J.-C. BAUMERT*, M. PICCO*, C. WEILER*, M. WAUTERS**, P. ALBART**, P. NYSSEN**

AUTOMATED ASSESSMENT OF SCRAP QUALITY BEFORE LOADING INTO AN EAF

AUTOMATYCZNE SZACOWANIE JAKOŚCI ZŁOMU PRZED ZAŁADUNKIEM DO EAF

The quality of steel scrap, to be used as the main feedstock for an electric arc furnace, is automatically assessed by a system developed for continuous monitoring of the scrap basket charging process. At the ArcelorMittal Differdange plant's scrap yard, four digital cameras combined with four laser distance scanners, installed on the gantry cranes, record pictures of every deposited scrap layer and scan their height distributions within the baskets. Machine-controlled image quality detection, followed by contour measurements and granulometry evaluation, up to automated scrap grade classification deal with the visual aspects of the charged materials. This knowledge is combined with information received from the scanners in order to determine the basket filling ratios and scrap densities. In order to avoid basket overfilling the total scrap volume is also monitored with this technique. Relating the height profile measurements to the loaded weights gives a direct assessment of the density of each scrap layer and grade.

Keywords: Electric Arc Furnace, Scrap Charging, Monitoring, Camera, Image Processing, Density

Jakość stalowego złomu, który jest wykorzystywany jako główny materiał wsadowy dla pieców łukowych, jest ustalana automatycznie dzięki zastosowaniu systemu ciągłej kontroli jakości złomu. Na złomowisku zakładu ArcelorMittal Differdange zainstalowano cztery cyfrowe kamery połączone z czterema skanerami laserowymi. Rejestrują one każdą dostarczoną partię złomu i określają jego rozkład w koszu załadunkowym. Wizualna analiza konturów oraz oszacowanie granulacji pozwala natychmiast określić jakość porcji złomu. Wiedza ta połączona z informacjami uzyskanymi ze skanerów pozwala określić współczynnik załadunku kosza i gęstość złomu. Celem zapobiegania przeładowania kosza tą samą techniką monitorowana jest także całkowita ilość złomu. Porównując zmierzoną wysokość z załadowaną wagą złomu można prosto wyznaczyć gęstość każdej warstwy złomu oraz jego rodzaj.

1. Introduction

In order to improve the operations of electric arc furnace based steelmaking and the scrap recycling ratio, ArcelorMittal, in collaboration with CRM, and other RFCS partners, is currently developing a system for online monitoring of the scrap charging process into the baskets. Scrap grade characterisation is of high importance, not only to control the liquid steel composition, but also to ensure reliable melting conditions. Scrap must be layered inside the basket according to its size distribution and density in a way to allow rapid formation of a liquid pool of steel in the EAF vessel, while providing protection for the sidewalls and roof from arc radiation. In order to monitor this loading process at the scrap yard of the Differdange plant, gantry cranes have been equipped with sensors for digital imagery and height distribution measurements of each deposited scrap layer. Together with already available weight measurements, every layer of scrap, transferred by the crane from the scrap stock piles, or railway wagons, into the basket, is analysed in terms of its visual aspect, granulometry, and density. This part of the system, already in industrial use for over one year, is applied for operator training and supervision of scrap charging practices. Making the connection between every basket load, consisting of up to 20 different layers with various scrap qualities, and its characteristics to the actual performance of the furnace, will allow optimising the charging practice. Figure 1 shows the schematic layout of the system with four sensor units monitoring four scrap baskets. Figure 2 shows a photograph of two units attached to one gantry crane. Besides

*   DARCELORMITTAL BELVAL & DIFFERDANGE S.A., RESEARCH CENTRE, ESCH-SUR-ALZETTE, LUXEMBOURG

**   CENTRE DE RECHERCHES METALLURGIQUES, LIEGE, BELGIUM

a short description of the installed system, this article focuses on our data processing work in order to extract useful information on the grade, quality and density of the charged scrap.

2. Description of the data acquisition system

As shown in figures 1 and 2, the two charging cranes are equipped with two sensor units each, mounted above the tracks which carry the 100 ton scrap baskets. Since the Differdange plant uses a dual shell EAF, up to four baskets may be loaded at the same time.
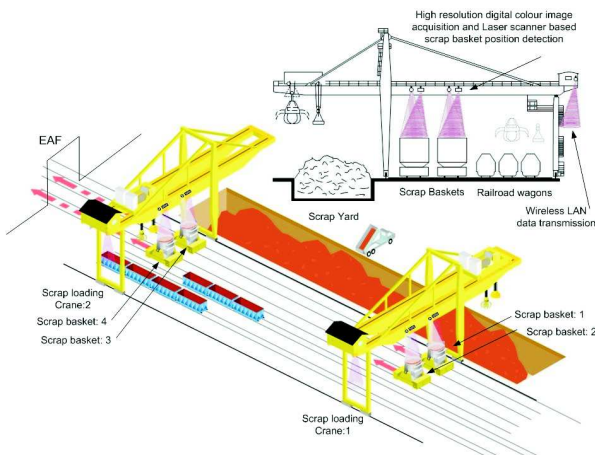

Fig. 1. Schematic layout of the system using four sensor units to monitor four baskets
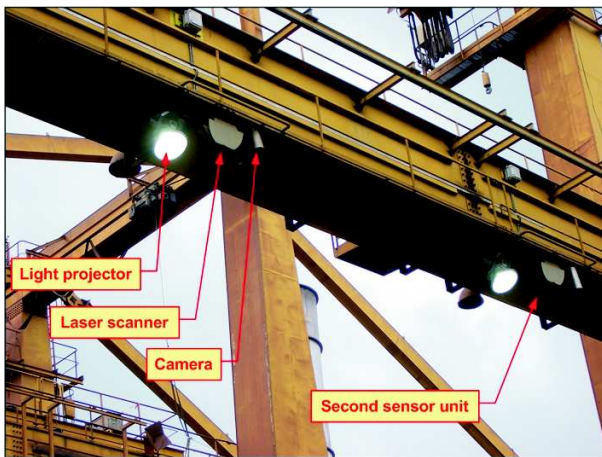

Fig. 2. Photograph of two sensor units attached to one gantry crane

Each sensor unit consists of a medium resolution colour digital camera, a precision laser distance scanner, and a powerful light projector used during night operation. Each time a layer of scrap is deposited by the crane, using its grab or magnet, into the basket the camera records a digital picture of this layer. Furthermore the laser distance measuring device scan across the diameter of the basket, recording a height profile of the

currently charge scrap pile. The data from all devices are transmitted via wireless LAN system to a central PC used to remotely control the complete system. This PC further records other important information, such as scrap weights continuously transmitted from the basket carriers, and positions of the crane along the scrap yard and its trolley. Using these data, values on scrap density can be calculated, and the position values allow a tracking where the scrap was picked up and in which basket it was loaded. A typical sequence of loaded scrap layers into one basket is shown in figure 3.

Fig. 3. Beginning of a scrap loading sequence for one basket

A lot effort was put into the development of the rather complex system control software, the most critical part being the correct synchroni-sation between image and scan acquisitions and the movements of the cranes, trolleys and baskets. Furthermore a user-friendly visualisation of all scrap layers within one basket load was prepared in order to help the operator and the process engineer to identify 'problematic' inputs to the furnace, such as 'wrong scrap type in wrong layer', 'very heavy scrap piece', or even 'dangerous scrap piece' (ex. hollow body).As an example figure 4 shows a typical display used during software development for checking the correct functioning of the system.
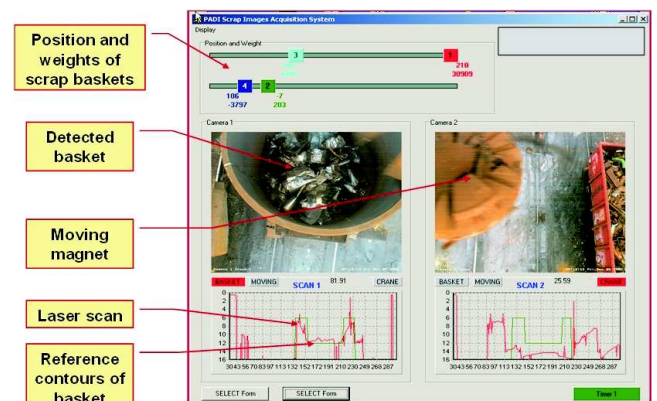

Fig. 4. Development screen of system control software

3. Pre-processing of the scrap layer images

Besides the 'manual' visual inspection of the collected scrap layer images by operators, new techniques have been developed to automate the scrap characterisation process. In a first step digital image processing is applied to extract information about scrap size distribution and granulometry. Once this information is available, charged scrap types may be automatically identified, for example by using artificial neural network classifiers.

Although a lot of effort was made to correctly trigger the cameras and scanners, from time to time erroneous data are recorded, mainly because of the numerous moves of both the cranes and the baskets during the charging process. Here the crane grab or magnet may cover up the underlying scrap layer in the image, or the image can be 'foggy' because of large quantities of dust emerging from the basket immediately after the charging of a new scrap layer. Before any automated classification can be made, it is crucial to eliminate all those images.

In a first step a correct region of interest (ROI) within the images must be defined in order to further analyse only the scrap related parts of the pictures. Since both the scrap baskets and the gantry cranes move during loading, the basket contours are not always well centred within the image. Therefore software routines were developed to automatically identify the position of the scrap baskets after the recording of each picture, followed by cropping to the ROI which only contains scrap parts, exempt from boundary effects, such as the edge of the basket or even parts outside the basket.

For this purpose we adapted an algorithm, proposed within the MATLAB® 'Image Processing Toolbox' (IPT) [1], based on normalised 2D cross-correlation [2] for feature extraction. In short, this technique consists in defining a (small) template image that is supposed to appear in all the images to be analysed and to find, or recover, this template and its position within the original image. Since in our case the goal is the precise location of the baskets within the images recorded by the four cameras installed on the loading cranes, the template(s) used are extracts of the images containing parts of the upper edge of the basket. Once the template is located within an image, the actual position of the centre of the basket is easily calculated, and a ROI may be defined around this centre. In our recorded scrap pictures, the basket may be either shifted towards the top or the bottom of the image, or may be well centred. In the later case neither the top nor the bottom boundary of the basket may be visible.

A further difficulty is the fact that the image contrast and colours strongly depend on the lighting conditions (day/night, sunshine/cloudy). Therefore we have
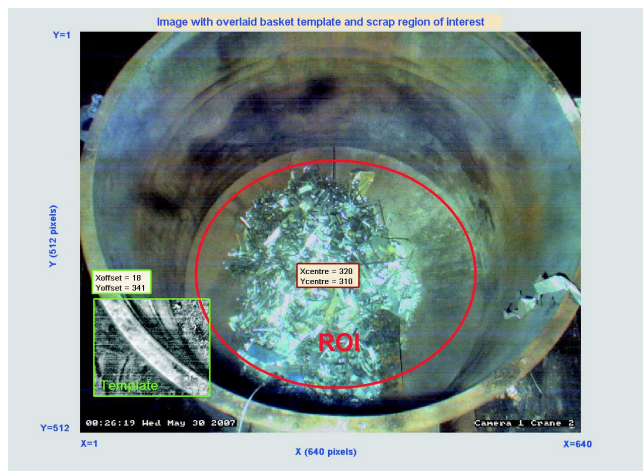

Fig. 5. Scrap/basket image with overlaid template and ROI

selected eight different templates, taken from different pictures, reflecting different parts of the upper basket edge and different contrast values. Every new image is cross-correlated with the eight predefined templates, taken at different locations on the basket rim, and the one with the highest peak in the cross-correlation function is retained. The x- and y- values of the correlation peak automatically indicate the position of this template as recovered in the new image. From these coordinates the centre of the basket is determined and an ROI is defined. Because of the slightly off-axis viewing directions of the camera into the round baskets, this ROI was defined as an elliptical section, resulting in a maximum size usable area. An example scrap/basket picture, together with an overlaid basket edge template and the position of the corresponding ROI is shown in figure 5. Once the full image is cropped to this ROI, the resulting picture will be further processed. Figure 6 shows all the processing steps from a raw scrap layer picture to the cropped image. Here template N°6 gave the best fit for locating the position of the basket.
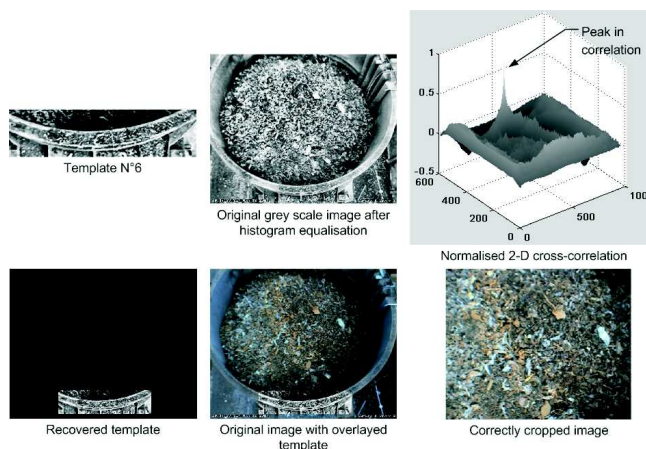

Fig. 6. Template 6 gives the highest correlation for a basket, centred laterally but slightly shifted towards the top of the image

As mentioned earlier, images showing a large amount of scattered dust, rising from the basket during loading (dry scrap during summertime) and masking most of the underlying scrap, are problematic for further extraction of scrap characteristics. Since these dust clouds (or fog) show a certain texture, contour algorithms, depending on their sensitivity, will detect fake edges which may be interpreted as large scrap pieces, similar to those encountered in industrial demolition or internally recycled scrap from a rolling mill. Therefore it is important to automatically detect these images and eliminate them before the scrap classification process.

Dust loaded, or foggy, images show a typical 'grey in grey' texture and their overall and local image grey, or intensity, values vary rather smoothly. Clear and sharp pictures of scrap pieces show a much coarser (industrial demolition, sheared) or a finer (shredded, turnings), but regular texture. Therefore statistical methods, for obtaining regional descriptors of the images, seemed to be a good approach to discriminate between foggy and clear images [3]. It turns out that the calculation of the local standard deviations of the grey values gives a good indication on the 'usability' of an image for further processing.

The function 'stdfilt' (MATLAB$^{\circledR}$ IPT) [1] produces an output image where each pixel contains the standard deviation of the 3-by-3 neighbourhood around the corresponding pixel in the input image. Larger neighbourhoods should not be used; otherwise images of very fine scrap parts, e.g. steel turnings, may yield standard deviation values similar to the 'foggy' images. The sum of the standard deviation values over the full image matrices is calculated and the corresponding values for foggy and clear images of different scrap types are com-

pared, as shown in the following figures. In our case, where all images were cropped to the same size, foggy images show much lower summed standard deviation values than the values obtained from clear images of different scrap classes, as shown in figure 7.
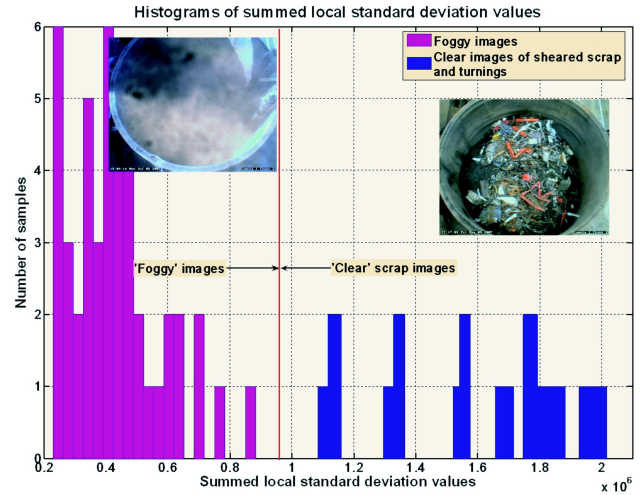

Fig. 7. Distributions of summed local standard deviations

4. Image processing for automated scrap type identification

After correct cropping and elimination of bad quality images, the next step of processing consists in contour extraction in order to detect the size distribution of the loaded scrap pieces and to define their granulometry. This technique, previously reported [4], again uses standard MATLAB$^{\circledR}$ IPT routines [1], where the 'Canny' contour detection algorithm works best for these images.
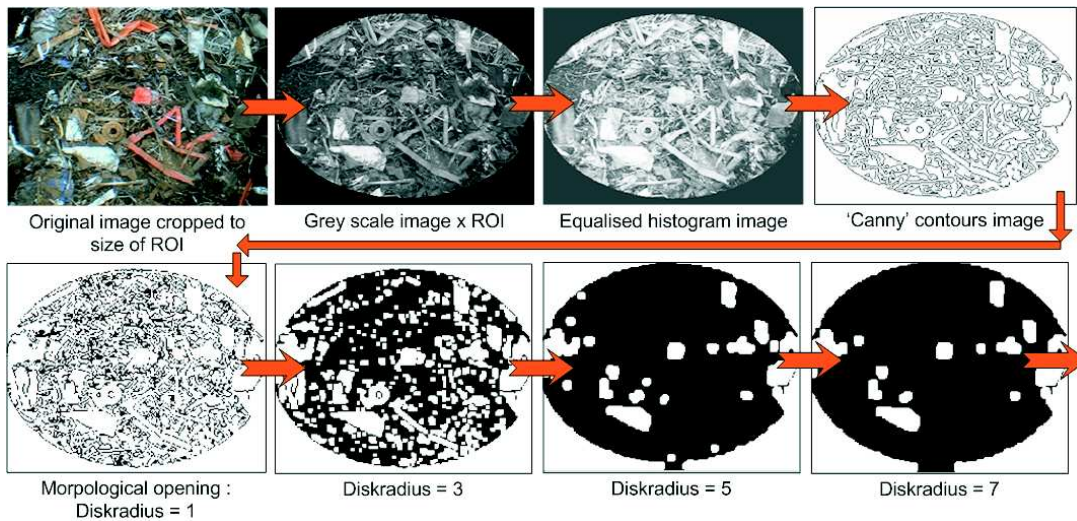

Fig. 8. Image processing steps for contour extraction and granulometry calculation

A so called 'granulometry' distribution is calculated by successively applying a morphological opening of the binary contour image with a structuring element, which in our case is a disk with increasing radius. Such an image processing sequence is shown in figure 8. The computation of the change in surface area between each image opening step ('loss of pixels') yields a distinct granulometry distribution for every scrap grade, as shown in figure 9.
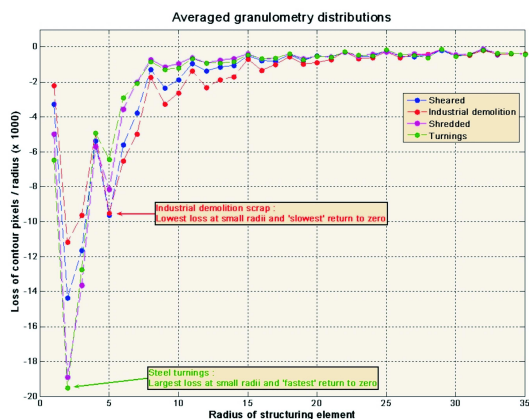
Classification obtained with the PNN

Confusion matrix	Sheared (50)	Industrial demolition (50)	Turnings (50)	Shredded (50)
PNN : Sheared	46	9	1	4
PNN : Industrial demolition	2	39	1	0
PNN : Turnings	0	0	45	7
PNN : Shredded	2	2	3	39

Fig. 9. Average granulometry distributions for four scrap grades

connected objects issued from the granulometry distributions. The layer of radial units stores pattern exemplars, taken directly from the training data. Finally the layer of linear classification units sums the outputs of pattern exemplars for each class and constructs an estimate of the probability of membership of that class.

The obtained classification results are summarised in table 1. Images of 50 samples each from four different scrap grades have been processed and their data fed to the classifier. The main diagonal of the confusion matrix shows the number of correctly identified samples.

5. Automated charged scrap grade classification

In order to closely follow up what kind of scrap was charged in practice for every layer and compare this information with the scrap mix predefined ahead for each heat at the EAF, it may be useful to automate the scrap identification process, also because of the large number of collected images. This problem was successfully solved with the help of a probabilistic neural network classifier (PNN) [5, 6], as shown in figure 10. The input layer consists of 36 units for radius data and number of
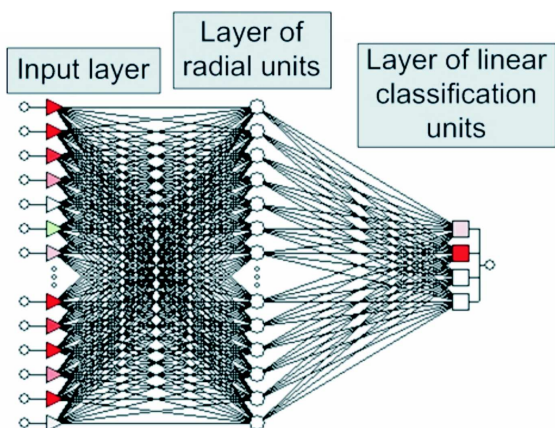
6. Height scan processing for scrap density assessment

The scrap level distribution in the basket is assessed by means of laser-based scanner measurements. Triggered at the same time as the corresponding camera, the scanner performs a complete scan within one second, each scan containing 360 measuring points in a 180° linear angle (figure 11). Each scan carries on distance measurements from the scanner to the physically intercepted points, here mainly the scrap basket located on its tracks.

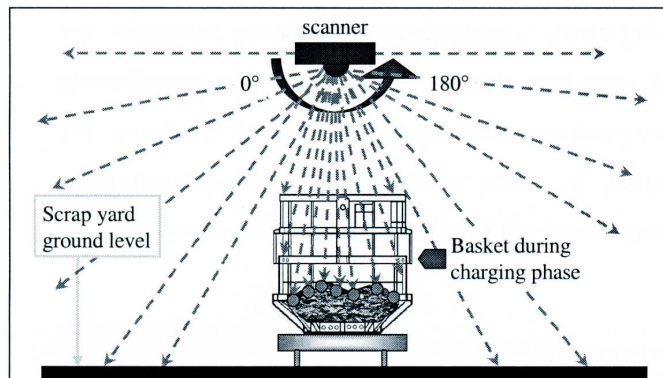Fig. 10. Probabilistic neural network classifier

Fig. 11. Scanning operation during the charging phase

An example of a basic scan is given in figure 12, the red marked discontinuous circles showing the area limited by the basket in the global signal. Processing of the raw scans is necessary in order to extract the height profiles of the scrap layers in the basket. A special scan data analysis algorithm has therefore been developed, with the objective to automatically extract these height profiles.
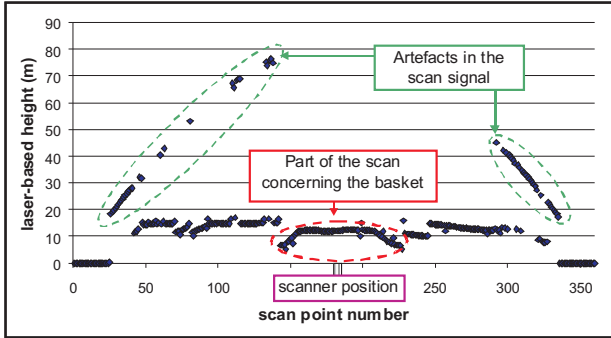

Fig. 12. Complete scan of the basket before processing

For each scan, the representative zone of the basket (blue squares in figure 13) has to be extracted from the global signal after elimination of parasitic values and basket edges. A so-called scrap profile is obtained. The scan is then further processed to get the average scrap level. The average scrap level is finally transformed into volume (knowing the basket geometry) and combined with the scrap weight signal to measure the scrap density of each scrap layer and grade.

The described monitoring system is able to follow the whole basket loading phase leading to the evaluation of the volume of each layer of scrap. The total scrap volume is also monitored with this technique in order to avoid overfilling. The drawings in figure 14 illustrate the evolution of the scrap height profiles as measured by the scanner during the charging sequence (60 ton basket,
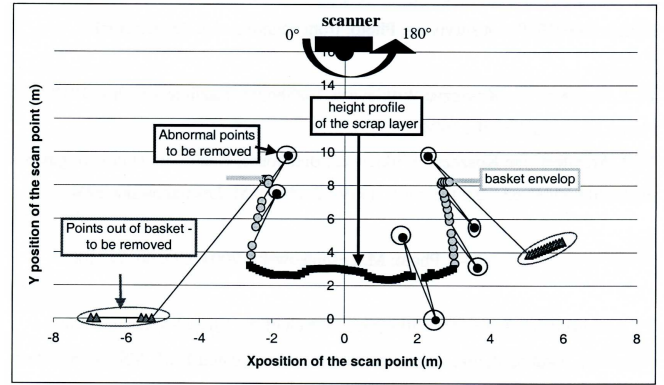

Fig. 13. Extraction of the useful data area from a scan

scrap mix 20). On the left-hand side the successive height profiles are shown, whereas the drawing on the right-hand side indicates the corresponding averaged heights. The lower level measured after charging of a so-called the 'YT' scrap grade (anthracite, dust and/or sand) illustrates the complex interactions between successive layers of material, such as 'settling-down' of the previous layers and filling-up of cavities.

Two campaigns of measurements have been carried out at the ArcelorMittal Differdange plant and a database of density values per class of scrap is currently being built. Statistics have been performed on this database. Figure 15 shows the averaged densities of different scrap grades, as measured with the monitoring system, in comparison with the European specifications. Light scrap grades (E1 and E8) have averaged density values of about 0.65 t/m^3, while heavier scrap grades show densities close to, or higher than, 1 t/m^3. Globally, these averaged densities appear to be in quite good accordance with the European recommendations. The averaged density of a complete basket (first or second basket) was estimated to 0.75 t/m^3, with values ranging from 0.5 t/m^3 and 1.5 t/m^3.
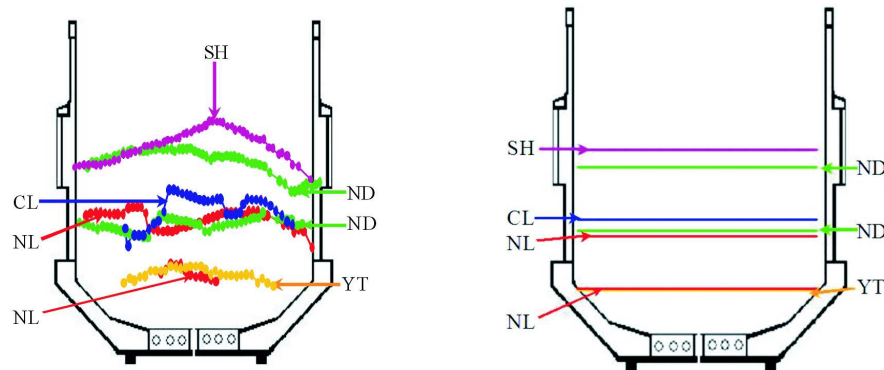

Fig. 14. Evolution of the height profile during the charging phase and the corresponding averaged height of scrap after scan processing
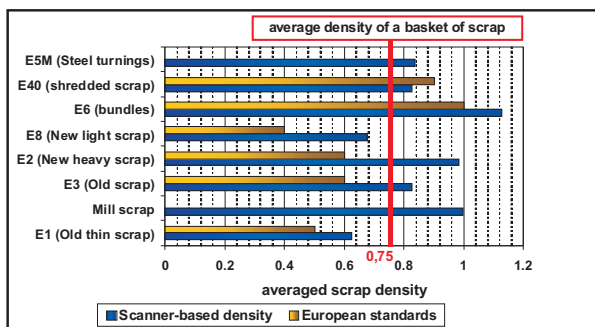
Fig. 15. Averaged scrap densities determined for each grade

While their averaged densities may show good trends, some scrap qualities are characterised by large fluctuations. This is clearly the case for the new light scrap (E8 grade) that normally charged as a first layer in the basket. Figure 16 illustrates the relationship between the scrap volume and its corresponding weight.
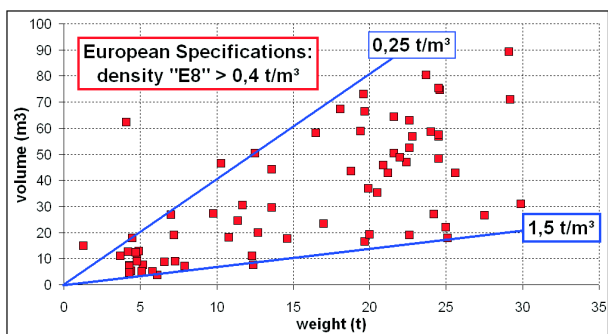

Fig. 16. Relationship between scrap volume and scrap weight for the 'NL' scrap grade
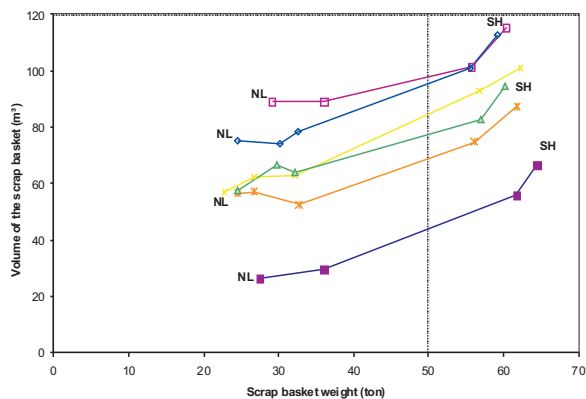

Fig. 17. Scrap volume evolution during the charging phase

Each point on the graph represents the sum of all successive layers of the "NL" scrap grade Density variations ranging 0.25 t/m^3 to 1.5 t/m^3 have been observed, leading to the conclusion that this particular scrap grade does not fulfil standard basic requirements ('NL' density > 0.4 t/m^3).

Moreover, a very interesting result, obtained with this scrap monitoring system, was the pinpointing of the influence of the light scrap on the charging pattern and on the total height of scrap pile in the basket. The graph of figure 17 shows the evolution of the scrap volume over the basket charging phase. As previously described, the large density range of the 'NL' scrap grade induces a large scatter in the final volume of scrap.

The trends in the volume increase are nevertheless reproducible, indicating that some rules of basket charging can be defined in reference to the grade of scrap being charged. This means that the charging pattern may be modelled, giving to the crane/charging operators a device able to assess dynamically the final filling level.

7. Conclusions

The first analysis of the scrap images and the density values database illustrates the consistency of the measurements performed by scrap monitoring system. While the assessment of densities for each scrap grade charged for the EAF is useful per se, the appraisal of the final charging volume requires nevertheless the knowledge of the complex interactions between the different scrap layers. The developed system proved its ability to achieve the goals of automated scrap charge monitoring.

REFERENCES

[1] MATLAB, Image Processing Toolbox 5, User's Guide, The Mathworks, Inc. 2005.
[2] J. P. L e w i s, Fast Normalized Cross-Correlation, (http://www.idiom.com/~zilla/Papers/nvisionInterface/nip.html)
[3] R. C. G o n z a l e z, R. E. W o o d s, Digital Image Processing, Second Edition, Prentice Hall, New Jersey 2002.
[4] M. P i c c o, J. C. B a u m e r t, Automatic Detection of Steel Scrap Grades Charged into an EAF using Artificial Neural Networks, Presentation at the International ATS Steelmaking Conference, Paris 2003.
[5] Trajan 6.0 Professional, Neural Network Simulator, Trajan Software Ltd. 2001.
[6] MATLAB, Neural Network Toolbox 5, User's Guide, The Mathworks, Inc. 2007.