AMI Artificial Intelligence and Machine Learning applications for EAF Optimization

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1. Introduction

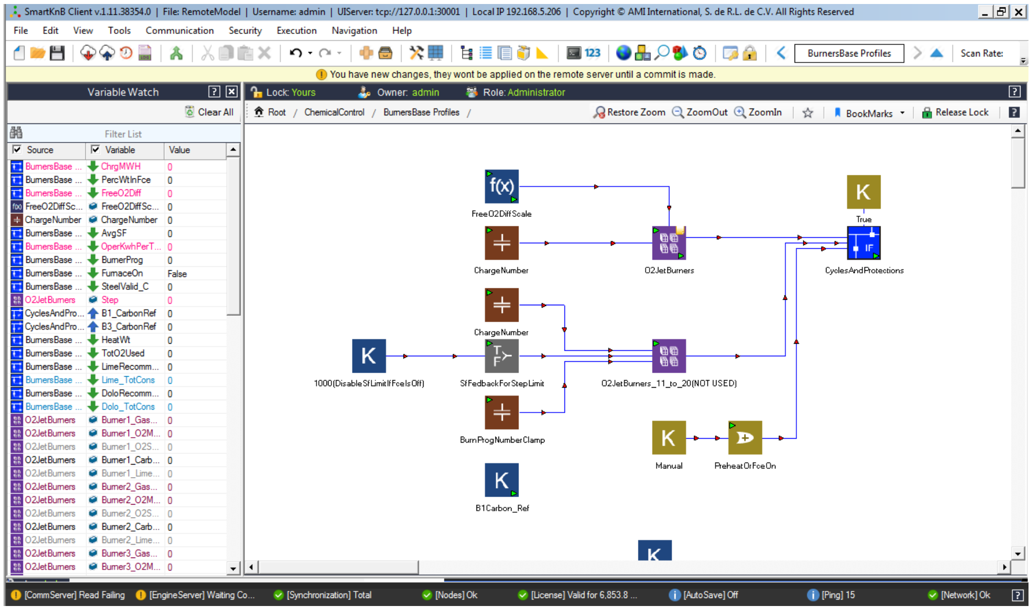
The amount of data available in the modern Electric Arc Furnace operation, even if only using standard instrumentation and automation, has proven to have enormous potential for process analysis and improvement using the latest Artificial Intelligence tools and algorithms, as they have been implemented on a dedicated software recently developed by AMI, the SmartKnB platform. SmartKnB is a graphic programming interface making possible to develop solutions merging data acquisition, complex process logic and machine learning models, all in the same user-friendly environment. Several applications have been developed and deployed in the field of EAF using the SmartKnB, for instance, to follow the process from the raw material intake, analyzing its characteristics in advance to optimize the melting and final steel composition. Also, capable of continuously evaluating correlations between the process and usage of consumables to find the most favorable operating point.

Finally, a scrap type classification based on image has also been implemented using a Convolutional Neural Network model in the software. The possibility of adding image processing and using advanced cameras capable of withstanding the harsh environment of a steel plant, will give immediate feedback to the AMI platform, opening a vast field of opportunities to put eyes on the process closer than ever.

2. SmartKnB Platform

The SmartKnB, like its predecessor Visual KB, is designed as a platform for the development of advanced control applications. For interaction with the real world, the software is capable of reading and writing data from different PLCs using some native PLC communications for some brands and OPC communications for others. It can also connect in the same way to Data Bases to obtain the required information about the process.

The code in SmartKnB is on-line programmable and it supports multiple users working at the same time in different parts of the system. The code is similar to a Flow Chart diagram and it is designed to visually represent the rules and algorithms, allowing the tool to accurately implement the Knowledge Base behind the control system. It allows the creation of several levels of sub-modules to encapsulate complex logic processes which can be easily replicated or transferred to a different area of the program or even to an entirely different operation. An example of the actual programming code is shown in the next picture.



The SmartKnB system includes several Artificial intelligence tools such as clustering algorithms, multiple stage Fuzzy Logic with profile based parameters, advanced instructions to achieve non-linear approximations or to set a multivariable based profile for a process parameter being controlled, just to name a few. If the user requires a very specific application development or prefers to use other programming languages like Python or C, it is also possible to create new instructions within the SmartKnB system environment using these languages.

Another important addition to the SmartKnB tools is the Machine Learning modules. These modules allow to develop Models using Machine Learning and then to import them into the SmartKnB to be used for On-Line control. These algorithms are not limited to Data variables only but it is also prepared to run Artificial Vision models. The models can be created on any platform the user prefers like Python, Math Lab, etc. which then can be imported into SmartKnB. Several applications have already been developed using these tools, as it is described in the following sections.

Other important capability of the SmartKnB is that it allows to create different sets of data which can be used to develop Machine Learning models or just to have historical records of the process. Several data sets can be created at the same time. These data logs can be accessed later for analysis or review, but they can also be used for simulation in the SmartKnB software, thus providing the capability to test newly developed algorithms with historical data sets, getting a simulated response.

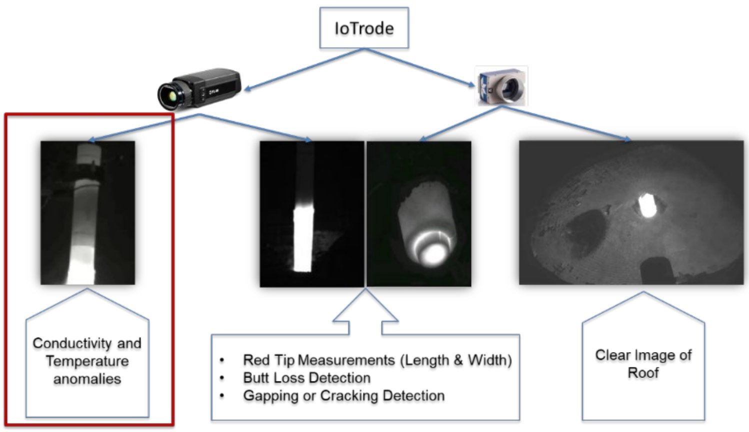
Finally, in order to facilitate the interaction with the system and make it more visual, SmartKnB has a tool for custom HMI development. This HMI enables the user to access directly instructions with the control parameter, turn on and off different switches to modify system behavior, watch data trends in graphs or use different types of indicators.

3. Machine Vision developments

The latest advances in machine vision and Artificial Intelligent are being gradually adopted by the steel industry. AMI is leading this process, integrating these new technologies to the existing EAF optimization models helping to improve process safety and give additional tools to optimize the overall performance.

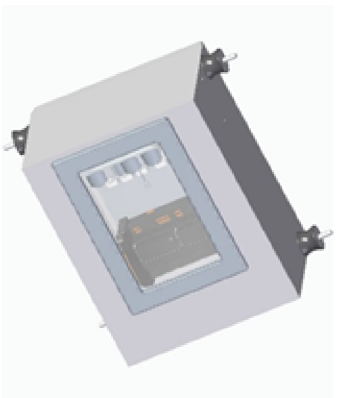
IoTrode

For analyzing the consumption of the EAF electrodes, AMI developed the IoTrode. This system uses high-definition cameras to measure the electrodes red tip oxidation. Registering the electrode tip deformation and oxidation makes possible to measure the real electrode consumption, per heat and per phase. This information is used by an adaptative control system to better use the electrode water cooling to minimize the red tip generation. Furthermore, all the data generated by the electrode high-definition images can be used to evaluate the quality of the different providers, as well as for inferring which process variable is affecting the most the electrodes consumption.



Scrap Classification for Continuous and Bucket charging

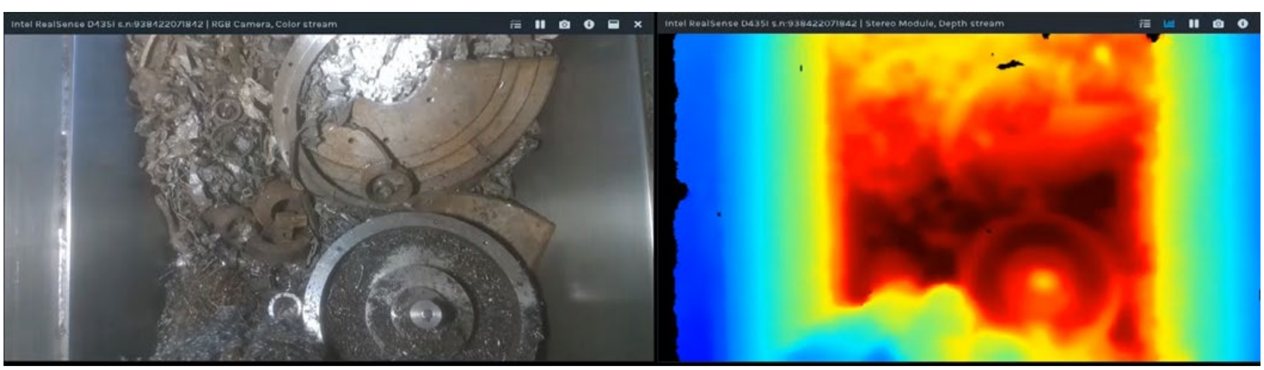
For the automatic scrap classification, AMI developed a system that uses sensor fusion technology and deep learning. The challenge is to classify and measure more than 30 different types of scrap, without human intervention, before the raw material is fed into the EAF. To achieve this a 3D camara is used. This camera provides stereo vision using two monochrome cameras with an infrared spectrum projector, together with high resolution color images. Using this technology and developing sensor fusion algorithms a high-resolution color image of the scrap together with the scrap volume is calculated in real time, either when preparing the buckets, or when feeding the scrap through a conveyor.



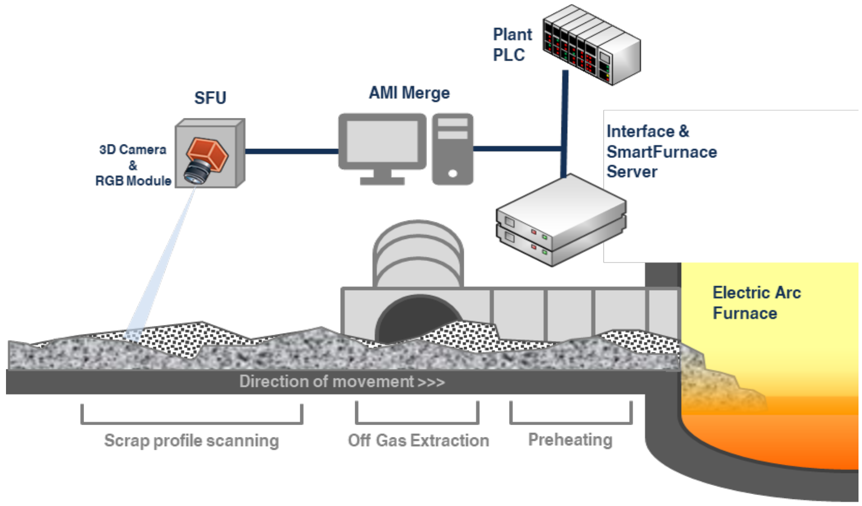
Sensor Fusion Unit

In order to automatically classify the scrap type based on 3D images, data-driven analytics, and machine learning (ML) were used. Having thousands of images from more than 30 different scrap types a data driven ML was the most direct solution. 70% of the data set was used as inputs for a transfer learning technique based on Convolutional Neural Network (CNN) model and the 30% remining was used for validation. Once a Convolutional Neural Network trained model validation accuracy surpass 95% the model was considered fitted and it was exported as an Open Neural Network Exchange Model (ONNX). ONNX is an open format to represent artificial intelligence models that is widely supported and can be found in many frameworks.

The trained scrap classifier ONXX model was imported into the SmartKnB platform and directly integrated to the rest of the EAF optimization. This versatility allows to develop complex machine learning solutions and integrate them easily with the existing EAF control systems.



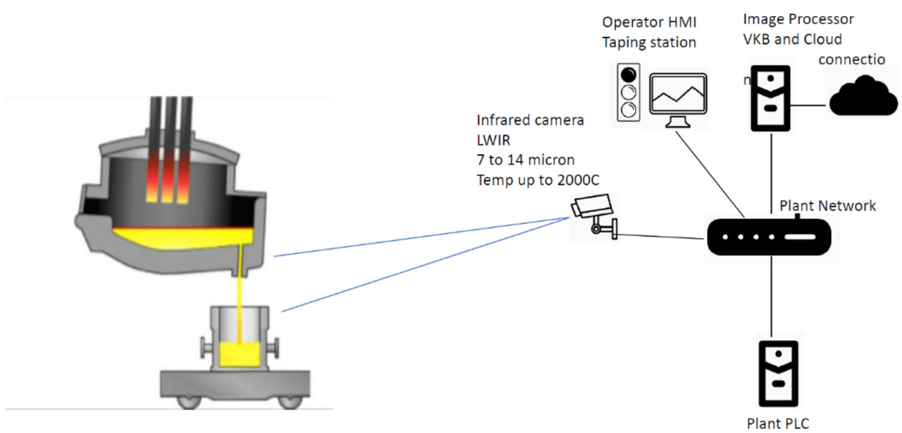
Knowing the exact scrap mix that is being charged in real time into the EAF, allows to optimize the available energy inside the furnace, improve the end point carbon and temperature estimations. The scrap classifier was implemented in a furnace continuously feeding scrap, and it is called IoConveyor. The system also measures the scrap speed on the conveyor and estimate the real feed rate. The objective was to generate this data in a detail and timing not available before, leading to better control of the feeding speed to avoid overheating or unmelted scrap. The system was installed in two major steel manufacture plants in the USA.

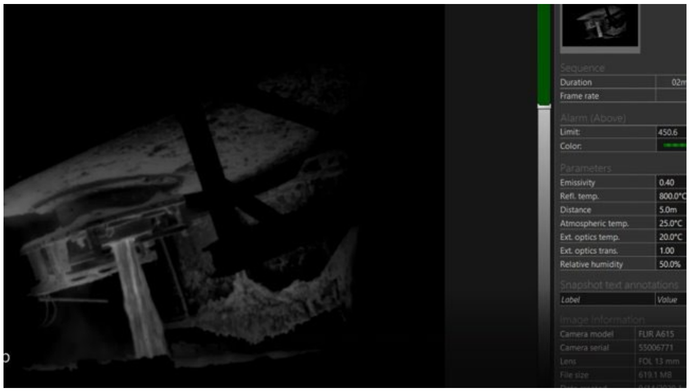


AMI is also developing a solution for scrap classification and mass estimation for bucket charge facilities. The IoBucket, based on the gained experience in the continuous conveyor to address the bucket charge challenge. This system will be tested in mid-2022.

IoTap

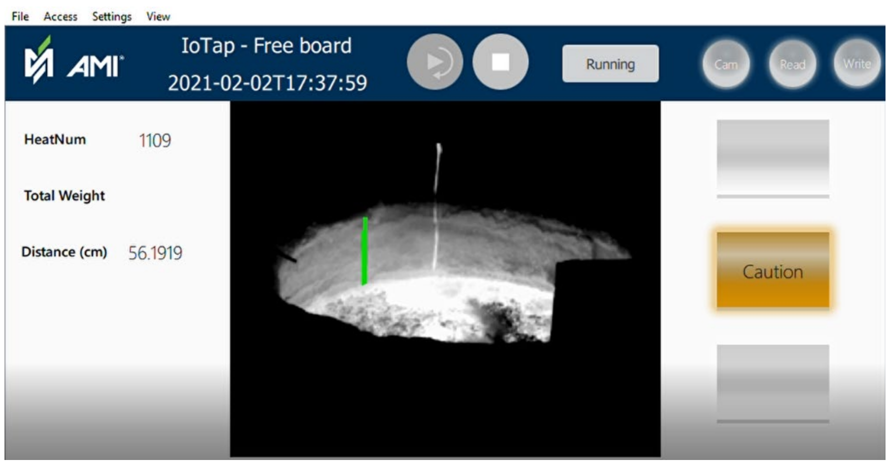
For detecting the slag carry over during tapping, AMI developed the IoTap. This system uses a high-resolution long wave infra-red camera suitable to measure temperatures of up to 3000 degrees C. The infrared images provide valuable information regarding the tapping process that cannot see by the human eye. Knowing the emissivity of the steel the slag can be differentiated and the system integrates the amount of slag that is passing from the EAF to the ladle. The steel producer can assure clean steel in the caster to avoid stickers and can decides when is necessary to remove the extra slag in the ladle.





Freeboard detection

Furthermore, an extra LWIR camera is placed focusing on the ladle free board. The actual freeboard is measured using image processing of the IR image and the tapping operator has online feedback of the ladle level to avoid splashing and brick wash out.



Conclusion

Taking a closer and more detailed look on existing Electric Arc Furnaces using smart vision systems, coupled with powerful data analysis tools, has shown that potential for improvements and optimization can always be found. The SmartKnB optimization platform is capable of processing data with much greater volume than ever before, opening new opportunities for understanding and improvement on the process efficiency and safety, while at the same time making it available to the user in a meaningful way.