the Consteel process.
   d. The average percentage of key chemical elements present in mix-type scrap: copper and chromium. It is assumed that other residual elements will also be homogenized while blending these two.
   e. Depending on the scrap type, checks are made for any restrictions on blending it in other piles. For instance, certain scrap types may have exclusive loading methods, such as loading only via basket, or may be utilized in a very restricted range of steel types. Consequently, such scrap types are kept in separate piles, and the model needs to be aware of this information.
   f. Supplier reputation: The model retrieves the supplier's reputation based on the supplier's name.
   g. Wait time while the truck has been in the sorting phase. The model prioritizes calling trucks to complete the lasagna rule, but trucks should not exceed the maximum time allowed on-site. When approaching the maximum time limit, the model prompts unloading for the truck.
2. Information about each scrap pile: At VSB, the scrap piles are fixed. For the STORM concept to function optimally, it is preferable to work with the notion of either closed or open piles for consumption (either the pile is being constructed or consumed).
   a. The maximum allowed capacity of each pile (in tons) should be registered.
   b. The quantity in stock for each pile should be updated after each scrap unloading.
   c. The name and location of each pile must be provided in the records (e.g., Yard 1, Yard 2, Yard 3...).
   d. The status of each pile should be updated. A pile will be closed for consumption until the stored scrap quantity reaches the specified maximum capacity. It will be open for consumption once it reaches the maximum volume. From this point, it will remain open until indicated that it will be closed again.
   e. Specify the accepted scrap group for each pile: mix, prime or another type of scrap with blending restrictions.

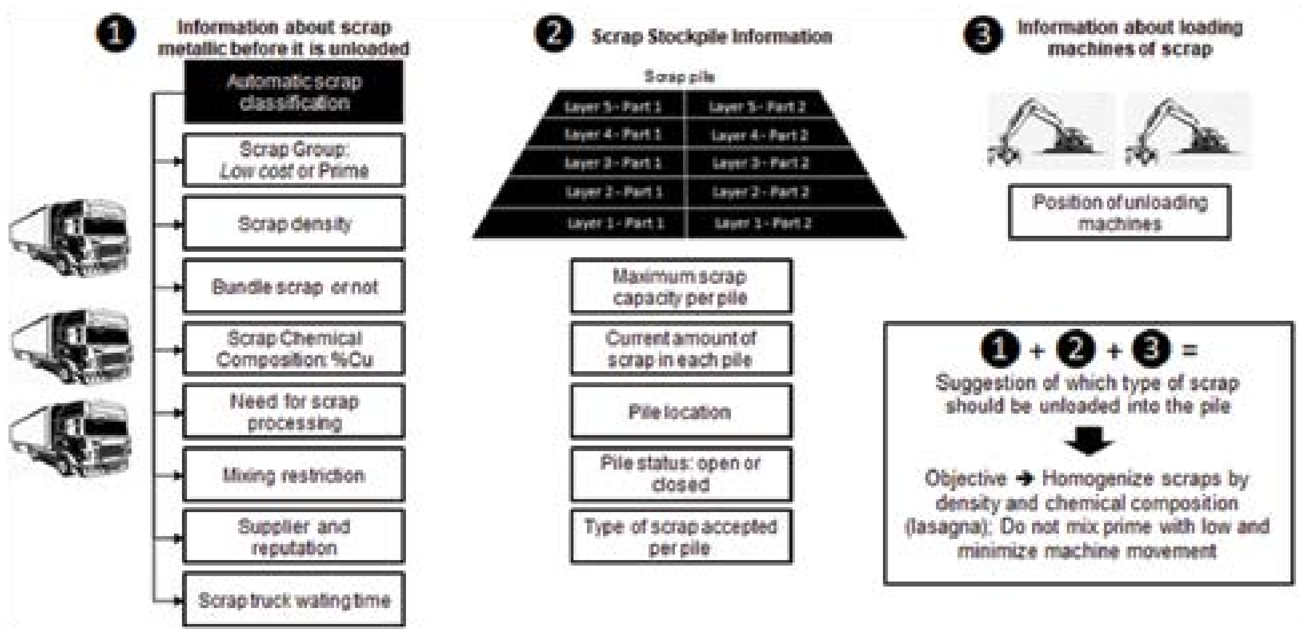
3. Another crucial piece of information is the real-time positioning of all machines available for loading and unloading scrap. While this information could be acquired through a GPS system installed on the machines, in the absence of such a system, STORM 2.0 assumes that, for the last pile that received scrap and still has the status "closed for consumption," there will be a machine in proximity to it.

Considering the information described in items 1, 2 and 3, the blending rule within the model will follow the following criteria to determine the discharge priority among the available scrap loads in the sorting phase, ensuring the creation of the lasagna:

1. The system considers the last piles for which any scrap unloading was recorded. It assumes that the unloading machines are close to these piles. For example, if the last piles with recorded scrap quantities were Pile A in Yard 2 and Pile H in Yard 3, it is assumed that the unloading machines are near these piles.
2. The model's first mission is to continue loading the piles near the machines while adhering to the lasagna rule.
   a. For the same layer, the same scrap type can be maintained.
   b. An average density will be targeted for all piles. The filling of the pile will be conducted to answer the following question: Is the average density of the scrap in the pile above or below the targeted density? If it is above, the model will request a truck with scrap density below the target. If it is below, the model will request a truck with a density above the target. The objective is to keep all piles with a similar average density, avoiding a pile with high density and another with low density.
   c. For the next layer, the priority will be to avoid using the same scrap type as the previous layer. However, if there is no other type of scrap waiting to be unloaded, changing the supplier should be prioritized.
   d. The priority will be to fill this pile until the maximum capacity registered for it is reached. If, at any point, there are no more trucks waiting to be unloaded that can complete the in-progress pile, the model will suggest the next pile with scrap volume closest to reaching the maximum capacity.
   e. Consider supplier reputation.
   f. Regarding chemical composition, piles will be registered as high-copper mix pile, low-copper mix pile and prime pile.
   g. Each pile will have a maximum percentage of packaged scrap.

Figure 3

Scheme of information required for mixing rule and automatic destination suggestion.



Results of Automatic Classification in STORM

STORM 2.0 was deployed for production in July 2023. Scrap classification occurs in two phases. The first classification involves inspecting the scrap on the surface of the truck. With STORM 2.0, the first classification is automatically performed by the AI model. However, this classification considers only the scrap on the surface of the truck. Therefore, a second classification remains necessary.

The first classification is now performed automatically. However, to conduct external validation of the model, a human classifier verifies the automatic classification result, and if necessary, adjusts the final result. Both the automatic and human classifications are stored, and this is used to check the model performance and also to retrain and enhance the model. This phase is crucial for evaluating and improving the real-world quality of automatic classification.

When the model does an inference for an image, it gives as a result the class of the scrap and the percentage of confidence for that class. In the case of confidence less than 50%, the result is not reliable, and the result is changed to "Unidentified Scrap." It happens when there is no scrap in the image; for example, an image that shows only truck parts (Fig. 4) or just the ground. Or when the model does not understand what scrap is on the image. The confidence in the results is related to the training phase. With more images and well-done labeling, the model will increase the confidence in classifications.

Fig. 5 shows scrap images taken by the fixed camera and with the model classification result. All the images were classified correctly and with high confidence, more than 90%. Only Scrap B had a lower confidence, just 58% but the model also classified it correctly. Scrap B is a kind of scrap that is similar to Scrap D in some cases, depending on how the image was taken. In this case, the confidence is lower, probably because the model understands that this image could be also classified as Scrap D or another class.

The automatic classification was monitored for six months. During this period, 5,271 trucks were received. Fig. 6 illustrates the distribution of outcomes in which the automatic classification appointed a class for each truck during this same period. It is observed that the automatic classification provided some classification for 82% of the trucks, and for 18% it could not identify the scrap class. As cited before, many factors can lead to low confidence in the model result and make the result Unidentified Scrap; one is when there are new situations on the images that are out from the trained data set distribution pattern. Because of it, is important to retrain the model and as time passes, better results will come.

Considering only the scraps that the model identified, these automatic classifications were compared to the classifications performed by human operators. The classifications made from June to October corresponded to the first model version. On the other hand, the results from November and

Figure 4

Examples of unidentified scrap.

Figure 5

Examples of scrap classifications with their respective confidence.

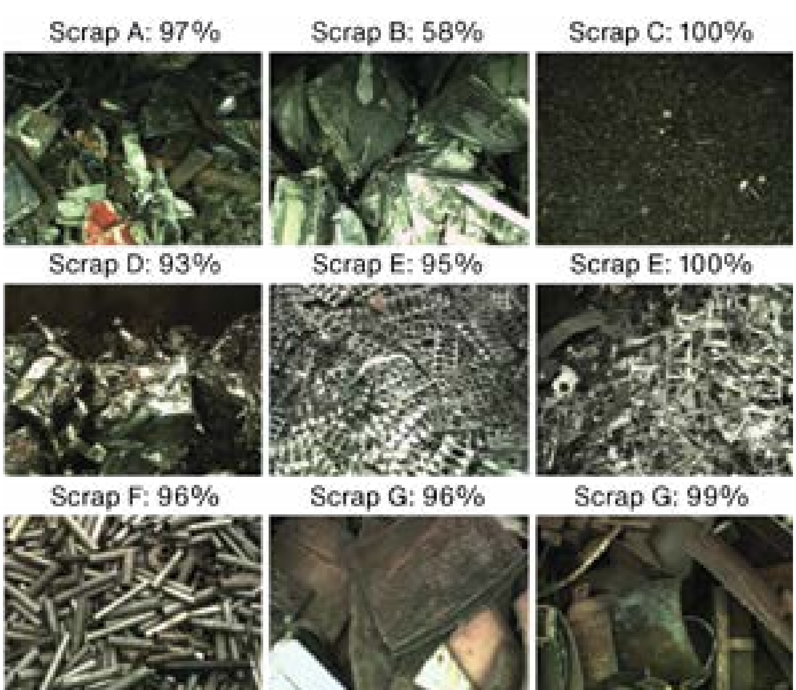


Figure 6

Distribution of unidentified and identified scraps by the automatic classification for 5,271 trucks.

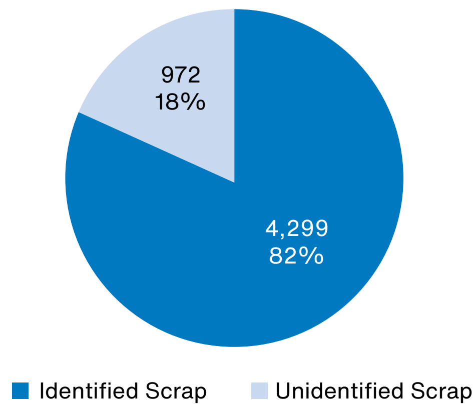
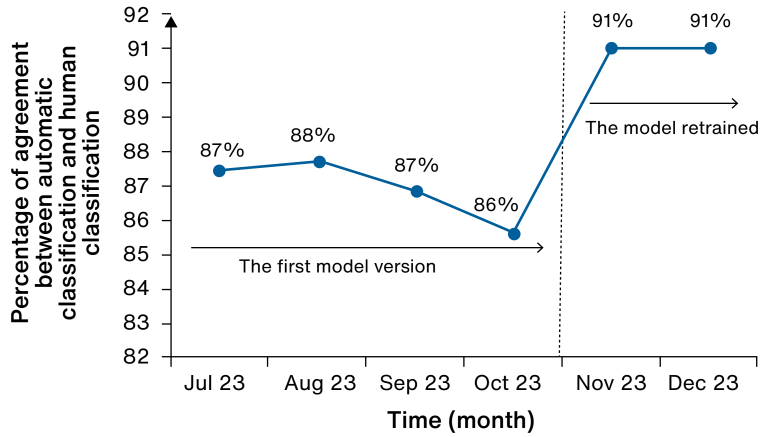


Figure 7

Percentage of agreement between automatic classification and human classification.



December resulted from the classifications made by the second model (version of the model presented in this article) that was retrained with more images. It is observed that for 91% of the classified trucks (Fig. 7), there was agreement between the automatic classification and the classification performed by the operator. This shows the benefit of model retraining.

The present work also described the development of the application component responsible for automatically suggesting the destination for blending different types of scrap to achieve homogenization of density and chemical composition. The application already has this functionality implemented. However, its effectiveness relies on the proper functioning of automatic classification. After the initial phase of monitoring and improvements to automatic classifications, the phase of automatic destination definition for storage, aiming at homogenizing the scraps, will be initiated, tested, and the results will be addressed in a forthcoming paper. Another ongoing development is the integration of STORM with the Value in Use 4.0 System, which is a system that suggests a metallic charge to minimize the cost of liquid steel and maximize yield or minimize the carbon footprint of the particular heat.

Conclusions

Automatic scrap classification represents a significant advancement in the efficient management of metallic scrap and the optimization of industrial processes. This article has highlighted various technologies employed in this context, ranging from machine learning algorithms to computer vision systems. However, the development of the STORM 2.0 application was not limited just to the use of the automatic classification model, but also involved the creation of a system that, based on automatic classification, manages the flow of metal scrap to the steel mill.

The development of STORM 2.0 involved the implementation of deep learning techniques for automatic classification, with the primary goal of translating tacit knowledge from human classification into a system with a reduced chance of error in this crucial task for an electric steel mill. Additionally, the system integrates information from the scrap truck sorting process to suggest the material's destination, aiming for improved quality to be delivered to the electric furnace. The automatic classification phase is already operational at VSB with an AI model accuracy of 96% for scrap used in the training data set. The automatic destination definition phase is currently undergoing validation and will be the subject of a future paper. However, it is essential to emphasize the importance of new model retraining phases to consider any new types of scrap that may be received. Another critical step is labeling, where true labels are defined for each image considered during training. Errors in this phase can result in inaccuracies in the model's output. A person with significant experience in scrap classification is highly relevant for this stage. The agreement between the results of automatic classification and human classification during the first six months at VSB was 91% of total classifications for which the model identified the scrap. This percentage can be improved with retraining and enhancements in the labeling phase. The percentage of scrap for which the result was undefined in the classification can also be reduced by improvements in the procedure for collecting scrap photos (camera position or timing of photo collection) or by adjusting the rule that determines the final classification of each load based on the multiple photos taken for the same load.

In summary, the automatic classification of scrap in an integrated system represents a crucial step toward improving the management of raw materials to be delivered to a steel mill and needs continuous improvement.

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