REVaMP

Deliverable 8.1

Retrofitting Equipment for Efficient Use of Variable Feedstock in Metal Making Processes - REVaMP

H2020-NMBP-ST-IND-2018-2020 / H2020-NMBP-SPIRE-2019

Grant agreement no. 869882

Start Date: January 1st, 2020

Duration: 48 months

Project Type: Innovation Action

Technical evaluation of the different retrofitting solutions and overall results of the industrial applications in the different demonstration cases

Due Date: October 31st, 2023

Submission Date: January 30th, 2024

Work Package: **WP 8 – Evaluation of retrofitting solutions at industrial scale**

Lead Beneficiary: **EUT**

Authors:

Partner	Name
EURECAT	**Manel da Silva López**
BFI	Bernd Kleimt
NCBJ	Martyna Grodzicka-Kobyłka, Tomasz Szczęśniak
SYSKON	Henryk Zastawny
POLON	Andrzej Gajderowicz
Fraunhofer ILT	Cord Fricke-Begemann
LSA	Markus Dargel
AMB	Jan Bartel
SIDENOR	Iñigo Unamuno
SIDENOR I+D	Diana Mier
GRUPAL ART	Tomas Baldi, Francesc Peregrín
AZTERLAN	Javier Nieves, Ibon Lizarralde, Clara Delgado
GHI HORNOS	Alain Campo
REFIAL	Represented by INATEC
INATEC	Jon Barrenetxea-Arando, Noelia Montes, Javier Munoz
CARTIF	Clemente Cárdenas
EXIDE	Nuria Jimeno

Dissemination level

PU	public	☒
CO	Confidential, only for members of the consortium (incl. the Commission Services)	☐

Table of contents

The REVaMP project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869882.

"This Deliverable report reflects only the authors' views and the European Commission is not responsible for any use that may be made of the information it contains."

1. About REVaMP

The main objective of the project “Retrofitting Equipment for Efficient Use of Variable Feedstock in Metal Making Processes” (REVaMP) is to develop, adapt and apply novel retrofitting technologies to cope with the increasing variability and to ensure an efficient use of the feedstock in terms of materials and energy.

For this purpose, existing metal production plants shall be retrofitted with appropriate sensors for scrap analysis and furnace operation. Furthermore, the selection of the optimal feedstock in terms of material and energy efficiency shall be improved by application of appropriate process control and decision support tools. Also, a solid scrap preheating system operated with waste derived fuel shall increase the energy efficiency of the melting processes. To monitor and control the process behaviour in an optimal way, model-based software tools will be developed and applied.

The retrofitting solutions will be exemplarily demonstrated within three different use cases from the metal making industry, namely electric and oxygen steelmaking, aluminium refining and lead recycling. The performance of the different technologies will be assessed, and the benefits will be evaluated in terms of economic and ecological effects, as well as cross-sectorial applicability in other process industries.

2. Summary

This deliverable D8.1, “Technical evaluation of the different retrofitting solutions and overall results of the industrial applications in the different demonstration cases”, is included in the work package WP 8 “Evaluation of retrofitting solutions at industrial scale”.

The objective of the present document is to summarize the main technical achievements of the project, comparing the technical advantages that the different retrofitting solutions developed in REVaMP project have over the baseline situation prior to their implementation in the different use cases. In order to assess the technical performance of each retrofitting solution, a common set of relevant criteria has been defined, and it was decided to which of the technical solutions they could be applied.

Once the criteria were selected, the specific way of measuring was defined in detail to assess the technical benefits associated with the implementation of the retrofitting solution in this specific industrial site.

Finally, the comparison with the baseline situation was conducted. The present document summarizes briefly this comparison between the situation post-implementation of the different retrofitting solutions and the status at the initial baseline.

3. Introduction

This document compiles the technical improvements of the different retrofitting solutions and methodologies developed within the REVaMP project, comparing their performance with the processes and situation before their implementation, as baseline.

As each retrofitting solution is applied in a different manner to each use case and end-user, it was decided to assess each implementation in an industrial site as different industrial solution. In Figure 1 it is presented the table used in the project proposal to define which retrofitting solution will be applied at each industrial site. In green have been highlighted those that will be technically assessed.

Use cases / Methodologies	Steel (AMB)	Steel (SID)	Al (GRU)	Al (REF)	Pb (EXI)
PGNAA, PFTNA (NCBJ, SYS)	Installation of Truck sensor (TRS) for large scrap volumes	Provides scrap samples for analysis with LSS at GRU	Installation of Large Sample Sensor (LSS) for scrap volumes up to 1 m^3	Provides scrap samples for analysis with LSS at GRU	Provides scrap samples for analysis with LSS at GRU
LIBS (ILT, LSA)	Installation	Provides scrap samples	Installation	Provides scrap samples	Installation
Melting furnace sensors, scrap preheating (AZT, GHI)	No	No	No	Installation of scrap Preheating equipment	No
Scrap mix optimisation (BFI, EUT, AZT, CAR)	Yes	Yes	Yes	Yes	Yes
Energy efficiency optimisation (AZT, BFI)	No	Yes	No	Yes	Yes
Model-based Control tools (BFI,EUT,AZT,CAR)	No	Yes	Yes	Yes	Yes
Material Flow Analysis (RWTH)	No	Yes	Yes	No	Yes
LCA, KPIs (RWTH, EUT, AZT)	No	Yes	Yes	Environmental indicators	Yes

Figure 1. Methodologies applied in REVaMP project to the different use cases and retrofitting solutions selected to be technically evaluated (highlighted in green).

In order to assess all the retrofitting solutions in the most homogeneous and comparative manner, a general table with the different possible criteria was developed, selecting those that could apply to each of the solutions developed in the REVaMP project. In the different are listed the criteria that could be used to evaluate the performance of each retrofitting solution.

Neutron sensor PGNAA, PFTNA	LIBS	Scrap preheating	Scrap mix optimisation	Energy efficiency optimisation	Model-based Control tools
-Accuracy -Resolution -Detection limits -Reproducibility -Robustness -Reliability -Calculation speed -Resource efficiency -Product quality -Productivity	-Accuracy -Resolution -Detection limits -Reproducibility -Robustness -Reliability	- Robustness -Reliability -Energy efficiency -Product quality -Productivity	-Accuracy -Reproducibility -Robustness -Reliability -Calculation speed -Resource efficiency -Product quality	-Reproducibility -Robustness -Reliability -Calculation speed	-Accuracy -Resolution -Reproducibility -Robustness -Reliability -Calculation speed -Energy efficiency -Resource efficiency -Product quality -Productivity

4. Neutron sensor based on PGNAA, PFTNA

4.1. Neutron sensor at ArcelorMittal Bremen

The truck (TRS) sensor was planned to be demonstrated and validated within the steelmaking plant of ArcelorMittal Bremen. However, as AMB did not manage to complete the radiation safety licenses and permissions required before installation of the neutron generator on the factory premises in due time, an alternative measurement plan has been introduced. The plan was to change the site of the TRS validation tests from AMB to a specially prepared measurement station in the experimental hall of NCBJ. AMB provided industrial steel scrap samples to NCBJ for the TRS measurement trials, in a form of six 1m^3 large bags filled with incinerated waste metals (E46) and turnings (E5). The measurements were made with the scrap placed inside a container in order to mimic the conditions present during the scrap analysis directly on a truck. In addition, since the chemical composition of industrial samples was not exactly known, a dedicated laboratory test stand was developed in order to accurately verify the performance of the designed TRS sensor. The base of the setup was a 3D mesh (cube) with a volume of 1x1x1m^3 build of steel bars with well-defined content. This test setup mimics the steel scrap density on a truck, allowing easy control of the chemical composition of the tested material by introducing bars of additional pure elements into the mesh.

4.1.1. Accuracy

Due to the lack of detailed knowledge of the elemental content of AMB industrial samples, the accuracy of the TRS demonstrator has been determined by comparison of results obtained by means of the neutron sensor for artificial samples (3D cube) with their well-defined composition. The accuracy for the four key chemical elements (Fe, Cu, Ni, Cr) has been verified by successive measurements of wide range of content of these elements in the 3D mesh.

4.1.2. Resolution

The resolution of the TRS system, understood as an amount of material under study, has been defined as a total volume of a single batch of steel scrap. In principle, such single batch can be a single truck and a total volume of a truck container. Nevertheless, a single measurement voxel has a volume of around $1m^3$ and a whole batch measurement requires the scanning of the container.

4.1.3. Detection limits

The detection limits of the TRS system were determined by statistics of the distribution of measurement results (root mean square error, etc.), in particular by analysis of calibration curves calculated for artificial samples (3D mesh) for a wide range of elemental content values. The general detection limit, established in Deliverable 1.2 of 1% of elemental content has been confirmed in the data analysis. It is worth noting, that even though the neutron activation methods are volumetric, the radiation emitted on the neutron source side (top side of the sample) has significantly stronger influence on the recorded energy spectra. Hence the limits increase with the depth of a sample.

4.1.4. Reproducibility

The reproducibility of the TRS system was confirmed by statistics of repeated measurements of selected scrap samples and artificial samples in the 3D mesh. The results obtained by means of the TRS demonstrator are very well reproducible as long as the setup geometry remains unchanged and the mean density of the material under study is similar. Measurement campaigns as well as preliminary data taking and calibration sessions took place on several weeks but regardless of such a wide time frame, the data points could be placed on common, single plots without deterioration of the results. One additional consideration must be taken into account during the measurements or system installation – due to application of large scintillation detectors (with large photomultipliers) the detection system is sensitive to magnetic fields.

4.1.5. Robustness

The robustness of the TRS system is connected with possible need of rejection/marking/correction of non-physical results. However, during all the measurement sessions none of such data was observed.

4.1.6. Reliability

Since the detection system in TRS consists of 14 scintillation detectors based on three different materials (LaBr, NaI, BGO), the reliability of the demonstrator has been determined by cross-validation of results by means of comparison of data from different parts of the detection system. The comparison of the above mentioned three types of scintillation material specific sub-systems, each consisting of 4 detectors, show consistent data. The observed differences in values of root mean square errors are determined only by properties of these scintillators such as energy resolution, detection efficiency and timing resolution.

4.1.7. Calculation speed

The calculation speed of the TRS demonstrator is real-time. The processor time and resources are loaded mainly due to requirement of the proper filtering of the recorded data in order to save only the events being in coincidence with the alpha particle detectors. The very detailed analysis of the material at different depths can, however, take more time and require offline analysis. Nevertheless, even in such a case the expected time frame are minutes. It is worth noting, that calculation speed is not an important limitation here, unlike the requirement of high statistics of events and gamma-rays recorded by the system. Hence the time required for a reliable measurement is at least tens of minutes.

4.1.8. Resource efficiency / Yield

The possible impact on the process performance after application of the TRS system could be savings in cost of the feedstock materials used in production. Good knowledge of the mean content of key chemical elements in the container feeding the furnace allows better raw material management.

4.1.9. Product quality

The possible impact on the product quality after application of the TRS system could be improved reliability and speed of reaching the target values of the final product. The better knowledge of the chemical composition of the raw materials allows more accurate creation of the charge material mix for the metallurgical furnace, which is later reflected in the improved final product quality.

4.1.10. Productivity

The impact on the productivity of the metallurgical process in the steel plant, after application of the TRS system, can be verified after detailed comparison of amount and quality of steel products obtained before and after the TRS sensor application. Such analysis requires time and implementation of the TRS system directly at the industrial site.

4.2. Neutron sensor at Grupal Art

The pilot installation initially planned at GRU was built at NCBJ and operated in the exact same conditions (due to lack of permissions for application of neutron source at GRU plant). Two versions of full LSS systems (NCBJ and SYS) were successfully installed and tested at NCBJ experimental hall in the first half of 2023. It should be emphasized that the test conditions at NCBJ were finally exactly the same as it would be in the case of tests at the GRU plant. Ultimately, three methods of data analysis were introduced: general calibration, machine learning and SYS-algorithm. During the LSS validation process the analysis was focused on the key chemical elements in the aluminium refining such as Al, Si, Fe, Cu and Mg for which contents above 1% were prevailing in the scrap samples.

4.2.1. Accuracy

The accuracy of the LSS demonstrator has been determined by analysis of deviations between the measured content of each of the key chemical element and the reference data provided by industrial partner for a given sample. Five industrial samples were delivered from GRU for the final tests of the LSS sensor. The samples contained aluminium chips and were labelled as: V-A, V-B, V-C, V-D, V-E. The percentage content of the key chemical elements was provided by GRU after measurements by means of Spark/Ark Optical Emission Spectrometry. Three methods of data analysis were introduced: general calibration, machine learning and SYS-algorithm. The direct comparison of these methods is not an easy task since the calibration and analysis algorithms differ significantly. During the LSS validation process the analysis was focused on the key chemical elements in the aluminium refining such as Al, Si, Fe, Cu and Mg for which contents above 1% were prevailing in the scrap samples. In the two tables below, a comparison of results obtained using the three above mentioned analysis methods is presented.

Table 4.1: Comparison of results achieved with LSS-NCBJ and LSS-SYS setups and analysis algorithms. Values of Root Mean Square Errors in relation to GRU data (a unit here is a % of content)

	Al	Si	Fe	Cu	Mg
NCBJ-LSS [% of content]	1.32	0.81	0.22	0.59	0.4
NCBJ-LSS-ML [% of content]	2.07	1.76	0.21	0.21	0.24
SYS-LSS [% of content]	3.03	2.6	0.27	1.14	0.26

Table 4.2: Comparison of results achieved with LSS-NCBJ and LSS-SYS setups and analysis algorithms. Values of Relative Errors in percent in relation to GRU data (mean value of a given element content).

	Al	Si	Fe	Cu	Mg
NCBJ-LSS [%]	1.41	18.4	54.7	79.2	115
NCBJ-LSS-ML [%]	2.22	39.7	52. 1	27.5	67.6
SYS-LSS [%]	3.25	58.7	65.9	153	73.7

4.2.2. Resolution

The resolution of the LSS demonstrator, understood as an amount of material under study, has been defined as a total volume of a single scrap container (about 2m^3) feeding the furnace. This is because, the mean content of the key chemical elements in a whole volume inserted into the furnace is important for the industrial process control and the final product quality. Nevertheless, the final mean content is a result of multiple, partial measurements performed on a material moving inside the vertical pipe with diameter of 25cm and at material height of about 25cm.

4.2.3. Detection limits

The detection limits of the LSS demonstrator were determined by statistics of the distribution of measurement results (root mean square error, etc.), in particular by analysis of calibration curves calculated for artificial samples for a wide range of elemental content values. The general detection limit, established in D1.2 of 1% of elemental content has been confirmed in the data analysis. The plot in Fig. 4.1 presents an example of the calibration curve obtained with varied Fe content.

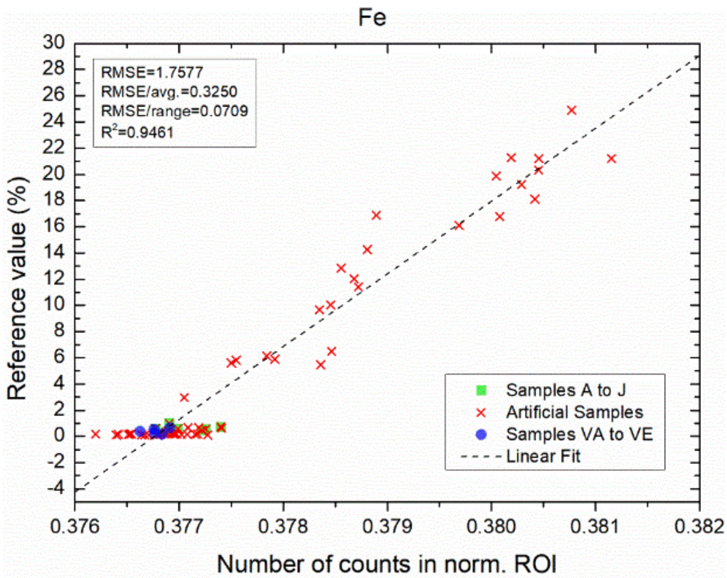


Fig. 4.1: Calibration line (dashed) obtained for Fe from artificial samples in a form of chips (red crosses) and from the first batch of industrial samples A to J (red crosses on green background). The blue circles are the verification data recorded with the second batch of industrial samples VA to VE (not taken into account during the fitting).

As it can be seen, the industrial samples (blue and green), as well as artificial samples (red crosses) having low Fe content are spread along the X-axis. This is because, in the case of low content chemical elements (below 1%) the direct interpretation of the spectra becomes extremely difficult. Nevertheless, the more sophisticated analysis methods can extend the detection limits. One of such method is the machine learning (ML) approach which takes into account the more subtle effects and correlations in the energy spectra. As it can be seen in Tables 4.1 and 4.2, when the given element content is at the level of 1% (Fe, Cu, Mg) the ML procedures allow a significant accuracy improvement.

4.2.4. Reproducibility

The reproducibility of the LSS demonstrator was confirmed by statistics of repeated measurements of selected scrap samples. The results obtained by means of the LSS demonstrator are very well reproducible as long the setup geometry remains unchanged and the mean density of the material under study is similar. Measurement campaigns as well as preliminary data taking and calibration sessions took place on several weeks but regardless of such a wide time frame, the data points could be placed on common single plots without deterioration of the results.

4.2.5. Robustness

The robustness of the LSS demonstrator is connected with the possible need of rejection/marking/correction of non-physical results. However, during all the measurement sessions none of such data was observed.

4.2.6. Reliability

The reliability of the LSS demonstrator has been determined by cross-validation of results by means of comparison of data from two separate multi-detection systems. As shown in Table 4.1 the comparison of two LSS setups, using different detection layouts and data analysis algorithms (NCBJ and SYS) show consistent data with similar values of root mean square errors.

4.2.7. Calculation speed

The calculation speed of the LSS demonstrator is real-time. The processor time and resources required for analysis are low and allow the calculations in less than seconds. However, the energy spectra require good statistics of events and are saved every 60s (NCBJ) or 100s (SYS). The measured value is the mean content of the chemical elements in a 2m^3 container.

4.2.8. Resource efficiency / Yield

The possible impact on the process performance after application of the LSS system could be savings in cost of the feedstock materials used in production. Good knowledge of the mean content of key chemical elements in the container feeding the furnace allows better raw material management.

4.2.9. Product quality

The impact on the product quality after application of the LSS system could be improved reliability and speed of reaching the target values of the final product. The better knowledge of the chemical composition of the raw materials allows more accurate creation of the insert for the metallurgical furnace, which is later reflected in the improved final product quality.

4.2.10. Productivity

The impact on the productivity of the metallurgical process in the aluminium plant, after application of the LSS system, can be verified after detailed comparison of amount and quality of aluminium products obtained before and after the LSS sensor application. Such analysis requires time and implementation of the LSS system directly in the industrial line in the plant.

5. LIBS sensor

The developed universal LIBS sensor has been tested in field trials in industrial recycling plants of all three use cases: aluminium, steel, and lead.

5.1 Accuracy

LIBS measurements in the different use case have been carried on a variety of materials: reference samples, cast samples, metal scrap pieces, metal batches and metal-containing bulk material batches.

The best means for evaluating the accuracy of the data for chemical composition derived from the measurements exist for reference samples, where LIBS data can be compared directly to certified reference values. Such comparison is also used to calibrate the LIBS sensor data. For measurement trials on cast samples and scrap pieces, data from alternative analytical methods are sometimes available, but with unknow accuracy itself. For the batch measurements, only estimates and correlations with statistical data are available for evaluation.

Due to the nature of the LIBS measurement principle, the accuracy is different for each element and each base material, and also dependent of the material condition and the measurement process. In general, the developed LIBS sensor fulfils the requirements of the plant operators in terms of accuracy as determined using reference samples for most cases. For example, GRU named target values for accuracy of 0.1 wt.-% for 8 out of 10 elements of interest. This level is approximately reached for all elements, except for Fe, where the calibration was not satisfying with the reference samples. A higher accuracy of 0.01 wt.-% was desired for Cr and Bi. Whereas the determination of Cr was demonstrated in this range, the evaluation of Bi was not possible due to missing references values in the desired range. In the use case of lead, the determination of the alloying elements was demonstrated by the calibration to exceed the required accuracy of 0.5 – 1 wt.-%, whereas it is slightly higher of the base element lead in the present concentration range of 90 – 100 wt.-%.

5.2 Resolution

The LIBS sensor is equipped with a multi-detector spectrometer, which provides a high spectral resolution of 40 – 60 pm over the measurement range. This allows the detection of individual elemental emission lines even in the line-rich spectra, as for example observed for high-alloyed steel.

The temporal resolution of the sensor is considered on different scales. The duration of each individual LIBS measurement is in the order of 10 – 50 µs, which is fast enough not be affected significantly by the movement of inspected material in relation to the sensor. The measurement repetition rate of 20 Hz allows the detection of each larger scrap piece, presented on a belt or bulk container, and high spatial coverage of fine-grained chips or granulates. For the data evaluation, a period of 1 minute can be used to incorporate over 1000 individual measurements, thereby providing a representative average of a larger fraction of the bulk material. For the operators, an information on chemical composition on this time scale would be appropriate and useful. Initially, an acceptable measurement time of 20 – 60 min was estimate by the industrial partners.

The spatial resolution of the sensor is higher than usually required. The 3D camera, the LIBS scanner positioning and the LIBS measurement spot size in below 1 mm. This enables the positioning of each measurement spot correctly on individual scrap pieces of all recycling feedstock materials tested in the project.

From the viewpoint of chemical analyses, it was shown that the sensor is capable of distinguishing the individual feedstock batches based on their average composition and also, in the case of aluminium old scrap, on the statistical distribution of individual measurements within a batch.

5.3 Detection limits

The detection limits of the LIBS measurements were not considered separately but are generally lying in the same range as the accuracy, when average values are considered. However, due to the measurement principle of frequently repeated individual measurements, contaminations can be detected in single particles of high content, whereas their influence on the average composition of the batch is 3 orders of magnitude lower.

5.4 Reproducibility

The LIBS measurements show a high reproducibility on the reference and cast samples, which is in the same order for the individual analyte/base element combination as the accuracy. For the analysis of feedstock material, a significant change of material properties has the potential to affect the measurement results. However, in the case of surface contaminations the incorporation of the laser pre-cleaning phase into each single measurement has clearly reduced the effect in comparison to direct LIBS measurements without pre-cleaning.

5.5 Robustness

The LIBS sensor system was successfully tested in 3 plant installations under different conditions. The operation was found to be very robust. Even for the dusty material encountered unexpectedly at EXI, both the 3D and LIBS measurements worked well. After truck transport of the equipment by the shipping company, only for the first campaign a relevant issue was observed and fixed afterwards. In the further repeated transports, the LIBS system turned out to be technically robust.

5.6 Reliability

During the on-site trials no degradation or variation of the performance of the LIBS sensor were observed. Also, during longer periods of testing under lab conditions no issues of reliability were encountered. No re-adjustments of the laser beam source, the spectrometer or other hardware components were required.

6. Scrap preheating system

Within REVaMP Project, the concept of scrap preheating was considered only as part of the aluminium scrap melting process within REFIAL's melting furnaces. For this, the REVaMP Scrap Preheater is defined in order to:

- **reduce the residence time** of aluminium scrap in the melting furnace, favouring an increase in the productive capacity of the aluminium melting process at REFIAL.
- **improve the energy efficiency** of the fusion process thanks to the use of an alternative waste-derived fuel (WDF).

6.1. Accuracy

The accuracy of the scrap preheating system can hardly be proven due to the fact that the final test for which it was created, was not possible to be executed. In any case, the variables results are shown in Table 6.1 at the most representative values. It shows description and designation of maximum and minimum values, as well as the decimal error displayed.

Table 6.1: Variable result outputs from scrap preheating system

Variables Description	Data Designation	Unit	Min Theoretic Value	Max Theoretic Value	Error displayed	Min Tested Value	Max Tested Value
Dates /Times	FECHA	(s)	(DD/MM/YYYY ; HH:MM:SS)		1 s	(DD/MM/YYYY ; HH:MM:SS)	
Temperature Combustion Chamber (°C)	TEMPERATURA_REGULACION_BOVEDA_CAMARA_SUCIA	(°C)	Ambient	1000°C	$1*10^{-8}$ °C	17,60000038	952,7000122
Temperature Post-Combustion Chamber (°C)	TEMPERATURA_SEGURIDAD_BOVEDA_CAMARA_LIMPIA	(°C)	Ambient	1000°C	$1*10^{-8}$ °C	22,08658791	1006,749146
Temperature Scrap (°C)	TERMOPAR _DE_CONTACTO_ENTRADA_CALENTADOR_CHATARRA	(°C)	Ambient	300°C	$1*10^{-8}$ °C	11,5	173,1000061
Temperature Scrap Chamber (°C)	TERMOPAR _DE_CONTACTO_SALIDA_CALENTADOR_CHATARRA	(°C)	Ambient	300°C	$1*10^{-8}$ °C	12,19999981	169,3000031
Power Post-Combustion Chamber (%)	POTENCIA_QUEMADOR_CAMARA_LIMPIA	(%)	0	100	$1*10^{-8}$ %	0	100
Power Combustion Chamber(%)	POTENCIA_QUEMADOR_CAMARA_SUCIA	(%)	0	100	$1*10^{-8}$ %	0	100
Flowrate Combustion Chamber(Nm^3)	caudal_inst_q_comb_totalizado Q1	(Nm^3)	0	indefinite	$1*10^{-6}$ Nm^3	0	145,075183
Flowrate Post-Combustion Chamber (Nm^3)	caudal_inst_q_post_totalizado Q2	(Nm^3)	0	indefinite	$1*10^{-6}$ Nm^3	0	268,6636981
Cummulative Sum of Flowrates (Nm^3)	consumo_total= Q1+Q2 (ACCUMULADO)(Nm3)	(Nm^3)	0	indefinite	$1*10^{-6}$ Nm^3	0	413,7388811

6.2. Reproducibility

The scrap preheating process bases itself on a scientific research publication with evidences of reproducibility. There is no evidence of the reproducibility of this particular scrap preheating system. Due to previous accuracy explained, this situation offers clues for new developments in the same direction to be projected with higher accuracy and industrial cases nearer to a commercial solution.

6.3. Robustness

Regarding the scrap preheating system robustness, it is a mechanically, robust machine with several adjustments needed to achieve accurate calculations on balance of masses and energies for this particular matter. The physical design complies with security and safety obligations.

Regarding the robustness of data, the data is correctly and digitally collected, measured, and complies with all kind of requirements planned at the initiation of the project, but the results are not as optimal as expected due to the several deviations that the project suffered.

6.4. Reliability

The system has been tested in conditions different from those for which it was designed.

- The system has been tested with natural gas as heating system. In these tests the operation of the pilot is reliable.
- The lack of an oxygen sensor inside the pilot has not allowed its testing/use with WDF as heater system. These tests are key to determining the reliability of the pilot.

6.5. Security

The installation, commissioning and testing of the pilot have been carried out under conditions different from those for which the pilot was designed.

Safety conditions have been evaluated based on this new operation. Under these conditions, the pilot is safe for use (evaluated and approved by the REFIAL Health and Safety Department).

6.6. Energy efficiency

The pre-heating system has been designed to obtain the calorific energy for pre-heating the scrap from the combustion gases generated by WDF combustion, so that energy demand from natural gas or oxyfuel combustion in the melting furnace is reduced (lower fluctuations of temperature in the furnace as there is no cool scrap charging and the heat supply for heating the charge up to the melting temperature decreases). For the WDF combustion, some natural gas is needed as assistant fuel to ignite the WDF.

Unfortunately, given the residual halogen content in the prepared WDF, the off-gases from the WDF combustion chamber require being subjected to a post-combustion process in which they are held above 1000°C for a few seconds to destroy dioxins. This legal requirement (operation conditions for co-incineration of waste, DIRECTIVE 2010/75/EU) has been implemented in the design of the pre-heater by GHI. The post-combustion step is fuelled by natural gas. The overheated off-gases are then used in the heat exchanger for the scrap preheating. However, the current configuration of the exchanger limits the outlet temperature to a maximum scrap pre-heating at around 100°C for wet scrap (170°C for dry scrap). Hence, the overall energy efficiency of the system plunges and the targets of reduction of natural gas consumption and improved energy efficiency in the retrofitted pilot furnace are not achieved (in spite of the reduced requirements of natural gas in the melting step).

The pilot has been installed and put into operation under an operating scheme different from the scheme for which it was designed. If initially the WDF was the planned energy system, in the end natural gas was the installed and tested energy system.

Initially the gas consumption was 170.2 Nm3/t of Al. Instead of using 50 kg of WDF per t of Al to achieve a 25 % reduction of Gas (127.65 Nm3/t), the preheating system consumption (minimum 95 Nm3/gas for preheating 1t Al mix) and the rotatory furnace (minimum 87.33 Nm3 gas for melting) would sum together 182.33 Nm3/gas for the whole process.

For this reason, it is concluded that the energy efficiency of the pilot may not be favourable with these design guidelines and its deviations. The demonstration of the industrial preheater used with WDF is still pending.

6.7. Product quality

The pre-heating step helps the scrap get rid from moisture and some organic contaminants, what is beneficial to obtain an alloy with lower contents of impurities and a higher metal yield by melting the preheated scrap in the rotary furnace.

6.8. Productivity

The main variable that will increase or decrease the productivity is **process time**. These process times, whether takt time for batches or lead time for the line time, are translated into consumptions, and consumptions into economic parameters. There are clues that the charging of pre-heated scrap at temperatures around 300 °C could results in shorter melting times in the pilot rotary furnace, less fuel consumption and, therefore, in an increased productivity of the melting step.

The constructed scrap preheating system has been designed to run in batches with manual management, both in the WDF combustion step and in the scrap-preheating in the heat exchanger. The current design tested during the demo trials at REFIAL shows several limitations for productivity that should be overcome for an upscaling of the system.

a) **Combustion and Post Combustion Chambers Preheating time too long:** On the one hand, the ramp up of these chambers must increase +50 ºC/hour. This means that the achievement of 1000 ºC target on both chambers lasts around 20-24 hours. This represent a huge consumption of fuel, whether it is gas or WDF, with its consequences in economic, environmental or social impact assessment. This ramp up should be started-up only once and maintained as much as possible for a continuous production.

b) **Discontinuous operation of the WDF combustion chamber:** Continuous feeding of the WDF in the combustion chamber should be implemented, as well as an ash discharge system, to allow for continuous operation of the preheating system. Otherwise, the preheater operates discontinuously, switching on and off, through three stages:

   - WDF loading stage;
   - combustion stage until WDF is consumed;
   - cleaning-reloading stage: cleaning of the combustion chamber by removing the ash and the unburnt WDF and loading a new WDF load; before opening the combustion chamber between cycles, some waiting time for chamber cooling must be accounted for.

c) **Scrap Preheating Chamber Preheating times:** On the one hand. in the scrap preheater chamber, 10 kg scrap batches are loaded manually, to match the charged mass per heat in the pilot rotary furnace. Long scrap pre-heating times make that step the bottleneck of the whole sequential process. Every time the door is open, the temperature decreases down to ambient temperature. In order to reach the setpoint temperature, needs more fuel due to this heat leak. On the other hand, the preheating thermosets revealed that the scrap took high temperatures much faster than the inside ambient temperature of the inside preheating chamber (between 6 and 10 minutes for Mix, E and H Scrap to reach 170 ºC). Extending the temperature curve assuming a linear function, the achievement of 300 ºC would be located between 12 and 20 minutes, when the industrial heating process for Aluminium is calculated around 20 minutes to perform from 15 ºC up to 300 ºC.

d) **Preheating Temperature too low:** The initial idea from the system was the scrap to achieve 350 ºC, but the final results gave a maximum temperature of 171 ºC. Not only not to achieve set point temperature requires more fuel, but also this low temperature means an enlargement of process times. The less temperature, the more time it will last to achieve the target melting at 750 ºC.

e) **Lack of Preheating scrap chamber feed system:** The current one-scrap chamber preheating system design causes the furnace to idle while waiting for the next preheated charge and the overall productivity to fall. Once the door is open, the heat escapes from the system. In the upscaling of the preheater, designs with a higher capacity scrap chamber in the exchanger or with several scrap chambers arranged in parallel should be studied to avoid “melting process starvation”, as long as the heat content in the off-gases of the after-burner allows.

6.9. Conclusions

- The pilot has been tested in conditions different from those for which it was designed (different fuel system, natural gas instead of WDF). For this reason, the conclusions drawn from these tests are the product of estimates and approximations.

- The maximum temperature reached in the tests by the different types of scrap (B, E, H and Mix) introduced into the preheating chamber is 150-160 ºC. A design improvement to increase the preheating temperature in the preheater was considered but it could not be implemented in time.

- It is thought that the system chosen to feed the incineration chamber with WDF is not appropriate
  - to maintain a WDF incineration level over time because the feeding is by opening the door and introducing WDF manually.
  - to maintain safety levels at work because the feeding is by opening the door and introducing WDF manually.
  - to discard the unburned ones generated because they must be removed before introducing the new WDF.

- The design chosen for the scrap preheater should comply with the specifications issued by the REFIAL Health and Safety Department:

- It should be at a height that makes it easier for the operator to manipulate the preheated scrap.
- The preheated scrap exit system should be through a try or support, never through a conveyor pallet.
- The distance between the preheater and the pilot furnace should be minimized.
- The opening door of the scrap preheater should not be removable from the preheater itself.

- A redesign to address several of the issues described in the previous points has been analysed. This concerns the addition of a scrap feeding system, the control of the oxygen inside the chamber by an appropriate oxygen sensor, the heat exchange system and the feeding system of the WDF. However, due to lack of time and budget to manufacture and test these solutions, they have not been implemented in the scope of the project.

- Despite the technical deviations, the conclusions obtained from the tests carried out on the REVaMP Scrap Preheater are that
  - the residence time in the melting furnace is shortened,
  - energy consumption is reduced,
  - and quality is maintained or improved.
  - Unfortunately, nothing can be said about the use of WDF as an alternative fuel in the pilot.

7. Scrap mix optimization models

7.1. Scrap mix optimisation at ArcelorMittal Bremen

The process considered for optimization consists of the characterization of the scrap available on the scrap yard, the scrap mix supplied to the respective furnace via the baskets and the resulting steel quality at tapping. In the AMB use case, the hot metal addition is considered as well. Restrictions include scrap availability, steel quality constraints, scrap charging restrictions as well as target tapping weight, with minimal cost as optimization target.

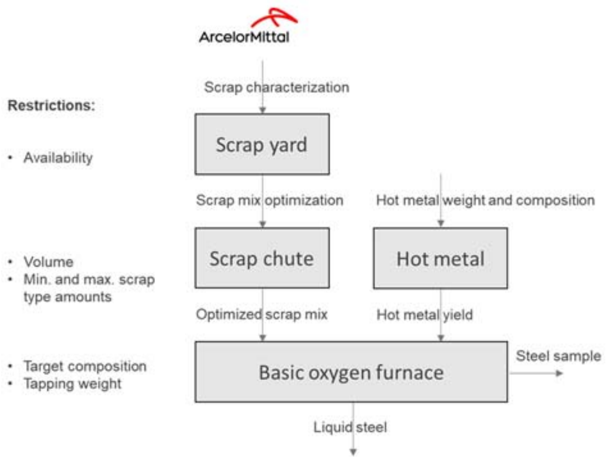


Figure 7.1: Process workflow for the steelmaking use case at AMB.

7.1.1. Accuracy

Accuracy evaluation starts at the scrap characterization stage, in which measured and calculated values based on a mass balance are compared. These values include tapping weight and relevant chemical elements for the use case. Regression metrics as well as diagrams are provided via the UI for an expert to evaluate the accuracy. This task should be performed by an expert as the accuracy results reflect the variability of the scrap properties, the uncertainty of the measurements and are heavily influenced by the considered timeframe. As the scrap mix optimization is based on the scrap characterization, the accuracy is directly linked to the latter.

7.1.2. Resolution

The developed software is an on-demand tool and could be used on a heat-by-heat basis. A more practical application windows would be to perform scrap characterization when a drift of accuracy is observed or events like supplier changes occur. For scrap mix optimization, in the AMB use case, due to no prior knowledge of the hot metal weight and composition, the optimization can be performed heatwise.

7.1.3. Reproducibility

Results are reproducible as no randomness is involved in the calculations.

7.1.4. Robustness

Filters can be applied by the user to deal with faulty data and anomalies. This ensures that the software is working in the foreseen operating window and provides meaningful results.

7.1.5. Reliability

The software has been developed based on commercial Matlab packages. As a standalone software, once configured, it should run reliably.

7.1.6. Calculation Speed

Calculations for both, scrap characterization and scrap mix optimization, take a few seconds (< 10). Considering that the software system is used for every heat (ca. 1 hour intervals), this calculation speed is more than sufficient.

7.2. Scrap mix optimisation at Sidenor

The process considered for optimization consists of the characterization of the scrap available on the scrap yard, the scrap mix supplied to the respective furnace via the baskets and the resulting steel quality at tapping. Restrictions include scrap availability, steel quality constraints, scrap charging restrictions as well as target tapping weight, with minimal cost as optimization target.

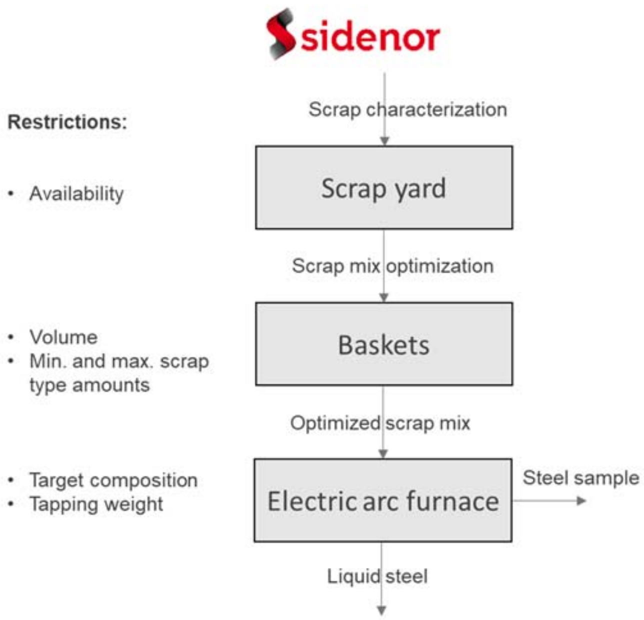


Figure 7.2: Process workflow for the steelmaking use case at SID.

7.2.1. Accuracy

Accuracy evaluation starts at the scrap characterization stage, in which measured and calculated values based on a mass balance are compared. These values include tapping weight and relevant chemical elements for the use case. Regression metrics as well as diagrams are provided via the UI for an expert to evaluate the accuracy. This task should be performed by an expert as the accuracy results reflect the variability of the scrap properties, the uncertainty of the measurements and are heavily influenced by the considered timeframe. As the scrap mix optimization is based on the scrap characterization, the accuracy is directly linked to the latter.

7.2.2. Resolution

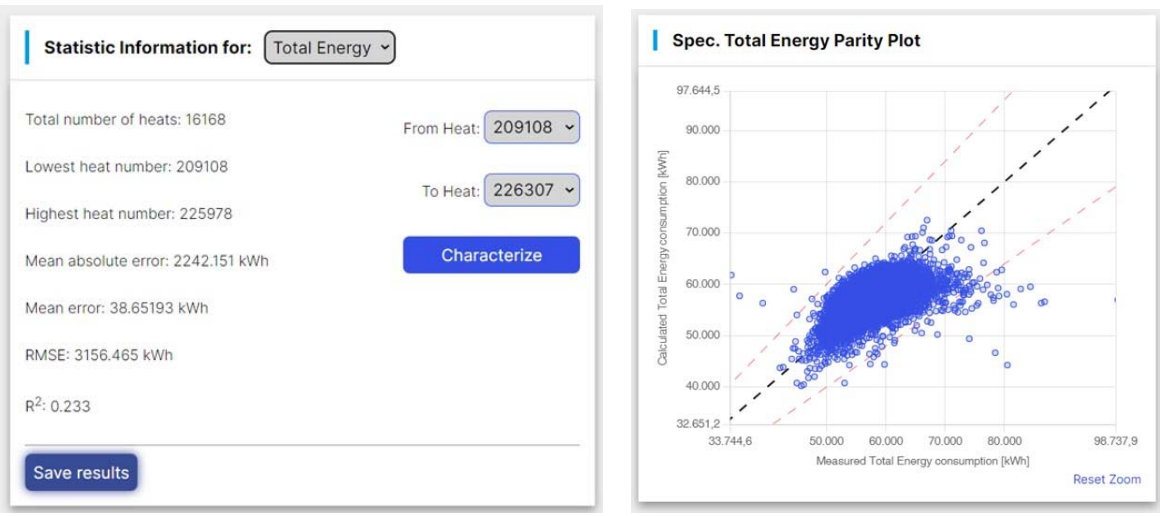
The developed software is an on-demand tool and could be used on a heat-by-heat basis. A more practical application windows would be to perform scrap characterization when a drift of accuracy is observed or events like supplier changes occur. For scrap mix optimization, production planning for a day or for a week are likely.

7.2.3. Reproducibility

Results are reproducible as no randomness is involved in the calculations.

7.2.4. Robustness

Filters can be applied by the user to deal with faulty data and anomalies. Additionally, adequate error handling is implemented to guide the user in creating applicable settings. This ensures that the software is working in the foreseen operating window and provides meaningful results. The figure below shows an example of the user interface to define the input data and to display the evaluation results.



7.2.5. Reliability

The system has been developed based on Flask, SQLite3 and Python and currently runs on the development server provided by Flask. To improve the reliability (e.g. automatic restarts) and safety, a basic orchestration via Docker Compose and the inclusion of a reverse-proxy server, e.g. NGINX server, could be considered.

7.2.6. Calculation Speed

Calculations for both, scrap characterization and scrap mix optimization, take a few seconds (< 10). Considering that the software system is used to plan days or weeks of production, this calculation speed is more than sufficient.

7.3. Scrap mix optimisation at Grupal Art

The scrap mix optimization procedure at Grupal Art is composed by three models. The first one is the Main Charge Mix model introduced in Deliverable 2.3, the second one is the Alloy Adjusting model, introduced in Deliverable 4.3, and the third one is the Micro-additions model presented in Deliverable 6.1. An image of the model interface is presented in Figure 7.3.

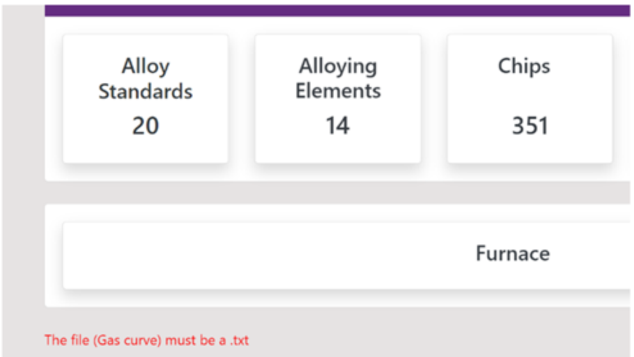


Figure 7.3: Process workflow for the steelmaking use case at SID.

7.3.1. Accuracy

The scrap mix optimizer allows to ensure a better profit for each element by maximizing the materials with a high content of alloying elements and low cost. The alloying materials are the most expensive ones. Therefore, the reduction of alloying materials by adding scraps with those alloying elements (Cu, Ti and Ni) significantly reduces the cost of each batch.

In the use of the model, it has been proved to be very reliable in the selection of scrap and chips rich in the alloying elements required by the alloy we want to produce. However, the model has been recently implemented and it is difficult to give an exact figure about the improvement that can be compared to the previous situation, without optimization model.

7.3.2. Reproducibility

To test the reproducibility of the Main Charge Mix Model and the Alloy adjusting model the optimization of the same batch was computed several times, considering the same initial conditions (raw material available in the workshop and furnace initial conditions). The results of both optimizations are the same for all the runs, proving the reproducibility of the models deployed.

7.3.3. Robustness

The ability of a model to handle and adapt to unforeseen conditions is crucial for its performance in real-world environments. Various tests were conducted to evaluate how the model behaves in scenarios where the input data is incomplete or contains errors.

Multiple tests were conducted using different synthetic datasets intentionally created with missing data and incorrect inputs to simulate realistic situations the model might encounter.

After conducting the tests, it was found that the model demonstrated remarkable robustness against missing data and incorrect inputs (outliers, contradictory information, or incompatible formats). Despite the presence of these challenges, the model was able to effectively detect them and alert the user to correct/adapt the inputs.

7.3.4. Reliability

The system, implemented using Django, SQLite3, and Python, has been designed with the importance of data integrity in mind. To prevent data loss in cases of platform failures or unexpected power outages, a series of measures have been integrated:

Database backup: Regular backup of the SQLite3 database has been configured. Through automated task scheduling, a periodic backup of the database is performed. This ensures that in the event of a system failure or unexpected power outage, data can be restored from the most recent backup, minimizing information loss.

Atomic transactions: Atomic transactions are used in database write operations. This ensures that insertion, update, or deletion operations are treated as a coherent unit. In the event of a failure during an operation, atomic transactions allow data to remain in a consistent state, thus avoiding corruption or partial loss of data.

Error control and exception handling: Error control mechanisms and exception handling have been implemented throughout the system. This helps capture and handle any unexpected errors or exceptions that may arise during execution. In the event of a failure or exception, relevant information is logged, and appropriate measures are taken to ensure data integrity.

7.3.5. Calculation Speed

Before the REVaMP project, there was no decision support system, therefore there is no possible comparison of the calculation speed with the previous System. In the previous situation, the feedstock materials used in the daily production were decided by the production manager. The initial materials were chosen from a database, that contained the composition analysed by the laboratory responsible. The change from the manual to the artificial intelligence model has increased several times the calculation speed, there is the need to analyse all the incoming material, but the time spent by the production manager is saved by the usage of the applied model. The actual calculating time with the implemented software is approximately 5 seconds.

7.3.6. Energy efficiency / savings

The energy savings cannot be calculated for one single batch, as there can be several different problems that may occur during the production deviating from the result. But, as a result of the year and taking into account that some of the solutions have been already implanted for a year, there can be a comparison between the two periods, September 2021 and August 2022 and the second period with the solutions implanted from September 2022 to June 2023. In order to eliminate the difference in the length of the period and possible differences in amount of material produced, the calculation have been done by ton of alloy produced. In the second period has been a reduction in energy consumption of roughly 10%.

7.3.7. Resource efficiency / Yield

The efficiency on the use of feedstock materials has highly improved after the project implementation. The new models and software deploy provides a better knowledge by analysing every kind of feedstock material, resulting in a better understanding and a more accurate addition of the feedstock materials to the furnace. Therefore, less consumption of alloying materials is needed, reducing the cost of the final production, as more alloying elements are recovered from the scrap.

The main reduction has been observed in the consumption of Copper, which has been reduced by 22%. Other elements, such as Titanium and Nickel, have been also reduced but in a less significant manner, because very few scrap materials have these elements present.

7.4 Scrap mix optimisation at Exide

The scrap mix optimization procedure at EXIDE is composed by two models. The first one corresponds to the statistical model of load in the furnaces. This model introduced in Deliverable 2.1, is oriented to predict the amount of lead that will be obtained at the end of the melting process and is part of one of the three modules that make up the smart visualization tool SVT.

In order to calculate the model parameters it is necessary to determine the amount of lead that has been charged into the furnace from the quantities of each raw material and its lead content. On the other hand, it is required to estimate the amount of lead that migrates to the slag. The lead concentration in different raw materials was determined by laboratory analysis in a large number of samples. The second model is an optimization problem for the charging of raw materials in the kettles that takes place in the refining process. The optimization algorithm described in deliverable 4.3 is part of the OPTICRIS application that was described in deliverable D 7.3. Each of the characteristics of these load optimization applications in both the melting and the refining processes will be described in the following subsections independently.

7.4.1 Accuracy

Scrap mix optimisation in melting process
There is a deviation between the amount of lead obtained versus the prediction from the raw materials loaded in the furnace. The error can be estimated at around 5% although it depends on the raw material that is loaded into the furnace. Some raw materials such as paste and metallics, having a large number of samples, present fewer errors, but in the case of ashes or sludge, where a smaller number of samples are available, the errors are larger. Another component of the error is due when raw materials are loaded that come from suppliers that have not been previously analysed in the laboratory and that present deviations from the average of the raw materials that arrive at the plant. In conclusion, the error will be determined by the composition of the raw material loaded in the furnace.

Lead bullion mix optimisation in refining process
The application of genetic algorithms determines that our solution will be one of the best among all possible solutions. From there, the precision can be compared either to other programs made with GA or to other multi-objective optimization techniques. In our case we compared it with the manual techniques that had been done until now and it was demonstrated that in all cases the accuracy was greater.

7.4.2 Reproducibility

Scrap mix optimisation in melting process
Being a statistical model, reproducibility is total since the model parameters are fixed. The parameters of the model must be adjusted with laboratory analysis depending on the supplier. For this reason, if we want our model to be replicable with other raw materials from new suppliers, the parameters must be retrained.

Lead bullion mix optimisation in refining process
In this case, reproducibility does not make sense since even if the same lead bullion blocks that are in the warehouse are used and the same alloys are made, the result will vary due to the characteristics of the optimizations with genetic algorithms.

7.4.3 Robustness

Scrap mix optimisation in melting process
The robustness of the model is determined in this case by the errors produced both in the variables that are introduced and by the outputs that the model gives us. Alarms have been established for the inputs that indicate to the user, for example, if the mass of a raw material is negative or if a character is entered by mistake. Likewise, these alarms are generated if the prices of raw materials are wrong.

Regarding the outputs, alarms have been established in the furnace loading output, warning the user that the furnace capacity limit has been exceeded and the charged raw material must be eliminated or reduced. Finally, indicate that different tests were established to check that the results are within normal values, comparing them with those that are usually done manually. In these some errors appeared that were corrected to achieve perfect functioning of the application.

Lead bullion mix optimisation in refining process

The optimization algorithm has been programmed to be as robust as possible. For this, the algorithm was designed with a test file to detect more than 30 errors in the execution of the program. Mainly the errors come from the loading of the files that contain the different lead bullion blocks, the prices of the alloys, the different elements with their maximum and minimum limits and the number of alloys to be optimized at the same time. For this, a panel shown in the Figure has been programmed to check that the main files have been downloaded correctly. This allows the user to correct these errors and continue executing the algorithm.

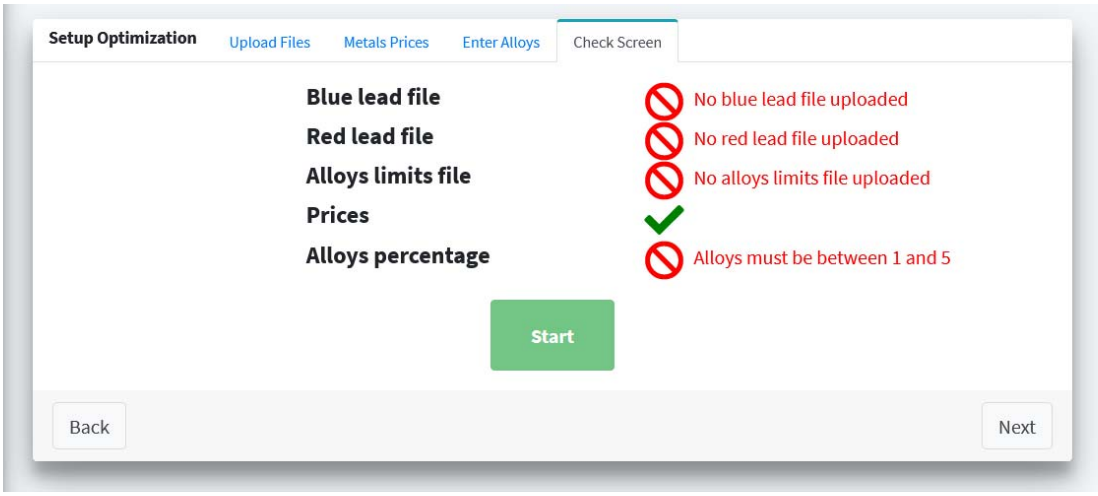


Figure 7.2: Screen to warn the user of defects when loading data files

7.4.4 Reliability

Scrap mix optimisation in melting process

This tool is reliable because the model is statistical and the calculated values are maintained.

Lead bullion mix optimisation in refining process

Because genetic algorithms use probabilistic transition rules in the search process that are used to guide the process towards regions of space in which, with high probability, the optimal one is found, they guarantee a good result, but they do not guarantee that it will be the best.

7.4.5 Calculation Speed

Scrap mix optimisation in melting process

Prior to the implementation of the model, loading was done manually using an Excel sheet, so information was only available on the masses of the raw materials. After implementation, the user will be able to obtain more information such as the price and the prediction of the final lead composition that they will obtain in each cast immediately at the same time as entering the inputs.

Lead bullion mix optimisation in refining process

The speed of the optimization algorithm allows us a recipe for the manufacture of a lead alloy in less than 5 minutes. In the case that 5 recipes are calculated a time, which is the maximum allowed by the application, the estimated time for the algorithm to converge is 15 minutes. This has been a great advantage in the preparation of recipes in the refining process, since the manual process that was previously done could take up to 15 minutes per recipe.

7.4.6 Raw Material and Energy efficiency / savings

Scrap mix optimisation in melting process
The estimated savings from this prediction model is difficult to quantify. Although it facilitates a more homogeneous distribution of the load in the furnace, there are more factors to achieve an adequate melting process in the furnace, such as the fluxes, the gas and oxygen flows and the pre-set times of the melting stages.

Lead bullion mix optimisation in refining process
The main saving in the optimization of the refining process is the reduction in the use of alloying elements, as the algorithm manages to combine the best blocks so that they fall within the limits set by the type of alloy. This reduces the use of pure alloying elements since the contents of these elements is already included in the lead bullion block. The energy saving is also significant since by not having to add or eliminate alloying elements in some stages of the process, the total process time can be reduced. An energy saving of around 5% can be estimated.

7.4.7 Conclusions

In the case of use of lead, one of the applications integrates the three evaluated modules. A first module that allows the visualization of the variables of the fusion process in the furnaces, another module that allows the optimization of the load in the furnace based on the raw materials and finally a tool that allows making decisions based on the analysis of the evolution of temperature in the furnace. The other application is based on the optimization of the charge in the kettles by obtaining the best combination of lead bullions blocks produced in the melting process in the furnaces. All these visualization, optimization and decision support tools represent a technological advance in the EXIDE plant since the use of these applications will allow plant personnel to optimize processes and save time and energy, thanks to the use of data that were not previously used and to models and algorithms that facilitate day-to-day planning.

8. Energy efficiency optimisation

8.1. Energy efficiency optimisation at Refial

8.1.1. Accuracy

On the one hand, since the complete process has had to be separated into different subprocesses to recreate the same conditions to achieve scientific and tested results, the accuracy of the results are far from the desired. On the other hand, the most important result is the proof of the reduction of smelting time depending on the thermal energy inputs.

8.1.2. Reproducibility

Due to previous accuracy explained, this situation opens new ways for new project to be developed with higher accuracy and industrial cases nearer to a commercial solution.

8.1.3. Robustness

Conclusions about robustness regarding energy efficiency are widely explained in section 6.2.3, and the main inefficiencies that these kinds of devices could generate have particularly related to the temperature losses due to poor isolation methods and processes.

8.1.4. Calculations

The Economic KPIs are described in the Impact section of the PTR, but they have their origin in the technical improvement as it shown in Table 8.1

Table 8.1 Economic KPIs originated by the technical improvements

Economic KPI	Explanation	% Improvement estimated
Reduce energy cost	Lower residence time of scrap in the furnace, and partially substitution of fossil fuel by alternative WDF.	**Objective1:** 25 %
Reduce WDF management cost	Lower cost for the production of the WDF, savings for avoiding landfill.	**Objective2:** 25 %
Increase throughput	Lower residence time of scrap in the furnace, providing more throughput.	**Objective3:** 10 %

In Figure 8.1 there is a comparison of the Pilot Baseline Case (A-PS) compared to Pilot Results (C-PS) for an Industrial Estimation Times, Temperatures and Objectives. Theoretical results from the WDF would be extrapolated to the parts that impact on preheating part of the process. The smelting process variables have their basis on the solution 1 and 2 to recreate the conditions of the scrap preheating system that affect to the scrap.

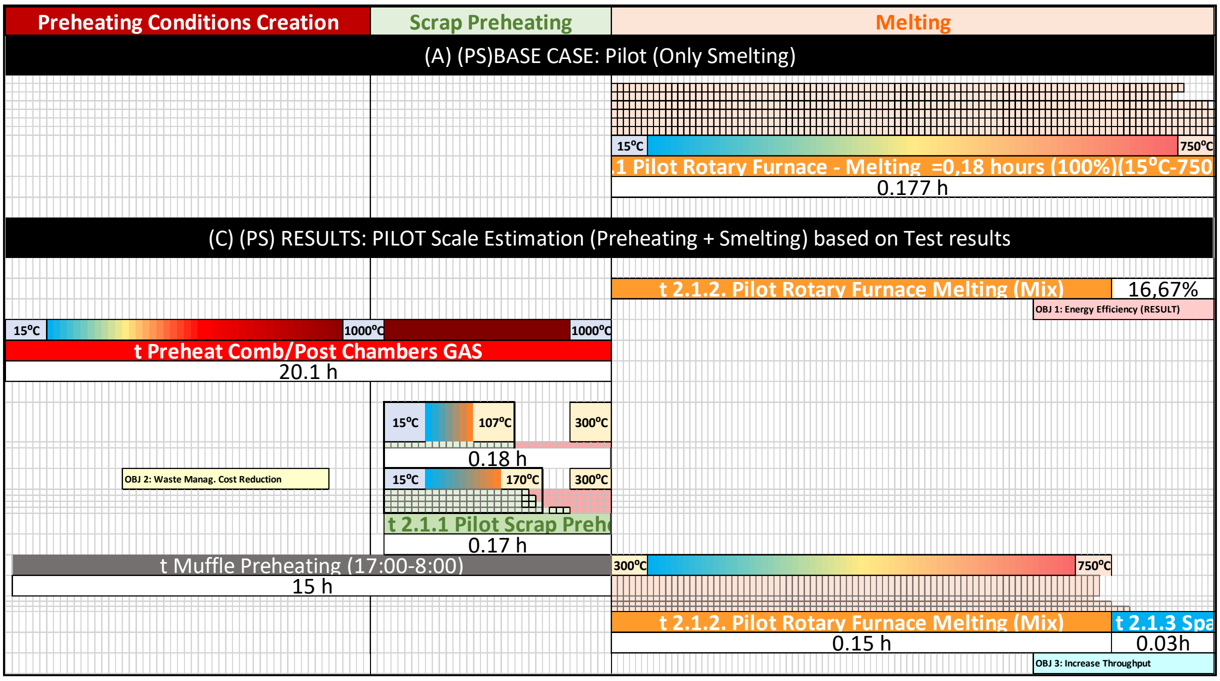


Figure 8.1: Comparison PILOT Base Case VS PILOT Results Case for an Industrial Estimation Times, Temperatures and Objectives

Depending on the length of process times the consumption is higher or lower. Depending on the isolation methods used for the development of the prototype, the requirement of consumption would also be bigger or smaller. In this case the reduction of smelting gas consumption was estimated to 25% (Objective 1), due to the separation of smelting process into preheating and higher initial temperature for smelting. The final calculations estimate for **Objective 1 that only a 16% (see Figure 8.2)** could be achieved what is also good news. It is a clue that the separation of processes has a thermal energy balances basis.

The WDF incineration cost comes from the time spent during the process to heat the combustion chambers that blow hot air through the exchanger into the scrap preheating chamber. In this case, as the WDF has been substituted by natural gas, the **Objective 2 is not technically proven**.

The increase of throughput estimated for **Objective 3 is relatively complained.** The smelting time is clearly reduced, but it has created a new possible bottleneck in the scrap preheating time. The problem here belongs to the particular design of the whole scrap preheating system due to the deviations from non-achieving the 300ºC with the gas substitution. When the electric muffles substituted the preheater system to recreate the conditions of preheated scrap, the smelting process was hopefully proved.

8.1.5. Energy savings

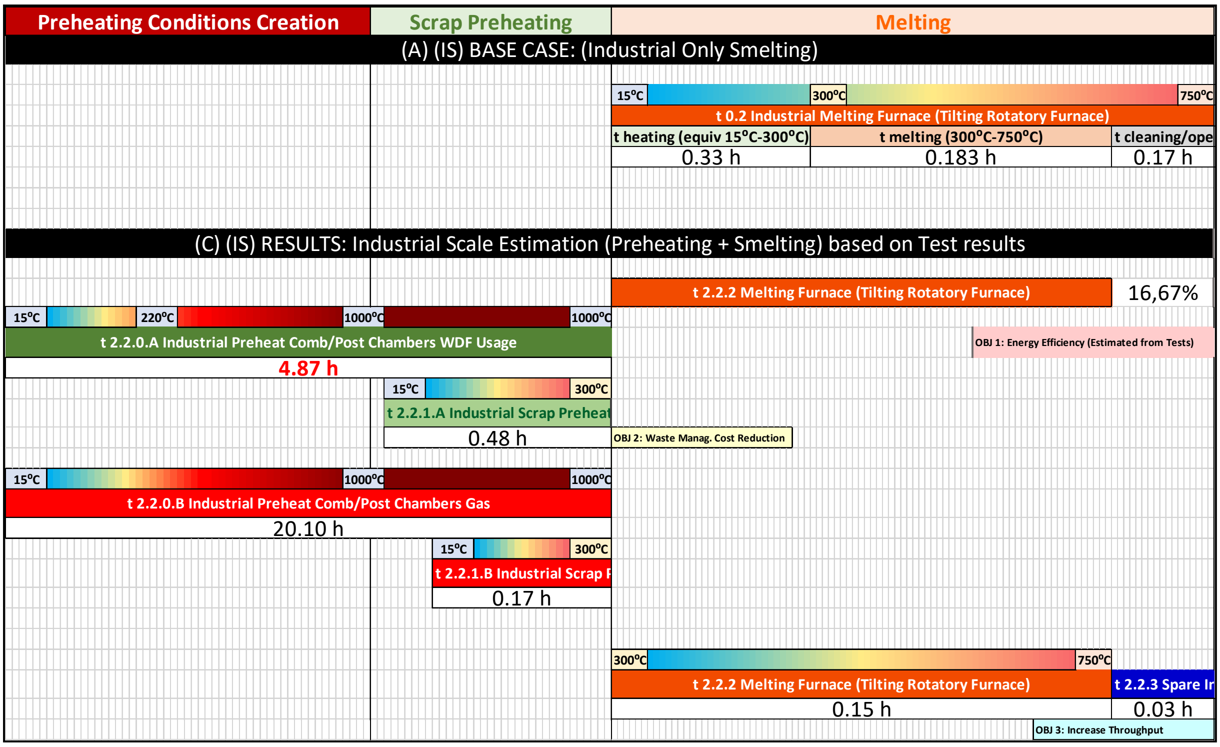


Figure 8.2: Comparison INDUSTRIAL Base Case VS PILOT Case Estimation Times, Temperatures and Objectives

In Figure 8.2 it is shown the comparison of Base line (A-IS) and Final results (C-IS) at industrial scale, assuming both deviations and solutions implemented.

Objective1: Reduce energy cost (through reducing time of consumption)
The initial smelting time (from 0ºC-750ºC) was calculated to 0.18h/batch. After the extrapolation from pilot tests up to an industrial scale there are founded clues that the smelting time (from 300ºC-750ºC) could be reduced to 0.15 h/batch. It means a **reduction of gas consumption of 16.6%** (the expensive source of fuel)

Objective2: Reduce WDF management cost (through usage of WDF)
The usage estimated (following the scientific article calculations) for the WDF is about 50 Kg for every tonne of produced Aluminium. To achieve the desired temperature in the scrap preheating chamber would require at least 0.48 h/batch. It is much longer than the 0.15 h from smelting process. This means that the scrap preheating process time is the new bottleneck, and much higher than the gas-based scrap preheating time (0.17 h in test) and far from the initial 0.18 h/batch. It would require four scrap preheating chambers in parallel to reduce time down to 0.12 h/batch successively. It would suppose a cost saving process the more it is used.

Objective3: Increased throughput (Through reduction of smelting time)
The reduction of smelting time gives the solution of the time reduction and increases the throughput of the smelting part of the whole process time. But the complete production process is now divided into two parts, and unfortunately the preheating time is not clearly proved. Muffles and natural gas have recreated the conditions to support the results, but there is a lack of test.

8.1.6. Conclusions

In the use case of Aluminium Scrap Preheating, the reduction of initial smelting process time is proved but in need of more tests to assure a possible industrial scaling. The preheating time may enlarge widely the complete process time which could be solved by parallel scrap pre-heating systems to shorten these times. The reduction of times in natural gas-based smelting reduces this energy input consumption and increases this equivalent energy efficiency, but there are cues that the energy efficiency using WDF could be viable and feasible.

8.2 Energy efficiency optimisation at Exide

The optimization of the energy in the lead use case has been carried out through a decision support tool that allows the user to regulate the set points of the gas and oxygen flow controllers supplied to the furnace burners as well as reducing the stages time of the melting process in rotary furnaces. This application is included within the 3 modules that comprise the smart visualization tool and can be found in deliverables D 4.2 and D7.3 carried out in the project.

8.2.1 Accuracy

The accuracy of the algorithm is not possible to quantify because it is actually difficult to obtain the optimal temperature evolution of the casting. The algorithm divides the different stages of melting process based on expert knowledge rules.

8.2.2 Reproducibility

Several tests were carried out on the same casting of the melting temperature and in all cases the division of the three parts of the stages of the melting process was the same, testing the reproducibility of the algorithm.

8.2.3 Robustness

Different validation tests were defined in the development of the application to detect errors mainly in the loading of the castings from the database since in this case the user only chooses the casting they want to analyze.

8.2.4 Calculation Speed

The algorithm that allows dividing the different stages of the melting process and calculating the statistical data is immediate. It should be mentioned that this tool is a decision support tool, so the information on processing time to set the setpoints of the gas and oxygen flow controls depends on the experience of the plant operator since they will have to perform analysis of the previous castings.

8.2.5 Energy efficiency / savings

Energy savings are determined by two parameters. The first is related to the pre-set times for each casting phase based on EXIDE's experience over the years. The second is linked to the set points of the natural gas and oxygen flows of the controls. The application of this tool has made it possible to reduce some of the time in the melting process phases and therefore reduce casting times. It can be estimated that energy savings of around 7% were achieved.

9. Model-based control tools

9.1 Model-based control tools at Sidenor

The model-based control tool for the steelmaking use case at SID follows the Model Predictive Control (MPC) principles for multivariate control over a prediction horizon, i.e. the internal dynamic model of the process, a cost function over the prediction horizon and an optimization algorithm minimizing the cost function using the control inputs. As prediction horizon a time window of 5 minutes with 10 second time step intervals has been chosen as a compromise between computation time and sufficient forecasting time for the operator.

The internal dynamic model was described in detail in Deliverables 2.2 and 4.1 and is based on online acquired input data, and as such the model predictions also adapt just like the monitoring tool to measurements of steel temperature and composition. Note that the predictions and control suggestions will only be available for the refining phase of the EAF process because the melting phase follows a defined procedure, which shall not be modified.

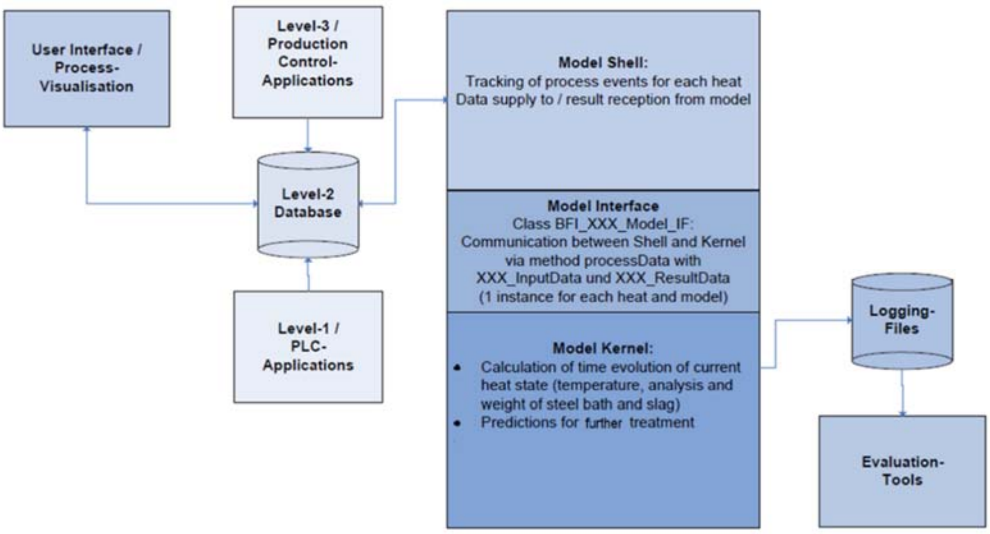


Figure 9.1: Deployment scheme of dynamic process model at Sidenor.

9.1.1 Accuracy

Evaluation tools complementing the dynamic process model are used to evaluate the model accuracy. In case of drifting a retraining of model parameters is performed to maintain the accuracy of the models. The results reported in Deliverable 4.1 suggest that the accuracy stays stable for at least a few months.

9.1.2 Resolution

The dynamic process model calculates the current heat state and forecast in intervals of 1 – 30 seconds. The interval can be adjusted based on the desired accuracy and limitations regarding data supply.

9.1.3 Reproducibility

Results are reproducible as no randomness is involved in the calculations.

9.1.4 Robustness

Data preprocessing and correction is integrated in the model software to ensure corrupt data and anomalies are not causing numerical issues during model calculation.

9.1.5 Reliability

The software is provisioned as compiled C++ library. Even in case of erroneous data supply, calculations can be resumed from the last calculated heat state.

9.1.6 Calculation Speed

Calculation speed is below 1 second and is therefore suitable for online monitoring

9.2 Model-based control tools at Grupal Art

Eurecat developed a model that was implemented in Grupal Art to assist controlling their process. This process control model took information from different process parameters and sensors at Grupal Art, in order to detect possible anomalies within Grupal Art production process. The main input for the model was the new gas flow sensor, installed at Grupal Art during REVaMP project.

9.2.1 Accuracy

The accuracy of gas flow measuring has increased several times, as before REVaMP project there was no reading or recording of the gas flow. The consumption of the gas flow was measured from a normal gas meter at the entrance of the factory, so therefore, only daily readings of the global plant consumption could be considered, without any possibility to differentiate from one furnace to the other.

From the REVaMP project, a new gas meter has been installed capable of reading the gas consumed every 15 minutes for each of the furnaces. This improvement permits us to know which furnace process is consuming more natural gas or the impact of any process modification implemented to minimize the gas consumption.

The control on natural gas consumption also gives information of the duration of the different process stages for the Decision support system, as in every stage of addition or extraction of material out of the furnace the gas is lowered to allow the workers to work close to the furnace and introduce or remove material. In a common gas flow curve like Figure 9.2, there are some troughs of natural gas, those are the moments where material is added or removed from the furnace.

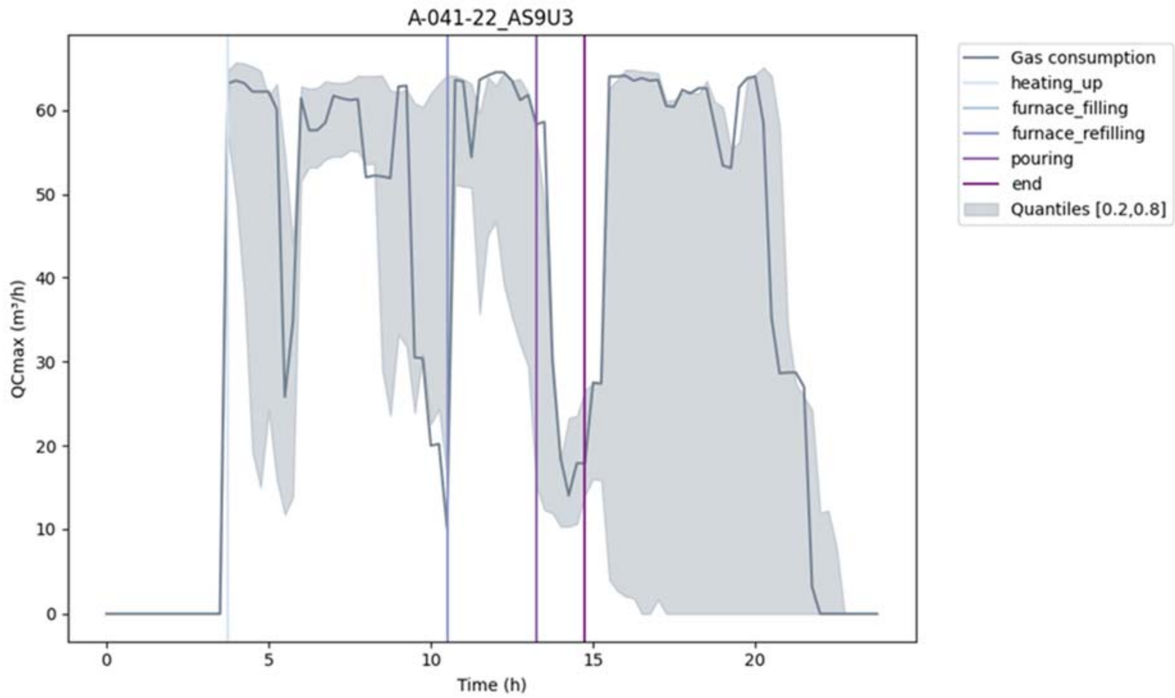


Figure 9.2: Gas flow chart measured at Grupal Art

9.2.2 Resolution

The resolution of the sensor has been lower than expected according to the information provided by the equipment supplier. It was supposed to have a reading of the gas consumed every minute, but the resolution of the sensor gave lectures lower than expected resulting in some readings of 0 consumption while the gas pipe was opened. In order to reduce the noise produced for these readings, was decided to use the accumulated value over 15 minutes, which gives much better results.

9.2.3 Detection limits

On one hand, the gas detection limit is 6m3/h. The detector does not read flows under that amount, giving a value of 0. On the other hand, the maximum volume flow that can read the detector is 100 m3/h. It also has a maximum working pressure of 16 bar. During the operation, the pipeline operates between 20 and 60 m3/h, inside the detection limits, so the sensor was correctly chosen.

9.2.4 Reproducibility

In order to assess the ability to obtain consistent and reproducible results, the reproducibility of the results obtained through multiple model runs was analysed.

The methodology involves executing the model several times using the same test dataset and parameters.

After conducting multiple model runs, a high reproducibility of results was observed. Consistent and comparable results were obtained in all runs, indicating that the model is stable and not influenced by random factors.

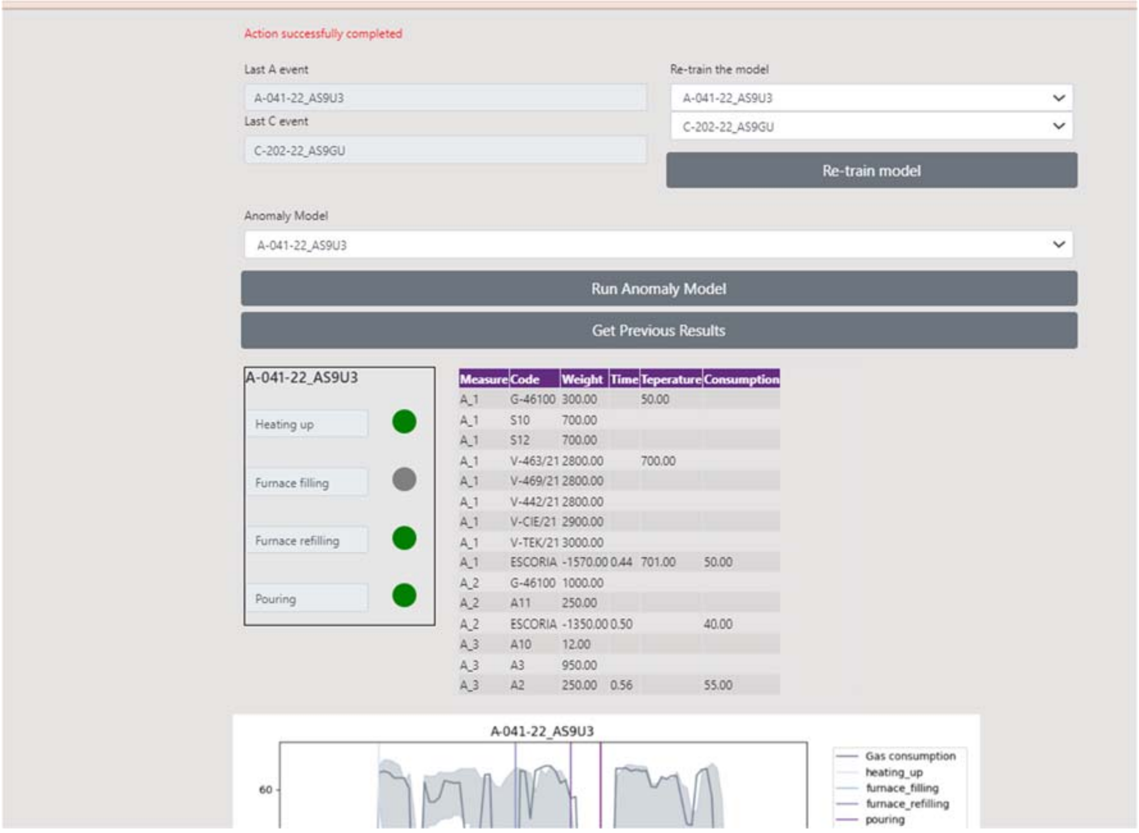


Figure 9.3: Image of the control process model user interface

The observed high reproducibility suggests that the model is robust and not subject to significant random fluctuations. The coherence of the results provides confidence in the model's ability to reliably address calculations.

8.1.7. Robustness

Since the robustness of the process control model depends on the robustness of the whole application deployed at Grupal Art. The tests conducted are the same as presented in section 7.3.3.

9.2.5 Reliability

Since the reliability of the model depends on the robustness of the whole application deployed at Grupal Art. The tests conducted are the same as presented in section 7.3.4.

9.2.6 Calculation speed

The gas and oxygen sensors are making measurements in real-time, previous to the installation, the calculation of the gas and oxygen consumption was by reading the consumer counter before and after the batch. Now there is a real-time measurement of the consumption of natural gas and oxygen, therefore, the calculation speed has increased to a real-time measurement. Even though the calculation speed of the sensors is in real-time, the model needs the information of the whole batch in order to detect an anomaly and, therefore it can only be used to evaluate the batch once it has been finished.

9.2.7 Energy efficiency / savings

The knowledge of real-time consumption allows to differentiate the consumption at the different stages of the production process. This differentiation allows us to focus on the different stages with a different approach to the problem. The initial stage of preparing and charging the furnace is nowadays shorter reducing the total production time and reducing the total time process and reducing the total energy consumption.

Before the REVaMP project, the consumption of natural gas was 150 m3/ton of aluminium, nowadays, there is a 15% reduction with a total consumption of 127 m3/ton of aluminium produced.

9.2.8 Energy efficiency / savings

In the case of the models implemented at Grupal Art, both models, optimization and process control, have been tested and all their features validated. The models showed to be reliable, robust and provide an important advantage to the prior situation, before the implementation of the models. Grupal Art observed benefits in terms of reduction on the energy consumption as well as a better use of the feedstock materials.

9.3 Model-based control tools at Refial

The model-based control tool at Refial has three parts:

(i) a real-time data visualization and distribution system to get information to the right people,

(ii) a manager that detects events, extracts data, distributes and requests the calculation of predictions, while determining deviations and, if necessary, launching the optimization and

(iii) a REST API service where the predictive models, optimizers and advisors are grouped. Below is shown the visualization of the GUI (except for the part associated with the preheater, which has not been possible to develop due to delays in its creation) (see Figure 9.4) and the documentation with Swagger where it is visualized how a prediction is launched (Figure9.5) and how an optimization is obtained (Figure9.6).

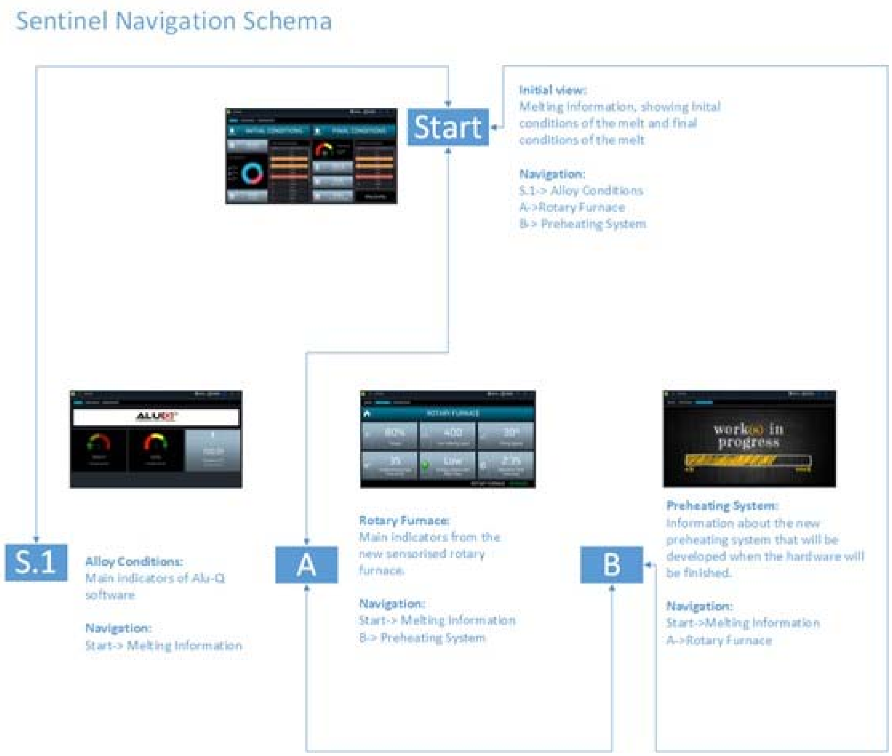


Figure 9.4: Navigation diagram of the monitoring tool

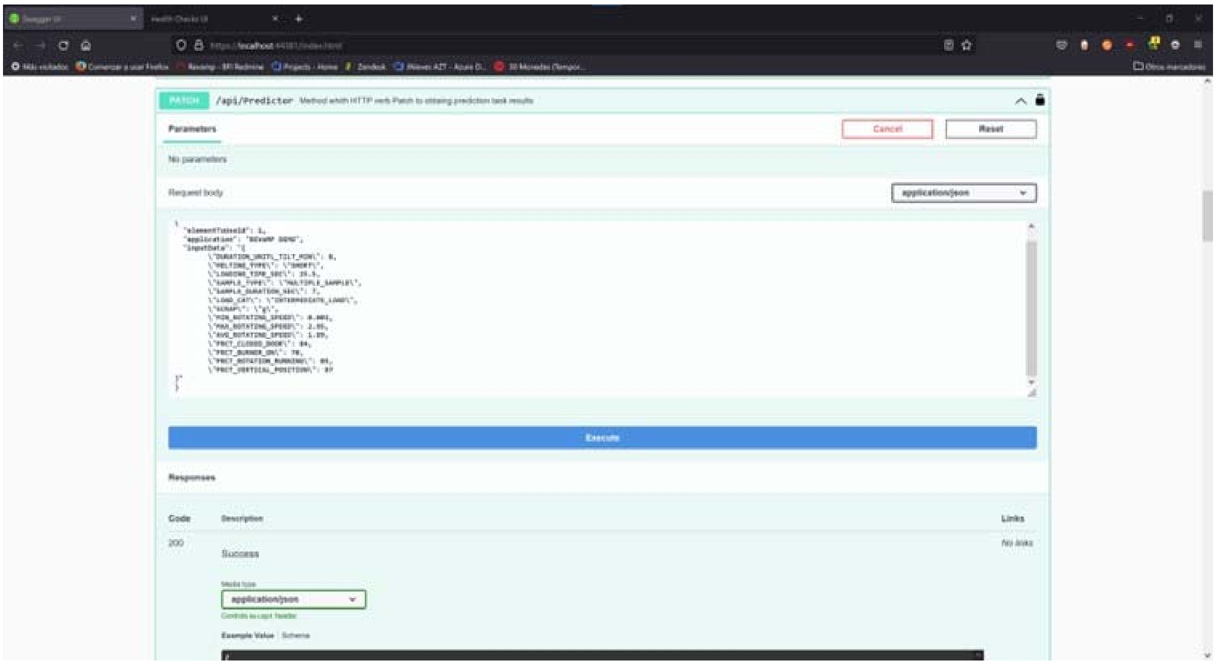


Figure 9.5: SaaS launching predictions (swagger documentation website)

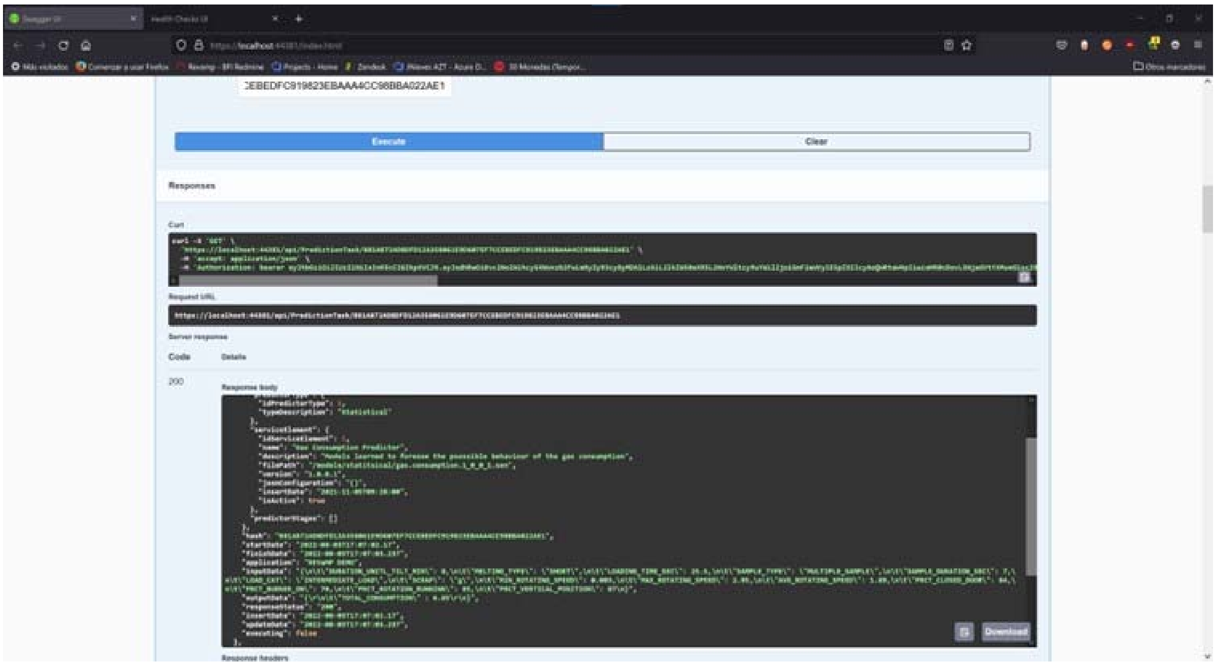


Figure 9.6: SaaS with optimization executed (swagger documentation website)

9.3.1 Accuracy

The created system is designed to maintain a high degree of accuracy. However, when using supervised learning, everything is based on the quality of the data. Thus, we must indicate that at this time, the data obtained for the studies and the generation of the models has low quality due to not having completed the preheating system and we are not able to carry out the full tests that includes it in the workflow. Nevertheless, it should be considered that, once it will be complete and quality information is generated, the results will be improved. Likewise, the optimization system uses these same models as part of its fitness function, so we are in the same situation that we have already mentioned.

9.3.2 Resolution

The optimization process is based on manufacturing events. In this way, when an event happens, the possible point at which we could find ourselves (t + 1 moment) is calculated and, if some anomalies are detected, that is, deviations, the optimization process will be launched. During the project, the appropriate baseline has been established and, taking into account those values, our decision support system will determine if the optimization algorithm has to be launched. Thus, our event driven system will be adapted to the fusion process and the generated events during the manufacturing.

9.3.3 Reproducibility

The generated system is a deterministic system that, given the same inputs, behaves in the same way. Thus, the determination moment for launching the optimization is clear, simple, and well determined. It is always detected in the same manner. On the other hand, the optimization system and its algorithm are not so deterministic. The search method does not follow a linear path and we can obtain different solutions for the same data. However, what it does is ensure that the degree of completion and quality of its result will be the same.

9.3.4 Robustness

The provided system is robust and is prepared to deal with failures. Despite this, this system depends on third parties. The system must use third-party data for its calculation. This second process or connection is the one that we have not been able to strengthen. Thus, that is why the strategy has been developed to manage failures or incorrect data sending.

9.3.5 Reliability

The visual part of the system is developed as a full Microsoft Windows desktop application. If there is an error and it is restarted, the information is always recovered from the injector system. This software is only a painting system.

The injection software for sending real-time data is created as a Microsoft Windows service. This type of solution allows us to determine the operation of the programs when detecting errors or crashes. In this way, for this software we have chosen to relaunch and restart it.

Finally, the calculation and optimization task, done as a SaaS service, has been created to be able to be deployed in Docker. This option, whether or not linked to an orchestration system such as Kubernetes, already functions in similar way as a Windows service. We assure that under failures it will be restarted. If we have an orchestration framework, we can ensure and manage its scalability in much more efficient way, as well as error recovery.

9.3.6 Calculation Speed

As already mentioned, the current division of the system shows that there are two clearly differentiated operations. The first of them is prediction or, in order words, trying to discover what will happen at an instant of time t+1. This activity is carried out with Machine Learning statistical models. In this case, predictions and correlations are activities that do not require a large amount of time. That is why the sum of these tasks does not exceed the second, just milliseconds.

Secondly, the optimization operations, which are done with an evolutionary programming algorithm, are more time consuming. In fact, we cannot establish first-hand how long it will take. However, the algorithm is configured with different parameterizations that help to manage time better (i.e., maximum number of generation). Given the problems associated with the generation of the preheater system, we are not able to tell the real average time in an optimization work for this system.

9.4 Model-based monitoring and control tools at Exide

Within the smart visualization tool developed in the lead use case, one of the modules was focused on monitoring the data from the combustion and aspiration processes in the furnaces that are collected from the PLCs and the production data obtained from excel files.

The accuracy of this tool depends on the data acquisition system, either due to errors in the sensors installed in the furnace, due to communications between the PLC and the server, or due to failures when collecting data from Excel files for integration them into the database.

The information analysed may detect errors or improve parameters of the melting process, but obviously the benefits of using this application cannot be determined quantitatively in the form of time or energy savings.

10. Overall conclusions

A technical evaluation of the different retrofitting solutions developed within the REVaMP project has been conducted. Due to the very different nature of the solutions, different evaluation criteria had to be applied.

As a main conclusion it can be stated that the majority of the retrofitting solutions fulfil the requirements for a permanent application in industrial operation. Some deficiencies had to be stated, especially regarding the scrap preheating system, as its application could not be performed in the full functionality as expected in the beginning of the project.